A Conceptual Methodology for Assessing Acquisition Requirements Robustness against Technology Uncertainties

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A Conceptual Methodology for Assessing Acquisition Requirements Robustness against Technology Uncertainties

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For Mom and Dad:

Xiè xie ni men

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

AA	Anti-Aircraft
ABM&S	Agent-based modeling & simulation
AEW&C	Airborne Early Warning and Control
AF	Air Frame
AFRL	Air Force Research Laboratory
ANN	Artificial Neural Network
AoA	Analysis of Alternatives
AoA	Activity on Arrow
AoN	Activity on Node
ASDL	Aerospace Systems Design Laboratory
BRAINN	Basic Regression Analysis for Integrated Neural Networks
CC	Command Center
CDF	Cumulative Distribution Function
CJCSI	Chairman of the Joint Chiefs of Staff Instruction
CJCSM	Chairman of the Joint Chiefs of Staff Manual
CLIs	Command Line Interfaces
CONOPS	Concept of Operations
CPM	Critical Path Method
CTEs	Critical Technology Elements
DARPA	Defense Advanced Research Projects Agency

DD	Degree of Difficulty
DES	Discrete Event Simulation
DMs	Decision-Makers
DoD	Department of Defense
DoDAF	Department of Defense Architecture Framework
DoE	Design of Experiments
DOTMLPF	Doctrine, Organization, Training, Materiel, Leadership and education, Personnel, and Facilities
DSS	Decision Support System
EM	Electromagnetic
EMD	Engineering and Manufacturing Development
ENTERPRISE	ENhanced TEchnology Robustness Prediction and RISk Evaluation
EW	Electronic Warfare
FAA	Functional Area Analysis
FLOPS	Flight Optimization System
FNA	Functional Needs Analysis
FSA	Functional Solutions Analysis
GT	Georgia Institute of Technology
IADS	Integrated Air Defense System
INCOSE	International Council on Systems Engineering
IPPD	Integrated Product and Process Development
IR	Intelligence & Reconnaissance
IRL	Integration Readiness Level

JCIDS	Joint Capabilities Integration and Development System
JDCS	Joint Defense Capabilities Study
JDCT	Joint Defense Capabilities Team
JIC	Joint Integrating Concept
JOA	Joint Operations Area
JROC	Joint Requirements Oversight Council
KPPs	Key Performance Parameters
L/D	Lift to Drag
LHC	Latin Hyper Cube
LOS	Line of Sight
M&S	Modeling & Simulation
MADM	Multi-Attribute Decision Making
MCDM	Multi-Criteria Decision Making
MCS	Monte Carlo Simulation
MDA	Milestone Decision Authority
MDAPs	Major Defense Acquisition Programs
MFE	Model Fit Error
MODM	Multi-Objective Decision Making
MOEs	Measures of Effectiveness
MRE	Model Representation Error
MRL	Manufacturing Readiness Level
MSA	Materiel Solutions Analysis

NASA	National Aeronautics and Space Administration
OEC	Overall Evaluation Criterion
PERT	Program Evaluation and Review Technique
PGMs	Precision Guided Munitions
PMs	Program Managers
PR	Propulsion
PRL	Programmatic Readiness Level
QFD	Quality Functional Deployment
QTA	Quantitative Technology Assessment
RAMs	Radar Absorbent Materials
RGS	Requirements Generation System
RSEs	Response Surface Equations
RSM	Response Surface Methodology
SAM	Surface-to-Air Missile
SEAD	Suppression of Enemy Air Defenses
SEAS	System Effectiveness Analysis Simulation
SMEs	Subject Matter Experts
SMEs	Surrogate Modeling
SOAR	Strategy Optimization for the Allocation of Resources
SOCRATES	Simulation-based, Object-oriented, Capability-Focused, Real-Time Analytical Technology Evaluation for Systems-of-Systems
SoS	Systems-of-Systems
SRL	Systems Readiness Level

ST	Stealth
TDPM	Technology Development Planning and Management
TIES	Technology Identification, Evaluation, and Selection
TIM	Technology Impact Matrix
TMAT	Technology Metrics Assessment and Tracking
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TPMs	Technical Performance Measures
TPRI	Technology Performance Risk Index
TRA	Technology Readiness Assessment
TRL	Technology Readiness Level
U.S.C	United States Code
UCAS	Unmanned Combat Aircraft Systems
UCAS-SEAD DST	UCAS-SEAD Decision Support Tool
UCAS-SEAD TPOT	UCAS-SEAD Technology Portfolio Optimization Tool
VERT	Venture Evaluation and Review Technique
WBS	Work Breakdown Structures
WP	Weapons

SUMMARY

In recent years the United States has shifted from a *threat-based* acquisition policy that developed systems for countering specific threats to a *capabilities-based* strategy that emphasizes the acquisition of systems that provide critical national defense capabilities. This shift in policy, in theory, allows for the creation of an "optimal force" that is *robust* against current and future threats regardless of the tactics and scenario involved. In broad terms, *robustness* can be defined as the insensitivity of an outcome to "noise" or non-controlled variables. Within this context, the outcome is the successful achievement of defense strategies and the noise variables are tactics and scenarios that will be associated with current and future enemies.

Unfortunately, a lack of system capability, budget, and schedule robustness against technology performance and development uncertainties has led to major setbacks in recent acquisition programs. This lack of robustness stems from the fact that immature technologies have uncertainties in their expected performance, development cost, and schedule that cause to variations in system effectiveness and program development budget and schedule requirements. Unfortunately, the Technology Readiness Assessment process currently used by acquisition program managers and decision-makers to measure technology uncertainty during critical program decision junctions does not adequately capture the impact of technology performance and development uncertainty on program capability and development metrics. The Technology Readiness Level metric employed by the TRA to describe program technology elements uncertainties can only provide a qualitative and non-

descript estimation of the technology uncertainties. In order to assess program robustness, specifically requirements robustness, against technology performance and development uncertainties, a new process is needed. This process should provide acquisition program managers and decision-makers with the ability to assess or measure the robustness of program requirements against such uncertainties.

A literature review of techniques for forecasting technology performance and development uncertainties and subsequent impacts on capability, budget, and schedule requirements resulted in the conclusion that an analysis process that coupled a probabilistic analysis technique such as Monte Carlo Simulations with quantitative and parametric models of technology performance impact and technology development time and cost requirements would allow the probabilities of meeting specific constraints of these requirements to be established. These probabilities of requirements success metrics can then be used as a quantitative and probabilistic measure of program requirements robustness against technology uncertainties. Combined with a Multi-Objective Genetic Algorithm optimization process and computer-based Decision Support System, critical information regarding requirements robustness against technology uncertainties can be captured and quantified for acquisition decision-makers. This results in a more informed and justifiable selection of program technologies during initial program definition as well as formulation of program development and risk management strategies.

To meet the stated research objective, the ENhanced TEchnology Robustness Prediction and RISk Evaluation (ENTERPRISE) methodology was formulated to provide a structured and transparent process for integrating these enabling techniques to provide a probabilistic and quantitative assessment of acquisition program requirements robustness against technology performance and development uncertainties. In order to demonstrate the capabilities of the ENTERPRISE method and test the research Hypotheses, an demonstration application of this method was performed on a notional program for acquiring the *Carrier-based Suppression of Enemy Air Defenses* (SEAD) using *Unmanned Combat Aircraft Systems* (UCAS) and their enabling technologies. The results of this implementation provided valuable insights regarding the benefits and inner workings of this methodology as well as its limitations that should be addressed in the future to narrow the gap between current state and the desired state.

CHAPTER 1 - INTRODUCTION

The United States "has [become] the dominant force in world politics" and few entities "in the international system [have] the capacity to challenge [the U.S.] for global leadership"[112]. Maintaining this superpower status requires the U.S. to continually "project its power, soft and hard, globally" [38]. The ability to project this power greatly depends on its military, arguably the most powerful military in the world despite having only the 8th largest troop size in the world:

Table 1 : Rank of Countries By Number of Troops [67]

Rank	Country	Active Troops	Reserves	Paramilitary	Total Troops
1	Iran	545,000	350,000	11,390,000	**12,285,000**
2	Vietnam	484,000	4,000,000	5,080,000	**9,564,000**
3	People's Republic of China	2,255,000	800,000	3,969,000	**7,024,000**
4	North Korea	1,106,000	4,700,000	189,000	**5,995,000**
5	Russia	1,037,000	2,400,000	359,100	**3,796,100**
6	India	1,325,000	1,155,000	1,293,300	**3,773,300**
7	South Korea	655,000	3,040,000	22,000	**3,717,000**
8	***United States***	***1,473,900***	***1,458,500***	***453,000***	***3,385,400***
9	Taiwan	290,000	1,653,500	22,000	**1,965,500**
10	Brazil	287,000	1,115,000	285,600	**1,687,600**

A key factor in the continuing dominance of the U.S. military is its emphasis on the development of technologically advanced systems that significantly enhance its effectiveness; a policy that dates back several decades.

At the height of the Cold War, the Soviet Union was capable of "producing some 1,300 new fighters a year," which was about "three to four times the [production rate] of the U.S. Air Force" [84]. In order to offset the Soviet Union's numerical superiority, the U.S. and its allies in western Europe had to be "prepared to fight and win out-numbered, both in the air and on the ground, through force multipliers" in the form of superior equipment [84]. The exploitation of advanced technologies provided such force multipliers.

Today, more than two decades after the breakup of the Soviet Union, the United States still continues its policy of sustaining and developing "key military advantages" in order to "dissuade potential adversaries from adopting threatening capabilities, methods, and ambitions" [167]. In order to maintain these advantages, however, the U.S. must continuously develop, and acquire technologically advanced systems for meeting current and future strategic objectives.

1.1 Current Defense Strategy Emphasizing Force Robustness

Developing and acquiring systems that meet current and future strategic objectives requires "peering ahead through the curtains of time; for a project started in the present will not be completed until sometime in the future, and the actual product will not be used until an even more remote time" [13]. Unfortunately, such programs are expensive and time consuming, averaging "16 to 18 years" [50]. Such an extended timeframe can lead to a situation where technologies that are state-of-the-art at program initiation may become obsolete by the time the new system becomes operational. Coupled with the fact that "certain needs of [the military] may not even be met by a system that is solely built with current technologies", it is clear that meeting future strategic objectives requires identifying and incorporating new technological solutions into future military systems [17].

In the past, military systems were developed using a "threat-based" strategy that acquired systems intended for countering specific, long-standing threats to national defense such as those posed by the Soviet Union. However, the attacks on September 11th, 2001, emphatically revealed to the U.S. a new generation of adversaries that threaten its national security. The Soviet Union and its massive Red Army were replaced by "shadowy networks of individuals [who] can bring great chaos and suffering to [the U.S.'s] shores for less than it costs to purchase a single tank" [107]. Operating with ever-changing tactics embedded within urban and mountainous environments, defeating these adversaries required a "'fundamental overhaul of the [U.S.] military" [99]. As part of this overhaul, systems built for "strategies of the past" would need to be replaced with a new generation of systems developed more suitable for today and tomorrow [34].

Unfortunately, recent patterns in defense spending have fallen "below [the] historical average" (see Figure 1) [153]. This means that the U.S. no longer has "the option of overwhelming force or an abundance of weapon systems to conduct war in the future" [34]. In order to meet current and future strategic objectives, focus must placed on the development and fielding of a single "optimal force to meet a wide variety of threats" rather multiple forces each specific to a "narrow set of threats" [71]. In other words, resources must be allocated in such a way that ensures the optimum return on strategic objectives.

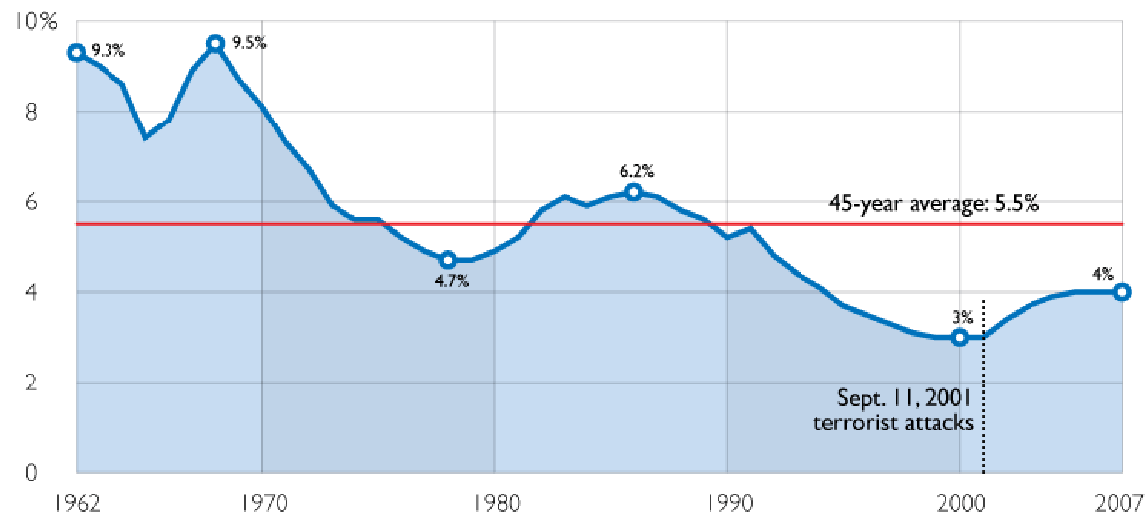

Figure 1: U.S. Defense Spending as Percentage of Gross Domestic Product 1962-2007 [170]

On September 30th, 2001, the Department of Defense (DoD) released the 2001 Quadrennial Defense Review. In this QDR, then Secretary of Defense Donald Rumsfeld outlined a new national defense strategy. This strategy, "built around the concept of shifting to a capabilities-based approach to defense," reflects the DoD's belief that "the United States cannot know with confidence what nation, combination of nations, or non-state actor will pose threats to vital U.S. interests or those of U.S. allies and friends decades from now" [127]. According to Secretary Rumsfeld:

> "A capabilities-based model – one that focuses more on how an adversary might fight rather than who the adversary might be and where a war might occur – broadens the strategic perspective. It requires identifying capabilities that U.S military forces will need to

> deter and defeat adversaries who will rely on surprise, deception, and asymmetric warfare to achieve their objectives " [127].

Based on this statement, it is clear that U.S. defense policymakers believe the shift to a capabilities-based defense and acquisition doctrine will allow the U.S. military to operate successfully against a wide spectrum of enemies, scenarios, and tactics. In other words, this shift will allow the DoD to design the future military to be *robust* or "capable of performing without failure under a wide range of conditions" [126].

1.1.1 Concept of Robustness

In product development and manufacturing, "robust design ensures product performances to be insensitive to various uncertainties and therefore results in high quality and productivity" [65]. It is based on the "fundamental principle…to improve product quality or stabilize performances by minimizing the effects of variations without eliminating their causes" [30]. According to Genichi Taguchi, one of the first pioneers of the robust design, a system is "robust" if it's *design* or controlled variable are set in such a way that the design requirements can still be met despite variations in the *noise* or uncontrolled factors [146; 180]. Within the current context, the controlled variables are the systems being acquired (via acquisition programs) and the noise factors are the enemies, scenarios, and tactics that these systems will be deployed against in order to meet the national defense requirements. A more detailed examination of this concept will be provided in the next chapter.

1.2 Technology Uncertainties Hampering Acquisition Robustness

In 2005, then Acting Deputy Secretary of Defense Gordon England commissioned an in-depth study of the acquisition process currently employed by the United State Department of Defense. As shown in Figure 2, this study was motivated by growing concerns over constant overruns in recent acquisition programs [41].

One of the main conclusions of this assessment was that acquisition program decision-makers (DMs) are not well-informed of the maturity of technologies that underlie achievement of the requirements or the impact it has on overall system effectiveness [14]. This lack of knowledge prevents DMs from understanding the impact of technology uncertainties on program capability, budget, and schedule requirements. As a result, recent acquisition programs have required longer and costlier development than previous programs, often spanning more than a decade [49; 50]. For example, recent major acquisition programs such as the F-22 *Raptor* stealth fighter and the RAH-66 *Comanche* helicopter have faced multiple setbacks caused by unexpectedly slow and difficult development of critical technologies [122; 123]. In fact, one of the contributing factors to the cancellation of the Comanche program was the lower-than-expect performance of its radars in detecting moving targets [53; 122].

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JUN -- 7 2005

MEMORANDUM FOR SECRETARIES OF THE MILITARY DEPARTMENTS
CHAIRMAN OF THE JOINT CHIEFS OF STAFF
UNDER SECRETARIES OF DEFENSE
COMMANDERS OF THE COMBATANT COMMANDS
ASSISTANT SECRETARIES OF DEFENSE
GENERAL COUNSEL OF THE DEPARTMENT OF DEFENSE
DIRECTOR, OPERATIONAL TEST AND EVALUATION
INSPECTOR GENERAL OF THE DEPARTMENT OF DEFENSE
ASSISTANTS TO THE SECRETARY OF DEFENSE
DIRECTOR, ADMINISTRATION AND MANAGEMENT
DIRECTOR, PROGRAM ANALYSIS AND EVALUATION
DIRECTOR, NET ASSESSMENT
DIRECTOR, FORCE TRANSFORMATION
DIRECTORS OF THE DEFENSE AGENCIES
DIRECTORS OF THE DOD FIELD ACTIVITIES

SUBJECT: Acquisition Action Plan

There is a growing and deep concern within the Congress and within the Department of Defense (DoD) Leadership Team about the DoD acquisition processes. Many programs continue to increase in cost and schedule even after multiple studies and recommendations that span the past 15 years. In addition, the DoD Inspector General has recently raised various acquisition management shortcomings.

By this memo, I am authorizing an integrated acquisition assessment to consider every aspect of acquisition, including requirements, organization, legal foundations (like Goldwater-Nichols), decision methodology, oversight, checks and balances – every aspect. The output of this effort, provided to me through the Under Secretary of Defense (Acquisition, Technology and Logistics), will be a recommended acquisition structure and processes with clear alignment of responsibility, authority and accountability. Simplicity is desirable.

This effort will be sponsored by the USAF with Dave Patterson as lead. The first action will be to establish a baseline of recommendations from earlier studies and to integrate all other acquisition reform activities into a single coordinated roadmap. This roadmap will determine the schedule to implementation and will be delivered to the DoD Leadership team within 30 days.

Restructuring acquisition is critical and essential. Accordingly, kindly cooperate fully with Dave in this assignment. Dave Patterson can be reached at (703) 695-8777. Thanks.

Gordon England
Acting Deputy Secretary of Defense

OSD 10870-05

Figure 2: Memorandum Authoring Assessment of U.S. DoD Acquisition Process [14; 41]

Table 2: Timeline of Recent Defense Acquisition Programs

Military System	Program Inception (Approximate)	Official Introduction
B-17 Flying Fortress	***1934***	***1938***
B-52 Stratofortress	***1945***	***1955***
B-2 Spirit	***1979***	***1997***
F/A-22 Raptor	***1986***	***2005***
F-35 Lightning II	***1996***	***2016 (tentative)***

As seen in Figure 3 below, technology development has inherent uncertainties that can only be reduced through development efforts that mature the technology. As a technology matures, so does the variability associated with its performance and development time and cost.

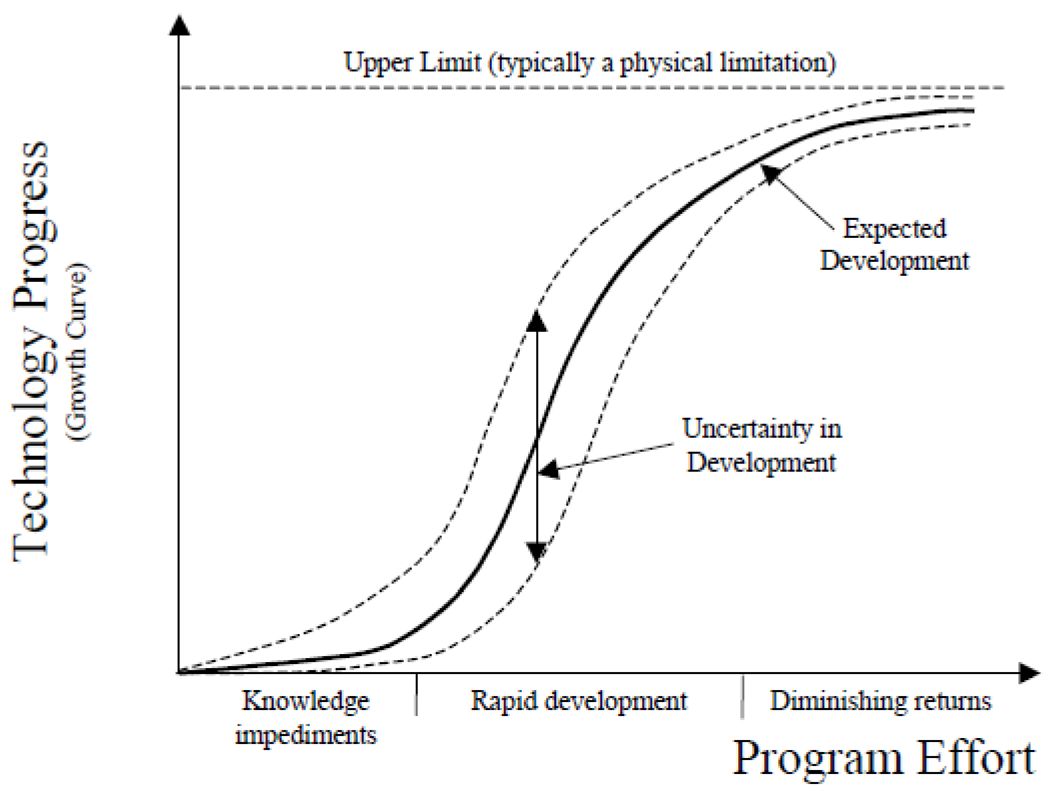


Figure 3: Generic Technology Development Growth Curve [92]

Unfortunately, the current state of U.S. and global economics, coupled with the identified trends in recent acquisition spending (Figure 1), prevents the DoD from developing all possible capability-enabling technologies before deciding which ones will be incorporated into future acquisition programs. As such, the uncertainties in the performance and development time and costs associated with program technologies must be captured for acquisition program mangers (PMs) and decision-makers early on in the acquisition lifecycle program requirements robustness against these uncertainties can be established.

1.3 Technology Readiness Assessment

In order to better capture the maturity and uncertainty levels of technologies for acquisition decision-makers, especially early on in the acquisition lifecycle, the DoD requires that all acquisition programs conduct a formal Technology Readiness Assessment (TRA) at Milestone B and Milestone C of the Defense Acquisition System (for ships, a preliminary assessment is also required at program initiation) [37]. The findings of these TRAs are used to support major program management decisions, most of which are made by Milestone B [31].

