DESIGNING FLEXIBLE ENGINEERING SYSTEMS UTILIZING EMBEDDED ARCHITECTURE OPTIONS

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INTERDISCIPLINARY STUDIES: SYSTEMS ENGINEERING

DESIGNING FLEXIBLE ENGINEERING SYSTEMS UTILIZING EMBEDDED ARCHITECTURE OPTIONS

JEFF G. PIERCE

Dissertation under the direction of Professor Sankaran Mahadevan

This dissertation develops and applies an integrated framework for embedding flexibility in an engineered system architecture. Systems are constantly faced with unpredictability in the operational environment, threats from competing systems, obsolescence of technology, and general uncertainty in future system demands. Current systems engineering and risk management practices have focused almost exclusively on mitigating or preventing the negative consequences of uncertainty. This research recognizes that high uncertainty also presents an opportunity to design systems that can flexibly respond to changing requirements and capture additional value throughout the design life. There does not exist however a formalized approach to designing appropriately flexible systems.

This research develops a three stage integrated flexibility framework based on the concept of architecture options embedded in the system design. Stage One defines an eight step systems engineering process to identify candidate architecture options. This process encapsulates the operational uncertainty though scenario development, traces new functional requirements to the affected design variables, and clusters the variables most sensitive to change. The resulting clusters can generate insight into the most promising regions in the architecture to embed flexibility in the form of architecture options. Stage Two develops a quantitative option valuation technique, grounded in real options theory, which is able to value embedded architecture options that exhibit variable expiration behavior. Stage Three proposes a portfolio optimization algorithm, for both discrete and continuous options, to select the optimal subset of architecture options, subject to budget and risk constraints. Finally, the feasibility, extensibility and limitations of the framework are assessed by its application to a reconnaissance satellite system development problem. Detailed technical data, performance models, and cost estimates were compiled for the Tactical Imaging Constellation Architecture Study and leveraged to complete a realistic proof-of-concept.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	Definition
ACS	Attitude Control System
AO	Architecture Option
BAC	Broad Area Collector satellite
BOE	Basis of Estimate
CAIV	Cost as an Independent Variable
CAL	Capital Allocation Line
CDL	Common Data Link
CDR	Critical Design Review
CER	Cost Estimating Relationship
CLIOS	Complex Large-scale, Interconnected, Open Socio-technical System
CMEA	Change Modes and Effects Analysis
CMG	Control Moment Gyro
CONOP	Concept of Operation
CONUS	Continental United States
CPF	Central Processing Facility
CPF	Cost Per Function
CPM	Change Potential Number
DCF	Discounted Cash Flow
DDL	Direct Downlink
DM	Datar-Mathews options valuation technique
DoDAF	Department of Defense Architecture Framework
DPI	Design Preference Index
DSM	Design Structure Matrix
DTA	Decision Tree Analysis
EOL	End-of-Life
EPS	Electrical Power System
FMS	Flexible Manufacturing Systems
FoS	Family-of-Systems
FPA	Focal Plane Array
FSEU	FPA Support Electronics Unit
GA	Genetic Algorithm
GAO	Government Accountability Office
GB	Gigabit
GM	Geometric Mean
GMC	Ground Motion Compensation
GPS	Global Positioning System
GSD	Ground Sample Distance

H	Edge Height Overshoot
HSDHU	High Speed Data Handling Unit
ICE	Independent Cost Estimate
IDEF0	Integration Definition for Function Modeling
IFOV	Instantaneous Field of View
IMINT	Imagery Intelligence
IOC	Initial Operational Condition
IPT	Integrated Product Team
IR	Infrared
ISR	Intelligence, Surveillance, and Reconnaissance
KPP	Key Performance Parameter
LCC	Life Cycle Cost
LCV	Life Cycle Value
LMLV	Lockheed Martin Launch Vehicle
L-O	Likelihood-Opportunity
LOS	Line-of-Sight
LRR	Launch Readiness Review
MAD	Marketed Asset Disclaimer
MATE-CON	Multi-Attribute Tradespace Exploration with Concurrent Design
MDL	Minimum Description Length
MOE	Measure of Effectiveness
MPT	Modern Portfolio Theory
MTF	Modulation Transfer Function
MTTA	Mean Time to Access
NIIRS	National Imagery Interpretability Rating Scale
NPV	Net Present Value
NRL	Naval Research Laboratory
NRO	National Reconnaissance Office
OTF	Optical Transfer Function
OV	Operational View
PC	Point Collector satellite
PDE	Partial Differential Equation
PDR	Preliminary Design Review
PSF	Point Spread Function
R&D	Research and Development
RER	Relative Edge Response
RO	Real Option
ROA	Real Options Analysis
ROE	Return on Equity
ROM	Rough Order of Magnitude
SAF	System Adaptability Factor
SCDL	Space-Common Data Link

s-DSM	Sensitivity-Design Structure Matrix
SE	Systems Engineering
SNR	Signal-to-Noise Ratio
SoS	System-of-Systems
SSPA	Solid State Power Amplifier
SWOT	Strengths, Weaknesses, Opportunities, and Threats
TDI	Time Delay Integration
TDRS	Relay Satellite
TICAS	Tactical Imaging Constellation Architecture Study
TPM	Technical Performance Measure
TSAT	Transformational Satellite Communication System
TSE	Traditional Systems Engineering
TWTA	Traveling Wave Tube Amplifier
UAV	Unmanned Air Vehicle
USCM-8	Unmanned Space Vehicle Cost Model Version 8
VE	Variable Expiration
WBS	Work Breakdown Structure
WGS	Wideband Gapfiller Satellite System

GLOSSARY OF KEY TERMS

Attributes: Fundamental capabilities of the system that represent the features or functions of the system needed or desired by the customer. An attribute should usually be stated in such a way that it describes what the system should do. The associated capability should also be stated in a manner that is solution independent. This permits consideration of different ways of meeting the need or of providing the feature or function.

Concept of Operation (CONOP): This type of document focuses on the goals, objectives, and general desired capabilities of the potential system without indicating how the system will be implemented to actually achieve the goals.

Engineering System: Large-scale, technology enabled, interconnected system where analysis and design are done at the enterprise level (within and between organizations) and the societal level (considering contextual factors such as social, political, institutional and economic factors). As such, the design process examines the interaction of system components rather than examining individual components (which is primarily the domain of the engineering scientist). Because of system scale and complexity, emergent properties are very likely to occur and the design process requires the inclusion of many system characteristics and impacts that were not adequately considered in previous design approaches (i.e., quality, reliability, survivability, sustainability and flexibility, etc.).

Family-of-Systems (FoS): A portfolio or group of systems singularly managed (e.g. military or defense projects) for the combined capability accomplished by the interaction and cooperation of the individual systems.

Flexibility: The property of a system that allows it to respond to changes in its initial objectives and requirements—both in terms of capabilities and attributes—occurring after the system has been fielded, that is, in operation, in a timely and cost effective way

[System] Function: A characteristic task, action, or activity that must be performed to achieve a desired outcome. For a product it is the desired system behavior. A function may be accomplished by one or more system elements comprised of equipment (hardware), software, firmware, facilities, personnel, and procedural data.

Life Cycle Value (LCV): The value delivered over the entire design life of a system where value is defined as total benefits, articulated and unarticulated, net of cost.

Model: A representation of a real world process, device, or concept.

Options-thinking (optionality): A conceptual design approach, or mindset, that seeks to identify new paths and illuminate opportunities that may have previously been underused or overlooked.

Unlike conventional decision analysis, which works with a predetermined set of possible decision paths, the options approach seeks to identify new paths and change the decision tree by adding flexibility for its own sake.

Operational Environment: The circumstances, objects, and conditions that will inßuence the completed system; they include political, market, cultural, organizational, and physical influences as well as standards and policies that govern what the system must do or how it must do it.

Operational Uncertainty: Related to the requirements (or demands) on, and environment of, a fielded engineering system. Aspects include: political uncertainty (pertaining to funding instability), lifetime uncertainty (pertaining to uncertainty in performing to the requirements during system lifecycle), obsolescence uncertainty (pertaining to uncertainty of performing to evolving expectation during system lifecycle), integration uncertainty (pertaining to uncertainty in the interactions with other necessary systems), cost uncertainty (pertaining to uncertainty in meeting operating cost targets), and market uncertainty (pertaining to uncertainty in meeting the demands of a changing market environment).

Operationalization: Research method terminology for the act of translating a construct into its manifestation—for example, translating the idea of design flexibility into the actual instantiation of options in the architecture, or translating the idea of what is desired to be measured into the real measure.

Operational Scenarios (synonyms: vignettes, threads): Deliberately anticipated use cases that embody, or encapsulate, the necessary functions or behavior of a fielded system in a forecasted environment.

Nadir: The direction looking directly below a location. It orbital mechanics, the nadir vector points from the satellite location to the center of the earth.

[System] Requirement: (a) A condition or capability needed by a user to solve a problem or achieve an objective. (b) A condition or capability that must be met or possessed by a system or system component to satisfy a contract, standard, specification, or other formally imposed document.

Risk Management: An organized method, or process, for identifying and measuring risk and devising options for handling or mitigating risk. Risk is a level of threat due to potential problems, where knowledge of the risk is an opportunity to avoid a consequence of occurrence.

System: An interdependent group of people, objects, and procedures constituted to achieve defined objectives or some operational role by performing specified functions. A complete system includes all of the associated equipment, facilities, material, computer programs, firmware, technical documentation, services, and personnel required for operations and support to the degree necessary for self-sufficient use in its intended environment.

System Architecture: An abstract description of the entities of a system and the relationships between those entities, intended to yield certain primary functions, plus other properties referred to as “ilities” (e.g., durability, maintainability, flexibility, etc.).

Systems Engineering (SE): The process by which a customer’s needs are satisfied through the conceptualization, design, modeling, testing, implementation, and operation of a working system.

System-of-Systems (SoS): A configuration of systems in which component systems can be added/removed during use; each provides useful services in its own right; and each is managed for those services. Yet, together they exhibit a synergistic, transcendent capability.

Uncertainty Management: An organized method, or process, for dealing not only with risk (level of threat for negative consequence), but with opportunities enabled by uncertainty. High levels of uncertainty present both potential downside consequences and upside benefits.

Value-centric: Engineering design focus, or perspective, that incorporates both cost and utility implications for design trade-offs and analysis.

Value-robust (synonyms: value-sustainable, persistent value): The ability to deliver value despite changes in context and stakeholder desires over the lifecycle of the system. Also, it is the ability to capture latent (hidden, unarticulated, dormant, or evolved) value.

CHAPTER I

INTRODUCTION

1.1 Motivation

Across a wide array of industries, organizations, projects, and disciplines, flexibility has become a key design concept. Businesses adjust strategies and redeploy resources as the competitive and consumer environments change; they use knowledge and labor capital in innovative ways to meet the demands of the uncertain future. Builders create reliable and safe structures that not only meet the demands of today, but have value across an extended lifetime where design loads may be subject to unforeseen change. Software designers maintain "hooks" in the code where additional features can later be included. From structures and architecture (Fox & Yeh, 1999) to manufacturing lines (Browne *et* al., 1994), the concept of flexibility has been studied and implemented across a diverse landscape of disciplines. This has yielded an equally diverse set of definitions, approaches, and implementation techniques. In the design of large, complex engineering systems, where the stakes are often the highest, the importance of flexibility is well known, but the structured means of designing it into the system architecture has yet to be resolved. System engineers have relied largely upon intuition and ad hoc methods, which are neither rigorous nor repeatable (Crossley, 2006). The systems engineering community by and large has neither adopted the philosophy nor developed the techniques required to design appropriately flexible systems. This motivates a rigorous examination of the way systems are designed and developed in particular relation to a system's ability to handle uncertainty and be valuable over the entire course of its design life.

1.2 Introduction

Simply understood, flexibility is the ability to respond to change. In relation to an engineered system, flexibility is the property (or attribute) of that system which is capable of undergoing classes of change with relative ease (Allen *et* al., 2001; Bartolomei *et* al., 2006). Flexibility can allow an engineered system to better handle unpredictability in the operational environment, threats from competing systems, obsolescence of technology, and general uncertainty in future system demands (Saleh, Hastings, and Newman, 2003).

The traditional systems engineering (TSE) process (Sage & Rouse, 1999; INCOSE SE Handbook, 2004) has worked well for monolithic system design which predominantly emphasizes a "design-to-spec" philosophy and manages uncertainty with safety factors derived from probabilistic analysis (de Neufville, 2004). This process remains well suited for systems that maintain relatively stable requirements for which a robust design, defined by Chen and Lewis (1999), and Saleh, Hastings, and Newman (2003), can adequately handle uncertainty. Modern engineering systems however are more expensive, complex, and interconnected than ever before. They operate longer and when utilized as part of a dynamic Family-of-Systems (FoS) or System-of-Systems (SoS), are subject to higher degrees of uncertainty than their monolithic predecessors[1]. This new breed of systems engineering problem requires more intentionality in handling risk and uncertainty.

The risk management practices associated with TSE have tended to focus on the mitigation of negative consequences, often disregarding uncertainties that create opportunities (Browning & Hillson, 2003). Years of emphasis on reliability analysis has perpetuated the prevailing mantra, "good designs never fail (Petroski, 1994)." This design philosophy is

[1] The increased complexity due to the larger number of systems, subsystems, and components creates more sources from which uncertainty can arise. Longer time scales allow uncertainty to grow larger. System interconnections and the associated uncertainty increase exponentially as systems are added.

distinctly one-sided. Concentration on failure prevention alone does not reflect the overarching objective to maximize the life cycle value (LCV) of a system—that is the value derived over the life of the system (Browning, 2005). Alternatively, a value-centric approach can harness uncertainty by recognizing the importance of proactively designing for opportunities (Browning, 2005; Ross & Rhodes, 2007; Saleh, Jordan, and Newman, 2007). High uncertainty therefore produces an opportunity to embed added value in a system design through the system's ability to flexibly adapt to emergent conditions.

1.3 Integrated Design Flexibility Framework

While many authors have eloquently discussed the topic of flexibility (see Chapter II), it is not apparent that any have proposed a general design approach that can be readily implemented by system engineers on real projects. The aim of this work is therefore: to develop a high level conceptual framework, with associated qualitative and quantitative techniques, that emphasizes compatibility with current systems engineering practices, and allows for informed and justified decisions regarding the incorporation of embedded flexibility in a system architecture.

The use of options, specifically "Real Options" has been proposed as a way to operationalize the concept of flexibility. Fundamentally, "options thinking" recognizes the existence of value in securing the freedom of choice as new information is revealed. Widely used in finance, options are typically contracts that allow the holder of the option to purchase (or sell) an asset (e.g. shares of common stock, other market traded security) at a predetermined exercise price at or before the expiration date. Similarly, a real option is a right, but not an obligation, to take some action at a certain cost within or at a specific time period (Dixit & Pindyck, 1994; Trigeorgis, 1996; Luenberger, 1998; Amram & Kulatilaka, 1999; Brennan & Trigeorgis, 1999; Mun, 2002; Copeland & Antikarov, 2003). A real option is not a contract to buy or sell an underlying financial asset; it is the ability to "do something," to take an action, or implement a change or alteration.

de Neufville (2002) identified two types of real options: 1) real options "on" projects, and 2) real options "in" projects. Real options "on" projects, similar to financial call options, give a business the right, not obligation, to invest in a project. Technology and the engineering design of the project are treated essentially as a "black-box." These options are concerned with "go" or "no-go" decisions and are predominantly defined as options for scaling, deferring, and abandoning a project. Real options "in" projects are internal to the design process, embedded in the architecture, and allow an engineering design to change as actual demands on the system develop. Real options "in" projects require in-depth technical domain knowledge to discover and exploit and have been applied to engineering design in an effort to "design in" flexibility (de Neufville, 2003). Browning and Engel (2008) proposed an additional classification for real options "in" projects, called "Architecture Options (AOs)." Adapted from Baldwin and Clark (2000), they define AOs in terms of system modularity, where each module in the system of interest is composed of a set of software and hardware components. Modules, they argue, accommodate uncertainty by allowing particular elements in the architecture to be changed more easily after the fact, and in unforeseen ways, with minimal extra-module interaction. The authors conclude that the more modules that exist within the system, the more options that are present, yielding a higher "option value." Whereas the extra-module interactions constitute the "option cost." This research has adopted the term "architecture options," but has defined this concept in a different way.

It is contended here that architecture options are not solely a function of the modularity of the system, but are instead *an encapsulation of a set of physical design components (or design variables) that necessarily enable an identifiable function or capability of value.* Each AO must be tied to a function or functions that fulfill a desired stakeholder need, whether articulated or unarticulated by the stakeholder, whether known precisely or forecasted. The AO value is then derived from the added capability enabled and not from the virtue of being modular. Furthermore, the AO cost is more generally a function of the implementation and operational costs associated with the exercise of the option and not of the sheer number of interfaces present between modules (although interfaces can play a role in defining the implementation cost). This distinction is important and will become apparent as the high level flexibility framework is next described.

A three stage approach has been developed in this research to discover, analyze and implement design flexibility in a system architecture. This approach is pictorially illustrated in Figure 1. Stage one deals with identifying the most promising regions in the system architecture for embedding AOs and subsequently developing detailed definitions for these candidate AOs for further valuation and selection. After candidate AOs have been identified through the architecture screening process, they are next valuated either monetarily or through stakeholder utility functions. A Real Options technique is extended to accomplish valuation which results in the mean option value and variance for each AO. An optimal subset, or portfolio, of architecture options is then selected in stage three of this approach by solving the objective function for maximizing lifecycle value and minimizing portfolio risk. AO risk is considered both in terms of the variance of the option payoff and the diversification of the underlying sources of uncertainty.

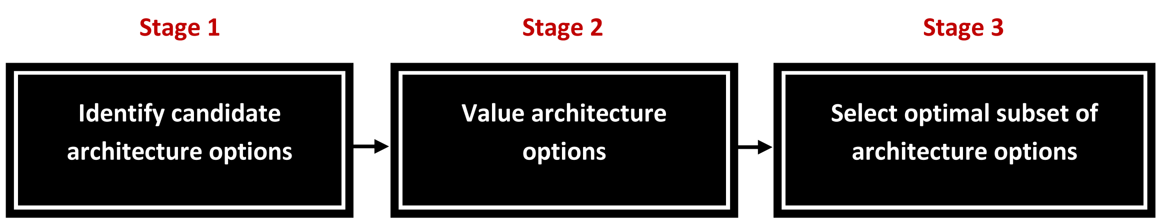

Figure 1: Three stage integrated flexibility framework for identifying, valuating, and selecting architecture options

1.4 Problem Statement and Research Question

System Engineers are faced with the challenge of designing and developing complex systems under uncertainty. The demands for increased design life, higher complexity, broader interconnectedness, and integration within a family-of systems have all contributed to higher levels of uncertainty in system operation. Current systems engineering and risk management methods, by focusing on negative outcome prevention, do not effectively handle this uncertainty. Flexibility embedded in the system architecture has been proposed as a technique to manage operational uncertainty and capture its upside potential. However, a formalized flexible design process does not currently exist. This presents a need for a disciplined and integrated uncertainty management approach that yields lifecycle value-driven systems that can better handle the uncertainty in the operational environment.

Research Question:

> How can system engineers design appropriately flexible systems that can deliver sustained value in the face of operational uncertainty over the system lifecycle?

1.5 Research Goal and Objectives

The goal of this research is to develop an uncertainty management approach (framework) within the systems engineering process that utilizes design flexibility to facilitate architecture decisions based on the maximization of life cycle value. Four distinct objectives have been identified and pursued in this research:

A. Develop a process for identifying candidate architecture options
B. Develop a systems engineering-compatible technique for valuing system architecture options
C. Develop an approach to identify an optimal subset of architecture options subject to budget and risk tolerance constraints
D. Demonstrate the flexibility framework by its application to an engineering system design problem and evaluate the approach for its extensibility into systems engineering practice.

1.6 Research Approach

In order to address the research question, the research design involves four main thrusts: knowledge capture and synthesis, theory and methodology development, framework integration, and framework implementation. *Knowledge capture and synthesis* explores how existing ideas and theoretical constructs currently used to understand flexibility can be grafted into new flexible design solutions. *Theory and methodology development* seeks to generate novel concepts and the necessary tools to support the framework development. *Framework integration* is where the proposed new methods are fit together as a cohesive whole. *Framework implementation* uses a real world design problem to test the proposed framework and characterize the salient issues for the system architect (e.g. data availability and collection, scenario planning, cost estimation, etc.). Framework implementation generates insights into the sensitivities of the design solution to the input parameters and also allows for an analysis of the limits, applicability, and deployability of the research. This research approach is captured in the flow diagram in Figure 2.

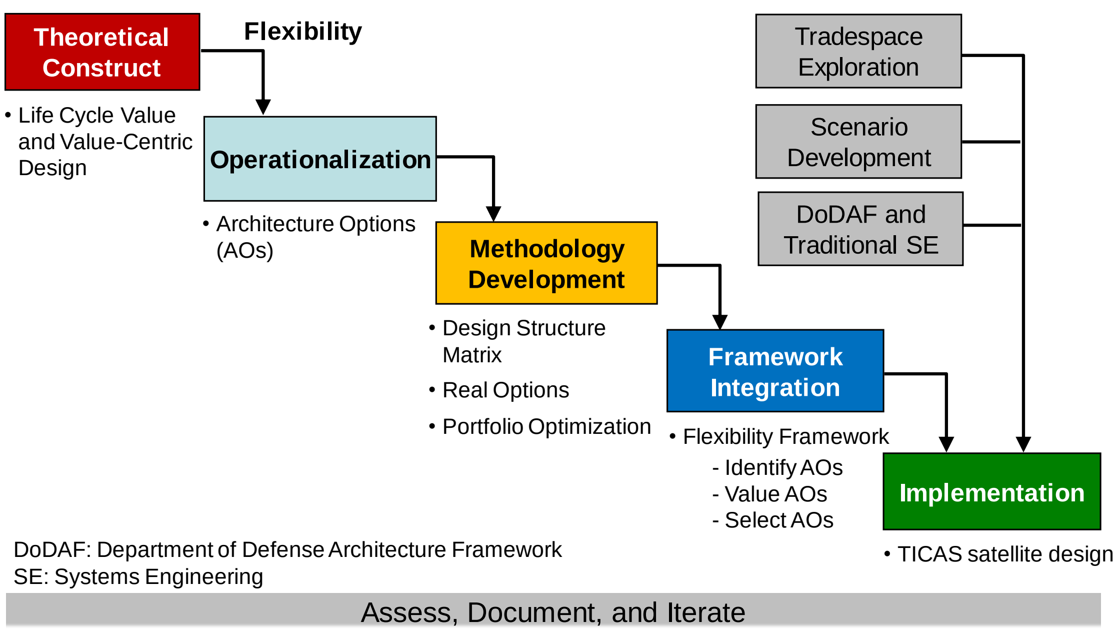

Figure 2: High level research approach.

1.7 Research Scope

Due to the expanse and complexity of the practices and techniques used to design engineered systems, a number of assumptions are required to limit the scope of any targeted investigation. In particular, the scope of this research is limited by the following assumptions:

1. The traditional systems engineering process as documented in Sage & Rouse (1999) and the INCOSE SE Handbook (2004) is adopted as the underlying design philosophy. This systems engineering practice follows the process of identification of customer needs, requirements analysis, functional analysis and decomposition, design synthesis and tradeoffs, and system verification/validation. This process provides the foundation for the eight step screening process presented in Chapter III.
2. A definition of flexibility is adopted that emphasizes a system's response to uncertainty in the operational environment which occurs after the system has been fielded (Saleh, Lamassoure, and Hastings, 2002). This research therefore excludes the type of flexibility found within the design process which is used to accommodate changes in requirements throughout the system development.
3. Architecture options are defined to be physically independent. This allows for the independent evaluation of the benefits, costs, and implementation characteristics of each architecture option irrespective of any potential physical overlap of the affected design parameters.
4. A baseline system architecture is assumed to exist which meets at least the threshold requirements for the critical mission. This allows for the evaluation of architecture options as an additional characteristic of the system and does not necessitate a full system optimization in assessing each individual architecture option.
5. The value of each architecture option is described by the mean and variance of the option payoff. Other statistical characteristics like the median or maximum values can be used

to enhance the understanding of the architecture option, but are not formally considered in the valuation and selection techniques.

6. Selection of an optimal portfolio of architecture options in Chapter V is based on the economic or financial understanding of risk. For the purposes of portfolio optimization, risk is defined in this research as the variance (or standard deviation) of the portfolio return (Markowitz, 1959). In this research, risk is the uncertainty in the value of the architecture option. Other definitions of risk which reflect characteristics like probability of failure (component level, system level, or mission level), technology maturity, or other external risks (e.g. environmental, societal, etc.) are not considered in this research.

1.8 Thesis Outline

The structure and flow of the thesis is depicted in Figure 3 and described as follows. **Chapter II** is an overview of flexibility in system design. This chapter covers current ways of thinking about flexibility and relevant valuation techniques. Special focus is devoted to how the measurement of flexibility in management, economics, and finance relates to flexibility embedded within the system architecture. **Chapter III** contains the first stage in the integrated flexibility framework: identification of candidate options for flexibility through an architecture screening process. This chapter develops an eight-step process that leverages the design structure matrix to organize and identify clusters of design variables that are sensitive to changes in system demands. **Chapter IV** proposes a new, intuitive methodology for valuing real options embedded in the system architecture. This method is not constrained by many of the assumptions needed for traditional option valuation and emphasizes compatibility with the systems engineering process. Mathematical measures of sensitivity are formulated to show how the option value changes as the input parameters change. **Chapter V** develops a portfolio optimization technique that can be used to select an optimal subset of architecture options subject to the budget and risk tolerance of the stakeholder. **Chapter VI** demonstrates the proposed framework by its application to an electro-optical spacecraft design problem. The methodology and related analytical techniques are applied for each stage of the integrated flexibility framework, followed by an assessment of its benefits and challenges. **Chapter VII** summarizes the dissertation and provides recommendations for areas of future research.

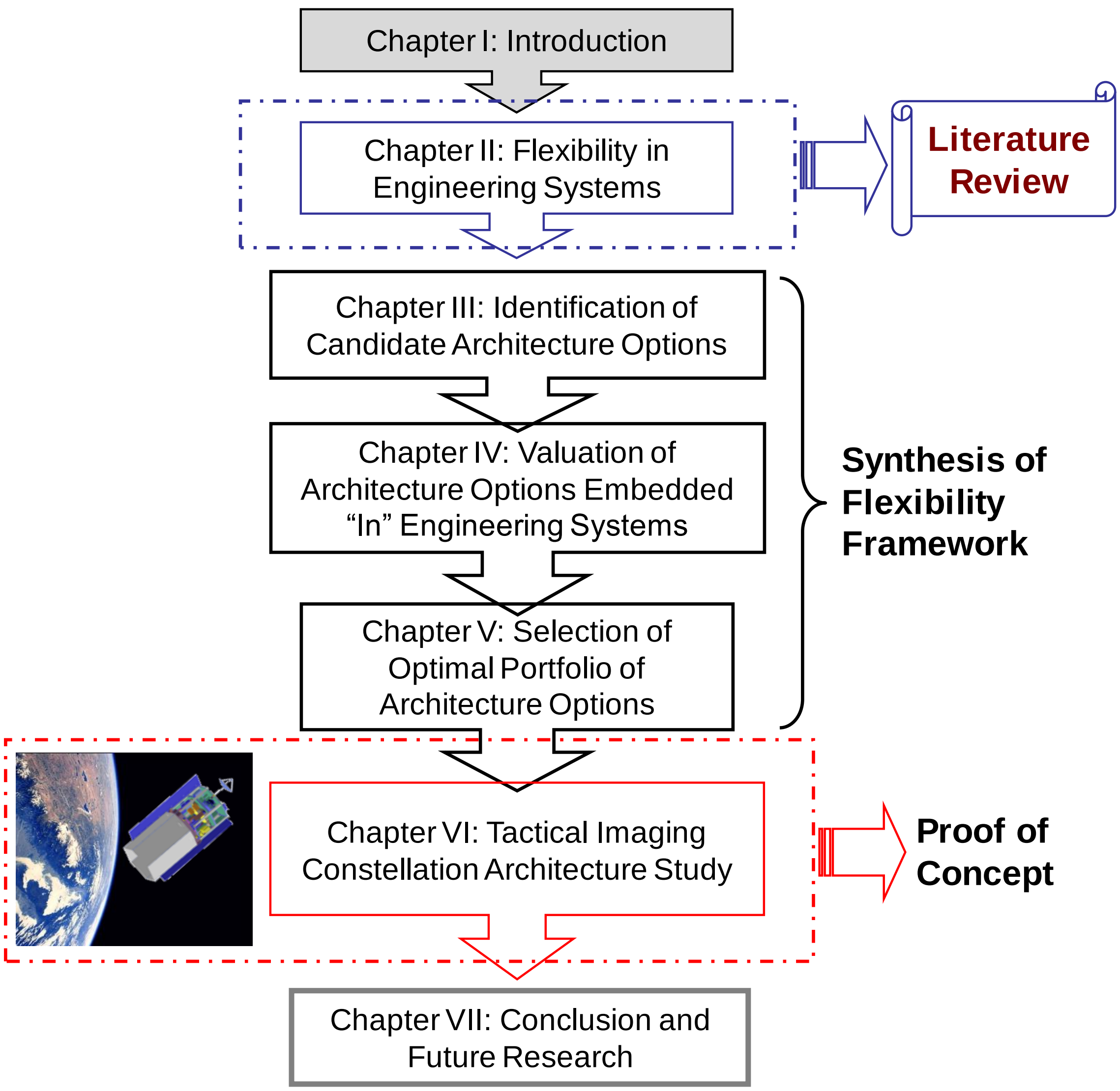

Figure 3: The dissertation flow.

CHAPTER II

FLEXIBILITY IN ENGINEERING SYSTEMS: A LITERATURE REVIEW

2.1 Introduction

This dissertation chapter explores the idea of flexibility and its introduction into system design, both in theory and practice. The topic is first motivated by explaining the theoretical construct of life cycle value which drives the desire for system flexibility. The concept and definition of flexibility is formally introduced and differentiated from its close synonyms. The context from which flexibility emerged is explored as well as some of the techniques that have previously been proposed to measure it. Finally, the conclusion is reached that there does not currently exist a formalized or codified process with associated quantitative tools that allow for a rigorous and defendable assessment of flexibility in the system architecture.

2.2 Value Centric Design as a Theoretical Construct for System Flexibility

The systems engineering and design community has seen an emphasis and proliferation of cost models[2]. Most projects employ some form of Life Cycle Cost (LCC) analysis or Independent Cost Estimate (ICE) and utilize techniques like Cost Estimating Relationships (CERs), "design to cost," or Cost as an Independent Variable (CAIV) to support the systems engineering and trade study process. To an outside observer, this emphasis on understanding project cost might indicate that engineering projects are exclusively cost sinks (Larson, Wertz, and D'Souza, 2005). While cost modeling can be useful, emphasis in the design community

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[2] Examples: SMC/Tecolote's Unmanned Space Vehicle Cost Model Version 8 (USCM-8), NASA/Air Force Cost Model (NAFCOM), Aerospace Corporation's Small Satellite Cost Model (SSCM), PRICE Systems cost model, Galorath's SEER, Aerospace Corp's CoBRA.

should also be placed on revenue and utility models (Saleh, Jordan, and Newman, 2007). Decision-makers must understand both the cost and revenue/utility of a system to adequately assess its value. Ross (2006) defines value as the relative worth, importance, or quality of a thing with respect to its ability to accomplish its purpose or effect. Simply understood as a perceived benefit net of cost, value has widely been proposed as a more complete and appropriate metric for system design (Browning, 2005; Ross, 2006; Ross & Rhodes, 2007; Saleh, Jordan, and Newman, 2007; Browning & Engel, 2008).

Ross and Rhodes (2007), and Ross (2007) extended the idea of value-centric design by referring to the concept of value robustness. They argue that for increasingly dynamic and interconnected environments, systems must be designed for enduring value; successful design strategies must create systems that can operate in a changing context, by adapting to shifting stakeholder needs and effectively leveraging uncertainty. A value robust system can best deliver a sustained level of value, even capture latent or unarticulated stakeholder value, as new demands and opportunities arise throughout the entire system life. As a design philosophy, one that is cost-focused may attempt to minimize LCC by selecting the low cost approach that meets the threshold level customer requirements. This approach does not necessarily reflect a best value solution. In comparison, a value-focused (or value-centric) approach will seek to maximize LCV and will more fully consider design solutions that cost more, but deliver higher levels of value over the system lifecycle. The desire for value robust systems that can operate under higher levels of operational uncertainty will inevitably drive the system architect toward more flexible design solutions that can deliver value even in the changing context.

2.3 Introduction to Flexibility

Systems are constantly faced with unpredictability in the operational environment, threats from competing systems, obsolescence of technology, and general uncertainty in future system demands. An analyst would conclude that systems that live longer and deliver more value are those that can more effectively deal with uncertainty and change. From a designer's perspective: if longer lifetime and increased value delivery are desired for a system, flexibility and adaptability must be embedded in the design (Saleh, 2003). A unique relationship can be established from these observations—that is, the relationship between uncertainty, flexibility, and design life. This is conceptually depicted in Figure 4. Higher uncertainty and longer design life require increased flexibility; alternately stated, more flexibility allows a system to operate longer and cope with more uncertainty.

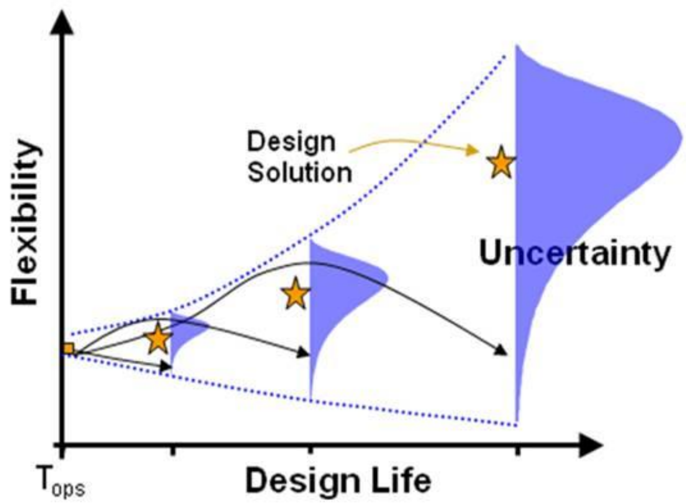


Figure 4: Conceptual model of the relationship between flexibility, uncertainty and design life. Longer design life and higher uncertainty necessitate increased system flexibility; in other words, highly flexible systems can handle more uncertainty over an extended useful life.

Although this relationship appears evident and foundational, system engineers have attempted in the past to accomplish one without the other. The design life of some current systems continues to rise while the concept of system flexibility has struggled to establish a codified definition, let alone a formal implementation process. Earth orbiting satellites, for example, are increasingly being developed for life spans of 15 years or more (e.g. geosynchronous communication satellites). This practice is driven by high launch costs, but is steeped more in the tradition of net present value (NPV) techniques that rely on out-year cash flows for investment and budgetary justification. These estimates are many times based on static assumptions--a snapshot in time--and do not reflect the dynamic operational environment.

2.4 Defining Flexibility

Intuitively, flexibility is interpreted as the ability to handle change. Somewhat more thoroughly, Allen (2001) and Bartolomei (2006) describe flexibility as "the property (or attribute) of a system that is capable of undergoing classes of changes with relative ease." But what is 'change' and how is 'relative ease' interpreted? At what point in the system lifecycle does this 'change' occur?

The appropriateness of a definition truly depends on the industry and application. Although insightful literature exists in relation to flexibility in manufacturing systems (Klahorst, 1981; Browne et. al., 1984; U.S.O.o.T. Assessment, 1984; Slack, 1987; Sethi & Sethi, 1990; Upton, 1995; De Toni & Tonchia, 1998; Nilchiani, 2005) and flexibility *of* the design process (Thurston, 1991; Wallace & Jakiela, 1996; Chen & Yuan, 1999; GAO-01-288, 2001; Saleh, 2001), this research has concerned itself primarily with flexibility as applied to engineering systems and management. There are a number of useful ways to define flexibility in engineering systems and management—some more conceptual and some aimed at quantification. This research has adopted ideas in both categories as a foundation for the proposed flexibility framework and related work. Any definition of flexibility, according to Saleh, Hastings, and Newman (2003), must address the following:

- The time associated with the occurrence of change, i.e., when the 'change' happens within the lifecycle of the system
- What is changing, e.g., the system's operational environment, the system itself, or the customer's desires or demands for the system
- Metrics of flexibility to enable the ranking of flexible design solutions.

Chen and Lewis (1999) attempt to clarify the understanding of ‘change’ such that flexibility is like “[…] a system of roads that permits a driver to reach from one point to another using several paths; it is the ease of programming the system to achieve a variety of functions, or the ease of changing the system’s requirements with a relatively small increase in complexity or rework.” These ideas are closely related to the concepts of network flexibility, where higher number of interconnections between nodes facilitates ease of movement and choice between multiple paths (Moses, 2003). Like the human brain changes by forming new pathways in order to complete new tasks, some have described 'changes' within flexible systems in a similar context.

From a system modeling perspective, Shaw, Miller, and Hastings (2001) argue, with an analysis of a communication satellite system, that flexibility is defined by the ease of movement from one design point to another on the tradespace design surface. This surface represents combinations of architecture design variables with the cost per function metric used to describe the ‘ease’ of movement. In contrast to strict multidisciplinary design optimization which searches for peaks and valleys, Shaw *et* al. described a flexible architecture as one that looks for plateaus or transitional regions in the tradespace.

Saleh, Lamassoure, and Hastings (2002) define flexibility in a way that emphasizes the timing and nature of the ‘change.’ Assuming that design modifications are used to accommodate any changes prior to the system being fielded: “[flexibility is] the property of a system that allows it to respond to changes in its initial objectives and requirements (both in terms of capabilities and attributes) occurring after the system has been fielded, that is, in operation, in a timely and cost effective way.” This definition implies that flexibility is necessary as a response to uncertainty in use—for if it were known exactly how the system was to be used over its lifetime, an appropriate design could exist from the beginning and flexibility would be completely unnecessary.

With its emphasis on changes occurring during operation (defining the ‘when’) and focus on changes to initial objectives (defining the ‘what’), Saleh’s definition has been adopted throughout this dissertation with the terms “system”, “design”, “requirements”, “capabilities”, and “attributes,” used in the sense defined by IEEE Std 1223 (1998). This definition serves as the foundation for our conceptual understanding of flexibility and responds to the first two needs identified by Saleh, Hastings, and Newman (2003) above.

Flexibility is the property of a system that allows it to respond to changes in its initial objectives and requirements—both in terms of capabilities and attributes—occurring after the system has been fielded, that is, in operation, in a timely and cost effective way.

2.4.1 Flexibility in Engineering Systems

Engineering systems are human-designed, technology-centered systems that are composed of interacting components and serve a given purpose (Moses, 2004). These systems can have significant complexity resulting from numerous interconnections, interactions, and interdependencies that make the system difficult to predict, manage, and design (Allen *et* al., 2001). An acronym given to a particular class of these systems is CLIOS: a Complex Large-scale, Interconnected, Open Socio-technical System. This type of engineering system has interactions not just between components and subsystems, but between social, political, economic, institutional, and physical systems (Sussman, 2000; Dodder & McConnell, 2005). Examples of CLIOS systems can be found throughout the transportation, aerospace, energy, manufacturing, and telecommunication sectors (de Weck & Eckert, 2007).

Engineering systems are many times required to operate in highly uncertain and rapidly evolving environments which make the system behavior difficult to predict. This uncertainty may occur because of changes in a dynamic market or in the wider economy. Changes in strategy, public policy, competitive forces, and technology all influence a customer’s demands on a system and contribute to the higher levels of operational uncertainty (de Neufville, 2004). As engineering systems across the spectrum are desired to last longer and deal with more uncertainty, the importance of flexibility in the system design becomes not just apparent, but imperative.

Numerous authors have taken up the challenge of defining and valuing flexibility in engineering systems, and while many of these methods have been elucidating and insightful, their mostly domain specific, qualitative, and descriptive nature has severely limited their general use and adoption by the systems engineering community.

A variety of domain specific methods to value flexibility have been proposed. For example, in the spacecraft design domain, Shaw, Miller, and Hastings (2001) introduced a cost per function (CPF) metric which represents the average cost of providing satisfactory satellite communication service between point A and point B within a defined market. The elasticity of the CPF to changes in four "quality-of-service" parameters—signal isolation (E_{Is}), information rate (E_R), information integrity (E_I), and information availability (E_{Av})—is proposed as a measure of flexibility. The metric is expressed as:

$$CPF = \frac{lifetime\_\cos t}{No.\_of\_satisfied\_users}$$

where the elasticity of the CPF given a change in the requirement is defined as *Type I adaptability* and is expressed as:

$$E_{Is} = \frac{\Delta CPF / CPF}{\Delta I_s / I_s}$$
$$E_R = \frac{\Delta CPF / CPF}{\Delta R / R}$$
$$E_I = \frac{\Delta CPF / CPF}{\Delta I / I}$$
$$E_{Av} = \frac{\Delta CPF / CPF}{\Delta Av / Av}$$

Type II adaptability is defined as the proportional change in CPF given a mission modification *X*, expressed as:

$$F\big|_X = \frac{\Delta CPF}{CPF}\bigg|_X$$

Type II adaptability is proposed as a metric of architecture comparison on the basis of how sensitive the communication satellite is to a mission change.

Nilchiani and Hastings (2003) explored the idea of provider-side flexibility using the application of an orbital transportation network (OTN), composed of satellites, orbital maneuvering vehicles, fuel depots, and service stations. Total provider-side service flexibility was calculated as the weighted average of the three flexibility types: *mix* flexibility (long-term), *volume* flexibility (mid-term), and *emergency* service flexibility (short-term). *Mix* flexibility is the ability to offer a variety of services with a given architecture and is expressed as:

$$f_m = \frac{S_m - E_m}{S - E}$$

where E is the total system lifecycle cost, S is the total lifecycle revenue, and m indicates multiple types of services are offered. *Volume* flexibility is the ability to respond to changes in quantity demanded and is expressed as:

$$f_v = \frac{\int_0^E e^{-rt_m}(S - E)\,p(S)\,dS}{I_{Risk-free}}$$

where $I_{Risk\text{-}free}$ represents the risk-free return on investments, and $p(S)$ is the lognormal distribution of system revenues over the range of uncertainties. The numerator represents the total discounted lifecycle profit. *Emergency service* flexibility is the ability to provide non-scheduled services and can be understood as the excess annual servicing capability of the system divided by the current level of annual service:

$$f_E = \frac{Cap_{\max}}{Cap_{current}}$$

The total service flexibility is calculated as the weighted average of the three flexibility types with w_i as the user-defined weight:

$$f = \frac{\sum_{i=M,V,E} w_i f_i}{\sum_{i=M,V,E} w_i}$$

Saleh (2001) proposed three types of customer-side flexibility along the two dimensions of system performance and mission: life extension, system upgrade, and mission change. While Joppin and Hastings (2003) extended this idea with the use of the Hubble Space Telescope to demonstrate the value of customer-side flexibility in a scientific mission. McVey (2002) proposed a framework for measuring on-orbit servicing flexibility, combining the economic aspects of markets with technological aspects of development, production, and operation costs. Each of these authors have taken a highly domain specific approach and have focused mainly on the analytical assessment of flexibility in space systems—a description rather than a prescription. Useful for particular applications and assessments, these metrics are limited in their extensibility to the wider systems engineering process.

Other authors that have contributed more generic flexibility metrics which are not specifically limited to a particular application. These approaches benefit from their general usefulness as mental models, but instead are limited by their mostly descriptive nature. Palani-Rajan *et* al. (2005) described a change modes and effects analysis (CMEA) process in order to introduce a change potential number (CPN). The CPN is based on an empirical study of how flexibility is dependent on the number of parts, functions, interfaces, types of interfaces, modules, and the manner of module arrangement. It is described as a number between one and ten that represents the product flexibility—one being very low flexibility requiring a new product to accommodate change, ten being very high flexibility requiring only very minor modification to accommodate change. This metric is calculated as:

$$CPN = \frac{1}{N}\sum_{i=1}^{N} \frac{\left[(Ri + Fi) - Oi + 8\right]}{27}$$

where F is design flexibility, O is occurrence, R is readiness, and N is the maximum number of potential change modes (or causes of change).

Browning and Engel (2008) defined a metric called the *system adaptability factor* (SAF), derived from the ISO/IEC 9126-1 standard for software engineering quality, combining six categories: functionality (F), reliability (R), usability (U), efficiency (E), maintainability (M), and portability (P). The SAF is proposed as the weighted average of the six constituent metrics:

$$SAF = w_F F + w_R R + w_U U + w_E E + w_M M + w_P P$$
$$\sum_{i=\{F,R,U,E,M,P\}} W_i = 1$$

Nilchiani (2005) extended the generality even further by proposing a six-element framework outlining the widely common elements of flexibility:

1. Boundary of the system to be studied
2. Aspects of system to which flexibility is applied
3. Time window in which flexibility is observed in the system
4. The uncertain and probabilistic nature of the future of the system
5. The degree of access to the system in order to apply the option or flexibility
6. Responses of the system to change through changes from the owner's, designer's, operator's, and user's perspective in the value delivery.

The author concludes that the final element, *response to change,* is the most salient as it characterizes the change in value-delivery which defines flexibility. He writes, "[...] the existence of a proper, timely, and cost-effective response is the difference between a flexible and a rigid (non-flexible) system."

Ross and Hastings (2006), and Ross, Rhodes, and Hastings (2007) attempt to address the question of the cost feasibility of flexibility by proposing a conceptual metric termed *filtered outdegree*. This metric represents the number of potential change mechanisms available to a design (i.e., transition paths to alternate design solutions), filtered by a cost threshold for adopting the transition path.

Many of these methods and metrics have emerged from the engineering community, however, application to systems engineering and design practice is limited by the qualitative, conceptual, descriptive, or case-specific nature of each approach. Alternatively, the management and finance communities have begun to embrace a different approach to flexibility which stems from widespread dissatisfaction with Net Present Value (NPV) analysis (Schwartz & Trigeorgis, 2001). It has been widely recognized in the finance community that NPV undervalues projects that contain flexibility and strategic interactions; these shortcomings have been known for a century (Fisher, 1907; Dean, 1951), but a means of addressing them had been unclear until recently. Myers (1984) first articulated a concept he coined “real options,” which has emerged as a way of thinking that helps managers formulate their strategic options and understand the value of future opportunities created by today’s investment (Amram & Kulatilaka, 2000). Real Options Analysis (ROA) builds upon the economic theory surrounding financial options valuation and has been proposed as a leading technique for analyzing and implementing flexibility early in the product or system lifecycle (Trigeorgis, 1996; Amram & Kulatilaka, 1999; Schwartz & Trigeorgis, 2001; Copeland & Antikarov, 2003; Mun, 2006). When embedded within a system design, real options have been characterized as architecture options (Browning & Engel, 2008). This type of “options thinking” establishes a theoretical basis for the quantitative modeling of flexibility in the design process (de Neufville, 2003). It offers a way for the system architect to understand how design decisions today will affect the system’s ability to deliver value throughout its lifecycle. The architecture option approach is extensible to a variety of engineering disciplines (i.e., it is not application specific) and provides a means to “design-in” flexibility from the front end rather than assess or describe it at the back end. The idea of optionality has therefore been adopted as fundamental to the operationalization of flexibility in engineering systems.

2.4.2 Flexibility in the Design Process

System requirements are rarely static. Requirements are more often in a state of revision and flux throughout the system development cycle. Funding changes, technology evolution, and uncertainty in the strategic and tactical environment can cause the stakeholder to continually adjust his demands on the system (Saleh, 2001). Uncertainty in the system's requirements can cause significant cost and schedule impacts. For example, the schedule for the Global Positioning System (GPS) Block IIF spacecraft was extended to nearly double the time originally estimated due to changes and additions to the original system requirements. Illustrated in Figure 5, new requirements on a system that arise during the development cycle can serious and costly design modifications.

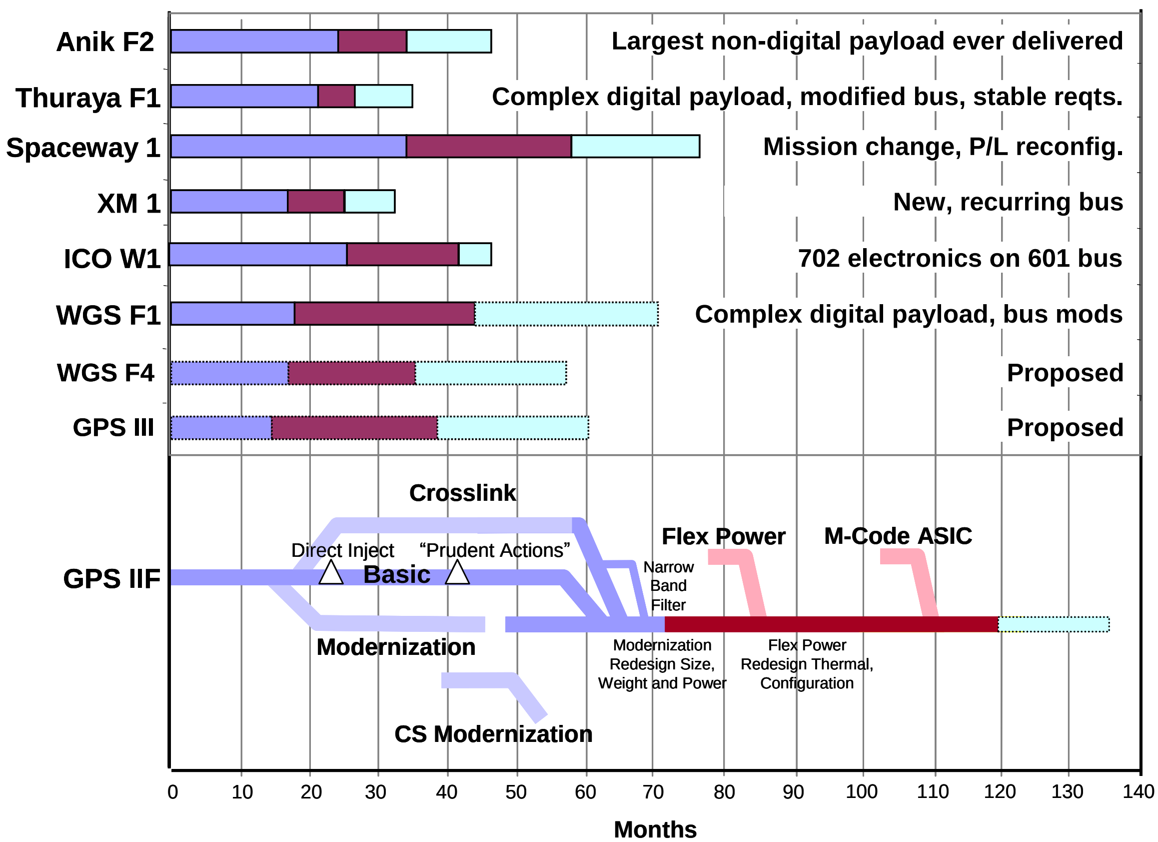


Figure 5: Result of requirements instability on spacecraft development schedule. Dark blue represents time required to PDR, maroon is time to CDR, light blue is time to delivery.

In dealing with this reality, Chen and Lewis (1999) pose the following question:

> "How does one capture the uncertainty—which characterizes the early stages of design—and offer flexibility in specifying the design requirements so that the designs that are marginally outside the precise level of performance are not worthless?"

It is clear that flexibility also plays a role and can be defined in relation to the uncertainty present within the design process. There is a major distinction here which should be noted. Both process and design flexibility, as defined earlier, describe an ability to handle change—process flexibility handles change prior to the fielding of the system, while design flexibility handles change after fielding. This distinction is illustrated in Figure 6.

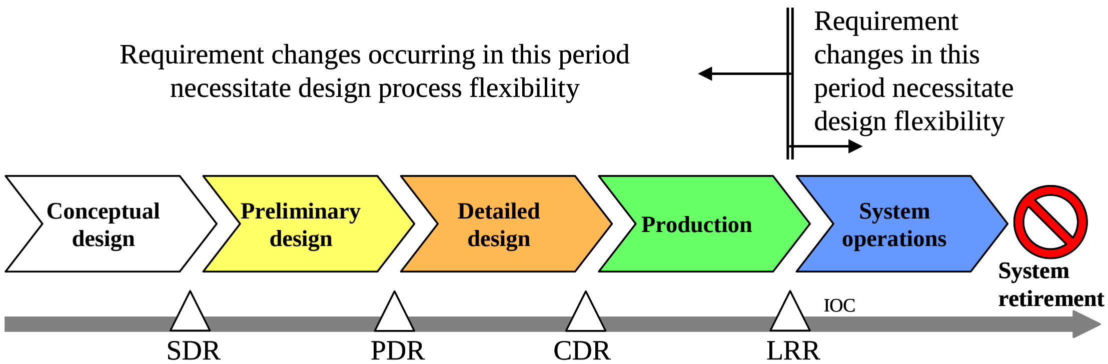


Figure 6: Distinction between design process flexibility and design flexibility.

Various authors have attempted to quantify flexibility in the design process and some of those approaches are introduced here. Thurston (1991) proposed a utility theory-based preference function to model the relationship between design decisions and the ultimate overall worth of a design. Wallace and Jakiela (1996) suggested a specification-based design evaluation method that imitates how specifications are used by product designers in a multidisciplinary design environment. Messac (1996) developed a "physical programming" approach that utilizes the aggregate preference function to reflect the preferences expressed in the class function of each attribute. Chen and Yuan (1999) proposed a probabilistic design approach that introduces the design preference index (DPI) and a preference function that measure the design flexibility and the subjective degree of desirability for each level of a performance attribute, respectively. The DPI is defined as the expected preference function value of design performance within the range of design solutions and is expressed as:

$$DPI = E[P(y)] = \int_{\bar{y}-\Delta y}^{\bar{y}+\Delta y} P(y)\, f(y)\, dy$$

where *P(y)* is a function defining the relationship between the degree of desirability *P* and the level of performance. It is defined between zero and one: one being fully acceptable or desired, zero being unacceptable. The probability density function, *f(y)*, describes the performance distribution when assuming random variations of designs in the box formed by the design ranges ±Δy.

Flexibility in the design process has been predominantly understood as a type of give-and-take relationship between the designer and customer. It is the combination of "[...] the customer's ability and willingness to lower product expectations, and the product developer's willingness and ability to invest more resources to reduce technical risks and other gaps before program start (GAO-01-288, 2001)." The ability to balance the customers' preferences (and degrees of satisfaction) with the realities of increased cost and schedule ultimately defines how flexible the design process is perceived to be.

2.4.3 Flexibility in Manufacturing Systems

Nowhere has flexibility been studied and applied more than in manufacturing systems. Dynamic markets, product customization, shorter product cycle times, and global competition have spurred the desire of businesses to implement flexibility in manufacturing as a competitive advantage. The emergence of computers and automation technology has contributed the necessary tools for the vision of flexible manufacturing to become realized. Publications in this area are prolific and the sheer volume of literature is daunting. There exists a wide variety of perspectives, formulations, and applications for flexible manufacturing systems (FMS) that range from the design of manufacturing cells and machine placement to scheduling, loading, and control. This section will give an overview of definitions and formulations of FMS to establish the context from which the current understanding of system design flexibility arose.

It was well known in early manufacturing that jobs spent a high proportion of time waiting for other jobs to clear a particular process and also for machines to be set-up. Early in the 1970's it was recognized that computers and numerical techniques could help automate job routing and control the manufacturing process—presumably, this would lead to higher efficiency. FMS was thereafter conceived. The U.S. Office of Technology Assessment (1984) defined FMS as:

> "[…] a production unit capable of producing a range of discrete products with a minimum of manual intervention. It consists of production equipment work-stations (machine tools or other equipment for fabrication, assembly or treatment) linked by a materials-handling system to move parts from one workstation to another, and it operates as an integrated system under full programmable control."

More concisely, a FMS is a manufacturing system in which there is some amount of flexibility that allows the system to react in the case of changes. Manufacturing flexibility generally falls into two broad categories: machine flexibility, and routing flexibility. Machine flexibility is the system's ability to be changed to produce new product types and perform a different order of operations. Routing flexibility is the system's ability to use multiple machines to perform the same operation and to absorb large-scale changes in volume, capacity, or capability. Klahorst (1981) proposed that flexible manufacturing systems are comprised primarily of work machines, a material handling system, and a central control computer. Other authors described manufacturing flexibility as a filter-buffer relationship, where flexibility acts as a buffer to the system against external perturbations; flexibility acts essentially as an uncertainty absorber (De Toni & Tonchia, 1998). Slack (1987) proposed a numerical description of manufacturing flexibility based on three values: the range of possible states, the time needed to move from one state to another, and the cost required to change the state. Upton (1995) focused on the system's ability to react to change by including a constraint to require little penalty in time, effort, cost, or performance to do so. Browne *et.* al. (1984) and Sethi and Sethi (1990) were some of the earliest works that provided a comprehensive classification of flexibility with eight and eventually eleven dimensions: machine, process, product, routing, volume, expansion, operation, production, material, program, and market flexibility. An ideally flexible system, they argue, would have the maximum amount of each of these flexibility types, constrained only by cost.

Manufacturing systems provided the early test bed and proving ground for many ideas in flexibility. Many of these ideas have been mirrored for application to engineering systems. To mention a few: Ross and Hasting's (2007) understanding of "changeability" resembles the De Toni and Tonchia's (1998) idea of flexibility as an uncertainty absorber; the "filtered outdegree" metric is conceptually patterned from Upton's ideas on flexibility cost constraints; the comprehensive classification of flexibility, whether with six-elements (Nilchiani, 2005) or eleven (Sethi & Sethi, 1990), is used in similar fashion; the System Adaptability Factor proposed by Browning and Engel (2008) has an early manufacturing analogue in the aggregation of constituent flexibility factors proposed by Browne et. al. (1984).

A massive volume of mathematical formulations exist in devising metrics for FMS. While not presented here, an extensive review can be found in Nilchiani (2005). The existing literature provides a wide variety of manufacturing flexibility measures and frameworks. Most of these measures are of particular application to manufacturing and cannot be generally applied to other types and fields of engineering activities. However, some fundamental ideas and metrics have reappeared in the emerging context of engineering system design. In the wider sense, these measures have elucidated the context from which our current understanding of flexibility has emerged while having the potential to help guide our future steps.

2.4.4 Flexibility in Management

Managerial flexibility[3] is management's ability to shift factors of production and allocate/transfer resources within the organization (Allen & Pantzalis, 1996). Alternatively, management harnesses flexibility when decisions can be postponed until more information is available, minimizing an organization's exposure to uncertainty. In either case, a plan of action is considered flexible when many contingencies exist, allowing management to alter course, defer decisions, and expand investments in light of uncertainty.

Managerial flexibility can be understood in the context of decision tree analysis (DTA) and real options (RO) thinking. Traditional discounted cash flow (DCF) methods used by management to value projects and decisions have increasingly been subject to harsh criticism for ignoring the value of managerial flexibility. This has led to a growing body of literature that has established the theoretical foundation for applying DTA and RO to the managerial decision process (Trigeorgis, 1996; Amram & Kulatilaka, 1999; Schwartz & Trigeorgis, 2001; Copeland & Antikarov, 2003; Mun, 2006). The real options technique, by waiting to make decisions that are subject to uncertainty, allows for downside protection and also upside opportunity. This topic will be discussed in detail in a subsequent section devoted to real option valuation.

2.4.5 Flexibility Versus Robust Design

Although similar, in that flexibility and robustness are both characterized by the ability to handle change, these two attributes have different sources and responses to change which should be clearly distinguished and disentangled. Saleh (2001) defines robustness as:

> "[…] the property of a system which allows it to continue satisfying a fixed set of requirements, in the environment or within the system itself, despite changes occurring after the system has entered service from the nominal or expected environment or system design parameters."

[3] The expression was introduced by Trigeorgis & Mason (1987)

In comparison, flexibility implies the ability of the system design to handle changes in requirements (i.e. new functionality after fielding). Saleh uses an insightful example of designing a system to last 50 to 100 years. What major challenges would this system face? He suggests that one would be primarily concerned with maintaining current functionality throughout the design life (indicative of design robustness), and creating new functions for changing requirements (indicative of design flexibility). This relationship between changes in the system's environment and system objectives can be conceptually illustrated with Figure 7.

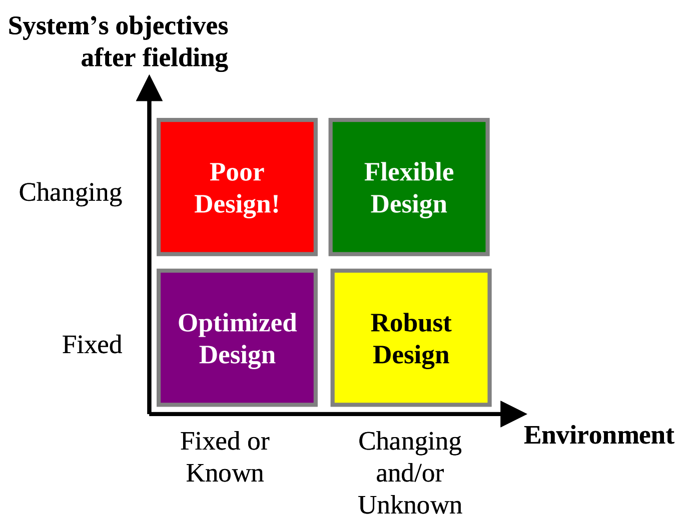


Figure 7: Flexibility and robustness as a function of environment and system's objectives, adapted from Saleh (2001).

2.4.6 Flexibility and the "ilities"

Traditional design criteria such as performance, cost, schedule, and risk have maintained preeminence in system design decisions. However, non-traditional evaluation criteria (collectively referred to as the "ilities") have become of greater interest as designers are more in tune with how the system delivers value over time. The "ilities" offer something different than the traditional static snapshot; they corporately define the degree to which systems are able to maintain or even improve function in the presence of change (McManus *et* al., 2007). These “ilities,” for example *versatility, changeability, robustness, adaptability, flexibility, scalability, modifiability, and survivability*, can be defined in terms of:

1. What changed?
2. Who or what instigated the change?
3. What is the mechanism of change?
4. What is the change effect?

McManus *et* al. (2007) proposed a three-dimensional framework to answer the first question of ‘what' changed. Changes, they argue, occur in the environment or *context*, in the user expectations or *needs*, and in the form of the *systems* themselves. Adding the fourth dimension of *time* allows the system engineer to interpret the “ilities” as a method of navigating these three types of change over the system operational life. The “ilities” corporately provide “a strategy for *system* change in response to changes in *needs* and *context*.” To illustrate this idea, McManus *et* al. proposed Figure 8 to represents the response of a system over various time increments (or epochs), given changes in the environmental context and user expectations. A system is considered *robust* if performance continues to exceed expectation given a change in context (epoch 2) or a change in needs (epoch 3). A system that can satisfy diverse expectations (epoch 4) or the addition of a new metric is considered *versatile*.

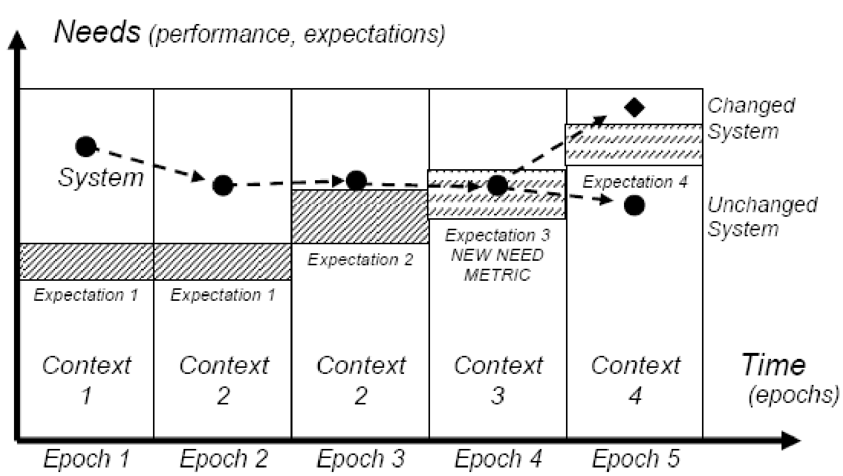


Figure 8: Illustration of system "ility" response to changes in context and need, source McManus *et* al. (2007).

Ross, Rhodes, and Hastings (2007) proposed a mental model to clarify and quantify questions 2, 3, and 4 from above. "Changeability" is first defined as the generic, overarching umbrella under which the other "ilities" reside—the ability of a system to alter form or function at an acceptable level of resource expenditure. The change event is then said to have three aspects: the *agent* of change (who or what instigated the change), the *mechanism* of change, and the *effect* of change. If the change agent is internal to the system (i.e. the system recognizes a need and changes itself autonomously), the change under consideration is characterized as an **adaptability-**type change. If the change agent is external to the system (i.e. something external must act on the system to implement a change), the change under consideration is characterized as a **flexible-**type change. If no change agent exists, the system is considered rigid. Next, the change mechanism defines the path by which the system can transition between its prior and post states. The more transition paths, or mechanisms, that exist between states, the more **changeable** a system. Finally, the change effect characterizes the difference between the prior system state and the changed state. When the change effect is a change to the level of an existing parameter (whether physical or functional), the system is considered **scalable**. If the change effect serves to change the membership of the parameter set, the system is considered **modifiable**.

The preceding discussion serves to disentangle the idea of flexibility from its close counterparts by adopting more precise definitions and taxonomy for these common "ilities" in an attempt to avoid common misinterpretations.

2.5 Options Theory

The use of options has been proposed as a way to understand the concept of flexibility. Fundamentally, "options thinking" recognizes the existence of value in securing the freedom of choice as new information is revealed. Widely used in finance, options are typically contracts that allow the holder of the option to purchase (or sell) an asset (e.g. shares of common stock, other market traded security) at a predetermined price at or before a predetermined date. The idea of considering optionality in engineering design and management is relatively new, but the fundamental thinking behind options emerged centuries ago. Options on tulip bulbs became popular in the 1600's as a way to mitigate demand and price fluctuations in the Dutch tulip market. Options and futures contracts were first formally traded when the Chicago Board of Trade was opened in 1848. But derivatives on stocks did not gain popularity until 1973, when the future Nobel Prize-winning publication of Black and Scholes (1972) demonstrated that call options could be properly priced. The Black-Scholes formula, by rigorously quantifying the value of an option, became the foundation of modern options trading and stimulated an entire field of research in contingent claims valuation.

2.5.1 Financial Options

Derivative contracts associated with financial assets or commodities traded in financial markets are referred to as financial options. Of the many types of derivatives that now exist in the market, the two most basic types of options contracts are: calls and puts. A call option gives the holder the right, but not the obligation, to buy an underlying asset at a predetermined exercise price before a predetermined expiration date. A put option gives the holder the right to sell the underlying asset under similar stipulations. The contract will specify an exercise price (or strike price) and the expiration date (or maturity). European-type options can be exercised only on the expiration date while American-type options can be exercised any time on or before maturity.

The value of such a contract securing the holder's right (without obligation) and the underwriter's obligation to fulfill the holder's right was an unsolved problem in economics throughout most of the 20^{th} century. Black and Scholes (1972) and Merton (1973) published a closed-form solution using a partial differential equation (PDE) that defines the movement of the option value over time. The solution relies on stringent market assumptions and specific boundary conditions that tend to limit the applicability of the formulation. Nevertheless, the Black-Scholes PDE solution imparts significant insight into the fundamental options problem and has single-handedly paved the way for research into the quantification of financial options and flexibility in general.

The Black-Scholes formulation can be applied only to a European-type option on a non-dividend paying asset. This requirement dictates that only one exercise time exists and that the asset yields no intermediate benefit. Further assumptions include:

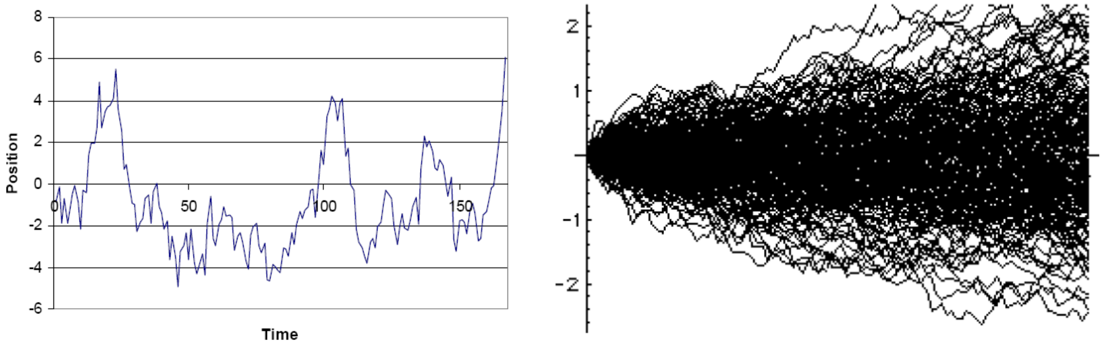
- Price assumption and efficient market: a quoted price for the asset exists and is set by an open and liquid market
- Replicating portfolio: a portfolio of the asset and its option can be established in each time period to yield a perfectly risk free portfolio
- Volatility assumption: the volatility of the underlying asset can be established from a long history of trades that generate good statistics
- Duration assumption: the volatility is stable over the life of the option.

The mathematical structure underlying the replicating portfolio and volatility assumptions necessitate two additional requirements:

- No arbitrage, and
- Geometric Brownian motion of the underlying asset.

Arbitrage involves profiting from transactions in two simultaneous markets. For example, if a stock could be purchased on the New York and London Stock Exchanges, arbitrage would be profiting from an uneven currency exchange rate that allowed a person to buy a stock in one market, exchange currency, and sell the stock (profitably) in the other stock exchange. The no arbitrage condition is important in that it allows for a hypothetical tracking portfolio to be set up in such a way that there is no uncertainty about the value of the portfolio (i.e. no risk), thus yielding a return equal to the risk-free rate.

Standard Brownian motion is the basis for modern options theory and is one of the most important stochastic processes that make up the standard model for stock prices. Simply put, a stock price that follows Brownian motion has a value next period equal to its value this period, multiplied by a continuous growth factor over some interval (illustrated in Figure 9):



One path of Brownian motion **200 paths of Brownian motion**

Figure 9: Brownian motion, source www.wikipedia.org

$$Z_{t_n} = Z_{t_{n-1}} + \varepsilon_n * \sqrt{\Delta t}$$

The growth rate, ε is a normally distributed random variable with mean 0 and standard deviation 1. The expected value at any future time is its current value. This process is also referred to a Wiener process. A more generalized formulation can be expressed as:

$$dx = adt + bdz\,.$$

Variables *a* and *b* are constants while *dz* is the basic Wiener process. The *b**dz* term is regarded as the variability of the path followed by *x*, while the *a**dt* term implies a drift rate of a per unit of time.

The movement of stock prices is essential in valuating stock options since the option tracks with the value of the underlying asset. With the assumption that the stock is a non-dividend paying asset, the price follows geometric Brownian motion:

$$dS = \mu Sdt + \sigma Sdz$$

where *S* is the stock price, μ is the expected return of the asset, and σ is the standard deviation of the return (volatility). If *f(S,t)* is defined as the price of the call option, an equation can be written using Ito's Lemma[4] that relates the Wiener process of *dS* to a similar Wiener process of *df* (Rogers & Williams, 2000). The equation for *df*, the change in the option price, is some function of the change in the stock price *dS* and time.

$$df = (\frac{df}{dS}\mu S + \frac{df}{dt} + \frac{1}{2}\frac{d^2 f}{dS^2}\sigma^2 S^2)dt + \frac{df}{dS}\sigma S dz$$

A hypothetical portfolio can be established that contains just the stock and its call option. The appropriately risk-free portfolio is *short* one call option and *long* an amount *df/dS* of shares. Because the stock and its option have the same source of uncertainty, as one goes up, the other will go down an equivalent amount. This portfolio is therefore risk-free and will yield the risk-free rate of return by definition. The value of this portfolio can subsequently be defined by:

$$\prod = -f + \frac{df}{dS}S$$

And the change in value of this portfolio is:

$$\Delta\prod = -\Delta f + \frac{df}{dS}\Delta S$$

The *no arbitrage* condition guarantees that the portfolio will remain riskless during time Δt. Thus,

$$\Delta\prod = r\prod\Delta t$$

where *r* is the risk-free interest rate. The two expressions can be set equal and the equation for *df* is substituted from above:

---

[4] Ito's lemma states that if a variable x follows a stochastic process of the form, $dx = a(x,t)\,dt + b(x,t)\,W\,dt$

where W is white noise, then any smooth function G(x,t) follows the process,

$$dG = \left(\frac{\partial G}{\partial x}a + \frac{\partial G}{\partial t} + \frac{1}{2}\frac{\partial^2 G}{\partial x^2}b^2\right)dt + \frac{\partial G}{\partial x}bW\,dt.$$

For derivation, see Ross (1996).

$$(\frac{df}{dt}+\frac{1}{2}\frac{d^2 f}{dS^2}\sigma^2 S^2)\Delta t = r(f-\frac{df}{dS}S)\Delta t$$

By simplification, this becomes:

$$\frac{df}{dt}+rS\frac{df}{dS}+\frac{1}{2}\sigma^2 S^2\frac{d^2 f}{dS^2}=rf \cdot$$

This is the Black-Scholes options pricing differential equation that can be solved utilizing the appropriate boundary conditions. In the case of a call option, the boundary condition is written as:

$$f = \max[S-X,0]$$

At time $t = T$, f equals the maximum of either zero (since an option is not an obligation) or the difference between the immediate stock price S, and the exercise price X. Solving the differential equation subject to the boundary conditions, the closed form solution is expressed for the value of a call option c:

$$c = S_0 N(d_1) - Xe^{-rT} N(d_2)$$

Where $N(d_1)$ and $N(d_2)$ are the cumulative standard normal distribution of the variables:

$$d_1 = \frac{\ln(S_0/X)+(r+\sigma^2/2)T}{\sigma\sqrt{T}}$$
$$d_2 = \frac{\ln(S_0/X)+(r-\sigma^2/2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}$$

The five parameters needed to determine the option price are:

1. S: the value of the underlying risky asset.
2. E: the exercise (or strike) price.
3. T: the time to expiration of the option.
4. σ^2: the standard deviation of the value of the underlying risky asset.
5. r_f: the risk-free rate of interest over the life of the option.

Although this formulation can seem cryptic, there is an intuitive interpretation of the solution. If the Black-Scholes solution is rewritten as,

$$c = e^{-rT}[e^{rT} S_0 N(d_1) - XN(d_2)],$$

it becomes clear that $N(d_2)$ is the probability that $S>X$ (i.e. that the option is exercised) and thus the product $X* N(d_2)$ is the strike price times the probability that the strike price will be paid—essentially this is the expected exercise cost. The expression $e^{rT}*S_0* N(d_1)$ is the expected future value of an asset S_0 that equals S if $S>X$, and equals zero otherwise. Taken together and discounted to the present, the difference between the two expressions is the expected value of the option at maturity (i.e. the difference between the expected benefit and the expected cost).

2.5.2 Traditional Valuation: Net Present Value

The single most widely used tool to value a project or business is discounted cash flows (DCF) analysis, which is used to bring the life cycle cash flows to their Net Present Value (NPV). Brealey and Myers (2000) define NPV as a project's net contribution to wealth. NPV represents the present value of a project's stream of future free cash flows, discounted back to the present. Cash flow is essentially net income (revenue – expenses) and when taken in combination with the initial outlay of funds is a common metric of the expected profitability of a project irrespective of uncertainty. The out-year cash flow streams are discounted to the present with a corporate hurdle rate, typically the Weighted Average Cost of Capital (WACC). If the net present value is greater than zero, a decision-maker might reasonably conclude that the project is worth pursuing.

$$\text{NPV} = \sum_{t=0}^{n} \frac{C_t}{(1+r_f)^t} \qquad \begin{cases} NPV > 0 \text{..................Invest} \\ NPV < 0 \text{........Do not Invest} \end{cases}$$

This method has allowed managers to compare projects that have different time horizons and cash flows. Recently, there has emerged widespread dissatisfaction with NPV analysis due to the belief that it undervalues projects that contain flexibility and strategic interactions. Flexibility to defer, switch, expand, or abandon a project based on forthcoming information is perceived to have value—this value is not represented using DCF and NPV (Schwartz & Trigeorgis, 2001). Net present value simply measures the expectation of cash inlays and outlays in a fixed environment and absent any options to change or alter the project if circumstances warrant it. NPV also forces the use of a single discount rate for all cash flows, which does not account for the possibility of rate fluctuations in the financial market or variations in the riskiness of those cash flows.

The shortcomings of DCF have been know for a century, many of them introduced by Fisher (1907) in his book on the rate of interest. Although these inadequacies had been identified, a means of addressing them was unclear. Dean (1951) proposed alternative ways of coping with these shortcomings, ranging from qualitatively applying professional judgment to applying quantitative handicaps to the mathematical analysis. This lack of quantification led to the understanding that NPV was biased toward projects that had high short-term returns and against projects with longer-term outcomes (e.g. R&D, technology development).

2.5.3 Real Options

Recognizing the gap that existed between financial theory and strategic investment, Myers (1984) first articulated a concept he coined "real options." Real Options Analysis (ROA) builds upon the economic theory surrounding financial options valuation and has been proposed as a leading technique for analyzing and implementing flexibility early in the product or system lifecycle (Trigeorgis, 1996; Amram & Kulatilaka, 1999; Schwartz & Trigeorgis, 2001; Copeland & Antikarov, 2003; Mun, 2006). Whereas a financial option is a contractual instrument that gives the owner the ability to buy or sell an underlying financial asset (e.g. securities), a real option confers the right to take a tangible action at a certain cost within or at a specific time period (Dixit & Pindyck, 1994; Trigeorgis, 1996; Luenberger, 1998; Amram & Kulatilaka, 1999; Brennan & Trigeorgis, 1999; Mun, 2002; Copeland & Antikarov, 2003). A financial option has a contract purchase price, or premium that is paid per share, while a real option has an implementation or development cost that the designer must invest up front. Table 1 compares the terminology between financial options and real options.

Table 1: Terminology comparison of Financial Options and Real Options.

Financial Options	Real Options
Usually exchange traded	Not usually traded
Contract with contingencies	Strategy with contingencies
Asset is a stock (S)	Asset is a program/project
Premium payment for option	R&D investments
Strike or exercise price (X)	Non-recurring launch cost
Risk free rate (r_f)	Risk free or investment rate
Time to exercise (t)	Time to commitment
Payoff is stock or cash	Payoff is operating profit
Variance of stock, sigma (σ)	Variance of operating profit

Real options theory has become, more broadly, a way of thinking that can help managers formulate their strategic options and understand the value of future opportunities created by today's investment (Amram & Kulatilaka, 2000). As an alternative to NPV, real options analysis has been widely utilized for the valuation of projects that include flexibility. Analogous to a financial "call" option which allows the investor to purchase shares of stock at a predetermined date and price, a real option allows the designer/manager to exercise an option on a real or tangible asset. The nature of options is asymmetrical—limiting downside risks to the premium paid for the option while simultaneously allowing for upside potential benefit (Figure 10). Real options can be used as a hedge against negative outcomes and also as opportunities to grow and expand (Amram & Kulatilaka, 1999). The more uncertainty that exists (i.e. higher volatility), the more valuable the real option becomes and the more incentive the designer has to keep the option available.

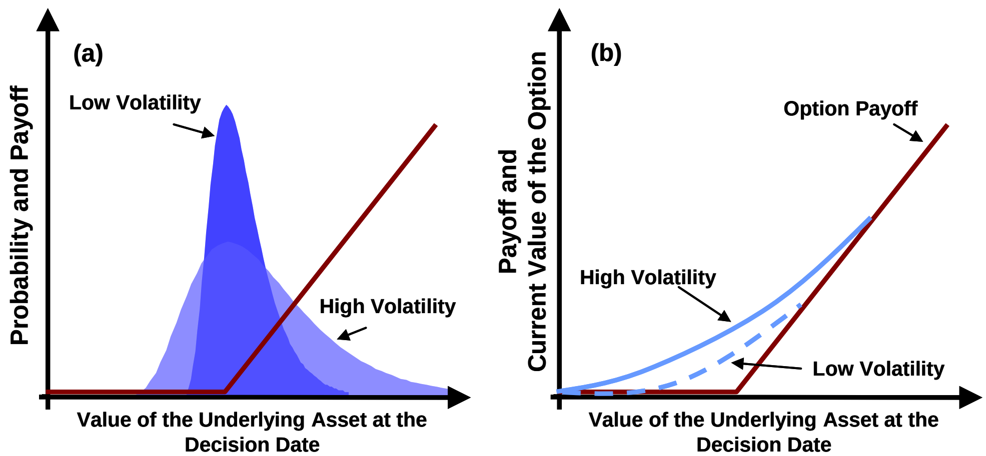


Figure 10: Total Risk and Option Value: (a) An increase in total risk widens the distribution of outcomes, creating more outcomes with a positive payoff. (b) The one-sided effect increases the value of the option.

2.5.3.1 Real Options "On" and "In" Projects

de Neufville (2002) identified two types of real options: 1) real options "on" projects, and 2) real options "in" projects. The vast majority of the real options literature and valuation techniques are concerned with options "on" projects, which treat both the technology and the engineering design as a "black box". These options are concerned with "go" or "no-go" management decisions and are predominantly defined as options for scaling, deferring, and abandoning a project (Gray *et* al., 2004). The major objective for applying real options "on" projects is to more fully understand the value of the project given the manager's ability to reserve the launch decision (and launch costs) for a later date and a more current business case analysis.

In comparison, real options "in" projects can be described as options internal to the design process, allowing an engineering design to adjust as actual demands on the system develop. This type of option is considered to be an embedded architecture option and requires in-depth technical domain knowledge to discover and exploit. Real options "in" projects can allow for the augmentation of a hardware design, addition of functionality to software, modification to operational modes, or expansion of a system attribute. The application of real options internal to the system has led to a broadened understanding of "optionality," and "options thinking," which has been proposed as a theoretical basis for the quantitative modeling of flexibility in system design (de Neufville, 2003; Browning & Engel, 2008). The major objective then for applying real options "in" projects is to help the system architect understand how design decisions today can affect the system's ability to deliver value throughout its lifecycle.

Real options "in" projects have not been studied as thoroughly as real options "on" projects and a consistent valuation technique does not yet exist. However, a number of authors have described example applications for the valuation of embedded real options (Markish, 2002; Chaize, 2003; Wang, 2005; Zhao & Tseng, 2003; Kalligeros & de Weck, 2004; Greden & Glicksman, 2004). Due to the nature of the valuation assumptions and requirements, these applications are many times thought to be contrived, unrealistic, and over-simplified (Kalligeros, 2006). Instead, system engineers continue to rely mainly on intuition and engineering judgment to define flexibility in the system design.

2.5.3.2 Real Options Provide a Unit of Analysis for System Flexibility

As demonstrated in the previous literature review, the lack of a consistent unit of analysis makes it difficult to study flexibility in an organized, methodical, or scientific fashion. A major reason why real options theory has gained interest and popularity centers on its ability to become a generalized unit of flexibility independent of the application domain. Although there are various definitions for real options, they all converge on the idea that a real option secures a right, not an obligation—this exemplifies the asymmetric human decision making structure that seeks to take advantage of upside potential while limiting downside risk. The differences between definitions are mainly in regards to scope. In a very narrow sense, real options have been defined as the extension of financial options theory to a non-financial (or real) asset (Amram & Kulatilaka, 1999), and in a much broader sense, as an opportunity to take an action or exert control over a process (Dixit & Pindyck, 1994; Luenberger, 1998; Copeland & Antikarov, 2003). The former seeks to include the valuation approach in the definition, while the later tends to emphasize the broadest theoretical application. Because this research is chiefly concerned with the type of flexibility that allows a system to respond to change after it is fielded, the definition proposed by Saleh, Lamassoure, and Hastings (2002) is adopted: [flexibility is] "the property of a system that allows it to respond to changes in its initial objectives and requirements (both in terms of capabilities and attributes) occurring after the system has been fielded, that is, in operation, in a timely and cost effective way." This definition necessitates the broader understanding of real options as a theoretical construct for embedding options in system architectures rather than as a straight forward extension of financial options theory. In actuality, embedded options almost never resemble financial options to an extent that would allow credible use of traditional valuation techniques due to the assumptions required for proper use. Understanding a real option more generally as the right, but not the obligation to take an action at a certain cost within a specified period of time, allows for a neatly defined, basic unit of flexibility. This approach is especially appealing because it is extensible to a variety of engineering disciplines (i.e., it is not application specific) and provides quantitative means to "design-in" flexibility from the front end rather than assess or describe it at the back end. Consequently, this research has adopted real options as a unit of analysis for system flexibility and further develops the concept of embedded architecture options for use in the system engineering process. The remaining challenge is not conceptual; it is more analytical. How can a real option be valued in a way that is both theoretically sound and practical for use in systems engineering? The following section investigates the current techniques available to value real options.

2.5.3.3 Valuation Methods for Real Options "On" Projects

The ability to determine a value for real options provides important insight into the value of opportunity and the value of flexibility. Traditionally, the value of flexibility has been treated intuitively. Real options valuation is intended to provide a systematic and quantitative approach that managers can use to actively manage uncertainty and decide which options are financially justified. However the valuation techniques available to practitioners often employ contradictory approaches and require underlying assumptions that can render the technique inaccurate or inappropriate for the application. Although practitioners widely agree on the merits and appeal of the basic concept, Borison (2005) comments in his detailed critique of real options valuation, "[…] that there is a good chance that one could either apply an unsound approach or make inappropriate use of a sound one." The following sections will provide an overview of the major analytic and discrete methods for valuing real options, the assumptions required, and the appropriateness (or practicality) of the technique for various applications.

2.5.3.3.1 Analytic Formulation (Black-Scholes)

The breakthrough work by Black and Scholes (1972) and Merton (1973) yielded not only a mathematically insightful and elegant solution to the options pricing problem, but a vast field of research and study that would span the disciplines of finance, management, decision science, computer programming, engineering, and strategic planning, to name a few. Valuation of real options, i.e. options not on financial assets, has been attempted predominantly as a direct analogue to financial options. The Black-Scholes formula for financial options, as discussed in an earlier section on financial options, is a closed-form analytic solution to a partial differential equation, derived specifically for a non-dividend paying, European-type option (exercised only at maturity), using one source of uncertainty, for a single underlying asset, with a constant and known exercise price. Applying arbitrage-enforced pricing and geometric Brownian motion to the behavior of the underlying asset, Black and Scholes created a theoretical replicating portfolio that, with the help of some Itô calculus (Rogers & Williams, 2000), can be used to solve the partial differential equation for a Call or Put option. The Black-Scholes expression for the value of a call option is:

$$c = S_0 N(d_1) - Xe^{-r_f T} N(d_2)$$

where $N(d_1)$ and $N(d_2)$ are the cumulative standard normal distribution of the variables,

$$d_1 = \frac{\ln(S_0 / X) + (r_f + \sigma^2 / 2)T}{\sigma\sqrt{T}}$$

$$d_2 = \frac{\ln(S_0 / X) + (r_f - \sigma^2 / 2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}$$

The five parameters needed to determine the option price are:

1. S: the value of the underlying risky asset.
2. X: the exercise (or strike) price.
3. T: the time to expiration of the option.
4. σ: the standard deviation of the value of the underlying risky asset.
5. r_f: the risk-free rate of interest over the life of the option.

When used to value real options, the analytic approach is perceived many times as cryptic and forced because of its financial terminology and incomprehensible assumptions associated with financial markets (Copeland, Koller, and Murrin, 1994; Amram & Kulatilaka, 1999). These assumptions include:

- European-style option: only one exercise time exists at maturity
- Non-dividend paying asset: contingent claim yields no intermediate benefit
- Efficient market: a quoted price for the asset exists and is set by an open and liquid market
- Replicating portfolio: a portfolio of the asset and its option can be established in each time period to yield a perfectly risk-free portfolio
- Volatility assumption: the volatility of the underlying asset can be established from a long history of price fluctuations that generate good statistics
- Duration assumption: the volatility is stable over the life of the option
- No arbitrage opportunities
- Geometric Brownian motion[5] (i.e. random walk) of the underlying asset

[5] Stochastic process that has a value next period equal to its value this period, multiplied by a continuous growth factor over some interval (Brush, 1968)

Real options “on” projects, which are not linked to a market-traded financial asset, rarely exhibit the behavior necessary to justify these assumptions, even for the most contrived applications (Kalligeros, 2006). Architecture options embedded “in” a project are even more difficult to link to a market-traded asset and will rarely, if ever, exist in an open, liquid market where the "no arbitrage" condition can be enforced. The Black-Scholes formulation is a mathematically insightful and elegant solution and therefore has wide academic appeal. However, when applied to real options embedded "in" projects, the analogy to financial options breaks down rapidly, making this technique, in most cases, mathematically unsuitable.

Borison (2005) describes the “Classical Approach” to real options valuation which appears most completely in Amram and Kulatilaka (1999), but earlier in Copeland, Koller, and Murrin (1994). This method adopts the Black-Scholes approach to financial options almost entirely. It assumes that a portfolio of market traded investments can be constructed to perfectly replicate the payoffs of the non-financial option. The no-arbitrage condition guarantees that the option price is equivalent to the price of the replicated portfolio. Market data is therefore used to determine the price and volatility of the underlying asset (i.e. replicated portfolio) which tracks the real option.

A variation to the classical approach, described by Luehrman (1997) and Luehrman (1998), uses subjective estimates for the value and volatility of the underlying investment opposed to the replicating market portfolio. This difference essentially detaches the valuation from market data and relies solely on subjective estimates for the inputs. The assumptions and solution mechanics are otherwise identical to the Black-Scholes classical approach.

2.5.3.3.2 Discrete Techniques

The other major options pricing technique is the discrete method that expands a lattice (binomial, trinomial, or multinomial) in discrete time to simulate the potential price path of the underlying asset. This method explicitly depicts the stochastic behavior of the underlying asset at each time step, thereby eliminating the need for a partial differential equation. Introduced by Cox, Ross, and Rubenstein (1979), the binomial lattice has been applied to a wide variety of options pricing scenarios (Copeland & Antikarov, 2003; Mun, 2006). It has become a popular options pricing technique in no small part due to its ability to conceptualize and depict uncertainty. In comparison to the abstract value of sigma, σ, in the Black-Scholes formulation, uncertainty is represented in the lattice as stochastic up and down movements of the underlying asset. This technique can be illustrated by solving the first two steps in the Binomial Lattice, where the evolution of the underlying asset value S_0 is represented by stochastic up and down movements in a binomial tree which yields option payoffs f_u and f_d (Figure 11).

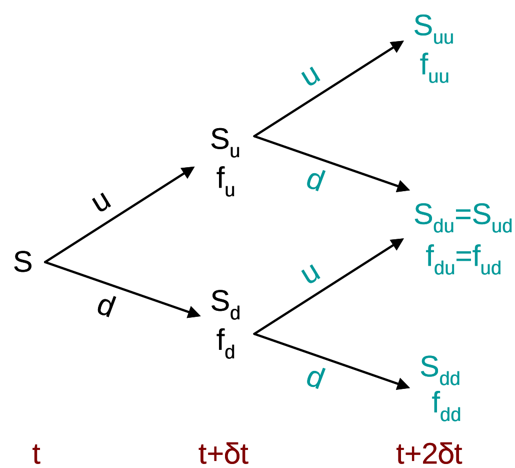


Figure 11: Two steps in a binomial lattice.

A single time step δt will yield the asset value of either S_u or S_d, with probabilities u and d, respectively. For real option valuation, a replicating portfolio is created with x shares of a stock and short one option such that the portfolio is risk free. Upward and downward movements would yield portfolio values:

$$\mathrm{S}_0 u * x - f_u$$
and
$$\mathrm{S}_0 d * x - f_d$$

The value x which balances the reciprocal relationship of the portfolio is found by setting the portfolio values equal, regardless of the direction of the movement:

$$\mathrm{S}_0 u * x - f_u = \mathrm{S}_0 d * x - f_d$$
$$x = \frac{f_u - f_d}{\mathrm{S}_0 u - \mathrm{S}_0 d}$$

Utilizing the no-arbitrage condition, the riskless portfolio must earn the risk-free interest rate (r). The present value of the portfolio is therefore:

$$\mathrm{e}^{-\mathrm{rT}}(\mathrm{S}_0 u * x - f_u)$$

The present value expression is set equal to the cost of establishing the portfolio:

$$\mathrm{e}^{-\mathrm{rT}}(\mathrm{S}_0 u * x - f_u) = \mathrm{S}_0 x - f$$
or
$$f = \mathrm{S}_0 x - \mathrm{e}^{-\mathrm{rT}}(\mathrm{S}_0 u * x - f_u)$$

By substituting x from above, this equation reduces to:

$$\boxed{f = e^{-rT}[p_u f_u + p_d f_d]}$$

where,

$$p_u = \frac{e^{rT} - d}{u - d}$$
$$p_d = 1 - p_u$$

The “up” and “down” movements can to be related to the volatility of the stock by:

$$u = e^{\sigma\sqrt{\Delta t}}$$
$$d = e^{-\sigma\sqrt{\Delta t}}$$

The lattice is solved sequentially at each node, forward then backward, while the recombination of nodes decreases the computational burden. Essentially, the binomial lattice is a graphical extrapolation of the Black-Scholes formula; as more nodes are added (i.e., as the time intervals shrink), the option value approaches that of the closed-form Black-Scholes solution. Although the representation of uncertainty is more comprehensible, the lattice technique inherits many of the same challenges described for the Black-Scholes approach in that it can be cryptic and improperly applied where the assumptions cannot be justified.

Copeland and Antikarov (2003) used a binomial lattice to solve their Marketed Asset Disclaimer (MAD) formulation. The MAD approach is significantly different from the "classical" PDE techniques in that it does not rely on the existence of a traded replicating portfolio. Instead, Copeland and Antikarov argue that the replicating portfolio is unnecessary because the NPV of the project itself is the best unbiased estimate of the market value of the project were it a traded asset. So the NPV of the project is used as an estimate of the price the project would have if it were traded on the open market. A risk-neutral binomial lattice is constructed with the NPV values that follow geometric Brownian motion and solved to obtain the option value.

2.5.3.3.3 Numerical Techniques

Numerical techniques are useful when analytical solutions cannot be obtained or would require too much effort. Both numerical integration and Finite Difference[6] techniques can be applied to solve the Black-Scholes PDE, allowing for a much larger set of boundary conditions. The underlying formulation remains the Black-Scholes approach, therefore the similarly restrictive assumptions and limitations still apply.

Real option valuation can also be accomplished through simulation. Simulation uses random numbers, typically through Monte Carlo trials, to generate possible paths of the evolution of the value of the underlying asset. The real option decision rule (e.g. Max[S-X,0]) is embedded

[6] The option price is found by converting the stochastic PDE into a set of difference equations that are solved iteratively working backward from the end. See Hull (2003) for a detailed exposition.

in each path, and the payoff is calculated directly for each trial and discounted at the risk-free rate. The expected value of the discounted payoffs is the estimated value of the option (Hull, 2003).

Monte Carlo simulation is not bound by the restrictive assumptions of other techniques. This type of valuation can handle path dependency where the value of the option depends on the particular path followed by the underlying asset—these options are known as compound options because they progress in phases and are usually influenced by several correlated sources of uncertainty. Simulation requires only that the stochastic process for the underlying asset be defined.

2.5.3.3.4 Decision Tree Analysis

Decision Tree Analysis (DTA), as a problem structuring and organizational tool, has been employed for real options valuation by explicitly representing each uncertainty as well as the contingent decisions based on that uncertainty. The decision tree is a sequence of decision and uncertainty nodes that end in a terminal node, with each branch indicating an option available to the decision-maker. DTA "rolls back" or solves the decision tree by selecting the option with the highest expected value at each decision node, resulting in the optimal choice sequence.

Two noteworthy methods utilize DTA to value real options: 1) the "Revised Classical Approach" and, 2) the "Integrated Approach." Both methods recognize a distinction between the sources of risk that influence corporate investments. The first type is market-priced or public risks, and the second is corporate-specific or private risks. The revised classical approach recommends the use of finance-based real options analysis only for investments dominated by public risks, where the stringent Black-Scholes assumptions are acceptable. If the investment is dominated by private risk, dynamic programming and decision analysis should be used instead. This view has been articulated most extensively by Dixit and Pindyck (1994) and Amram and Kulatilaka (2000). The integrated approach recognizes that corporate investments may not be completely categorized as dominated by public or private risk, but more likely a mix of both. Smith and Nau (1995) and Smith and McCardle (1998) proposed that for public risks, a replicating portfolio should be identified and assigned “risk neutral” probabilities; for private risks, subjective probabilities should be assigned. Therefore, the “risk adjusted decision tree” will represent both public and private risks explicitly and can be rolled back and solved for the option value.

2.5.3.3.5 An Intuitive New Valuation Technique: The Boeing Approach

The valuation of real options in most real world applications necessitates the relaxation of one or more of the standard Black-Scholes assumptions. While financial options are analyzed for traded securities that can be routinely observed and for which historical data exist, real options have tangible assets underlying their value which can be impossible to observe. A market value and volatility for such assets rarely exists.

A recent advancement has occurred in options pricing that has uncovered a new mechanism for calculating the value of real options "on" projects. The valuation approach has been developed and published by The Boeing Company's Computational Finance and Stochastic Modeling group and validated at Stanford University (Datar & Mathews, 2004; Mathews, Datar, and Johnson, 2007; U.S. Patent 6862579).

The Boeing Datar-Mathews (DM) technique is able to avoid the stringent assumptions and limitations of previous methods by utilizing the language and frameworks of standard discounted cash flow analysis (DCF) as opposed to partial differential equations. The DM method yields the same results as the Black-Scholes and binomial lattice techniques (given the same inputs and discounting methods), but does not necessitate the existence of a replicating tracking portfolio, Brownian motion of the underlying, or arbitrage enforced pricing (Mathews & Salmon, 2007).

The DM method can be understood as an extension to the NPV technique that includes distributions of outcomes at each time period, adjustment for risk aversion, and an algorithm for rational economic decision making. Implemented in a spreadsheet, the DM formulation is as follows:

$$\text{Real option value} = Average\left[MAX\left(\overline{\text{operating profits}} - \overline{\text{launch cost}}, 0\right)\right].$$

The overscore bar indicates the present value distribution at time 0. Where NPV calculates the discounted cash flow of a singular most-likely forecast, the DM method incorporates uncertainty in the estimate of future benefit by simulating the operating profit and launch cost at each time step. Using a Monte Carlo procedure, "trials" are drawn from the distribution and discounted to a decision base year. To account for different levels of underlying risk, a differential discount rate is applied. Operating profit is discounted to the base year with the hurdle rate commensurate with market risk because future cash flow is subject to market uncertainty. The launch cost is discounted to the base year with the investment rate which is reflective of a more secure and controllable source of capital. Net profit is then calculated by taking the difference of the two discounted cash flows. For each Monte Carlo trial, a rational decision-making algorithm is applied that expends the launch cost and reaps the operating profit only for outcomes where the forecasted net profit is positive. If the forecasted net profit is negative at the decision point, the project is abandoned and the launch expenditure is retained. The real option value can be described then as the average net profit appropriately discounted to the decision date and subject to the rational choice of pursuing only those scenarios where a profitable outcome is forecasted.

Using variables familiar to traditional options pricing, the DM algorithm can be succinctly expressed as:

$$Z_{t1}^{t2}(\mu, r) = E[e^{-\mu(t2-t1)}S_{t2} - e^{-r(t2-t1)}X_{t2}]^{+}$$

where μ and r are the discount rates, S is the operating profit, and X is the exercise or launch cost, evaluated from t_1 to t_2. The option value, Z, is the expected value of the *MAX* of the difference between the discounted benefits and costs.

The Datar-Mathews technique avoids the complex assumptions required for traditional options valuation by utilizing data directly from the business forecast. The value of sigma (σ) is not necessary as a specific input because it is calculated from the Monte Carlo analysis. The value today of the operating profit (S_0) is also not needed as a specific input; this allows S to be represented by other than a lognormal distribution which is required for Black-Scholes and Binomial methods. The DM method allows for a variable (or stochastic) strike price and accommodates time-varying and differential discount rates required to reflect the differing levels of risk inherent in each cash inlay and outlay. This technique combines versatility with intuition and communicates it in the common language of financial forecasts. Versatility and generality allow the technique to be adapted for and expanded into the domain of embedded options, while intuitiveness and transparency are key for adoption into systems engineering practice.

2.6 Modeling the System

In order to identify flexibility options within a system, the system must first be understood and modeled. According to Browning (2001), modeling a complex system requires:

1. decomposition of system into subsystems about which relatively more is known;
2. definition of relationships between the subsystems that give rise to the system behavior;
3. definition of the external inputs and outputs and their impact on the system.

There are a number of different approaches for accomplishing these system modeling tasks, including: Unified Program Planning (Hill & Warfield, 1972), Quality Functional

Deployment (Cohen & Levinthal, 1990), Axiomatic Design (Suh, 1998), CLIOS[7] method (Sussman, 2000; Dodder & McConnell, 2005), System Architectures[8] (Maier & Rechtin, 2000), and the Design Structure Matrix (Steward, 1981). A detailed exposition of the merits and shortcomings of each methodology can be found in Bartolomei (2007). Of these methods, the design structure matrix is most conducive to quantitative analysis and has the additional advantage of simplicity. Bartolomei (2007) recognized that the DSM technique could be extensible to exogenous, e.g. environmental and functional, variables, which more specifically allows for the impact analysis of operational uncertainty. Due to its compact, visual, and analytically advantageous format, an extended variation of the DSM is used in this research as a system model to facilitate the identification of architecture options.

As a brief introduction, the DSM is a succinct way of addressing the modeling issue by re-structuring the flow of information in a complex system design (Kusiak, 1990; Gebala & Eppinger, 1991; Eppinger, 1994; Kusiak & Larson, 1994; Gulati & Eppinger, 1996). The DSM is an information exchange model which provides an elegant representation of the interactions that exist between the elements of a decomposed system or product (Steward, 1981). The use of the DSM to represent the physical, task, and organizational views of engineering systems has expanded in recent years as there are over one hundred papers that demonstrate the value and/or extend the use of this matrix (Bartolomei, 2006).

For purposes of implementation, the DSM is a square matrix representation of a directed graph, where the nodes of the graph correspond to the column and row headings in the matrix and

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[7] CLIOS: a Complex Large-scale, Interconnected, Open Socio-technical System. This type of engineering system has interactions not just between components and subsystems, but between social, political, economic, institutional, and physical systems.

[8] Most notably, the Department of Defense Architecture Framework (DoDAF) which includes system, technical, and operational views (SV, TV, OV, respectively).

the arrows correspond to the marks[9] inside the matrix. These marks indicate whether Task A and Task B are parallel (independent) design tasks, series (dependent) design tasks, or coupled (interdependent) design tasks which require iterative information flow. This is illustrated in Figure 12. The matrix can be populated by decomposing the architecture to the desired level of resolution and defining the intensity of each relationship. A common taxonomy can be used to describe each relationship in terms of constituent components (e.g., spatial, energy, information, and material-related), with an intensity on a scale like that of -2 to 2 (Browning, 2001). There are four different types of DSM models applied to various levels of abstraction: *team*, *component*, *activity*, and *parameter*. Traditional views within these types include *activities*, *objects*, *functions*, and *objectives* (for a detailed description of each level of abstraction and type, see Sharman and Yassine (2007)).

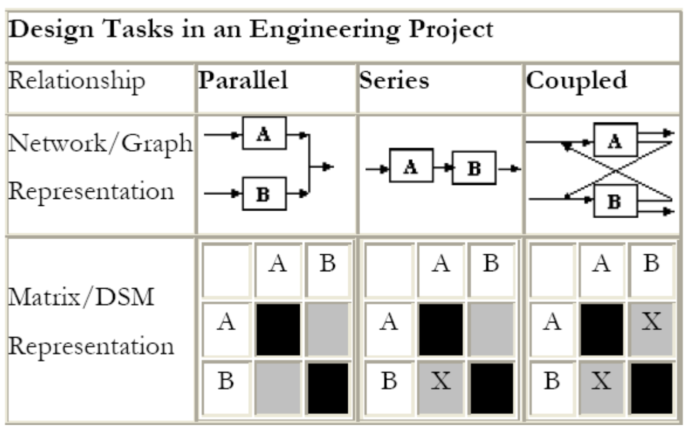

Figure 12: Definition of DSM relationships (http://www.dsmweb.org).

Analysis of the DSM most often uses a clustering algorithm to organize and consolidate the system representation. Clustering of the DSM elements (i.e. rearranging the order) can find subsets, or modules, that are mutually exclusive or minimally interacting. Clusters can contain

[9] A mark in the matrix simply identifies that a relationship exists between the elements. Numbers and/or other metrics can be used to signify the intensity of the relationship.

most, if not all, of the interactions internally and the links between separate clusters can be minimized or eliminated (Gutierrez, 1998; Frick & Schulz, 2005). A wide range of clustering algorithms can be found in Alexander (1964), Hartigan (1975), Gutierrez (1998), Thebeau (2001), and Whitfield, Smith, and Duffy (2002).

2.7 Chapter Summary

Systems are constantly faced with unpredictability in the operational environment where threats from competing systems, technology obsolescence, and general uncertainty in future demands require systems to respond to changing requirements. However, uncertainty generates an opportunity to design the system to respond to change and deliver additional value to the stakeholder across the system lifecycle. As large, complex systems are required to operate longer under higher levels of operational uncertainty, and as system engineers transition from a cost-focused to a value-focused design philosophy, flexibility will increasingly become an important design characteristic. Yet there does not exist a codified process or accepted technique to rigorously define an appropriately flexible system architecture.

Flexibility can be understood as the property of a system that allows it to respond to changes in its initial requirements occurring during operation, in a timely and cost effective way. Many existing methods and metrics used to define and value system flexibility have emerged from the engineering community. However, application to systems engineering and design practice is limited by the qualitative, conceptual, descriptive, or case-specific nature of each approach. Alternatively, the management and finance communities have begun to embrace a different approach to flexibility which stems from widespread dissatisfaction with NPV analysis. Widely recognized that NPV undervalues projects that contain flexibility, real options analysis has emerged as a way to understand flexibility and quantify its value. The Black-Scholes and Binomial Lattice techniques have been proposed to value real options as a direct analogue to financial options. However, real options rarely exhibit the behavior necessary to justify the stringent assumptions required for valuation, even for the most contrived applications. Real options embedded "in" the system architecture will almost never be linked to a market-traded financial asset where arbitrage pricing can be enforced. Although the traditional options valuation techniques demonstrate a mathematically insightful and elegant solution with wide academic appeal, real world applications cause the analogy to financial options to break down rapidly, making traditional techniques, in most cases, mathematically unsuitable.

The Datar-Mathews technique has articulated a new mechanism for options valuation which is not constrained by the mathematical structure and market assumptions of the Black-Scholes approach. The Datar-Mathews technique uses the taxonomy and framework of standard discounted cash flow analysis, but also includes distributions of outcomes at each time period, adjustment for risk aversion, and an algorithm for rational economic decision making. By avoiding the underlying assumptions required for traditional valuation, the Datar-Mathews mechanism allows for potential application of real options to system design problems which are not completely analogous to financial options.

CHAPTER III

A SCREENING PROCESS TO IDENTIFY OPTIONS FOR EMBEDDED FLEXIBILITY IN ENGINEERING SYSTEMS

3.1 Introduction

One of the most significant challenges in applying an architecture options approach to flexible design is the problem of identifying the most promising points within the system to create options (Bartolomei, 2006). This is the challenge undertaken in Stage 1 of the proposed integrated flexibility framework (Figure 13). The identification of these architecture options (AO) requires knowledge of both the physical and non-physical aspects of the system as well as insight into the sources of uncertainty and dynamic behavior of that system. System engineers must be able to bound or narrow the options space and focus on the options most likely to produce added value. Additional expenditure of resources can then be justified to investigate, in greater detail, a smaller, more manageable set of potential architecture options. This chapter proposes an eight step screening process that can help the system engineer discover opportunities for embedded flexibility by identifying promising regions in the architecture where AOs can be explored and exploited. This process emphasizes compatibility with common systems engineering practice to facilitate deployability into industry.

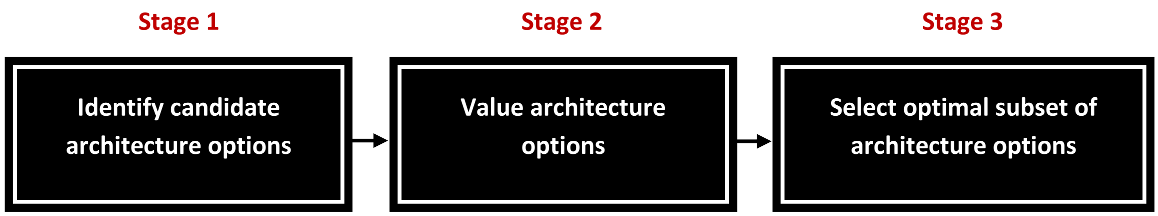

Figure 13: Three stage integrated flexibility framework for identifying, valuating, and selecting architecture options.

3.2 Screening Process for Candidate Architecture Options

This section develops an architecture options screening process that has intended utility for system architects and system engineers. At a high level, the output of this process, which is a set of candidate architecture options, can be useful to project managers for design decisions and resource allocation, but the following exposition is intended predominantly for those charged with the direct implementation and execution of the system design process. The AO screening process is meant to exist within the systems engineering process, and thus be compatible with company best practices, and should be implemented at the early conceptual design phase of the project prior to Preliminary Design Review (PDR), but feasibly up through Critical Design Review (CDR). Inputs to the screening process include company best practices for systems engineering and risk management, which can be adopted entirely or tailored for the individual project. In many cases, the risk management practice will consist of identifying, assessing, mitigating, and tracking program risks with a major emphasis on negative outcome prevention—this can serve as the foundation for an expanded "uncertainty management" practice that is concerned also with the positive ramifications and potential upside benefits of uncertainty. In assessing design solutions that manage uncertainty, this approach assumes that the implementation of flexibility occurs in a constrained tradespace in the neighborhood of a baseline architecture that meets the requirements associated with the critical mission. Essentially, this requires that the types of flexibility considered must be augmentations to an existing design solution—a design solution synthesized from a rigorous systems engineering and tradespace exploration process like that described in Ross and Diller (2003), Shah (2004), Hastings and McManus (2004), Ross *et* al. (2004), and Ross and Hastings (2005).

An effective screening model for AOs must accomplish at least 3 major objectives: 1) it must reasonably encapsulate and describe the uncertainty in the operational environment; 2) it must translate how the operational uncertainty will affect the functional and physical demands of the system, and 3) it must be able to quantitatively represent and organize the system such that the regions in the architecture most impacted by the operational uncertainty, vis-à-vis the functional and physical demands, are made evident. This chapter lays out and expounds upon eight steps, illustrated in Figure 14, to accomplish these objectives:

STEP 1: Define the set of potential operational scenarios and score each scenario for its likelihood and opportunity.

STEP 2: Determine the unique functional requirements associated with each scenario.

STEP 3: Complete a functional-to-physical mapping of functional requirements to physical design parameters by populating an expanded design structure matrix.

STEP 4: Perform an analysis of the sensitivity of design parameters to changes in functional requirements, and normalize subsequent sensitivity-DSM.

STEP 5: Apply an appropriate clustering algorithm that organizes the sensitivity-DSM into regions of highest sensitivity with minimal interaction between clusters.

STEP 6: Combine operational uncertainty information from STEP 1 with sensitivity information from STEP 4 and STEP 5 to visualize sensitivity-opportunity regions with "Hoodoo" plot.

STEP 7: Allocate resources to explore the most promising regions in the architecture and complete a detailed definition for the widest reasonable set of candidate architecture options.

STEP 8: Insert the detailed AOs back into the system DSM and estimate AO-AO correlation metrics.

EXIT process and proceed to the valuation and selection of AOs (Chapters IV and V).

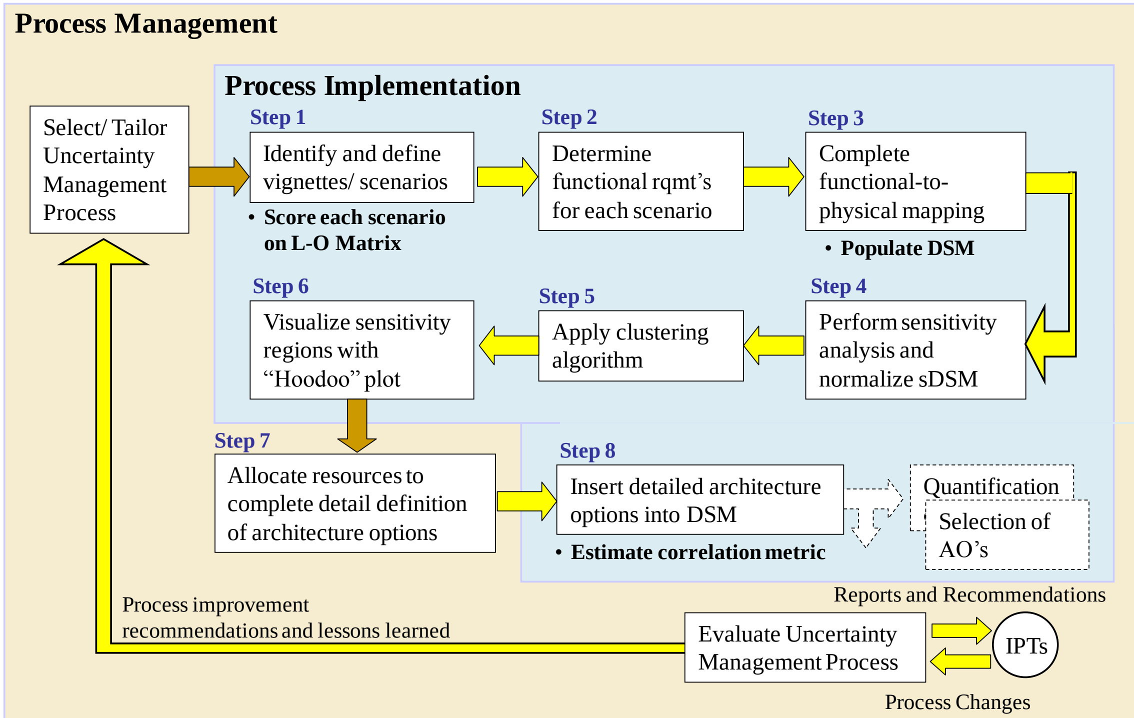

Figure 14: Architecture options screening process flow diagram.

Each of the eight steps serves a necessary and distinct purpose in the screening process. The uncertainty in the operational environment must first be understood and defined in Step 1. The uncertainty drives the necessary system functions which are derived in Step 2. These functions must then be understood in relation to the physical design variables that they affect. This mapping creates the necessary link between operational uncertainty and design implications. The first three steps in large part follow the traditional systems engineering practice of operational concept development and functional analysis/decomposition. The design variables most sensitive to changes in the operational demands are identified and organized in Steps 4 and 5. The resulting groupings indicate a natural partitioning of variables within the system that must change in order to accommodate the operational uncertainty. Step 6 combines the groupings with the underlying potential and significance of the driving operational uncertainty. This fusion of information provides insight into the regions in the architecture where flexibility will be most promising. The process concludes with the detailed definition of the candidate set of architecture options which must be tempered in size and scope by the available resources.

3.2.1 Step 1: Identify and Define Scenarios

The attribute of flexibility has little to no value for a system that will operate in a completely known, static, and defined environment. In this case, the system designer can optimize the solution around known variables and can rely on robustness to handle any variability of performance and operating conditions. Operational uncertainty[10] is the driver for flexible design. Where uncertainty is present, the designer is incentivized to keep options available for future use. Step 1 of this process embraces uncertainty and encapsulates, or bounds, it through robust scenario development. Traditional methods for quantifying variability-type uncertainty with probability density functions and other stochastic processes cannot adequately represent the changing demands of a system that is subject to changing mission requirements. The objective for this step is to provide a series of scenarios, or vignettes, focused on varying missions and operational tasks to ensure complete assessment of the functions of a system in a realistic operational context. This is a process of encapsulating and containing as much epistemic uncertainty as possible (Ferson *et* al., 2004).

In addition to the traditional systems engineering practice of developing the system Concept of Operations (CONOPS), Step 1 defines multiple distinct or adjacent CONOPS. This set can be represented as a set of scenarios:

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[10] Operational uncertainty: Related to the requirements (or demands) on, and environment of, a fielded engineering system. Aspects include: political uncertainty (pertaining to funding instability), lifetime uncertainty (pertaining to uncertainty in performing to the requirements during system lifecycle), obsolescence uncertainty (pertaining to uncertainty of performing to evolving expectation during system lifecycle), integration uncertainty (pertaining to uncertainty in the interactions with other necessary systems), cost uncertainty (pertaining to uncertainty in meeting operating cost targets), and market uncertainty (pertaining to uncertainty in meeting the demands of a changing market environment) (Hastings, Weigel, and Walton, 2002).

$$S = \{s_1, s_2 \ldots s_c\}.$$

The system CONOPS is many times displayed with operational views (OV) classified as OV-1 through OV-7 within the Department of Defense Architecture Framework (DoDAF V2.0, approved May 28, 2009). These views describe, textually and graphically, the operational nodes and elements, assigned tasks and activities, and information flows between nodes. This research contends that a high level representation of organizations, missions, nodes and elements, geographic configuration, connectivity, and information flow, like that included in DoDAF OV-1 and OV-2, is sufficient for bounding the operational space. As an example, a communication satellite may be designed for a single critical mission, in this case to facilitate unmanned air vehicle (UAV) transmissions, and is designed firstly to meet all associated threshold requirements, pictorially represented in Scenario 1 of Figure 15. A robust scenario development process might identify potential secondary, tertiary, and quaternary missions, and would define the set of associated operational requirements. Additional missions could include communication between mobile units, support for counter terrorism operations, and broadband data backhaul from overseas to the continental U.S. (CONUS). These scenarios would require different types and quantities of onboard transponders, different power requirements, different processing and compression capabilities, and different ground segment complexity. The level of detail needed for a high level operational view, OV-1 or OV-2, is illustrated in Figure 15 by showing mission tasks, required elements, geographical configuration, connectivity, and information flow.