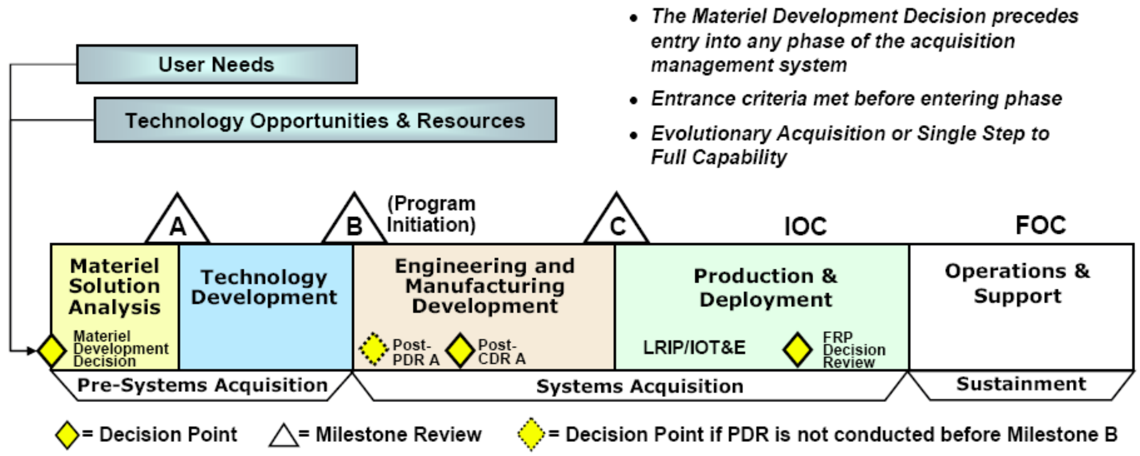


Figure 4: Overview of the Defense Acquisition System [168]

According to the *DoD Technology Readiness Assessment Deskbook*, the TRA is a "systematic, metrics-based process and accompanying report that assesses the maturity of certain technologies" [37]. It's goal is to "surface data and assess information" relevant to the maturity of the Critical Technology Elements (CTEs) in each acquisition program and report on "what has been accomplished to date" [35]. The findings of the TRA are then used by Program Managers and decision-makers to make critical program decisions such as resource allocation and risk management (Please refer to the *TRA Deskbook* for a more detailed overview of the TRA process) [37].

The metric used by the TRA to assess technology maturity is the Technology Readiness Level (TRL) scale. The TRL scale is a 9-level evaluation metric originally developed by the National Aeronautics and Space Administration (NASA) in the 1980s as a tool for supporting the subjective quantification of technology maturity and allows for the "consistent comparison of maturity between different types of technology" [175; 91]. It is "a common language for discussing and quantifying technology maturity" [182]. These levels, ranging from 1 to 9, "span the earliest stages of scientific investigation [Level 1] to the successful use in a system [Level 9]" [37]. Table 3 lists NASA's definitions for each level.

Table 3: NASA TRL Definition [91]

TRL Value	Capabilities Demonstrated
1	Basic principles observed and reported
2	Technology concept and/or application formulated
3	Analytical and experimental critical functions and/or characteristic proof-of-concept
4	Component and/or breadboard validation in laboratory environment
5	Component and/or breadboard validation in relevant environment
6	System/subsystem model or prototype demonstration in a relevant environment
7	System prototype demonstration in an operational environment
8	Actual system completed and qualified through test and demonstration
9	Actual system proven through successful mission operations

The TRL value for each CTE is established by collecting the development and performance data of each CTE and presenting them to independent reviews, who then decide on TRL of each CTE based on their interpretation of the provided data.

1.3.1 Role in Acquisition Decision-Making

The TRA is currently used to support nearly all major acquisition decision junctures, including all major milestone reviews. According to the *TRA Deskbook*,

> "Programs that enter the Engineering and Manufacturing Development (EMD) phase of the Defense Acquisition System and have immature technologies will incur cost growth and schedule slippage. Therefore, Title 10 United States Code (U.S.C.) Section 2366b requires, in part, that the Milestone Decision Authority (MDA) certify that the technology in Major Defense Acquisition Programs (MDAPs), including space MDAPS, has been demonstrated in a relevant environment (TRL 6) before Milestone B approval" [168].

Another TRA is conducted prior to Milestone C to serve as "a check that all [Critical Technology Elements] are maturing as planned" and reflect "the resolution of any technology deficiencies that arose during the EMD phase" [36]. Programs that receive Milestone C approval then enter the Production and Deployment phase. If one or more CTEs do not meet the TRL threshold, one of the following occurs [36]:

- Program restructured to use only CTEs at acceptable TRLs
- Program delayed to mature CTEs to acceptable TRLs
- Program requirements modified
- Program cancellation

This requirement, which can be waived under extraordinary circumstances involving national security, helps to reduce the likelihood of setbacks and overruns due to technology uncertainties throughout the acquisition process.

In addition to the two formal TRAs, DoD doctrine also recommends that an early evaluation of technology maturity be conducted before Milestone A during the Analysis of Alternatives (AoA) portion of the Materiel Solutions Analysis (MSA) phase to help "evaluate technology alternatives and risks" [37]. During the AoA, potential materiel solutions and their associated technology elements are evaluated "based on a cost-benefit" analysis comparing the impact on identified capability need(s) to the acquisition cost for each solution [37].

The mandated iterations of TRA throughout the acquisition lifecycle clearly indicate the importance of technology maturity and uncertainty information to acquisition decision-makers. This information not only helps program managers and decisions-makers decide which technologies should be developed for the program but is also used to assess the potential risks associated with technology development. However, the qualitative nature of the TRL metric limits its usefulness in informing decision-makers of the impact of technology uncertainties on program and system requirements robustness.

1.3.2 Limitations

Even though the findings of the TRA (i.e. the TRL values for the program CTEs) are used by acquisition program manager and decisions-makers for measuring and comparing the developmental progress of critical program technology elements, the TRL metric alone cannot give a complete picture of the risks involved in adopting a particular technology for the program and "should not be the sole means of discovering technology risk" [35]. The lack of correlation between uncertainties in the performance and development of program technologies prevents an informed assessment of requirements robustness against technology uncertainties.

1.3.2.1 Development Uncertainties

Technology development can be broken down into a set of activities that have to be completed in series and/or in parallel in order for the technology to reach full maturity. Unfortunately, the time and cost required to successfully complete each activity are uncertain ahead of time. These uncertainties "[result] in the possibility of exceeding initial estimates for cost and time and thereby exceeding the required cost and time for the [program]" [85]. Capturing these uncertainties ahead of time would better inform the program manager and decision-makers of the impacts of technology development uncertainties on program budget and schedule. The TRL metric by itself does not describe these uncertainties and cannot be used to account for the variations in program budget or schedule caused by these uncertainties.

1.3.2.2 Performance Uncertainties

The change to capabilities-based acquisition is partly motivated by the fact that the military no longer has "the option of overwhelming force or an abundance of weapon systems to conduct war in the future" [34]. Instead of developing systems that are specific only to a "narrow set of threats," emphasis is now placed on fielding a single "optimal force to meet a wide variety of threats" [71]. Since the overall capabilities of this force depend on the capabilities of its component assets, which in turn depend on the performance of their component technology systems, uncertainties in the performance of the individual technology systems that make up each asset will translate to variations in overall system capability (and thus overall force capability). Once again the TRL metric is limited in capturing these relationships for acquisition decision-makers. The qualitative nature of the TRL metric makes it impossible to quantify the variations in system capabilities caused by technology performance uncertainties.

Clearly, an assessment of technology uncertainty levels and subsequent impacts on program requirements is not only useful but necessary for informed decision-making through the acquisition process. During the Analysis of Alternatives, information regarding the amount/degree of uncertainty associated with candidate technology solutions can help decision-makers identify the combination of capability-enabling technologies that best meet program capability, budget, and schedule requirements. The technology portfolio that ensures the highest likelihood of program success (i.e. meet requirements) once technology uncertainties have been taken into account is therefore the most "robust" solution for that program.

During periodic program reviews, the assessed robustness (i.e. sensitivity/insensitivity) of program requirements against technology uncertainties can help identify potential areas of risk and formulate the necessary strategies for minimizing/eliminating these risks.

In its current form, the TRA process (specifically the use of the Technology Readiness Level metric) cannot capture the impact technology performance and development uncertainties have on program capability, budget, and schedule requirements. As a result, decision-makers are still not sufficiently informed of the risks and consequences of technology immaturity.

1.4 Research Objective

Current defense acquisition policy emphasizes the acquisition of systems that provide capabilities crucial to national defense and are robust against current and future threats under varying scenarios, objectives, and tactics. Unfortunately, performance and development uncertainties associated with the technologies being developed and implemented for these systems have resulted in undesirable variations in the budget, schedule, and effectiveness of recent acquisition programs. To better inform acquisition decision-makers of the uncertainties associated with the Critical Technology Elements of each program, the DoD currently requires a Technology Readiness Assessment to be conducted at critical decision points early on in the acquisition lifecycle. The results of the TRA are used to support technology evaluation and selection during the Analysis of Alternatives phase of the acquisition lifecycle as well as periodic program reviews conducted for assessing program development progress and developing risk mitigation/management strategies.

Unfortunately, the Technology Readiness Level metric currently employed by the TRA does not lend itself well to capturing impacts of technology uncertainties on program requirements and thus prevents acquisition decision-makers from assessing program robustness against such uncertainties. The ability to capture and quantify these impacts on program capability, budget, and schedule requirements and the resulting variations in them would greatly enhance acquisition decision-making and result in more robust defense systems. As such, the objective of this research is:

> ***Research Objective: Develop an approach for assessing the robustness of acquisition capability, budget, and schedule requirements against the performance and development uncertainties associated with immature program technologies in support of early phase acquisition decision-making.***

Because of the varied and complex nature of defense acquisition, it is probable that multiple iterations of method formulation/refinement are required to create a valid, defensible requirements robustness assessment methodology for acquisition decision-making. Since such an undertaking would require more resources than those available/expected for a single Ph.D. thesis, the focus of this work is to propose a general approach that narrows the gap between the current state-of-the-art and the desired end-state.

1.4.1 Research Questions

The Research Questions posed and will be addressed in this thesis are as follows:

Research Question I

> ***How can the impact of technology performance and development uncertainties on capability, budget, and schedule requirements be quantified to provide acquisition decision-***

makers with a more informed assessment of program robustness?

<u>Research Question II</u>

How can a program technology development portfolio that is robust against technology performance and development uncertainties be identified?

<u>Research Question III</u>

How should program requirements robustness data be presented to the decision-makers so that it is informative and useful for acquisition decision-making?

The first RQ addresses the issue of how technology performance and development uncertainties can be captured for acquisition decision-makers and is directly related to the research motivation. The second RQ comes from the fact that results of such an analysis are used during the Analysis of Alternatives pre-Milestone A of the acquisition lifecycle to evaluate and select candidate program technologies. The third and final Research Question stems from the fact that acquisition decision-making is a difficult undertaking that requires taking into account a myriad of information and analysis results. This data must be presented in a timely, efficient, and intuitive manner so that the DMs can identify the relevant information they need in order to make critical program decisions.

1.5 Research Overview

This document is organized into seven chapters. In Chapter 2 the author provides a discussion of the relevant theoretical background information pertaining to the Research Questions of this thesis. This includes relevant material regarding *robustness assessment*, *technology forecasting*, *multi-criteria decision-making*, and *analytical decision support* techniques.

Chapter 3 provides an examination of current implementations of the techniques discussed in Chapter 2 within the aerospace and acquisition communities. Strengths and limitations of each implementation are identified and used to formulate the Hypotheses listed in Chapter 4.

In Chapter 5, the author describes the formulated methodology for addressing the research motivation and questions identified in the previous section. This methodology provides a structured and transparent process for utilizing existing technology performance and development analysis techniques so that the variations in program capability, budget, and schedule requirements associated with technology uncertainties can be measured.

In Chapter 6, the proposed method is demonstrated on a notional proof-of-concept problem. This example application allows the performance/effectiveness of the proposed methodology in meeting the research objectives to be evaluated and Hypotheses tested. The final chapter summarizes the conclusions and observations drawn from this research and identifies potential areas for future work.

CHAPTER 2 - BACKGROUND

Chapter 1 identified the need for a more comprehensive assessment of acquisition program robustness against technology performance and development uncertainties. In this chapter, relevant background associated with the three Research Questions is provided. This information will be used in conjunction with the results of the benchmark assessment that will be conducted in Chapter 3 to construct the Hypotheses for this research.

2.1 Robustness Assessment

According to Fowlkes and Creveling, traditional robust assessment is conducted through statistical experiments [42]. This can be done by collecting data based on physical experimentation or with the help of computer-based modeling & simulation environments where mathematical models are used to generate the necessary robustness assessment data [30].

Two measures of robustness are typically used: *variance* and *percentile difference* [65]. The first approach calculates the variance σ^2 of a performance metric Y using the formula below:

$$\sigma_Y^2 = E\left[(Y - \mu_Y)^2\right] = \int_{-\infty}^{\infty} [g(\mathbf{x}) - \mu_Y]^2 f_{\mathbf{x}}(\mathbf{x}) d\mathbf{x}$$

(1)

Where μ_Y is the mean of Y, which is calculated by:

$$\mu_Y = E[Y] = \int_{-\infty}^{\infty} g(\mathbf{x}) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}$$

(2)

Where f_x is the joint probability density function of the random variables **X**, and E stands for the expectation operator [65]. The calculated variance values of the performance metric or metrics can then be used to assess the robustness of the system, with an inverse relationship between variance and robustness.

In 2004 a new robustness measure called *percentile difference* was proposed by Du and Chen [40]. In this approach, the percentile difference in the performance variations of Y is defined by:

$$\Delta y_{\alpha_1}^{\alpha_2} = y^{\alpha_2} - y^{\alpha_1}$$

(3)

Where y^{a1} and y^{a2} are two values of Y given by:

$$\text{Prob}\{Y \leq y^{\alpha_i}\} = \alpha_i \ \ (i = 1, 2)$$

(4) [16]

Where a_1 and a_2 are cumulative distribution functions of Y taken at 0.05/0.1 and 0.95/0.99, respectively.

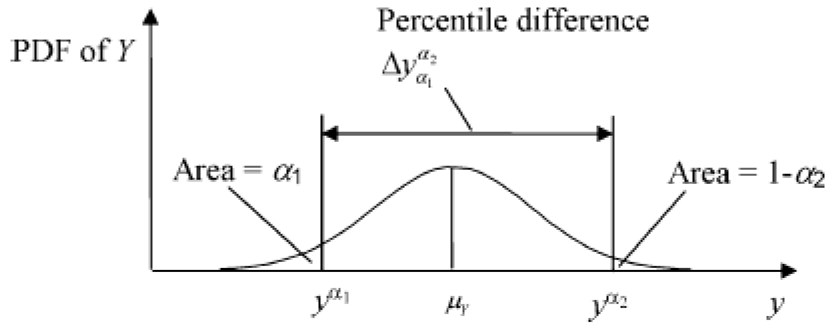


Figure 5: Illustration of the Percentile Difference Robustness Concept [65]

Similar to the *variance* technique, the robustness of the system is inversely proportional to the calculated percentile difference values. The lower the percentile difference values, the higher level of insensitivity the system has to noise variables and conditions and is therefore more robust.

Both of these techniques assume the robustness goal of minimizing variation around a desired mean performance metric *Y*. However, since acquisition program metric requirements typically have constraints placed on them (e.g. <$200M budget), they should be taken into account as part of the robustness assessment metric. For example, the percentile difference technique could be modified to show the percentile of the distribution that falls within acceptable ranges for each metric requirement constraint (the greater %, the better). The selection of the appropriate robustness assessment approach and evaluation metrics depends on the specific needs of each application. In general, physical experiments are unlikely to be suitable for early acquisition decision-support due to the time and resources required to conduct such experiments. In addition, the relatively immature state of the program means that candidate systems and technology subsystems are unlikely to be at a level appropriate for physical experimentation. As such, *forecasting* techniques are necessary for generating the necessary robustness assessment data.

2.2 Technology Forecasting

In order to assess the robustness of program capability, budget, and schedule metrics requirements against technology performance and development uncertainties, it is necessary to estimate the variations in the requirements caused by these uncertainties. However, as noted in the previous section, the immature nature of program technologies during the early phases of the acquisition lifecycle makes the application physical experimentation techniques for estimating these variations is both impractical and inappropriate. As such, *forecasting* techniques are typically used.

According to Twiss, the objective of forecasting "is to provide the means whereby a systematic approach can be applied to obtain a better view of the future, one that is sufficiently sound to give an adequate foundation for decision making" [160]. This view of the future provides decision makers with information that is useful or even necessary for critical decision-making activities such as risk assessment, project planning, and robustness assessment. Obviously, the ability to "predict" the future is extremely desirable not just to acquisition decision-makers but all decision makers in general. As such, forecasting techniques are used in a variety of fields including economics, biology, and even weather prediction. While there are many different forecasting techniques designed for various applications, almost all of them fall under one of two categories; qualitative or *judgmental* techniques and quantitative techniques.

2.2.1 Qualitative Techniques

Qualitative forecasting techniques, commonly referred to as j*udgmental forecasting*, rely on the opinions and judgments of relevant Subject Matter Experts (SMEs) to generate the required technology forecast data. These techniques can be applied when no historical or quantitative data is available and require relatively small amount of resources to implement. Three common techniques are examined in the proceeding sections.

2.2.1.1 Surveys

The simplest and most straightforward way of obtaining judgmental forecasting data is to have SMEs answer a set of survey questions and extract the relevant forecasting data from their answers. These surveys can be conducted in person, over the phone, by mail, or electronically (by email or online). Such techniques are commonly used in research fields such as marketing research and public opinion polls.

While surveys are an efficient and standardized way of collecting information from a larger number of respondents, the usefulness of the outputs depend on the reliability of the communications medium (e.g. lost mail, internet access, etc…) as well as the motivation and promptness of respondents on answering the survey questions. Also, if the survey questions are not formulated accurately and precisely with all of the assumptions laid out clearly, different respondents could have different interpretations of the questions and result in different responders providing answers that don't necessarily reflect the original intent of the survey.

2.2.1.2 Scenario Writing

In this approach, alternative outcome scenarios are identified for different sets of initial conditions and assumptions. The list of possible scenarios are then organized according to their likelihood of occurrence and presented to the decision-makers. Decisions are then made based on the results of each scenario and the likelihood of each scenario occurring.

For forecasting the impact of technology performance and development uncertainties on acquisition program metric requirements, application of this technique would require identifying potential levels of impact of each technology's performance and development uncertainties on each metric requirement. Aside from the fact that quantitative estimations of technology impacts are difficult to obtain from expert opinion alone, the sheer number of potential scenarios that have to be considered would make the process time-consuming and burdensome. The complexity and size of this analysis increases exponentially with the number of technologies and metric requirements being considered.

2.2.1.3 The Delphi Technique

The Delphi Technique was developed by the RAND Corporation to perform judgmental forecasting [124; 152]. According to Olaf Helmer, one of the developers of this technique:

> "The so-called Delphi Technique is a method for the systematic solicitation and collation of expert opinions. It is applicable whenever policies and plans have to be based on informed judgment, and thus to some extent to virtually any decision-making process" [60]

Under traditional open-forum discussions and debate consensus building activities, "certain psychological factors, such as specious persuasion, the unwillingness to abandon publicly expressed opinions, and the bandwagon effect of majority opinion" inject subjectivity and bias into the collected data [60]. During a Delphi technique application, direct debate is replaced by "a carefully designed program of sequential individual interrogations (best conducted by questionnaires) interspersed with information and opinion feedback derived by computed consensus from the earlier parts of the program" [60]. This means that participants have no knowledge of who else is participating or what their answers are (this also eliminates the requirement for them to be in geographical proximity with each other, an added plus).

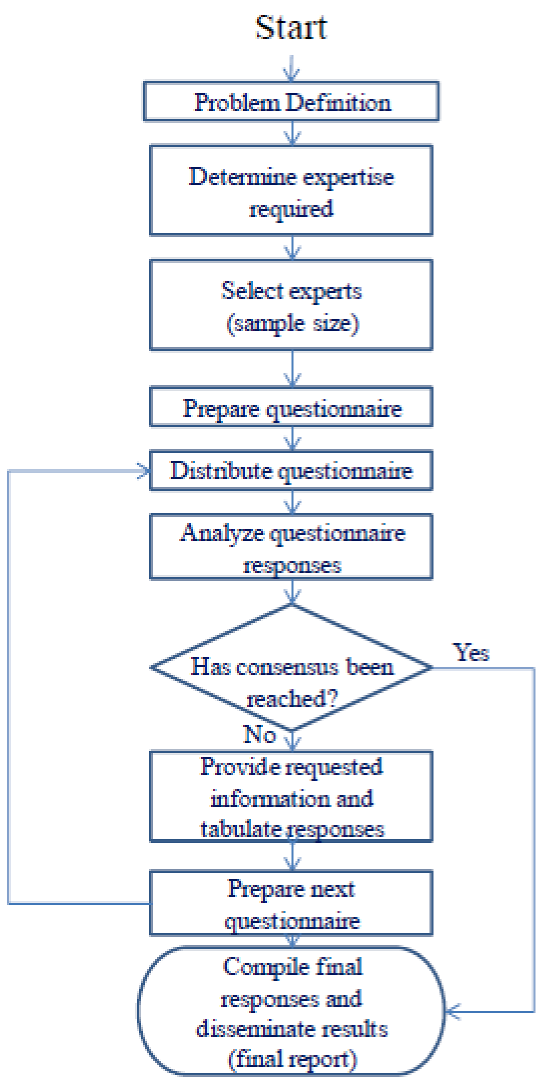


Figure 6: Delphi Technique Procedure [124]

The general process for following the Delphi technique is shown in Figure 6 above. The first few steps deal with defining the scope and breadth of the problem at hand and identifying the group of respondents that will be surveyed. Once the initial questionnaire has been sent out to the experts and their answers (including reasoning and assumptions) have been collected, the data is compiled and evaluated statistically for consensus. If consensus is reached the final outcomes are compiled and reported. On the other hand, if no consensus is reached, "another questionnaire is dispatched which not only includes the questions but also the statistics of the group and the reasons provided by the experts" [124]. The added information provides all respondents with potentially useful information that maybe only one or two had access to previously and can now be used by the group as a whole to refine their votes and "come to a common understanding" [124].

Generally speaking, the "Delphi [technique] is probably the most widely used technique for technology forecasting" [160]. It's popularity can be attributed to "the relative ease with which [the Delphi technique] can be conducted and "enables a wide range of people…to become involved" [160]. The fact that the output consensus data is "something that was arrived upon by all or majority of the members" and the iterative data gathering process that provides each voter with the reasoning and assumptions used by the other votes for their previous votes "provides a great amount of insight and traceability for the process by allowing planners to understand not only what consensus was reached by also what information framed that opinions" [124].