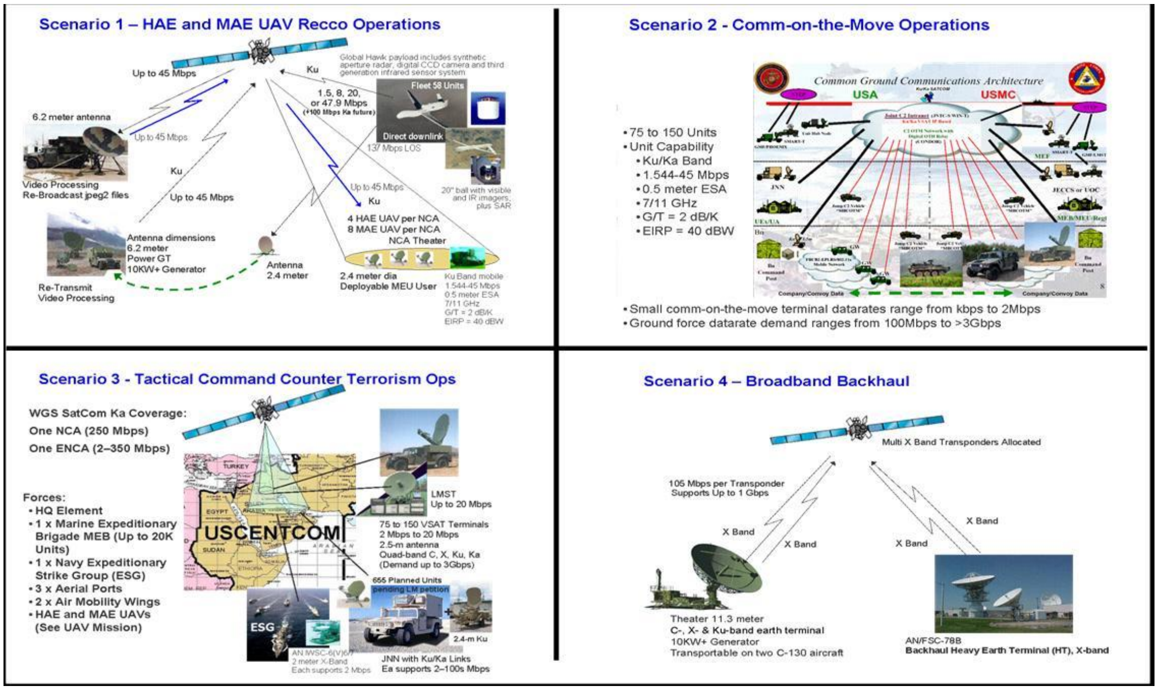

Figure 15: Example operational views of communication satellite primary mission and alternate mission scenarios.

It would be most convenient for the system engineer if a credible probability of occurrence could be related to each scenario; the uncertainty could then be understood concretely. Early in the conceptual phase however, probabilities are illusive and attempts to distill the likelihood of a scenario would likely be met with skepticism. This research proposes a second part to the scenario development step which resembles, in a symmetric way, the traditional risk management practice of utilizing a 5x5 matrix to represent the likelihood and consequence of program risks. The traditional vertical axis which represents the likelihood of a risk event is adapted in this case to represent the likelihood of a flexibility-instigating scenario. The horizontal axis—for risk events, representing the consequence of occurrence—instead represents the opportunity associated with the scenario. The horizontal axis can also be understood as the conditional impact score, that is, if the scenario occurs, how much impact it will have on the system's ability to generate value to its stakeholders. Depicted in Figure 16, the likelihood-opportunity (L-O) matrix qualitatively indicates the ability, whether marginal, moderate, or promising, of a scenario to induce the need for flexibility in the system design.

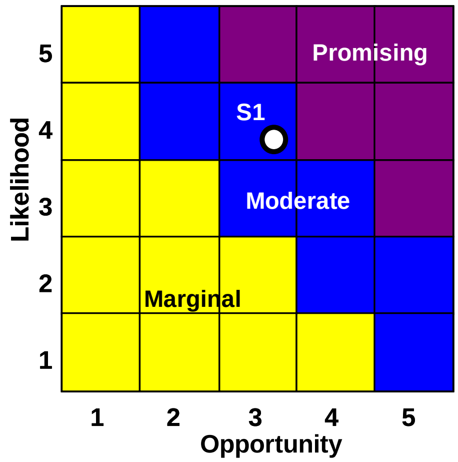

Figure 16: Likelihood-Opportunity Matrix for scoring scenarios.

Scoring each scenario, similar to scoring program risks, requires the solicitation of expert opinion and engineering judgment. However, scoring a scenario that represents operational use cases and alternative system user requirements necessitates interaction with the users and/or stakeholders. Whereas the technologist may be the most credible source for information related to technical performance risk, the *user* is the most fundamental source for potential mission demands. A basic rubric is proposed to assist the collaborative effort of scoring each scenario when only limited types of information are available. In traditional risk management, the likelihood score for program risks is generally adjudicated based on factors like hardware/software maturity and technology readiness levels (Mankins, 1995), complexity, quantity of interfaces, and degree of legacy or heritage design. Where an explicit probability is unavailable, it is proposed that the likelihood of a scenario can instead be credibly based on factors like: stakeholder environment, operational environment, design life, and system characteristics (Table 2). In traditional risk management, the consequence of a program risk event is typically distilled in terms of program cost, schedule, and technical performance. This research proposes that the opportunity associated with a scenario is more appropriately adjudicated in terms of change in required performance, competitive environment, system value, and strategic importance (Table 3).

The likelihood of the scenario and the degree of its opportunity (both represented on a scale of 1 to 5) are multiplied to result in a qualitative measurement for the expected value potential available in the flexibility-instigating scenario. The notation to allow each scenario to carry its L-O score becomes:

$$S_i^{LO(s_i)} = \left\{ s_1^{LO(s_1)}, s_2^{LO(s_2)} \ldots s_c^{LO(s_c)} \right\},$$

where *LO(*s_i*)= Likelihood(*s_i*) * Opportunity(*s_i*)*.

3.2.1.1 Likelihood and Opportunity: A Scoring Rubric for Scenario Assessment

Assessing the likelihood and opportunity of a scenario requires a high level of collaboration between the system engineer, the technologist, the stakeholder, and the end user. The end user must contribute insight into the potential use cases of the system. The stakeholder must communicate the level of desire or utility in accommodating the end users' potential needs. The technologist must leverage his knowledge of the design to communicate the feasibility of the performance or capability required. The system engineer must consolidate and combine this information with any information that can be observed about the nature of the system or of the environment in which the system will operate. This is the crux of the assessment: utilizing and exploiting information that is **available** during the conceptual design phase to forecast the likelihood of an event and categorize the magnitude of its impact if the event occurs.

The pertinent question is then: what does the system engineer know and how can he use that knowledge to inform his scenario assessment? Steiner (1998), and Steiner (1999) introduced a set of distinguishing features for what he called, "enduring architectures." Reinhardt *et* al.

(2001) describe how enduring architectures can be beneficial for complex and highly unprecedented systems that exist in an unknown market (or environment). Fricke and Schulz (2005) provide further context in which to judge the appropriateness of a changeable architecture. An attempt has been made to combine this context with an understanding of Porter's 5 Forces (Porter, 1980) and SWOT[11] analysis to distill a set of proxies that can be useful in scenario assessment. The intention here is not to graft any one approach in a wholesale manner, but instead to merge relevant ideas from each approach to create a helpful scoring rubric.

The specific proxies and scoring guidance found in Table 2 and Table 3 are based on our determination of what the system engineer knows at the outset of product development. He does not necessarily know the numeric probability of an event occurring, nor does he know the quantifiable value of accomplishing an additional task. The system engineer does however know something about the stakeholder environment, the operational environment, the competitive environment, the actual system in question, and the higher level strategic picture. For example, if the stakeholder environment is centralized and the operational environment is highly predictable, or if the design life of the system is relatively short, there would be a relatively low likelihood of alternative scenarios coming to fruition. But if the stakeholders are decentralized with divergent value assessments, and if the operational environment is unproven or undefined, combined with a long system design life, a higher likelihood for alternative mission scenarios would be expected.

Utilizing proxies to assess the magnitude of the conditional impact is somewhat less intuitive; the rationale will therefore be explained briefly. Three useful characteristics are proposed, first being "performance." The question can be asked of a scenario: how much performance is required and is it available from other systems? This draws on the system

[11] SWOT Analysis, and acronym for Strengths, Weaknesses, Opportunities, and Threats, is a strategic planning method used to ensure a fit between the external situation a firm faces (threats and opportunities) and its own internal qualities or characteristics (strengths and weaknesses) (Hill & Westbrook, 1997).

engineer's knowledge of the competitive environment (i.e. other systems able to perform the capability necessitated by a scenario). The magnitude of the conditional impact is low if very minimal change in required performance is required to accommodate a scenario -or- if another system can readily accommodate the need. Conversely, the opportunity impact is high if a significant change in required performance is required -or- if no other system can accommodate the need. The second proxy is system cost, or value. This characteristic draws on the system engineer's knowledge of his own system, i.e., the cost of the system in question. System cost can be somewhat associated with stakeholder utility or value, which can subsequently give some insight into how much utility can be gained by using the system in alternative ways. This is certainly not always the case, but can be a general guideline. Higher utility could possibly be found in using a $10 million dollar piece of test equipment in a new way in comparison to using a $10 thousand dollar asset. Thirdly, the system engineer has knowledge about how the system in question relates to the higher level strategic picture. Is the system strategically important, or rare? Is the system an integral part of a larger operational context? If the system functions as a lynch pin in a larger SoS, or if it cannot be easily substituted by adjacent systems, the magnitude of the conditional impact when new mission requirements arise will be high. The strategic characteristics of a system can also be understood in terms of two of Porter's 5 Forces: barriers to entry, and startup costs. These are proxies for how irreplaceable the system is and how integral it is for performing at the highest contextual level.

The following are four examples of scenario scoring:

1. High likelihood, Low impact: During the construction of a parking garage, assume a scenario where Starbucks Coffee has indicated that it will open a location across the street. There is a good business case for the new location and therefore good reason to believe that the store will open as indicated, so the score for likelihood is assessed as high (5). However, the parking garage will not need a high level of delta performance to accommodate the new traffic. Also other parking across the street can easily accommodate the delta requirement.

Therefore the conditional impact, or opportunity score, can be rated for this scenario as low (1)—minimum delta performance required -and- competitive entities exist to accommodate need.

2. High likelihood, High impact: During the development of a national reconnaissance satellite system, assume the scenario exists in which the system stakeholders have high utility for timely imagery transmitted to the warfighter on the battlefield. An emerging program, TSAT, is under development which would deploy a constellation of communication satellites within 5 years to provide a communication crosslink for other satellites and enable imagery downlink in theater. TSAT has been developed through critical design review (CDR) and has been appropriated the remaining production funds. Although the system is still in the production phase, a case can be made for assessing the likelihood of TSAT on-orbit capability as medium high (4). Based on the fact that the reconnaissance satellite has a high asset value, is of national strategic significance, and is an integral component of a larger SoS intelligence collection capability, the opportunity for in-theater imagery downlink using TSAT is assessed as high (5).
3. Low likelihood, Low impact: Many scenarios would fall into this category. A short design life, consolidated stakeholder, or predictable operational environment would indicate low likelihood for alternative scenarios. Low system cost, few barriers to entry, the existence of competing systems, or small delta performance required would indicate minimal conditional impact on the system's ability to deliver additional value to stakeholders.
4. Low likelihood, High impact: A bridge is being built for vehicle traffic across a major river, e.g. river Tagus at Lisbon (Gesner & Jardim, 1998). The scenario exists where a train will need to be accommodated across the bridge sometime during its design life. The stakeholder environment is very stable and the operational environment is well understood and observable. Although there is currently no demand or plan for the train, the design life of the bridge is comparatively long enough to warrant a medium low likelihood assessment (2). If

the train is needed, the bridge will need to accommodate twice its original load and require a high level of performance delta. There exists no other bridge across the river (no competing solutions) and there are high startup costs for any substitute solution. For these reasons, the conditional impact for this scenario is assessed as high (5).

Step 1 identifies and scores a set of vignettes/scenarios to provide sufficient encapsulation of the operational uncertainty, which as a function of the scenario detail, will enable subsequent steps in the screening process to understand the design impacts related to accommodating potential mission demands. Assessing the likelihood and conditional impact of each scenario requires judgment and industry sense. It is not an automated scoring technique, but like the longstanding risk matrix scoring method, it is a qualitative and subjective assessment that can help system engineers gain insight into the system design implications of uncertainty. To more completely understand the design impacts, the system engineer must first translate the mission demands into concise functional requirements. This is described in Step 2.

Likelihood/Probability of Opportunity

Likelihood

Score	Probability	Stakeholder Environment	Operational Environment	Design Life
1	Not Likely (0-20%)	Singular stakeholder with well understood value assessment	Well defined, predictable OE, observable legacy mission exists	Very short design life
2	Low Likelihood (20-40%)	Consolidated stakeholder	Consistently defined OE, analogous missions observable	Short design life
3	Likely (40-60%)	Centralized stakeholders with consistent value assessment	Some uncertainty in OE, unobserved mission	Moderate design life
4	Highly Likely (60-80%)	Decentralized stakeholders	High uncertainty in OE, must interoperate with adjacent systems	Long design life
5	Near Certain (80-100%)	Large, highly decentralized stakeholders with divergent value assessments	Complex, interconnected SoS OE, emerging mission largely undefined	Very long design life

Table 2: Scoring guidance for scenario likelihood.

Given that the opportunity occurs, what is the magnitude of the conditional impact?

Opportunity (Conditional Impact)

Score	Performance	System Value/ Utility	Strategic
1	Minimal or no performance delta required <1%, other systems exist to seamlessly perform desired function	Very low cost system, high technology turn over, high rate of obsolescence	Few barriers to entry, low startup costs for competing or substitute systems, minimal or no strategic importance
2	Small performance delta required, other systems can be easily modified to perform desired function	Relatively low cost system, comparative technology turn over and obsolescence rate	Surmountable entry conditions, limited strategic importance
3	Moderate performance delta required, other existing systems could be utilized with moderate cost	Moderate cost system, sustainable or evolvable technology churn	Moderate barriers to entry, comparable startup costs, some strategic significance
4	High performance delta required, other systems could be utilized with significant cost	High cost, high value system, national or strategic significance	Very desirable component of larger operational context
5	Very high performance delta required >20%, or major degradation in capability, new system would be required otherwise	Very high cost, high value system. Complex, highly unprecedented, one-of-a-kind system	Necessary component of larger operational context

Table 3: Scoring guidance for scenario conditional impact.

3.2.2 Step 2: Determine Functional Requirements for Each Scenario

Step 2 requires a functional analysis of the system to define those additional functions required to accomplish the mission scenarios developed in the previous step. The functional analysis translates the mission needs for each scenario into a coherent description of system functions[12]. Functions are discrete actions of persons or things necessary to perform the mission. A complete functional decomposition is not required in this step as would be performed in traditional systems engineering practice (Sage & Rouse, 1999; INCOSE SE Handbook, 2004)—the derived functions are maintained at a level where independent, discernable utility can be traced to the function. In other words, the function should be at high enough level to provide uncoupled utility, on its own, instigated by the scenario. This recommendation will necessarily be enforced as an assumption in future work aimed at valuing architecture options that provide specific system functions; low-level, decomposed functions cannot properly be valued when conditional on other functions. For each scenario, this is represented as:

$$s_1 = \left[\mathbf{FR}^1\right] = \left[FR_1^1, FR_2^1, ...FR_\xi^1\right]$$
$$s_2 = \left[\mathbf{FR}^2\right] = \left[FR_1^2, FR_2^2, ...FR_\xi^2\right]$$

Using the operational views in Figure 15 as an example, if "Scenario 4" occurs and a satellite communication system is desired to be used for broadband data backhaul to the continental U.S., stakeholder value is derived only by performing all the functions required for data backhaul. A subset of functions that does not enable the data backhaul, e.g. requisite transponders without needed data compression software, does not elicit value. This assumption helps to define, as will be seen in subsequent steps, the architecture option as a conglomeration or

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[12] System function: "A characteristic task, action, or activity that must be performed to achieve a desired outcome. For a product it is the desired system behavior. A function may be accomplished by one or more system elements comprised of equipment (hardware), software, firmware, facilities, personnel, and procedural data (INCOSE, 2004)."

compilation of design parameters that enable a set of system functions that together perform a desired mission task.

There are a number of useful techniques familiar to system engineers to accomplish a functional analysis. These include: functional hierarchical diagrams, functional flow block diagrams, Integration Definition for Function Modeling (IDEF0) diagrams, N2 charts, state diagrams, specification trees, and timelines. Step 2 aims to repeat a traditional systems engineering functional analysis for each alternative mission scenario where the basic top-down process includes (Defense Systems Management College, 2001):

- Define the system in terms of functions, then decompose the top-level functions into lower-level subfunctions,
- Translate higher-level performance requirements into detailed functional criteria—that is, identifying how well the functions have to be performed,
- Identify and define all internal and external functional interfaces,
- Complete functional partitioning to group functions that logically fit with the components likely to be used in order to minimize functional interfaces,
- Examine all appropriate life cycle functions as well as functions of existing or adjacent systems that will interoperate with system,
- Assess alternative functional approaches to meet requirements,
- Reconsider scenario-imposed requirements to resolve functional issues.

An equally valid, and somewhat simpler, approach to this step would consider system attributes opposed to functions. Consistent with a multi-attribute tradespace exploration (MATE) process described in the SSPARC final report to the National Reconnaissance Office (Hastings & McManus, 2004), system attributes are, "what the user truly cares about." A distilled set of attributes can be conceived that represent quantitative metrics that the decision maker needs to consider. Sometimes described as key performance parameters (KPP), measures of effectiveness (MOE), or Technical Performance Metrics (TPM), these attributes should consider all relevant user needs and be of reasonable fidelity and predictability from high-level engineering models. This research has adopted the terminology of "attributes" to represent the set of functional requirements that provide an independent, quantifiable capability or a level of desired performance.

The set of system attributes associated with a scenario can be represented as:

$$\mathrm{A} = \{a_1, a_2, \ldots a_\eta\},$$

that contain functional requirements:

$$\{FR_1^1, FR_2^1, \ldots FR_\xi^1\} \in a_1.$$

3.2.3 Step 3: Complete Functional-to-Physical Mapping and Populate DSM

Step 3 translates the functional requirements into physical parameters and/or design variables. In this step, the design structure matrix (DSM) is utilized as a modeling technique to represent the system, its interfaces, and the intensity of its relationships. The DSM provides a succinct, quantitative way for organizing and re-structuring information in a complex system, with the additional advantage of simplicity. For an excellent review of the DSM technique used for system decomposition and integration, see Browning (2001). The assumption is made in this step that a system level DSM has been developed for the baseline architecture that performs the critical mission. With this existing DSM as the point-of-departure, Step 3 extends the DSM to include exogenous, e.g. environmental and functional, variables. Proposed by Bartolomei (2007), the extension of the DSM beyond the system boundary, enables additional insight into the system behavior affected by the stakeholders and other external system drivers (illustrated in Figure 17). The relationship between endogenous and exogenous variables is explored in this step as a means to understand how each scenario-generated functional requirement affects the physical design variables. The system engineer must ask and answer the question: what design parameters and physical characteristics are impacted in order to meet a new or changed functional requirement?

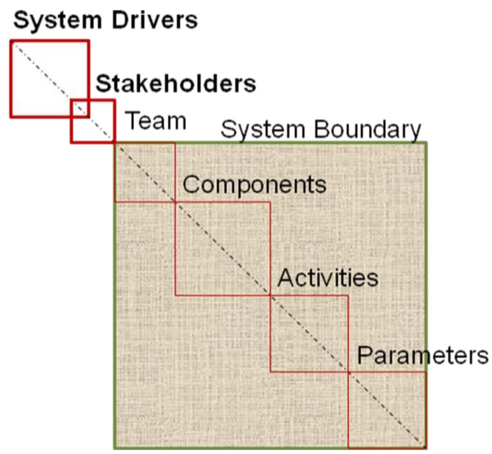

Figure 17: DSM extension can represent relationships between endogenous and exogenous system variables

Consider a system with κ design variables, represented by the design vector:

$$\mathbf{x} = \{x_1, x_2, \ldots x_\kappa\}.$$

For tractability, design variables should be limited to those which have the largest effect on the system attributes, i.e. the set of functional requirements that provide stakeholder value. Defining the design vector is more appropriately described as an exclusionary process that determines which design variables can be left out while still adequately representing the attributes of the architecture. Through the use of a system model, the relationships between design variables can be observed and the system attributes can be calculated from a given design vector. The corresponding DSM can be represented as:

$$DSM(i, j)$$

where the DSM is a square matrix with κ rows and columns, whose entries *i,j* and *j,i* are equal to "1" (or sometimes denoted with an "X") if the two variables *i* and *j* are coupled. The variable η is the number of system attributes relevant to the decision maker, where each attribute can also be expressed as a set of its constituent decomposed functional requirements. An expanded DSM can be constructed to include the η attributes and their relationships to the κ design variables. A notional DSM is illustrated in Figure 18.

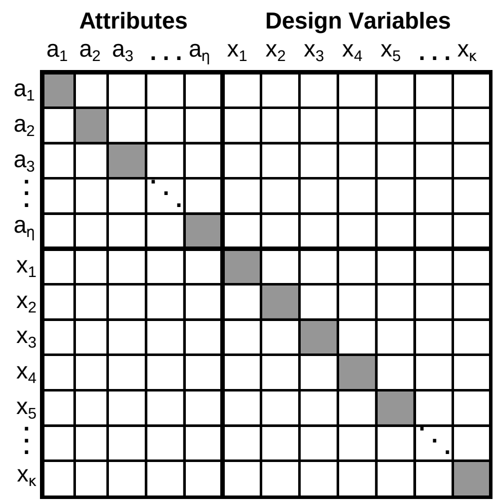

Figure 18: Notional DSM structure with system attributes and design variables.

3.2.4 Step 4: Perform Sensitivity Analysis and Normalize sensitivity-DSM

Step 4 represents the conceptual centerpiece for identifying architecture options. It is our argument that flexibility in the form of AOs will be most promising when embedded in the regions of the architecture most sensitive to changes in functional requirements, specifically those functional requirements associated with the identified user scenarios. An analysis is performed in Step 4 that calculates the change required in one variable due to the change of another. This procedure answers the question: what design variables must change, and by how much, in order to accommodate changes in the mission demands, i.e. system attributes. Kalligeros (2006) proposed the idea of a sensitivity-DSM (sDSM), where entry *i.j* of an sDSM represents the normalized sensitivity of parameter *i* to unit changes in parameter *j* in the neighborhood of a particular architecture solution. The sDSM was used in that case to find regions in the architecture most *insensitive* to change for the purpose of finding platform (i.e., standardized) components. Potential platform components are those that act as a "bus" in some way (Yu, Yassine, and Goldberg, 2007), or as an interface between other customized systems, having usefulness across product variants. Our screening process is instead concerned with the highly sensitive regions in the architecture which shed light on the critical areas for flexibility as the system is asked to accomplish different tasks. The sDSM can also be defined as a square matrix with κ rows and columns, whose normalized entry *i,j* represents the percent change in variable *i* caused by a percent change in variable *j*. A particular set of design variables is denoted as:

$$\mathbf{x}^* = \{x_1^*, x_2^*, \ldots x_\kappa^*\}.$$

So the sDSM is defined as:

$$sDSM(i,j) = \left(dx_i^* \middle/ dx_j^* \right) \left(x_i^* \middle/ x_j^* \right).$$

Unlike the DSM which is valid for all designs, the sDSM is calculated for a particular design solution and therefore necessitates the assumption of an existing baseline architecture as the point-of-departure for the analysis. The sDSM represents sensitivities between design variables (i.e., how design variables change in response to other design variables), and is next extended to include the sensitivities of design variables to changes in functional requirements. The south-west quadrant of Figure 18 contains these sensitivities and can be represented as:

$$sDSM(i,j) = \left(dx_i^* \middle/ da_j \right) \left(a_j \middle/ x_i^* \right).$$

This step in the screening process is concerned only with the south-west and south-east quadrants which contain the sensitivities of design variables to changes in functional requirements and other design variables; the upper regions in Figure 18 would contain sensitivities of functional requirements to changes in other functional requirements and design variables. These upper regions would provide little insight for the purposes of this architecture screening process and will not be considered here.

Each design element is affected in one of two ways: directly from the change in functional requirement, or indirectly from a propagated change in another design element. This process is concerned with the combined total change, due to both sources, and can express this change with the sum:

$$\Delta x_i = \sum_{j=1}^{\eta} \frac{\partial x_i^*}{\partial a_j^*} \Delta a_j^* + \sum_{j=1}^{\kappa} \frac{\partial x_i^*}{\partial x_j^*} \Delta x_j^* .$$

This formulation states that the required change in x_i is the cumulative change caused by all the functional requirements *and* other design elements to which x_i is sensitive in the neighborhood of x_i^*. The resulting matrix is populated with these sensitivity values which can either be normalized to the largest value or binned for simplicity. A binning strategy might assign integer values on a 1 to 5 scale to represent the least to most sensitive relationships.

3.2.5 Step 5: Apply Clustering Algorithm

The next step in this process helps the system engineer manipulate the visual structure of the data. This organization provides further clarity of the data which helps generate insight into the relationships that exist between elements. Clustering of DSM elements by rearranging the order of the rows/columns can help find subsets, or modules, that are mutually exclusive or minimally interacting. Step 5 uses a DSM clustering technique to consolidate the elements in the system architecture that are most sensitive to changes in the functional requirements. These sensitivity regions, when combined in Step 6 with the L-O score for each scenario, can help reveal the most promising areas in the architecture to embed flexibility.

DSM clustering has been proposed by numerous researchers as a means to improve system architectures (McCord & Eppinger, 1993; Pimmler & Eppinger, 1994). Illustrated in Figure 19, clusters can contain most, if not all, of the interactions internally and the links between separate clusters can be minimized or eliminated (Gutierrez, 1998; Fricke & Schulz, 2005). This type of data partitioning can help identify highly coupled subsets and separate them from uncoupled elements. Traditional use of DSM clustering allows the system engineer to identify natural groupings within the system, for example: to identify subsystems, create the work breakdown structure (WBS), develop the integrated product team (IPT) structure, or separate parallel tasks from sequential or iterative. For this analysis, our main emphasis is on segregating physical design elements that are highly responsive to the changes imposed by future use cases or scenarios.

	Function 1	Function 2	Function 3	Function 4	Function 5	Function 6	Function 7	Function 8	Function 9	Function 10
Function 1		x							x	
Function 2	x									
Function 3										x
Function 4							x	x		
Function 5										x
Function 6		x						x	x	
Function 7				x				x		
Function 8										
Function 9						x				
Function 10			x							

	Function 1	Function 2	Function 9	Function 6	Function 4	Function 7	Function 8	Function 3	Function 5	Function 10
Function 1		x	x							
Function 2	x									
Function 9				x						
Function 6		x	x				x			
Function 4						x	x			
Function 7					x		x			
Function 8						x				
Function 3										x
Function 5										x
Function 10								x		

Figure 19: Clustering algorithm applied to a DSM (Fricke & Schulz, 2005).

There is a wide range of clustering algorithms, a sample of which can be found in (Alexander, 1964; Hartigan, 1975; Gutierrez, 1998; Thebeau, 2001; Whitfield, Smith, and Duffy, 2002). However, there are some key features that must be present to adequately perform Step 5 in this process:

- The algorithm should be able to handle non-binary matrix entries
- The algorithm should be able to find the optimal number of clusters
- The algorithm should be able to detect "bus" elements, i.e., those that have sensitivity interaction widely across the system
- The algorithm should be able to detect overlapping clusters.

One algorithm in particular meets these needs. Yu, Yassine, and Goldberg (2007) proposed a clustering algorithm that uses an objective function based on the minimum description length (MDL) principle (Rissanen, 1978; Barron, Rissanen, and Bin, 1998; Grünwald & Rissanen, 2007), and a genetic algorithm as a search strategy. The MDL principle is interpreted as follows:

> Among all possible models, choose the model that uses the minimal length for describing a given data set (that is, model description length plus mismatched data description length) [*sic*].[13]

The MDL approach has fundamental roots in *inductive inference* where the goal is to find laws or regularities underlying some given data set that can be used to gain insight, clarify, or predict future data. Stated succinctly by Grünwald (2000), the MDL Principle is that, "any regularity in the data can be used to compress the data, i.e. to describe it using less symbols than the number of symbols needed to describe the data literally." In Step 5 the MDL idea is adopted to describe the sDSM with the simplest (i.e. symbolically shortest) model which compresses the dataset into discrete clusters that contain the given elements while also indicating which, if any, elements have been wrongly included or excluded in or from those clusters. The MDL algorithm is implemented by minimizing the objective function that sums the *model description* with the *mismatched data description*. The model description is:

$$\sum_{i=1}^{n_c}\left(\log n_c + cl_i \cdot \log \kappa\right),$$

where n_c is the number of clusters in the sDSM, κ is the number of rows or columns in the sDSM, cl_i is the number of nodes in the ith cluster. The logarithm is of base 2 which indicates that $\log \kappa$ bits are needed to describe n_c. Another matrix sDSM´ is then constructed with elements d'_{ij}, which is used to compare the compressed model description with the original data. Where the

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[13] Yu, T.-L., A.A. Yassine, and D.E. Goldberg, *An Information Theoretic Method for Developing Modular Architectures Using Genetic Algorithms.* Research in Engineering Design, 2007. **18**(2): p. 91-109

two models differ, $d'_{ij} \neq d_{ij}$, a mismatched data description is used to indicate if the mismatch is one-to-zero (Type-I) or zero-to-one (Type-II). The mismatched data description is:

$$\sum_{(i,j)\in S_1} \left(\log\kappa + \log\kappa + 1\right) + \sum_{(i,j)\in S_2} \left(\log\kappa + \log\kappa + 1\right),$$

where the first log κ indicates i and the second indicates j with one extra bit to describe the type of mismatch. In order to use nonbinary matrix entries, define the following two mismatch sets:

$$S_1 = \sum_{d'_{ij}=1} (1 - p_{ij})$$
$$S_2 = \sum_{d'_{ij}=0} p_{ij}$$

where S_1 is the set of Type-I mismatches and S_2 is the set of Type-II mismatches. The sDSM entries are normalized to $p_{ij} = (d_{ij} - d_{min})/(d_{max} - d_{min})$, where $d_{max} = \max_{i,j} d_{ij}$ and $d_{min} = \min_{i,j} d_{ij}$. Entry ij then has a probability $(1 - p_{ij})$ to be a type-I mismatch if it is inside a cluster, and a probability p_{ij} to be a type-II mismatch if it is outside clusters.

The goal of the clustering algorithm is to find model **M** that minimizes the objective function:

$$f_{DSM}(\mathbf{M}) = (1-\alpha-\beta)\left(n_c \log n_n + \log n_n \sum_{i=1}^{n_c} cl_i\right) + \alpha[|S_1|(2\log n_n + 1)] + \beta[|S_2|(2\log n_n + 1)],$$

which, written after some arithmetic manipulation, is the sum of the model description over all clusters and the mismatched data description over both mismatch sets. Weighting factors α and β are inserted to mimic the behavior of manual clustering; these coefficients represent the user's preference for including versus excluding elements in a cluster. The value used for the weighting factors is dependent on individual preference and the application domain. Manual calibration can also be used after the data is clustered to reflect the preference in a specific application. This tuning of the clustering algorithm will alter the resulting data partition and may reveal alternate organizational structure and different design aspects within the architecture.

3.2.6 Step 6: Visualize Sensitivity Regions

Step 6 fuses the Likelihood-Opportunity scores from the scenarios in Step 1 with the design sensitivity information from Step 4 to display a clustered 3D architecture plot. Figure 20 displays an example of the two plots, a 3D bar plot and a 2D color map (known also as a contour or topographic map), that is combined to create a "Hoodoo" plot. The "Hoodoo" plot, which is a reference to the natural geologic rock formations found in desert regions like Bryce Canyon National Park, is able to display information regarding structure (i.e. magnitude and clustering of the sensitive regions) while also displaying the underlying topography (i.e. the likelihood and impact of the instigating scenario). It can also be thought of as downtown Manhattan built on a hilly landscape—the insight is available when viewing the skyline from a distance to see the overall city structure. When viewed separately, the sensitivity and scenario information can certainly be useful. However, the Hoodoo plot combines the relevant information in a novel and consolidated way in order to more effectively reveal the important data characteristics.

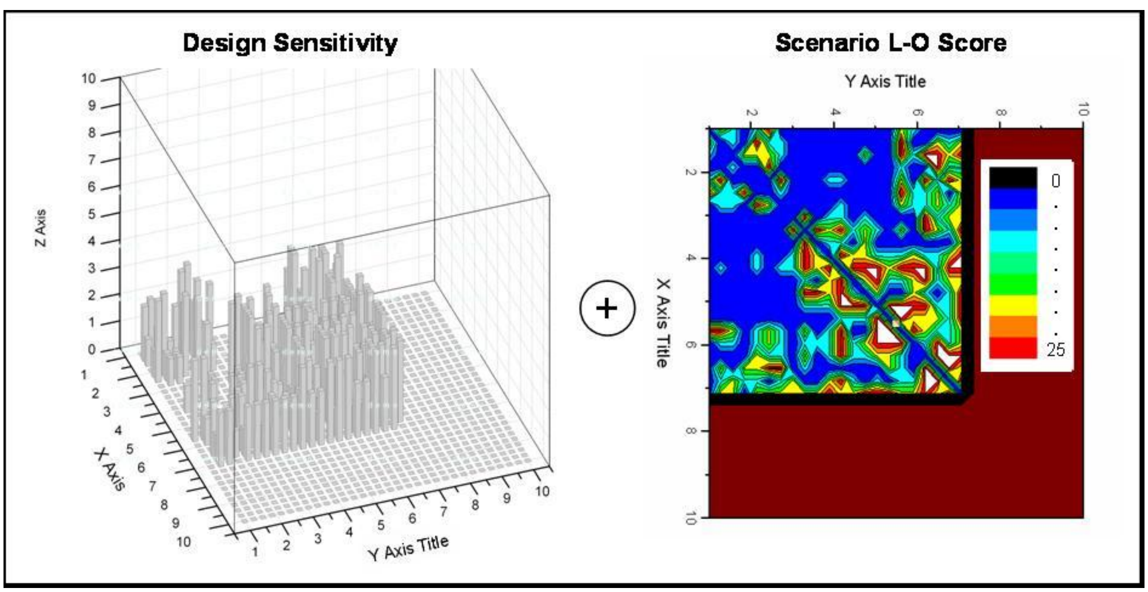


Figure 20: Combine 3D Bar Plot from sensitivity analysis with 2D contour map from Likelihood-Opportunity score to create "Hoodoo" Plot.

The visualization can be either highly resolved, showing all levels of detail, or highly simplified, showing binned data and only three colors for the L-O score. Compressed down to a 2D plot in Figure 20, the sensitivity data is categorized as low, medium, and high (· , * , @) while the L-O score is shown as low, moderate, and promising (yellow, blue, purple). The color of each node in the "Hoodoo" plot is generated from the L-O score of the scenario from which the system attribute is affected. That is, all downstream design elements related to the change in a system attribute will take on the L-O score of the driving scenario. If multiple scenarios affect a system attribute, the attribute will propagate (to the design elements) the L-O score from the highest "impact" scenario and need not be additive. The notation as follows states that, for each element in the sDSM, if the absolute value of the cumulative change in x_i—caused by all the functional requirements (viewed through the system attributes) *and* other design elements to which x_i is sensitive in the neighborhood of x_i^*—is greater than zero, then the node is colored according to the highest LO score of the scenario that contains the affected functional requirements:

$$\begin{aligned}
&For\left(sDSM(i,j)\right),\\
&If\left|\sum_{j=1}^{\eta}\frac{\partial x_i^*}{\partial a_j^*}\Delta a_j^* + \sum_{j=1}^{\kappa}\frac{\partial x_i^*}{\partial x_j^*}\Delta x_j^*\right| > 0,\\
&\quad sDSM(i,j) = Yellow \,\middle|\, Max[LO(s_i)] \le 6 \cap \left(a_j\left\{FR_\xi\right\} \subset s_i\left[\mathbf{FR}\right]\right)\\
&\quad sDSM(i,j) = Blue \,\middle|\, Max[LO(s_i)] \le 12 \cap \left(a_j\left\{FR_\xi\right\} \subset s_i\left[\mathbf{FR}\right]\right)\\
&\quad sDSM(i,j) = Purple \,\middle|\, Max[LO(s_i)] > 12 \cap \left(a_j\left\{FR_\xi\right\} \subset s_i\left[\mathbf{FR}\right]\right)\\
&Else\left(sDSM(i,j)\right) = No_Color
\end{aligned}$$

If the functional requirements that are contained in a system attribute are also a subset of the functional requirements that constitute the scenario vector, it can be said that the scenario drives the change seen in the sDSM element. The "Hoodoo" plot, whether 2D or 3D, can then be used to identify regions in the architecture that are sensitive to changes caused by a scenario, while displaying the opportunity (or relative impact) of that scenario. This research asserts that the confluence of these aspects represent the most promising regions to embed flexibility in the form of architecture options.

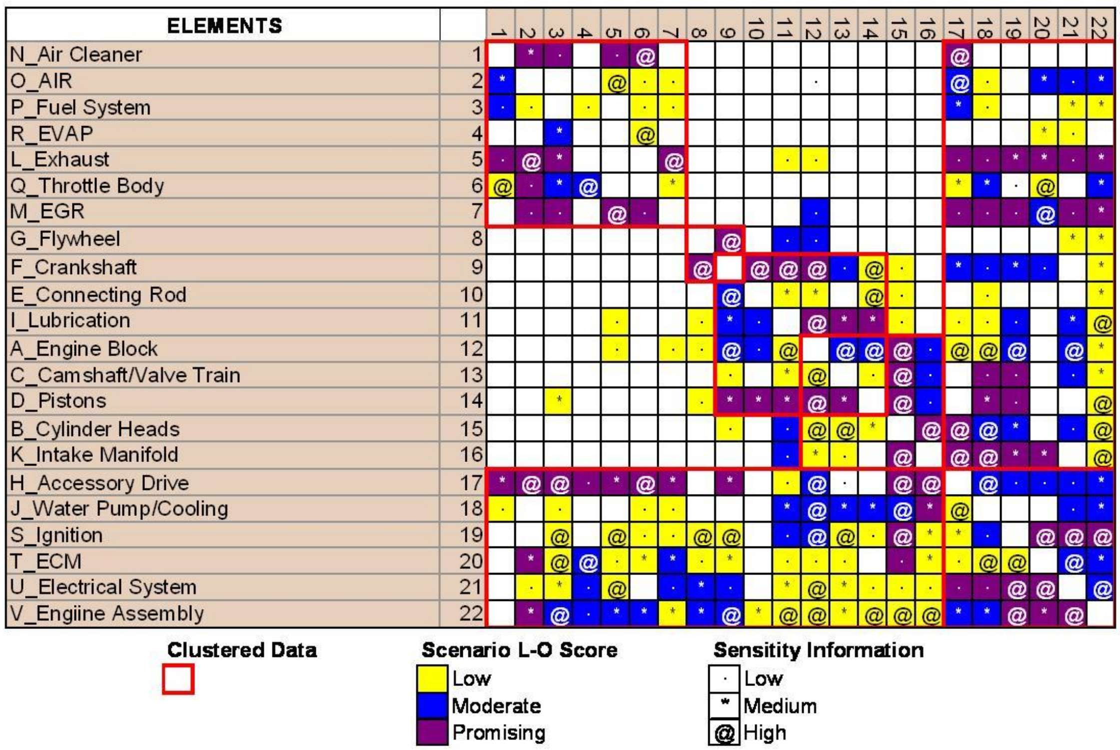


Figure 21: Conceptual plot of sensitivity data combined with L-O scenario data.

3.2.7 Step 7: Complete Detailed Definition for AOs

While a robust screening process can help identify promising regions in the architecture to embed AOs, the detailed definition of feasible AOs is an inherently creative endeavor and cannot reasonably be automated. For example, a screening process can identify the elements in the spacecraft electrical power system that are sensitive to changes in future power demand, but cannot specify the best option available to accommodate that change. The system engineer in collaboration with specialty engineers and domain experts must decide if more efficient multi-junction solar cells, next generation traveling wave tube amplifiers (TWTA), or multiple in-series solid state power amplifiers (SSPA), are the better implementation option for the desired effect.

This type of analysis can require significant time and resources and necessitates the prerequisite of a managerial-type decision point. For this reason, Step 7 of the screening process exits the implementation phase and requires a management resource allocation decision. The unconstrained management objective is to complete detailed definitions for the largest set of candidate architecture options to allow for broad analysis and deliberation. However, this objective is realistically constrained by available time, resources, and engineering labor pool as well as external stakeholder preferences and other programmatic considerations. Step 7 requires a management decision for resource allocation and establishes the constraints on the size and completeness of the actual set of AOs available to the system architect for consideration and implementation. Step 7 subsequently requires completion of the detailed definition for all AOs under consideration. The output of this step is a functional and physical description of each architecture option, including necessary hardware, software, internal and external interfaces, technology maturity assessment, and any other preliminary design review (PDR)-level of design description deemed appropriate.

3.2.8 Step 8: Insert Detailed AOs into DSM and Estimate Correlation Metric

The final step in the screening process is to insert the well-defined AOs into the system DSM and populate the element relationships. The resulting DSM will have all candidate AOs embedded simultaneously in the system design—this is not necessarily a design solution nor is it meant to be completely realistic. The purpose of this DSM is twofold: first, to discover the extent to which AOs have overlapping physical characteristics, and second, to trace the physical design of the AO back to the top level scenario.

This research recognizes the importance of discovering how AOs are physically related, that is, how the implementation of one AO affects, or is affected by the existence of another. The question can be asked: does one AO, by nature of its physical design, augment or influence the implementation of another AO? To approach this question, the following assumption is required:

AOs in the DSM cannot be mutually exclusive--there is no sense to analyze the relationship between AOs that cannot exist at the same time. To be clear, the exercise of two AOs can be mutually exclusive (where only one can be utilized in operation), but the physical characteristics required to embed each AO cannot be mutually exclusive. Where only one of a set of AOs can be implemented at a time (e.g., the TWTA and SSPA solutions), a single option must be chosen for the overlap analysis. Iterations to this analysis can be completed to substitute and accommodate the excluded alternate options. For tractability, a quantitative answer to the posed question is not attempted. However, the supersaturated DSM is used as a tool to understand the relationships between AOs in the system context in order to accomplish some of the following: filter out incompatible AO pairs, discover opportunities to pursue AOs that have common implementation elements, coordinate vendor requests for information (RFI), develop a high level architectural strategy for AO mix, consolidate reference data in preparation for detailed AO pricing, and develop a more complete understanding of the physical commonalities between AOs that both help and hinder system level synthesis.

The second way the supersaturated DSM is used is similar to the common systems engineering practice of requirement traceability. However, instead of tracing system performance back to the parent requirement, the AO physical design parameters is traced, by route of the functional requirements, back to the driving mission scenario. The purpose here is to understand how candidate AOs satisfy multiple functional requirements derived from different scenarios (i.e. sources of operational uncertainty) and subsequently estimate a measure of correlation between AOs. If two AOs satisfy functional requirements associated with the same scenario, they have an overlapping source of uncertainty—these are defined as perfectly positively correlated. If two AOs satisfy functional requirements associated with two different scenarios, the AOs are uncorrelated given the scenarios are independent. Functional requirements which are shared between scenarios are partially correlated AOs. AOs will be negatively correlated if they satisfy functional requirements associated with negatively correlated scenarios. The correlation coefficient, ρ, can be estimated as:

$$\rho_{ij} = 1, \text{ if } AO_i \text{ and } AO_j \text{ satisfy functional requiremtents associated with the same scenario}$$
$$\rho_{ij} = 0, \text{ if } AO_i \text{ and } AO_j \text{ satisfy functional requiremtents associated with two different independent scenarios}$$
$$0 < \rho_{ij} < 1, \text{ if } AO_i \text{ and } AO_j \text{ satisfy requirements that are shared between scenarios}$$
$$-1 < \rho_{ij} < 0, \text{ if } AO_i \text{ and } AO_j \text{ satisfy functional requiremtents assciated with negatively correlated scenario}$$

In the more complicated case where ρ_{ij} is between zero and one, a preliminary correlation value can be assigned based on the number of functional requirements that are shared between the AOs and the relative value potential of each functional requirement. A qualitative scale similar to Table 4 has widely been proposed to guide engineering judgment and correlation coefficient interpretation.

Table 4: Interpretation of correlation coefficient.

Correlation	Negative	Positive
Small	−0.3 to −0.1	0.1 to 0.3
Medium	−0.5 to −0.3	0.3 to 0.5
Large	−1.0 to −0.5	0.5 to 1.0

An exact numeric value at this stage is not essential and will be in some ways arbitrary and should not be observed too strictly (Cohen, 1988). After the architecture option is valued as described in Chapter IV, a more rigorous treatment of the correlation coefficient is presented based on the AO's statistical properties that become discernable.

3.3 Conclusion

Flexibility in the system design can be understood as the set of architecture options which allow the system to respond to changes in its initial objectives in a timely and cost effective way. Architecture options are sets of physical design components that enable a distinguishable function with discernable value predicated on an uncertain mission scenario. A screening process can be used during conceptual design to identify the most promising regions within the system to create options. The system engineer is then able to investigate a smaller, more manageable set of potential architecture options. An eight step screening process is presented that encapsulates and describes the operational uncertainty, translates it into functional and physical demands on the system, and organizes and represents the most promising regions with a compact system model. After the candidate architecture options are identified through the screening process, they can be valued with the technique described in the following chapter.

CHAPTER IV

VALUATION OF FLEXIBILITY IN THE SYSTEM ARCHITECTURE

4.1 Introduction

As system designers embrace the notion that it is more appropriate to seek to maximize the life cycle value of a system than to solely minimize the life cycle cost, flexibility becomes a critical characteristic. Flexibility embedded in the system architecture can allow the system to perform new functions to accommodate changing demands over time, thus capturing latent stakeholder value. In order to make flexibility-informed design decisions, the value of flexibility must be quantified. The previous chapter developed the idea of architecture options: tangible design opportunities that accomplish a distinguishable function with discernable value in light of an uncertain mission scenario occurring. Architecture options were employed as a way to operationalize the concept of system flexibility. This chapter will discuss the second part of the three stage integrated framework (Figure 22) for designing appropriately flexible systems: valuing architecture options.

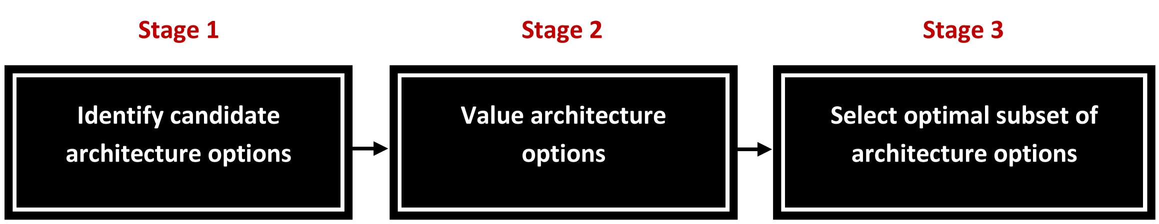


Figure 22: Three stage integrated flexibility framework for identifying, valuing, and selecting architecture options.

An architecture option valuation technique is developed in this chapter that embraces the theoretical underpinnings of real options analysis while avoiding the constraining mathematical structure and market assumptions necessary for traditional methods like Black-Scholes and Binomial Lattice. Based on a recent development in real options analysis (Mathews, Datar, and Johnson, 2007), real options "on" projects can be valued in a more intuitive and robust way. See Section 2.5.3.3.5 for an overview of the Datar-Mathew (DM) technique. This advancement has enabled this research to augment and extend the DM valuation technique to handle real options embedded "in" the system in a way that can better facilitate adoption by the technical and systems engineering communities.

The following sections will present the Variable Expiration technique and define each of the input parameters of the algorithm. Discussions are included regarding how the new technique handles benefit stream forecasts for both commercial and military projects, variable exercise cost, and risk aversion through differential discounting. Finally, analytic valuation tools are presented to describe the more intricate behavior of architecture options and the sensitivities of option value to changes in the input parameters. This flow is illustrated below in Figure 23.

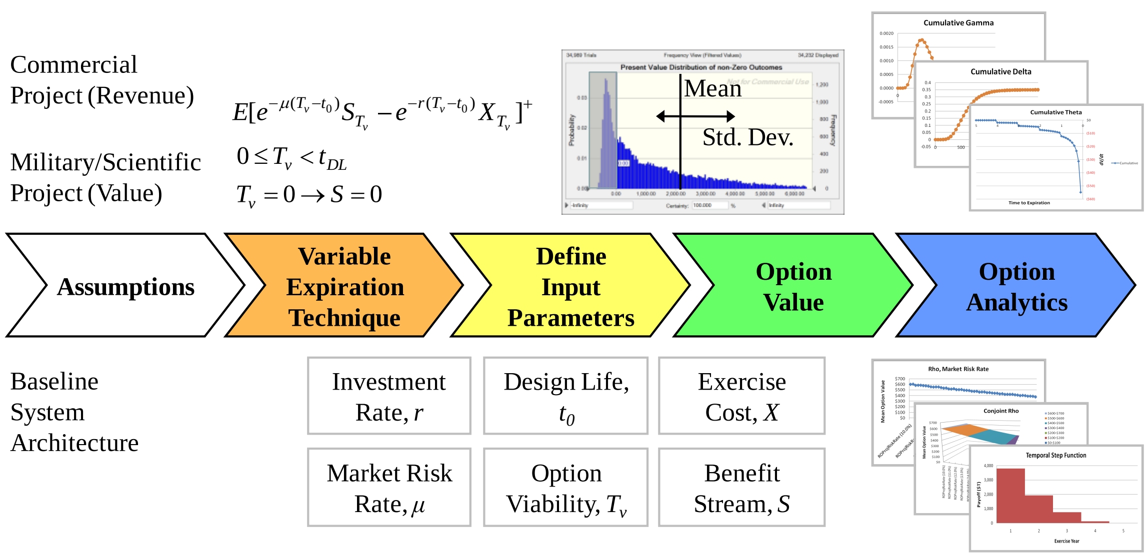


Figure 23: Variable Expiration option valuation chapter flow.

4.2 Valuation of Architecture Options Using a Variable Expiration Technique

Architecture options embedded "in" the system behave differently, compared to a manager's real option "on" a project, and require additional considerations for proper valuation. The decision point for real options "on" a project is predefined as the investment gate where the irreversible launch cost is expended to pursue the venture. This real option is handled appropriately with a European-type option with only one exercise opportunity at expiration. Real options embedded "in" the architecture can theoretically be exercised at anytime during the design life of the system. This option more resembles an American-type option in that the exercise date is not predefined but is instead bounded by the expiration date. However, an additional consideration exists in that the embedded option is subject to a second source of uncertainty beyond the uncertainty in the price path of *S*--that is the *viability* of the option. An embedded option will generate value only if the scenario exists to allow its usage. When the scenario occurs that instigates the exercise of an embedded option, that option is described as "viable." This occurrence is uncertain and therefore must be characterized by a random variable. Even after an option becomes viable, there remains uncertainty in the value that can be derived, or in a commercial sense, the profit that can be generated, through the exercise of the option. A new technique is developed in this research that allows for the valuation of options that exhibit both uncertainty in the option payoff and uncertainty in the option expiration date. These options are characterized in this research as variable expiration (VE)-type options.

Although architecture options can be exercised any time before expiration, the rational decision maker will exercise only when the operating profit forecast is positive and will abandon otherwise. In the case where scenarios (as described in the previous chapter) encapsulate the uncertainty in option viability, the forecast will be positive only when the relevant scenario occurs. Therefore option viability is defined by the likelihood function of the mission scenario or potential business case. When the uncertainty in option viability is merged with that of option payoff, a new variable expiration-type option is defined that more closely reflects the behavior of real options "in" projects. The valuation logic is implemented as follows:

$$\text{Real option value} = Average\left[MAX\left(\overline{\text{operating profit}\Big|_{\mathrm{T_v}}^{t_{DL}}} - \overline{\text{launch cost}\Big|_{\mathrm{T_v}}}, 0\right)\right].$$

The overscore represents the present value distribution. The uncertainty related to option viability is represented with the random variable T_v and defines the first economically rational opportunity to exercise the option. If annual forecasts are used, T_v will have an integer value between zero and the design life in years, t_{DL}. The case where the option never becomes viable, i.e., the instigating scenario never occurs, is represented as T_v equal to zero, which zeroes out the operating profit for that trial. Conceptually, as T_v extends further in time, there are fewer years to reap the benefits of the architecture option after exercise. The algorithm can also be stated as:

$$\begin{aligned}
&Z_{t_0}^{t_{DL}}(\mu, r) = E[e^{-\mu(T_v - t_0)} S_{T_v} - e^{-r(T_v - t_0)} X_{T_v}]^{+} \\
&0 \le T_v < t_{DL} \\
&T_v = 0 \rightarrow S = 0
\end{aligned}$$

A Monte Carlo simulation is performed to evaluate the expected value of the appropriately discounted cash flows, conditioned on rational decision-making at the option viability date. Valuing an embedded option in this way can be understood as owning a market basket of European-type options--one for each expiration year--and prorating their value by the probability of becoming viable in that year (or time step). This technique utilizes the same validated logic as the DM method, described in the literature review Section 2.5.3.3.5, and extends it for use with embedded real options. It is not constrained by the complex market assumptions of traditional valuation methods and instead utilizes the terminology and frameworks familiar to financial forecasts.

4.2.1 Defining S and T_v: "Temporal Step" Value Functions

In financial options, the variable S is the uncertain value of the underlying asset or stock. It fluctuates with a mean, standard deviation, and drift rate in Black-Scholes and an up and down probability in binomial lattice technique. S_0 is the market consensus, and observable, value of S today in Year 0 (i.e., the stock price listed on the exchange or in newspapers). In real options, the value of S is the stream of future operating profits which is neither observable or known with certainty. The analogue to S_0 is the present value distribution of the cashflows which are consolidated through discounting the flows to particular dates.

For architecture options, S can similarly be a stream of operating profit, but more generally is the future stream of potential benefits generated by the utilization the option. It is the delta benefit in each year above the benefit derived from the baseline system architecture. This benefit stream is contingent on "if" the option becomes viable and also "when" the option becomes viable. Option viability is defined by the likelihood function represented by T_v. If the option never becomes viable, S is zero for all years and no delta benefit will be derived over the design life. If T_v is greater than zero, S will be comprised of the benefit stream starting in year T_v and extending through the system design life. In terms of operating profit (i.e., revenue and cost), S can be estimated with some of the common business variables described in Table 5. Arbitrary numbers are included as representative quantities to demonstrate the calculations.

Table 5: Estimation of the most likely change to operating profit with typical business inputs.

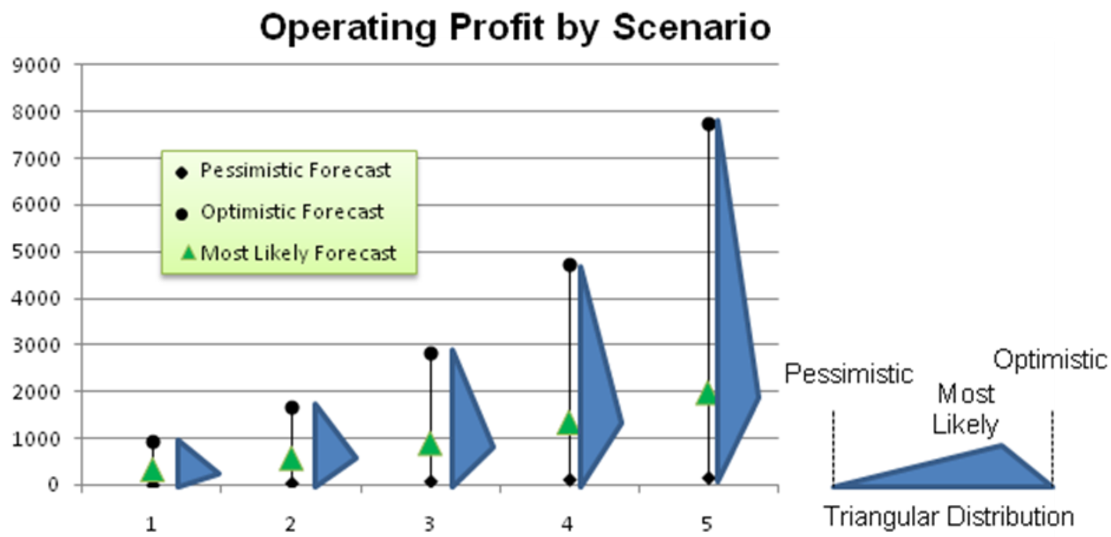
Most Likely Delta from Baseline Business Case						
	Year					
($T)	0	1	2	3	4	5
Unit ΔPrice	**25**					
First Unit ΔCost	**30**					
Target Learning Curve		0.85	0.85	0.85	0.85	0.85
Unit ΔCost		14	11	10	9	8
Unit Δquantity - 40% year/year growth		**30**	42	59	82	115
ΔRevenues (Unit ΔPrice * Unit ΔQuantity)		750	1050	1470	2058	2881
Recurring ΔCosts (Unit ΔCost * Unit ΔQuantity)		405	462	563	703	889
ΔOperating Profits (ΔRevenue - Recurring ΔCost)		**345**	**588**	**907**	**1355**	**1992**

Uncertainty is included in the business forecast by varying any of the independent variables, most commonly the price, quantity, and unit cost. Distributions of almost any kind can be applied to develop a time-varying stochastic forecast. A simple method is to develop a pessimistic and optimistic business case to define the bounds of a triangular distribution in each analysis year. Table 6 describes a pessimistic and optimistic case and Figure 24 illustrates the numbers.

Table 6: Pessimistic and optimistic forecasted change to operating profit using typical business inputs

Pessimistic Delta from Baseline Business Case						
	Year					
($T)	0	1	2	3	4	5
Unit ΔPrice	**20**					
First Unit ΔCost	**30**					
Target Learning Curve		0.90	0.90	0.90	0.90	0.90
Unit ΔCost		20	18	16	15	15
Unit ΔQuantity - 20% year/year growth		**15**	18	22	26	31
ΔRevenues (Unit ΔPrice * Unit ΔQuantity)		300	360	432	518	622
Recurring ΔCosts (Unit ΔCost * Unit ΔQuantity)		298	318	353	399	456
ΔOperating Profits (ΔRevenue - Recurring ΔCost)		2	42	79	119	166

Optimistic Delta from Baseline Business Case						
	Year					
($T)	0	1	2	3	4	5
Unit ΔPrice	**30**					
First Unit ΔCost	**30**					
Target Learning Curve		0.80	0.80	0.80	0.80	0.80
Unit ΔCost		9	7	5	4	4
Unit ΔQuantity - 60% year/year growth		**45**	72	115	184	295
ΔRevenues (Unit ΔPrice * Unit ΔQuantity)		1350	2160	3456	5530	8847
Recurring ΔCosts (Unit ΔCost * Unit ΔQuantity)		399	470	603	800	1079
ΔOperating Profits (ΔRevenue - Recurring ΔCost)		951	1690	2853	4729	7769



Delta Operating Profits						
Year	0	1	2	3	4	5
Pessimistic Forecast		2	42	79	119	166
Optimistic Forecast		951	1690	2853	4729	7769
Most Likely Forecast		345	588	907	1355	1992

Figure 24: Change in operating profit for pessimistic, most likely, and optimistic business case scenarios represented with triangular stochastic distributions.

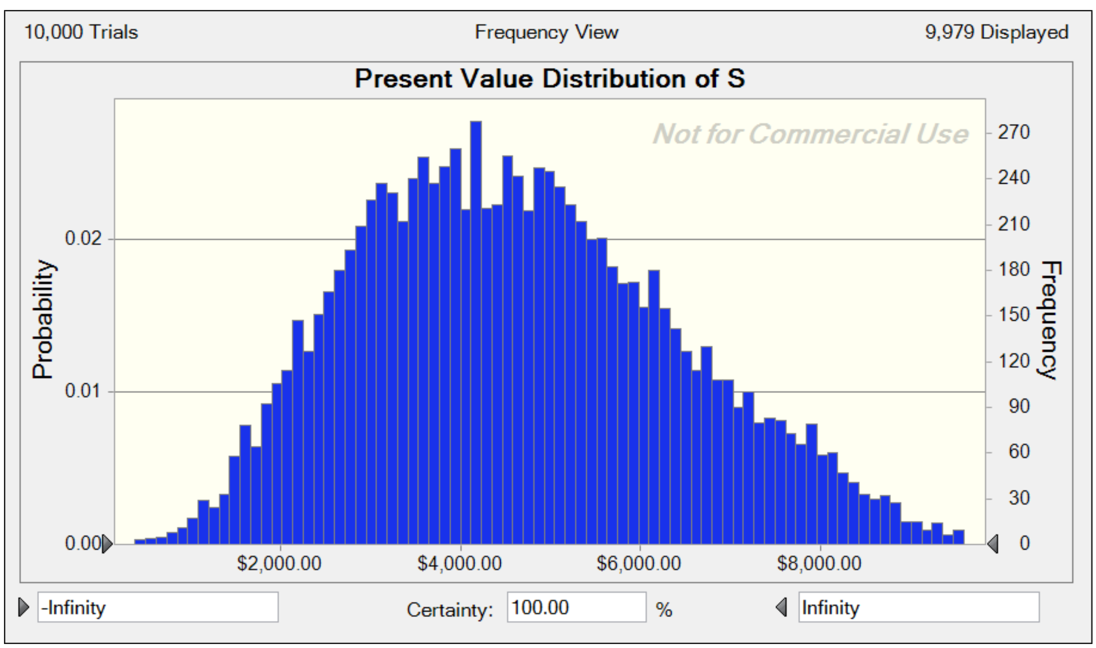


Figure 25: Simulated present value distribution of multi-scenario operating profit forecasts.

A Monte Carlo simulation is used to simulate the operating profit in each year. The market discount rate of 15% is used to generate the present value distribution, S_0, at Year 0 (Figure 25). When the business concern is cashflow, the analysis is very straight forward in looking at revenue and cost. The forecasting question in defining S is: Given the occurrence of an instigating scenario in Year X, what impact does the exercise of architecture option Y have on the independent variables that affect operating profit? However, many times in systems engineering, the organizational concern is not necessarily cashflow, but is the value or utility derived from a system. This requires a more intricate analysis of the system, it's attributes, and the preferences of its stakeholders.

An important assumption in this research is that the architecture option is treated as an independent addition to a baseline architecture that fulfills the critical mission. This allows for the independent evaluation of each AO and does not require iterative optimization of the entire system design with the inclusion of each AO. An end-to-end design optimization can certainly be incorporated into this analysis, but would require linked models of the entire architecture and reliance on techniques like multi-attribute tradespace exploration with concurrent design (MATE-CON). This level of modeling will be an important extension in future research, but is not included here.

The value derived from exercising an architecture option is linked with performing a new or changed mission either with a completely new capability or a change to an existing system attribute. This linkage necessitates an adequate understanding of the utility derived from the capability required for each instigating scenario. Value/utility functions in general are more difficult to estimate in comparison to operating profits in the commercial sector which leads to a mostly subjective forecast. In addition, large systems may have multiple stakeholders with diverse value assessments. This makes the development of value functions even more challenging and may require a combinatorial or holistic approach that assigns weighting factors to each stakeholder (Hastings & McManus, 2004; Ross, 2006; Browning & Honour, 2008).

The simplest case can be modeled by assuming a constant and predefined utility of some magnitude which is delivered each year by performing a capability linked to the exercise of the architecture option, shown at top in Figure 26. This stream of utility can be appropriately discounted to the base year as a point estimate of the AO's total lifecycle utility. The only relevant uncertainty in this case is the scenario's likelihood distribution which defines the option viability. A more complex case will model the uncertainty of the utility derived. Each annual utility forecast can be represented with a distribution in the same way as described for the cashflow analysis. This case is shown with lognormal distributions at bottom in Figure 26. In modeling the random variables, it has been found that defining the random forecast values as partially correlated to the forecast values in adjacent years (e.g., ρ=0.7) provides additional realism to the model, as illustrated in Appendix A. This will result in a present value distribution for the additional utility. The final layer of complexity occurs when utility is understood as a function of performance. In many cases, the stakeholder will have nonlinear utility assessments for varying levels of performance. If a scenario requires a particular capability, and that capability has a dynamic range, there will be varying levels of utility in that range. For example, if a scenario for the Global Positioning System (GPS) requires an increase in broadcasted signal power to overcome enemy jamming, there will be a range of utility associated with varying levels of power. As the signal power capability increases, the utility derived may asymptotically approach a maximum value. The traditional utility function that varies with performance essentially represents the present value of the most likely utility stream. This can be used in one of two ways when assessing architecture options. First, it can be used to help identify multiple, mutually exclusive AOs that can be compared with one another for inclusion in the architecture; this can be applied as a feedback loop into the first stage of the flexibility framework. Second, it can help the system engineer include actual performance variability in the utility forecasts for *S*. This level of analysis requires the close consultation of engineers, stakeholders, and end users.

Simply stated, S can be understood as an uncertain stream of benefit attached to the exercise of an AO; S_0 is the appropriately discounted contribution to lifecycle value.

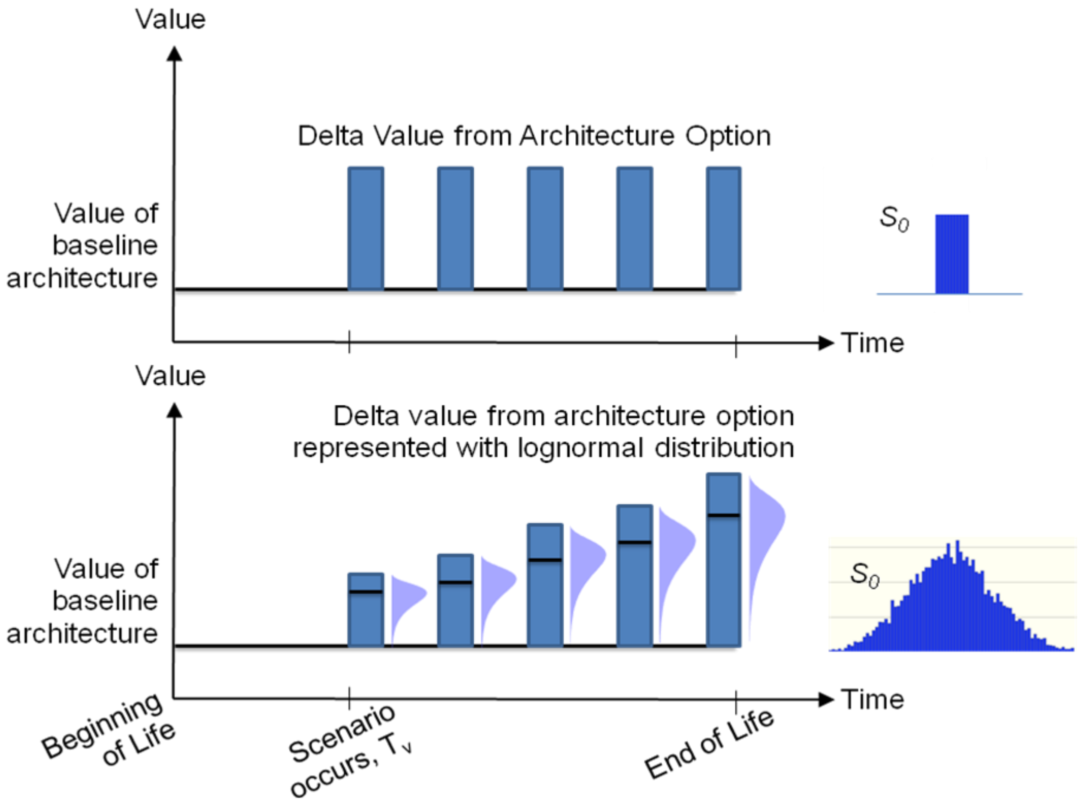


Figure 26: At top, value stream generated by architecture option that excludes forecast uncertainty and results in a single value for S_0. At bottom, value stream that includes forecast uncertainty and results in a present value distribution for S_0.

Our Variable Expiration technique incorporates the uncertainty of the instigating scenario by defining the option expiration as a random variable. T_v represents the first rational opportunity to exercise the architecture option and can be described with a probability distribution. A simple way to represent T_v is with a discrete (or Bernoulli) distribution. This representation is appropriate many times when the scenario likelihood is communicated as a lifetime probability. For example, if the stakeholder believes there is a 35% probability that a scenario will occur sometime during the five-year system design life, a discrete distribution can be created that splits the probability between the operational years as displayed in Figure 27.

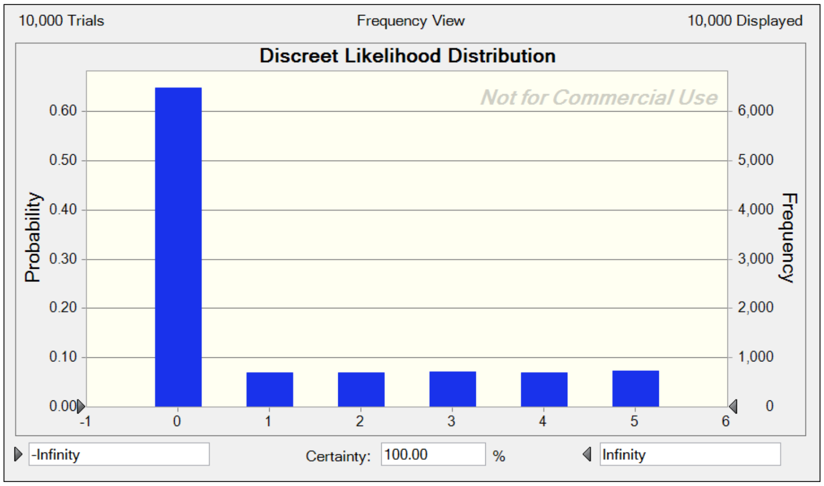


Figure 27: Discrete likelihood distribution to represent uncertainty of the instigating scenario.

The value of the architecture option is directly related to when the option is exercised. The problem can be simplified by "discretizing" the expiration dates, most simply into years. The architecture option can be thought of as a group of European-type options, one for every analysis period. The value of the European option is augmented by the scenario likelihood function. If a discrete distribution is used for the scenario, the expected value of each European option can be multiplied by the probability that the option will become viable in that period. The VE technique calculates the values directly from the forecasts, not from the mean value, but it is conceptually helpful to understand the option value as a function of the viability date and the mean option value at that date. Figure 28 illustrates this idea with two Monte Carlo trials: one with option viability earlier in the lifecycle resulting in a longer stream of benefits, the other showing viability later in the lifecycle and fewer benefit years. Using the mean of many Monte Carlo trials for each analysis year, shown by the histograms on the left, a "Temporal Step" value function can be constructed which is constituted by the mean values of the discounted benefit stream for each year (in base year dollars). This representation depicts the relationship between future benefit stream and the scenario likelihood assessment, and when combined with the exercise price, can bring insight into the timing required of a scenario in order to break even with the upfront architecture option expenditure.

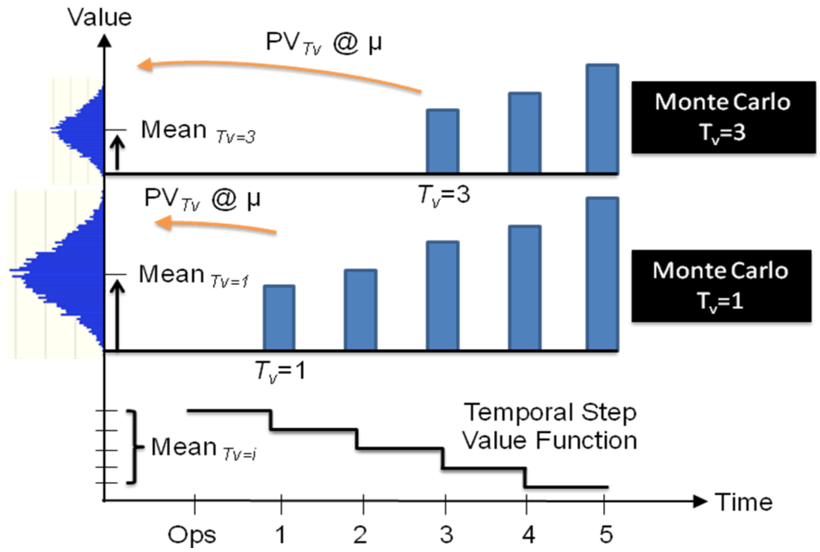


Figure 28: Present value distribution of benefit stream varying with option viability date. Also, notional Temporal Step value function composed of the associated mean values.

4.2.2 Defining *X*: Strike / Exercise Price

For exchange traded options, the strike price, *X*, is a contractual price at which the stock can be purchased at a later date. The price is predetermined and fixed; traditional valuation methods like Black-Scholes require this. The strike price (or exercise price) for real options "on" a project represents the one-time, irreversible launch cost required to build, manufacture, or otherwise fully commit to the project. For architecture options embedded "in" the system, the exercise price is the one-time initiation or system augmentation cost. This includes the total system upgrade cost, which is expended only if the instigating scenario occurs *and* if the net forecasted benefit is positive. The recurring operational costs associated with the AO like maintenance, support, and additional management of the new capability are not included in the exercise cost--those costs are incorporated in forecast *S*. The expense required for complex system upgrades in many cases is uncertain because of the uncertainty in upgrade scope and extent as well as variations based on the timing of the upgrade. The Variable Expiration technique can handle this type of uncertainty in *X* by representing it as a stochastic value as illustrated in Figure 29.

The exercise cost/price for architecture options can be estimated with a Rough Order of Magnitude (ROM) or a more complete costing procedure substantiated with a detailed Basis of Estimate (BOE). A BOE will include the costing methodology, the sources of data used, mathematical calculations, and associated assumptions and resulting judgments. The level of detail will vary significantly depending on the expectations and requirements of the customer, maturity of the program definition, and the availability of relevant historical information. The format and requirements for preparing BOE rationale will typically be specified in the contract pricing instructions, but will many times include common techniques and practices such as:

- Projections from history
- Similar-to (Analogous)
- Cost Estimating Relationship (CER)
- Parametric Cost Models
- Manufacturing Labor Standards
- Level-of-Effort
- Detail Task Buildup
- Supplier Proposals/Quotes
- Expert Judgment
- Basic Task Units (BTUs)
- Labor Conversion Factors
- Improvement Curves

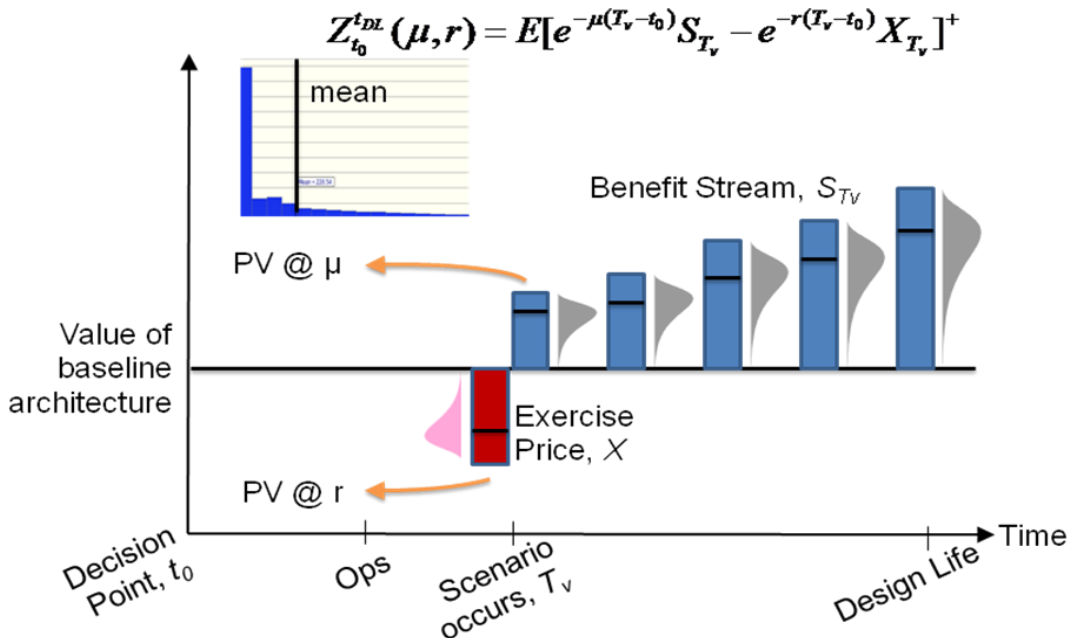


Figure 29: Variable Expiration option valuation accommodates stochastic exercise price.

4.2.3 Defining *r*, *μ*: Risk Aversion

The Variable Expiration technique uses a differential discounting method that applies an "investment" rate, r, to the exercise price and a "market-risk" rate, μ, to the operating profit stream. The use of two discount rates instead of one allows us to more closely reflect the different types of underlying risk. The exercise price, or launch cost, is relatively secure, where management exerts control and discretion over the funds. The launch cost is expected to be incurred only if there is good prospects for a successful investment. Therefore, the investment rate, r, takes a value closer to the risk-free rate used in Black-Scholes, and represents the least expensive source of capital--in corporate finance, this will typically be the general obligation corporate bond rate. In comparison, the market-risk rate, μ, is higher as it reflects market uncertainty and the return rate required as a corporate investment hurdle.

Differential discounting is a risk adjustment technique that essentially shifts the relative values of different cash flows at Time 0 to reflect risk aversion. The launch cost is cash-on-hand

and valued more highly than the uncertain stream of potential operating profit. The manager may be quite risk averse as he stands to lose the cash-in-hand in comparison with the uncertain benefits dependent on market risk. Therefore the launch cost is discounted at a lower rate than the operating profit; this reflects risk aversion and translates to perceived reduction in the chances of a positive outcome in the Monte Carlo generated present value distribution.

The discounting method employed here is different from traditional options valuation methods and is worth discussing briefly. Many have argued that the beauty of *directly* applying the Black-Scholes formulation to real options centers on its ability to align disparate investor risk orientations to a single risk-free rate. This is accomplished with a risk neutral construct enabled by arbitrage enforced pricing. To explain, consider that a traded market asset has stochastic components that are perfectly correlated with a real option and consider further that arbitrageurs can short sell the real option. A portfolio can be theoretically constructed that perfectly replicates the real option. If then, there is any mismatch between the return on the real option and that on the traded asset, an arbitrageur can gain riskless profit by shorting one and long the other. In an open liquid market, this opportunity will not last as arbitrageurs will enforce a single price and bring the situation into equilibrium. This dynamic helps us prove that there is a market price for risk that holds in the worlds of risk preference and risk neutrality. Black-Scholes embraces this theoretic phenomenon and performs risk-neutral valuation to determine option value independent of individual risk preference. As can be seen in the Black-Scholes formulation, $S_0N(d_1)$ is the probability of the exercise of the stock, and $Xe^{-rt}N(d_2)$ is the risk-neutral probability of exercise. Although both expressions are "probabilities," neither is the true exercise probability as would be understood by risk-averse individuals or corporations; they are both risk-neutral measures of theoretic probability. Black-Scholes therefore uses only the risk-free discount rate and forces all inputs to be stated in Time 0 values. The binomial lattice similarly relies on the risk-neutral construct and its associated market assumptions, but requires an additional translation to the risk-free world with the application of a risk-free probability multiplier at each node.

The Variable Expiration technique, like that of the DM method, avoids the risk neutral construct and the requirements for a replicating portfolio by using differential discount rates that directly reflect risk aversion as well as the differing levels of underlying risk. True probabilities can therefore be used in the valuation which allow the technique to be more intuitive and transparent for management and systems engineering decisions.

4.3 Architecture Option Valuation in the Collaborative Environment

Complex system design occurs many times within large organizations that merge highly specialized enterprise functions into an interdependent collaboration. Valuating architecture options requires inputs from numerous enterprise functions and is overviewed in Table 7.

Table 7: Input responsibility and method within the enterprise.

Variable	Contributor	Method
Benefit Stream, *S*	Management	Combination of the following
Commercial Project:		
Unit Cost	Engineering, Vendors	Bottom-up hardware, software and labor estimate, historical projection
Unit Price	Marketing	Market analysis, consumer behavior, business forecasting
Unit Quantity	Marketing	Market analysis, consumer behavior, business forecasting
Military/Scientific Project:		
System Attributes	Engineering, Stakeholders	Systems engineering process
Utility Function	Engineering, Stakeholders	Expert solicitation, Delphi method
Value Assessment	Engineering, Stakeholders	Expert solicitation, Delphi method
Augmentation Cost, *X*	Engineering, Vendors	ROM, BOE, CERs, ICE, parametric, Bottom-up build and labor
Investment Rate, *r*	Finance	Corporate bond rate
Market Rate, μ	Finance	Corporate hurdle rate
Design Life, t_{DL}	Engineering, Stakeholders	Mean mission duration, reliability analysis
Option Viability, T_v	Systems Engineering, Stakeholders, End Users	Scenario / Vignette Planning, DoDAF OV-1, OV-2

4.4 Analytics for Variable Expiration Technique

Using the data in Table 5 and Table 6 combined with the discrete likelihood distribution in Figure 27, this section formulates various analytic measures in order to better understand the more intricate behavior of the architecture option value. The data in Table 5 and Table 6 describe a most likely, pessimistic, and optimistic business case scenario related to the exercise of an architecture option. Changes to the quantity sold, price, and unit cost are forecasted, resulting in revenue and cost projections that directly translate to operating profit. Triangular distributions, with correlation coefficients of 0.7, are created to represent the operating profit in each year, illustrated in Figure 24. The implementation cost (i.e. exercise price) is represented by a normal distribution with mean of $700 and standard deviation of 10%. The Variable Expiration technique is implemented with 100,000 trials in a Monte Carlo simulation using the stochastic modeling software Crystal Ball. For instances where the option becomes viable, based on the discrete T_v distribution, the difference between the appropriately discounted operating profit and implementation cost is calculated at Year 0 and displayed in Figure 30. The option viability year shifts the operating profit stream to that year and is extended through the remaining design life; an inflation rate of 1% per year is also applied to the future operating profit forecasts. A rational economic decision making algorithm is then applied where negative projected outcomes are abandoned and positive projected outcomes are pursued by the exercise of the architecture option. The higher resolution depiction of the present value distribution, Figure 31, shows the abandoned negative outcomes. The mean option value of $485 is determined by truncating the negative outcomes and calculating the residual mean (Figure 32).

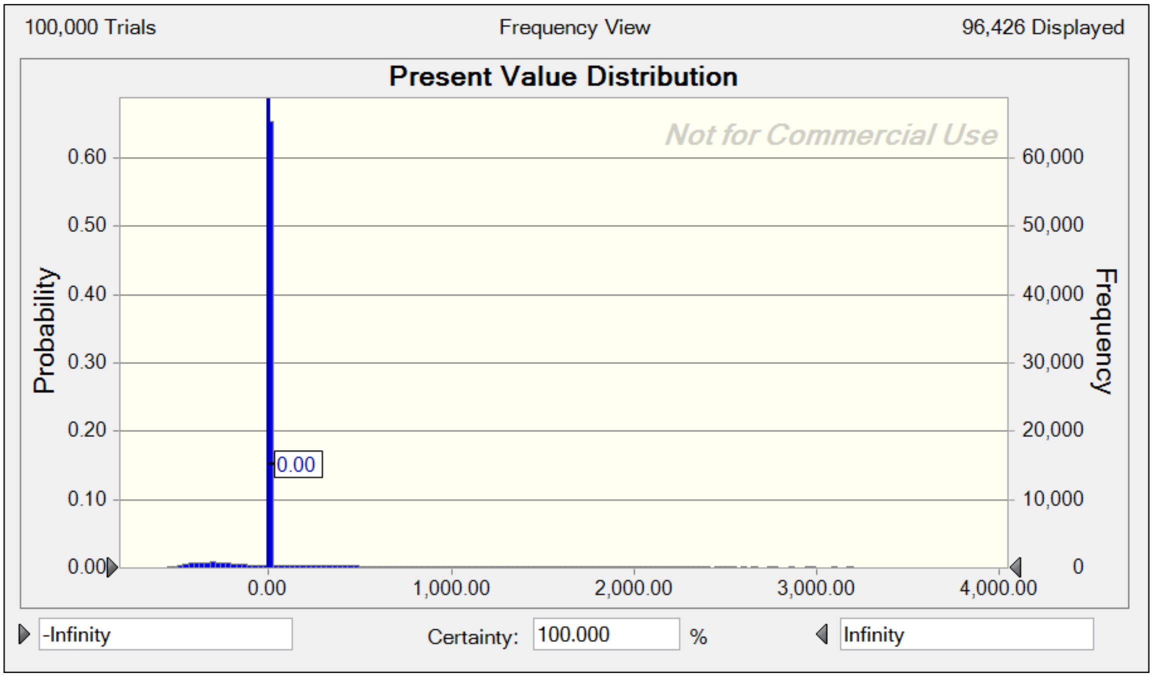


Figure 30: Present value distribution that is the difference between the appropriately discounted operating profit and the initiation cost.

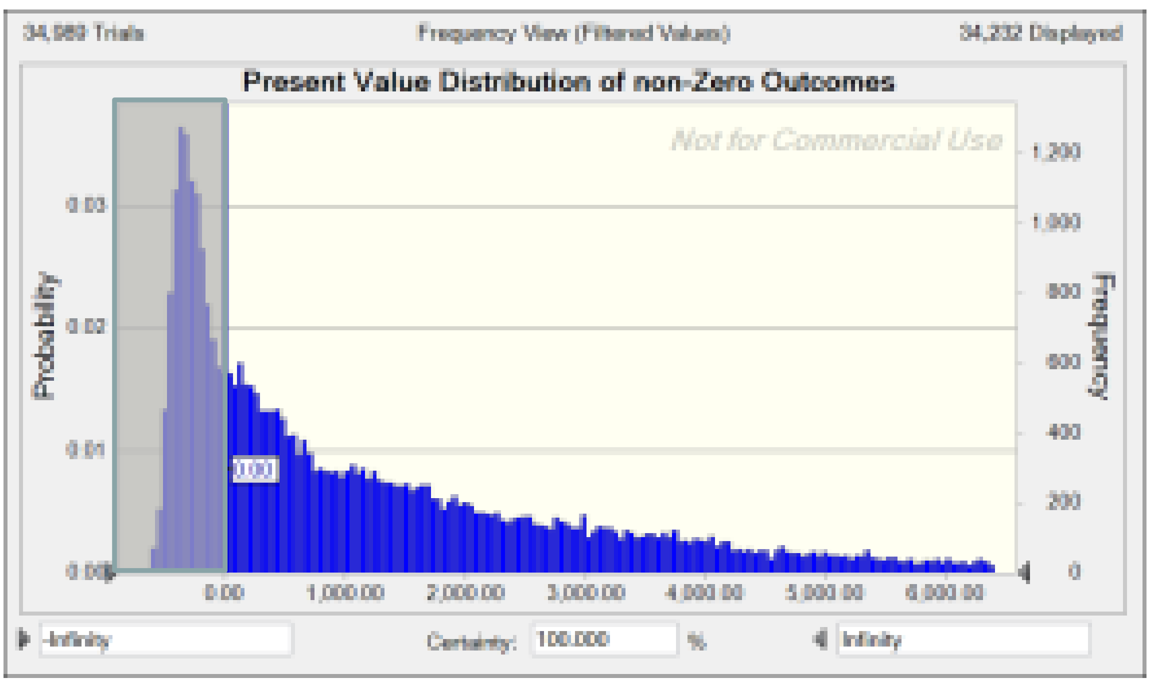


Figure 31: Close-up of present value distribution showing abandoned negative outcomes.

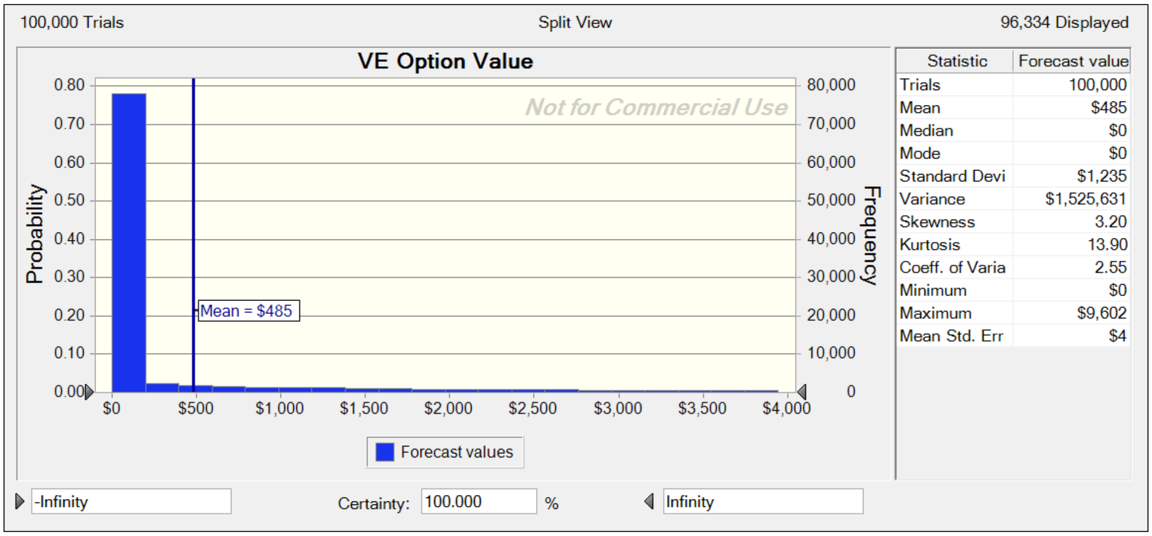


Figure 32: Truncated present value distribution to find mean option value.

The assessment of the architecture option is informed mainly by the mean value, however, other statistics and analytics can bring important insight into the behavior of the option. The span of outcomes is reflected in the maximum of \$9,602 and represents the upper bound, while the standard deviation of \$1,235 reflects the dispersion of outcomes. Other second and third order analytics can be important for revealing sensitivities of the option value to changes in the input parameters. In traditional Black-Scholes analysis, these analytics are commonly referred to as the Option Greeks: Delta, Gamma, Vega, Theta, and Rho (excluding other higher order derivative measures). However, the common formulations, treated extensively by Hull (2003), do not translate exactly to the proposed variable expiration technique. The traditional formulation has therefore been used as a foundation to extend the analytical techniques for use with variable expiration-type options. This transformation and the resulting mathematical formulations are discussed in the following sections.

4.4.1 Option Delta

The option Delta is a measure of the rate of change of the option value with respect to changes in the price of the underlying asset. Delta is calculated with the first derivative of the option value with respect to asset price:

$$\text{Delta} = \frac{dC}{dS}$$

The Variable Expiration technique regards the asset price, S, differently than traditional valuation methods. It is not the fluctuating stock price, but instead is interpreted as the present value distribution of the future benefit stream. Changes in S_0 therefore cannot have precise attribution in the stochastic model since infinite combinations of the structure of the benefit stream, S, can result in identical changes to S_0. However, some of the closed form Black-Scholes algebraic formulations can still be utilized if the VE parameters are translated into the Black-Scholes construct. By appropriately discounting the VE benefit stream to Time 0, translating the standard deviation to an annualized volatility measure, and assuming a lognormal distribution of the outcomes, the mean and standard deviation of the future value distribution can be used to approximate an equivalent stock price, S, and subsequently utilize the Black-Scholes algebra to estimate Delta. For Variable Expiration options, Delta can be represented as the sum of the individual Deltas for the portfolio of European-type options that theoretically constitute the architecture option, multiplied by the probability of option viability in the respective time period:

$$\text{Delta} = \frac{dC_{VE}}{dS_{VE}} = \sum_{i=1}^{DL} \frac{dC_i}{dS_i} * P(T_v)_i$$

$$\frac{dC}{dS} = N(d_1) = \Phi(\frac{\ln(S_0/X) + (r_f + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}$$

where,

$$\sigma = \sqrt{\ln(1 + (StdDev/Mean)^2} \Big/ \sqrt{T}$$

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{\frac{-y^2}{2}} dy$$

For architecture options, Delta will take on a value between zero and one: zero if the option value is insensitive to changes in S_0, and one if the option price moves point-for-point with the change in $S_0*P(T_v)$. This occurs typically when S_0 is deep in-the-money, i.e. much larger than X. Individual Deltas for each expiration year are shown in Figure 33 and the cumulative Delta for the VE option is shown in Figure 34.

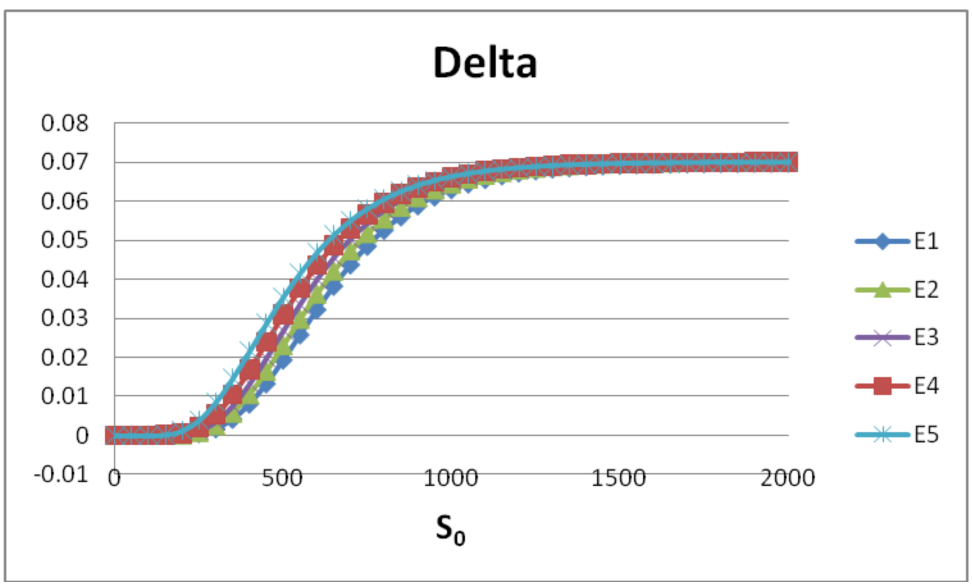


Figure 33: Constituent Deltas for each expiration year.

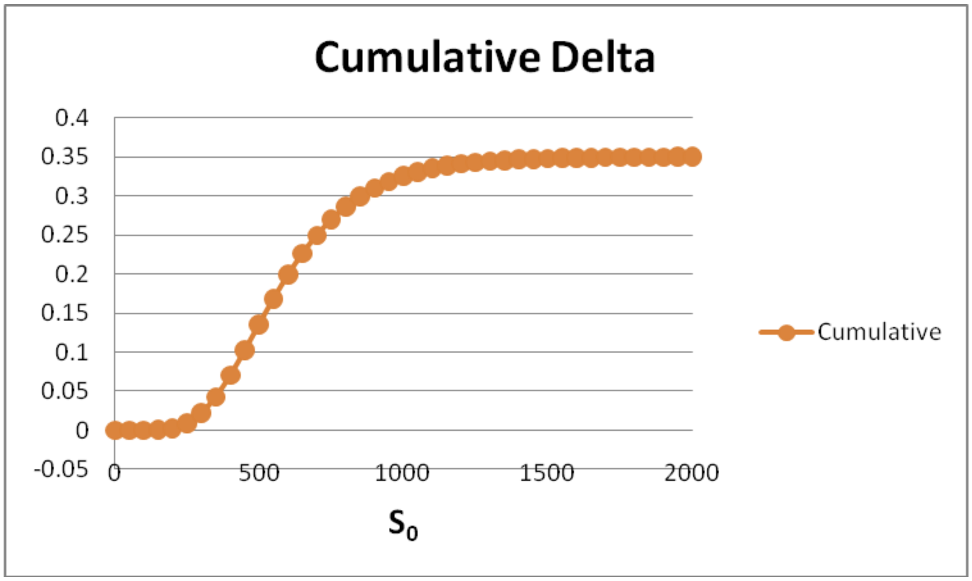


Figure 34: Cumulative Delta for architecture option.

4.4.2 Option Gamma

The option Gamma is the second derivative of the value function with respect to the underlying price. Using Black-Scholes notation, Gamma can be calculated with the standard normal probability density function as:

$$\text{Gamma} = \frac{d^2C}{dS^2} = \frac{\phi(d_1)}{S\sigma\sqrt{T}}$$

where,

$$\phi(x) = \frac{e^{-\frac{x^2}{2}}}{\sqrt{2\pi}}$$

Gamma is also understood as the rate of change of Delta with respect to the underlying price and can be used to identify where the option value is changing most quickly with changes in S_0. It is sometimes useful to identify the range of S_0 where Gamma is neutralized; the architecture option in this range will have a more predictable and consistent value movement, zero or $P(T_v)$. This plot is displayed in Figure 35.

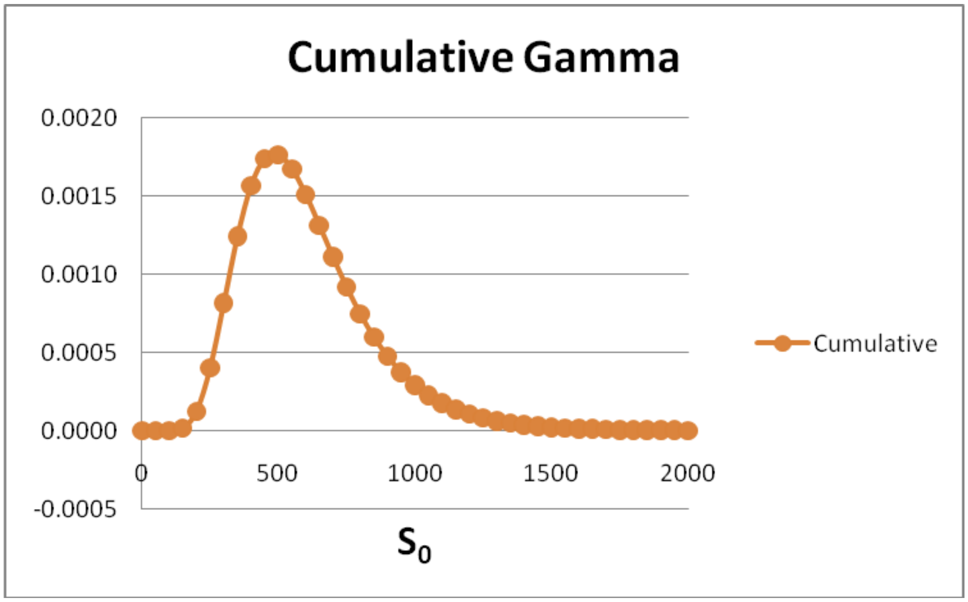


Figure 35: Cumulative Gamma for architecture option.

4.4.3 Option Vega

The option Vega is the derivative of the option value with respect to the volatility. It represents the theoretical change in value of the option given a one percent change in volatility. The formulation for a Variable Expiration option is:

$$\text{Vega} = \frac{dC_{VE}}{d\sigma_{VE}} = \sum_{i=1}^{DL} \frac{dC_i}{d\sigma_i} * P(T_v)_i$$

$$\frac{dC}{d\sigma} = S * \phi(d_1)\sqrt{T}$$

The VE technique does not specifically use a measure of volatility, since uncertainty in the benefit stream is calculated directly from the forecasts as a standard deviation. However, the standard deviation of the future value distribution can be annualized and translated into volatility for each expiration year. This yields the option Vega shown in Figure 36 and Figure 37. Vega displays how sensitive the option value is to changes in the level of uncertainty and typically peeks at-the-money (i.e., where the mean of the discounted present value distribution is equal to the initiation cost).

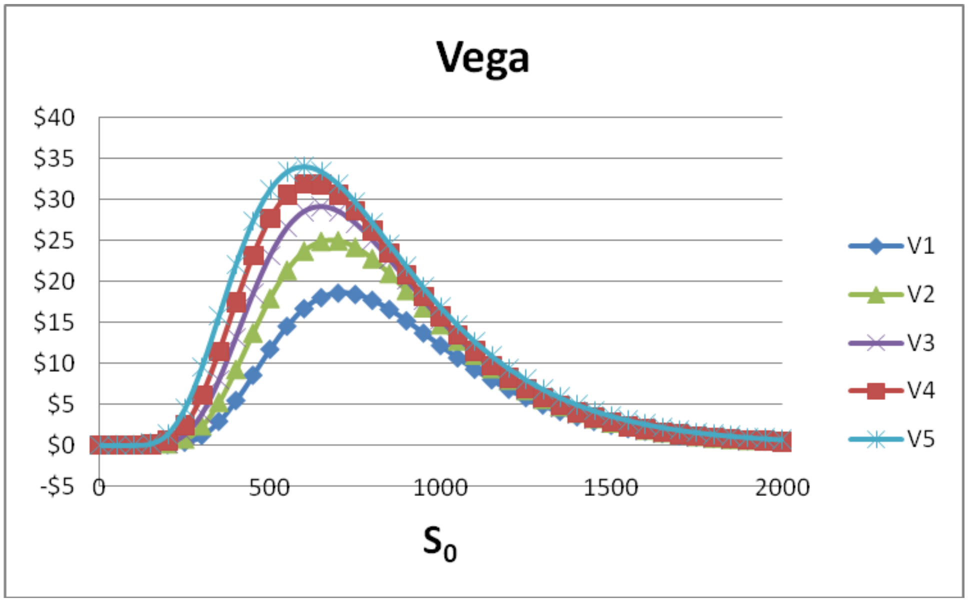


Figure 36: Constituent Vegas for each expiration year.

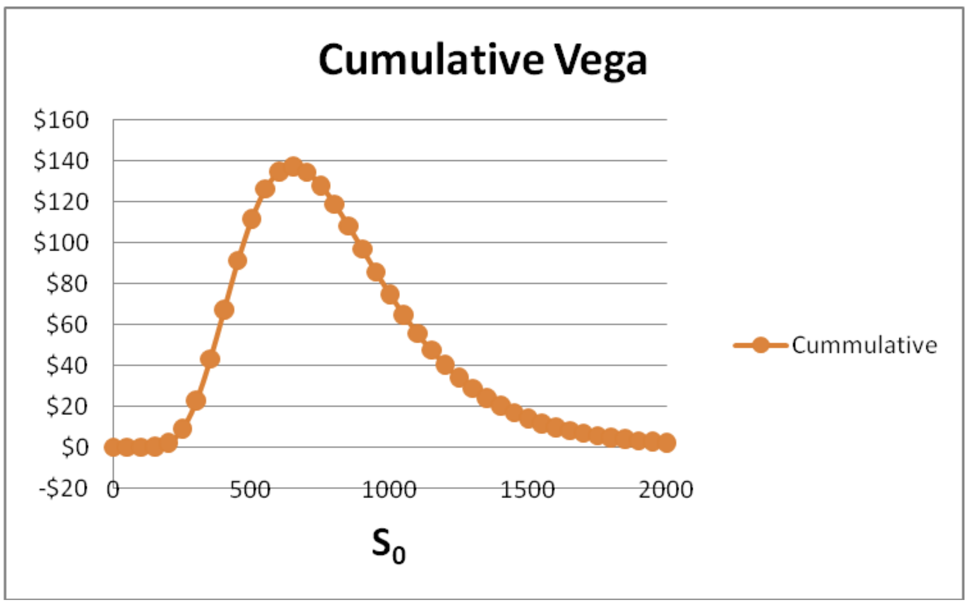


Figure 37: Cumulative Vega for architecture option.

4.4.4 Option Theta

The option Theta is the derivative of the option value with respect to the time. It represents the change in option value given a one day decrease in time to expiration--essentially instantaneous time decay. The architecture option has a finite life and each day that passes reduces the uncertainty in the option value. Uncertainty is what gives the option additional time value above its intrinsic value. It would therefore be expected that the option value would decrease with time as fewer opportunities remain to successfully exercise the AO. The formulation of Theta for a Variable Expiration option is:

$$\text{Theta} = \frac{dC_{VE}}{dT_{VE}} = \sum_{i=1}^{DL} \frac{dC_i}{dT_i} * P(T_v)_i$$

$$\frac{dC}{dT} = -\frac{S * \phi(d_1)\sigma}{2\sqrt{T}} - rX\Phi(d_2)$$

As shown in Figure 38 and Figure 39, Theta drops off rapidly as the option maturity approaches. Also, the cumulative stepwise behavior is a result of the consecutive exclusion of the unexercised annual benefit.

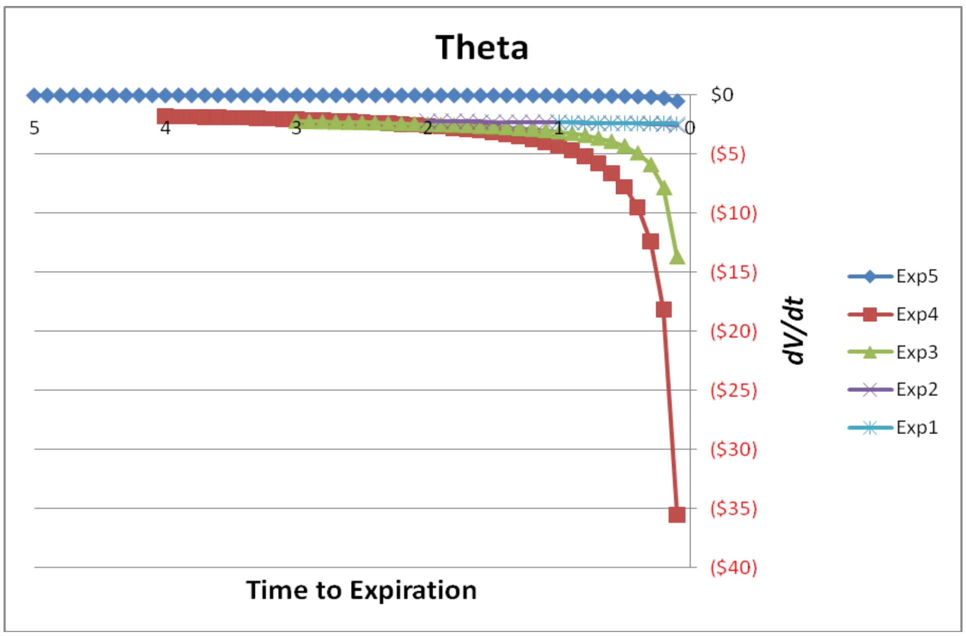


Figure 38: Constituent option Thetas for each expiration year.

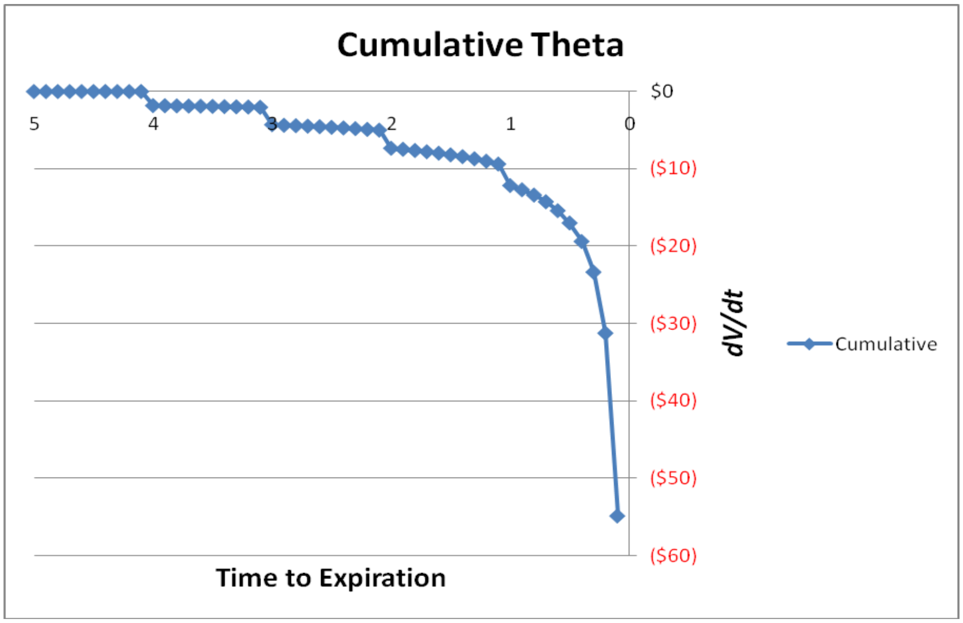


Figure 39: Cumulative Theta for architecture option.

An alternative way to understand the impact of passing time is to revisit the Temporal Step value function from Section 4.2.1. By combining the benefit stream with the exercise cost for each time period, an option value function can be constructed (Figure 40) which depicts the mean payoff if the architecture option were to be exercised in a given year. The Temporal Step value function is contingent on option exercise, however the combined intrinsic and extrinsic value of the option to the system designer is associated with the *expected* payoff. Probability information for option viability must be combined with the contingent value function to produce Figure 41 which depicts the total expected value of the architecture option as time passes. These representations can elucidate timing information associated with when an option must be exercised or when a scenario must occur to allow for a successful exercise of the architecture option.

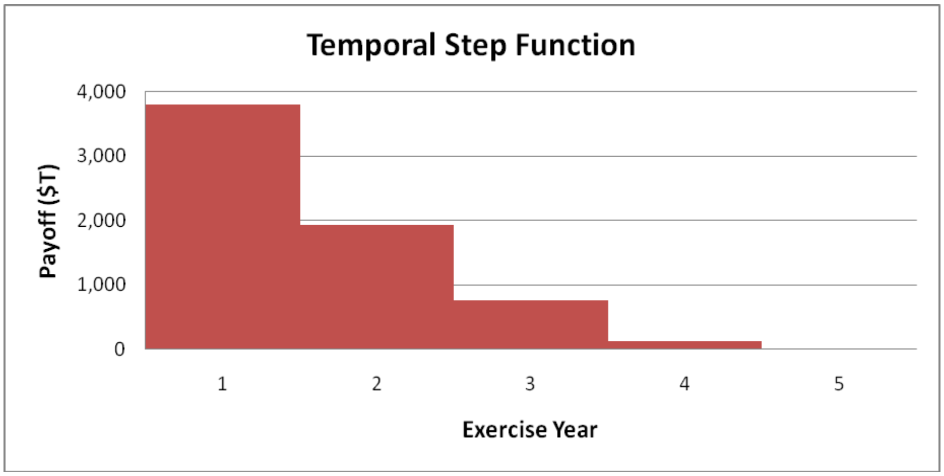


Figure 40: Temporal Step value function.

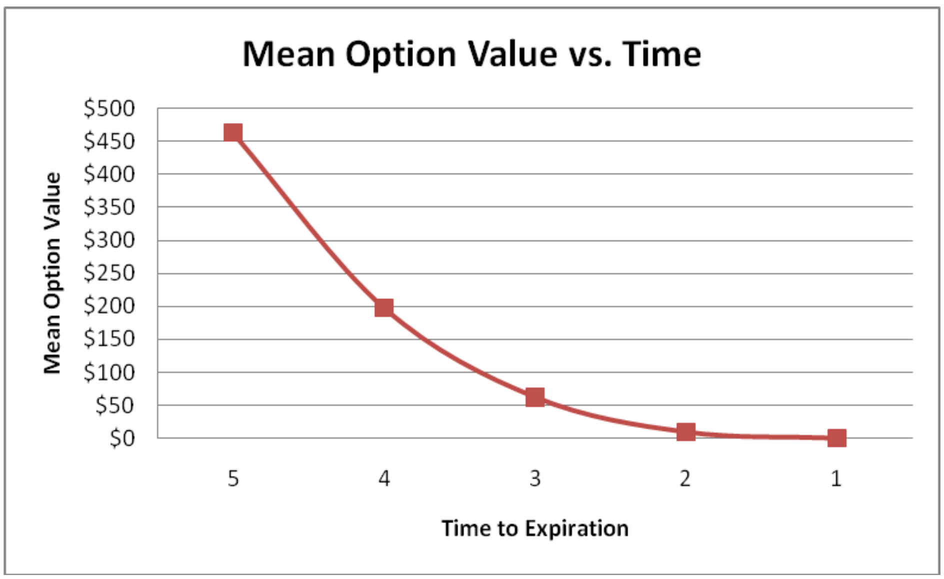


Figure 41: Mean option value decreases over time.

4.4.5 Option Rho

The traditional option Rho measures the sensitivity of option value to changes in the risk-free interest rate. The VE technique however uses differential discounting and avoids the risk neutral construct and subsequently the risk-free rate. The VE valuation technique is instead performed in the world of risk preferences and, at its core, is a comparison of risk-adjusted returns between a safe investment (discounted at private risk) and a risky investment (discounted at market risk). When the corporate bond rate is used as the investment rate, the valuation contrasts the value of prospective risky operating profits against paying off corporate bond holders. A higher investment rate therefore signifies a more expensive source of capital and a more risky cash outflow. This outflow is not valued as highly when risk-adjusted and is a smaller hurdle for positive NPV outcomes resulting in an increased option value, shown in Figure 42. A similar interpretation applies to the market rate in that higher market risk causes the prospective operating profits to be perceived as less valuable and will reduce the mean option value seen in Figure 43. The option Rho is consequently redefined here as the sensitivity of the option value to changes in the investment rate and the market risk rate, both separately and conjointly, as in Figure 44. These metrics are generated through iterative Monte Carlo runs for varied discount rate inputs.

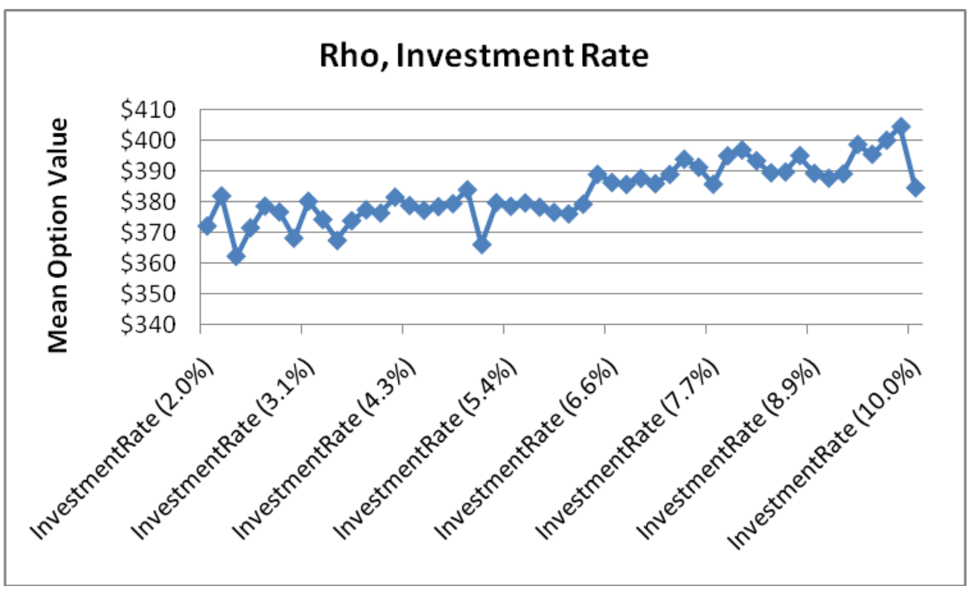


Figure 42: Option Rho for Investment Rate.

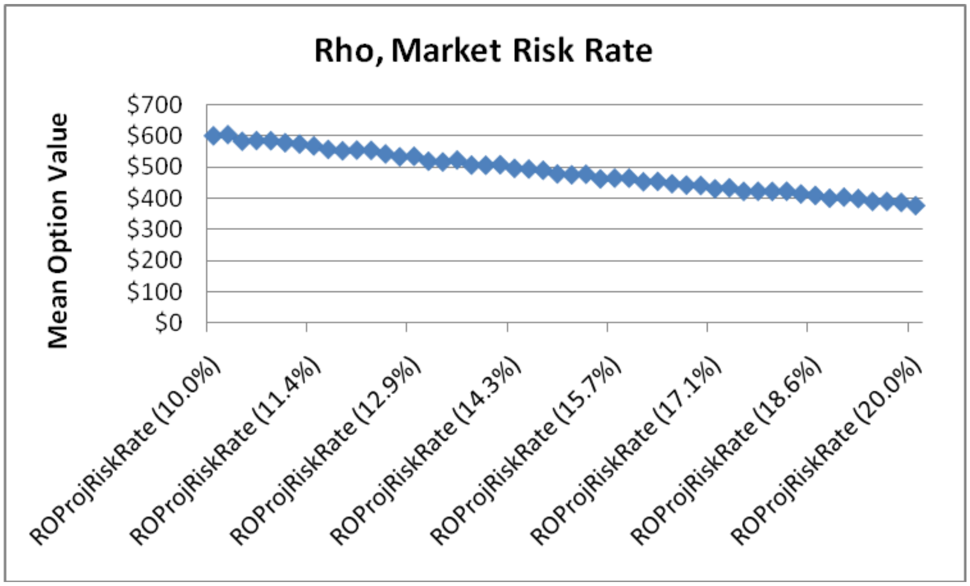


Figure 43: Option Rho for Market Risk Rate.

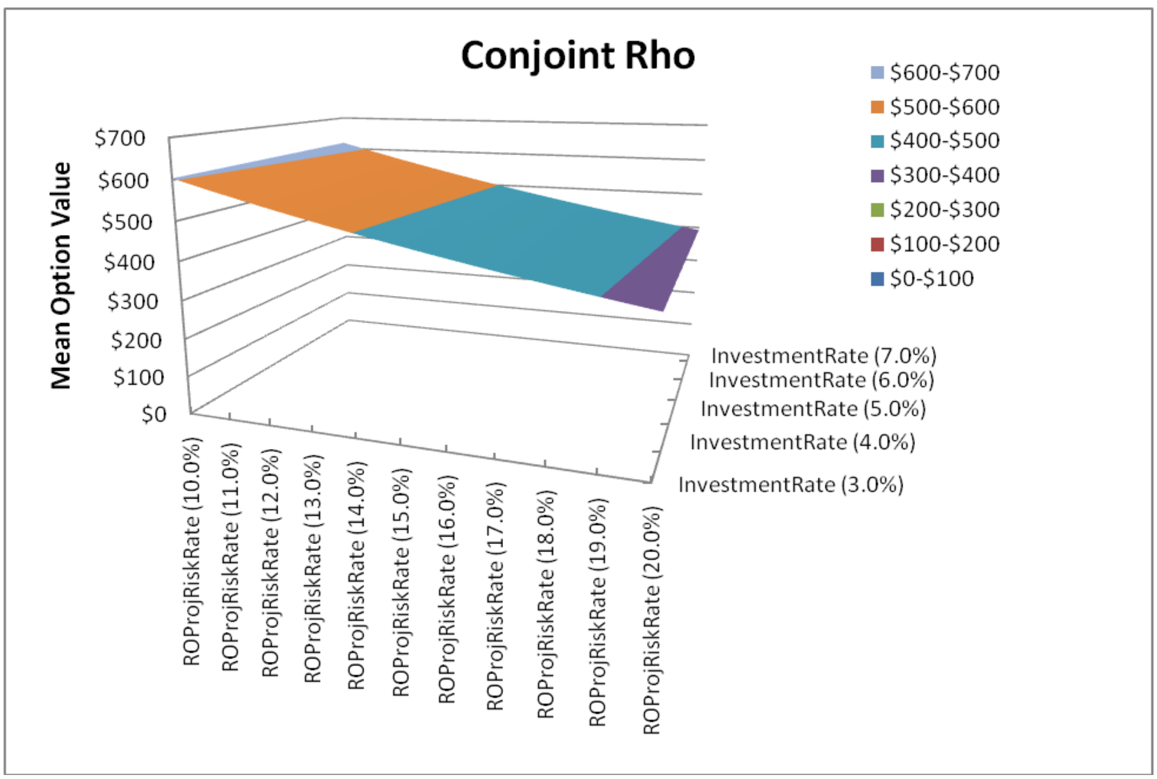


Figure 44: Option conjoint Rho.