Typically, a Delphi technique is iterated up to 3 rounds with a voting group size between fifteen to forty respondents [160]. However, the number of rounds and voting group size needed to rigorously forecast the impact of technology performance and development uncertainties on program metric requirements could significantly increase due to the number of technologies typically considered for an acquisition program and the complexities associated with translating technology uncertainty to program requirement. Also, having full knowledge of the distribution of the rest of the votes will allow the participants to change their votes from an outlier to one that is more in line with the other respondents “simply to complete the exercise sooner” [124; 152].

In general, judgmental forecasting techniques are used when quantitative data is not available or prohibitively expensive. However, considering that many consider an ideal forecast to “be based solely upon numerical factual data linked to an explicit set of quantitative relationships and produced by a logic that yields consistent results”, they should be used only when quantification is not possible [160]. As such, quantitative technology forecasting techniques are examined in the next section so that their applicability for the problem at hand can be investigated.

2.2.2 Quantitative Techniques

Unlike the judgment-based techniques examined in the previous section, the techniques that will be examined in this section rely on gathered quantitative data to generate forecast data. Traditionally, historical data have been used to identify and establish trends and mathematical relationships for predicting future behaviors. However, with the advent of cheap and powerful computer processors, forecasting using computer-based modeling & simulation environments is becoming more and more common. This section will examine techniques from both approaches.

2.2.2.1 Time Series Forecasting

A *time series* is "a set of observations measured sequentially through time" with the measurement being made continuously or at discrete intervals [29]. According to Chatfield, the main objectives of time series analysis are [29]:

- *Description*: To describe the data using summary statistics and/or graphical methods. A time plot of the data is particularly valuable (see Figure 7).
- *Modeling*: To find a suitable statistical model to describe the data-generating process. A *univariate* model for a given variable is based only on past values of that variable while a *multivariate* model for a given variable may be based, not only on past values of that variable, but also on present and past values of other (predictor) variables. In the latter case, the variation in one series may help to *explain* the variation in another series.
- *Forecasting:* To estimate the future values of the series.
- *Control:* Good forecasts enable the analyst to take action so as to control a given process, whether it is an industrial process, or an economy or whatever.

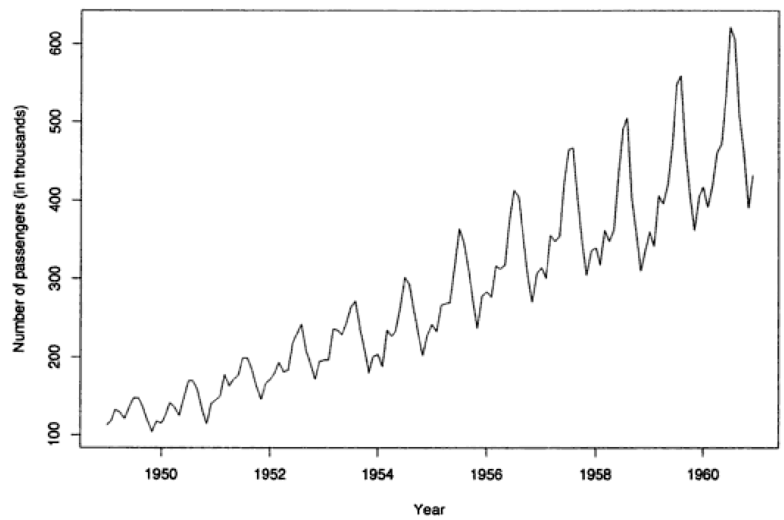


Figure 7: Example Time Series Plot of the Number of International Airline Passengers from 1949 to 1960 [29]

It should be noted that these objectives are interlinked with each objective being a prerequisite of the next objective (for example, *Description* and *Modeling* are prerequisites for a *Forecasting* time series analysis) [29].

In general, time series forecasting analysis relies on *trend projection*, *trend projection and seasonal variations*, or *smoothing* methods for generating forecast data.

2.2.2.1.1 Time Series Forecasting Using Trend Projection

This method uses the underlying long-term trend of a time series data to forecast its future values. It is typically used "when a series exhibits steady upward growth or a downward declines, at least over several successive time periods" [29]. An example of this type of behavior is the Consumer Price Index of medical care costs in the U.S.

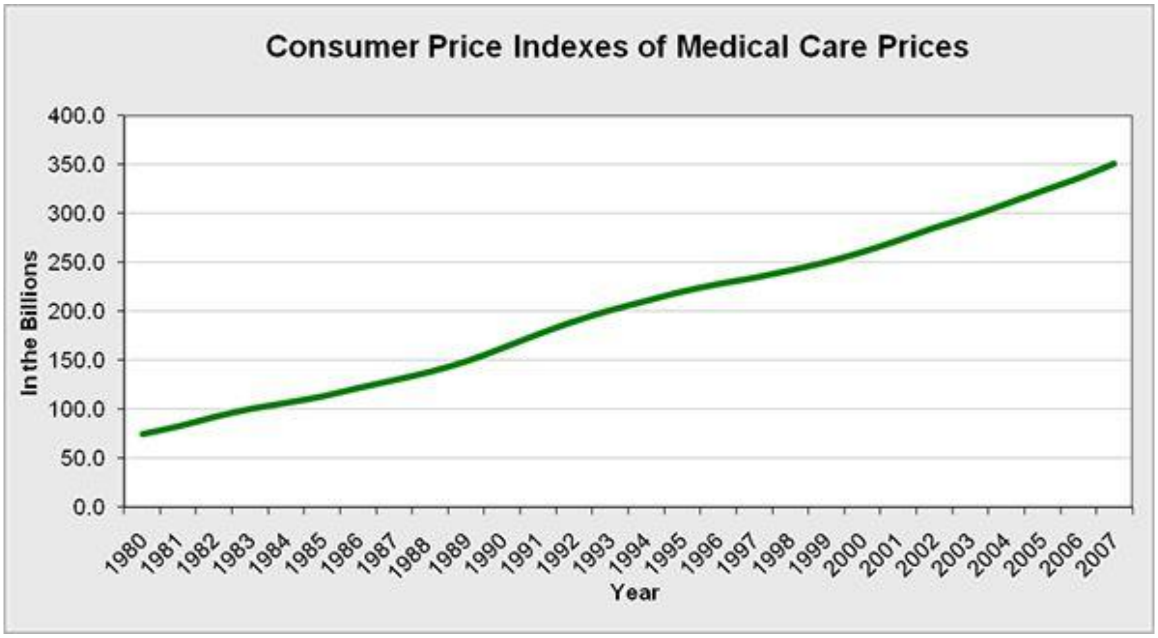


Figure 8: Example Time Series Plot with Steady Upward Trend [161]

In general, the behavior of a time series dataset is described using the following equation:

$$\mu_t = \alpha_t + \beta_t t$$

(5) [29]

Where:

- μ_t is the forecast value at time t
- α_t denotes the local intercept
- β_t denotes the local slope

The local intercept and local slopes are allowed to vary as a function of time in a stochastic fashion because it was "found that a deterministic linear trend rarely provides a satisfactory model for real data" [29]. In the past, these values were fixed because of the computational difficulties associated with their estimation but computer software now exist for estimating these values and provides a more accurate capturing of the time series data trends.

2.2.2.1.2 Time Series Forecasting Using Trend Projection with Seasonal Variations

In many instances, the behavior of time series data has consistent and repeated variations in its trend even though there is a general overall behavior is consistent (i.e. upwards/downwards). These variations are typically cyclic and repeat every X amount of time (years, months, weeks, or even days). For example, the ice cream sales are always much higher in the summer months than other months of the year and this seasonal variation occurs every year. The international airline passenger data from Figure 7 also exhibits seasonal variation behavior with peaks around the summer months and valleys in the winter months (typically the busiest and slowest months for international travel).

Typically, time series forecasting using trend projections with seasonal variations requires an iterative approach where preliminary estimates of the overall trend and seasonal variations are found separate (seasonal variations are first "removed" from the data), "typically with a fairly simple moving average" [29]. These estimates are revised using more sophisticated techniques such as *smoothing* (see next section) until more refined (i.e. accurate and precise) estimates are obtained.

2.2.2.1.3 Time Series Forecasting Using Smoothing Methods

In the situation where a time series dataset displays no statistically significant trends, cyclical, or seasonal behaviors, the time series is *smoothed* so it can be used to generate forecast data. Typically, this is done with the use of a *moving averages* method that uses the average of a number of previous data points or periods (typically a subset of the entire time series) to generate an average that is used to forecast the next data point value. It is called a "moving" average because as new data points are forecasted, they are added to the subset used to forecast future points while the oldest data points are removed from this set at the same time. For example, if a forecaster is using a time series moving average sampling size of 3 data points or periods, then the data point at future time t + 1 (time t being the current time) is calculated using the equation below:

$$X_{t+1} = \frac{X_{t-2} + X_{t-1} + X_t}{3}$$

(6)

Where

- X_{t+1} is the forecasted value at time t + 1
- X_{t-2} is the time series value from three time periods ago
- X_{t-1} is the time series value from two time periods ago
- X_{t-2} is the time series value from the previous time period

Once the new data point is generated, it can then be used to forecast the value at time t + 2 using the equation below:

$$X_{t+2} = \frac{X_{t-1} + X_t + X_{t+1}}{3}$$

(7)

Obviously, the accuracy of this approach depends on the length of time period (i.e. size of sample dataset) used to calculate the moving averages. Typically, iterative experiments are conducted ahead of time to identify the moving average sampling size that yields the highest accuracy for forecasts.

In addition to the approach described above, which is commonly referred to as a *simple moving average* technique, three other moving average techniques are commonly used to smooth time series data:

- *Cumulative moving average*
- *Weight moving average*
- *Exponential moving average*

These other technique different from the simple moving average technique in how the moving averages are calculated.

Generally speaking, the time series forecasting techniques do not appear to be suitable for predicting the variations in acquisition requirements caused by technology development and performance uncertainties. They focus solely on the temporal aspect of prediction (i.e. value of X will be Y at time Z) and thus cannot be used to forecast requirements variations under varying technology assumptions, scenarios, and other non-temporal parameters that significantly affect these variations. As such, other forecasting techniques that can take these additional parameters into account are needed.

2.2.2.2 Causal Forecasting

Causal forecasting techniques use the cause-and-effect relationship between the forecast variable and other variables or factors that affect its value. The most widely known method under this technique is called *regression analysis*, a statistical techniques used to develop a mathematical model of the relationships between a set of variables. These relationships can then be used to predict or forecast values for one or more variables within the set if the values of the other variables are known or assumed ahead of time. In this context, the variable that is being forecasted is call the *response variable* and the other variables are called the *independent* variables.

The simplest form of regression analysis is one that approximates a linear relationship between a response variable and a single independent variable. This is called a *simple linear regression*. In general, accurately forecasting complex behaviors such as the performance of aerospace systems requires regression against multiple independent variables (also commonly called parameters). A widely used technique for regressing against multiple independent variables is the *Response Surface Methodology*.

2.2.2.2.1 Response Surface Methodology

Response Surface Methodology (RSM) "comprises a group of statistical techniques for empirical model building and model exploitation. By careful design and analysis of experiments, it seeks to relate a response, or output variable to the levels of a number of predictors, or input variables, that affect it" [26]. It has been successfully implemented in chemical and mechanical engineering, chemistry, agriculture, and more recently aerospace systems design fields [25; 81; 93].

The RSM attempts to capture the behavior of a process or model using a polynomial equation:

$$R = b_o + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} b_{ij} x_i x_j + \varepsilon$$

(8)

Where:

- R is the dependent parameter (response) of interest
- b_i are regression coefficients for the first order terms
- b_{ii} are coefficients for the pure quadratic terms
- b_{ij} are the coefficients for the cross-product terms
- $x_{i,j}$ are the independent variables
- ε is the error associated with neglecting higher order effects

This equation is typically generated through the application of a *least squares* data fitting technique that identifies the set of coefficients and error/intercept term that minimizes the squares of the errors of the predicted data from the original regression data. The generated equations are generally referred to as *Response Surface Equations* (RSEs).

In general, the RSM is good for applications where the responses and parameters are homogenous and continuous in nature. However, they do not handle problems that involve both continuous and discrete behaviors in the responses and/or the input parameters.

Causal methods such as RSM appear more appropriate for the given problem than previously examined forecasting techniques because of their ability to capture the impact of multiple factors and parameters such as technology performance impact values and development time and costs on responses such as system effectiveness and development budget and schedule. However, generating the mathematical models for forecasting these responses requires regression against a dataset that contains information relevant to establishing the relationships between the responses and the independent variables. Depending on the technologies and acquisition requirements being considered, such data may or may not be readily available.

2.2.2.3 Artificial Intelligence Forecasting

In recent years, the exponential rise in the processing power of computers have led to the development of forecasting methods that rely on computer artificial intelligent or AI. These methods take in knowledge (either by training data sets or pre-coded algorithms and logical statements) and generate forecasts for a specific problem domain. Two commonly used AI forecasting techniques used in engineering applications are *Expert Systems* and *Artificial Neural Networks*

2.2.2.3.1 Expert System

An *Expert System* is an algorithm for making automatic decisions or predictions for a specific problem area in lieu of a human expert [141; 52]. On the surface, they appear to be analogous to traditional computer models that use mathematical and/or physical relationships to calculate desirable outputs. However, according to Siddall, Expert Systems are generally used instead of traditional computer modeling techniques when [141]:

- Physical modeling is not possible, and intuitive relationships are used for the predictions, provided by an expert in the field.
- There are a large number of inputs or variables that enter into the prediction.
- The relationships between the outputs and inputs, or in other terminology, between the dependent and independent variables, are all in the form of IF/THEN logic rules.

Expert systems was the first types of AI decision/prediction method to be successfully implemented, original in the field of medical diagnosis [141]. However, they have been adopted by other fields, including aerospace engineering fields [120; 143]. Depending on its implementation, an expert system can be made to produce qualitative *and/or* quantitative data. However, similar to previous methods, they require significant relevant expert knowledge and/or historical data in order to provide useful data. Such data can be scare regarding the impact of immature technology systems on acquisition requirements during the early phases of the acquisition lifecycle.

2.2.2.3.2 Artificial Neural Networks

An Artificial Neural Network (ANN) is a mathematical or computational prediction/forecasting model "based on the principles of neuron interaction in the brain" [1; 119]. This technique is based on the conjecture that "mimicking the low-level structure of the brain is the best way to achieve artificially intelligence" [72]. As such, an ANN typically consists of an interconnected group of *artificial nodes* and *neurons* analogous to the human nervous system that can be trained to perform a variety of tasks including data processing, data classification and pattern detection, robotics control, and regression analysis.

As discussed in the Section 2.2.2.2, regression analysis is a commonly used prediction/forecasting technique with the RSM being a popular regression approach. When regressing using an ANN, a set of filters called *hidden layers* are used to map the relationships between the set of responses (*output layer*) and input independent/input parameters (*input layer*). Within each hidden layer are *hidden nodes* which are analogous to neurons. Figure 9 below is an example diagram illustrating the connections for a single hidden layer ANN.

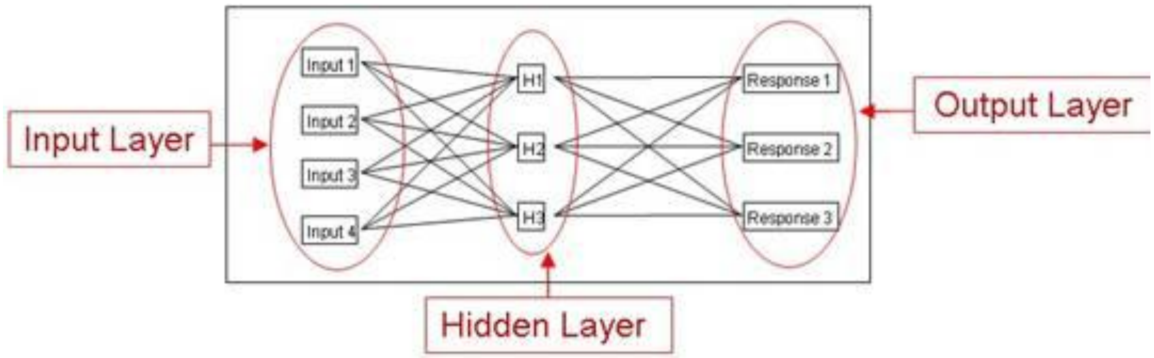


Figure 9: Conceptual Artificial Neural Network Diagram [72]

It should be noted that the correct number of hidden layers and nodes depends very much on the problem and is typically an iterative process that only concludes when the generated ANNs are within acceptable accuracy tolerances.

While the mathematics behind ANNs are quite complex are lie outside the domain of the current discussion, it should be noted that in general ANNs provide "an advantage over [RSM] because they have the ability to capture nonlinearities and will work with discrete inputs or outputs" [176]. As such, they are better suited for handling and predicting non-homogenous data and responses with both discrete and continuous elements. However, like all regression analysis techniques, they require training data. For this problem at hand this means representative data of the variations in acquisition metric requirements associated with technology performance and development uncertainties.

2.2.2.4 Simulation-based Forecasting

As has been stated repeatedly in the previous sections, quantitative forecasting techniques require relevant historical data to be available in order to be applicable.

However, such historical data is unlikely to exist during the early phases of a new acquisition program whose goal is to acquire capabilities not available with current assets. As such, judgmental techniques are typically used because of the availability of subject matter experts who can rely on their experiences and expertise to *extrapolate* the necessary forecast data. However, as computer processing power continue to grow exponentially, so does the fidelity of computer-based modeling & simulation environments that can simulate the performance and development of new systems and technologies without having to actually build them ahead of time. These environments rely on mathematical, physical, and/or logical relationship models to generate forecast data instead of relying on historical data, which allows them to potentially predict event that have not occurred previously but can possibly occur. The remainder of this section will examine three popular categories of computer-based models; *empirical relationship models*, *physics-based models*, and *discrete even simulations*.

2.2.2.4.1 Empirical Relationship Models

Empirical models are computer models based on information and data gained by means of observation, experience, or experiment. These models utilize empirical relationship formulas derived using experimental and observations to provide estimate output metrics. Examples of empirical models used by the aerospace/defense industry include Missile DATCOM and NASA's Flight Optimization System (FLOPS) code. Both of these models utilize equations regressed against historical data to calculate output system performance metrics such as weight and range [98]. Because of the reliance on historical data, these models are well suited for forecasting the performance and development of technologies similar or derived from existing one and whose performance parameter fall within the range of values used to generate the empirical relationships. However, for novel technological systems who are drastically different from existing systems or whose performance parameters cannot be interpolated using empirical formulas, such formulations are not appropriate and require a different type of modeling technique.

2.2.2.4.2 Physics-based Models

Physics-based models operate by solving mathematical equations derived from the laws of physics. Their reliance on actual mathematical and physics-based relationships to calculate output metrics instead of empirical data makes them well suited for assessing novel solutions and concepts. Well known example of a physics-based models in the aerospace field are computations fluid dynamics models, which solve fluid dynamics equations for problems involving fluid flows [8]. Because of the reliance on governing physical laws, these methods are well-suited for capturing the physical interactions between a system and its environment (i.e. performance parameters such as speed, range, etc…) and the impact of technologies on these physical interactions.

While physics-based models are well suited for forecasting the physical metrics (e.g. speed, weight, drag, etc…) associated with a system and its technologies, it is limited in forecasting capabilities-based metrics which are scenario/mission objective dependent and are often affected by non-physical parameters such as human logic and judgment. In order to forecast the impact of technology performance and development on these metrics, the relationships between the physical performance metrics such as speed, weight, and payload and capabilities-based metrics such as percent of enemy killed and time to mission completion need to be established ahead of time. Unfortunately, these relationships can be extremely difficult to quantify and could result in qualitative relationships correlating system performance and capability.

2.2.2.4.3 Discrete Event Simulation

In recent years, the need to account for temporal and logical relationships in computer-based models has led to the development and use of discrete event simulations (DES). In a DES, the operation of a system is represented as a chronological sequence of events and each event "occurs at an instant in time and marks a change in the state in the system" [125]. The changes in the state of the system can be based on logical, temporal, and physical relationships and rules programmed into the DES. This approach is more appropriate for the simulating the impact of technologies on system effectiveness since it can be used to simulate the sequence of events during a military scenario and the changes in the states of the military systems and sub-systems caused by these events. This information can then be aggregated to describe the overall behavior of the simulation, which in this case would be the capability metrics associated with the mission. If the impact of technology infusion on system state variables can be established and defined, then the impact of technologies on overall mission level metrics can be captured. This provides an effective way of quantifying the impact of system technologies on scenario outputs.

An example of such a simulation is the System Effectiveness Analysis Simulation (SEAS) tool. SEAS is a "government-owned, agent-based military utility analysis tool sponsored by Air Force Space Command, Space and Missile Systems Center, Directorate of Developmental Planning (SMC/XR)… designed specifically to give military operations research analysts and decision makers a flexible means to quickly explore new warfighting capabilities" [137]. According to the creator of SEAS,

> "SEAS represents the latest in analytic simulation technology and offers a powerful agent-based modeling and simulation environment in which small-to large-scale joint warfighting scenarios can be constructed and explored to quantify the effectiveness of various system designs, architectures, and concept of operations (CONOPS). The ability to represent networked military units and platforms reacting and adapting to perception-based scenario dynamics in a 3-D physics-based Battlespace, makes SEAS ideally suited for exploring effects-based operations, network centric warfare, and transformational warfighting concepts [137]."

Based on these descriptions, DES environments like SEAS environment allows the analysts to directly forecast the impact of technology performance on system capability metric requirements and without pre-defining the relationships between physical performance metrics to mission/scenario capability metrics. Unfortunately, the downside of using a DES is the significant amount of computer coding and algorithms needed to produce a realistic simulation. This can require more time than available during early acquisition decision-making junctures. However, considering the amount of time and money typically associated with defense acquisition programs, this early upfront investment may be money and time well-spent.

Whether they are used by themselves or coupled with another forecasting technique (e.g. regression analysis, ANNs, etc…), computer-based models allows for quantitative forecasts to be generated even if there is insufficient or complete lack of historical and/or existing data. As the processing power of modern computers continue to grow, higher fidelity models that generate more accurate and realistic forecasts can be used. However, the creation and maintenance of these models can be time-consuming and costly. In addition, expert knowledge is still needed to ensure that the assumptions, relationships, and logic embedded within these models are valid. In general, this approach seems more appropriate for problems with little or no existing/historical data available but requires quantitative and objective forecasts. The need to forecast the impact of technology performance and development uncertainties on acquisition requirements fits this description.