4.4.6 Using Option Analytics

Although this research is chiefly concerned with the mean value and dispersion of the option value, as communicated in the Stage 3 selection process presented in Chapter V, second and third order sensitivities can reveal important aspects of option behavior. These sensitivities can guide the analysis toward the most important variables and best use of investigative resources. The option Delta can serve as a broad filter by defining the threshold where changes in the benefit stream lead to either no change in option value, or maximum change in option value. The maximum change for VE-type options will not be one-for-one, but is commensurate with the likelihood function (in this 0.35/1.00). This generates insight into how changes to the likelihood function (e.g. lifetime probability) will ultimately affect the option value. The option Delta is also used in Section 5.5.1 to quantify the change in option value as the system performance changes in response to changes in cost (See Figure 50 for illustration).

The option Gamma can be used to identify if the option is relatively stable. When the forecasted value stream is much below or above the exercise cost, the option value will react predictably to perturbations in this quantity (the straight line segments of the option Delta). In the nonlinear range however, the option value is not as predictable, and leads to a wider variation of the impact of change. For analysis purpose, neutralizing the option Gamma helps stabilize the model.

The option Vega describes how the uncertainty in the benefit stream forecasts affects the option value. Where the option value is highly affected, the analyst is inclined to stringently verify the assumptions and inputs. Where the option Vega indicates only a minor impact from uncertainty, the fidelity of the inputs may be moderated without significant impact.

The option Theta, as well as the other time varying analytics, help to discover when the option must be exercised to meet an objective. Objectives may include: breaking even, minimum level of return, rank ordering of options, etc. If the option Theta drops sharply early in the design life of the system, this may indicate that the option has only a narrow time window to be advantageously exercised. Also, if the Temporal Step Value function is high only for the first year and negligible otherwise, the mean value may erroneously suggest a strong architecture option, while overlooking the constraint of exercising the option in the first year.

The option Rho is a straight forward depiction of how the option value changes as the discount rates are changed. This sensitivity reveals how important the discount rate is to the overall analysis. In general, a longer design life will cause the discount rates to have a more significant impact on the option value as the compounding cumulative effect is realized. Also, when the discounted value stream approaches the exercise cost, the discount rates become more important as the rational exercise decision is at the margin.

4.5 Conclusion

This chapter presents the second stage of an integrated framework for use in designing appropriately flexible system architectures. Existing methods devised to assess system flexibility have been constrained by a conceptual, descriptive, or domain-specific nature that has seriously limited their applicability for systems engineering. This research employs real options, specifically architecture options, as a generic unit of analysis for flexibility. Real options analysis can be applied across engineering domains while it more accurately reflects the asymmetric human decision process that seeks to limit downside risk and take advantage of upside opportunity.

Real options valuation methods have predominantly been applied to options "on" projects which deal exclusively with managerial flexibility. A consistent means to value system flexibility as part of the design process has, to this point, been elusive. Traditional analytic and discrete valuation techniques are heavily constrained by the financial market assumptions required for proper usage; this fact has discouraged the larger engineering community from pursuing real options as a design tool.

The Datar-Mathews technique has revealed an alternative mechanism for option valuation which avoids the stringent market assumptions and enhances the overall transparency and versatility of option valuation. This chapter uses the underlying logic of the Datar-Mathews technique to extend real options analysis to options embedded "in" the system architecture. To reflect the behavior of architecture options, a new technique is developed that allows for variable expiration of the option. The VE technique combines the uncertainty of the instigating scenario with the uncertainty inherent in the option payoff. The mean option value is derived by comparing the risk-adjusted returns from the stream of operating profit with that of the option initiation cost and subsequently applying a rational economic decision algorithm. Implementation of the VE technique is readily accomplished by a combination of spreadsheet notation and stochastic modeling.

Option valuation metrics are devised in this chapter to assess option value sensitivity and are presented as a tool to understand the intricacies of option behavior. The option analytics can help system designers understand the ramifications and tradeoffs between model inputs and can guide the analytical emphasis toward the most important variables. Each real option in this analysis is treated individually with respect to the delta value stream generated by exercising the option. However, overall system flexibility is defined by the conglomeration of multiple, distinct architecture options. The next chapter presents an approach for selecting an optimal subset of architecture options that maximizes the expected portfolio return while minimizing risk.

CHAPTER V

ARCHITECTURE OPTION SELECTION THROUGH PORTFOLIO OPTIMIZATION

5.1 Introduction

In Chapter III, architecture options were introduced as a conceptual vehicle to understand system flexibility. The architecture option was defined as set of physical design characteristics that enable functional capabilities which responds to the needs generated by an uncertain mission scenario. A screening process was described to identify promising regions in the architecture where options could be embedded. Real option theory was then employed in Chapter IV to value the architecture option. A new technique was described to allow valuation of real options that have variable expiration characteristics based on scenario uncertainty. This chapter deals with stage three (Figure 22) in the integrated flexibility framework and develops an optimization-based approach by which the system engineer can select a subset of architecture options to compose an optimal portfolio. This portfolio defines the system flexibility and yields a quantitative measure of risk and return.

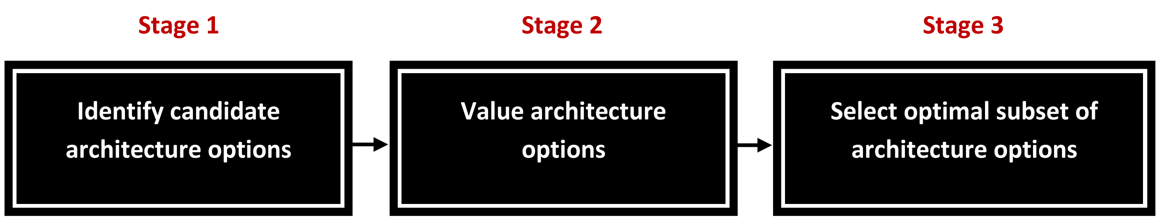


Figure 45: Three stage integrated flexibility framework for identifying, valuing, and selecting architecture options.

5.2 Selection of Optimal Portfolio of Architecture Options

Budgets and risk aversion prohibit systems from being infinitely flexible. What then is the right level of flexibility--what we've previously described as the 'appropriate' level of flexibility? The appropriate level of flexibility depends on characteristics like the following:

- extent of uncertainty in the operational environment,
- availability of architecture options in the design space,
- cost and feasibility of augmenting the system during operation,
- mean and variance of the potential benefit stream,
- design life of the system,
- risk aversion of the stakeholders,
- size of the initial investment necessary to secure the architecture option in the design.

Instead of addressing each of these factors individually, these factors can be consolidated by leveraging the AO identification from Chapter III and the AO valuation from Chapter IV to distill the concept of 'appropriately flexible design' into two underlying ideas: 1) maximization of life cycle value (LCV), and 2) minimization of risk through diversification. From this, two major premises are derived which together serve to define the optimal portfolio of architecture options:

> *Premise 1*: An optimal subset of architecture options will maximize the expected life cycle value of the system for a given level of risk.
>
> *Premise 2*: An optimal subset of architecture options will minimize portfolio risk for a given level of expected life cycle value.

5.3 Life Cycle Value

Flexibility, in itself, is not valuable simply by virtue of being flexible. Flexibility has value only when associated with a system or entity that generates utility from its exploitation. An appropriately flexible system therefore is a system that utilizes flexibility to maximize its life cycle value--that is the total value derived by the stakeholder during the system design life. Value is simply the perceived benefit net of cost, and in comparison to life cycle cost, has been extolled as a more complete and useful metric for system assessment (Amram & Kulatilaka, 2000; Browning, 2005; Ross, 2006; Ross & Rhodes, 2007; Saleh, Jordan, and Newman, 2007; Browning & Engel, 2008). Proposed by Saleh (2007), LCV can be expressed as:

$$V(T_{Life}) = \int_0^{T_{Life}} [u(t) - \theta(t)] e^{-rt} dt - C_{IOC}(T_{Life})$$

where $u(t)$ is the revenue/utility model, $\theta(t)$ is the operating cost model, and the difference is discounted to the present and integrated over the design life of the system. C_{IOC} is the development and production cost required to reach initial operational capability; this is represented as a function of the system design life, T_{Life}. The LCV expression represents the accumulation of the discounted operating profits (revenue - cost) minus the development cost. The methodology here is compatible with the proposed VE option valuation technique and is therefore expanded to include the value of flexibility in the LCV calculation.

$$V(t_{DL}) = \int_0^{t_{DL}} [u(t) - \theta(t)] e^{-rt} dt - C_{IOC}(t_{DL}) + \sum_{AO_p} \left(Z_{t_0}^{t_{DL}}(\mu, r)_{AO_p} - C_{AO_p} \right)$$

where the VE option value from Chapter IV is:

$$Z_{t_0}^{t_{DL}}(\mu, r) = E[e^{-\mu(T_v - t_0)} S_{T_v} - e^{-r(T_v - t_0)} X_{T_v}]^+$$

C_{AOp} is the initial investment cost required to include AO_p in the system design. This formulation represents the system life cycle value, including the benefits associated with a portfolio of architecture options minus the up-front development cost for each AO in the portfolio. Depicted in Figure 46, the yellow shaded region represents the potential value desired by the stakeholders above that derived from the baseline system architecture. Life cycle value is maximized as the system is able to capture increasingly more latent stakeholder value, depicted in light blue, through the exercise of architecture options.

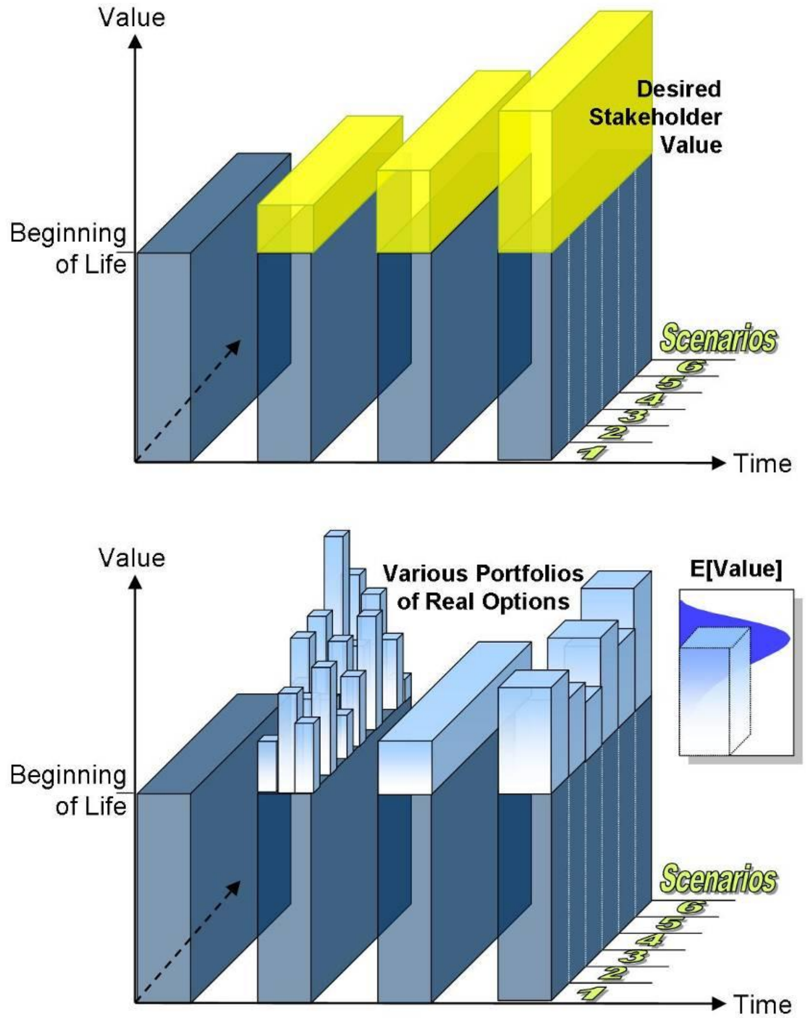


Figure 46: Maximization of life cycle value with a portfolio of real options. 3-dimensional depiction of value delivery over time. Desired stakeholder value (yellow) increases over time. A portfolio of architecture options (light blue) captures latent value across different operational scenarios.

To maximize the system life cycle value given the program budget, *B*, the objective function can be written:

$$\max_{p=0,\ldots n} E\left[V(t_{DL})\right]$$
$$s.t.$$
$$\left[C_{IOC}(t_{DL}) + \sum_{AO_p} C_{AO_p}\right] < B$$

In order to maximize the expression, $E[V(t_{DL})]$, the AO summation term need only be maximized. This is true because of the assumption that a baseline architecture exists that can be assessed independently of the AO portfolio, which allows the definite integral and the development cost to be treated as constants. Two other assumptions are made: first, the delta cost associated with each AO is fully captured in the C_{AOp} term and does not affect the C_{IOC}. Second, the design life is considered to be fixed. Although the value of the AO is certainly dependent on the design life, it is recommended that future research address the wide ranging implications of varying this factor in the analysis. These assumptions simplify the objective function to:

$$
\begin{aligned}
&\max_{p=1,\ldots n} E\left[\sum_{AO_p}(Z_{t_0}^{t_{DL}}(\mu, r)_{AO_p} - C_{AO_p})\right] \\
&s.t. \\
&\sum_{AO_p} C_{AO_p} < b
\end{aligned}
$$

where now the budget variable, b, represents the management funds available to pursue flexibility in the design. In combination with maximizing LCV, an optimal subset of architecture options should minimize risk. This objective can be accomplished through risk diversification.

5.4 Risk Minimization through Uncertainty Diversification

The concept of maximizing return while simultaneously minimizing risk was first developed by Markowitz (1952) and is now referred to as modern portfolio theory (MPT). Markowitz recognized that portfolio variance could be reduced through diversification. Whereas the leading method for selecting investments at the time had been to carefully analyze the intricacies of each investment or firm for its relative potential. This emphasis on individual asset potential might lead an investor to have owned all railroad stocks based on their appealing risk-reward characteristics. This concept of portfolio risk was born and Markowitz demonstrated that, as assets are included in the investment portfolio, total risk (defined by the portfolio variance) decreases. Consequently, the expected portfolio return is the weighted average of the expected returns of the individual assets. A Markowitz portfolio is defined as the portfolio that achieves the highest expected return for a given level of risk. Conversely, this portfolio has the lowest risk for a given level of expected return. The set of all Markowitz portfolios define a curve in risk-reward space called the Efficient Frontier (Markowitz, 1959).

The variance of an individual asset is the expected value of the sum of squared deviations from the mean:

$$Var(R) = \sigma_R^2 = E[(R-\mu)^2].$$

The portfolio variance for a simple portfolio containing just two assets can be expanded:

$$\sigma_p^2 = (w_A\sigma_A + w_B\sigma_B)^2 = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + 2w_A w_B \rho_{AB}\sigma_A\sigma_B$$

where w_i represents the relative portfolio weight or proportion of the asset. The last term in this expression contains the correlation coefficient, ρ_{AB}, which defines the extent of co-movement of the asset return. If ρ_{AB} is equal to +1, the returns of assets A and B are perfectly positively correlated, and the portfolio risk will be equal the weighted sum of the individual asset risks. If ρ_{AB} is equal to 0, the assets are perfectly uncorrelated, and the portfolio variance is the weighted sum of the individual variances. Negative values of correlation coefficient represent inversely correlated assets and the portfolio will have an even lower variance than if the assets were completely uncorrelated. Figure 47 depicts a notional pair of assets with expected returns of 3 and 5 and standard deviations of 2 and 3, respectively. Each mark represents a random proportion of each asset contained in the portfolio. Roe equals -1 defines the top leading edge of risk-reward performance; Roe equals +1 shows the poorest performing portfolios. Roe values between -1 and +1 define portfolio in between.

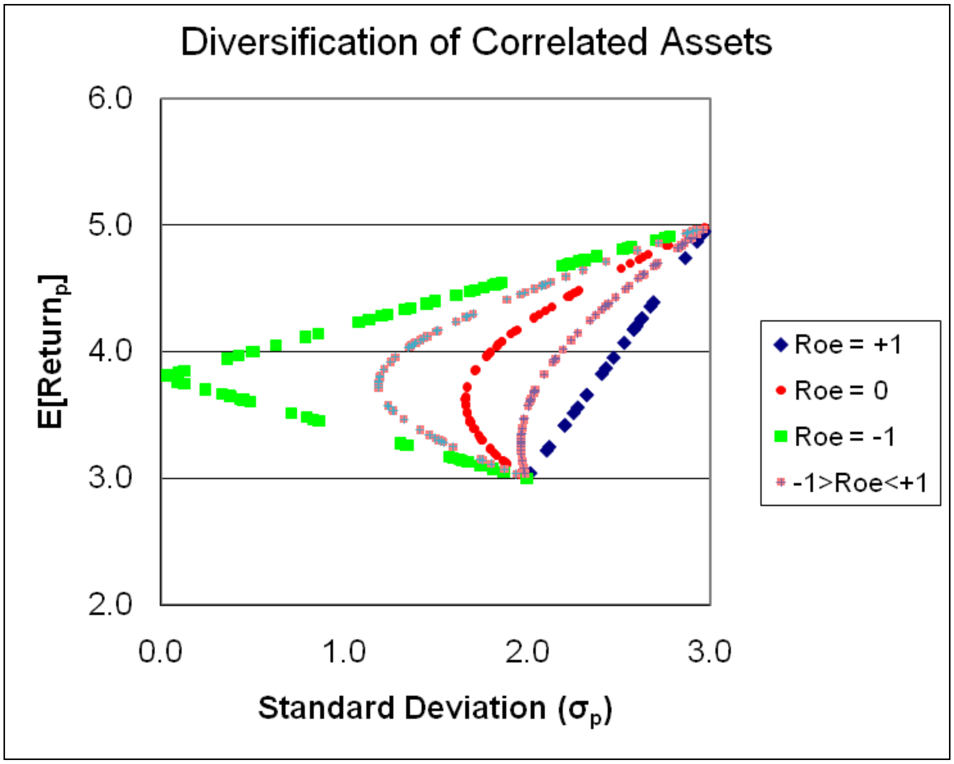


Figure 47: Diversification of correlated assets.

The notation is expanded to a portfolio of many assets by:

$$Var(r_p) = \sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j Cov(r_i, r_j)$$

where the Covariance is defined as:

$$Cov(r_i, r_j) = \rho_{ij} \sigma_i \sigma_j$$

so,

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \rho_{ij} \sigma_i \sigma_j$$

Matrix notation can be used by defining **V** as the covariance matrix and **w** as the vector of portfolio weights of each asset:

$$\sigma_p^2 = \mathbf{w}^{\mathbf{T}} \mathbf{V} \mathbf{w}$$

The minimum risk portfolio, containing *n* number assets, can be found by solving for the set of portfolio weights that minimizes the Lagrange function Λ for portfolio variance:

$$\text{Min } \sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \rho_{ij} \sigma_i \sigma_j$$

$$s.t.$$

$$\sum_{i=1}^{n} w_i = 1$$

$$\Lambda = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \rho_{ij} \sigma_i \sigma_j + \lambda_1 \left(1 - \sum_{i=1}^{n} w_i\right)$$

λ_1 are the Lagrange multipliers and other variables are as previously defined. By taking the partial derivatives of the Lagrange function with respect to each of the variables, w_1, w_2,..., w_N, λ_1, and setting them equal to zero subject to the Lagrangian constraints, the resulting values will define the minimum risk portfolio.

5.5 Optimal Portfolio

The optimal portfolio of architecture options is one that lies on the efficient frontier, where there exists no combination of options that yield a larger expected return for a given level of risk. Mathematically, the efficient frontier is the intersection of the set of minimum risk portfolios with the set of maximum expected LCV portfolios.

Two types of systems engineering situations will typically exist. The first is when the system architect has identified a range of performance valid for the architecture option, where the cost to enable varying levels of delta performance will increase with the level of performance desired. For example, to continue a brief satellite scenario from Chapter IV, if the architecture option exists which increases GPS signal power to combat enemy jamming, the more power enabled, the more the stakeholder is satisfied (to a certain extent), and the more it will cost. The architecture question exists: how much of the available program funds should be allocated to embed signal power flexibility as opposed to the other available architecture options? The second situation is when the cost to embed each architecture option is known; the cost can be known precisely or treated as a stochastic variable[14]. The optimal portfolio decision in this situation consists of determining which set of the defined architecture options to "purchase." Portfolio selection for each of these situations is described next.

5.5.1 Architecture Options on a Continuum

Having a pool of money such as management reserve, discretionary funds, spiral development funding, or otherwise, the system architect will want to know how to most efficaciously expend those dollars. When considering architecture options that are continuous in nature (i.e., additional performance and utility is achieved with additional cost), the optimal portfolio will allocate the available resources among the set of options that results in a minimum variance, maximum return portfolio.

To demonstrate this process, an example portfolio has been created which contains undetermined proportions of six large capitalization stocks. These stocks were chosen mainly to exhibit both positive and negative correlation between asset returns. Ten years of data, from 2000 to 2010, were compiled to calculate the average annual return, annualized standard deviation, and correlation coefficients between assets. Summary data are listed in Table 8, Table 9 and Table 10.

---

[14] Variability in initiation cost can be included by defining C_{AOi} as a random variable which simply augments the values of the existing $E[V(t_{DL})]$ and σ_{AOi} which are calculated in Chapter IV.

Table 8: Average annual return, Annualized standard deviation

Asset	Average Return	Standard Deviation
Hewlett-Packard (HPQ)	9.58%	13.64%
Boeing (BA)	5.52%	13.58%
Chevron (CVX)	2.98%	10.02%
Lockheed Martin (LMT)	11.70%	8.34%
Caterpillar (CAT)	7.89%	16.00%
Exxon Mobile (XOM)	2.24%	10.29%

Table 9: Correlation matrix

	HPQ	BA	CVX	LMT	CAT	XOM
HPQ	1	0.090329	0.268221	-0.18478	-0.31399	0.576522
BA	0.090329	1	0.041045	0.651821	0.450723	0.627282
CVX	0.268221	0.041045	1	-0.0542	-0.12079	0.270371
LMT	-0.18478	0.651821	-0.0542	1	0.365603	0.359357
CAT	-0.31399	0.450723	-0.12079	0.365603	1	-0.07049
XOM	0.576522	0.627282	0.270371	0.359357	-0.07049	1

Table 10: Covariance matrix

	HPQ	BA	CVX	LMT	CAT	XOM
HPQ	0.018618	0.001674	0.003668	-0.0021	-0.00686	0.008097
BA	0.001674	0.018448	0.000559	0.007387	0.009795	0.00877
CVX	0.003668	0.000559	0.010043	-0.00045	-0.00194	0.002789
LMT	-0.0021	0.007387	-0.00045	0.006961	0.004881	0.003086
CAT	-0.00686	0.009795	-0.00194	0.004881	0.025601	-0.00116
XOM	0.008097	0.00877	0.002789	0.003086	-0.00116	0.010595

The asset proportions, **w**, that yield the minimum variance portfolio can be found by:

$$\text{Min } \sigma_p^2 = w_i w_j Cov(r_i r_j)$$

$$s.t.$$

$$\sum_{i=1}^{n} w_i = 1$$

$$\Lambda = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j Cov(r_i r_j) + \lambda_1\left(1 - \sum_{i=1}^{n} w_i\right)$$

The only constraint is that the asset proportions sum to one. For computational convenience, the optimization can be performed with the Solver function in Microsoft Excel and does not require the Lagrange calculations by hand. Also, it is many times useful to utilize matrix notation which can be expressed with:

$$\text{Min } \sigma_p^2 = \mathbf{w}^T \mathbf{V} \mathbf{w}$$

where,

$$\mathbf{w} = \begin{bmatrix} w_i \\ \vdots \\ \vdots \\ w_n \end{bmatrix} \qquad \mathbf{V} = \begin{bmatrix} \rho_{ii}\sigma_i^2 & & & \\ \rho_{ij}\sigma_i\sigma_j & \rho_{jj}\sigma_j^2 & & \\ \vdots & & \ddots & \\ \rho_{in}\sigma_i\sigma_n & \cdots & \cdots & \rho_{nn}\sigma_n^2 \end{bmatrix}$$

Solving for the minimum variance portfolio results in an expected return of 6.95%, standard deviation of 1.04%, and the following portfolio composition:

$$\mathbf{w} = \begin{bmatrix} 17\% \\ 10\% \\ 21\% \\ 22\% \\ 16\% \\ 14\% \end{bmatrix}$$

The set of intersecting minimum variance, maximum return portfolios can be generated by adding a constraint to the optimization which specifies a desired level of expected return, E^*. Therefore for each level of expected return, a minimum variance portfolio can be calculated and plotted to find the set of optimal risky portfolios.

$$\begin{aligned}
&\text{Min } \sigma_p^2 = w_i w_j Cov(r_i r_j) \\
&s.t. \\
&\sum_{i=1}^{n} w_i E(r_i) = E^* \\
&\sum_{i=1}^{n} w_i = 1 \\
&\Lambda = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j Cov(r_i r_j) + \lambda_1\left[E^* - \sum_{i=1}^{n} w_i E(r_i)\right] + \lambda_2\left(1 - \sum_{i=1}^{n} w_i\right)
\end{aligned}$$

Figure 48 shows the optimal portfolios in red along the efficient frontier and the minimum variance portfolio with a blue square. The gains from diversification are readily observed when compared to any of the individual assets pictured as green triangles. The portfolios illustrated along the black dashed line are also minimum variance portfolios, but because an investor will always prefer a higher return for the same level of risk, these portfolios are dominated and can be discarded.

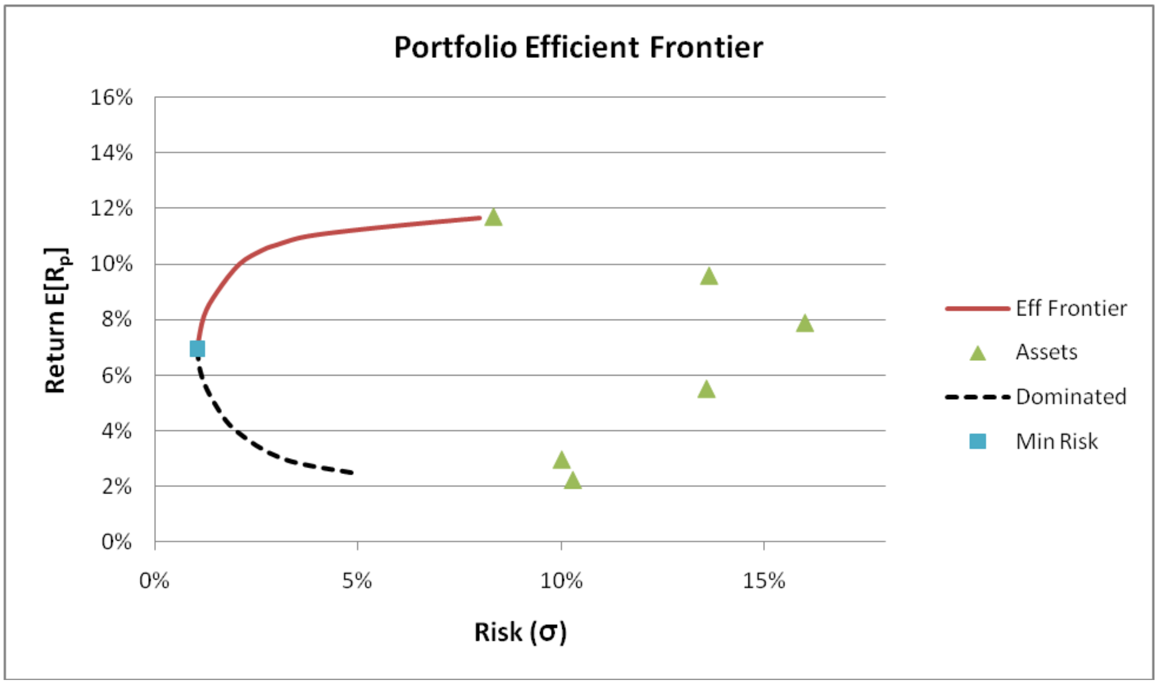


Figure 48: Minimum variance portfolio and efficient frontier.

Each of the portfolios along the efficient frontier are optimal portfolios, where one cannot be declared better than another. However, using information about a riskless asset, that is, the "risk-free" rate of return, the portfolio can be found that maximizes the "reward-to-variability" ratio. Known as the Sharpe ratio (Sharpe, 1966), this metric measures the excess return per unit of risk against a riskless benchmark asset--the incremental return of the portfolio compared to the incremental increase of risk. In this example, the risk-free asset has been defined as the 10-yr

U.S. Treasury Bill which yields the risk-free rate, R_f = 3.85%. The portfolio that maximizes the Sharpe ratio can be found by:

$$\begin{aligned}
&\text{Max } S = \frac{E[R_p] - R_f}{\sigma_p} \\
&s.t. \\
&\sum_{i=1}^{n} w_i = 1
\end{aligned}$$

The result is a portfolio with expected return of 8.12% and a standard deviation of 1.2%, composed of asset proportions:

$$\mathbf{w} = \begin{bmatrix} 23\% \\ 8\% \\ 16\% \\ 30\% \\ 17\% \\ 5\% \end{bmatrix}$$

The final step in finding the optimal portfolio balances the investor's willingness to trade off risk against expected return. The Sharpe ratio defines the slope of a line, described as the capital allocation line (CAL), that originates at the riskless asset and intersects the optimal risky portfolio, shown in Figure 49. This line represents the set of portfolios that contain just the optimal risky asset and the riskless asset. The optimal combination is found at the intersection of the investor's utility function and the CAL. Utility functions for varying degrees of risk aversion can be plotted as a set of indifference curves that represent the indifference of an investor to combinations of risk and return. According to Chen (2008), a common utility function is used by the Association of Investment Management and Research (AIMR) to describe investor risk-return preference. This function increases with expected return and decreases with the portfolio variance, multiplied by a risk aversion coefficient, A:

$$U = E[R_p] - A\sigma_p^2$$

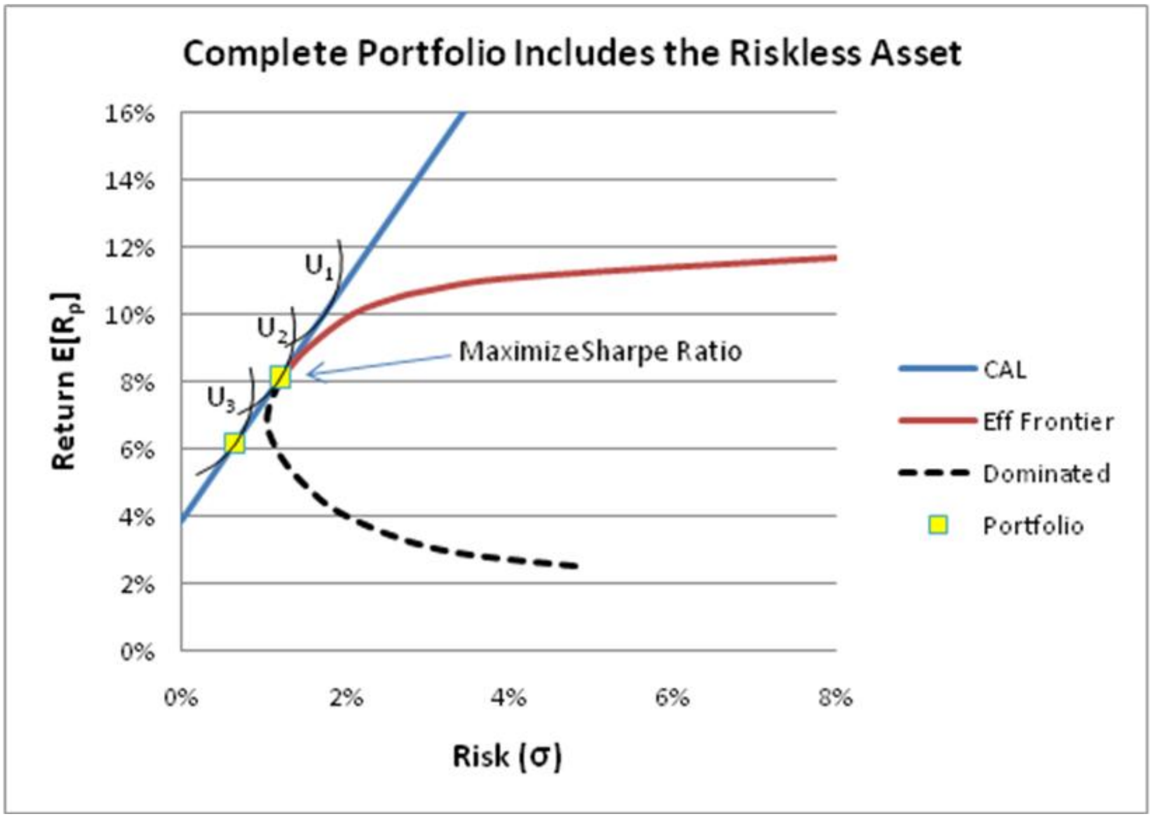


Figure 49: Complete portfolio contains the optimal risky portfolio and the riskless asset.

The optimal complete portfolio, *C*, which includes some proportion of the risky portfolio, *y*, and the risk-free asset, is found as the investor seeks to maximize his utility:

$$
\begin{aligned}
&\operatorname{Max}\ U = E[R_C] - A\sigma_C^2 \\
&s.t. \\
&y \le 1
\end{aligned}
$$

where,

$$
\begin{aligned}
&E[R_C] = R_f + y[E[R_p] - R_f] \\
&\sigma_C^2 = y^2\sigma_p^2
\end{aligned}
$$

By reserving some portion of cash in hand for allocation to the riskless asset, risk can be decreased further from the minimum variance portfolio. Alternatively, if additional cash is borrowed at the risk-free rate to fund the purchase of the risky portfolio, a leveraged portfolio can be created, along the CAL, that has risk-reward characteristics beyond the efficient frontier. This represents the highly risk tolerant investor.

This example demonstrates optimal portfolio selection using data from the stock market and is further grounded in the realities of the financial markets with the use of the risk-free T-Bill as the investment benchmark. When translated to fit systems engineering applications, some subtle differences arise in collecting and using the relevant data. These differences involve the calculation of expected return, standard deviation, asset correlation, risk-free rate, and portfolio weights.

For architecture option selection, the expected value and standard deviation of the AO is calculated by the truncated present value distribution from Chapter IV. Both measures are reported with respect to the entire design life, t_{DL}. Therefore, the average annual return and annualized standard deviation must be converted by:

$$E[AO_i] = E[AO_i] / t_{DL}$$
$$\sigma^2_{AO_i} = \sigma^2_{AO_i} \Big/ \sqrt{t_{DL}}$$

Architecture option correlation is calculated by dividing the covariance of the two random variables, AO_i and AO_j, by the product of their standard deviations:

$$\rho_{ij} = \frac{Cov(AO_i, AO_j)}{\sigma_{AO_i}\sigma_{AO_j}} = \frac{E\left\lfloor (AO_i - \mu_{AO_i})(AO_j - \mu_{AO_j}) \right\rfloor}{\sigma_{AO_i}\sigma_{AO_j}}$$

This calculation is possible when the occurrence of each scenario is treated as the random variable, T_v, for example a Bernoulli distribution, which flows into a value function for the AO that satisfies functional requirements associated with that random event. Each AO, having its own stochastic value stream, also reflects the random value of the scenario and, after Monte Carlo simulation, yields an expected value and variance. The correlation coefficients can be calculated and used to populate the correlation matrix, **C**. In Step 8 of the Chapter III AO screening process, a procedure is described that assigns a correlation coefficient to AO_i-AO_j pairs. If two AOs satisfy functional requirements associated with the same scenario, they have an overlapping source of uncertainty—these are defined as perfectly positively correlated, $\rho_{ij} = 1$. If two AOs satisfy functional requirements associated with two different scenarios, the AOs are perfectly uncorrelated, $\rho_{ij} = 0$. When functional requirements are shared between scenarios, these AOs are partially correlated and require the statistical calculation above.

The return on the U.S. treasury bill is not always an appropriate benchmark for the risk-free rate. A more appropriate benchmark for AO portfolio selection is the corporate bond rate. This rate represents the firm's least expensive source of capital and reflects the shareholder's perspective of comparing the risky portfolio to that of paying off the bond holders.

The final difference between optimizing a portfolio of stocks and a portfolio of continuum architecture options relates to how the portfolio weights are interpreted and calculated. When an investor purchases shares of stock, whether one share or one thousand shares, the investment return on a percentage basis remains consistent. Therefore, when a portfolio is composed of varying proportions of stocks, the proportion does not affect the expected rate of return of each asset. Optimization can be accomplished by solving for the respective weights without regard to how the selected weights change the expected return of the asset. This should not be blindly assumed when dealing with architecture options. The expected rate of return for an architecture option is the difference between the mean option value and option cost, divided by the option cost.

$$E[R_{AO_i}] = \frac{E[V_{AO_i}] - C_{AO_i}}{C_{AO_i}}$$

If the expected rate of return is assumed to be constant for all levels of proportional investment, it is necessary that the expected value increases in the same proportion to the option cost (e.g., additional 10% in cost yields additional 10% in option value to keep rate of return constant). This assumption allows the portfolio optimization to proceed without regard to the total budget available or portfolio weights. In many cases, this is not a good assumption and a more complete treatment of this issue requires additional computational steps in the analysis.

The core of the issue is to determine how changes in option expenditure (cost) affect the expected value of the option. This can be accomplished first by propagating the delta cost, determined by the asset weight, back through the AO cost model and utility function. The new utility value is translated into mean option value by integrating under the "Delta" curve developed in the option analytics section in Chapter IV. This yields a new option value for the new cost and is conceptually illustrated in Figure 50.

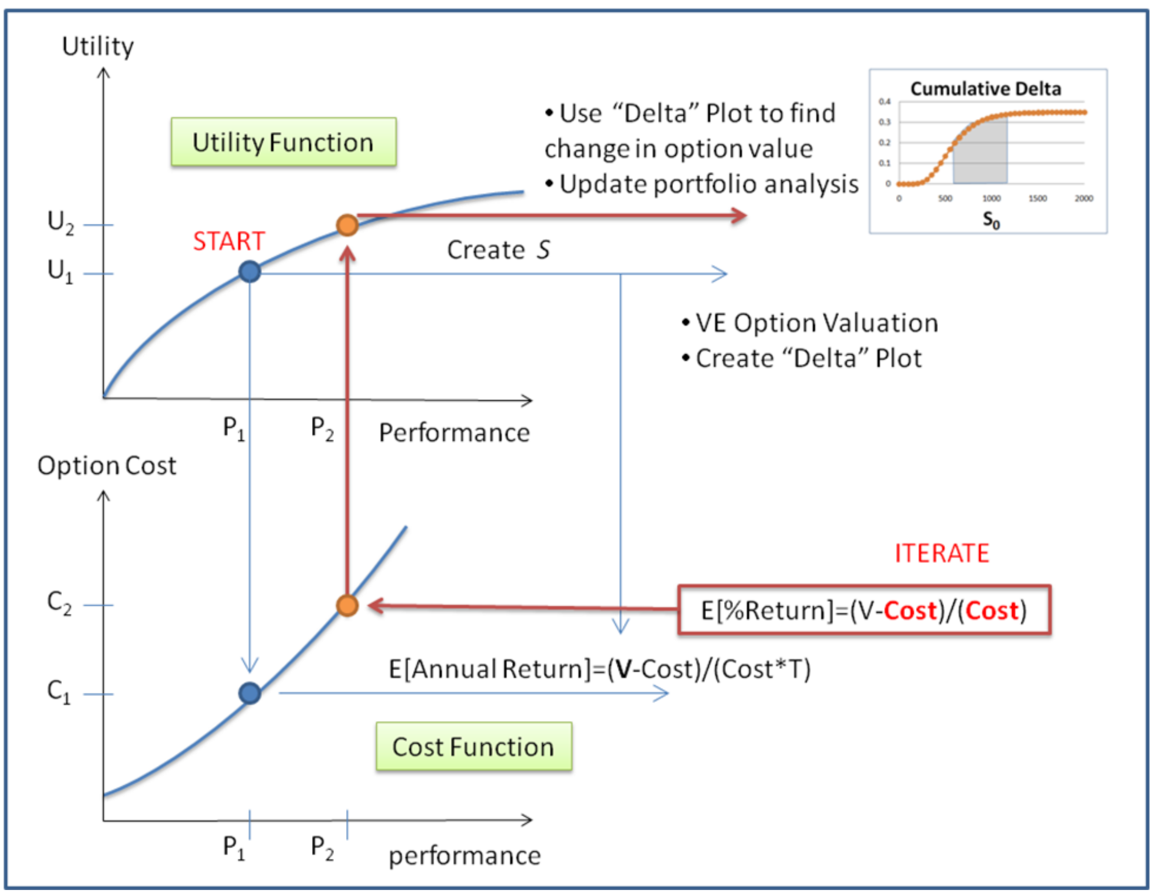


Figure 50: Change in option value given a change in option cost.

As the proportion of AO_i in a portfolio changes, the total expenditure on that AO changes depending on the total dollars being allocated to the portfolio (i.e., the flexibility budget). A change in option expenditure can be traced to a change in performance through the Performance-Cost curve. The resulting delta performance can be traced to a change in stakeholder utility through the traditional utility function. The utility function is the basis of estimate for the future benefit stream forecast, *S*, defined in Chapter IV. *S* is discounted and consolidated to S_0 at Time 0 and is a driving factor in the VE option valuation. The option "Delta" is the first derivative of option value with respect to S_0 and reveals the sensitivity of the option value to changes in S_0. Integrating under the "Delta" curve results in the total value change due to a change in S_0. The option "Gamma" measure can also be useful to indicate where the "Delta" curve is neutralized or linear, meaning that changes in S_0 lead to a linear change in option value (essentially multiply delta S_0 by $P(T_v)$). The expected rate of return is updated with each iteration to the portfolio composition, and is always measured against the initial utility that served as the basis for the estimate of *S*.

5.5.2 Discrete Architecture Options

The second situation that typically occurs involves architecture options with known cost (including options with cost variability). The optimal portfolio decision is not one of weights, per se, but of yes-no decisions. The optimal portfolio contains a finite set of architecture options which yields the highest level of expected return for a specified budget, *b*, given the level of risk. This situation can be represented by a binary integer objective function where AO_{bp} is a 0-1 variable. If it is 0, the AO is not included in the portfolio; if it is 1, the AO is included in the portfolio.

$$
\begin{aligned}
&\max_{\substack{AO_{bp}\in\{0,1\} \\ p=1,\ldots n}} E[LCV] = \sum_{AO_p} (Z_{t_0}^{t_{DL}}(\mu, r)_{AO_p} - C_{AO_p}) * AO_{bp} \\
&s.t. \\
&\sum_{AO_p} AO_{bp} * C_{AO_p} < b \\
&w_i = C_{AO_p} \Big/ \sum_{AO_p} AO_{bp} * C_{AO_p} \\
&\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \rho_{ij} \sigma_i \sigma_j = S^*
\end{aligned}
$$

Values from the stock market example are used again here in combination with the vector $\mathbf{C}_{AO}$ which is defined to contain the design cost of each architecture option:

$$
\mathbf{C}_{AO} = \begin{bmatrix} 400 \\ 33 \\ 300 \\ 800 \\ 500 \\ 100 \end{bmatrix}
$$

Portfolio risk-return combinations are limited to the values resulting from the set of portfolios defined by the mixed sum of all possible combinations of architecture options, shown with blue diamonds in Figure 51. The efficient frontier is defined by the set of portfolios that maximizes expected return, subject to the budget, *b*, for all achievable values of risk. In this sense, portfolios that lie on the efficient frontier on the "dominated" underside of the curve, are not necessarily inefficient portfolios because of the budget constraint. It is true that for the given level of risk, a higher rate of return is possible by the portfolio directly above the one in question, however the higher rate of return is accomplished with a higher total design cost. The budget constraint therefore legitimizes all portfolios on the efficient frontier. If the budget is sufficiently large, the system architect would select the optimal portfolio that maximizes the Sharpe reward-to-variability ratio, which in this case is the same portfolio that minimizes risk. The CAL originates at the corporate bond rate (5% being used here) and intersects the selected portfolio; this line represents all proportions of the risky portfolio and the risk-free alternative (paying off bond holders). The portfolio that exists at the intersection of the stakeholder utility function, (which represents stakeholder indifference between risk-return combinations), and the CAL is the complete optimal portfolio of architecture options.

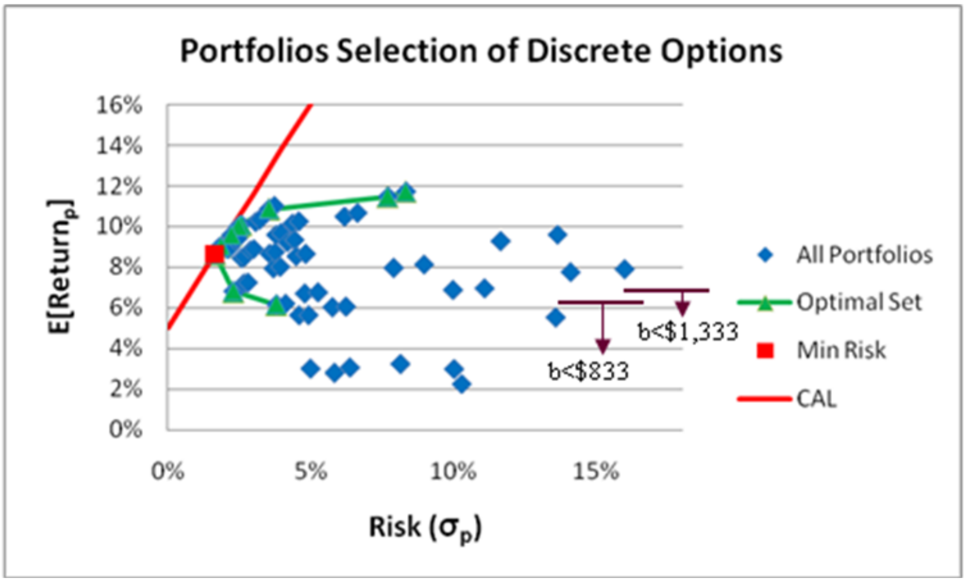


Figure 51: Portfolio selection of discrete architecture options given design budget constraint.

5.6 Conclusion

After identifying and valuing architecture options, the system architect is faced with the decision of which set of options to pursue. The optimal subset of architecture options is defined by the maximization of life cycle value and minimization of risk through diversification. Some systems engineering situations require the assessment of architecture options that exist on a continuum, where additional performance and value can be generated with additional expenditure. Other situations require a go, no-go decision on a set of discrete, fixed-price architecture options. In both cases, optimal portfolios can be constructed that minimize the portfolio risk for a given level of expected return or conversely maximize the expected return for a given level of portfolio risk. The set of optimal portfolios can be identified and selected based on stakeholder risk tolerance and available budget. A decision is then be made to expend all available funds toward the risky portfolio, or conserve some allocation for the riskless asset. This proportion is determined by the intersection of the stakeholder indifference curve with the capital asset line, and results in the complete optimal portfolio of architecture options.

CHAPTER VI

THE TACTICAL IMAGING CONSTELLATION ARCHITECTURE STUDY: A PROOF OF CONCEPT FOR EMBEDDED ARCHITECTURE OPTIONS

6.1 Introduction

Flexibility embedded in the system design has application across a wide variety of engineering domains. Generally, whenever there exists uncertainty in system operation, where changes may occur in the mission objectives, there also exists an opportunity to design the system to adapt and respond to that change. Flexibility has been studied and assessed in a variety of contexts, but rarely treated in an integrated way that separates the application domain from the process. In the previous chapters, a framework has been proposed that approaches the concept of flexibility from an application independent perspective. A generic process has been described that leverages current systems engineering practices and the familiar taxonomy of financial markets to identify, value, and select architecture options that can be embedded in the system design to provide operational flexibility. This chapter provides a proof of concept by demonstrating the proposed methodology on a U.S. intelligence, surveillance, and reconnaissance (ISR) system called the Tactical Imaging Constellation Architecture Study (TICAS).

6.2 Background

The Tactical Imaging Constellation Architecture Study was a 1995 concept definition activity headed by the Naval Research Laboratory (NRL) in collaboration with the Jet Propulsion Laboratory (JPL), Lawrence Livermore National Laboratory (LLNL), and four aerospace industry partners: TRW, Spectrum Astro, Ball Aerospace Technical Corporation, and Hughes Aerospace Corporation. The stated objective for the TICAS contract was to:

> "Develop and define a high performance satellite constellation using 1995 enabling technologies to provide earth image data meeting anticipated future needs. The constellation shall use lightweight launch vehicles."[15]

Concept development was completed through Phase II but was never built. The final report of the TICAS investigation recommended a system architecture composed of a family-of-systems which included two Point Collector (PC) satellites and two Broad Area Collector (BAC) satellites. The constellation was designed to meet both tactical and national imagery needs which consisted of requirements for high resolution point targets with ground sample distance (GSD)[16] on the order of 3-inches, and also broad area lower resolution imagery with GSD between 10 and 80-inches. Demands for high resolution imagery typically occur in relatively constrained regions of less than 4 nmi^2, whereas demands for coarse imagery can span wide regions of hundreds of square nautical miles. Competing design objectives therefore existed in that collecting high resolution imagery compels the design to lift the largest possible telescope mirror to the lowest altitude which, due to orbital geometry, limits the frequency and expanse of visible earth access. Coarse imagery of large areas would require either large amounts of time (on the order of weeks) or large numbers of satellites. For this reason, the TICAS constellation was composed of low flying Point Collector satellites to satisfy demands for high resolution imagery, and high flying Broad Area Collector satellites to meet wide area imagery needs.

6.3 Proof of Concept

This section attempts to rigorously apply the three stages of the proposed flexibility framework (Figure 52). Actual TICAS design and performance models are used in stage one to identify promising regions in the architecture to embed flexibility based on operational scenarios derived from expert interviews within the satellite reconnaissance community. Both parametric

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[15] TICAS Phase II Final Study Report (1996)

[16] See Appendix C for exposition on ground sample distance.

and bottom-up life cycle cost estimates are combined with value functions for Intelligence Community key performance parameters (KPPs) to complete stage two valuation of flexibility options. Stage three explores combinations of architecture options which optimize the life cycle value of the imagery constellation for given levels of program budget and risk. The proposed framework is subsequently assessed for its strengths and weaknesses as well as the extensibility, usefulness, and limitations of the framework when applied to real world system design problems.

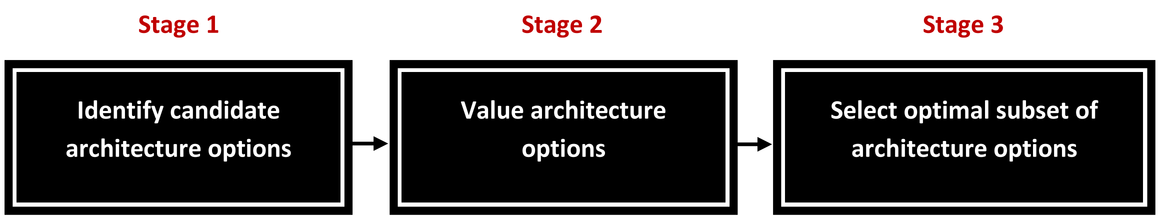

Figure 52: Three stage integrated flexibility framework for identifying, valuing, and selecting architecture options.

The TICAS system architecture was chosen for this proof of concept for several reasons. First, the TICAS constellation of satellites allows for an assessment of a family-of-systems (FoS) with a single design authority that exhibits optimization preferences at the high-level FoS context. Secondly, satellites in general provide an interesting context to analyze flexibility because the domain tends to stretch the limits of the flexibility framework to the extremes. Once the satellite is launched into orbit, there does not exist an opportunity to physically access or alter the spacecraft; all potential functionality that is dependent on the physical state of the spacecraft is essentially cast in stone at launch. Unlike aircraft, e.g., the B-52 Stratofortress, that can be upgraded and altered after initial operation, a satellite design must contain all attributes of flexibility in the initial system architecture. Satellites also tend to be complex, high-technology, and expensive. Complexity requires extensive and intricate relational models to describe the interconnections within the design which makes it more challenging to identify opportunities for flexibility. High technology systems tend to have higher uncertainty in performance, due to limited testing, which makes it difficult to accurately predict system behavior in operation. Satellites are inevitably expensive and produced in small quantities which makes the stakes in this domain extremely high and the ramifications of design decisions incredibly important. Spacecraft design can arguably be described as an extreme case for the application of the proposed integrated flexibility framework. This allows us to assess the effectiveness of the proposed methodology for even the most challenging system design problems.

A third reason the TICAS was selected as a proof of concept is because of the quantity and availability of technical design data. The NRL and the National Reconnaissance Office (NRO) have gone to great lengths, at significant expense, to collect and compile descriptions, data, and analytical models related to the TICAS investigation. It is highly unusual to have the quantity of detailed design material available which has been made available for TICAS. Industry contractors typically prefer to keep detailed models and pricing data proprietary for competitive reasons. Also, ISR projects are often times developed in the classified environment which prohibits general access to any information. The nature of the industry-laboratory partnership combined with the willingness of the NRL-NRO to archive the TICAS investigation material have provided a unique opportunity to gain insight into the design and requirements of a potential national system.

Lastly, TICAS was chosen because of the intimate involvement that the author had in compiling and analyzing the technical design material. The author worked at the NRO in 2008 with the TICAS principal investigator to leverage the technical material in order to establish a curriculum to teach electro-optical spacecraft design. An NRO internal course, IMIMT 501, was developed which utilizes TICAS architecture principles and analytical models to demonstrate spacecraft design techniques.

6.3.1 Baseline System Architecture

The TICAS baseline system architecture serves as the point-of-departure for this analysis and consists of a space segment, ground segment, and launch segment. The space segment is composed of two "Broad Area Collector" satellites and two "Point Collector" satellites, illustrated in Figure 53.

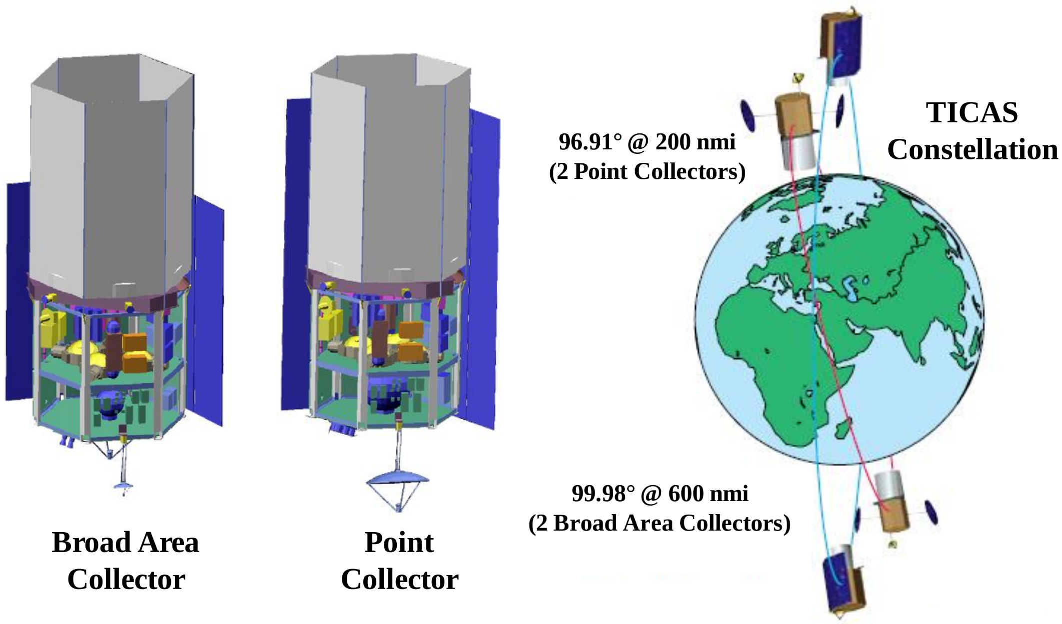

Figure 53: TICAS Constellation with Broad Area and Point Collector satellites.

The BAC satellites provide the majority of broad area visible spectrum imagery from a sun-synchronous[17] orbit with altitude of 600 nmi. Each BAC satellite can use a pushbroom imaging strategy to collect 100,000 nmi^2 of imagery per orbit, with better than 12-inch GSD at nadir and 20-inch GSD at 40° look angle. The BAC can also use a whiskbroom imaging strategy

[17] Sun-synchronous orbit requires that the rate of precession of the satellite around the earth is equal to the period of the earth around the sun. This is accomplished by choosing a satellite inclination such that the steady shift in right ascension matches Earth's revolution about the sun. Sun-synchronous orbit preserves the solar illumination angle throughout the year which can be advantageous for image comparisons.

to collect up to 20,000 nmi^2 of area per orbit surrounding a specified site[18]. The BAC additionally incorporates a multi-spectral capability over four visible to near-IR spectral bands with better than 80-inch GSD.

The PC satellites are in a lower, 200 nmi, sun-synchronous orbit and provide the majority of visible spectrum high resolution point target images. The PC can collect 120 point targets per orbit per satellite. These images have an area of 2 nmi by 2 nmi with 3-inch GSD at nadir and 13-inch GSD at a 20° look angle. In addition to visible spectrum collection, the PC configuration can provide infrared imagery in the same two by two nmi ground footprint with 18-inch GSD at nadir. A critical parameter for the relatively low altitude PC satellite is the revisit time required to collect high-end resolution at a specific site. The PC satellite capability to achieve a specific GSD anywhere in the world is summarized in Table 11.

Table 11: TICAS PC satellite performance (worldwide average).

Revisit Time (Days)	GSD (Inches)
11.9	3
1.6	4
0.7	5

The TICAS Ground Segment provides tracking, telemetry, and command (TT&C), image data acquisition and processing, direct downlink (DDL), and mission management. The ground segment architecture is depicted in Figure 54. All imagery data collected by both BAC and PC satellites is transmitted to a central processing facility (CPF), via a 1000 Mb/s link to a geosynchronous relay satellite, for processing, image construction and dissemination. Collected imagery is stored in the 1,024 Gbit onboard solid state data recorder (SSDR) until it can be transmitted to the CPF, occurring at least once per orbit. Satellite commanding is sent through a

[18] See Appendix D for description of imaging collection strategies.

32 kb/s forward command link via the relay. The BAC satellite provides an additional direct downlink capability to get near-realtime broad area imagery to the warfighter in theater. The DDL approach allows Theater Commanders to have "dynamic ownership" and tasking authority of the satellite while the asset is overhead which then transmits realtime imagery to a tactical processing facility (TPF) at 274 Mb/s. The direct downlink capability is contingent on the completed development of a space common data link (CDL) and Class IV ground equipment that is fully interoperable with upgraded legacy Class I equipment.