2.2.3 Probabilistic Forecasting

For many forecasting problems, the inputs (assumptions, opinions, historical data, and model parameters) cannot be determined with absolutely certainty. The uncertainties associated with the forecast inputs carries over to the generated outputs and thus result in data that may or may not be valid. As such, these uncertainties must be accounted for when generating forecasts.

For forecasting techniques that rely on utilize qualitative, subjective data, input uncertainties can be described using *Possibility Theory* or *Fuzzy Logic* approaches [147; 188]. However, the qualitative nature of the data only allows for the uncertainties to be approximated, typically qualitatively (i.e. *very unlikely, unlikely, likely,* and *very likely*). While these approaches allow for some accounting of the uncertainties associated with forecasting inputs, it falls short in quantitatively and objectively describing the input uncertainties and their impact on output data. Thus it would not be possible to the quantitatively and objectively capture impact of technology performance and development uncertainties acquisition program requirements for robustness assessment. Such analysis requires *probabilistic forecasting.*

Unlike deterministic forecasting, where one value is generated for each metric being forecasted, probabilistic forecasting generates a set of potential values for each forecast metric *and* the probability of each value occurring. An obvious example of this is weather prediction. When one watches/reads the weather forecast, the information is presented in the form of a weather event paired with the probability of that event happening (e.g. 70% chance of rain, 30% chance of snow, etc…). This coupling of outcome scenarios with probability of occurrence for each outcome allows for more informed decisions (e.g. brings an umbrella; buy snow boots, etc…).

Generating probabilistic forecasting data requires a probabilistic analysis of the forecast environment. A widely used approach is *Monte Carlo Simulations*.

2.2.3.1 Monte Carlo Simulation

A Monte Carlo Simulation is a probabilistic analysis technique that allows uncertainty to be "modeled and its effects quantified" [95]. It is "the most accurate probabilistic technique to simulate reality, or uncertainty, by randomly generating values within a pre-specified range" [81]. These values are generated by "assigning probability estimates to the design, operational, or technological input parameters of an analysis code (within a range of interest)" [18]. This approach "guarantees that all values are kept as possible solutions" [18; 81]. Fox and Mavris suggest three "efficient" implementations of the Monte Carlo method with computer-based forecasting [43; 94]:

- Method I: Linkage of an analysis code with a Monte Carlo simulation
- Method II: Linkage of a meta-model of an analysis code with a Monte Carlo simulation
- Method III: Approximate the Monte Carlo with a Fast Probability Integration technique

The end result of each method is to generate the "cumulative distribution function (CDF) for each of the desired objectives or metrics" [81]. Figure 10 below is a graphical representation of these three methods:

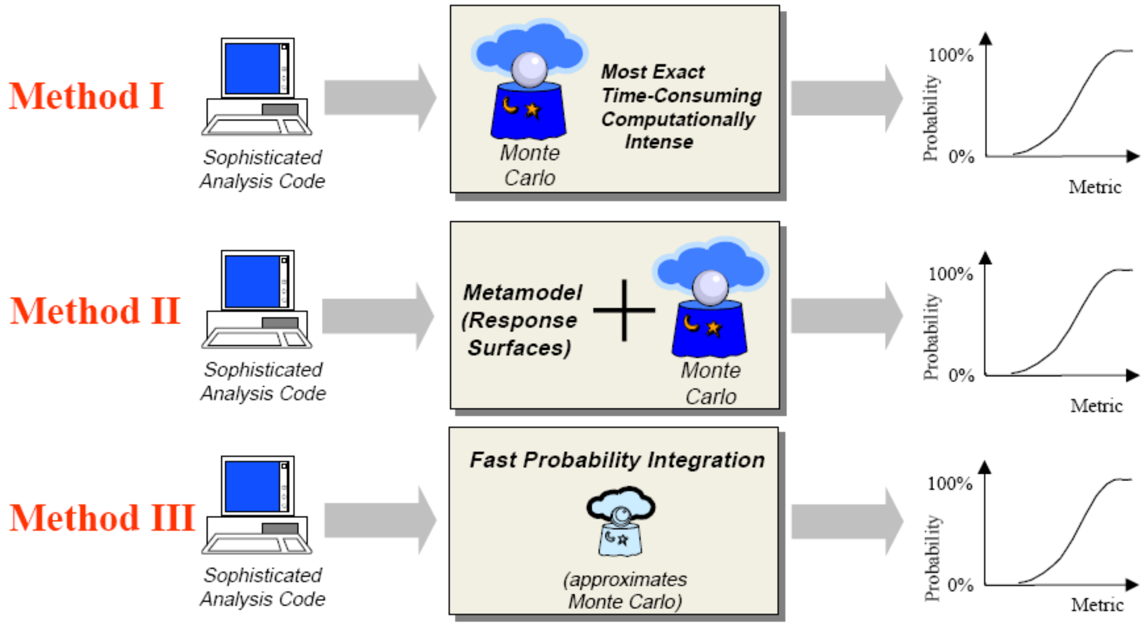


Figure 10: Monte Carlo Simulation Methods [81]

The Monte Carlo analysis method selected for conducting the probabilistic analysis depends greatly on the computational requirements of the analysis code/environments and the availability of processing power. For high-fidelity analysis codes such as a physics-based models that are computationally intensive, Method II is desirable. Two commonly used examples of SMs are response surface equations (see 2.2.2.2.1) and artificial neural networks (see 2.2.2.3.2). However, as is the case with all models, the price for this reduction is the loss in accuracy.

On the other hand, for quick-running models (empirical models methods typically requires far less computations resources because they are based on historical data and not physics-based formulations), Method I allows for the most exact and accurate uncertainty analysis. Regardless of the method selected, the accuracy and precision of the simulation results "is proportional to the square root of the number of [analysis samples] used" to generate the outputs [101]. Depending the specific application, this loss in accuracy can be insignificant when compared to the reductions in computational resources.

Clearly, a probabilistic forecasting of the impacts of technology performance and development uncertainties on program requirements is necessary in order to adequately capture the variations in the requirements for robustness assessment.

2.2.4 Conclusions

As stated earlier, the immature and uncertain state of program technologies during the early phases of an acquisition program requires makes conducting statistical robustness assessment difficult (and often impractical considering the potential time and resources required to conduct the large scale experiments necessary to generate such data). Therefore, techniques for forecasting technology performance and development impact on program requirements need to be considered.

Traditionally, such forecasts are made using judgmental methods that rely on subject matter expert opinions and experiences. These methods require only gathering and processing the opinions of relevant subject matter experts to determine the relationship between system capability and technology performance. However, the qualitative and inherently subjective nature of these relationships means that only imprecise uncertainty analysis techniques such as Possibility Theory or Fuzzy Logic can be used to capture the impact these uncertainties have on system capabilities [188]. While these imprecise uncertainty descriptors do provide a measure of uncertainty evaluation, their vague and subjective nature cannot provide acquisition decision-makers with adequate knowledge regarding the impacts of technology uncertainties on program requirements in order for them to make the necessary program decisions for ensuring robustness against technology uncertainties. However, the subjective and sometimes qualitative nature of these techniques leads to imprecise and biased forecasts. In order to provide acquisition decision-makers with quantitative and objective forecast data, quantitative techniques are needed.

Traditional quantitative forecasting techniques (time series forecasting, regression analysis, etc…) require existing and/or historical data to be available. Such data is unlikely to be available for a new acquisition program where one or more new technologies are being developed for a new or derivative system for novel applications with new requirements. In certain instances, however, it may be possible to correlate performance and development data from similar programs and applications in the past but these correlations are likely to be based on the opinions of subject matter experts and carry with them the same complications as all judgmental forecasting techniques. As such, more and more forecasting is done with computer-based modeling and simulation environments.

Computer-based modeling & simulation approaches to estimating technology impact on system performance/capability represent an effective compromise between the rapid efficiency of opinions-based methods and high-fidelity analysis of physical experiments. By combining the computational prowess of modern computers with the knowledge of relevant SMEs, computer models and simulations can be created to mimic the operations and behaviors of a system in relevant scenarios (as is done with physical experiments). The utilization of SME input during model creation and simulation set-up allows for their expertise is embedded into the analysis process while the computers can conduct multiple simulations under varying conditions and assumptions without requiring a single shot being fired or aircraft flown.

Even though these environments require significantly more upfront investment cost to create and maintain than judgmental or historical data-based techniques, they allow for more quantitative and objective forecasting. In addition, they can be coupled with probabilistic analysis techniques to capture the uncertainties associated with model inputs and describe the variations in model outputs associated with these uncertainties. For assessing acquisition requirements robustness, this means the potential variations in requirement metrics caused by technology performance and development uncertainties can be quantitative estimated and the resulting outputs can be used as a measure to assess the robustness of the program, its requirements, and technologies.

2.3 Portfolio Selection

One of the most important decisions during the early phases of defense acquisition is the selection of program technology development portfolio. The selection of the technologies in this portfolio occurs early on during the Analysis of Alternatives portion of the Materiel Solutions Analysis phase (Pre-Milestone A). During this process, proposed materiel solutions for achieving the desired capabilities and their associated technologies are evaluated and the solution that best meet program and decision-maker requirements is selected. The technology portfolio is then developed during the Technology Development phase and the program is officially initiated at Milestone B once this phase has been completed.

Generally speaking, during this process multiple candidate solutions are presented to decision-makers accompanied with their strengths and limitations. After each alternative has been evaluated, the optimal or most appropriate solution is selected. As is the case with most selection decisions, the optimality or "goodness" of each alternative requires examining its performance across a set of criteria or objectives and deciding which one performs the best overall. To assist decision-makers in identifying the best solution(s) out of a set of alternate solutions, *Multi-Attribute Decision Making* (MADM) techniques are typically used.

2.3.1 Multi-Attribute Decision Making

MADM techniques are typically used for problems that "involve the selection of the 'best' alternative from a pool of preselected alternatives described in terms of their attributes" [18]. These methods evaluate and score each alternative against a set of evaluation criteria and the solutions are ranked according to their scores. This ranking process helps decision-makers identify which alternative out of the set of candidate solutions best meets their requirements and preferences. Two commonly used MADM techniques are the Overall Evaluation Criterion (OEC) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).

2.3.1.1 Overall Evaluation Criterion (OEC)

The OEC technique is a simple and straightforward process that assigns a score to each alternative using the following equation:

$$F(x) = \sum_{i=1}^{n} w_i f_i(x) \tag{9}$$

Where:

- w_i is weight of criteria i
- f(x) is value of the criteria for the

This technique "provides a simple process for computing a score for each alternative in order to assign a corresponding ranking" [124]. However, "the simplicity of the OEC formulation also presents some drawbacks" [124]. The simple addition of scores to calculate the OEC for each alternative means that alternatives that perform extremely well in the heavily weighted criteria but score poorly in other criteria could have a very high OEC score while others whose perform equally well across all categories would have a less score even though "in actuality they are the more preferable solutions" [124].

2.3.1.2 Technique for Order Preference by Similarity to Ideal Solution

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) utilizes the Euclidean distance between each alternative and the "ideal" positive and negative alternatives to compute a score. The best alternative is the one who has the smallest distance to the positive "ideal" solution and the longest negative "ideal" solution.

The first step in the TOPSIS technique is to normalize each alternative's value for each criterion and is accomplished using the equation below:

$$r_{ji} = \frac{x_{ji}}{\sqrt{\sum_{j=1}^{M} x_{ji}^2}}$$

(10)

Where:

- N is the number of criterion
- M is the number of alternatives
- x_{ji} is the value of the jth alternative for the ith criterion
- r_{ji} is normalized value of the jth alternative against the ith criterion

Then the "idea" positive and negative values are calculated:

$$r_i^* = \frac{x_i^*}{\sqrt{\sum_{j=1}^{M} x_{ji}^2}}$$

(11)

$$r_i^- = \frac{x_i^-}{\sqrt{\sum_{j=1}^{M} x_{ji}^2}}$$

(12)

Where

- x_i^* is the maximum value for criteria i across all alternatives
- x_i^- is the minimum value for criteria i across all alternatives
- r_i^+ is the positive ideal value
- r_i^- is the negative ideal value

With the positive and negative "ideal" values calculated, the Euclidean linear distance for each alternative j, S_{j+} and S_{j-} respectively can be calculated using these equations:

$$S_{j+} = \sqrt{\sum_{i=1}^{N}(w_i r_{ji} - w_i r_i^{+})^2}$$

(13)

$$S_{j-} = \sqrt{\sum_{i=1}^{N}(w_i r_{ji} - w_i r_i^{-})^2}$$

(14)

The final scores of each alternative (c_j) can then be computed using:

$$c_j = \frac{S_{j-}}{S_{j+} - S_{j-}}$$

(15)

Using the TOPSIS method, the problem of selecting an alternative because it performs extremely well in only the heavily weighted criteria using an OEC is eliminated. The negative Euclidean distances for the non-heavily weighted criteria for these solutions will prevent it from being assigned a high rank/score.

Generally speaking, MADM techniques are most appropriate when the number of solutions has been pared down by previous down-select efforts and only a small subset of the original solution set is left, or there exist only a small number of solutions to begin with. Otherwise, if the initial solution set is very large or if no prior down-select has been conducted or is possible, every solution alternative needs to be evaluated and ranked. For problems involving a large number of alternatives, this full-factorial analysis is often impractical. In such instances, a more appropriate approach is to use *Multi-Objective Decision Making* (MODM) techniques to identify optimal solutions across the range of evaluation criteria or *objectives*.

2.3.2 Multi-Objective Decision Making

Unlike MADM techniques, which seek to rank a pool of alternatives based on their attributes, MODM techniques seek to "optimize a design of a concept in order to achieve optimal benefits" [17; 124]. In other words, MODM techniques generate the pool of alternatives that have an optimal balance between conflicting objectives. These optimizers seek to "find the best values for a variety of [parameters] which produce the best response" [124]. For the problem of optimizing a technology portfolio against a set of conflicting objectives, this means identifying the set or sets of technologies that best meet program capability, budget, and schedule requirements and constraints. This requires a multi-objective optimization technique that can handle the discrete and combinatorial nature of the problem while ensuring adequate sampling of the available design space. One particular approach, the Multi-Objective Genetic Algorithm (MOGA), has been shown to be particularly appropriate and effective in optimizing program technology portfolios.

2.3.2.1.1 Multi-Objective Genetic Algorithm

Genetic Algorithms are a group of search techniques used to find/search for solutions in an optimization problem. They are based "on the principles of the evolution via natural selection, employing a population of individuals that undergo selection in the presence of variation-inducing operators such as mutation and recombination (crossover)" [51]. GAs "attempt to utilize these same processes to optimize a solution for a given mathematical problem" [124]. This concept was invented by John Holland and developed by him and his students, whose efforts culminated in Holland's book; *Adaption in Natural and Artificial System* [63].

At the heart of the GA optimization technique is the *chromosome* associated with each member of the population. Each member's chromosome "represents the settings of the independent variables of the optimization and a separate solution to the problem" represented by that member [124]. These settings are used to calculate the *fitness* of each member during the GA selection process. Members that are more fit "reproduce in greater numbers and are a dominant species while those that are less fit die off and become extinct" during the GA selection process [124]. In theory, after multiple iterations of this process only members whose chromosomes represent the optimal settings for the problem at hand will survive.

The generic steps involved in a GA selection are depicted in Figure 11 below:

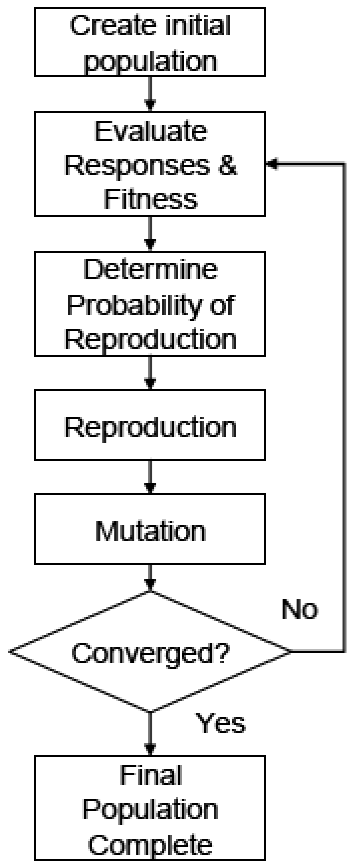


Figure 11: Generic Genetic Algorithm Process Flowchart [124]

At the beginning of a GA selection/optimization process, an initial population is created by randomly generating a pre-determined number of chromosome settings (it should be noted that the number of chromosomes in the population will remain constant throughout the entire process). According to Gen and Cheng, chromosome are typically represented as a binary string so that the evolutionary processes that are applied to each member of population throughout the GA process are easier to implement [48]. Once the initial population has been created, the fitness of each member is calculated and used to determine the probability of reproduction for each member.

Once each member's fitness and probability of reproduction have been established, offsprings of the initial population are created by randomly selecting two parents and mixing parts of their chromosomes (the probability that a member will be chosen to reproduce depends on its probability of reproduction determined in the previous step). Figure 12 below shows how two offsprings are generated from two parents using *genetic crossover*.

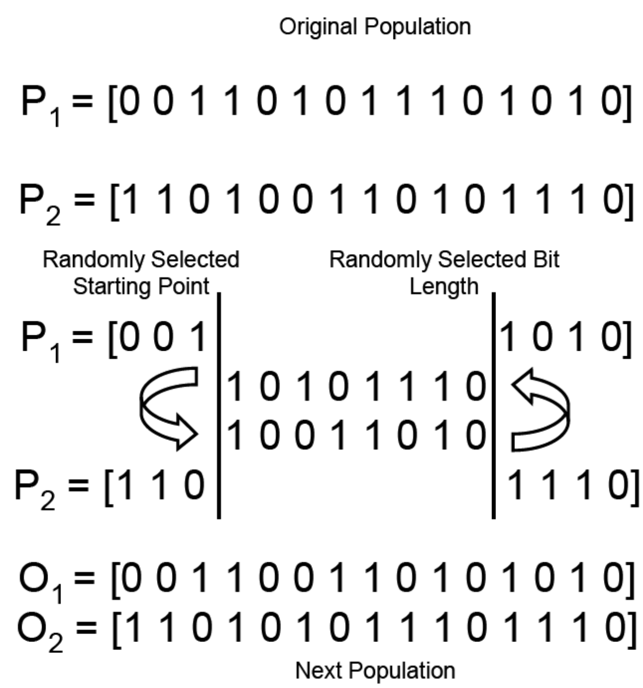


Figure 12: Genetic Algorithm Crossover Reproduction

The process depicted above is repeated until the number of offsprings is equal to the number of parents.

Typically, *reproduction* is followed by *mutation*, where members of the offspring population are randomly selected to have one or more bits in their chromosome switched to the opposite value (i.e. 0 to 1, 1 to 0). These genetic mutations "introduce traits into a population that otherwise would not exist" and encourage genetic diversity but introducing settings that were not part of the original chromosome population [124].

After *reproduction* and *mutation*, the fitness values of the new population is calculated and compared to the values from the previous population to determine if *convergence* has been achieved. If so, the process is complete. Otherwise, the probability of reproduction of the new population is established and *reproduction* and *mutation* and repeated. This entire process iterates until one or more convergence criteria have been met.

The most critical aspect of the GA optimization process is the determination of population member fitness value. While multiple approaches exist for doing this (see Table 4), these approaches fall within one of two general categories: fitness calculations using objective functions or Pareto dominance-based rankings.

Table 4: Popular Multi-Objective GA Implementations [82]

Algorithm	Fitness Assignment	Advantages	Disadvantages
VEGA	Each subpopulation is evaluated with respect to a different objective	First MOGA Straightforward implementation	Tend to converge to the extreme of each objective
MOGA	Pareto ranking	Simple extension of single objective GA	Usually slow convergences
WBGA	Weighted average of normalized objectives	Simple extension of single objective GA	Difficulties in nonconvex objective function space
NPGA	No fitness assignment, tournament selection	Very simple selection process with tournament selection	Problems related to selection of tournament size
RWGA	Weighted average of normalized objectives	Efficient and easy implement	Difficulties in nonconvex objective function space
PESA	No fitness assignment	Easy to implement, Computationally Efficient	Prior informationed needed about objective space
PAES	Pareto dominance is used to replace a parent if offspring dominates	Random mutation hillclimbing strategy; Easy to implement, Computationally Efficient	Not a population based approach
NSGA	Ranking based on non-domination sorting	Fast convergence	Problems related to selection of tournament size
NSGA-II	Ranking based on non-domination sorting	Single parameter (N), well tested, efficient	Problems related to selection of tournament size
SPEA	Raking based on the external archive of non-dominated solutions	Well tested, no parameters for clustering	Complex algorithm
SPEA-2	Strength of dominators	Improved SPEA, makes sure extremem points are preserved	Computationally expensive fitness and desnity calculation
RDGA	The problem reduced to bi-objective problem with solution rank and density as objectives	Dynamic cell update, robust with respect to the number of objetives	Difficult implementation
DMOEA	Cell-based ranking	Includes efficient techniques to update cell densitities, adaptive to set of GA parameters	Difficult implementation

2.3.2.1.1.1 Fitness Calculation Using Objective Functions

This approach combines the individual objective functions into a single composite function (or move all but one objective to the constraint set) and utilizes methods such as weighted sum or utility theory to calculate a single objective fitness for a given solution [82]. Both of these methods require a "proper selection of the weights or utility functions to characterize decision-maker preferences" [82]. For example, the classical GA fitness calculation scheme relies on a weighted sum approach that assigns a weight w_i to each normalized objective function $z'_i(x)$ so that the problem is converted to a single objective problem with a scalar objective function as follows [82]:

$$\min z = w_1 z_1'(x) + w_2 z_2'(x) + \cdots + w_k z_k'(x)$$

(16) [82]

Where:

- z_i' is the normalized objective function for the i^{th} objective for a given population member and
- Sum of w_i*'s* is 1

While straightforward and easy to implement, this approach requires the user to assign weights to each objective function ahead of time. Accurately capturing decision-maker preferences for each objective can be difficult, especially when the number of objective functions is large. Also, this approach results in only a single optimal solution being identified while most decision-makers want to be presented with a set of potential solutions. Generating such a set of candidate solutions would require the optimization to be run multiple times under different weighting scenarios.

2.3.2.1.1.2 Fitness Assignment Using Pareto-Rankings

Pareto-Ranking approaches "explicitly utilize the concept of Pareto dominance in evaluating fitness or assigning the selection probability to solutions" [82]. In this approach, the population is first ranked according to a dominance rule and then each solution is assigned a fitness value according to its rank in the population. The first use of such a technique was proposed by Goldberg and the procedure is as follows [54]:

- Step 1: Set $i = 1$ and $TP = P$
- Step 2: Identify non-dominated solutions in TP and assigned them set to Fi
- Step 3: Set $TP = TP*Fi$. If $TP = \emptyset$, go to Step 4, else set i = i + 1 and go to Step 2
- Step 4: For every solution x∈P at generation t, assign rank $r_1(x,t)=i$ *if* $x \in F_i$
- P is the current population and TP is a temporary population used by the procedure

In the procedure above, F_i's are called non-dominated fronts and F_1 is the Pareto front of population P [82].

A MOGA using a Pareto-ranking approach for fitness assignment results in the entire Pareto optimal solution set or a representative subset. This allows the decision-makers to see the sacrifices in one or more objectiveness that must be made in order to achieve improvements in one or more other objectives while still maintaining overall solution optimality. The solutions in this set can then be ranked/scored using a MADM technique to identify the solution that best meet decision-maker requirements and preferences.

Unfortunately, the process of identifying solutions on the Pareto Fronts is difficult to implement and convergence time significantly increases with number of objectives and possible number of unique population members (i.e. number of gene combinations). As such, implementing a Pareto-Ranking MOGA for a complex problem with many objectives such as acquisition program technology portfolio optimization requires significant computational resources and programming ability. Ultimately, the selected MOGA implementation should match the specific needs and requirements of a given optimization problem.

2.3.3 Conclusions

In order for program requirements to be robust against technology performance and development uncertainties, the impact of these uncertainties on program requirements must be taken into account during the technology portfolio selection process (i.e. during Analysis of Alternatives). Unfortunately, the conflicting nature of program capability, budget, and schedule requirements requires trading off between the robustness of these requirements for candidate solutions so that the best compromise can be identified. The problem is further complicated by the fact that in certain requirements will be emphasized more than others (e.g. stealth characteristics over payload).

For problems with multiple conflicting criteria such as this, a *Multi-Attribute Decision Making* technique can be used to streamline the selection process. This class of technique specializes in identifying the best solutions from a pool of solutions based on multiple evaluation criteria. However, in the absence of a preselected pool of solutions, these techniques require an evaluation of ALL possible solutions. For an acquisition problem with tens or even hundreds of possible technologies, the number of solutions that would have to be evaluated becomes unmanageable.

For problems concerned with choosing from a large, infinite, or uncountable number of alternatives *Multi-Objective Decision Making* techniques are preferred. As demonstrated by Raczynski, Multi-Objective Genetic Algorithm, a type of MODM technique, shows particular promise for identify candidate technology portfolios optimized to meet multiple requirements [124]. This technique implements process analogous to the selection, reproduction and mutation processes observed in evolution theory to identify the candidate or candidates that are most "fit." For optimization problems where the "solution landscape" is unknown ahead of time and multiple optimal solutions exist, a MOGA based technology selection approach is most appropriate and effective in identify optimal solutions for the decision-makers.

2.4 Decision Support

Thus far the background research has focused on techniques for generating data for supporting decisions (i.e. forecasting, selection, and optimization techniques). In order to be useful however, the generated analysis data need to be formatted and presented to acquisition decision-makers in a manner that maximizes their ability to extract the relevant trends and behaviors in the data and use that information to support their decisions. This information should be presented in a structured and intuitive manner so that acquisition decision-makers are not overwhelmed by the potentially large amount of data outputted by these analyses. Clearly, acquisition decision-support requires blending human decision elements with computer analysis data into a single structured decision-support framework that rapidly and efficiently present relevant data to the decision-makers. In today's computer-oriented society, this is commonly done using a computer-based Decision Support System (DSS).

2.4.1 Computer-based Decision Support Systems

A computer-based Decision Support System (DSS) is a software product that helps users apply analytical and scientific methods to decision making [20]. More specifically, it is an "interactive, flexible, and adaptable computer-based information system, especially developed for supporting the solution of a non-structured management problem for improved decision making"[158]. According to Keen and Scott-Morton:

> "the concept of [decision support systems] evolved from two main areas of research: the theoretical studies of organizational decision

> making done at the Carnegie Institute of Technology during the late 1950s and early 1960s, and the technical work on interactive computer systems, mainly carried out at the Massachusetts Institute of Technology in the 1960s"[79]

They first became popular as decision support tools "in the 1970's and 1980's with the rise in popularity of the desktop computer," which provided analysts with easy access to significant computing resources and "allowed for large data sets to be expressed in manageable formats which managers would more easily understand" [124]. According to Arnott and Pervan:

> "DSS theory stems from the belief that in making a decision there are both structured and unstructured elements. The structured elements are things such as the cost data or other numerical information which a computer is extremely efficient at process and understanding. The unstructured elements are those which cannot necessarily be quantified but greatly influence whether a project fails or succeeds, such as personnel interactions, organizational politics, and other qualitative ideas. These elements are best handled by a human so that a DSS does not attempt to solve the problem itself but, merely inform and aid the [decision-maker]" [12].

The commonly agreed-upon characteristics of a DSS are:

- *Designed specifically to facility decision processes* [7]

- *Support rather than automate decision-making* [7]
- *Be able to respond quickly to the changing needs of decision-makers* [7]
- *Incorporate both data and models* [157]
- *Strives to improve the effectiveness of the decisions, not the efficiency with which decisions are being made* [157]
- *Provide support for decision makers mainly in semi-structured and unstructured situations by bringing together human judgment and computerized information* [159]
- *Designed to interact directly with the decision maker in such a way that the user has a flexible choice and a sequence of knowledge-management activities* [64]

According to Raczynski, the use of a DSS "allows the planner and decision makers to have the information obtained throughout the [assessment process] placed in a single useable environment for tradeoffs and planning to occur" [124]

A DSS typically consists of three main components; a user-interface that provide the human-computer interaction, the database manager that "contains all the compiled information and dispenses it to various calculations and models", and the "models themselves which represent the data in various ways to determine underlying meaning which would not be evident from just visualizing the data itself directly" [124]. An effective DSS requires an efficient and seamless integration of all three components [11].

Arguably the most important aspect of a DSS is the design and layout of the user interface. After all, the purpose of the DSS is "not merely to simply display the data but also aid the decision maker by helping to visualize trends" [124]. In order words, rather than simply providing numerical tables or charts, a more effective way to "describe, explore and summarize [a set of data] is to look at a picture of those numbers" [156]. A good graphical representation can allow the information to be more easily recognizable to the decision-maker [124]. Ultimately, "the display of the information in the DSS should be based on what questions are being answered" [124]. The data and visualization should match the information needs of the user and the decision-makers in order for a DSS to aid and improve decision-making. An example is provided in Figure 13 of the user interface of a computer-based DSS created by Raczynski to support technology funding decisions for the U.S. Navy. The combination of the interactive and graphical elements of the DSS's user-interface allows decision-makers to be provided with the "reasons, causes, or explanations of events or decisions" [124]. While trends in the data can be used to provide these reasons, causes, or explanations, a "good graphical presentation can allow the information to be more easily recognizable to the decision maker"[124].

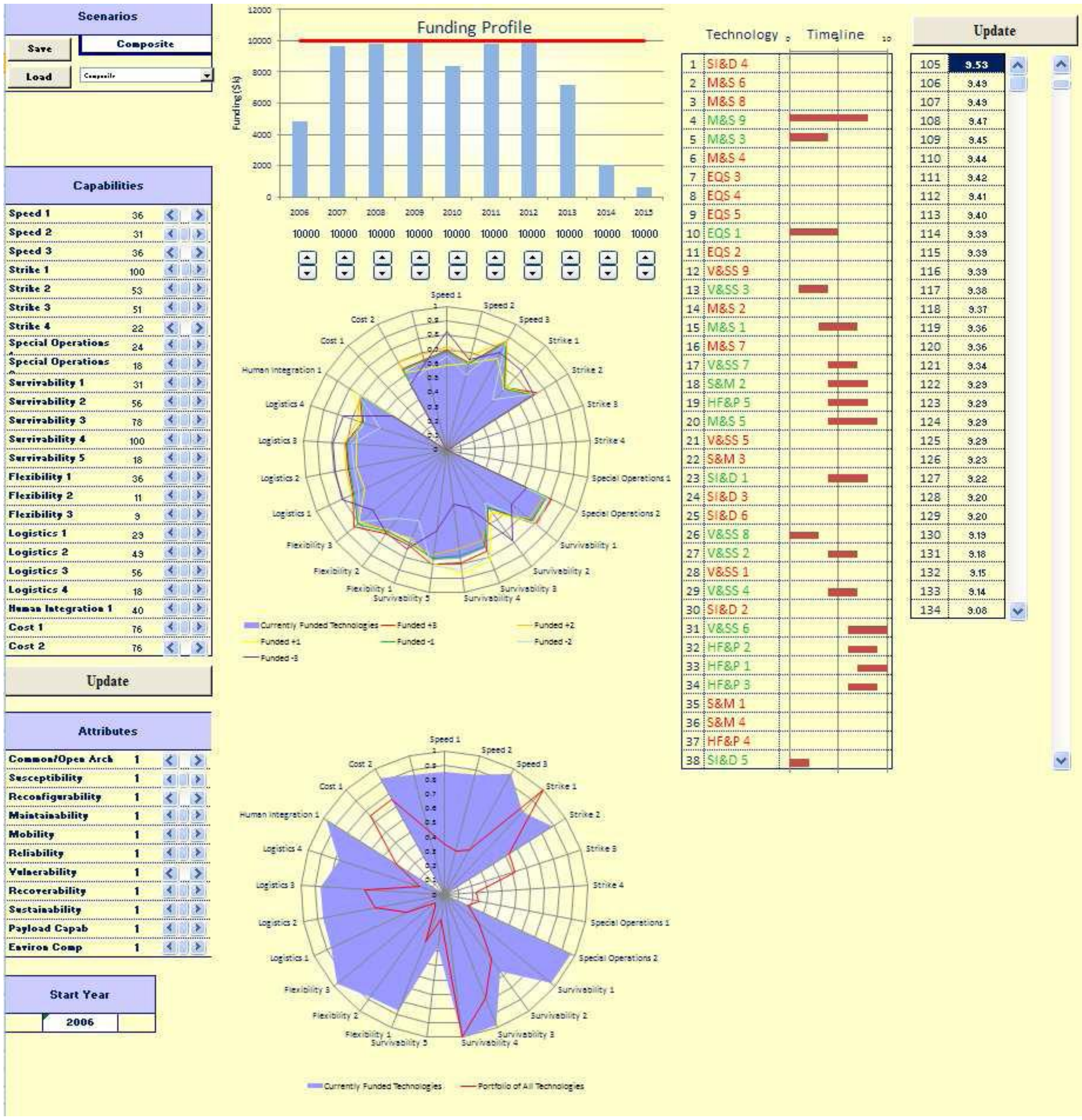


Figure 13: Example of a Computer-based Decision Support System Front-End User Interface [124]

2.4.2 Conclusions

The adage "a picture is worth a thousand words" refers to the idea that a complex idea that requires lengthy quantitative or qualitative explanations can be conveyed with a single image or graphic. Computer-based Decision Support Systems build on this concept by allowing for interactive quantitative, qualitative, and/or graphical elements displays to provide assist decision-makers in identifying the relevant information needed for their decisions. For early acquisition decision-support, the use of a computer-based DSS would assist decision-makers in evaluating the impact of technology performance and development uncertainties on program capability, budget, and schedule requirements in order to assess program robustness against such uncertainties. In addition, the interactive nature of a DSS would also allow DMs to assess program robustness against varying program requirements (i.e. changes in metric constraint values). This provides an assessment of program robustness against current and future program requirement uncertainties that enables DMs to better formulate program development and risk management strategies.

In the next chapter, current implementations of the techniques discussed chapter within the aerospace and acquisition communities are examined

CHAPTER 3 - BENCHMARKING

In the previous chapter, theoretical background material related to the research focus and associated Research Questions was provided and observations were drawn based on the material. In this chapter, current aerospace and acquisition implementations of some of the examined approaches are reviewed and evaluated. This *benchmarking* process will allow the gaps and limitations of existing techniques to be identified and be used as a starting point for the development of a conceptual robustness assessment methodology for supporting early phase acquisition decisions.

3.1 Air Force Research Laboratory Transition Readiness Calculator

The Air Force Research Laboratory (ARFL) Transition Readiness Level Calculator is a Microsoft Excel-based assessment tool that takes the user through a series of questions for a given technology and based on the user's answers, calculates the resulting TRL value of the given technology. The process is repeated for each technology to determine the TRLs for a set of technologies. Figure 14 is a snapshot of the summary screen for the AFRL TRL Calculator.

The TRL Calculator provides a straightforward and standardized way for assessing technology maturity. The use of a standard set of survey questions ensures that each technology will be evaluated "equally." The portability of the Calculator allows multiple sources to be surveyed, increasing efficiency. Because the TRL only represents "one dimension of technology maturity" and "measuring technology maturity is a multi-dimensional problem, " the assessment tool includes two additional technology maturity dimensions: the Manufacturing Readiness Level (MRL) and the Programmatic Readiness Level (PRL) [110].

While the inclusion of the MRL and PRL metrics helps make the AFRL Transition Readiness Level Calculator, like the TRL metric, it can describe the current development status of technologies and does not provide a clear and direct way of forecasting the uncertainties and risks associated with each technology.

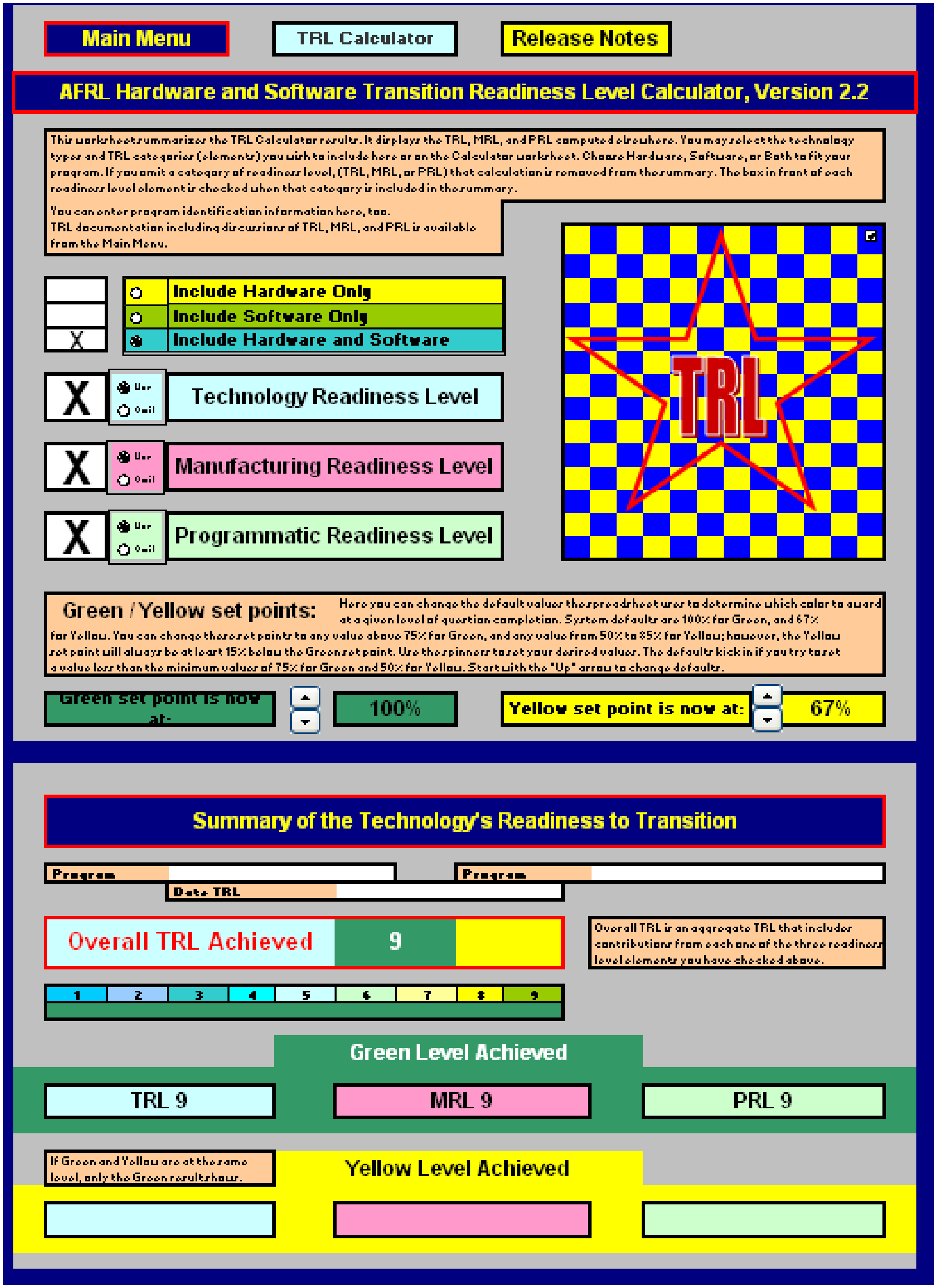


Figure 14 : A Snapshot of AFRL TRL Calculator Main Screen [109]

3.2 Systems Readiness Level

The Systems Readiness Level (SRL) scale, developed at the Stevens Institute of Technology by Sauser, Ramirez-Marquez, Magnaye, and Tan, expands the TRL concept to the systems level. It incorporates the TRL scale with the Integration Readiness Level (IRL) to "provide an assessment of overall system development" in order to "identify potential areas that require further work to facilitate prioritization" [132]. The IRL scale, also developed at the Stevens Institute, is designed to reflect the "interfacing of compatible interactions for various technologies and the consistent comparison of the maturity between integration points" [131]. Like the TRL, the IRL scale has nine values, with each increasing value representing higher levels of demonstrated integration. Table 5 below shows the definitions for each of the nine IRL values.

Table 5 : Integration Readiness Level Definition [55]

IRL	Definition
1	An Interface between technologies has been identified with sufficient detail to allow characterization of the relationship
2	There is some level of specificity to characterize the Interaction (i.e., ability to influence) between tech-nologies through their interface
3	There is Compatibility (i.e., com-mon language) between technologies to orderly and efficiently integrate and interact
4	There is sufficient detail in the Qual-ity and Assurance of the integration between technologies
5	There is sufficient Control between technologies necessary to establish, manage, and terminate the integration
6	The integrating technologies can Ac-cept, Translate, and Structure In-formation for its intended application
7	The integration of technologies has been Verified and Validated with sufficient detail to be actionable
8	Actual integration completed and Mission Qualified through test and demonstration in the system environment
9	Integration is Mission Proven through successful mission operations

The calculation of the SRL for a given system starts with the TRL and the IRL matrices. The TRL matrix, *[TRL]*, is an nx1 vector containing the TRL values for each of the technologies in the system:

$$[TRL]_{nx1} = \begin{bmatrix} TRL_1 \\ TRL_2 \\ \cdots \\ TRL_n \end{bmatrix}$$

(17)

Where TRL_i is the TRL value for technology i.

The IRL matrix, *[IRL]*, is a *nxn* matrix that "illustrates how the different technologies are integrated with each other from a system perspective" [132] :

$$[IRL]_{nxn} = \begin{bmatrix} IRL_{11} & IRL_{12} & \cdots & IRL_{1n} \\ IRL_{21} & IRL_{22} & \cdots & IRL_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ IRL_{n1} & IRL_{n2} & \cdots & IRL_{nn} \end{bmatrix}$$

(18)

Where IRL_{ij} is the IRL value between technologies i and j.

The values within the IRL matrix above represent "a systematic measurement of the interfacing of compatible interactions for various technologies and the consistent comparison of the maturity between integration points" [131].

Based on these two matrices, the SRL matrix, *[SRL]*, is determined by:

$$[SRL]_{nx1} = [IRL]_{nxn} \times [TRL]_{nx1}$$

(19)

Where *[SRL]* is a vector of SRL_i's, each representing the "readiness level [of technology i] with respect to every other technology in the system while also accounting for the development state of each technology through the TRL" [132].

To calculate the overall SRL value for the entire system, each SRL_i is normalized and summed:

$$SRL_{Overall} = \frac{\sum_{i=1}^{N} \frac{SRL_i}{n_i}}{N}$$

(20)

Where

- N is the total number of technologies
- n_i is the number of integrations with technology i plus its integration to itself.

The calculated value from (20, ranging from 0 to 1, can be used to "determine the maturity of a system and its status within a developmental lifecycle" [132]. Table 6 below show how the five ranges of SRL value corresponds to the Acquisition Lifecycle Phases.

Table 6 : Systems Readiness Level Definition

SRL Value	Acquisition Phase	Definition
0.90 to 1.00	Operations & Support	Execute a support program that meets operational support performance requirements and sustains the system in the most cost-effective manner over its total lifecycle
0.80 to 0.89	Production	Achieve operational capability that satisfies mission needs
0.60 to 0.79	System Development & Demonstration	Develop system capability or (increments thereof); reduce in-tegration and manufacturing risk; ensure operational support-ability; reduce logistics footprint; implement human systems integration; design for production; ensure affordability and protection of critical program information; and demonstrate system integration, interoperability, safety and utility
0.40 to 0.59	Technology Development	Reduce technology risks and determine appropriate set of technologies to integrate into a full system
0.10 to 0.39	Concept Refinement	Refine initial concept; develop system/technology strategy

The SRL scale offers a more comprehensive assessment of technologies by examining both the demonstrated maturity (TRL) and interoperability (IRL) of the technologies at the system level. However, like the AFRL Transition Readiness Level Calculator and the TRL metric, it only examines what's been accomplished thus far in the development of the system and its component technologies and does not provide a direct forecasting of the impact of the technology on program robustness or risk.

3.3 Technology Performance Risk Index

The Technology Performance Risk Index (TPRI) is "a methodology to measure the performance risk of technology in order to determine its transition readiness" and is used to track technology readiness through a life cycle or at specific time to support a milestone decisions [89]. According to Mahazat, "the index is based on the system's performance requirements and the ability of the technology to achieve that performance" [89]. The performance requirements are represented by Technical Performance Measures (TPMs) threshold values that divide the performance envelope "into acceptable and unacceptable risk regions" [89].

The first step in calculating the TPRI of a given technology is to calculate the achieved performance, A_{ij}, at time i for each TPM j. There are two equations for calculation A_{ij}. The first is for the case when performance must be decreased to meet the established TPM threshold and the second is when it must be increased. (21 and (22 below show the calculations for these two cases respectively:

$$A_{ij} = \min\left\{\frac{TPM\_threshold}{m_{ij}}, 1\right\}$$

(21)

$$A_{ij} = \min\left\{\frac{m_{ij}}{TPM\_threshold}, 1\right\}$$

(22)

Where:

- A_{ij} is the measured performance at time i for TPM j,
- m_{ij} is the measured performance for the same conditions
- *TPM_threshold* is the established threshold for the given TPM j.