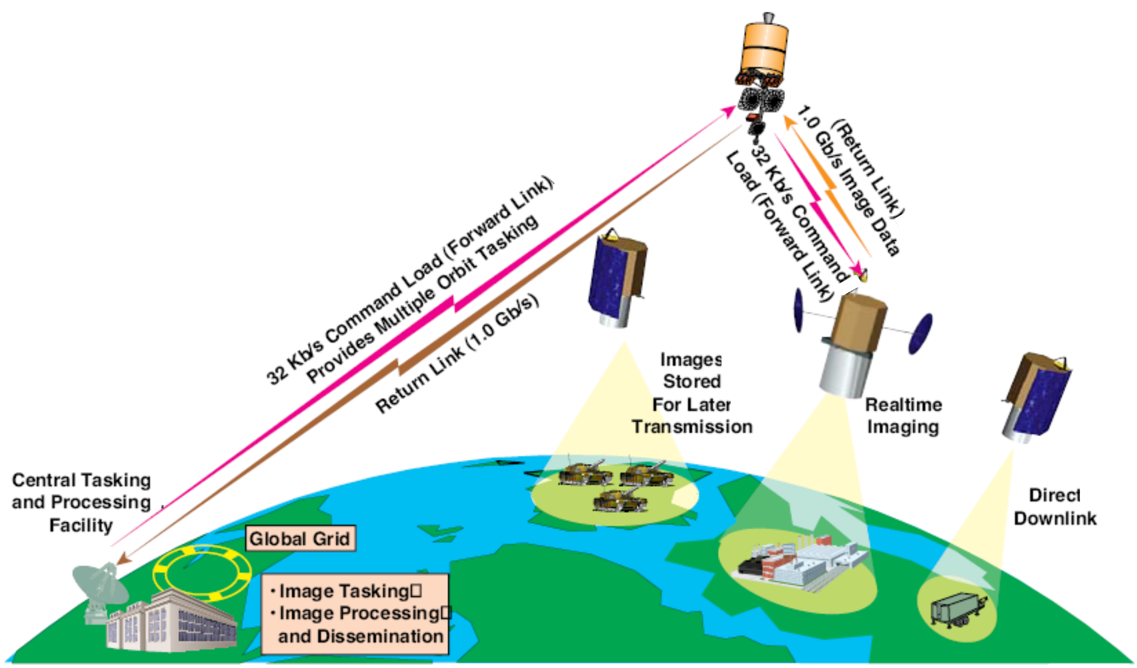

Figure 54: TICAS Ground Segment architecture.

A critical parameter for the ground segment is "timeliness." Measured in minutes, timeliness is the time between tasking request and product correlation. This duration is dependent on the connectivity between tasking request and imagery collection (responsiveness), and also the latency between imagery collection and product delivery (freshness). Timeliness is the sum of responsiveness and freshness; this parameter is a function of the number of collectors and their orbital characteristics, observation opportunities, projected weather, relay availability, and satellite health and status.

The TICAS Launch Segment utilizes a combination of Lockheed Martin Launch Vehicles (LMLV) and Boeing's Delta II class launch vehicles to inject the PC and BAC spacecraft into 200 nmi circular orbit. The LMLV3-8 launch vehicle is used to insert the BAC vehicles into a 200 nmi parking orbit where onboard satellite propulsion raises the BAC to its final 600 nmi orbit. The Delta II 7920 is used to insert the heavier PC satellites into final 200 nmi sun-synchronous circular orbit. A total of four launches from the Western Test Range (WTR) are required to populate the TICAS architecture to full operational capability estimated for the year 2001. The launch vehicle selection is summarized in Table 12.

Table 12: TICAS baseline launch vehicle selection.

Satellite	Injection Altitude (nmi)	Injection Inclination (deg)	Satellite Wet Weight w/20% Margin (lb)	Launch Capability		
				Throw Weight (lb)	Launch Margin (%)	Launch Vehicle
Point Collector #1	200	96.91	6429	7730	16.8	Delta II 7920
Point Collector #2	200	96.91	6429	7730	16.8	Delta II 7920
Broad Area Collector #1	200	99.98	5703	5725	0	LMLV3-8
Broad Area Collector #2	200	99.98	5703	5725	0	LMLV3-8

6.3.2 Flexibility Framework Stage One: Screening for TICAS Candidate AOs

Illustrated in Figure 55, this section applies the proposed eight steps of the AO screening process to identify areas in the TICAS system architecture where flexibility may have the most potential.

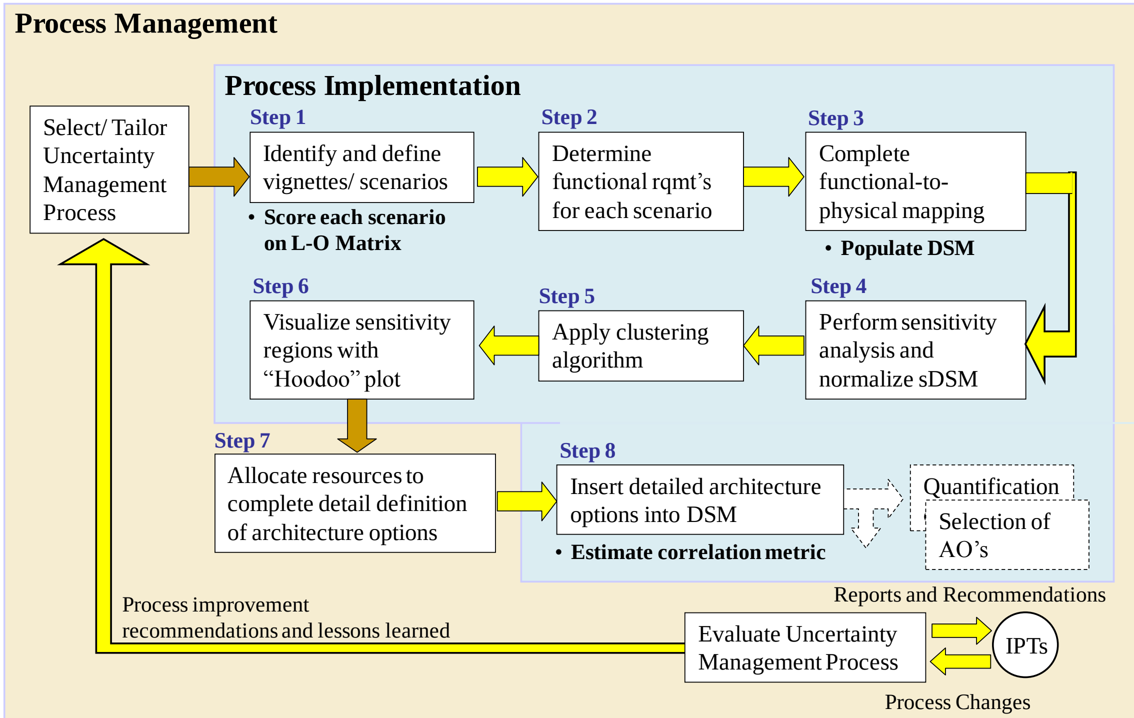

Figure 55: Architecture options screening process flow diagram.

6.3.2.1 Step 1

The concept of operation (CONOP), as depicted in Figure 56, reflects the TICAS baseline system architecture. The CONOP describes how the system is intended to operate in order to meet the threshold requirements of the stakeholders; this can be characterized as the critical mission. In Step 1, alternate mission scenarios are developed that attempt to more completely represent potential demands on the system in a realistic operational context.

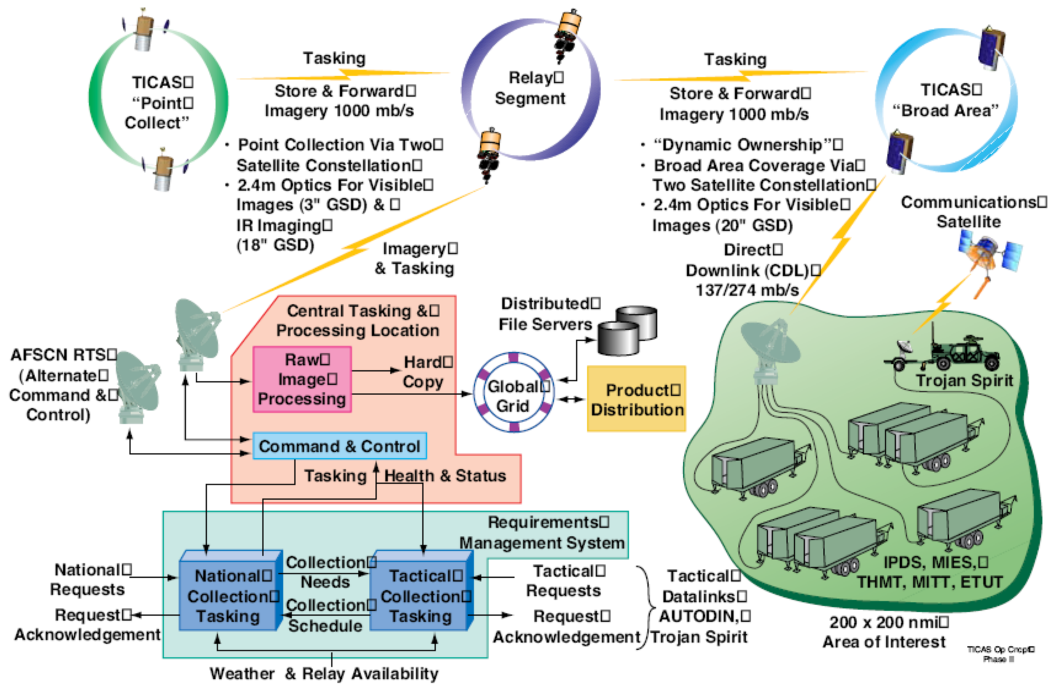

Figure 56: TICAS system concept of operation which represents the baseline system architecture.

In consultation with the Principal Investigator for TICAS and in a 2008 interview with the Director of Operations for a national reconnaissance constellation, a set of vignettes has been developed which represents some of the uncertainty that the TICAS would have faced in the operational environment. Insight into operational uncertainty for TICAS is undeniably retrospective since the pertinent question asked during expert interviews was essentially: "given the current environment, what functionality or capability do you wish the existing system had in order to better accomplish current objectives?" The goal of a robust scenario development process is to uncover as many potential stakeholder needs as possible and qualify them with information available during concept definition. The set of representative alternate operational scenarios that can, to a certain extent, encapsulate operational uncertainty for TICAS is described with the following six vignettes and is illustrated for selected operational views in Appendix E:

1. Conflict in Space: As space dominance continues to provide the United States with an asymmetric wartime advantage, potential adversaries will attempt to disrupt America's freedom of action in space by both destructive and non-destructive means.
2. Availability of Advanced Communication Relay: The demand for bandwidth and high-rate data transfer is outpacing the current military and commercial capability. The disparity between supply and demand is only expected to increase. New technologies and space communication constellations (e.g., WGS, TSAT, TDRS-H, -I, -J) are being developed to close this gap and provide advanced space relay capabilities that can increase data transfer by orders of magnitude in the coming decade (circa 1996).
3. Desire for More Frequent Point Collection: Struggles for regional power and international tension will create an environment where hostile nations will continue to pursue clandestine nuclear programs. Detection of activities associated with possible nuclear facilities will require timely and consistent access to high resolution imagery over denied areas. National reconnaissance capability may be required to significantly reduce imaging constellation revisit time (i.e., mean time to access) for high resolution imagery.
4. Need for Direct Downlink for In-Theater Operations: National assets are utilized for both strategic and tactical purposes. During a time of conflict, overhead reconnaissance assets may be desired to transmit tactical imagery directly into the theater of battle where Theater Commanders will have tasking priority and near realtime access to imagery products as the satellite passes overhead.
5. Need for Increased Broad Area Search: Where specific intelligence is scarce, overhead reconnaissance capability can be used to search wide areas for activities or infrastructure related to terrorist training camps, illicit crop production, nefarious maritime vessels, etc. As autonomous feature extraction and search and identification algorithms are improved, large amounts of imagery can be processed and flagged for detailed analysis. These occurrences may require increased broad area search capability.

6. Desire for Realtime Anomaly Resolution: Unproven, one-of-a-kind systems inevitably encounter anomalies during operation. During times of conflict and/or great national urgency, imagery systems will be desired to maintain operational availability with little or no downtime. System anomalies must be diagnosed and resolved quickly and seamlessly.

The six representative scenarios, $S=\{s_1,s_2,...,s_6\}$, are scored for their likelihood and opportunity in Table 13 and pictured in Figure 57.

Table 13: Scenario scoring for likelihood and opportunity.

Scenario, s_i	Likelihood-Opportunity Score, $LO(s_i)$	Comments
Scenario 1: Conflict in Space	(1) * (5) = 5	Consolidated, knowledgeable stake holder, high-value strategic system in larger SoS context
Scenario 2: Availability of Advanced Communication Relay	(4) * (3) = 12	Forecasted bandwidth environment strongly indicates the need for additional crosslink/downlink capabilities; moderate impact on system value
Scenario 3: Desire for More Frequent Point Collection	(4) * (5) = 20	Regional political environment suggests high likelihood of covert foreign programs; only limited and/or expensive options exist to supplement TICAS PC capability
Scenario 4: Need for Direct Downlink for In-Theater Operations	(3) * (5) = 15	Moderate likelihood of conflict requiring realtime tactical imagery. Timely data has high potential to transform battle space.
Scenario 5: Need for Increased Broad Area Search	(4) * (2) = 8	Increased search capability relies on unproven autonomous image feature extraction. Search function has mainly strategic value and is not always time critical.
Scenario 6: Desire for Realtime Anomaly Resolution	(5) * (1) = 5	TICAS will almost certainly encounter anomalies during operation, however, rarely do they pose significant threat of prolonged system outage. Also, other systems in TICAS FoS can supplement capability during anomaly resolution.

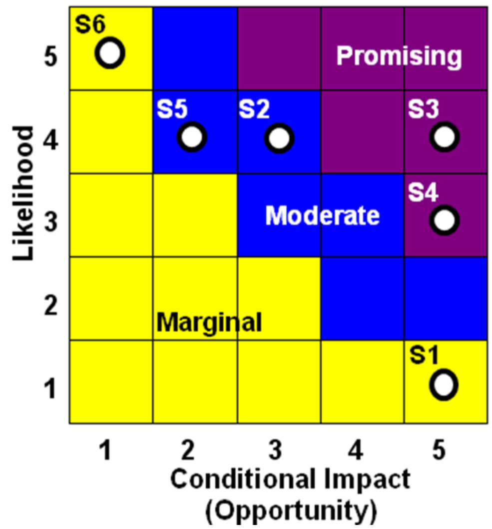

Figure 57: Likelihood-Opportunity Matrix for TICAS scenarios.

6.3.2.2 Step 2

Specific system functions are identified that would enable TICAS to respond to each operational scenario. These functional requirements are listed in Table 14 and do not explicitly specify a design solution or particular implementation. However, the scenario itself may naturally indicate particular solution approaches.

Table 14: Additional functional requirements associated with TICAS operational scenarios.

Scenario 1: Conflict in Space
FR1.1: Spacecraft shall be capable of maneuvering to avoid destructive attack
FR1.2: Spacecraft shall be capable of protecting optics and electronics from non-destructive attack
FR1.3: System shall be capable of identifying source of attack through geolocation
Scenario 2: Availability of Advanced Communication Relay
FR2.1: System shall establish and maintain contact with advanced relay constellation and be capable of transmitting data at rates between 1.2 and 3.6 Gbit/s
FR2.2: TICAS Ground Segment shall support advanced relay frequency band and data rate
FR2.3: BAC satellite power subsystem shall be capable of transitioning to bandwidth-limited imaging instead of power-limited

Scenario 3: Desire for More Frequent Point Collection
FR3.1: System shall be capable of repositioning constellation orbital parameters to reduce revisit time required to collect imagery with GSD <5 inches
FR3.2: BAC shall be capable of transitioning to point collection operational mode
Scenario 4: Need for Direct Downlink for In-Theater Operations
FR4.1: System shall be capable of transmitting imagery to tactical processing facilities in-theater over a Space Common Data Link
FR4.2: Ground Segment shall support in-theater priority tasking through "Dynamic Ownership"
Scenario 5: Need for Increased Broad Area Search
FR5.1: System shall be capable of increasing contiguous and total imaging area capability
FR5.2: System shall have adequate throughput and memory to support increased imaging volume
Scenario 6: Desire for Realtime Anomaly Resolution
FR6.1: Spacecraft shall collect realtime onboard anomaly data and transmit to ground processing facility via SGLS omni-directional transponder while in safe-mode
FR6.2: System shall be capable of diagnosing anomaly
FR6.3: System shall complete timely anomaly disposition

Subsets of system functions that affect high level performance characteristics can be consolidated by defining system attributes. Due to the fact that TICAS was designed to meet national imagery requirements, the system attributes are derived from those key performance parameters defined by the imagery intelligence (IMINT) community. Attributes common across the IMINT community fall into four general categories: image quality, frequency and timeliness of target access, quantity of imagery (e.g., number of points targets, size of contiguously sampled area), and geolocation[19] of imagery.

[19] Geolocation is the attribute that describes how accurately the system can determine the location of the image on the earth. As the spacecraft better knows where it is (orbit position knowledge) and where it's looking (attitude and line of sight knowledge), the system can reduce geolocation circular and linear error probabilities.

As the most fundamental attribute, image quality in space reconnaissance is described in terms of the empirically derived National Imagery Interpretation Rating Scale (NIIRS). NIIRS covers a range of spatial scales from entire ports and airfields down to the slots in the heads of screw fasteners[20]. Some examples are listed in Table 15. NIIRS is objectively assessed through the measurable aspects of image quality described by Leachtenauer *et* al. (1997) in the General Image Quality Equation (GIQE):

$$\text{NIIRS} = 11.81 + 3.32 * \log_{10}(RER_{GM} / GSD_{GM}) - 1.48 * H_{GM} - G / SNR .$$

The GIQE expresses NIIRS as a function of ground sample distance in inches (*GSD*), signal-to-noise ratio (*SNR*), and the optical modulation transfer function characterized by the relative edge response (*RER*), edge height overshoot (*H*), and the noise gain (*G*) due to sharpening. The signifier *GM* represents the geometric mean. Typically, the NIIRS value is dominated by the GSD term where NIIRS 5 and 7.5 roughly correspond to 20-inch and 3-inch GSD. However, the factors derived from the modulation transfer function (MTF) are foundational to image quality. The relationship between MTF and NIIRS is described in Appendix F.

Table 15: NIIRS interpretation example.

NIIRS Rating	Image Interpretability
0	Interpretation precluded due to poor quality
1	Detect a medium-sized port facility
2	Detect large hangars at airfields
3	Detect a large surface ship in port
4	Detect an open missile silo door
5	Identify rail cars by type
6	Identify automobiles as sedans or station wagons
7	Identify individual rail ties
8	Identify windshield wipers on a vehicle
9	Detect individual spikes in railroad ties

[20] For a detailed set of examples that analysts use to rate the quality of an image, see: http://fas.org/irp/imint/niirs.htm.

Each operational scenario identified for TICAS requires (or will result in) some change to one or more system attributes in order to respond to the new functional requirements. For simplicity, the functional requirements for each scenario are replaced by the affected system attribute, shown in Table 16. Figure 58 shows both IMINT community defined attributes and TICAS specific attributes and displays the predicted performance of the baseline system architecture relative to the threshold requirements.

Table 16: Mapping of alternate mission scenarios to the affected system attributes via the identified functional requirements.

Scenario, $S=\{s_1,\ldots,s_6\}$	**Functional Requirements $s_i=[FR_1,\ldots,FR_\xi]$**		**Attribute, $A=\{a_1,\ldots,a_{13}\}$**	**Key Performance Parameter**	**Units**
s_1	FR1.1, FR1.2, FR1.3 FR6.1, FR6.2, FR6.3	$\in$	a_1	Operational Availability	%
s_2			a_2	Number of Imaging Bands	No.
s_3			a_3	NIIRS 5, Mean Time to Access, 40°	hr.
s_4	FR3.1, FR3.2	$\in$	a_4	NIIRS 7.5, Mean Time to Access, 40°	hr.
s_5			a_5	Best NIIRS	
s_6	FR2.1, FR2.2, FR2.3 FR4.1, FR4.2	$\in$	a_6	Timeliness	min.
			a_7	Geolocation, horizontal	ft.
			a_8	Geolocation, vertical	ft.
	FR5.1, FR5.2	$\in$	a_9	Panchromatic Global Area	$knmi^2$
			a_{10}	Panchromatic Global Points	pts.
			a_{11}	Contiguous Area	$knmi^2$
			a_{12}	Panchromatic Regional Area	$knmi^2$
			a_{13}	Panchromatic Regional Points	pts.

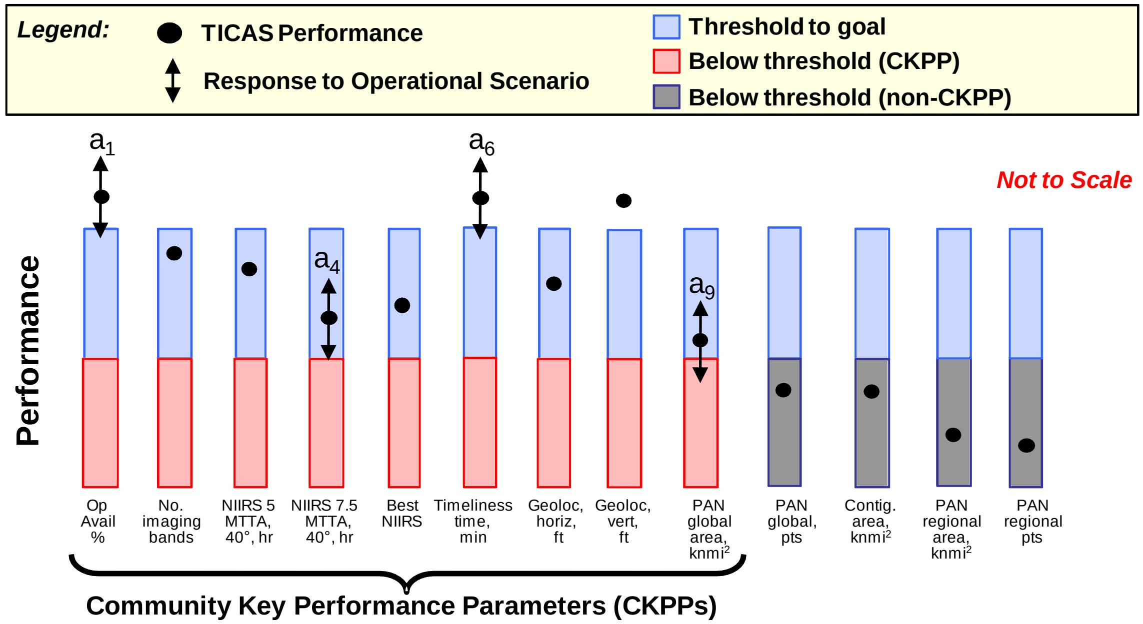

Figure 58: TICAS system attributes and performance of the baseline system architecture.

6.3.2.3 Step 3

The TICAS system attributes are subsequently mapped to design variables; this flowdown is displayed for selected attributes in Figure 59. Highly detailed models will allow fine resolution into the design variable interaction but may unnecessarily complicate the problem. Effectively defining the functional to physical mapping is more accurately a process of selective exclusion--deciding which design interactions can be simplified or bypassed while retaining an insightful system model.

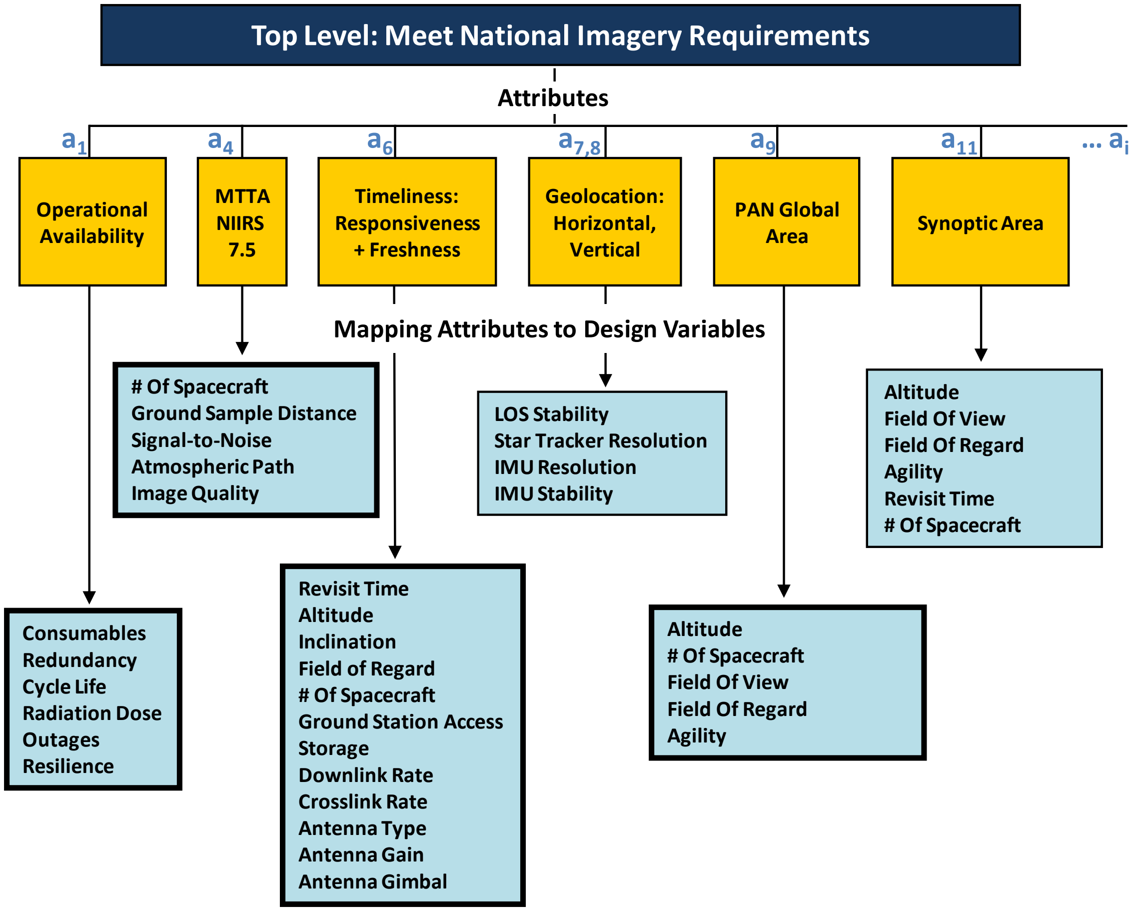

Figure 59: Functional to physical mapping of attributes to design variables. Bold outlined boxes contain design variables affected by TICAS operational scenarios via relevant system attributes.

A design structure matrix (DSM) is populated with the TICAS system interactions and hierarchy derived from the system block diagram, which is included in Appendix G. Lattix LDM[21], a system architecture modeling tool, is used to manage and organize the system interactions. Figure 60 displays the high level subsystem view which shows the number of interactions between and within subsystems as well as the connection to the identified system attributes. The expanded 107-element TICAS DSM model and element list can be found in Appendix H. Detailed mathematical models exist to define the matrix dependencies for many of the TICAS subsystems: photometry and radiometry models for the optical subsystem (OS),

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[21] http://www.lattix.com

transfer function control loops for the attitude determination and control subsystem, communication link budgets for both wide and narrow band communication subsystems, battery charging and load profiles for the electrical power subsystem (EPS), etc. Describing each of these mathematical models in detail is not particularly useful for this analysis, however a closer look at the optical subsystem is included in the next step to demonstrate the level of fidelity that can be incorporated into the AO screening process.

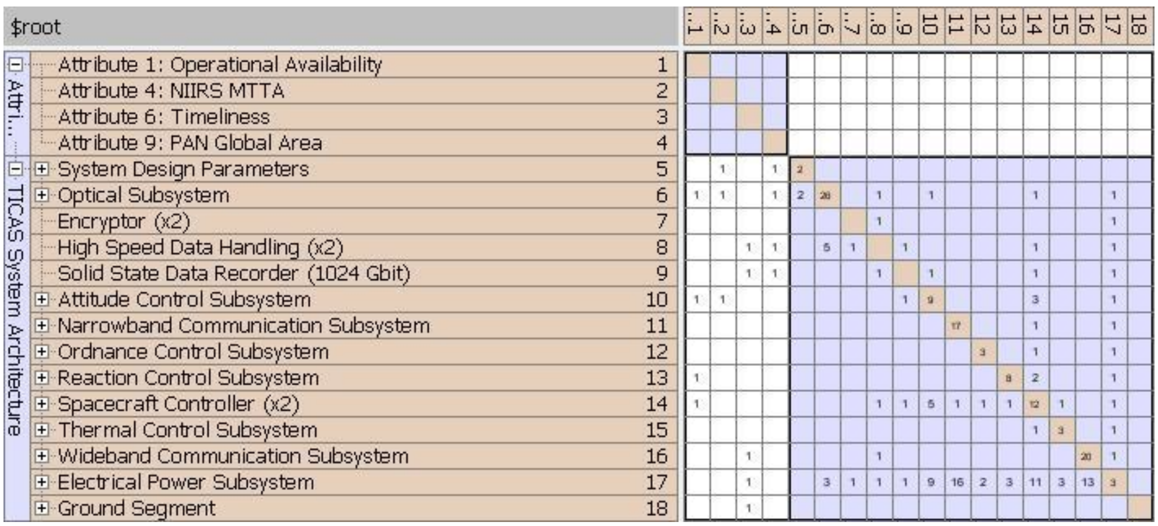

Figure 60: Design structure matrix representation of the TICAS system architecture including impact from system attributes. Values displayed in the diagonal elements represent the number of intra-subsystem relationships while off-diagonal values represent the number of relationships between subsystems. Dependencies of a row element are signified across the columns.

6.3.2.4 Step 4

A sensitivity analysis is completed to quantify the extent to which the TICAS design variables must change in order to accommodate the changing requirements. Tornado diagrams and Spider plots have been used to discover the most sensitive design variables as the system attributes are changed. The TICAS system model is large and the relationships are complex. For this reason, a single mission scenario and its affected system attribute have been chosen as a representative example to demonstrate this step in the framework. Therefore, a detailed description of the design implications of accommodating Scenario 3 (i.e. desire for more frequent point collection) is presented through the lens of the necessary changes that the scenario would require from the NIIRS Attribute (4). Scenario 3 and its affected attribute were selected because they directly affect the optical subsystem; this subsystem constitutes the bulk of what makes an electro-optical satellite unique among its satellite peers. The relationships between orbits, optics, sensors, and spacecraft motion, make for a complex and interesting set of design variables and trade-offs.

The NIIRS attribute is modeled using physical and mathematical relationships related to photometry, radiometry, optics, orbital mechanics, and digital image processing. These relationships are captured in the spreadsheet depicted in Figure 61 and are presented in a logical tree structure that represents the hierarchy of dependency in the model.

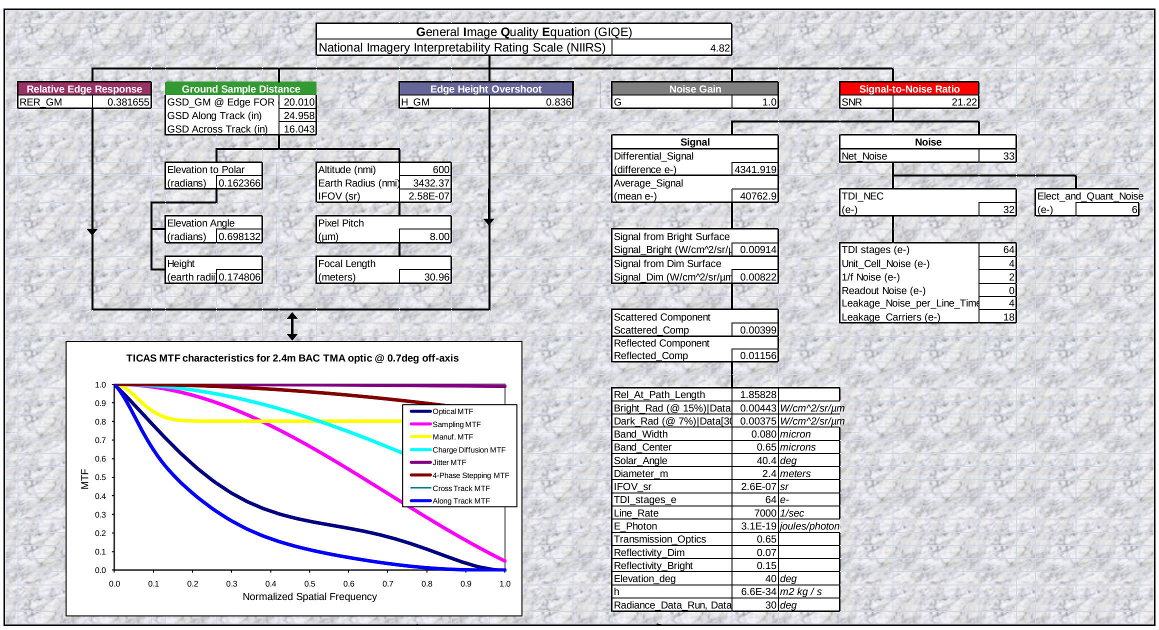

Figure 61: TICAS optical subsystem image quality mathematical model.

The Tornado and Spider plots in Figure 62 indicate that the most sensitive design variables to changes in the NIIRS attributes are focal length, pixel pitch, relative edge response, elevation angle, altitude, and edge height overshoot. It is apparent to the spacecraft designer that focal length and pixel pitch define instantaneous field of view (IFOV), which in combination with altitude describes the ground sample distance. Therefore the sensitivity model essentially finds that changes in NIIRS will require significant changes to GSD, some change to image quality (as represented by RER and H, quantified by the modulation transfer function), and smaller changes to the variables that constitute the signal-to-noise ratio (the largest being atmospheric path as defined by the elevation angle). Additional information regarding the feasible ranges of the design variables can be included in the analysis to find not just the level of sensitivity (i.e., the slope of the line in the Spider plot), but also the direction of the sensitivity in the feasible range. For instance, NIIRS is sensitive to pixel pitch, but the feasible range represents decreases to NIIRS. Comparatively, NIIRS is sensitive to altitude where the feasible range has the potential to increase the attribute value. This information is useful for the detailed definition of the architecture option in Step 7.

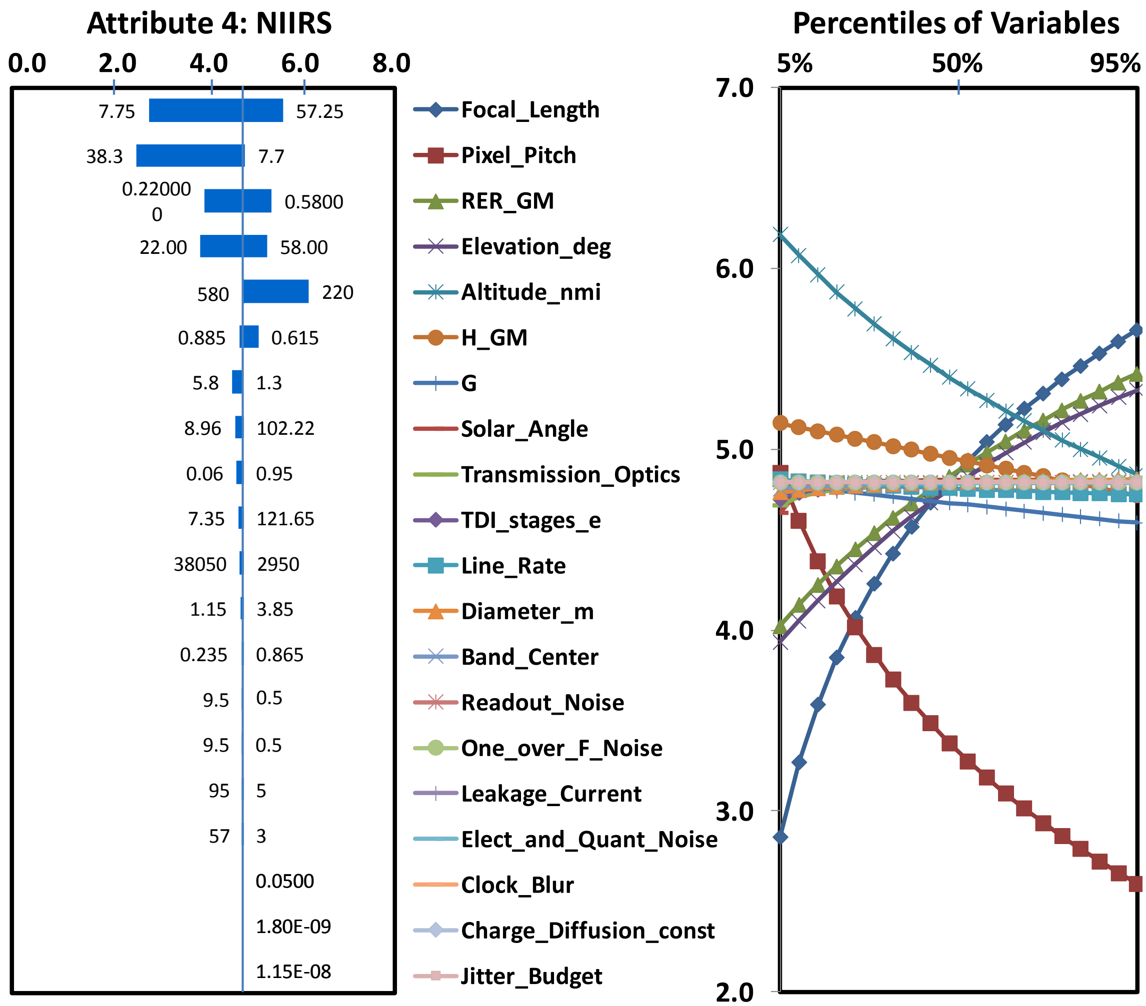

Figure 62: Tornado (left) and Spider (right) plots are used to discover the level of sensitivity between the TICAS design variables and the NIIRS attribute.

The sensitivity information is binned using a scale of zero to five, five being the most sensitive. Going down the list of design variables, the top two were assigned the most sensitive value of 5, while those at the bottom of the list are assigned to bin of value 1. The sensitivity value is propagated through the DSM three tiers/levels (i.e., not necessarily through transitive closure) and the judgment was made to use the highest value if a design variable is affected by multiple relationships simultaneously. The TICAS sensitivity-DSM is populated with the resulting values, with the subset of affected elements displayed in Figure 63.

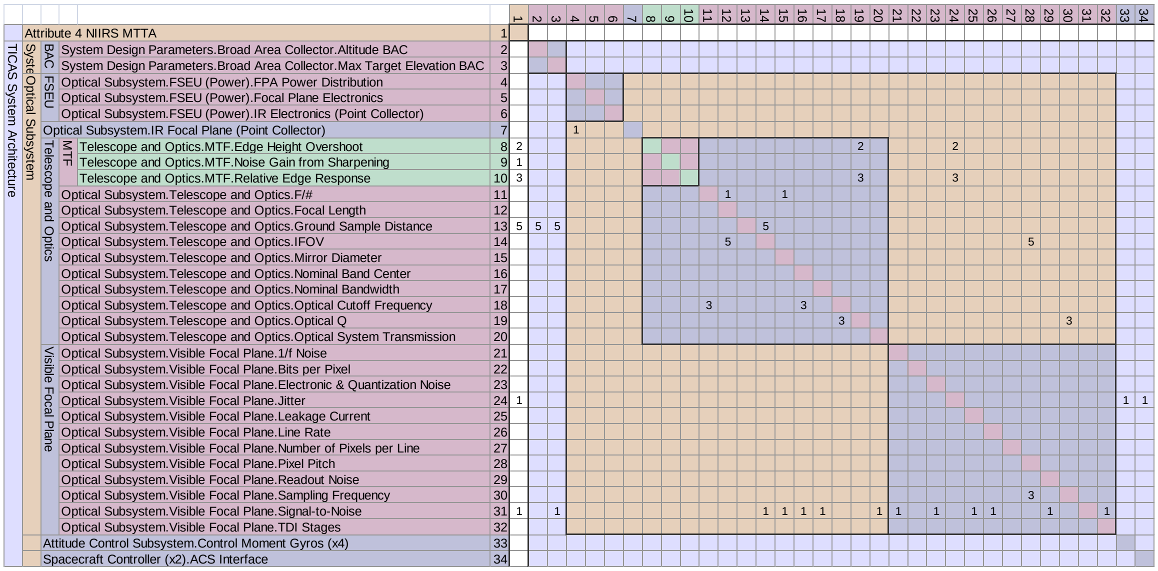

Figure 63: TICAS sensitivity-DSM for NIIRS Attribute 4.

6.3.2.5 Step 5

The TICAS s-DSM is clustered using an algorithm that seeks to minimize the model description length. All parent subsystems and organizational hierarchy are dissolved to allow reordering of the design variables. A comprehensive search strategy would generate all possible architectures and exhaustively evaluate each one to determine the best. This search strategy is only possible for small matrix sizes as the numbers of possible architectures increase as (2^n-1), where n is the number of elements in the matrix. Even with modern computing capability, exhaustive search is many times prohibitively expensive. Therefore a genetic algorithm (GA) search strategy is employed using *(λ+μ)* selection, uniform crossover, and mutation.

The GA search is initiated with λ=100 as the initial population of chromosomes. Uniform probability of crossover (p_c=0.5) is used to randomly switch parent genes until μ=10,000 offspring chromosomes are produced. *(λ+μ)* selection chooses λ best chromosomes, as determined by the MDL fitness function, and passes them to the next generation until the process is terminated at a predetermined 200 iterations. Weighting factors α and β are embedded in the search strategy to mimic the behavior of manual clustering. Yu, Yassine, and Goldberg (2007) found in their study of a 10MWe gas turbine that $\alpha : \beta$ set to 35:190, most accurately reflected the user's preference for including versus excluding elements in a DSM cluster. The corresponding weighting values of $\alpha \approx 0.1037$ and $\beta \approx 0.5630$ have been adopted for TICAS s-DSM clustering, but recommend a case-specific application of α and β values based on user preference. The resulting clustered s-DSM displayed in Figure 64, contains 3 clusters (labeled Candidate AO3.1, AO3.2, and AO3.3) and 1 sensitivity bus (AO3.4). These clusters represent groups of design variables that are responsive to a change in Attribute 4; a change to Attribute 4 is instigated by Scenario 3. Therefore, the four clusters represent four candidate AOs for Scenario 3, which are subsequently assessed to determine if a detailed definition (Step 7) is warranted for each.

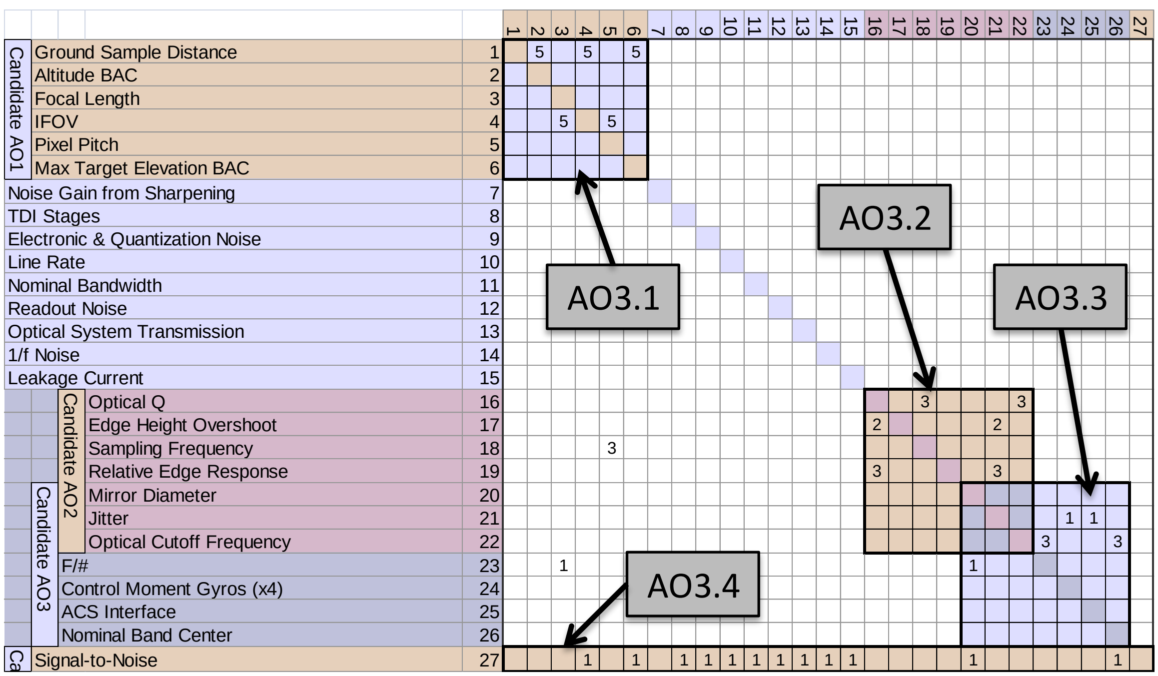

Figure 64: Clustered s-DSM showing three clusters and one bus.

6.3.2.6 Step 6

The "Hoodoo" plot shown in Figure 65 is constructed from the TICAS sensitivity matrix and the likelihood and conditional impact scores of the instigating scenarios (See Section 3.2.6

for process description). The clustered design variables sensitive to changes in the TICAS NIIRS Attribute 4 were generated from a scenario that was scored as promising ($LO(s_3)$ = 20), and are therefore displayed in purple. The confluence of high sensitivity and high impact reveals groups of design variables, or otherwise regions in the design space, where architecture options for TICAS should be studied and defined in greater detail.

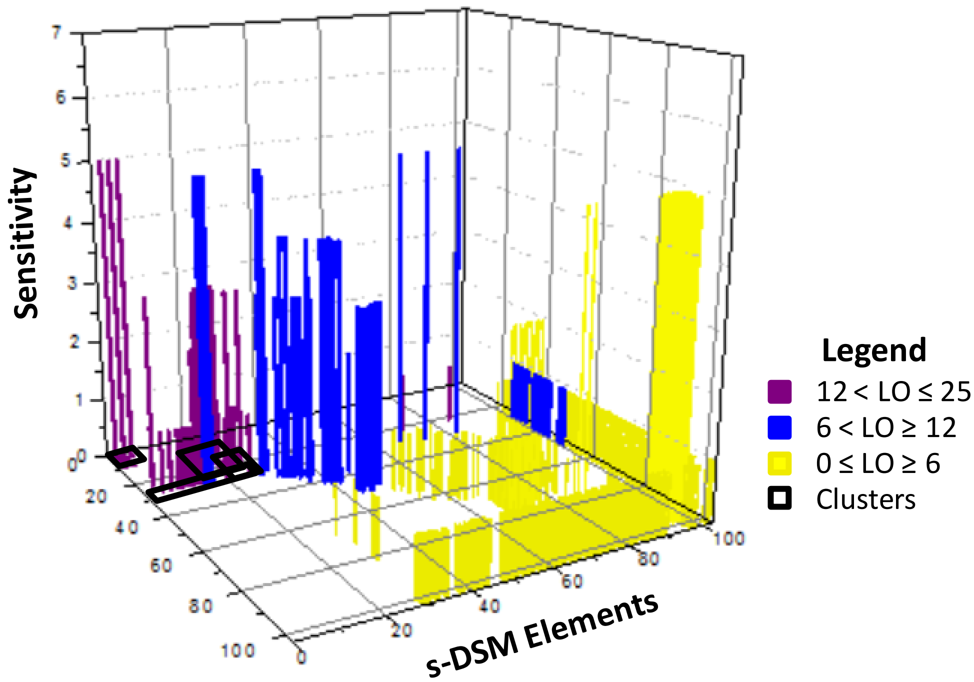

Figure 65: Hoodoo plot of TICAS sensitivity-DSM with clusters shown for Scenario 3/Attribute 4.

6.3.2.7 Step 7

As discovered with the Tornado plot and design variable clustering, there can be more than one way to approach the requirements of a particular operational scenario. In fact there may be many creative or innovative design solutions that address the underlying operational uncertainty. For this reason, a constraint must be set on the time, energy, and resources expended to define potentially numerous architecture options. For the TICAS analysis, at least one candidate AO is identified for each underlying scenario. The range of options is discussed in relation to Scenario 3/Attribute 4, while a summary is presented for the other candidate AOs.

Scenario 3 requires more frequent access to high NIIRS imagery. As this requirement is propagated through the system design via Attribute 4, it is clear that two approaches exist: 1) add PC satellites to the constellation, or 2) increase NIIRS capability of the BAC satellites and use as point collectors. The first approach is infeasible due to high cost and production lag time, and was therefore excluded as an architecture option. The second approach is described with the NIIRS attribute for the BAC satellite. Four clusters were identified (Figure 64) in the s-DSM which essentially represent four different architecture approaches to increasing the BAC NIIRS capability:

1. AO3.1: Reduce GSD by altering flight operations and observational geometry
2. AO3.2: Increase image quality by changing modulation transfer function and sampling characteristics
3. AO3.3: Tighten control on spacecraft attitude and line-of-sight (LOS) pointing to reduce jitter and blur
4. AO3.4: Increase signal-to-noise ratio

Reducing GSD for AO3.1 requires a change to either orbit altitude or IFOV[22]. IFOV is a function of telescope focal length and pixel pitch, which are two parameters that are not readily changeable in the field. Effective pixel pitch can only be increased using pixel aggregation; smaller pixel pitch, as is needed to reduce GSD, would require an alternative focal plane array at the back end of a more complex beam splitter optical design. A graphic showing the TICAS optical subsystem is included in Appendix I. Effective focal length can also be marginally adjusted with a more complex optical design or with the use of a focus mechanism, but not

[22] The IFOV is the range of incident angles seen by a single detecting element in the focal plane.

realistically in a way that significantly reduces GSD during operation. Reducing the range to the target is a more effective way to reduce GSD on orbit (see Figure 66).

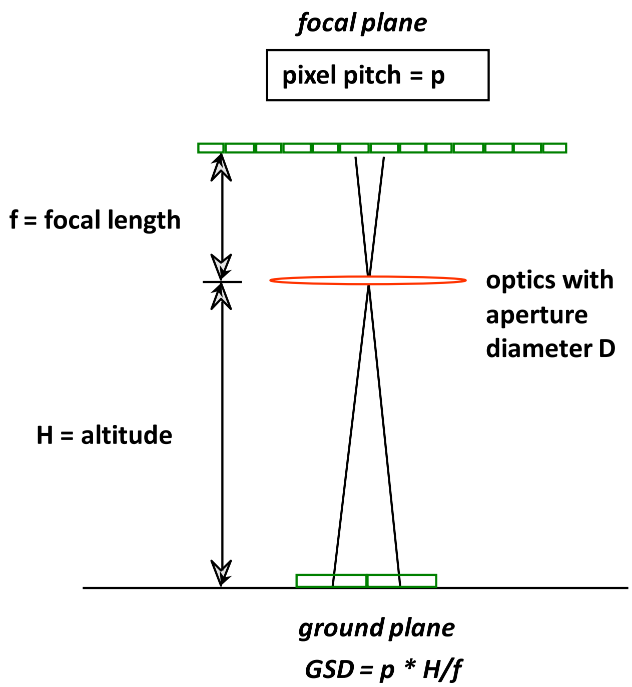

Figure 66: Nadir ground sample distance.

Increasing image quality by changing the system modulation transfer function is the mechanism of AO3.2. Objects in the image scene are filtered by the MTF; the MTF essentially describes how the system blurs the image. Factors contributing to the MTF are mirror diameter, optical aberrations, manufacturing defects, sensor effects like sampling, charge diffusion, 4-phase clocking, and pixel crosstalk. MTF contributions from successive uncorrelated factors can be treated multiplicatively (e.g. Optical MTF * Sensor MTF), while phase correlated terms like successive optics must be handled as a system. These factors are shown in Figure 67. MTF characteristics are usually firmly defined before launch and cannot be significantly altered in the field. Recent developments in piezoelectric actuators have shown promising capability for on-orbit mirror aberration correction, but this expensive technology is usually reserved for large segmented reflectors and was not available during the TICAS development.

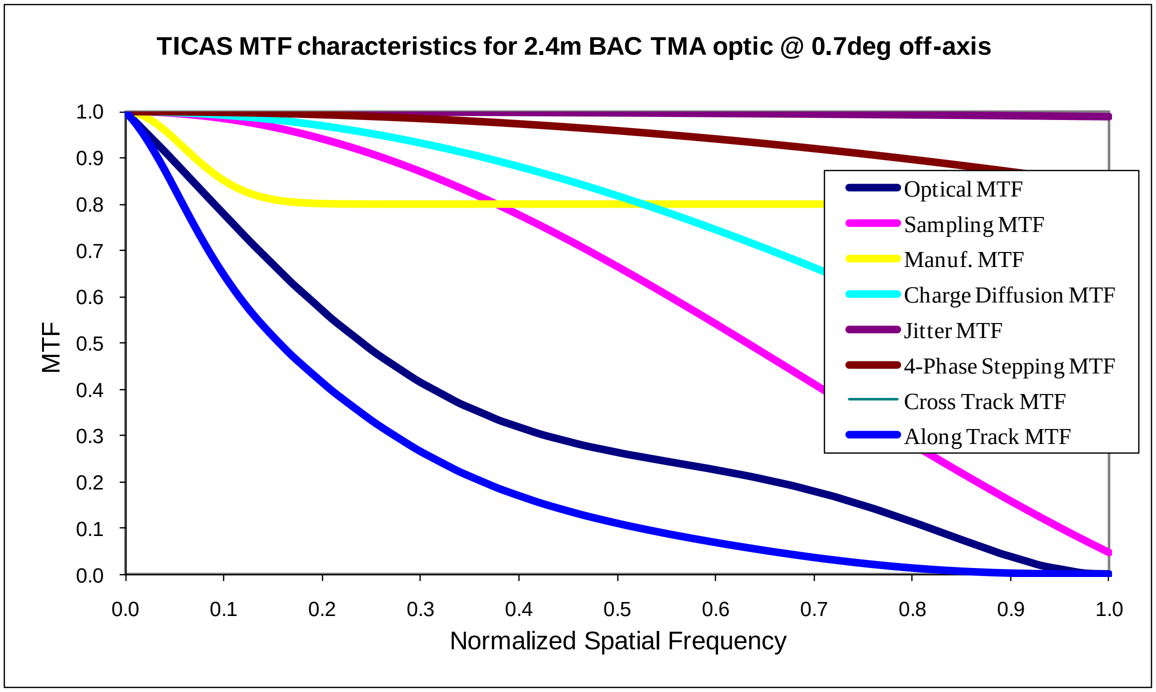

Figure 67: Modulation transfer function components for TICAS three-mirror anastigmat design.

The contribution to system MTF that *can* be controlled on-orbit is related to jitter. AO3.3 captures the major design variables related to spacecraft stability, including control moment gyros (CMGs), attitude control system (ACS) interface, and F/# [23]. Despite having distinctly different operational requirements in terms of coverage and collection approach, the attitude control subsystems for the BAC and PC spacecraft are identical (Figure 68) and are both capable of broad area and point collection modes. This fact indicates that there is not an appreciable NIIRS gain related to changing the TICAS ACS design variables as they were designed and selected in order to meet the jitter requirements derived from both optical system configurations. The TICAS estimated jitter performance has RSS total of 37 *nrad/axis* at 3σ, against the design requirement of 67 *nrad/axis at* 3σ.

[23] The F/# describes the ratio of focal length to mirror diameter. Fast optics, with small F/#, are compact and more agile. Slower optics, with large F/#, typically hang farther out from the pointing control mechanisms and require more time to slew and settle.

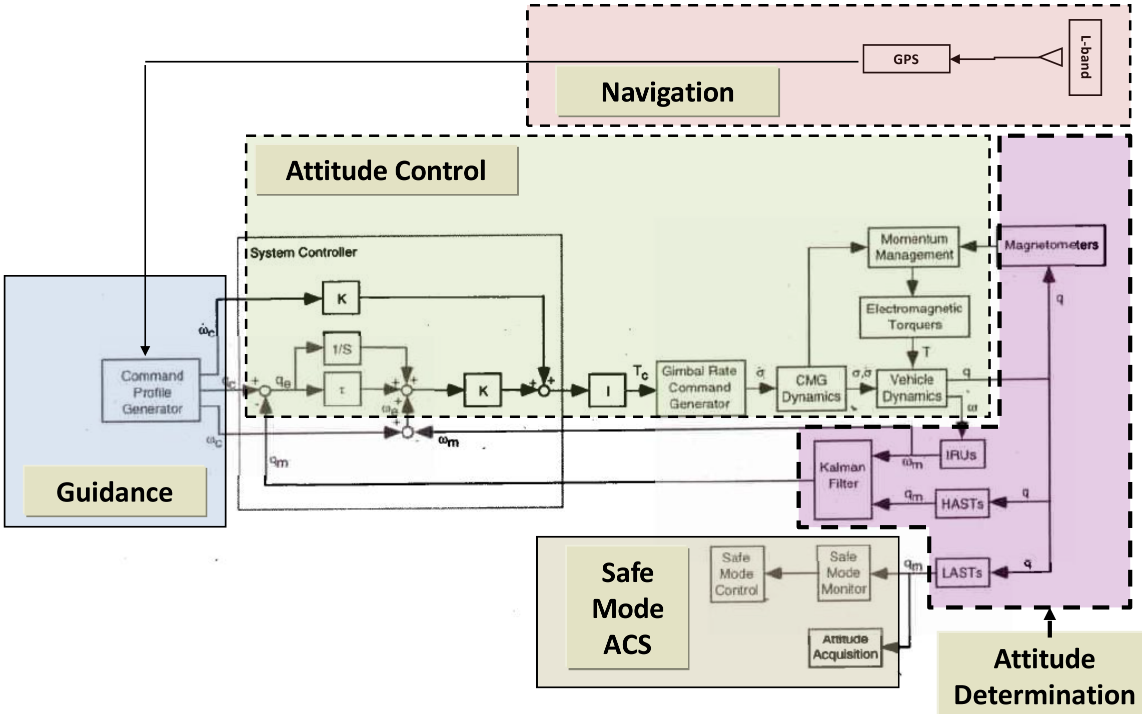

Figure 68: TICAS attitude control subsystem is designed to meet both the broad area and point collection stability and control requirements.

AO3.4 captures the NIIRS dependency on the signal-to-noise ratio, which is mainly a function of atmospheric path (i.e. elevation angle), illumination (i.e. solar angle), and detector noise parameters. The best NIIRS occurs at nadir with an elevation angle of 90 degrees. Illumination is not a design parameter per se because it is defined by the solar angle kept constant by the sun-synchronous orbit[24]. Additionally, after a minimum threshold of SNR is reached, there is very little NIIRS gain associated with improving the signal relative to the noise. In the TICAS optical system model, even infinite SNR would increase NIIRS from 4.82 to 4.86. For this reason, AO3.4 is not an extremely effective architecture option.

After analyzing the design variables that are sensitive to the NIIRS attribute, AO3.1 was selected for detailed definition and valuation. Architecture option AO3.1 is generally defined as

[24] Illumination characteristics: (i) 17.8° average daytime solar elevation at 40° north latitude at Winter solstice; (ii) 28.9° average daytime solar elevation at 40° north latitude at Spring equinox; (iii) 40.4° average daytime solar elevation at 40° north latitude at Summer solstice.

an orbit maneuver that lowers the BAC operational altitude, reducing the nadir ground sample from 11.3 in. to 3.0 in., and increasing NIIRS from approximately 5.64 to 7.54 at nadir. A comparison of the GSD before and after the orbit maneuver is depicted in Figure 69.