The calculated A_{ij} can then be used to calculate the $TPRI_j$ of the given technology for TPM j using:

$$TPRI_j = 1 - \frac{A_j}{1 + (1 - A_j)DD_j}$$

(23)

Where DD_j is the Degree of Difficulty (DD).

The DD is a metric that ranges from 0 to 1 and is used to quantify the anticipated risk (0 for no risk and 1 for guaranteed failure) associated with the technology achieving the TPM threshold.

To calculate the TPRI for a given technology across the entire spectrum of TPMs, the individual $TPRI_j$'s are summed and normalized:

$$TPRI = \frac{\sum_{j=1}^{n} 1 - \frac{A_j}{1 + (1 - A_j) DD_j}}{n}$$

(24)

Where n is the number of TPMs and this process is repeated for every technology across all TPMs to obtain the TPRI values for the technologies.

The TPRI provides "a means to assess potential technologies and assist the decision maker in where to apply resources to address unmet requirements" through the development life cycle of the technologies [89]. It relies on expert judgment to quantify the potential difficulties associated with a given technology for meeting performance metric thresholds. While this approach provides a rapid and quantitative measure of technology risk, it does not provide decision-makers with the ability to assessment the robustness of the performance metrics against uncertainties associated with each technology. Additionally, the separate treatment of each technology makes it difficult to gauge the overall risks associated with a group of technologies.

3.4 Strategy Optimization for the Allocation of Resources

The Strategic Optimization for the Allocation of Resources (SOAR) methodology formulated by Dr. Christopher Raczynski at the Georgia Institute of Technology provides a “framework for strategic planning and resource allocation” for an organization [124]. It utilizes “a top down approach…[and] starts with the creation of the organization’s vision and its [Measures of Effectiveness (MoEs)]” [124]. These MoEs are then prioritized and potential solution programs are identified. Information deemed pertinent by the decision-maker (e.g. cost, schedule, risk, and applicability) are then collected for each program. Using subject matter experts, “the relationships between levels of the hierarchy are mapped” and “these connections are then utilized to determine overall benefit of the programs to the vision of the organization” [124]. The use of a Multi-Objective Genetic Algorithm enables the creation of a trade-space of potential program portfolios for allocating resources. The final decision framework is then presented to the decision-maker “through the use of a Decision Support System which collects and visualizes all the data in a single location” [124]. Iterations of the process may be required if additional information is needed to make the decision. Figure 15 below provides a visual summary of the SOAR methodology.

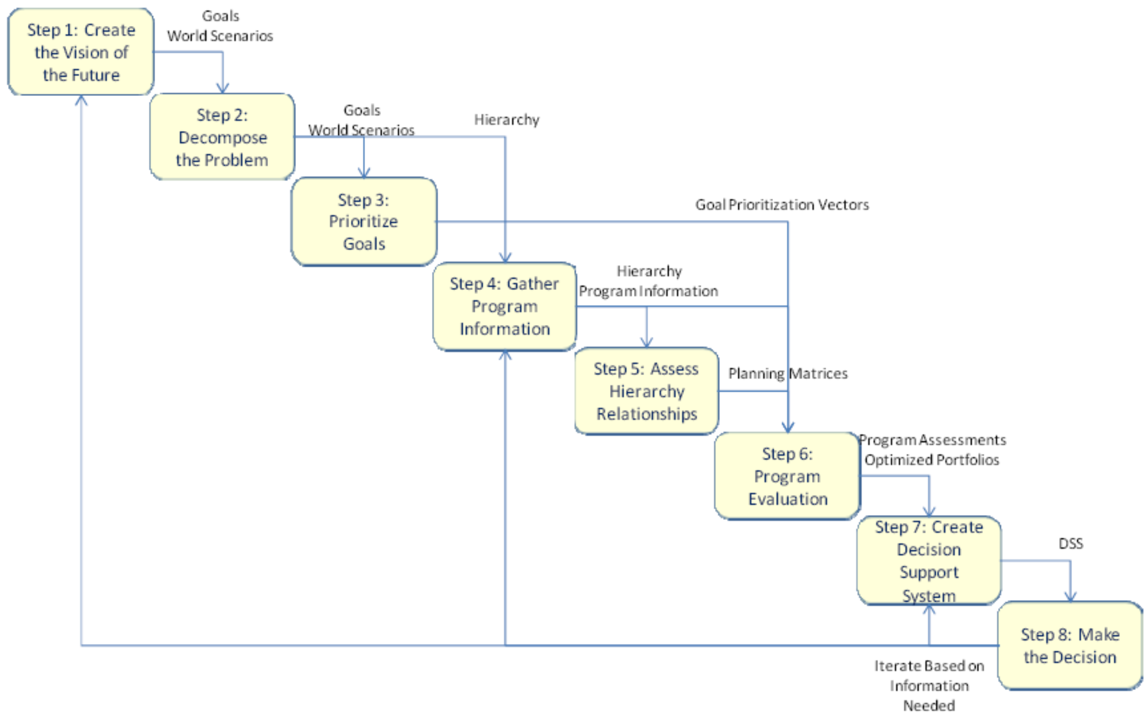


Figure 15 : Strategy Optimization for the Allocation of Resources Methodology [124]

The SOAR methodology "integrates features of strategic planning into a single methodology" to provide a comprehensive, rigorous, and transparent process for resource allocation. It takes into account multiple technology readiness dimensions including: technology maturity (TRL), technology interoperability (with other technologies), technology integration (with overall system), technical risk (likelihood that the technologies will not be complete or perform worse than expected), schedule risk (likelihood that the technology will not meet the specified time constraints), and cost considerations. The use of the Integrated Product and Process Development (IPPD) systems engineering process adds credibility and decision-maker buy-in to the process. The standardized techniques used to conduct the SME surveys make the process more straightforward and efficient (time and money-wise). All of this results in a framework that allows the decision maker to perform "rapid tradeoffs of criteria to find the portfolios which created the greatest benefit at an acceptable cost" [124].

The SOAR methodology solicits expert judgment in establishing qualitative relationships between technology programs and their impact on overall capability, budget, and schedule metrics and objectives. A MOGA-based optimization is then conducted using these relationships to identify the most optimal technology portfolios for meeting the objectives and the results are presented to decision-makers using an interactive computer-based Decision Support Systems that allows for rapid and visual tradeoffs between candidate solutions.

Unfortunately, the judgment-based forecasting technique used by the SOAR methodology relies exclusively on subjective expert opinions contains an inherent element of bias due to the subjectivity of the SMEs. This means that the results can be skewed to favor certain programs or technology types, depending on the backgrounds of the SMEs surveyed. Also, there is no accounting of uncertainty in the method and thus technology performance and development uncertainties and their impact on program requirements and objectives are not captured. Additional uncertainty analyses are necessary in order to provide a forecast of requirements robustness against these uncertainties.

3.5 Technology Identification, Evaluation, and Selection

The Technology Identification, Evaluation, and Selection (TIES) methodology, developed by Kirby in the Aerospace Systems Design Laboratory (ASDL) at the Georgia Institute of Technology (GT), "was created as a response to the paradigm shift" in the aerospace industry [81]. According to Kirby, this shift was the result of a "changing global socio-economical and political environment" and called for "solutions that are beyond evolutionary databases and demands consideration of all aspect of the system's life cycle" [81].

TIES uses "statistical and probabilistic methods, including Response Surface Methods and Monte Carlo Simulation " to address the "multi-criteria problem in the presence of design, operational, and technological uncertainty" [81]. These methods enable the creations of "a forecasting environment whereby the decision-maker has the ability to assess and trade-off the impact of various technologies without sophisticated and time-consuming mathematical formulations" [81]. This environments allows the creation of "a family of design alternatives for a set of customer requirements" [81]. Figure 16 provides a visual summary of the TIES methodology.

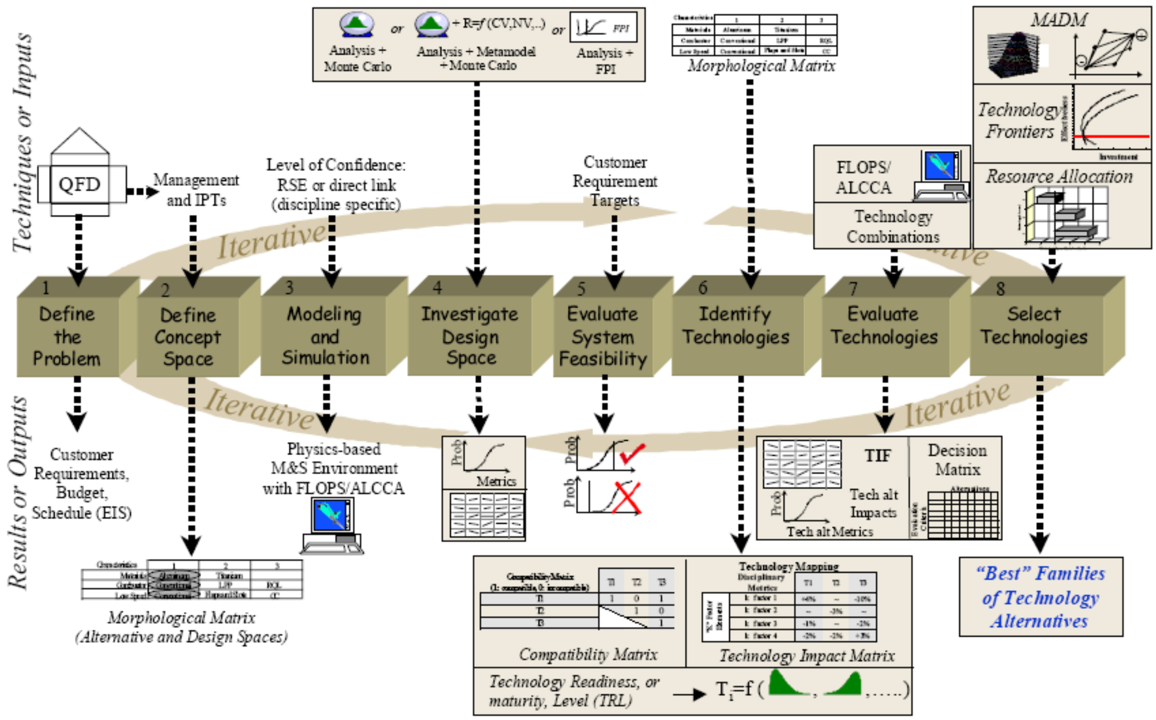


Figure 16 : Technology Identification, Evaluation, and Selection Methodology [81]

Unlike the previous techniques, TIES offers a more comprehensive and structured approach to technology evaluation and forecasting. Through the use of computer-based modeling & simulation environments, technology performance and impacts can be forecasted quantitatively without the high cost of physical experimentation or the subjectivity of SME data. The M&S environment is then used in conjunction with Response Surface Methodology go generate Response Surface Equations (a form of regression analysis forecasting) to reduce the computational burden associated with the computation models and enable the creation of rapid parametric trade-off environments where the impact of changing requirements can be captured almost instantaneously for the decision-makers. Monte Carlo Simulations can then be conducted using the quick-running RSEs instead of the original models to generate quantitative forecasts of each technology's impact on performance and economic metrics. Finally, the use of Multi-Attribute Decision Making (MADM) techniques enables a transparent and structured prioritization of candidate technology solutions based on decision-maker preferences. This aids in identifying the set of technology alternatives that best meets performance and economic requirements with minimal risk.

3.6 Technology Metric Assessment and Tracking

The Technology Metrics Assessment and Tracking (TMAT) methodology is a stochastic process for tracking the progress and contribution of technology portfolios towards strategic goals for decision-making [3]. It contains five steps and is founded on the strength of three methods [3]:

- The technology metrics tracking program initiated for the High Speed Research Program Task 23 led by Clay Ward and further modified in HSR Phase II Task 11 [178; 177]
- The NASA Intercenter Systems Analysis Team annual benefits assessments performed for the Office of Aerospace Technology
- The Technology Identification, Evaluation, and Selection (TIES) method led by Michelle Kirby [81]

The TMAT process is depicted in Figure 17 and incorporates the following elements:

- Systems-Engineering methods to decompose top-level program objectives down to quantitative technology metrics

- Technology Audit scheme for eliciting information from Subject Matter Experts (e.g. estimates on potential benefits and penalties associated with technology infusion)
- Modeling & Simulation environment for evaluating technology impact on system metrics
- Response Surface Equations (RSEs) for enabling rapid assessments and tradeoffs of technology impacts on program objectives
- Monte Carlo simulations for probabilistically assessing the impact of technology uncertainties

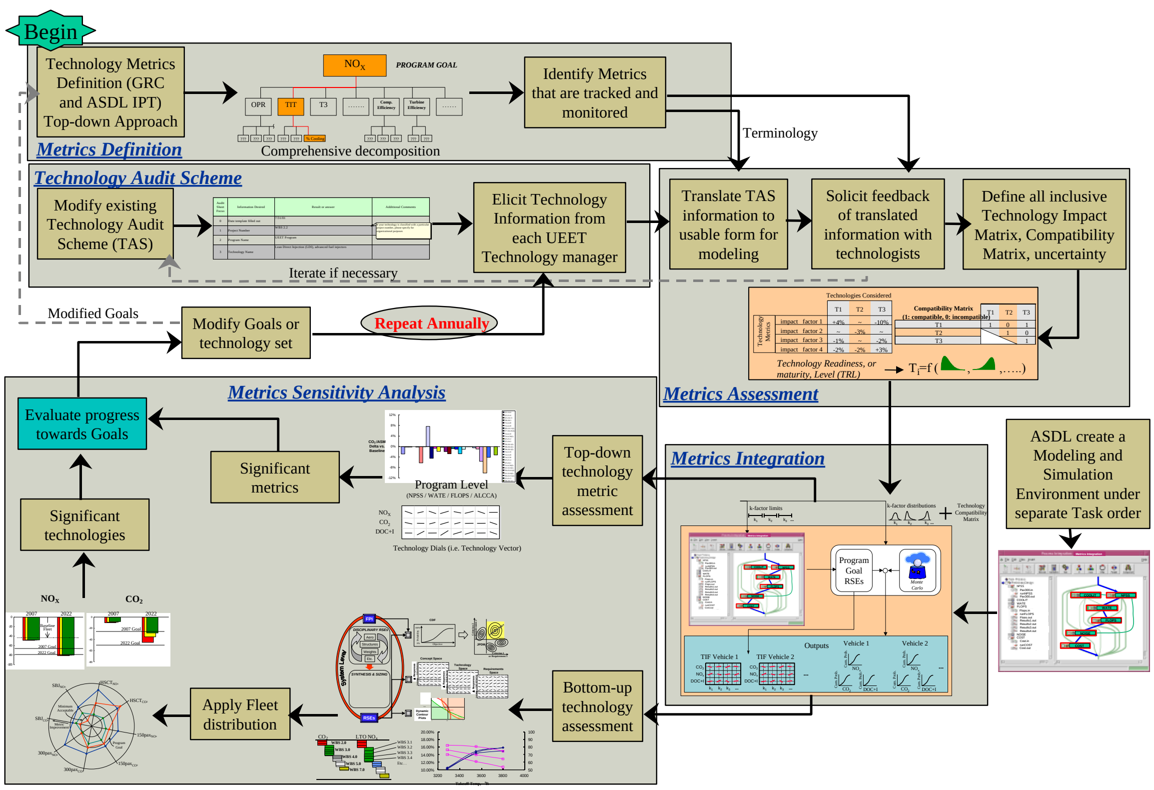


Figure 17: Technology Metrics Assessment and Tracking Process Overview [2]

The TMAT process was originally used to "track the progress of technology developments within NASA's Ultra Efficient Engine Technology Program" [3]. The combination of computer-based M&S, RSM techniques, and probabilistic analysis techniques allows it to account for the temporal aspects of technology development so that "the maximum payoff of technology investments may be pursued and the associated risks measured" [3]. The assessment can be conducted periodically to allow decision-makers to make decisions that maximize system performance and minimize risk [3].

3.7 Technology Development Planning and Management

The Technology Development Planning and Management (TDPM) process was formulated by Largent to better capture the risks and uncertainties associated with technology development activities. According to Largent, TDPM is "a process with two main foci" [85]:

- A method for systematically identifying areas of performance uncertainty in a technology and planning activities to reduce the uncertainties and maximize the performance
- A structured method for assessing the initial project plan for project management, cost, and schedule risk, and re-assessing the project while development activities are being completed

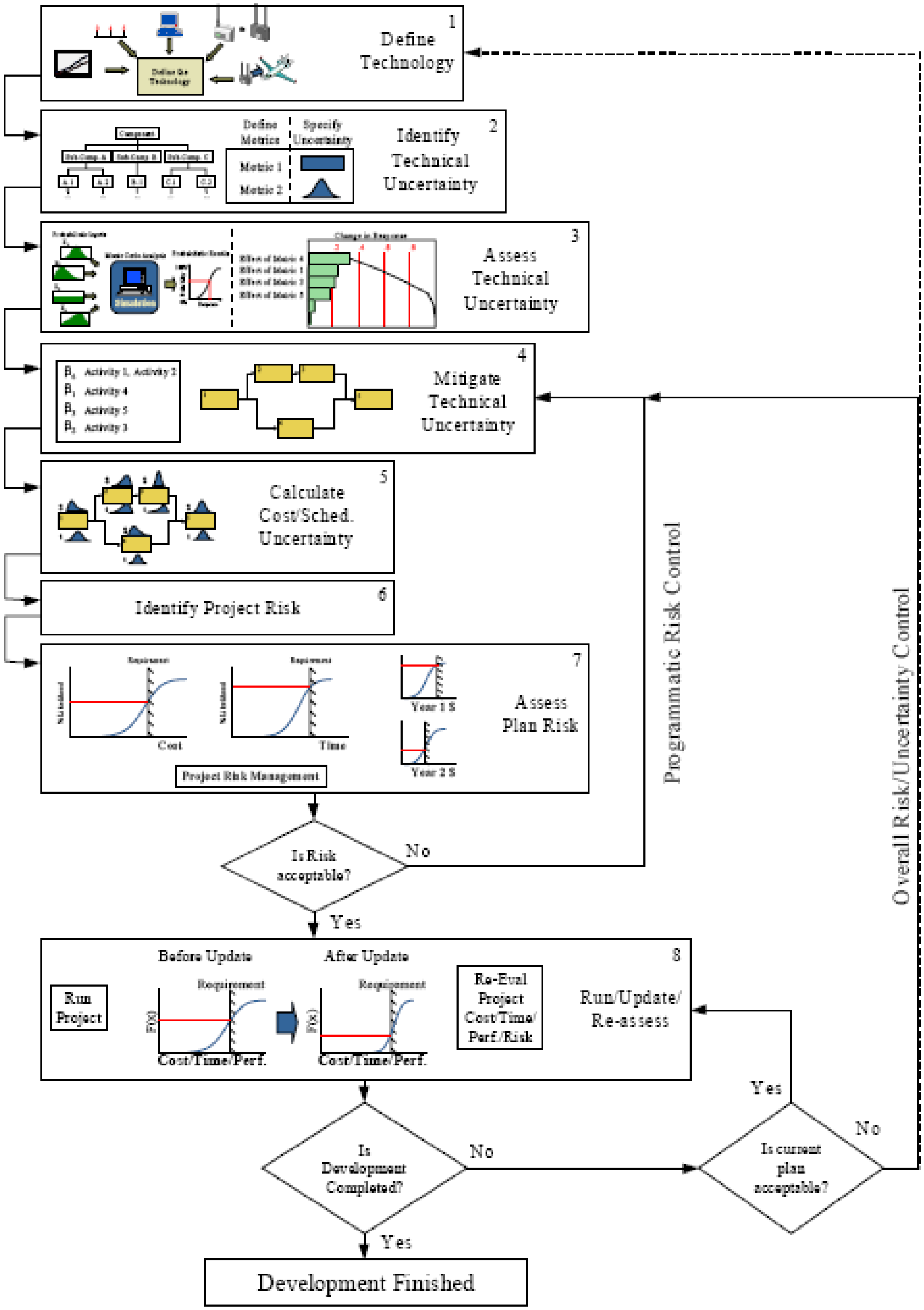


Figure 18: Technology Development Planning & Management Process Overview [85]

In the TDPM process, performance metric uncertainties caused by technology immaturity are identified through the use of M&S, Surrogate Models, and a Monte Carlo simulation environment (similar to TIES and TMAT methods). These metrics are then ranked in terms of criticality and importance to the decision-makers. Technology development activities that have to be performed to reduce these are then identified and modeled using the Project Network Analysis techniques. A Monte Carlo Simulation is then conducted on these models to establish a set of "empirical probability distribution functions that represent the probabilistic cost and time" associated with the development of each technology. This information can then be combined with project risk management techniques to identify the risks to program budget and schedule caused by technology development uncertainties. The method also has the ability to update performance metric uncertainties with new development data when they are available. The output of the TDPM process is a set of "probabilistic data for [technology development] cost [and] time" that enable informed decisions regarding the development and use of technologies [85].

3.8 Quantitative Technology Assessment Program

The United States Air Force Research Laboratory has been actively engaged in research efforts to "integrate new methodologies and tools with existing 'industry-standard' tools to effectively test the effects of new technology on air vehicle capability" [185]. This approach requires the ability to "quantify the impacts of any proposed technology on each key capability" [151]. To meet these research goals, AFRL initiated the Quantitative Technology Assessment (QTA) to provide "meaningful mission effectiveness analysis that quantitatively measure the value of technologies" [27]. QTA program summary is provided below:

> "Since 2003, AFRL has continued to be capability driven with a focus on user needs. This requires integrated technology solutions, system of systems assessment capabilities in representative scenarios, and the ability to develop and measure capability based metrics to chart progress. The Air Vehicles Directorate has been adopting Modeling and Simulation (M&S) processes that are more customer focused and capability driven to support evolving AFRL needs. This has required a major focus on the adaptation of systems engineering (SE) practices. Adaptation of the SE practices provides the science and technology community connectivity between the desired capabilities and the projected qualities associated with advancements in technology products. This process is referred to as Quantitative Technology Assessment (QTA). The outputs of the process provide quantitative information to help guide technology investment decisions" [4].

Essentially, the goal of the QTA program is to evolve existing SE tools and methods in order to "provide a traceable forward and backward path between the performance parameters associated with each technology product to the desired system-level capability" [5]. This transparent tracing between technology performance parameters and system capabilities is achieved "through direct linking of simulation tools" (see Figure 19) [21].

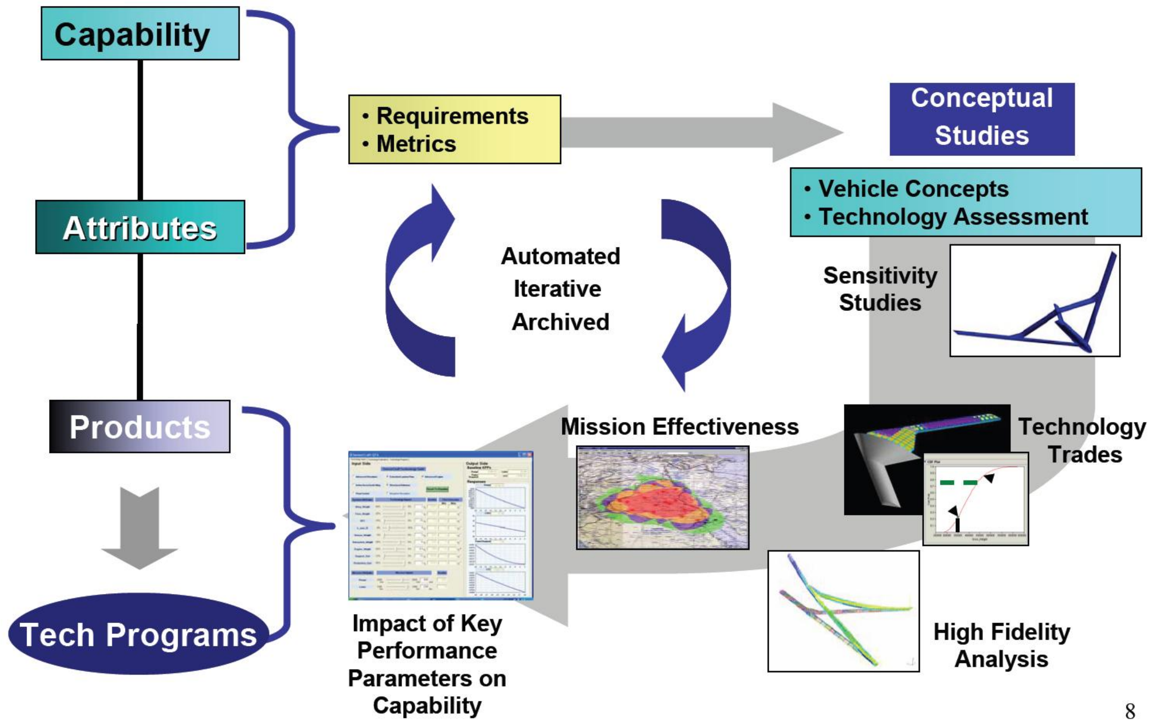


Figure 19: Quantitative Technology Assessment Process Overview [27]

Even through the process described by Figure 19 is generic, it is clear that the goal of the QTA process is to utilize computer-based M&S environments to generate performance and capability forecasts associated with technologies and vehicle concepts. This allows for quantitative and objective forecasts to be generated and used for decision-support when identifying critical capability-enabling technology programs.

3.9 Simulation-Based, Objective-oriented, Capability-focused, Real-time Analytical Technology Evaluation for Systems-of-systems

Biltgen's Simulation-based, Object-oriented, Capability-Focused, Real-Time Analytical Technology Evaluation for Systems-of-Systems (SOCRATES) methodology, also developed at ASDL, is a "synthesis of aspects" from Kirby's TIES methodology and the Air Force's Quantitative Technology Assessment (QTA) program [21]. It combines the following elements to achieve its analytical objectives:

- Use of systems engineering mapping techniques like Quality Functional Deployment (QFD), Functional Decomposition, and Activity Diagrams to identify and define capabilities-based metrics
- DoD-specific techniques like the Department of Defense Architecture Framework (DoDAF) to define the relationships between elements within given scenarios
- Agent-based modeling & simulation (ABM&S) techniques that capture the combined behaviors of multiple independent yet interrelated agents or system within a given scenario

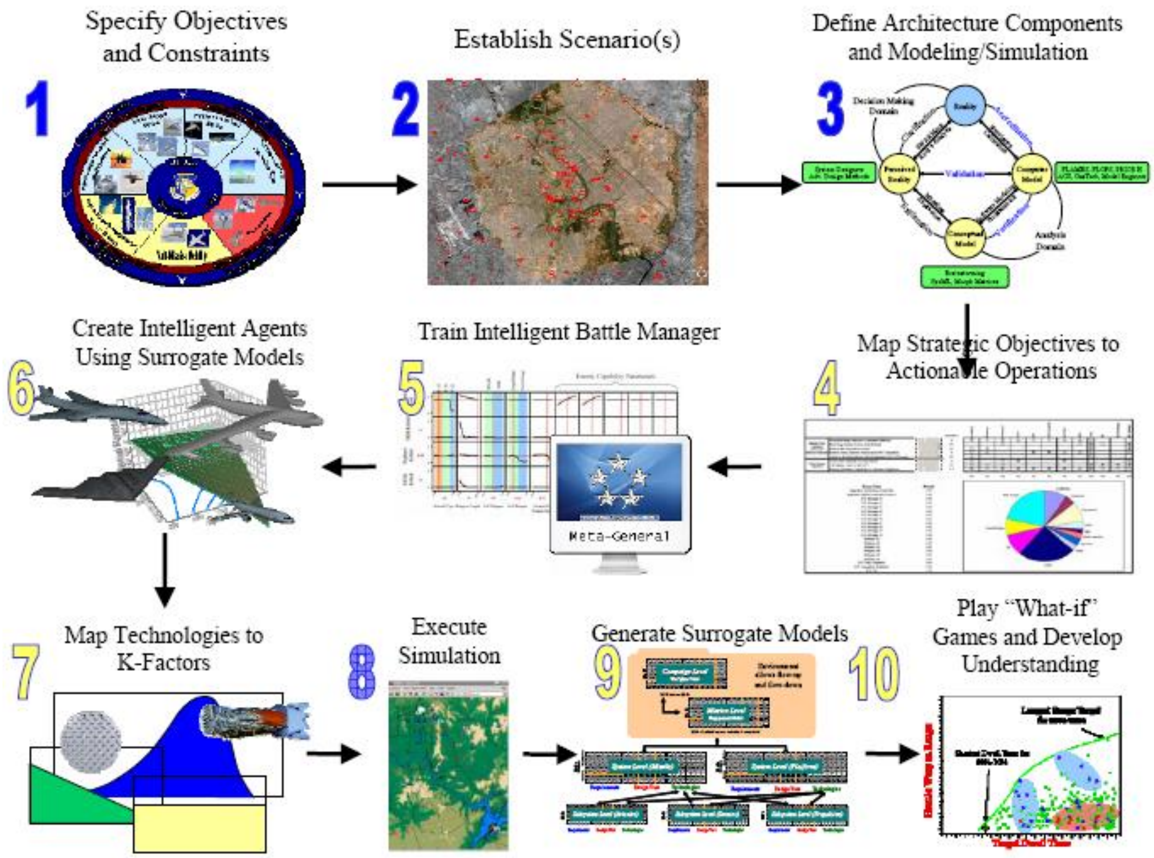


Figure 20 : Simulation-Based, Objective-oriented, Capability-Focused, Real-Time Analytical Technology Evaluation for Systems-of-systems Methodology [21]

Like TIES, SOCRATES uses Surrogate Modeling techniques in conjunction with a M&S environment to enable the creation of a parametric trade-off environment to "quantitatively assess technology impacts" [21]. Using these models, "a series of 'what-if?' games can be played to evaluate technologies under a variety of conditions" and "conclusion can be drawn regarding the effectiveness of a technology or portfolio or technologies" [21]. Unlike TIES, SOCRATES captures the impact of technologies at the capabilities/SoS level by it evaluating the impact of technology parameters (and therefore impacts) on Measures of Effectiveness. Unfortunately, it does not specifically account for the uncertainties associated with technology performance impact and thus provides only a deterministic analysis of these impacts.

3.10 Strategic Assessment of Risk and Technology

The Strategic Assessment of Risk and Technology (START) process is a general methodology that “offers systems for quantifying the features of each [technology] development candidate, assessing its risk, and calculating its probable return-on-investment” [181]. It was developed at NASA’s Jet Propulsion Laboratory (JPL) in 2005 by a team headed by Dr. Charles R. Weisbin for the purposes of “technology selection and analysis of technological options that are in their early stages of development” [149; 181]. The general procedure followed by the START team for this type of analysis consists of the following steps and has been successfully applied to several NASA optimization studies [181; 106]:

1. Develop a clear, complete statement of the problem to be studied.
2. Identify the decision-maker's goals and priorities and the associated metrics.
3. Design or select one or more architectures (precise scenarios) to accomplish the goals.
4. If working with a mission architecture, allocate its constituent activities to the available agents (e.g., astronauts and robots) and resources, and calculate the optimal scheduling.
5. Identify and assess the capabilities and/or technologies required by the architecture.
6. Characterize the capabilities and/or technologies.

7. Evaluate and rank the capability or technology candidates to identify which to fund for development.
8. Assess the relative return on investment for competing architectures (if comparing architectures)
9. Validate the results.
10. Recommend an optimal portfolio and present its trade-offs to the decision maker.
11. Adjust inputs as desired, and repeat the analysis process until a satisfactory result is achieved.

According to Dr. Weisbin and his team, the application of these steps will provide defensible predictions of the cost of new technologies, determinations of when diminishing returns make further development inadvisable, and an optimization of technology portfolios at various budget levels [181].

Like SOAR methodology, the emphasis of the START process is to generate and present optimal technology portfolios based on their contributions to overall capabilities and not on the robustness assessment. While it allows for the inclusion of quantitative data, the generic nature of this procedure makes it difficult to determine how it can be used to support requirements robustness assessment for acquisition decision-making activities. There is no specific accounting of technology performance and development uncertainties, optimization techniques for generating optimal portfolios, or structured decision-support process.

3.11 Conclusions

In this chapter, current aerospace and acquisition technology assessment and forecasting approaches were examined. This investigation began with two techniques similar to the TRA and relied on an expert judgment to establish one or more *readiness level* metrics that described the current developed state of the system and technologies. While rapid and straightforward to perform, these techniques are limited in their ability to forecast, qualitatively or quantitatively, the impact of technology performance and development uncertainties on program requirements. They are intended for determining if program development has reached specific maturity thresholds and thus are not appropriate for forecasting requirements robustness against technology uncertainties.

The TPRI method relies on expert judgment to assess the potential difficulties in meeting specific performance thresholds associated with each technology through the use of judgment-based *Degree of Difficulty* parameters. While the inclusion of quantitative performance data and threshold values results in a more objective assessment of technology risk, the method does not account for potential uncertainties technology performance. It also does not account for development metrics or uncertainties.

Of the judgment-based techniques examined in this chapter, the SOAR methodology by Raczynski is by far the most comprehensive in terms of supporting acquisition decision-making. The method established qualitative relationships between technologies and program capability, budget, and schedule requirements and uses these relationships, coupled with a Multi-Objective Genetic Algorithm, to generate candidate portfolio solutions that are presented to decision-makers in a graphical and interactive computer-based Decision Support System that allows for real-time tradeoff analysis between the candidate solutions. Unfortunately, this method does not account for uncertainty in these relationships and the reliance on expert-opinion introduces elements of bias into the output decisions.

Like the SOAR methodology, NASA's START process aims to identify optimal technology portfolios based on technology contributions and costs. Unfortunately, the generic nature of the START methodology makes it difficult to determine how it can be used to support requirements robustness assessments or how this information can be used to support early phase acquisition decision-making.

The TIES methodology and its relative, the TMAT process, rely on computer-based modeling & simulation environments to generate quantitative technology performance forecasts. In these two methods, this information is coupled with a Multi-Attribute Decision Making technique to rank order technology portfolios for meeting decision-maker requirements and preferences. Unfortunately, they only account for the impact of technology performance uncertainties on output metrics. Furthermore, TIES's use of MADM techniques for rank-ordering solutions instead of MODM optimization techniques can become computationally impractical if the number of possible combinations is extremely large or computational costs are high.

Largent's TDPM process was developed to capture technology development uncertainties for support program planning and development decisions. In this method, time and cost parameters are assigned to technology development activities and Project Network Analysis techniques are used to calculate the overall development budget and schedule for each technology project. Uncertainty analyses are then conducted using Monte Carlo Simulations to generate the potential range of budget and schedule variations in the development of each technology. This information can then be used to support technology project planning and development decisions. Unlike the other quantitative assessment methods, this method focuses on forecasting the impact of technology development uncertainties on program budget and schedule for program risk assessment. Unfortunately, it is limited to only addressing technology development uncertainties and does not investigate the impact of technology performance uncertainties on system performance and capability requirements. Furthermore, Largent states that it is not intended to be used for selecting the best technology or technologies for a given application [85] and thus requires additional analyses to support pre Milestone a Analysis of Alternatives decisions.

Biltgen's SOCRATES method was created to meet the objectives of the Air Force's Quantitative Technology Assessment program. It is meant to be used as a method for capturing the impact of technologies on capability requirements. This is done through the use of agent-based models, which are a special type of Discrete Event Simulations that allow the impact of technology performance parameters to be aggregated into scenario/mission objective metrics. Unfortunately, the method does not provide a process of capturing the performance uncertainties associated with technologies and the resulting impact on system capability metrics. It also does not take into account potential development uncertainties associated with each candidate technology or their implications on program requirements. Finally, it does not prescribe a process of identifying the optimal solutions for meeting capability requirements and there is no structured decisions support process.

While multiple technology forecasting techniques currently exist and are being used within the aerospace and acquisition communities, none adequately provide the necessary forecasting capabilities needed to support early phase acquisition decision-making. As such, a new approach is needed. Before this new approach can be formulated, the Hypotheses for answering the Research Questions posed in Chapter 1 must be constructed.

CHAPTER 4 – HYPOTHESES

In this chapter, the materials presented in the previous two chapters are used to construct Hypotheses for answering the Research Questions posed in Chapter 1. Experiments for testing these Hypotheses will also be posed.

4.1 Hypothesis I

The first RQ asks:

> ***How can the impact of technology performance and development uncertainties on capability, budget, and schedule requirements be quantified to provide acquisition decision-makers with a more informed assessment of program robustness?***

Based on the material provided, it is clear that forecasting techniques are needed to establish the relationships between program requirements and technology uncertainties. It was observed that quantitative forecasting techniques are more suitable for generating the necessary robustness assessment data. In general, these techniques rely on relevant existing and historical data to make future predictions. However, for new acquisition program, historical data regarding the impact of the candidate program technologies on program capability, budget, and schedule requirements may not available or are not sufficiently relevant (i.e. required additional relationships mapping). This is why judgment methods have been used historically to perform these types of assessment. However, with the advent of cheap, powerful computer processors, there is a shift (see discussion of Air Force's QTA program in Section 3.8) towards using computer-based modeling & simulation environment that can produce objective and quantitative data. The parametric nature of these models allows them to be easily coupled with a probabilistic analysis technique such as Monte Carlo Simulations. The result is a probabilistic analysis environment that can take into account the potential variations in the inputs (i.e. technology performance and development uncertainties) and output potential fluctuations in the outputs (i.e. variations in program metric requirements). This information can then be used to support program robustness assessments. Based on these observations and conclusions, Hypothesis I, formulated to address Research Question I, is as follows:

Hypothesis I

> ***A probabilistic and quantitative forecasting of the impacts of technology performance and development uncertainties on program requirements will provide a more informed assessment of the robustness of these requirements against such uncertainties.***

To test this Hypothesis, the author will first formulate a methodology for utilizing probabilistic and quantitative technology performance and development forecasting environments and then implement it on a notional acquisition problem. The results of this proof-of-concept implementation will be compared to output results from existing methods to demonstrate the potential gains in acquisition decision-making knowledge.

4.2 Hypothesis II

The second Research Question asks:

> ***How can a program technology development portfolio that is robust against technology performance and development uncertainties be identified?***

During the early phases of the acquisition lifecycle (pre Milestone A during Analysis of Alternatives phase), candidate program technology programs are evaluated and a program technology development portfolio is selected based on these evaluations. In order to ensure the robustness of selected technologies, robustness assessment data must be taken into account during the evaluation and selection process. This requires taking into account the robustness of multiple requirements for different technology combinations and identifying the solution or solutions that best meet decision-maker requirements and preferences. A simple but effective way of doing this is to use a Multi-Attribute Decision Making technique that aggregates each alternative's performance across the entire set of evaluation criteria into a single overall score. The scores for each alternative can then be used to rank-order them and the alternative with the highest score would represent the optimal solution given the set of requirements and preferences.

While effective, these techniques are more appropriate when a down-selection of the solution set has already been conducted, with only a small subset of optimal solutions being evaluated, or the solution set is small to begin with. Otherwise, it will be necessary to conduct a full-factorial analysis where every single possible technology combination is evaluated. For an acquisition program with dozens or even hundreds of potential technology development opportunities, the sheer size of the solution set becomes unmanageable. In these situations, Multi-Objective Decision Making techniques are more appropriate. Unlike the MADM techniques whose objective is to rank-order solutions based on their attributes, MODM techniques set out to identify optimal solutions based on a set of pre-determined objectives. These techniques do not require the solution set to be small or a down-select to be conducted ahead of time and a set of optimal solutions according to decision-maker requirements and preferences. These solutions can then be evaluated using a MADM technique for the final down-select.

During the literature review in Chapter 3, it was observed that Raczynski's use of a Multi-Objective Genetic Algorithm optimization scheme was quite effective for generating optimal technology portfolios for early phase acquisition lifecycle decision-support. The discrete and multivariate nature of this particular approach allows it to take into account the multiple conflicting program requirements and identify potential portfolios that best meet these requirements. As such, Hypothesis II is as follows:

Hypothesis II

> ***A technology evaluation and selection process that utilizes a Multi-Objective Genetic Algorithm in combination with probabilistic and quantitative technology uncertainty impact forecasting environments will allow for the creation of technology portfolios that are robust against technology performance and development uncertainties.***

To test this Hypothesis, the author will create and utilize a MOGA-based optimization process to create a set of candidate technology portfolios that best meet program requirements and robustness metrics. The resulting portfolios will then be evaluated in their ability to meet these objectives to see if they indeed meet program requirement and robustness criteria. Portfolios that adequately meet these objectives would then confirm the usability of a MOGA technology portfolio optimizer for acquisition programs.

4.3 Hypothesis III

In order for probabilistic and quantitative technology uncertainty M&S environment analyses and MOGA-based technology portfolio generation process to be useful in improving acquisition decision-making, their output results must be packaged and presented to program managers and decision-makers in a manner that most easily allows them to understand the underlying trends and relationships between technology uncertainties and program requirements and the tradeoffs in program robustness metrics between candidate technology portfolios. This lead to the final Research Question:

> ***How should program requirements robustness data be presented to the decision-makers so that it is informative and useful for acquisition decision-making?***

It was observed during the literature review process that a computer-based Decision Support System would allow "large data sets to be expressed in manageable formats which managers could more easily understand" [124]. The interactive and visual nature of a computer-based DSS also allows the user/DM to rapidly assess the tradeoffs between candidate solutions against a multitude of evaluation metrics, which aids in the selection of the solution that best meets decision-maker criteria (e.g. robustness against technology uncertainties). This observation led to Hypothesis III:

Hypothesis III

> ***Creating a structured and interactive computer-based Decision Support System will allow the decision-makers to make more-informed decisions for ensuring program robustness against technology performance and development uncertainties.***

To test this Hypothesis, the author will create a computer-based DSS that incorporates probabilistic and quantitative analysis technology analysis elements and demonstrate its usefulness during critical acquisition decision points such as technology portfolio selection during AoA and program progress/risk assessment reviews during major Milestone reviews.

In the next chapter, a general methodology for assessing the robustness of acquisition program requirements against technology performance and development uncertainties is formulated. An example application of this method is then provided in Chapter 6 and the results of this implementation are used to test the validity of the three Hypotheses constructed in this chapter.

CHAPTER 5 – FORMULATION

The objective of this thesis is to develop an approach for assessing the robustness of acquisition program capability, budget, and schedule requirements against technology performance and development uncertainties for supporting early phase acquisition decisions such as portfolio selection and program risk evaluation. Based on the materials provided thus far, such an approach should utilize the following elements:

- Computer-based probabilistic and quantitative technology performance and development forecasting environments for generating requirements robustness statistical data
- A Multi-Objective Genetic Algorithm for identifying candidate optimal technology portfolios
- Interactive and graphical computer-based Decision Support System for supporting informed decision-making

The method described in this chapter represents a general approach formulated using the materials provided in Chapters 2 and 3 to provide a probabilistic and quantitative assessment of acquisition requirements robustness against the performance and development uncertainties of program technologies.

5.1 Assumptions and Prerequisites

Before the formulation details are provided, it is necessary to first define the assumptions, prerequisites, and associated context of the proposed method within the acquisition process. This will help the reader better understand the uses of this methodology and how it can be used to support acquisition decisions.

As previously established, the primary objective of this method is to provide acquisition decision-makers with a probabilistic and quantitative assessment of requirements robustness against technology performance and development uncertainties. The need for such an assessment first begins during the Analysis of Alternatives portion of Materiel Solution Analysis Phase of the Defense Acquisition System (see Figure 4). During the AoA, the Critical Technology Elements associated with candidate materiel solutions are evaluated and the results of this comparison are used to select the materiel solution and associated technologies to be developed for program. The goal is to identify the set of technologies for each materiel solution best meet program requirements now and in the future. In order to support these activities, one of the outputs of the proposed method needs to a set of candidate technology portfolio solutions optimal for meeting to decision-maker criteria for requirements robustness. Through the use of a computer-based Decision Support System, decision-makers can visualize the tradeoffs in robustness criteria between alternate portfolios and select the portfolio that best meet their requirements and risk preferences. During subsequent program reviews, the tools and environments used can be infused with new technology uncertainty data and assumptions to provide decision-makers with an updated assessment of program requirements robustness.

The proposed methodology is divided into four phases; *Problem Definition*, *Modeling & Simulation*, *Technology Portfolio Optimization*, and *Decision Support*. Each phase is comprised of a series of steps that contributes to accomplishing the objectives of that phase and the overall objectives of the methodology. The remainder of this chapter will focus on the description and justification of each phase and when appropriate, the inputs, outputs, and techniques associated with each phase will be provided.