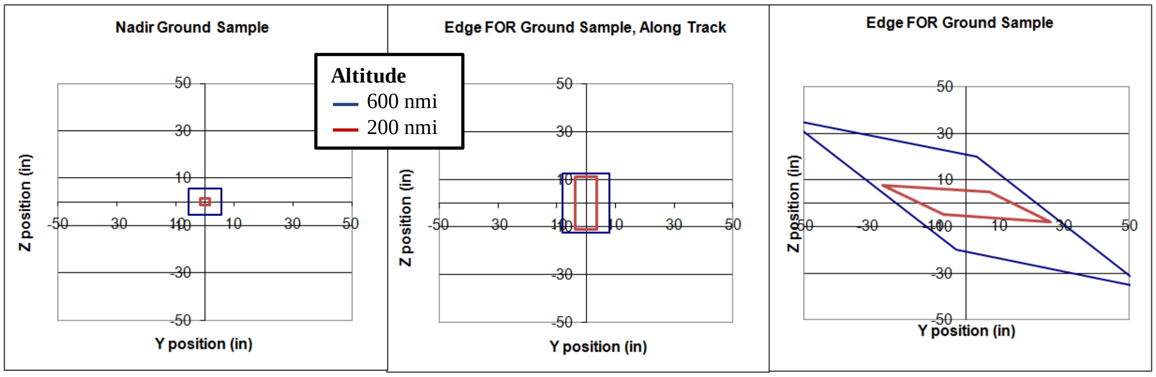

Figure 69: Ground sample at nadir and edge of field of regard for BAC and PC altitudes.

The BAC architecture must be modified in several ways to accommodate this operational capability. Most pressingly, the spacecraft must have the fuel available for the altitude change and orbit maintenance at the lower altitude, characterized as ΔV. The baseline BAC propulsion subsystem was designed to raise the orbit from the 200 nmi insertion altitude to the operational altitude of 600 nmi. AO3.1 would select the larger Delta II 7920 launch vehicle to insert the BAC satellite directly into the 600 nmi orbit. The comparable fuel saved from orbit raising would be used to lower the orbit if and when AO3.1 is exercised. Additional fuel is also required to overcome orbital decay at the lower altitude due to atmospheric drag[25]. Outlined in Table 17, an additional 776 lbs of fuel (940 - 164 lbs) is required to accomplish AO3.1; this does not require a change in the propulsion system design except in regards to the size of the tankage. Other design implications are as follows:

[25] ΔV required for orbital maintenance is estimated at the maximum value of 4,677 ft/s, which assumes that the AO3.1 is exercised at the beginning of a five year operational life.

- Variable FPA clocking, from 22,300 Hz to 11,150 Hz, to match the FPA line rate to the apparent ground speed.
- Incorporate the gimbaled antenna for wideband communication utilized in the PC design
- FPA Support Electronics Unit (FSEU) must perform A/D conversion at eleven bits/pixel and 6 GB/s data stream to the High Speed Data Handling Unit (HSDHU). The new performance requirement is less than the baseline capability of 20 GB/s and therefore does not require a design change.
- The BAC electrical power profile will change in accordance with Appendix J. The baseline BAC electrical power system is designed to generate 3940 W at end-of-life (EOL), whereas the PC is designed for 3500 W (EOL), which includes approximately 230 W to support the PC infrared (IR) detector and cryocoolers which are not included in the BAC. Therefore the EPS capability of the baseline BAC spacecraft is sufficient to accommodate point collection imaging power requirements with no significant design change.

Table 17: TICAS ΔV and propellant estimates.

	Baseline Architecture		Architecture Option
Parameter	**PC**	**BAC**	**BAC AO3.1**
Launch Vehicle Selection	LMLV3-8	LMLV3-8	Delta II 7920
Injection Error (± 20 nmi ± 0.06°) (ft/s)	63	63	55
Orbital Adjust & Maintenance (± 1 nmi @ 200 nmi) (ft/s)	4,677	25	4,677
Orbital Boost and Disposal (ft/s)	1279*	1279**	1279 + 1279*
Total ΔV w/10% Margin (ft/s)	6,621	1,504	8,019
Total Fuel Requirement (lb)	776	164	940

*Boost to 600nmi disposal orbit

**Boost to 600nmi operational orbit

The screening process is completed for each instigating scenario and related system attributes. Candidate architecture options are defined with the summary included in Table 18.

Table 18: Summary table of TICAS architecture options.

Scenario 1: Conflict in Space
AO1.1: Incorporate optical power limiting filter to protect sensor from high intensity laser attack.
AO1.2: Select electronics that are additionally radiation hardened for prompt dose and total dose radiation.
Scenario 2: Availability of Advanced Communication Relay
AO2.1: Include X/Ka-band gimbaled antenna with required amplifier and electronics capable of data rates between 1.2 and 3.6 Gbit/s. EPS to have power margin to transition to bandwidth-limited imaging.
Scenario 3: Desire for More Frequent Point Collection
AO3.1: Conduct orbit maneuver to lower the BAC operational altitude from 600 nmi to 200 nmi.
Scenario 4: Need for Direct Downlink for In-Theater Operations
AO4.1: Complete development of Space-Common Data Link (SCDL) and ground segment priority tasking operational mode. Design BAC for SCDL downlink and in-theater command uplink.
Scenario 5: Need for Increased Broad Area Search
AO5.1: Raise PC spacecraft to 600 nmi "disposal orbit" early to increase field-of-regard for broad area search.
AO5.2: Use pixel aggregation on PC to contribute to broad area search at 200 nmi.
Scenario 6: Desire for Realtime Anomaly Resolution
AO6.1: Develop and maintain anomaly resolution and simulation laboratory with engineering development units and flight software. Collect additional onboard health and status data and incorporate related tunable "switches" into design.

6.3.2.8 Step 8

The final step in the AO screening process consists of inserting all detailed candidate AOs back into the DSM of the baseline system architecture. The purpose is to discover the extent to which AOs have overlapping physical characteristics and to trace the physical design of the AO back to the top level instigating scenario. For the TICAS analysis, it is assumed that all candidate AOs are physically independent and that traceability to the instigating scenario is directly defined. These assumptions make Step 8 unnecessary for this analysis. Correlation coefficients for the candidate architecture options will be generated from the simulation in Stage Two.

6.3.3 Flexibility Framework Stage Two: Valuation of TICAS AOs

This section applies the proposed Variable-Expiration (VE) option valuation technique to the architecture options identified for the TICAS architecture. Value and cost information has been compiled from archived TICAS reports and cost spreadsheets in order to conduct AO valuation. Historical references and engineering judgment has been used to estimate the interest rate, inflation rate, and lifetime probabilities for the underlying mission scenarios. Understanding the imprecise nature of forecasting and our limited capacity to uncover every design implication of an architecture option, this analysis does not rely on absolute precision, but on consistency. An idea widely embraced in the field of life cycle cost (LCC) modeling is that a good LCC model is not always one that yields a final value closest to reality, but instead one that allows the system architect to make informed and consistent trade-offs between design variables; essentially, the absolute value is not as important as the change in value between design decisions. With this in mind, the variables needed for AO valuation have been derived from all available data and treated consistently in the model. Detailed estimates for the value forecasts and cost models will be described for architecture option AO3.1, as with the previous section, with a summary included for all other AOs.

6.3.3.1 Scenario Likelihood

Based on the volatile geopolitical environment in the Middle East and the perceived growing threat of clandestine foreign nuclear programs, the likelihood of Scenario 3 was scored as "highly likely (4)" which translates to a lifetime probability of between 60% and 80%. This valuation will use 60% for the random variable T_v, distributed equally within the TICAS five-year design life.

6.3.3.2 Value Stream Forecast

The value stream (S) is probably the most difficult quantity to forecast precisely for military and scientific projects. Whereas commercial applications can rely on revenue and cost data to substantiate operating profit forecasts, military projects must rely on stakeholder communication and national directives to justify value assumptions. In the case of TICAS, key performance parameters (KPPs) have been established by the Intelligence Community, as illustrated in Figure 58, which communicate threshold and objective-level requirements for national reconnaissance systems. This establishes a bound on the value function, where limited value is derived below the threshold requirement, and maximum value is derived at or around the objective level. The change in performance for the TICAS constellation as a result of AO3.1 can be calculated as the change in mean time to access (MTTA), which is also called "Revisit Time." MTTA, measured in hours, is a function of geographic latitude as shown in Figure 70. Therefore, the MTTA KPP is specified at 40° North latitude, which broadly defines the geolocation of the Middle East.

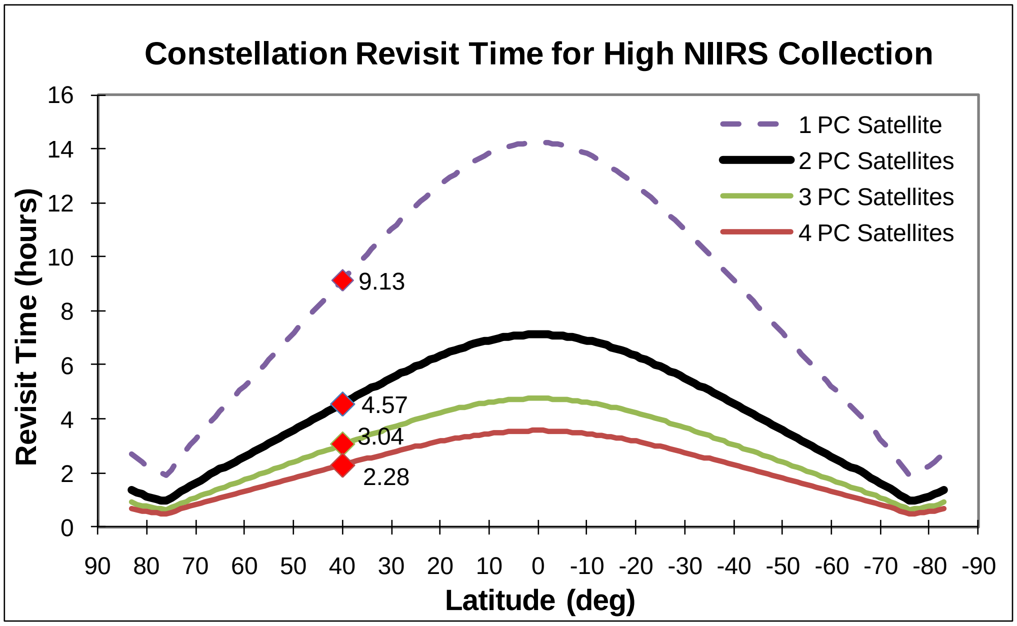

Figure 70: TICAS constellation revisit time for high NIIRS (5.23 @ edge of FOR and 7.54 @ nadir). Dashed line represents one PC satellite failure with performance below baseline architecture.

The performance characteristics are mapped to the stakeholder value function shown in Figure 71. Uncertainty in the stakeholder value derived is estimated with a 20% uncertainty factor applied across the entire performance range (dashed lines). The additional value derived from AO3.1 (ΔValue) is the difference between the value derived from the baseline architecture and that derived from the augmented architecture given the exercise of the AO.

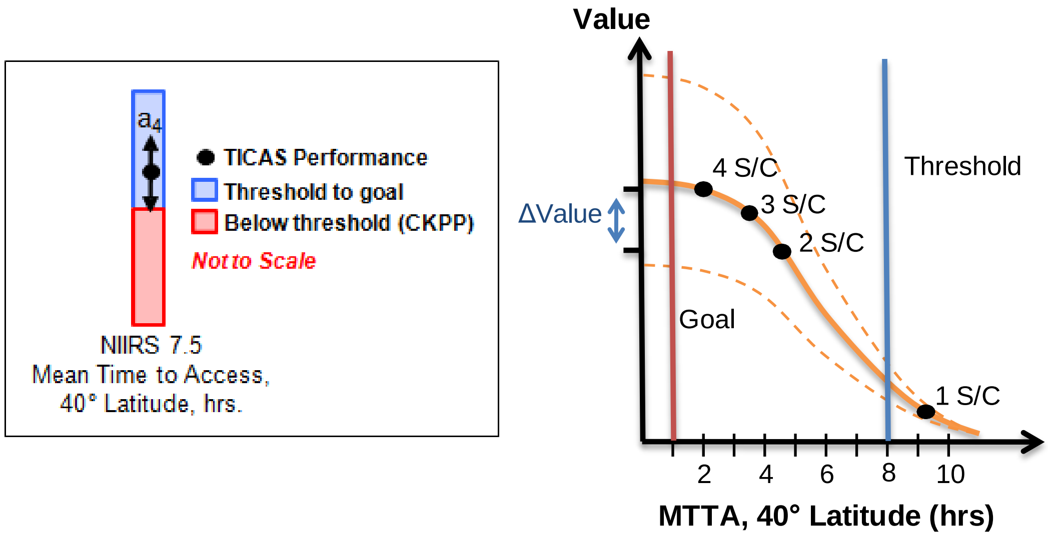

Figure 71: TICAS MTTA system attribute extracted from Community-KPPs (Left), combined with the MTTA performance model, is used to create stakeholder value function (right).

A triangular distribution is created to represent the uncertainty in the value function for each year within the design life using a most likely value of $70M and a 20% lower and upper bound (Figure 72).

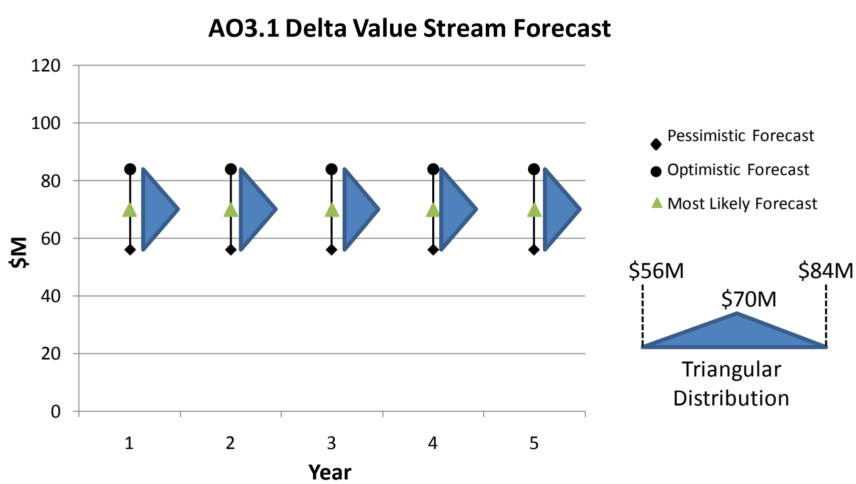

Figure 72: Triangular distributions are used to represent the uncertainty in the value derived from AO3.1.

6.3.3.3 Exercise Cost

The exercise cost, X, is the one time irreversible expenditure that is required to exercise AO3.1; this expenditure of time and resources occurs during operation at the option viability date. There are presumably some small costs required to transition the spacecraft from broad area search collection to point collection. These activities may include additional staffing, analysis, training, software transition costs, etc. However, these are minimal due to the fact that Point Collectors will already exist in operation and protocols will have been established to manage this type of reconnaissance capability. The significant exercise cost is associated with the down-time of the spacecraft. The BAC xenon-ion propulsion system is used to lower the orbit to 200 nmi in a series of nearly continuous burns. Two burns are performed each orbit for 43 minutes each, meaning that 86% of each orbital period is used for orbit lowering. These autonomous maneuvers require a total of 173 days to reach the new orbit. Image collection cannot occur during orbit transfer and therefore the cost to exercise AO3.1 is 173 days of 86% inactivity. This quantity is monetized as the prorated fraction of the total life cycle cost of the TICAS constellation. The NRO conducted an Independent Cost Estimate (ICE) for the TICAS constellation which resulted in the LCC estimate shown with the cumulative distribution function in Figure 73. If both BAC satellites are transitioned to high NIIRS point collection, 1/2 of the constellation will be inactive for 8.15% (0.86*173days / 5yrs*365days) of the design life. Using the appropriate portion of the total LCC, the exercise cost is represented with the lognormal distribution with mean $179M and standard deviation $157M (Figure 74).

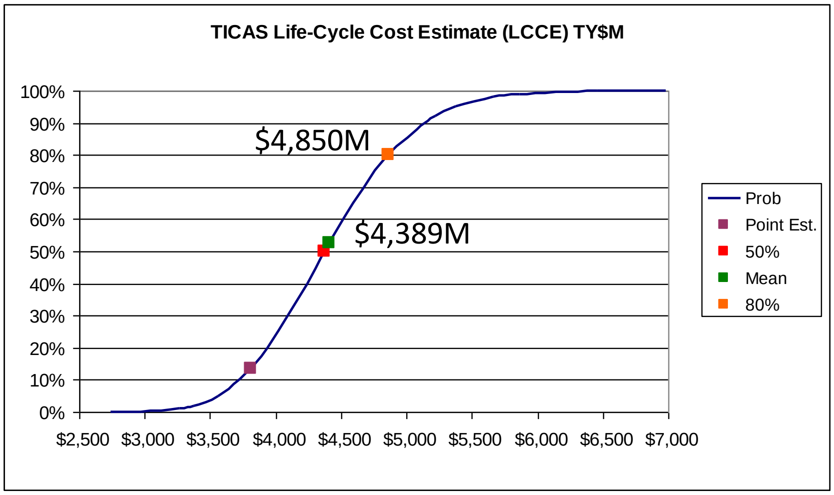

Figure 73: Cumulative distribution function from NRO independent LCC estimate of TICAS.

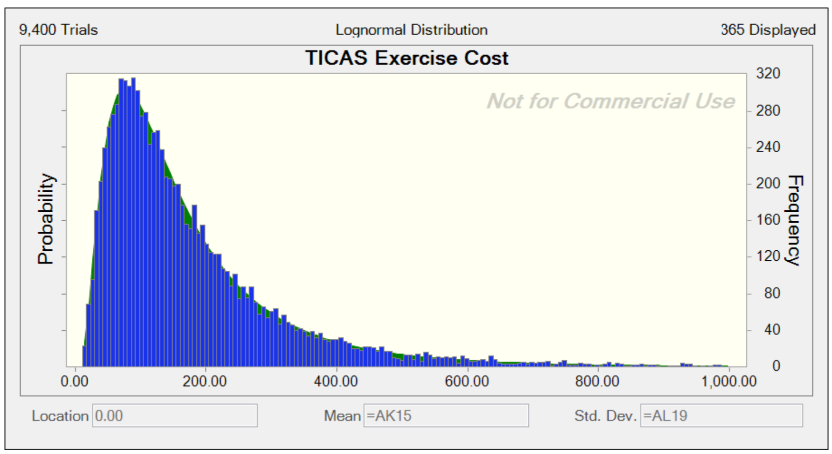

Figure 74: AO3.1 exercise cost approximated by lognormal distribution derived from TICAS LCC.

An alternative way to approximate the exercise cost associated with the TICAS orbit transfer down-time is to estimate the price of the corresponding imagery if it were instead purchased from a commercial satellite imagery provider. In late 2001, Space Imaging announced its new pricing for IKONOS satellite imagery products[26]. For newly tasked 1m (39 inches)

[26] The Space Imaging company launched the world's first one-meter resolution, commercial Earth imaging satellite, IKONOS, on Sept. 24, 1999. Pricing in 2001 can be found at: http://www.spaceref.com/news/viewpr.html?pid=6911

resolution panchromatic imagery, the stated price from Space Imaging was $25/sq. km. For 4m multi-spectral imagery, the price was $18/sq. km. The aggregate area collection capability of the two BAC satellites is 40,000 nmi^2 per day. Therefore, 86% of 173 days of inactivity results in a missed opportunity to collect an equivalent 20,412,045 sq. km. For an equal proportion of panchromatic and multi-spectral collection, the IKONOS market price in 2001 would have been approximately $438,858,968 before any government discount. This estimate is at the medium high range of the LCC-based estimate (+1.66σ), which likely reflects the difference between the cost of a system and the price required to make a profit. This analysis has selected the LCC-based approach because it includes uncertainty information as opposed to a market based point estimate.

6.3.3.4 Discount Rates and Inflation

Two discount rates are used in this analysis. The exercise cost is discounted to the decision date using the 10-yr U.S. Treasury note, averaged across the TICAS operational life from 2001 to 2006. This rate of 4.44%[27] represents the average rate at which the government borrowed money during the stated timeframe. The value stream is discounted at a higher market risk rate. Government investments, such as a national reconnaissance system, do not have a stated "required rate of return" on that investment; a direct analogy to a private sector investment does not readily exist. However, if the assumption is made that the open and competitive bidding process yields a system that delivers value on par with the average profit expectations of the contractor, contractor data can reasonably be used as a government sector proxy. The return on equity (ROE)[28] averaged across the Aerospace & Defense Sector is 18.00%, while the average ROE for the Communication Services Sector (which includes commercial satellite imagery

[27] http://www.federalreserve.gov/releases/h15/data.htm

[28] Return on Equity demonstrates how well a company uses investment funds to generate earnings growth.

providers like DigitalGlobe and GeoEye) is 11.86%. The less restrictive value of 11.86% has been chosen for this analysis, understanding that the stakeholders of a government program (i.e., taxpayers) do not keep the government as accountable as would company shareholders. An inflation rate of 2.55% is used in the analysis which is the average annual inflation rate between 2001 and 2005[29].

6.3.3.5 Variable Expiration Architecture Option Valuation

The inputs required to conduct Variable-Expiration option valuation for AO3.1 are pictorially represented in Figure 75. The architecture option valuation is completed using 100,000 Monte Carlo trials, resulting in a mean option value of approximately $27M and standard deviation of $52M. The stochastic results of the simulation are included in Figure 76. Analytical plots that describe the sensitivity of the option value to changes to the input parameters as well as option value change over time have been generated and are presented in Figure 77 and Figure 78.

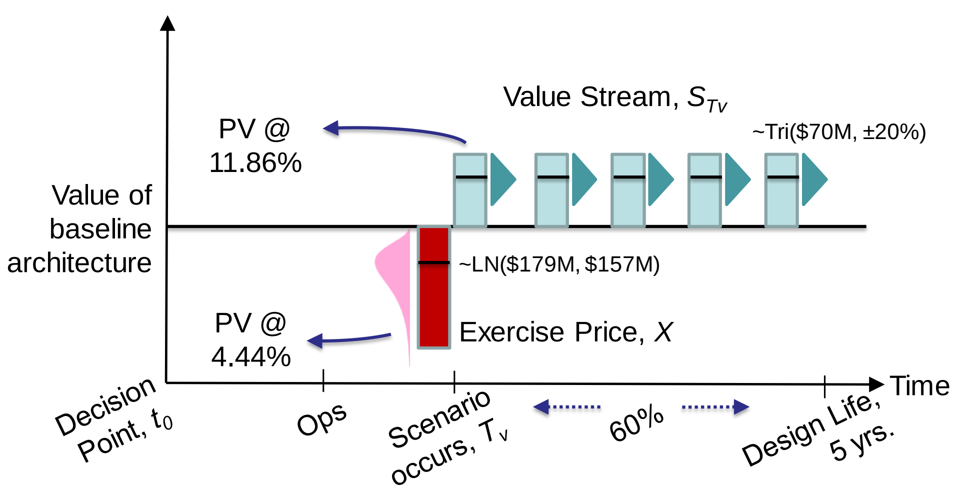

Figure 75: TICAS AO3.1 inputs required for VE-option valuation.

[29] U.S. Bureau of Labor Statistics: ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt

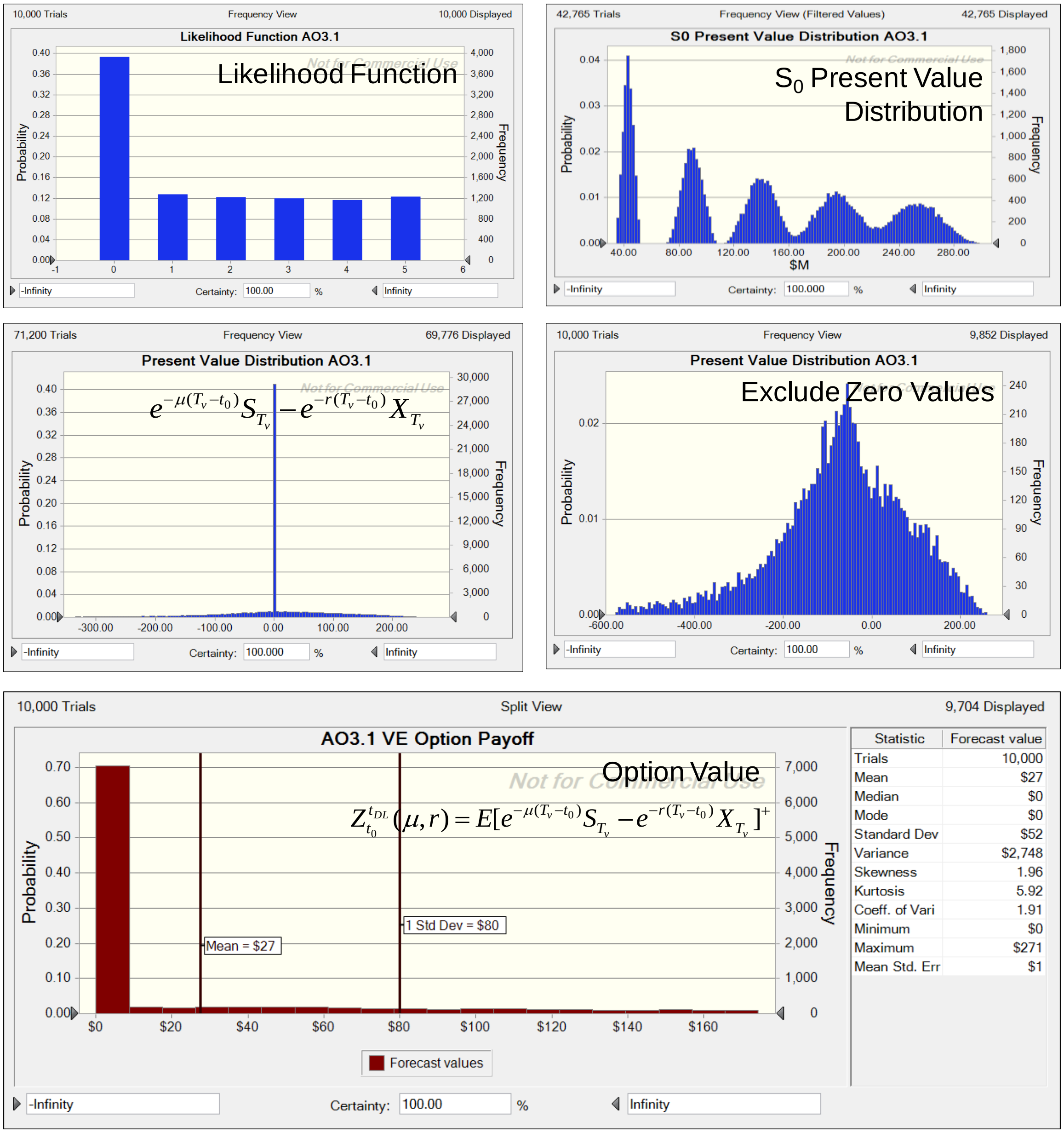

Figure 76: AO3.1 Summary stochastic results.

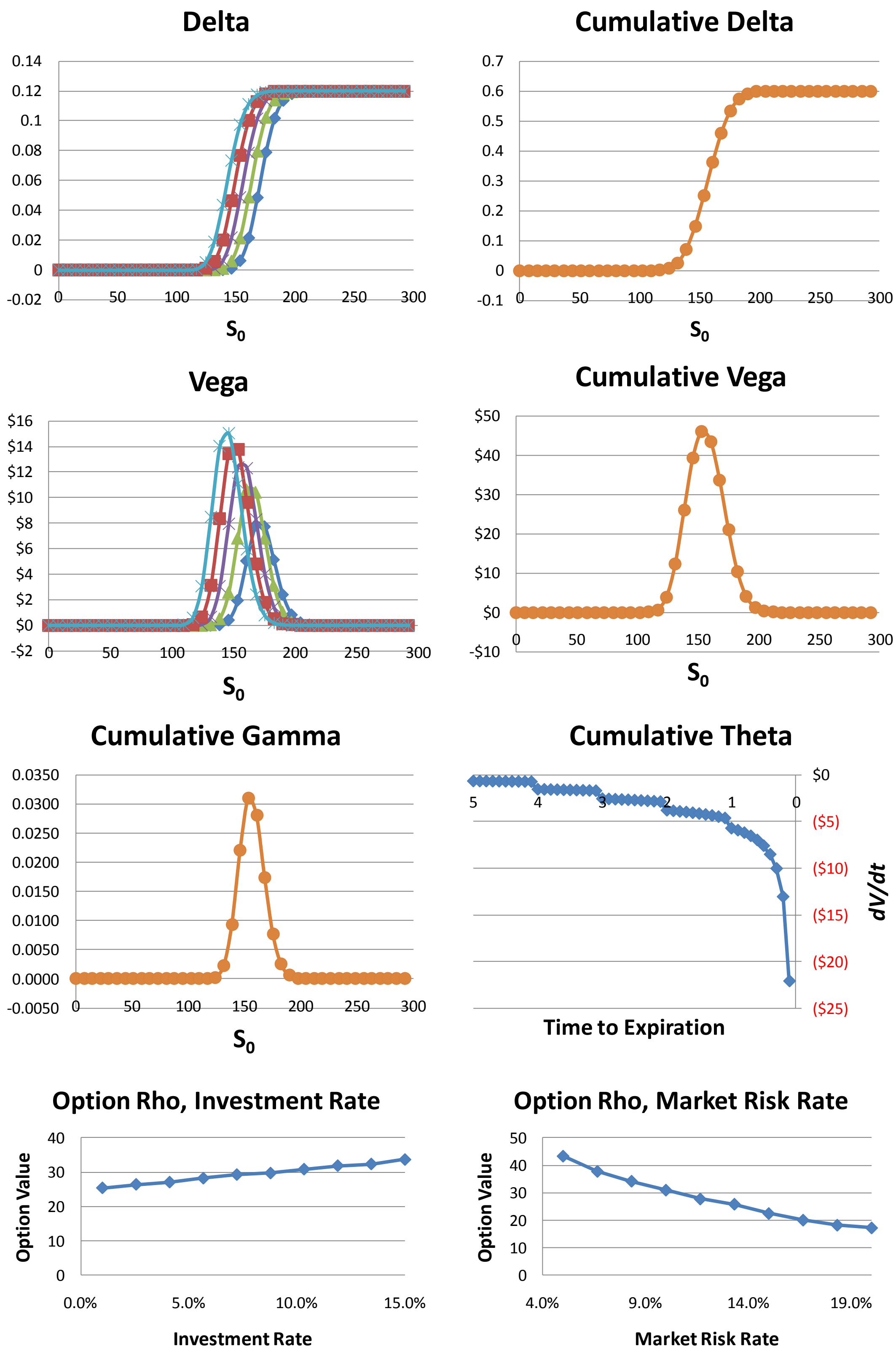

Figure 77: VE option value sensitivities for TICAS AO3.1.

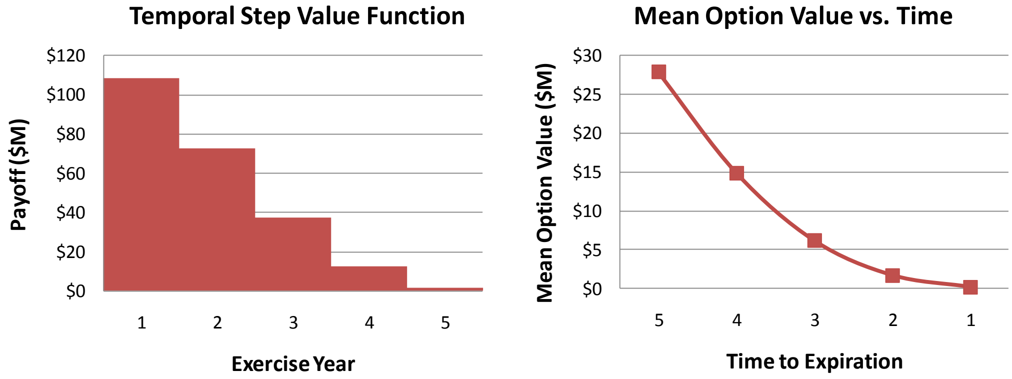

Figure 78: Total option payoff and AO mean value over time.

A similar valuation process has been conducted for the entire set of candidate TICAS architecture options previously identified in Table 18. A summary of the input parameters and AO value results is listed in Table 19. The stacked temporal step value function, Figure 79, is used to compare the set of AOs and develop a general sense of the rank potential of the candidate set.

Table 19: Summary of inputs and results for TICAS candidate AOs.

	Input Parameters						Results	
	Lifetime Probability, T_v	Value Stream, S	Exercise Cost, X	Investment Rate, r	Market Risk Rate, μ	Inflation Rate, r_i	Mean Option Value	Standard Deviation
AO1.1	0.20	~Tri($15M, 80%)	~LN($2M, $12M)	4.44%	11.86%	2.55%	$5.98M	$15.11M
AO1.2		~Tri($25M, 80%)	~LN($1M, $3M)	4.44%	11.86%	2.55%	$10.28M	$24.70M
AO2.1	0.60	~Tri($20M, 50%)	~LN($2M, $1M)	4.44%	11.86%	2.55%	$23.70M	$26.05M
AO3.1	**0.60**	**~Tri($70M, 20%)**	**~LN($179M, $157M)**	**4.44%**	**11.86%**	**2.55%**	**$27.26M**	**$52.43M**
AO4.1	0.50	~Tri($40M, 40%)	~LN($65M, $25M)	4.44%	11.86%	2.55%	$16.85M	$31.04M
AO5.1	0.60	~Tri($55M, 50%)	~LN($179M, $157M)	4.44%	11.86%	2.55%	$24.05M	$60.28M
AO5.2		~Tri($5M, 80%)	~LN($1M, $0.5M)	4.44%	11.86%	2.55%	$5.65M	$6.64M
AO6.1	0.80	~Tri($10M, 80%)	~LN($3M, $3M)	4.44%	11.86%	2.55%	$14.33M	$13.27M

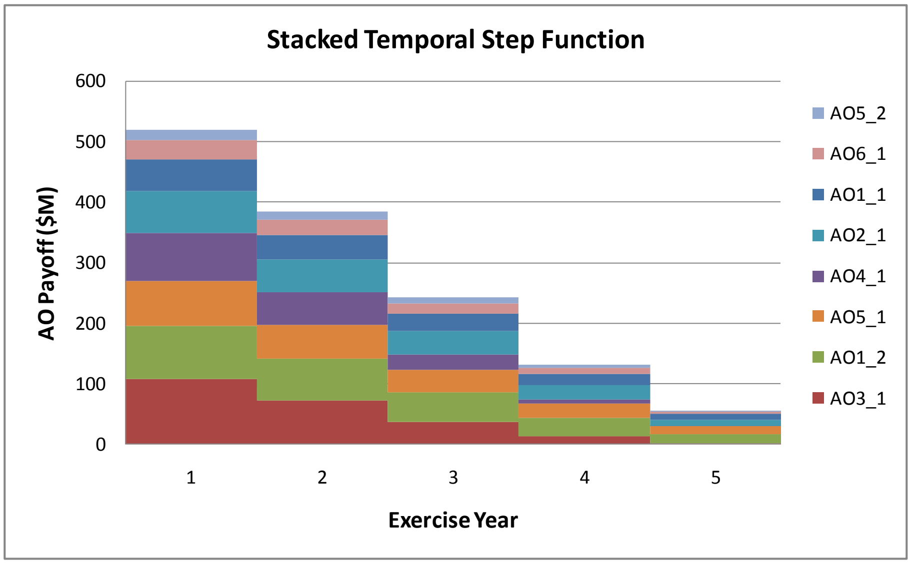

Figure 79: Stacked temporal step value function for TICAS candidate AO set.

6.3.4 Flexibility Framework Stage Three: TICAS AO Portfolio Selection

The mean option value quantified in Stage Two is the expected value of the architecture option--that is, the threshold amount a rational decision maker would spend to obtain the AO. The expected return on the AO investment is the amount gained above and beyond the cost to obtain the option. Therefore, in order to determine the expected return, the implementation cost required to obtain the option must first be estimated. The expected return is then annualized, along with the standard deviation, which yields risk and return data points for each candidate TICAS AO. A portfolio optimization process is conducted to help select the subset of AOs that minimizes risk for the level of return that is within the program budget and stakeholder risk tolerance.

Detailed cost estimations for the TICAS system were conducted during the original architecture study. These estimates were composed of data derived from parametric analysis, analogues to similar satellite projects, and piecewise hardware and software build-ups. A second cost estimating activity was completed by the NRO in an Independent Cost Estimate in order to validate and enhance the original estimate. Data from both sources have been leveraged to estimate the implementation cost for each embedded architecture option. The estimation process is described for AO3.1 and a summary table is provided for the other TICAS candidate AOs.

6.3.4.1 Implementation Cost Estimation

Three cost drivers were identified in relation to implementing TICAS AO3.1: inclusion of a gimbaled crosslink antenna, resized spacecraft propulsion system, and selection of an alternate launch vehicle. FPA variable clocking and decreases to the performance required from the FSEU, HSDHU, and EPS, were not determined to have non-recurring or recurring cost implications. The cost estimate for the required design changes is organized using the standard NRO Work Breakdown Structure (WBS) in Figure 80, and the lower level WBS for the spacecraft bus, Figure 81. The affected portions of the system architecture are highlighted in the WBS.

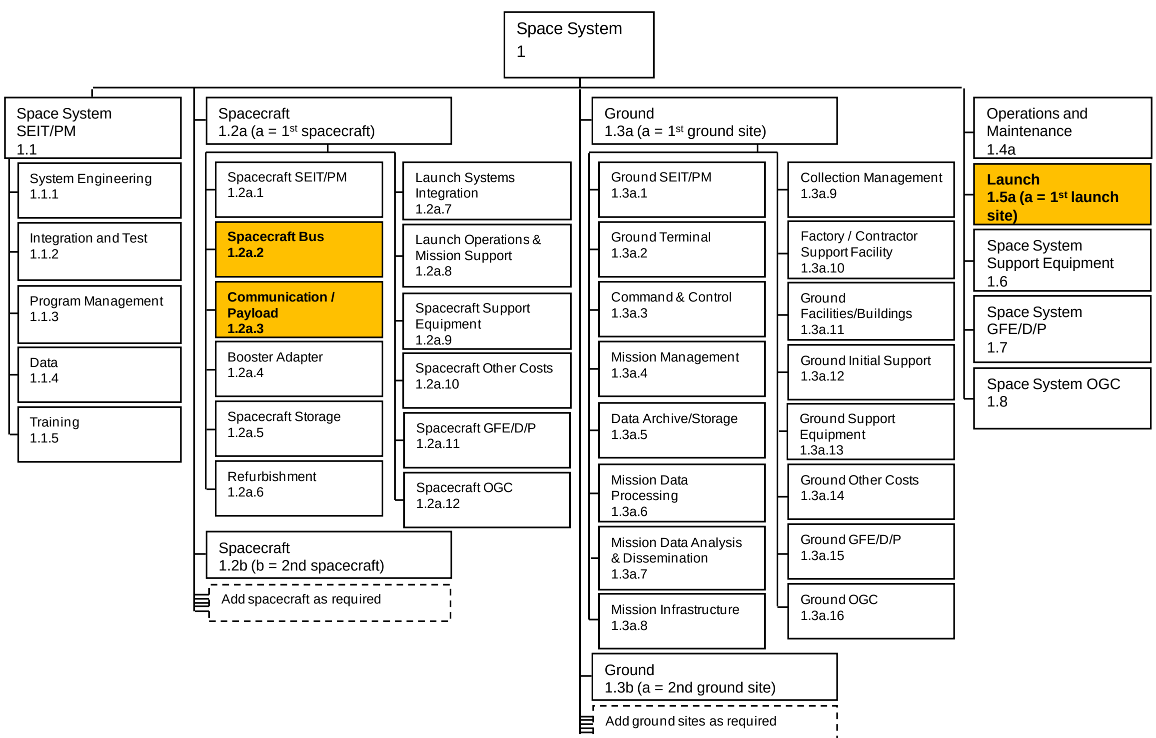

Figure 80: Standard NRO work breakdown structure.

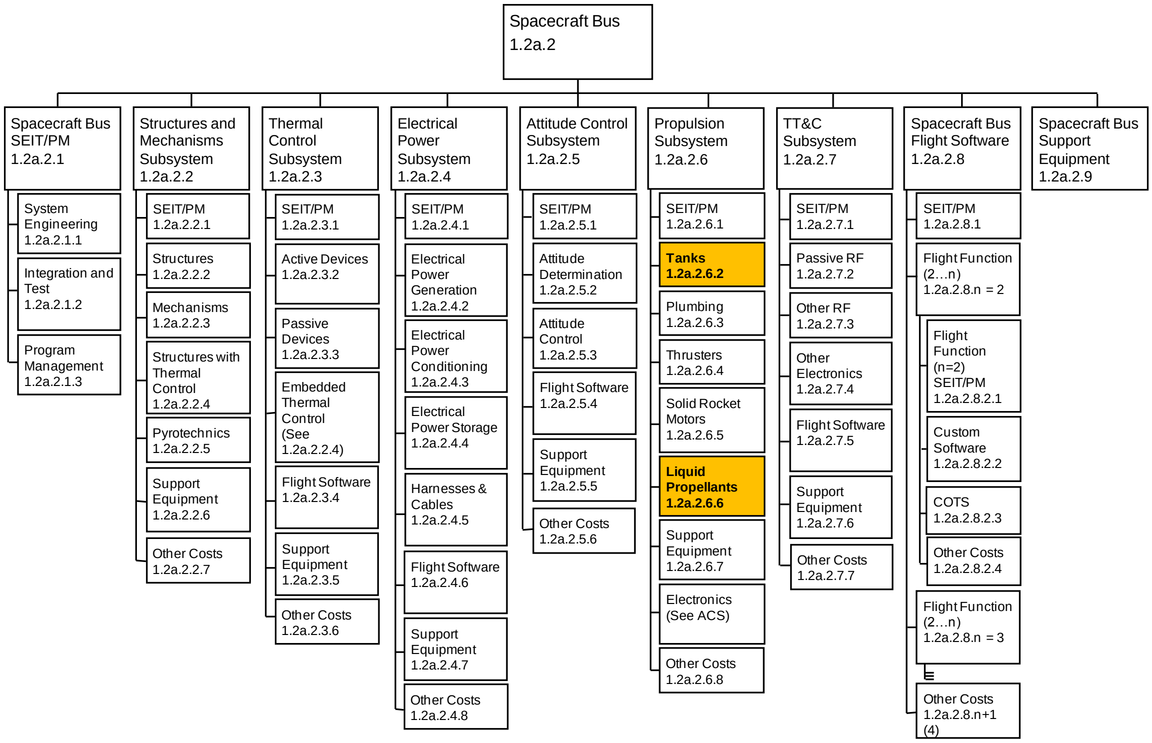

Figure 81: Lower level standard NRO work breakdown structure detailing the spacecraft bus.

A gimbaled crosslink antenna for wideband communication must be included in the BAC design in order to maintain connectivity at the lower altitude. Due to the fact that the PC spacecraft also requires this functionality, there is no non-recurring cost associated with the change, only a relatively minor recurring cost for the azimuth-elevation gimbal drive and gimbal electronics. As shown in Table 20, the existing cost estimate for the communication payload is based on the widely utilized parametric Unmanned Space Vehicle Cost Model, Eighth Edition (USCM 8)[30]. These estimates are based on cost-estimating relationships (CERs), specifically weight and power. The USCM 8 CER for the communication subsystem recurring cost is approximately $63K/lb in FY 2000 dollars. Weighing 23 lbs and using an average 11.3 W of power, the antenna gimbal cost is estimated at **$1.45M**.

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[30] https://www.uscm8.com

Table 20: Summary TICAS non-recurring and recurring cost estimate for first unit PC spacecraft, and associated ground and launch segments.

Element (BY$07)	NR ($M)	Rec ($M)	Total ($M)	Source
Spacecraft	$ 371.7	$ 297.3	$ 669.0	Sum
Spacecraft SEPM	$ 34.2	$ 48.4	$ 82.6	CER from USCM 8
Spacecraft AI&T	$ 46.3	$ 40.0	$ 86.3	CER from USCM 8
Spacecraft Optical Payload	$ 122.3	$ 108.8	$ 231.1	Sum, ROM
Spacecraft Communication Payload	$ 44.1	$ 39.7	$ 83.8	Sum, CER from USCM 8
Spacecraft Bus	$ 70.9	$ 56.7	$ 127.6	Sum, CER from USCM 8
Flight Softward	$ 27.8	$ -	$ 27.8	Analogy from other space programs, Aerospace Corp.
Booster Adaptor	$ 7.0	$ 3.2	$ 10.2	Analogy from NRO IMINT Program
Spacecraft Support Equipment	$ 19.1	$ -	$ 19.1	Analogy from NRO IMINT Program
Spacecraft Transportation & Storage	$ -	$ 0.4	$ 0.4	Analogy from NRO IMINT Program
Spacecraft Propellant	$ -	$ 0.1	$ 0.1	Analogy from NRO IMINT Program
Ground	$ 509.5	$ -	$ 509.5	Sum
Ground SEIT/PM	$ 163.3	$ -	$ 163.3	NCG CER
Ground Terminal	$ 16.1	$ -	$ 16.1	Sum
Command & Control	$ 72.0	$ -	$ 72.0	Sum
Mission Management	$ 106.0	$ -	$ 106.0	Sum
Data Archive & Storage	ncluded in Other Element		n/a	
Mission Data Processing	$ 86.3	$ -	$ 86.3	Sum, Partial Mission Partner
Mission Data Analysis & Dissemination	Mission Partner		n/a	n/a
Collection Management	Mission Partner		n/a	n/a
Mission Infrastructure	$ 38.2	$ -	$ 38.2	Sum
Factory/Support Faciilty	$ 8.0	$ -	$ 8.0	Sum
Ground Sustainment (Dev - Launch)	$ 19.6	$ -	$ 19.6	CER
Launch	$ 12.4	$ 57.5	$ 69.9	Sum
Launch Integration	$ 12.4	$ 12.9	$ 25.3	Analogy from Government Launch Office
Launch Operations & Mission Support	$ -	$ 5.2	$ 5.2	CER from USCM 8
Launch Vehicle	$ -	$ 39.4	$ 39.4	Open Source Documentation

The BAC propulsion subsystem must be scaled to accommodate the larger ΔV capability required for AO3.1. Extracted from the TICAS mass and power tables for both BAC and PC spacecraft, the BAC propulsion subsystem will need to grow from 45 lbs to 175 lbs, not including liquid propellant. There is no significant non-recurring cost for this change, however, the recurring cost is estimated with the appropriate USCM 8 CER:

$$\text{FY\$2000} = 65.808 * \text{DryWeight}^{0.686}$$

The change in recurring cost is calculated as $2,275K - $896K = $1,379K. The additional liquid propellant will add approximately $100K per BAC spacecraft for a total propulsion subsystem change in cost of **$1.48M** per space vehicle.

The most significant implementation cost for AO3.1 is the change in launch vehicle selection due to the requirement to lift more weight to a higher altitude. The baseline design for the BAC spacecraft utilizes a LMLV3-8 launch vehicle, later renamed Athena II, which was priced at $26M in 2000[31]. AO3.1 requires the selection of a more capable launch vehicle, the Delta II 7920, which was priced at an inflation adjusted $32.72M in 2000. The difference is **$6.72M** per launch vehicle.

The total implementation cost of AO3.1 for both BAC spacecraft is calculated as: 2 * (1.45M + 1.48M + 6.72M) = **$19.3M**.

A rough order of magnitude (ROM) cost estimation has been conducted for the entire set of candidate TICAS architecture options with the results listed in Table 21.

Table 21: TICAS architecture option implementation cost estimates.

Architecture Option	Implementation Cost
AO1.1	$4.0M
AO1.2	$5.0M
AO2.1	$14.0M
AO3.1	**$19.3M**
AO4.1	$11.0M
AO5.1	$15.0M
AO5.2	$3.0M
AO6.1	$10.0M

6.3.4.2 Architecture Option Correlation Matrix

Correlation coefficients between each architecture option is calculated from the option value data generated during the Monte Carlo simulation. If two TICAS AOs are responsive to the same mission scenario (e.g., AO1.1 and AO1.2), those AOs will have perfectly positively correlated results; if two AOs are responsive to independent mission scenarios, the correlation between their values will be zero. If two AOs are responsive to negatively correlated scenarios, their values will also be negatively correlated. There also exists a case where two AOs cannot be simultaneously exercised--that is, their exercise is mutually exclusive. This requires an additional

[31] http://www.astronautix.com/lvs/athena.htm

feature in the AO valuation algorithm that checks for the coincident AOs (which are disallowed) and forces the selection of the single AO that has the higher payoff in that trial. This effectively decreases the number of successful outcomes for each mutually exclusive AO and therefore decreases the expected value. AO3.1 and AO5.x were defined as mutually exclusive in this simulation because they require the system to accomplish opposite objectives; therefore the additional selection algorithm is applied within the simulation. Each of the six mission scenarios are assumed to be independent for this analysis. The resulting correlation matrix is shown in Table 22. The statistical models do not exactly replicate the underlying correlation of the AOs, therefore correlation values can also be entered manually, as in Table 23.

Table 22: Correlation matrix for TICAS architecture options, simulated values.

	AO1.1	AO1.2	AO2.1	AO3.1	AO4.1	AO5.1	AO5.2	AO6.1
AO1.1	1							
AO1.2	0.87318	1						
AO2.1	-0.00332	-0.00416	1					
AO3.1	0.00466	0.00487	0.00209	1				
AO4.1	-0.00129	-0.00241	0.00030	0.00337	1			
AO5.1	-0.00056	0.00136	0.00385	-0.18132	-0.00208	1		
AO5.2	0.00010	-0.00080	-0.00318	-0.31858	-0.00518	0.33221	1	
AO6.1	0.00095	0.00071	0.00292	0.00462	0.00149	-0.00019	0.00445	1

Table 23: Correlation matrix for TICAS architecture options, manual values.

	AO1.1	AO1.2	AO2.1	AO3.1	AO4.1	AO5.1	AO5.2	AO6.1
AO1.1	1							
AO1.2	1	1						
AO2.1	0	0	1					
AO3.1	0	0	0	1				
AO4.1	0	0	0	0	1			
AO5.1	0	0	0	0	0	1		
AO5.2	0	0	0	0	0	1	1	
AO6.1	0	0	0	0	0	0	0	1

6.3.4.3 TICAS AO Portfolio Selection

The set of optimal portfolios is discovered by minimizing the risk (i.e. variance) for every possible level of expected return. Expected return is calculated as the difference between the mean architecture option value and the implementation cost, as a percentage, and annualized across the five year TICAS design life. The associated risk is the standard deviation of the AO value, as a percentage, also annualized across the same time period. The TICAS AOs are treated as discrete variables, where they are either included fully in the architecture or excluded. As can be seen by the difference in risk-reward characteristics between the individual TICAS AOs (gold circles) and the portfolios (blue diamonds) in Figure 82, there is significant benefit to be had by diversifying the portfolio across the underlying sources of uncertainty. Each portfolio along the efficient set is an optimal portfolio that minimizes risk for the commensurate level of return. The optimal portfolio that maximizes the Sharpe ratio is discovered for both simulated and manually entered correlation coefficients, highlighted with red squares in Figure 83. A summary of the optimal portfolios is included in Table 24 for varying levels of budget and risk aversion--AOs indicated with a "1" are included in the portfolio and those with a "0" are excluded.

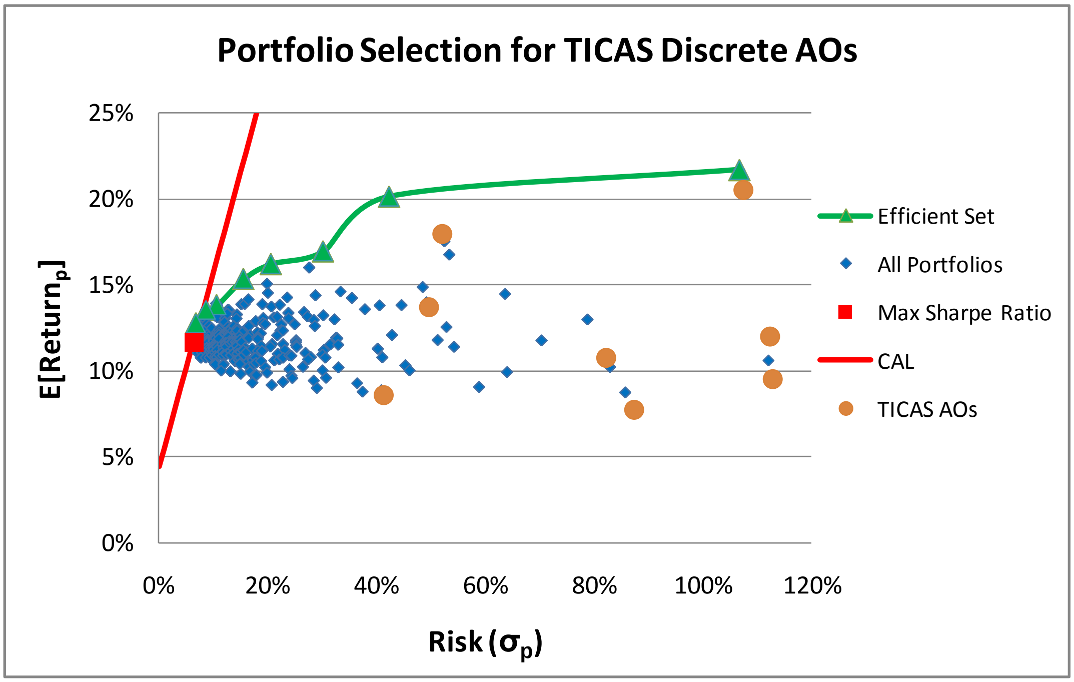


Figure 82: Optimal portfolio selection for TICAS architecture options, simulated correlations.

Table 24: Optimal portfolios with corresponding implementation cost, simulated correlations.

Risk (σ_p)	E[Return$_p$]	Portfolio Cost ($M)	AO1.1	AO1.2	AO2.1	AO3.1	AO4.1	AO5.1	AO5.2	AO6.1
1.06689	0.21690	5.0	0	1	0	0	0	0	0	0
0.42346	0.20132	8.0	0	1	0	0	0	0	1	0
0.30219	0.16942	12.0	1	1	0	0	0	0	1	0
0.20635	0.16199	22.0	0	1	1	0	0	0	1	0
0.15585	0.15332	26.0	1	1	1	0	0	0	1	0
0.10666	0.13801	37.0	1	1	1	0	1	0	1	0
0.08728	0.13523	36.0	1	1	1	0	0	0	1	1
0.06864	0.12741	47.0	1	1	1	0	1	0	1	1
0.06312	0.11650	81.3	1	1	1	1	1	1	1	1

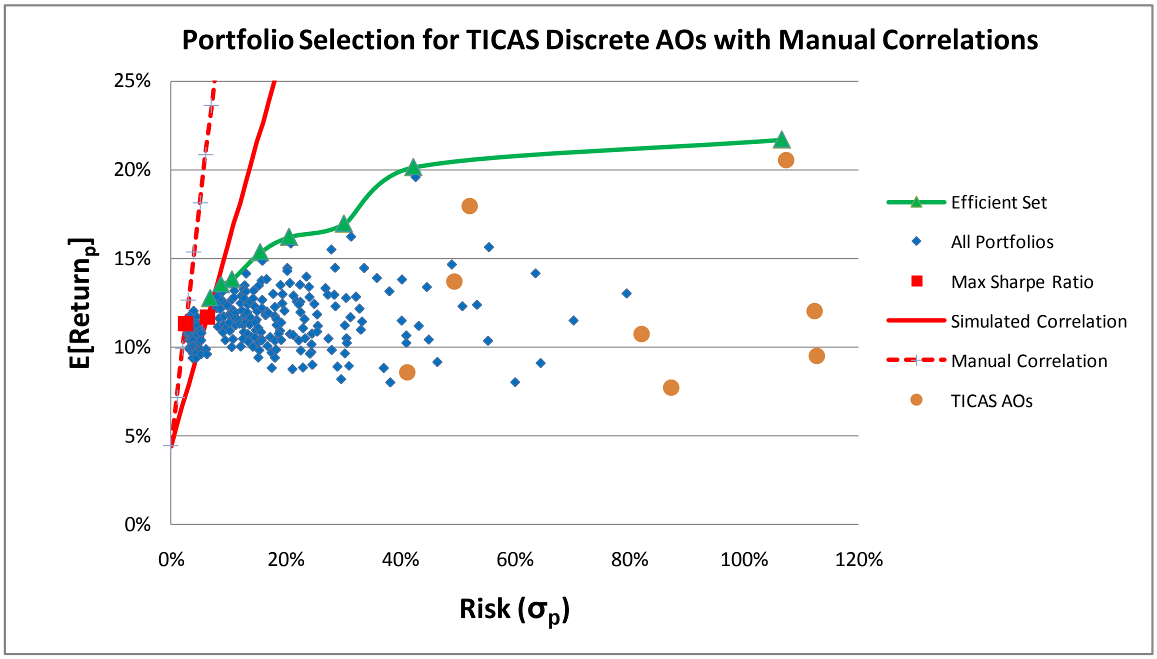


Figure 83: Optimal portfolio selection for TICAS architecture options, manual correlations.

6.4 Assessment and Limitations

Defining and selecting architecture options in a complex system design is by no means automatic. Implementation of the proposed flexibility framework is an inherently creative activity that requires in depth technical analysis within the application domain. For this reason, several subtleties and complexities were discovered in each stage of the implementation which should be mentioned briefly.

6.4.1 Stage One Assessment

We found that it is critical to make simplifying assumptions about the design element relationships. The analysis must focus on a prioritized or dominate set of interactions rather than on the existence of any level of interaction. We found that if we were to look far enough downstream, almost every design variable was affected by every other. The Lattix DSM tool allowed for the identification of first, second, and third tier interactions, all the way to transitive closure. The effects of functional requirement changes on downstream variables was limited to direct and secondary interactions to allow for insightful results. Also, the physics models that mathematically define the interactions were designed to capture the driving relationships within the system and exclude some lower-level interactions.

Managing the number of elements in the model is a major challenge early in the conceptual design because of the uncertainty about which variables will be important. However, because the computational burden grows exponentially with each additional element, DSM size becomes a major consideration. The genetic algorithm used for clustering a 34-element matrix required upwards of 48 hours of computational time using a 2.26 GHz Intel processor.

With small matrix sizes, manual clustering of the sDSM can be equally useful. Recognized by Yu, Yassine, and Goldberg (2007), the genetic algorithm must be calibrated to individual preferences for including versus excluding cluster elements. Instead of trying to calibrate the model for each application, manual manipulation of the final clusters can accomplish much of the calibration a posteriori, especially when the system contains natural or common subsystems that organically cluster the interrelationships. Users must understand that the clustering algorithm is a tool to get to the most insightful model and not a definitive termination of the analysis.

With respect to using system attributes vice functional requirements to define the effects of scenario instigated change, an important tradeoff was found to exist between increased complexity and increased model resolution. System attributes (e.g., MTTA NIIRS, timeliness, operational availability, etc.) provide a concise and stakeholder-focused way to quantify the significance of performance change. Directly aligned with the stakeholders' perception of value, system attributes also make for a more credible value forecast in Stage Two. The major drawback is that not every scenario requires a change to a system attribute and not every functional requirement fits nicely into an attribute. In the case of TICAS Scenario 1 which deals with a "conflict in space," the system attribute obviously affected is "operational availability." However, the initial assessment of TICAS operational availability did not reflect the risk of adversarial attack. Instead, it reflected system reliability, part redundancy, and design life factors. Therefore the magnitude of change to the attribute is not completely consistent with the ability to mitigate a space attack. Proper assessment of the value of the "conflict in space" AOs must distinguish the value at the functional requirement level when the attribute is not an adequate match to the actual AO.

Sensitivity of the design variable to a change in an attribute (or functional requirement) needs to be coupled with information regarding the feasible range of the design parameter in order to more fully capture the potential for flexibility. A variable can be highly sensitive to change in the neighborhood of the baseline architecture, but a truer measure of flexibility potential needs to define the possible values for that variable. We found that pixel pitch for the TICAS detector was highly sensitive to changes in the NIIRS attribute. However, the current value for that design variable was already a technological challenge, pushing the state of the art for space systems--the design variable did not have realistic ability to change in the direction that would accommodate the NIIRS requirement. We found that the s-DSM must be coupled with a Tornado or Spider plot that defines the feasible ranges of the design variables.

The flexibility framework is intended to help system designers expand the frame of reference to potential operational scenarios, feasible design modifications, and promising architecture changes. This broad perspective is stifled somewhat by the assumption we have made which requires a baseline system architecture as a point of departure for the implementation. Although a necessary assumption for this research, a baseline system architecture biases the designer toward expansion or alteration of the current design solution and does not fully encourage ingenuity and creativity, which we believe is essential to architecture option definition. The baseline TICAS propulsion system is an electric xenon ion design which was originally selected for its light weight and efficiency to handle orbit maintenance and correction. When used for substantial orbit raising, the electric propulsion system takes much too long to reach final orbital altitude and therefore results in significant downtime cost. If the system was originally designed with AO3.1 included in the architecture, an alternative propulsion system may have been selected. Consideration of new system design concepts as part of the flexibility analysis requires efficient tradespace exploration coupled with the architecture option approach. We see this area as an interesting and promising stream of future research.

6.4.2 Stage Two Assessment

The Variable Expiration option valuation technique is no exception to the rule of "garbage-in, garbage-out." The space industry in particular has incredible difficulty with cost estimation credibility. Decades of underestimating and overrunning has contributed to a widespread distrust of all satellite cost models. However, we have found that consistency in the selection and application of cost estimating tools may not always result in a precise value, but a set of values across the design space that allows for insightful decision making, trade-offs, and architecture choices. Estimating cost based solely on weight and power may seem artificial to the average observer, especially one involved with business and financial forecasts in the commercial sector. However, parametric models are an industry standard for satellite programs partly because they provide the necessary consistency for design trade studies. We had a choice in the TICAS AO3.1 analysis to use a parametric LCC-based cost estimate or a more clever, market-based estimate. We found that it was preferable to use the LCC-based approach because it provided greater consistency and comparability with other estimates.

If cost is hard to estimate precisely, value may be impossible. Value estimates are inevitably based on a right understanding of the customer (or stakeholder). When the customer may not fully understand himself, this challenge becomes immense. System attributes and utility functions have great merit, but present additional uncertainty in already uncertain mission scenarios. Market-based revenue and cost forecasts will almost always be preferred where they are available, but scientific and military missions will continue to require judgments of value. For TICAS, we would prefer to have "less rational" value assignments made by the stakeholder, rather than completely justifiable value assignments made by the system engineer. For this reason, system attributes, community-KPPs and other stakeholder communications of value are far more desirable as the basis of value stream forecasts than would be an arbitrary assessment required for functional requirement valuation.

Discount rates are much more evident in commercial applications where a corporate bond rate is available, as is a required rate of return for the firm. For the TICAS analysis, the U.S. Treasury note was used to estimate the cost of investment capital. This assumes that the organization spending the money can choose to retain the money and instead pay down the national debt. If this were the case, the stated discount rate is a great analogy. However, after money is allocated and appropriated to a government entity by the congress, that money finds a way to be spent; if it is not spent (and spent fast enough), another program will siphon it off and spend it somewhere else. This reality suggests that additional investigation is required to fully define a government analogy to the investment rate.

How risk averse are decision makers within government agencies? The market risk rate used in this analysis assumes they are as risk tolerant as decision makers in the aerospace and defense private sector. Government service employees, even executives, do not have the same accountability nor incentives present in the private sector; risk tolerance is a function of these factors. As opposed to a return on equity or required rate of return that defines acceptable market risk, government risk taking decisions will have more to do with the political hazard associated with wasting taxpayer money or failing with a project. Further research is needed to more clearly identify a government analogy to ROE.

6.4.3 Stage Three Assessment

Portfolio optimization can identify the best subsets of AOs, but for TICAS and other systems designed in similar organizational environments, the best portfolio is not always the right portfolio. Large defense programs, including space systems, have requirements driven and defined to a high degree by external factors. These programs are defined at the national policy level via national (imagery) requirements. The result is that almost all requirement trades are made above the system architect's level. Performance and funding choices for space systems are dictated by the high level acquisition process and are many times outside of the control of the acquiring agency. Even if promising AOs are discovered, the decision to embed those options in the system architecture lies higher up the command chain. This realism does not take away from the merits of AO selection, only in that it adds another layer of necessary stakeholder communication and validates the need for transparency and clarity in the flexibility framework.

Practical considerations within the application domain can significantly impact the usefulness of the flexibility framework. Most military weapon systems have life cycle costs dominated by post development costs: production, training, operations, sustainment, depot costs, etc. These typically far outweigh the cost of initial development. This funding dynamic can be much more amenable to the additional up-front costs necessary to embed flexibility as these programs can better absorb early expenditures. Space systems exist in stark contrast as the majority of costs are realized during system development and initial deployment (launch). This creates serious competition for funding and little tolerance for unsubstantiated system requirements.

6.5 Conclusion

This chapter presents a proof of concept for the proposed three stage flexibility framework. The Tactical Imaging Constellation Architecture Study was chosen for its complexity, realism, and depth of technical detail. The proposed screening process was conducted to help define a set of candidate architecture options within the system design. Potential operational scenarios were identified and subsequently scored for their likelihood and conditional impact. Changes to functional requirements and system attributes necessitated by each operational scenario were determined and flowed to the impacted design variables.

Sensitivity analysis was used to identify the TICAS design variables most reactive to the potential changes. The most sensitive design variables were clustered and visualized to help identify the most promising flexibility regions in the architecture. A set of candidate architecture options was created and defined in detail.

Each architecture option was valuated with the proposed Variable Expiration real options technique. Implementation costs, exercise costs, value streams, and discount rates were estimated from archived data and used as inputs to the option valuation. Mean option values and standard deviations were calculated for each AO and retained for subsequent AO selection. Analytical plots were generated which describe the sensitivity of the option value to changes in each of the input parameters.

For varying levels of budget and risk tolerance, optimal subsets of architecture options were identified through portfolio optimization. An assessment of the complexities and limitations of the flexibility framework was presented along with recommendations for future research.

CHAPTER VII

SUMMARY AND FUTURE NEEDS

7.1 Summary of Contribution

This research set out to determine what characteristics enable systems to remain persistently valuable throughout their operational life and if these characteristics could be rigorously incorporated in future system designs. It was concluded that uncertainty in the operational environment can significantly affect the system's ability to remain valuable. This leads to the risk of a system becoming obsolete or being unable to respond to changing needs. It was found that traditional systems engineering techniques approach this concept almost exclusively by focusing on the prevention of negative outcomes associated with uncertainty. A growing number of authors have recognized that operational uncertainty also creates an opportunity to deliver additional value to the stakeholder if the system can flexibly adapt to the new requirements. This research concludes that the maximization of life cycle value for a system designed to operate in an uncertain environment relies heavily on the characteristics of flexibility embedded in the architecture.

In order to study and assess the concept of flexibility in a consistent and methodical way, the Architecture Option (AO) has been defined as a unit of analysis. Different from previous definitions, the AO is proposed to be an encapsulation of a set of physical design components (or design variables) that necessarily enable an identifiable function with discernable value, instigated by a change in operational objectives. This research contends that an appropriately flexible design will contain some combination of architecture options, exercised (or utilized) if and when they are warranted, which maximizes the life cycle value of the system. Consequently, this research embarked on the challenge of designing an integrated framework that seeks to communicate a process and develop a toolset that enables system engineers to make flexibility-informed design decisions.

Existing literature to this point has not treated embedded design flexibility in a comprehensive way. Descriptive measures, conceptual frameworks, and case-specific methods have not resulted in a general flexible design approach that can be applied across engineering disciplines. This research has developed a comprehensive, three stage integrated flexibility framework that can identify, value, and select an optimal subset of architecture options to embed in the system design and provide operational flexibility. This framework is not case specific and it incorporates both qualitative and quantitative tools that are application independent.

Stage One of the framework developed an eight step architecture option screening process that identifies and encapsulates operational uncertainty, traces new functional requirements to the affected design variables, and clusters the variables most sensitive to change. These clusters are combined with information from the alternate use cases to generate insight into the most promising areas in the architecture to embed flexibility. The proposed process is compatible with existing systems engineering practice and adopts some of the traditional system engineering techniques related to operational concept development, functional analysis and decomposition.

Stage Two developed an architecture option valuation technique, grounded in real options theory, that is able to value options with variable expiration. Architecture options by nature have uncertainty in the exercise date and therefore require a valuation technique that can handle variable expiration. Traditional options valuation approaches were determined to be overly constrained by market assumptions and complex mathematical structures which made their usage unrealistic and many times inappropriate. Instead, this research found that the Datar-Mathews valuation mechanism could be augmented to accommodate embedded architecture options with variable expiration. The challenges and intricacies of the valuation approach are presented with a discussion regarding the compatibility of the technique with existing business and market forecasting frameworks. This is a significant step forward for the use of real options analysis to value embedded architecture options using a more transparent economic mechanism which can lead to greater adoption by industry and other users.

In Stage Three, a portfolio optimization technique was developed to select an optimal subset of architecture options. Embracing the premise that an optimal portfolio of AOs will maximize the system's expected life cycle value and minimize portfolio economic risk, an optimization algorithm was proposed for both discrete and continuous AOs. The set of optimal portfolios which lie along the efficient frontier is found to represent the subsets of architecture options which yield the lowest level of economic risk for any given level of expected return. The selected optimal portfolio is found to be dependent on the budget and risk tolerance of the stakeholder.

Finally, the feasibility, extensibility and limitations of the integrated framework were assessed by its application to a satellite system development problem. The flexibility framework was applied to the Tactical Imaging Constellation Architecture Study, which was a complex family-of-systems design activity in 1996. Detailed technical data, performance models, and cost estimates were compiled and leveraged to assess the flexibility framework with as much realism as possible. Given the alternate mission scenarios identified in Stage One, it was found that system flexibility in the form of a portfolio of TICAS architecture options could yield between 11.7% and 20.1% expected annual return with associated risk of between 6.3% and 42.3%, respectively. The budget required for these portfolios ranged from the low end of $8.0M to the high end of $81.3M. A detailed assessment of each stage of the framework was presented along with the challenges uncovered by applying the framework to a realistic system architecture.

This research was interdisciplinary at its core. Ideas from diverse disciplines including system architecture, stochastic modeling, risk management, finance, and optimization were fused in order to develop an integrated approach to designing appropriately flexible systems. The importance of design flexibility has been recognized across a wide variety of industries, from engineering and technology to real estate and infrastructure development. For this reason, the contribution of this research is also potentially wide and diverse. These contributions fall into the following five categories:

1. A screening process for identifying candidate architecture options within a system design
2. A valuation technique for embedded architecture options
3. A methodology for selecting an optimal portfolio of architecture options
4. An integrated framework for considering "system design flexibility"
5. Insight into the challenges of applying flexibility to a complex system design problem.

7.2 Future Needs

In the course of conducting this research, a variety of topics were handled that exist in a relatively new and undeveloped research environment. In Stage One, we found that the ability to adequately encapsulate operational uncertainty is critical to identifying candidate architecture options. We currently rely on scenario planning and vignette development ideas from business forecasting and market research. However, for military and scientific missions, revenue and cost are replaced by other more subjective parameters. Developing scenarios around unarticulated stakeholder demands is significantly more challenging than around predicted consumer behavior. This topic is ripe for study and will be critical in capturing the uncertainty that pervades the operational environment.

The MDL-GA algorithm used for DSM clustering in Stage One is the only technique we could identify which allows for overlapping, non-binary, clustering with bus identification. Therefore it is hard to compare the efficacy of the algorithm compared to other available techniques. The algorithm worked well for this application, but it will need to be applied and validated across other domains. The weights used to calibrate the clustering algorithm were adopted from the algorithm authors without validation of the intra-cluster preferences of specific stakeholders. The preference for inclusion versus exclusion of elements in the cluster is a stream of research we feel can be tested rigorously and scientifically using actual programs and specific stakeholders.

Options valuation is a relatively new field all together. Applying theories and tools from Finance to the systems engineering domain has inherent complexities. Practitioners will inevitably need to familiarize themselves with financial concepts and frameworks to guarantee the right application of the techniques. Underlying assumptions, implementation of stochastic models, development of stakeholder value functions, consistency in cost modeling, and the use of specific discount rates to characterize risk all require substantial insight into the intricacies of the technique. Although we believe the theoretical and practical foundation has been laid for the use of real options in system architecture, additional research that expounds on the nature and complexities of option valuation along with further automation is seen as beneficial and useful.

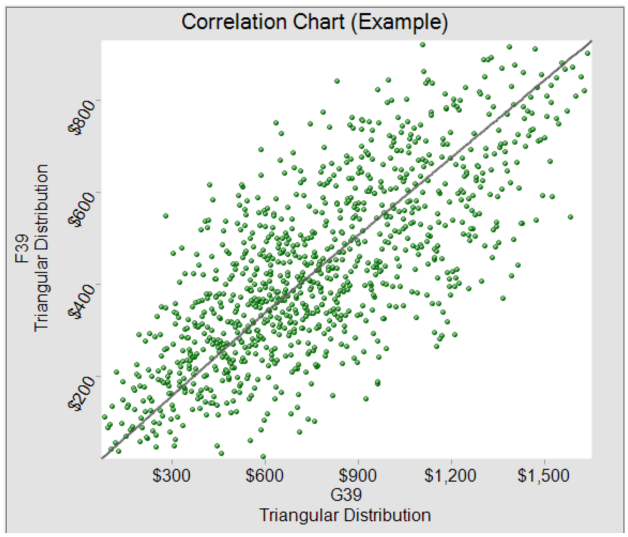
A pivotal assumption was made in this research to assume the existence of a baseline system architecture that meets the threshold requirements of a defined critical mission. This allowed us to treat flexibility essentially à la carte and value each AO independently. Complexities involving significant physical overlap of architecture options (which would affect selection) and complications involved with analyzing the types of flexibility that fundamentally alter the design solution were not addressed comprehensively. We believe this will be a critical extension of the research: incorporating the flexibility framework within a rapid, iterative architecture generation and assessment process. Similar to a multi-attribute tradespace exploration process with concurrent design, we believe future research in full scale design simulation that embraces flexibility will be fruitful.

Validation of any proposed framework is the gold standard of quality assessment. Finding an objective benchmark for comparison is the real challenge. In regards to flexibility, the question has been asked: "Are we trying to value the unimaginable? Yes. Does the unimaginable have value? Yes." This reveals the quandary when claiming a particular valuation technique or process is objectively valid. We can make the assessment that the proposed framework does indeed work for a particular application under certain restrictions, assumptions and constraints. How well it works is subject to interpretation. Future research is recommended to search for an objective benchmark or standard to compare the framework and results. A clever way to validate real options as a method to value flexibility has been proposed in relation to valuing the stock price of companies like Google and Amazon. It was recognized that the market price of Google and Amazon stock well exceeded the traditional valuation based on the discounted stream of future earnings normalized by the shares outstanding. The reason the stock price so outpaced the valuation was theorized to be because these companies existed in highly uncertain markets and had invested significantly in portfolios of real options to scale up, scope up, switch up, study and start their business activities. The value of flexibility embedded in the organization was proposed to fill the observed valuation gap and real options analysis was used to test this theory. For future research, we believe this type of validation is possible for architecture options if we can find a suitable proxy or market-based benchmark that allows for objective comparison.

APPENDIX

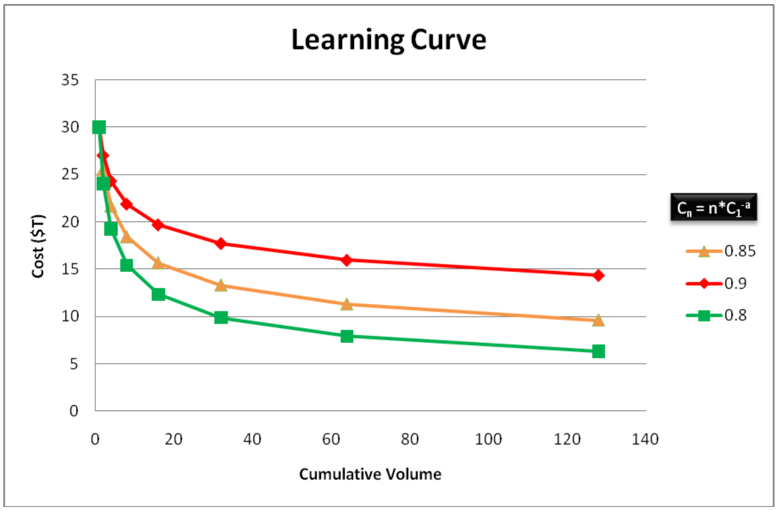
A. DEFINING CORRELATION OF RANDOM VARIABLE DISTRIBUTIONS

Random distribution forecast values can be defined as partially correlated with the adjacent forecast to provide additional realism to the model, illustrated in the figure below. If the forecast in a particular year is high, the forecasts in the years on either side should also be relatively high to maintain rational consistency.



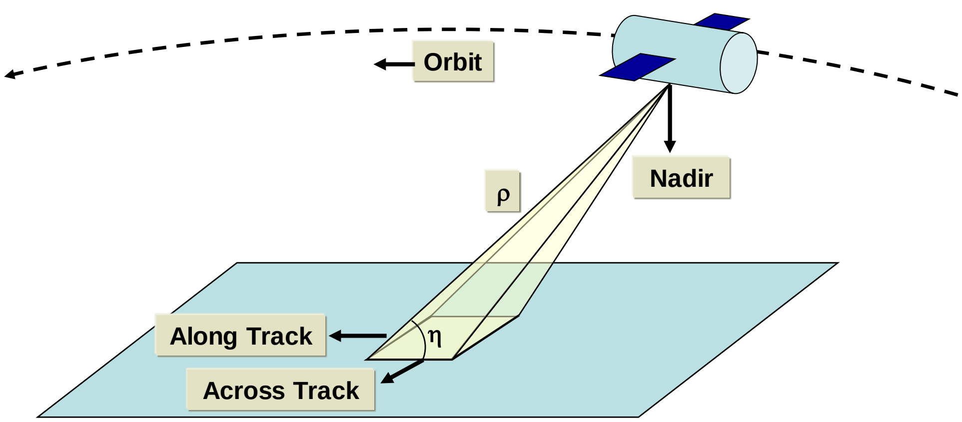
B. LEARNING CURVE APPLIED TO BUSINESS FORECAST EXAMPLE

The typical learning curve is used to define how costs will decrease for every doubling of cumulative volume produced. When defining an optimistic versus pessimistic business forecast, the learning curve can be used to implement this market sentiment and disposition. Typical values in the aerospace and defense industry are between 80% and 90% learning.



C. GROUND SAMPLE DISTANCE

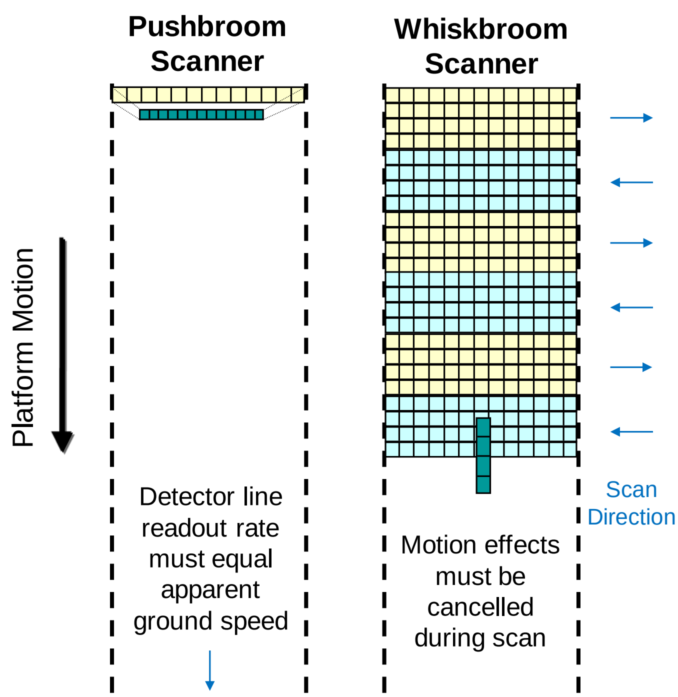
The ground sample is the projection of a single detector pixel, through the optical system, along the line of sight to the ground. The ground sample distance is the separation of adjacent samples, measured as the (IFOV * altitude) at nadir. As the observational altitude increases and the slant angle diverges from nadir, the ground sample becomes oblique, and the distance between adjacent samples grows.



ρ	Range
η	Elevation Angle
GSD Across Track	ρ x IFOV
GSD Along Track	ρ x IFOV/sin(η)
Nominal GSD is Geometric Mean	GSD = ρ x IFOV/SQRT(sin(η))

D. PUSHBROOM AND WHISKBROOM IMAGING STRATEGIES

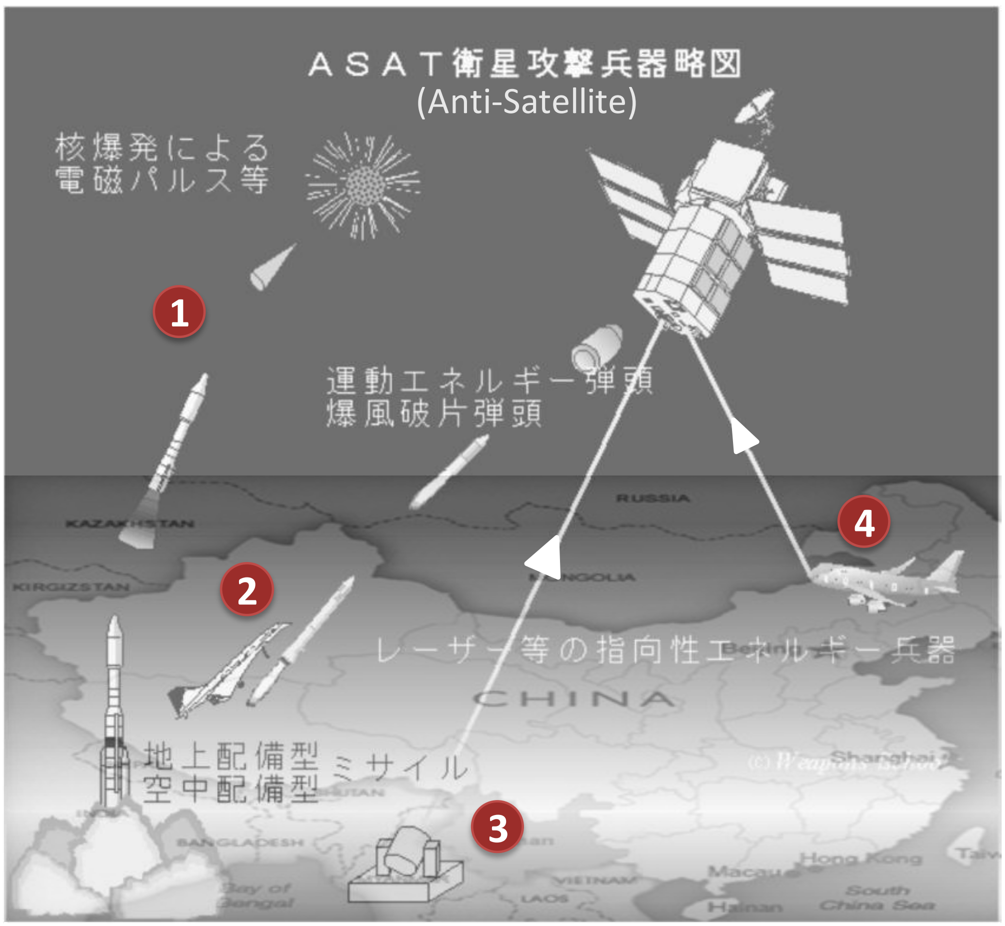
Several imaging techniques are used to optimize image quality under varying levels of lighting, motion, stability, and required SNR. Of these technique, the TICAS spacecraft uses a strategy that sweeps the detector line array either along the direction of vehicle motion ("pushbroom") or back-and-forth across the direction of vehicle motion ("whiskbroom"). The pushbroom strategy maximizes total area collection, while the whiskbroom strategy maximizes the contiguous area collection around a particular ground site. Ground motion compensation (GMC), or nodding, and time delay integration (TDI) are used with these scanning strategies to increase the effective exposure time and therefore the photons on the detector.



E. TICAS OPERATIONAL VIEWS OF MISSION SCENARIOS

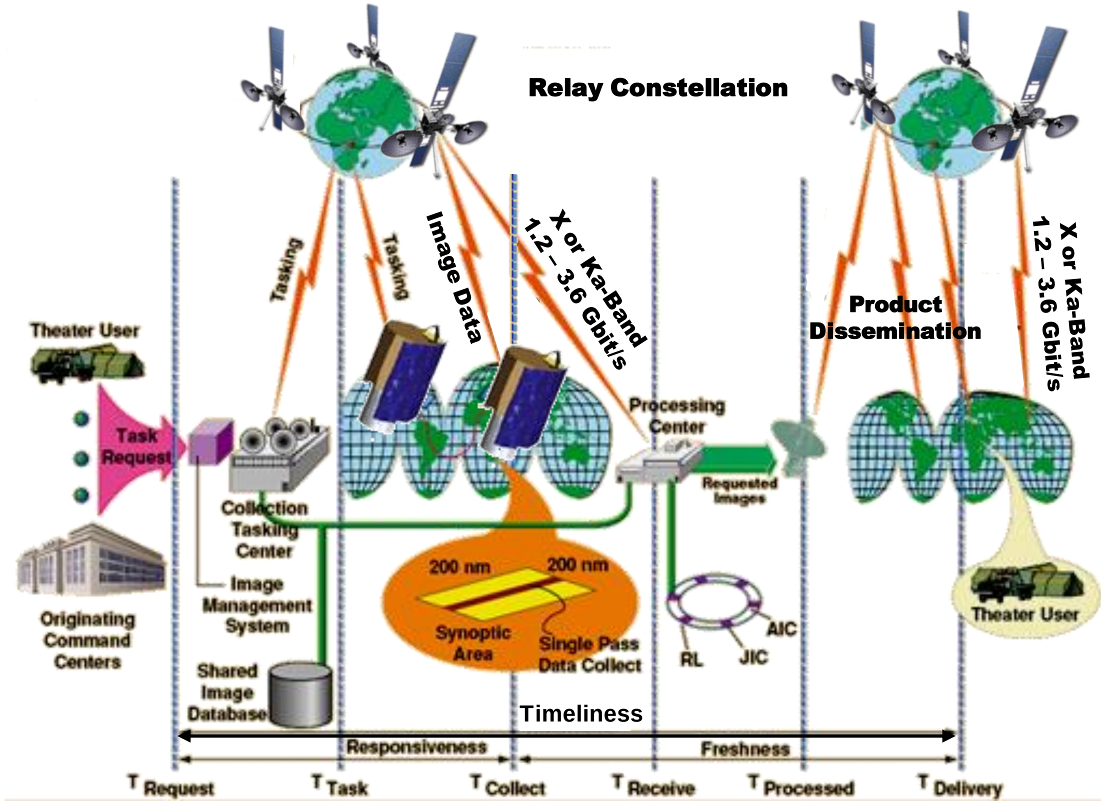
Consistent with the DoDAF Architecture Framework, high level Operational Views (OV-1 and OV-2) are presented here for the TICAS mission scenarios. These examples represent the varying levels of detail and structure that can serve to encapsulate and define the changing TICAS operational environment.

Scenario 1: Space Protection

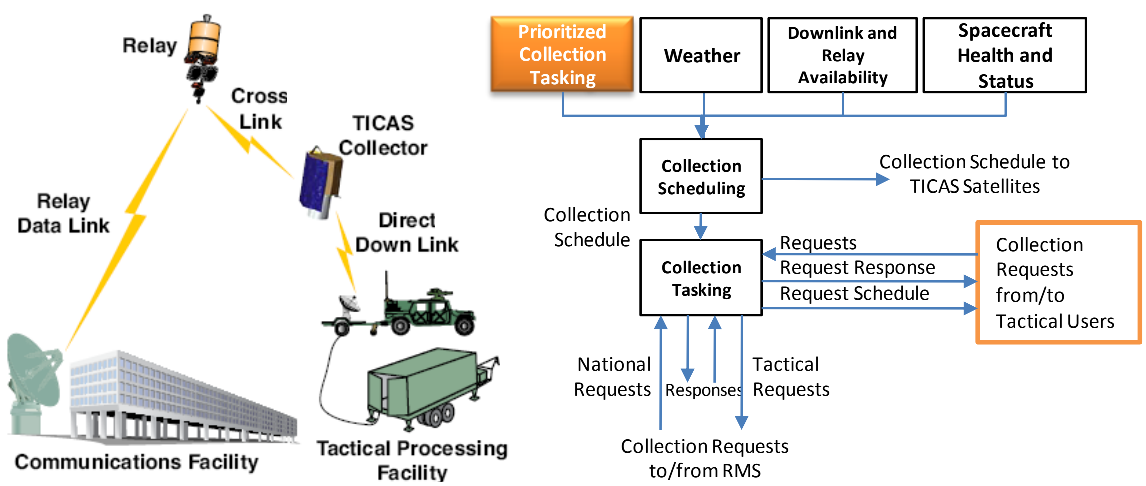


❶ Atmospheric nuclear detonation
❷ Kinetic kill vehicle
❸ Ground based laser
❹ Airborne laser

Scenario 2: Advanced Communication Relay

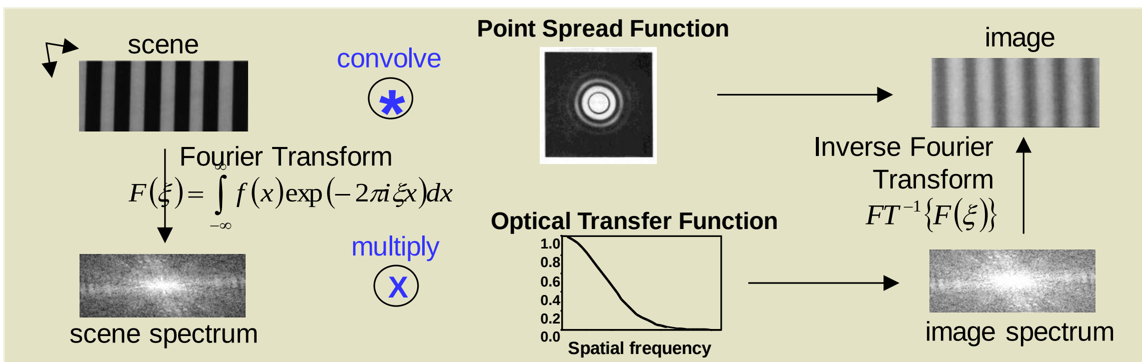


Scenario 4: Direct Downlink for In-Theater Operations



F. MODULATION TRANSFER FUNCTION IN RELATION TO NIIRS

A scene is just the sum of many points, and therefore an image is the sum of the point spread function (PSF) multiplied by each point in the scene. Illustrated along the top path in the figure below, this process is a convolution operation. The Fourier Transform is used to mathematical transform the operation from a convolution (shift, multiply, add operation) into a simple multiplication. The Fourier Transform of the PSF is the optical transfer function (OTF). The OTF measures the optical system's ability to transfer contrast as a function of spatial frequency.

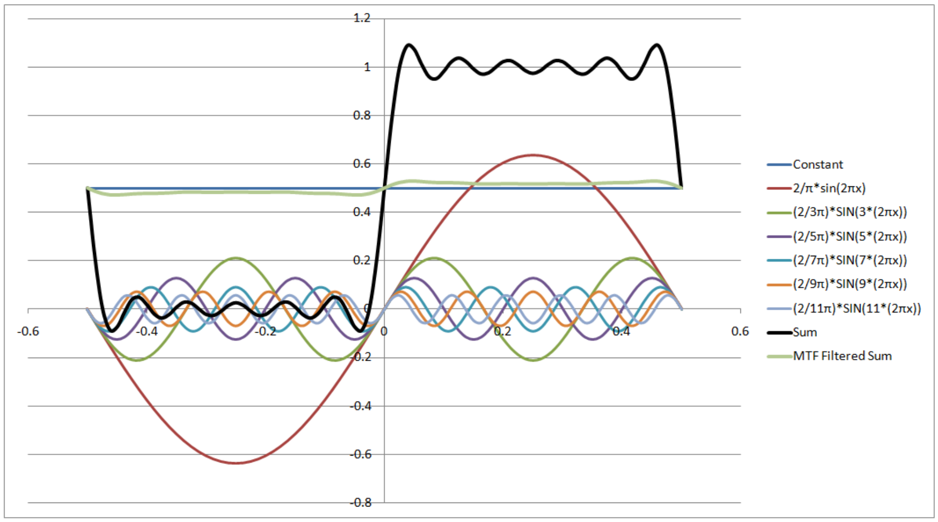


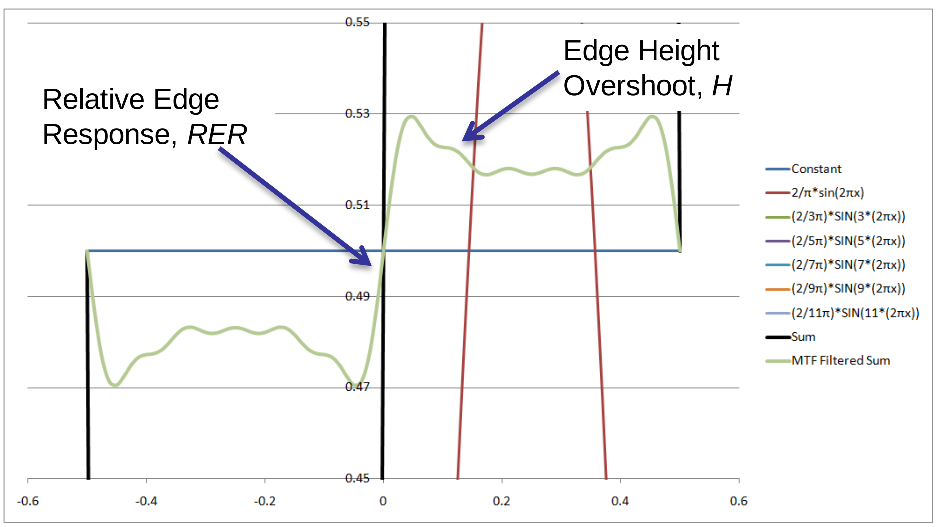
- The ***brightness*** of each pixel represents the ***amplitude*** of the sine
- The ***location*** of each pixel represents the ***frequency*** of the sine (in 2D)
- The ***phase*** of each pixel (not shown) represents the ***shift*** of the sine

The system transfer function describes the ways the system blurs an image, including optical aberrations, manufacturing defects, spacecraft jitter, detector effects, etc. The transfer function can be described with an amplitude and phase term:

$$H(\xi,\eta)=A(\xi,\eta)\exp[2\pi i\phi(\xi,\eta)]$$

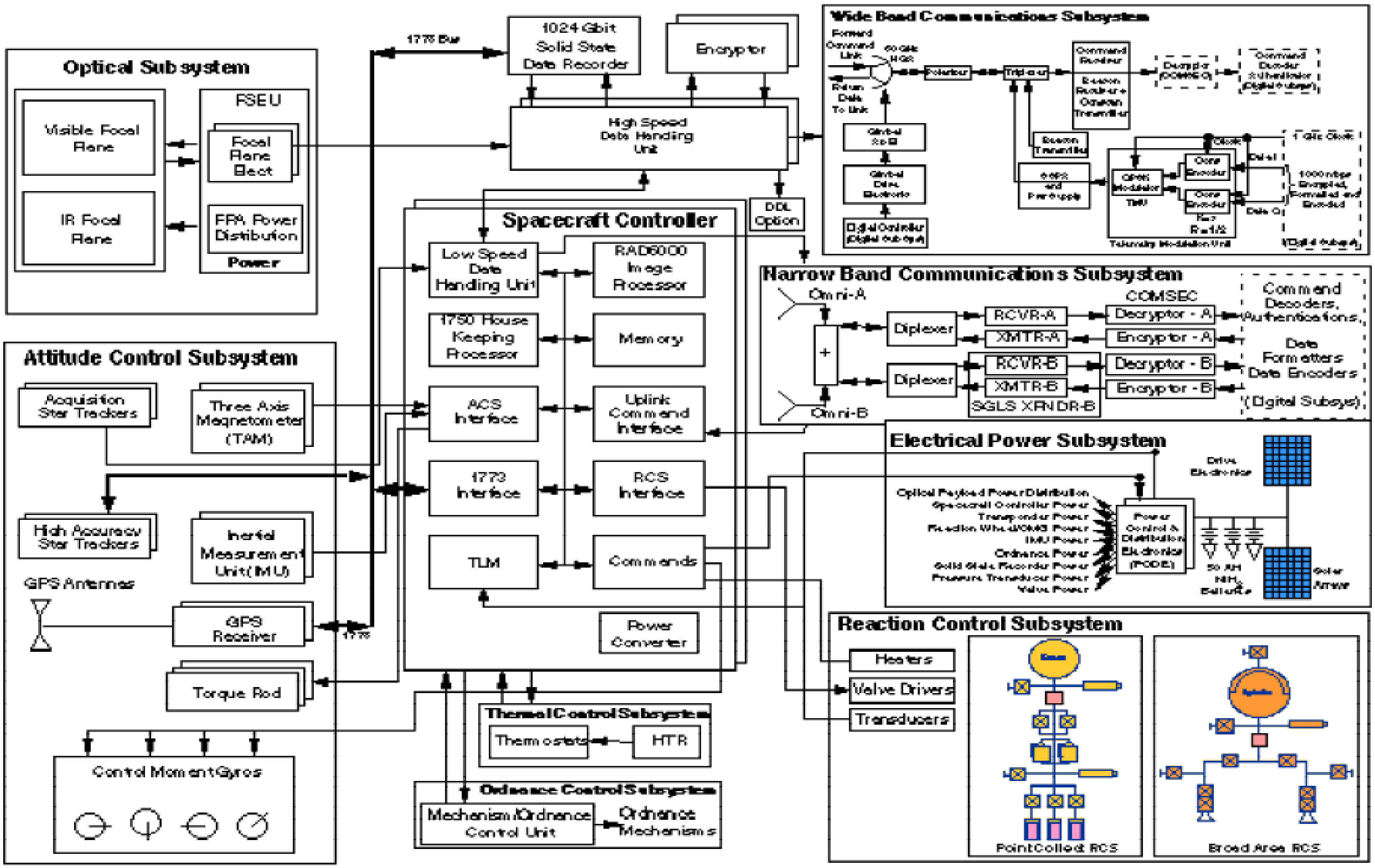
The MTF is the absolute value of the amplitude term and measures the system's ability to resolve ground spatial dimension. If the scene contains a sharp edge that is desirable to resolve, the ideal spatial signal would look like a step function. Displayed in the figure below, the step function is composed of sine waves and is filtered by the MTF as a function of spatial frequency (i.e., different frequencies are affected differently).



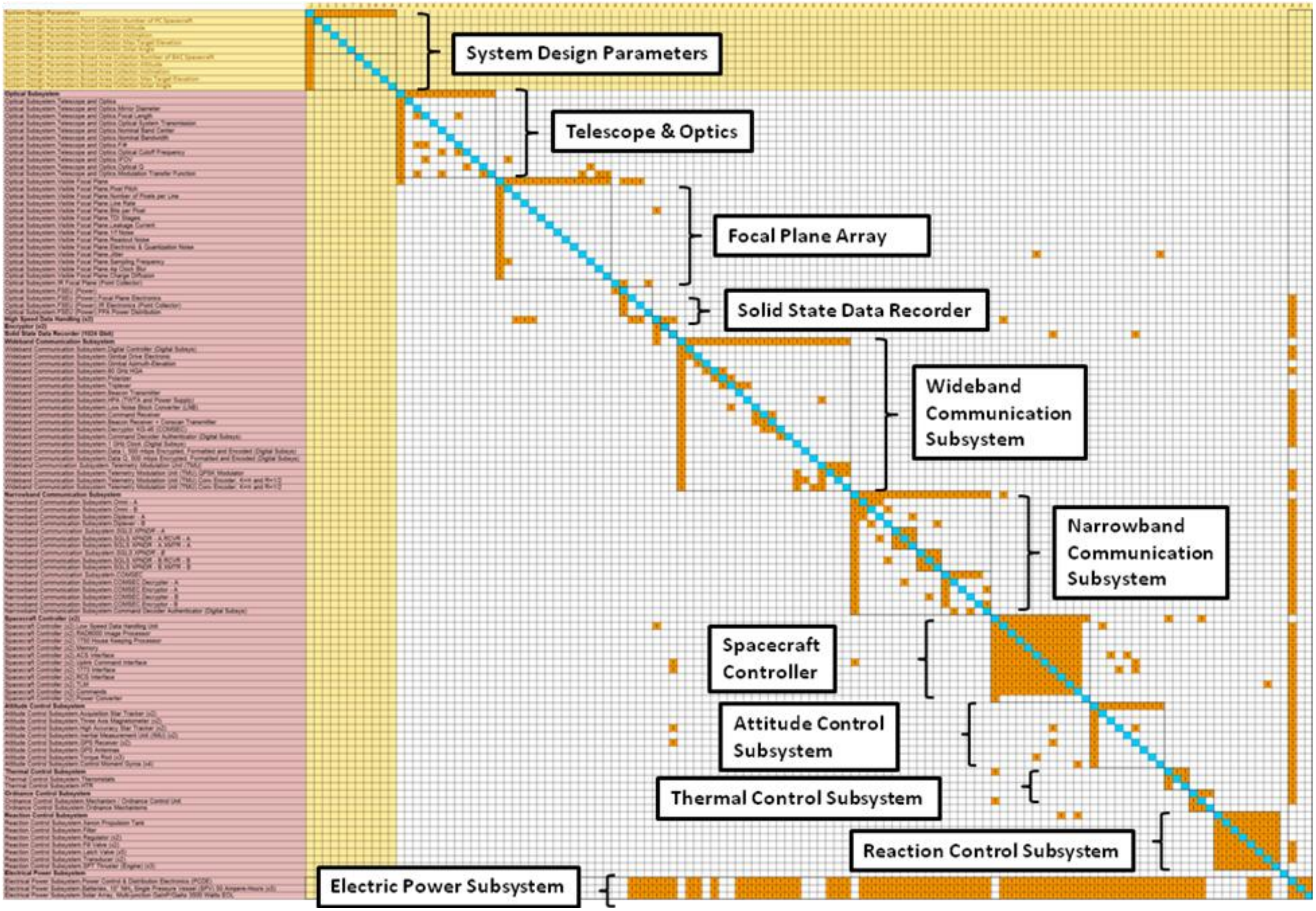


Using the TICAS 3-mirror anastigmat optical MTF shown earlier in Figure 67, the scene step function is filtered and transmitted as the image represented by the green line. The slope of the transmitted step function is characterized by the Relative Edge Response term in the NIIRS equation, while the "ringing" is captured by the Edge Height Overshoot term.

G. TICAS SYSTEM BLOCK DIAGRAM



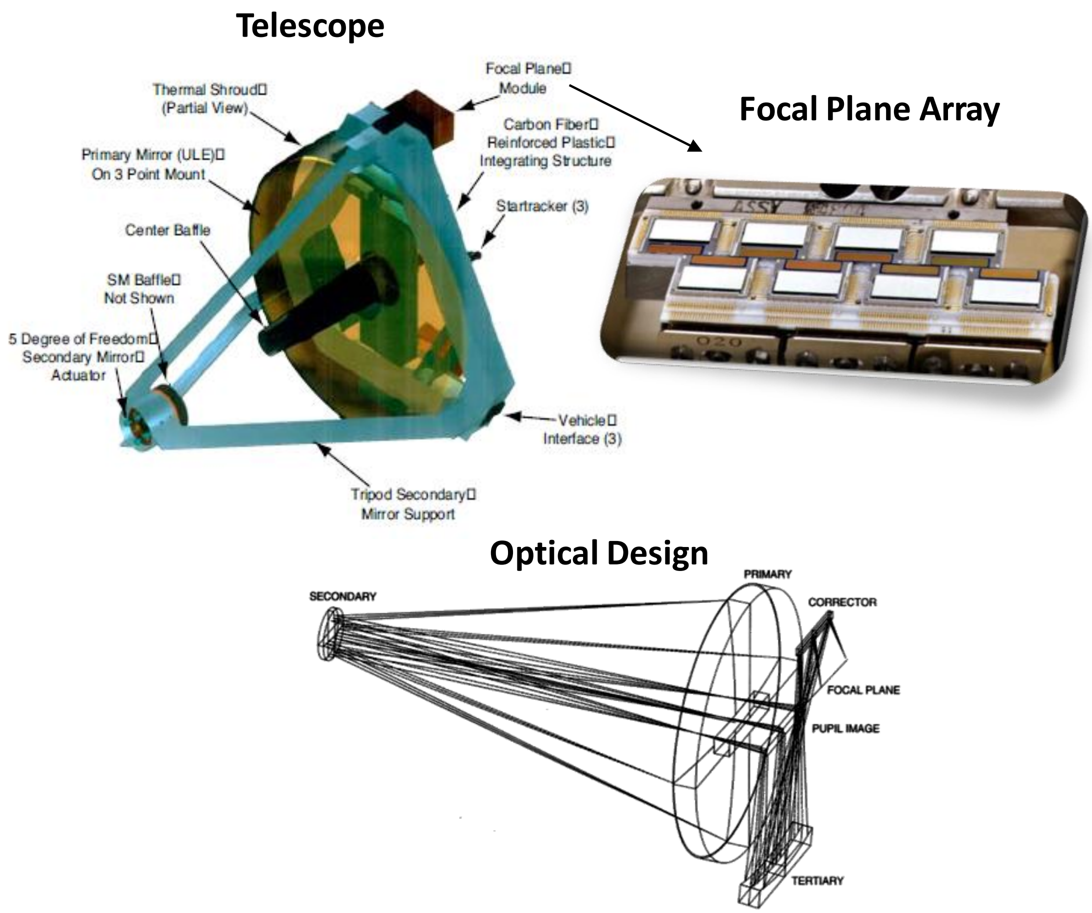
H. TICAS SYSTEM DESIGN STRUCTURE MATRIX



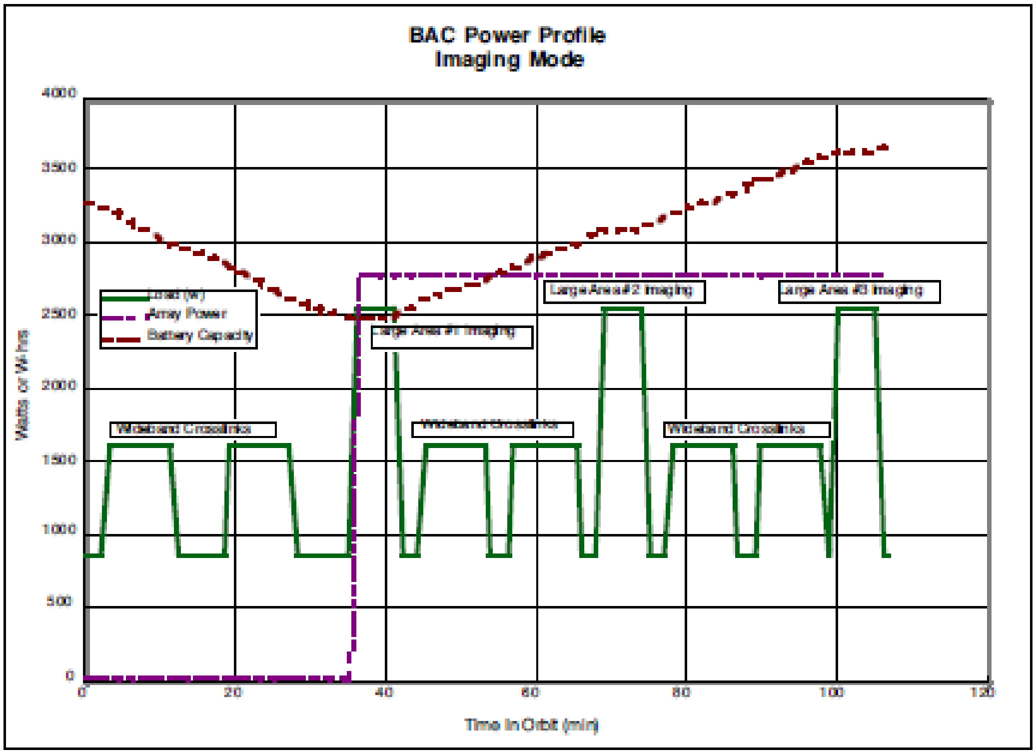
TICAS System Architecture	
System Design Parameters	
System Design Parameters.Broad Area Collector	
System Design Parameters.Broad Area Collector.Altitude	1
System Design Parameters.Broad Area Collector.Inclination	2
System Design Parameters.Broad Area Collector.Max Target Elevation	3
System Design Parameters.Broad Area Collector.Number of BAC Spacecraft	4
System Design Parameters.Broad Area Collector.Solar Angle	5
System Design Parameters.Point Collector	
System Design Parameters.Point Collector.Altitude	6
System Design Parameters.Point Collector.Inclination	7
System Design Parameters.Point Collector.Max Target Elevation	8
System Design Parameters.Point Collector.Number of PC Spacecraft	9
System Design Parameters.Point Collector.Solar Angle	10
Optical Subsystem	
Optical Subsystem.FSEU (Power)	
Optical Subsystem.FSEU (Power).FPA Power Distribution	11
Optical Subsystem.FSEU (Power).Focal Plane Electronics	12
Optical Subsystem.FSEU (Power).IR Electronics (Point Collector)	13
Optical Subsystem.IR Focal Plane (Point Collector)	14
Optical Subsystem.Telescope and Optics	
Optical Subsystem.Telescope and Optics.Mirror Diameter	15
Optical Subsystem.Telescope and Optics.F/#	16
Optical Subsystem.Telescope and Optics.Focal Length	17
Optical Subsystem.Telescope and Optics.IFOV	18
Optical Subsystem.Telescope and Optics.Nominal Bandwidth	19
Optical Subsystem.Telescope and Optics.Optical Cutoff Frequency	20
Optical Subsystem.Telescope and Optics.Nominal Band Center	21
Optical Subsystem.Telescope and Optics.Optical Q	22
Optical Subsystem.Telescope and Optics.Optical System Transmission	23
Optical Subsystem.Telescope and Optics.Modulation Transfer Function	
Edge Height Overshoot	24
Noise Gain from Sharpening	25
Relative Edge Response	26
Optical Subsystem.Visible Focal Plane	
Optical Subsystem.Visible Focal Plane.1/f Noise	27
Optical Subsystem.Visible Focal Plane.4φ Clock Blur	28
Optical Subsystem.Visible Focal Plane.Bits per Pixel	29
Optical Subsystem.Visible Focal Plane.Charge Diffusion	30
Optical Subsystem.Visible Focal Plane.Electronic & Quantization Noise	31
Optical Subsystem.Visible Focal Plane.Jitter	32
Optical Subsystem.Visible Focal Plane.Leakage Current	33
Optical Subsystem.Visible Focal Plane.Line Rate	34
Optical Subsystem.Visible Focal Plane.Number of Pixels per Line	35
Optical Subsystem.Visible Focal Plane.Pixel Pitch	36
Optical Subsystem.Visible Focal Plane.Readout Noise	37
Optical Subsystem.Visible Focal Plane.Sampling Frequency	38
Optical Subsystem.Visible Focal Plane.TDI Stages	39
High Speed Data Handling (x2)	40
Solid State Data Recorder (1024 Gbit)	41
Attitude Control Subsystem	
Attitude Control Subsystem.Acquisition Star Tracker (x2)	42
Attitude Control Subsystem.Control Moment Gyros (x4)	43
Attitude Control Subsystem.GPS Antennas	44
Attitude Control Subsystem.GPS Receiver (x2)	45
Attitude Control Subsystem.High Accuracy Star Tracker (x2)	46
Attitude Control Subsystem.Inertial Measurement Unit (IMU) (x2)	47
Attitude Control Subsystem.Three Axis Magnetometer (x2)	48
Attitude Control Subsystem.Torque Rod (x3)	49
Encryptor (x2)	50

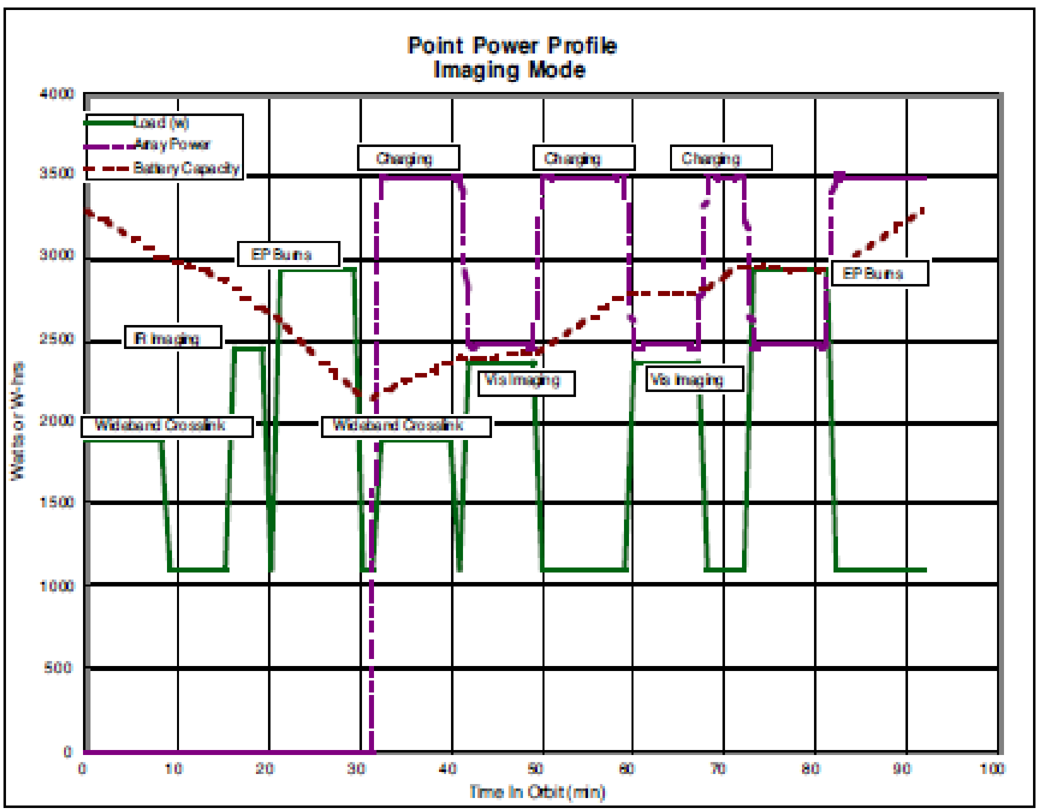
Wideband Communication Subsystem	
Wideband Communication Subsystem.Telemetry Modulation Unit (TMU)	
Wideband Communication Subsystem.Telemetry Modulation Unit (TMU).Conv Encoder, K=π and R=1/2	51
Wideband Communication Subsystem.Telemetry Modulation Unit (TMU).QPSK Modulator	52
Wideband Communication Subsystem.1 GHz Clock (Digital Subsys)	53
Wideband Communication Subsystem.60 GHz HGA	54
Wideband Communication Subsystem.Beacon Receiver + Conscan Transmitter	55
Wideband Communication Subsystem.Beacon Transmitter	56
Wideband Communication Subsystem.Command Decoder Authenticator (Digital Subsys)	57
Wideband Communication Subsystem.Command Receiver	58
Wideband Communication Subsystem.Data I, 500 mbps Encrypted, Formatted and Encoded (Digital Subsys)	59
Wideband Communication Subsystem.Data Q, 500 mbps Encrypted, Formatted and Encoded (Digital Subsys)	60
Wideband Communication Subsystem.Decryptor KG-46 (COMSEC)	61
Wideband Communication Subsystem.Digital Controller (Digital Subsys)	62
Wideband Communication Subsystem.Gimbal Azimuth-Elevation	63
Wideband Communication Subsystem.Gimbal Drive Electronic	64
Wideband Communication Subsystem.HPA (TWTA and Power Supply)	65
Wideband Communication Subsystem.Low Noise Block Converter (LNB)	66
Wideband Communication Subsystem.Polarizer	67
Wideband Communication Subsystem.Triplexer	68
Narrowband Communication Subsystem	
Narrowband Communication Subsystem.COMSEC	
Narrowband Communication Subsystem.COMSEC.Decrypter - A	69
Narrowband Communication Subsystem.COMSEC.Decrypter - B	70
Narrowband Communication Subsystem.COMSEC.Encryptor - A	71
Narrowband Communication Subsystem.COMSEC.Encryptor - B	72
Narrowband Communication Subsystem.SGLS XPNDR - A	
Narrowband Communication Subsystem.SGLS XPNDR - A.RCVR - A	73
Narrowband Communication Subsystem.SGLS XPNDR - A.XMTR - A	74
Narrowband Communication Subsystem.SGLS XPNDR - B	
Narrowband Communication Subsystem.SGLS XPNDR - B.RCVR - B	75
Narrowband Communication Subsystem.SGLS XPNDR - B.XMTR - B	76
Narrowband Communication Subsystem.Command Decoder Authenticator (Digital Subsys)	77
Narrowband Communication Subsystem.Diplexer - A	78
Narrowband Communication Subsystem.Diplexer - B	79
Narrowband Communication Subsystem.Omni - A	80
Narrowband Communication Subsystem.Omni - B	81
Ordnance Control Subsystem	
Ordnance Control Subsystem.Mechanism / Ordnance Control Unit	82
Ordnance Control Subsystem.Ordnance Mechanisms	83
Reaction Control Subsystem	
Reaction Control Subsystem.Fill Valve (x2)	84
Reaction Control Subsystem.Filter	85
Reaction Control Subsystem.Latch Valve (x5)	86
Reaction Control Subsystem.Regulator (x2)	87
Reaction Control Subsystem.SPT Thruster (Engine) (x3)	88
Reaction Control Subsystem.Transducer (x2)	89
Reaction Control Subsystem.Xenon Propulsion Tank	90
Thermal Control Subsystem	
Thermal Control Subsystem.HTR	91
Thermal Control Subsystem.Theromstats	92
Spacecraft Controller (x2)	
Spacecraft Controller (x2).1750 House Keeping Processor	93
Spacecraft Controller (x2).1773 Interface	94
Spacecraft Controller (x2).ACS Interface	95
Spacecraft Controller (x2).Commands	96
Spacecraft Controller (x2).Low Speed Data Handling Unit	97
Spacecraft Controller (x2).Memory	98
Spacecraft Controller (x2).Power Converter	99
Spacecraft Controller (x2).RAD6000 Image Processor	100
Spacecraft Controller (x2).RCS Interface	101
Spacecraft Controller (x2).TLM	102
Spacecraft Controller (x2).Uplink Command Interface	103
Electrical Power Subsystem	
Electrical Power Subsystem.Batteries, 10" NiH2 Single Pressure Vessel (SPV) 50 Ampere-Hours (x3)	104
Electrical Power Subsystem.Power Control & Distribution Electronics (PCDE)	105
Electrical Power Subsystem.Solar Array, Multi-junction GaInP/GaAs 3500 Watts EOL	106
Ground Segment	
Central Processing Facility	107

I. TICAS OPTICAL SUBSYSTEM



J. ELECTRICAL POWER PROFILE FOR BAC AND PC IMAGE COLLECTION





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