5.2 Phase I: Problem Definition

The first step in any assessment is to define its goals and objectives. For the proposed method, this means identifying and defining the capability need or needs driving the acquisition program, potential solutions and associated technology elements to be evaluated, and the set of relevant program requirements and robustness assessment metrics. Since the proposed method is first initiated during the Analysis of Alternatives, most of these elements have already been defined for the program and the bulk of this phase consists of extracting them from relevant capability requirements definition documents. If necessary, program managers and/or decision-makers can be queried regarding potential program robustness metrics. As such, this phase consists of four steps:

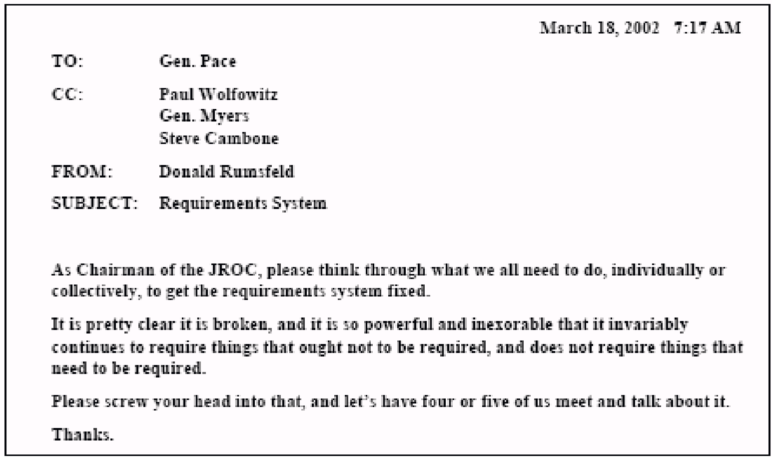
- Step 1: Describe Capability Need(s)

- Step 2: Define Solution Concepts & Enabling Technologies
- Step 3: Identify Relevant Scenarios and Requirements
- Step 4: Define Robustness Metrics

Currently, capability acquisition needs and requirements are defined using the Joint Capabilities Integration and Development System (JCIDS) and the Capabilities-based Assessment (CBA), so the necessary problem definition data should come from the output products of these two processes.

5.2.1 The Joint Capabilities Integration and Development System

A few months following the September 11th attacks, then Secretary of Defense Donald Rumsfeld issued a memo (see Figure 21) to the Chairman of the Joint Requirements Oversight Council (JROC), General Peter Pace, and asked him to come up with ways to fix the Requirements Generation System (RGS) [129]. The RGS was the standard DoD process (at the time of the memo) for producing "information for decision makers on the projected mission needs of the warfighter" [44; 45]. Along with the Acquisition Management System and the Planning, Programming, and Budgeting System, it formed the DoD's three main decision support systems for defense acquisitions (see Figure 22). The outputs of these three systems guided the development of future defense acquisition programs.



March 18, 2002 7:17 AM

TO: Gen. Pace

CC: Paul Wolfowitz
Gen. Myers
Steve Cambone

FROM: Donald Rumsfeld

SUBJECT: Requirements System

As Chairman of the JROC, please think through what we all need to do, individually or collectively, to get the requirements system fixed.

It is pretty clear it is broken, and it is so powerful and inexorable that it invariably continues to require things that ought not to be required, and does not require things that need to be required.

Please screw your head into that, and let's have four or five of us meet and talk about it.

Thanks.

Figure 21: Memo from Secretary Rumsfeld Regarding the Requirement System [70]

According to Figure 21, Secretary Rumsfeld believed that the RGS was "broken" and continued to require thing that "ought not to be required and [did] not require things that need to be required" [129]. It was not adaptable to the DoD's "policy shift from a threat-based assessment of warfighter needs to a capabilities-based assessment [one]" [133].

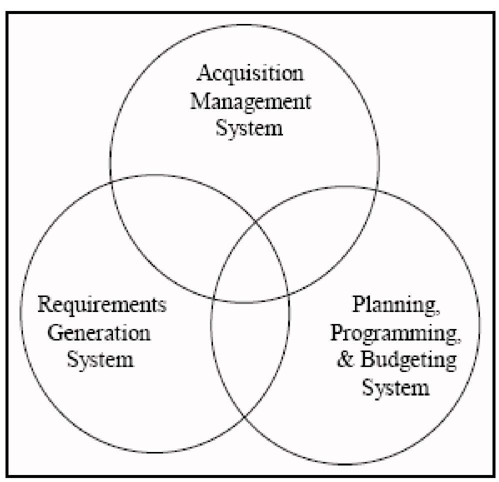


Figure 22: Principal DoD Decision Support Systems in 1999 [44]

Shortly after this memo, Secretary of Defense Paul Wolfowitz officially cancelled the DoD 5000 series Acquisition Policy Documents operating at the time [186]. Pertaining this cancellation, Deputy Secretary Wolfowitz discussed the need for a new set of DoD 5000 policies that "fosters efficiency, flexibility, creativity, and innovation" [186]. The goal of these new policies is to guide "the effective pursuit of strategic and operational outcomes" [57]. The two aforementioned memos (along with probably countless others), lead to the development of a new set of capabilities-based acquisition policies and procedures.

In 2003, the DoD officially replaced the Requirements Generation System, which had been the formal "method for identifying warfighter requirements for the previous 30 years" [133]. It was replaced by the Joint Capabilities Integration and Development System (JCIDS). Like the RGS, JCIDS defines acquisition requirements and evaluation criteria for future defense programs. However, instead of concentrating "on the systems and system infrastructure piece of the solutions" like the RGS , JCIDS "focuses on delivering and refining full-spectrum solutions…which result in new or improved capabilities" [77]. Figure 23 below illustrates the main differences between JCIDS and RGS:

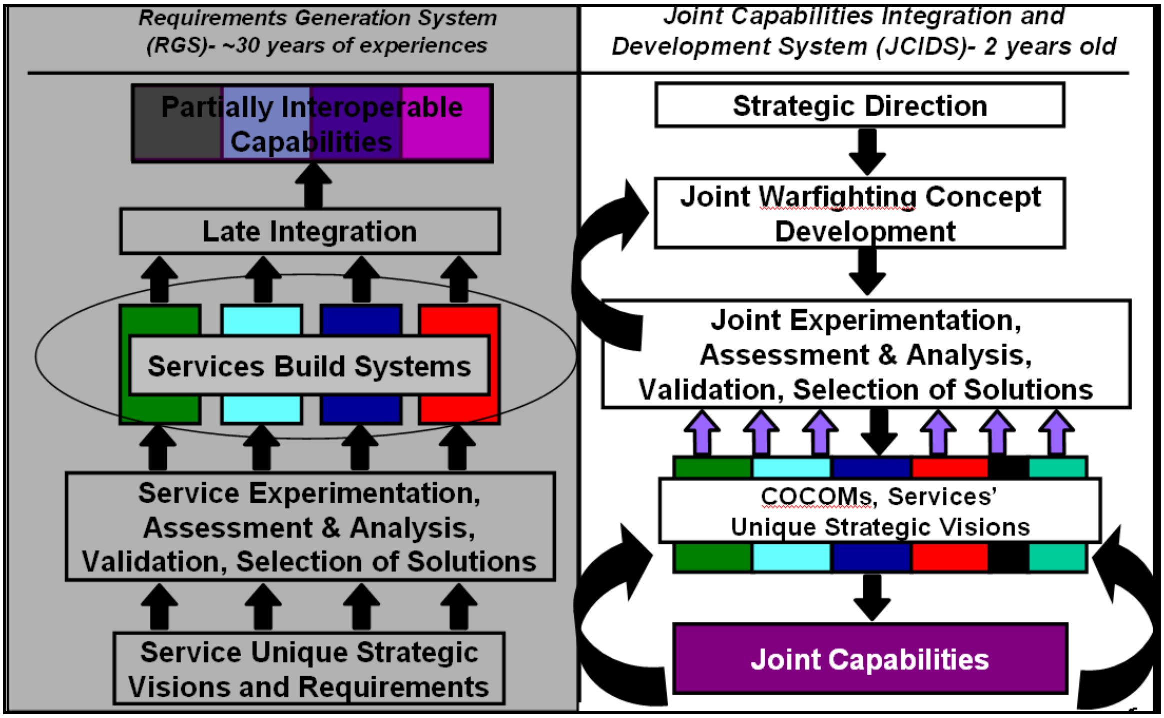


Figure 23: RGS vs. JCIDS [78]

The DoD developed JCIDS using the findings of *The Joint Defense Capabilities Study* (JDCS) conducted by the Joint Defense Capabilities Team (JDCT) to "examine and improve the DoD processes for determining needs, creating solutions, making decisions, and providing capabilities to support joint warfighting needs" [76]. The JDCS was chartered by Secretary Rumsfeld and completed in January of 2004. It set out to create a set of findings that would serve as a roadmap for the DoD and guide it to the desired end state; a "streamlined, collaborative, yet competitive process that produces a fully integrated joint warfighting capability" [128]. Please refer to referenced material for details regarding the JDCS.

JCIDS is supported by two separate documents; the Chairman of the Joint Chiefs of Staff Instruction (CJCSI) and the Chairman of the Joint Chiefs of Staff Manual

(CJCSM). The CJCSI provides a top-level description of the process and outlines the organizational responsibilities while the CJCSM defines performance attributes, key performance parameters, validation and approval processes, and associated document content. In essence, the CJCSI says what JCIDS does and who should do it while the CJCSM says how to do it.

Since the initial release, the DoD has revised the JCIDS process several times. There have been three additional updates to both the CJCSI and CJCSM to date. The most updated versions, CJCSI 3170.01G and CJCSM 3170.01D, were release in May of 2009 [97; 96]. A summary of the updates with document number and release date can be found in Table 7.

The current JCIDS Instruction document, CJCSI 3170.01G, describes JCIDS as a process that "implements an integrated, collaborative process to guide development of new capabilities through changes in joint doctrine, organization, training, materiel, leadership and education, personnel, and facilities (DOTMLPF) and policy" [139]. Its primary responsibilities are highlighted in Figure 24.

Table 7: CJCSI and CJCSM Update Summary [104; 103; 105; 134; 135; 139; 140; 97]

Document Name	Published Date
CJCSI 3170.01C	June 24, 2003
CJCSI 3170.01D	March 12, 2004
CJCSI 3170.01E	May 11, 2005
CJCSI 3170.01F	May 1, 2007
CJCSI 3170.01G	March 1, 2009
CJCSM 3170.01A	March 12, 2004
CJCSM 3170.01B	May 11, 2005
CJCSM 3170.01C	May 1, 2007
CJCSM 3170.01D	July 31, 2009

According to the Defense Acquisition Guidebook, JCIDS "informs the acquisition process by identifying, assessing, and prioritizing joint military capability needs" [165]. At the heart of the JCIDS process is the Capabilities-Based Assessment. This assessment is the "basis for the development of JCIDS [outputs] and results in the potential development and deployment of integrated, joint capabilities" [140]. The outputs of this assessment are used to define the needs and requirements of new acquisition programs.

What is a JCIDS responsibility…	*What is NOT a JCIDS responsibility…*
• Ensures the joint force has the capabilities to perform across the range of operations	• Is not capabilities-based planning
• Is a primary interface to the DoD acquisition system	• Is not DoD 5000
• Implements an integrated process to guide new capabilities development	• The JROC is not JCIDS
• A key linkage on how the future joint force will fight	• Joint Concepts are not JCIDS
• Provides the analytic baselines to support studies to inform capability development	• The Analytic Agenda is not JCIDS
• Leverages expertise to identify improvements to existing capabilities and to develop new warfighting capabilities	• Is not designed to obtain or address near-term funding or urgent warfighting needs (JRAC) but some changes are being considered to make more agile

Figure 24: Summary of JCIDS Responsibilities [78]

5.2.1.1 The Capabilities-Based Assessment

The CBA "defines capability needs, capability gaps, capability excesses, and approaches to provide those capabilities within a specified functional or operational area" [140]. The latest guidance on the CBA cites three major phases [69]:

- The Study Definition Phase
- The Needs Assessment Phase
- The Solutions Recommendations Phase

Note that in previous JCIDS and CBA documents, these three phases were referred to as the Functional Area Analysis (FAA), the Functional Needs Analysis (FNA), and the Functional Solutions Analysis (FSA) phases, respectively [139] and their relationship is depicted in Figure 25. These three phases work in a serial fashion, with the outputs from one phase feeding into the next.

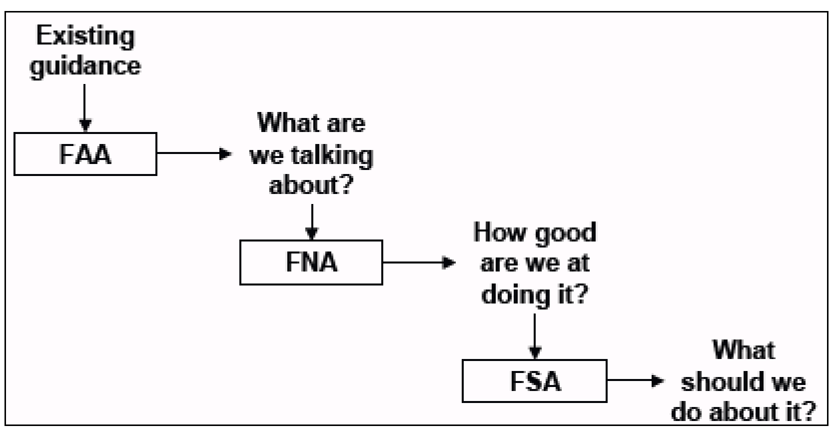


Figure 25: Flow of Information Between CBA Elements [68]

At the beginning of the Study Definition Phase (and of the CBA overall), military scenarios that are relevant to the defense strategy are first defined and selected. Desirable strategic capabilities are identified by defining the objectives and associated effects for each scenario. Doctrinal approaches for meeting these objectives and providing the intended effects can then be collected to develop a set of functions and tasks. A set of quantitative and/or qualitative measures (i.e. MoEs or Key Performance Parameters (KPPs)) is then defined, along with acceptable/required output ranges, so that DoD's ability to perform these tasks and provide the required capabilities can be measured. The established scenarios, capabilities, and measures are then used during the Needs Assessment Phase to evaluate existing assets and solutions. If the assessed MoE and KPP values of existing solutions do not fall within the acceptable ranges established during the Study Definition Phase, the Solutions Recommendations Phase is initiated to identify potential solutions to bridge the capability gaps. If the decision-makers select a materiel solution, the Defense Acquisition System (shown in Figure 4) is initiated and the outputs of the CBA are fed into the Materiel Solutions Analysis to help define the needs and requirements of the acquisition program.

5.2.2 Step 1: Describe Capability Need(s)

In this step, the underlying capability needs and requirements that are driving the potential acquisition programs is identified and described. Typically, capability needs are derived from Joint Integrating Concept (JIC) documents. According to the DoD, a JIC is defined as:

> "an operational-level description of how a joint force commander, 8-20 years into the future, will perform a specific operation or function derived from a JOC and/or a JFC. JICs are narrowly scoped to identify, describe, and apply specific military capabilities, decomposing them into fundamental tasks, conditions, and standards. Further analysis and expansion of tasks, conditions, and standards is accomplished after JIC completion in order to effectively execute CBA. Additionally, a JIC contains illustrative vignettes to facilitate understanding of the concept" [32].

These documents describe the ways and means military commander will want to operate in the future and the combination of these ways and means represents the capability needs of the future.

In the absence of a JIC, then the motivation must come from "appropriate strategic guidance" [69]. This guidance can be in the form on National Military Strategy, National Defense Strategy, or other strategic guidance documents.

While this step may seem repetitive since the capability needs has already been described by JCIDS/CBA output documents, it is imperative that the scope and breadth of the assessment be cleared defined up front before any analysis is performed. Additionally, this step allows further clarification of the capability need or needs being addressed so that there will be no confusion as to why the capability requirements used to assess program robustness were selected or even what these capability requirements measure.

5.2.3 Step 2: Describe Solution Concepts & Enabling Technologies

During the JCIDS/CBA process, potential solutions for addressing capability needs are identified and selected. Solutions that are materiel (i.e. requiring equipment/hardware), lead to acquisition programs. During the AoA, materiel solutions are evaluated and the most appropriate solution is selected for development. In this step, relevant background information regarding materiel solutions (and associated technology alternatives) that will be analyzed is identified and investigated in preparation for further analysis. Similar to the previous step, this involves identifying and collecting relevant information on the materiel solution and its associated enabling technologies, including:

- Description of materiel solution architecture
    - The structure of the materiel solution's "components, their relationships, and the principles and guidelines governing their design and evolution over time" [97].
    - "A framework or structure that portrays relationships among all the elements of the [materiel solution]" [10]
    - Descriptions of the materiel solution's "tasks, operational elements, and information flows" providing desired capability(s) [145].
- Description of the materiel solution's enabling technologies
    - What are the technologies that, once developed, will enable the materiel solution to meet capability requirements?
    - Describe of technology application

        - A description of the physical and mathematical formulations behind the technology is needed to define their implementation as a solution for meeting capability requirements.
    - Describe technology compatibility and interoperability
        - Establishing the compatibilities between technologies prevents the selection of incompatible technologies during the Analysis of Alternatives.
        - The degree of established interoperability between technologies can be used by the decision-makers as a criterion for selecting program technology portfolio.
    - Describe technology maturity and uncertainty
        - Describe the maturity level of the enabling technologies.
        - Define the performance and development uncertainties associated with each immature technology alternative.

The purpose of this step is not only to describe the materiel solution and associated enabling technologies being evaluated by the assessment, but also to identify the uncertainties associated with immature enabling technologies that jeopardize the materiel solution's effectiveness. This information will be used during Phase II to create the Modeling & Simulation environments that will capture the impact of the materiel solutions and its associated technologies as well as during Phase III to probabilistically evaluate the impact of technology uncertainties on program requirements.

5.2.4 Step 3: Identify Relevant Scenarios and Metric Requirements

Once the capability need or needs and associated enabling solutions have been identified and described, the next step is to define the evaluation metrics that will be used by acquisition decision-makers to determine the success/failure of the program. Typically this consists of a set of quantitative metrics decomposed from/associated with program budget, schedule and capability requirements

  - In addition to the MoEs and KPPs associated with the capability needs being addressed, the set of evaluation criteria should also include cost and time metrics that are relevant to the development of the materiel solution and its enabling technologies. This assures that the relevant capability, cost, and schedule risk implications associated with the materiel solution's immature elements are captured by the assessment.

- Acceptable metric thresholds/constraint values
  - Defining the acceptable/desirable range of values for each metric will provide the Program Managers and decision-makers with a quantitative assessment of the solution's ability, or more importantly, its inability to meet each requirement in light of technology uncertainties.

The output of this step is the set of program requirement metrics, each with an accompanying constraint/threshold range that quantifies the capability and development requirements for the materiel solution or solutions being assessed.

5.2.5 Step 4: Define Robustness Metrics

The last step of Phase I is to define the program robustness evaluation criteria. As noted in Section 2.1, robustness is typically measured using *variance* or *percentile difference*. However, depending on the application, modified forms of either metric or other statistical measurements can be used as long as they meet decision-maker requirements for robustness assessment.

5.2.6 Summary

In this phase, relevant problem background information is identified, collected, and processed into assessment evaluation scenarios and robustness metrics. This process typically involves examining strategic defense and military documents as well as JCIDS/CBA requirements definition documents and extracting the information needed to conduct a robustness assessment on candidate capability enabling solutions and associated technology elements. Since the techniques used by the DoD to identify capability needs, define relevant scenarios, and generate enabling solutions are outside the scope of this research and are generally left to the individual JCIDS/CBA teams, the author will only focus on the required inputs and for these steps. For identifying relevant program robustness metrics, standardized methods for capturing decision-maker/customer needs and organization internal brainstorming activities can be used or if decision-maker input is available, more structured and accepted methods such as Quality Function Deployment or the Seven Management and Planning Tools are applicable. Regardless of the techniques used, the outputs of Phase I should be the set of enabling solutions and associated technology elements to be assessed, the scenarios within which they will be evaluated, and metric requirements that will be used to assess the robustness of candidate solutions.

Inputs

- Strategic Guidance
- JCIDS/CBA output documents
- Decision Maker preferences

Techniques

- Brainstorming activities
- Seven Management and Planning Tools (e.g. Relations diagrams, Prioritization matrices, etc…)
- Robustness Assessment Techniques (i.e. standard or modified versions of the variance or percentile difference techniques)

Outputs

- Set of enabling solutions, associated technology elements, and their expected impacts
- List of program robustness assessment metrics derived from program requirements and decision-maker preferences

5.3 Phase II: Model Creation

In Phase II, computer-based technology performance and development forecasting models are created and combined with a probabilistic analysis process such as Monte Carlo Simulations. The resulting analysis environment will provide a probabilistic and quantitative forecasting of the impacts of technology performance and development uncertainties on program capability, budget, and cost requirements. This environment and its outputs can then be imported into a MOGA-based optimizer in Phase III in order to generate candidate technology portfolios for meeting decision-maker robustness requirements and preferences.

This phase consists of the following steps:

- Step 5: Create Technology Forecasting Models
- Step 6: Create Probabilistic Forecasting Environments

5.3.1 Step 5: Create Technology Forecasting Models

In this step, technology performance and development models are created. The purpose of these models is to quantify the impact of technology performance and development parameters on the relevant requirements and robustness metrics identified in Step 4. Presumably, technology performance impact and development are modeled separately.

5.3.1.1 Modeling Technology Impact on System Capabilities

In order to assess the impact of technology performance uncertainties on system capabilities, it is necessary to first create a parametric and quantitative model whose inputs reflect technology performance and whose outputs can be used to measure system performance and effectiveness metrics. This requires capturing the *systems-of-systems* (SoS) nature of the problem.

5.3.1.1.1 Introduction to Systems-of-Systems

The concept of a *system-of-system*s has been increasing in popularity in recent years, especially within the defense acquisition community. Multiple definitions of a SoS current exist:

- The International Council on Systems Engineering (INCOSE): "a set of different systems so connected or related as to produce results unachievable by the individual system alone" [66; 83]
- The Department of Defense: "a set or arrangement of systems that results when independent and useful systems are integrated into a larger system that delivers unique capabilities" [96]

Based on these definitions, it seems that a SoS is analogous to a large-scale complex system with multiple sub-system components. In fact, many contend that a SoS is simply a large-scale complex system. However, Maier has identified "five principal characteristics that are useful in distinguishing very large and complex but monolithic systems from true systems-of-systems" [90]:

- ***Operational Independence of the Elements:*** If the system-of-systems is disassembled into its component systems the component systems must be able to usefully operate independently. The system-of-systems is composed of systems which are independent and useful in their own right.
- ***Managerial Independence of the Elements:*** The component systems not only can operate independently, they do operate independently. The component systems are separately acquired and integrated but maintain a continuing operational existence independent of the system-of- systems.

- ***Evolutionary Development:*** The system-of-systems does not appear fully formed. Its development and existence is evolutionary with functions and purposes added, removed, and modified with experience.
- ***Emergent Behavior:*** The system performs functions and carries out purposes that do not reside in any component system. These behaviors are emergent properties of the entire system-of-systems and cannot be localized to any component system. The principal purposes of the systems-of-systems are fulfilled by these behaviors.
- ***Geographic Distribution:*** The geographic extent of the component systems is large. Large is a nebulous and relative concept as communication capabilities increase, but at a minimum it means that the components can readily exchange only information and not substantial quantities of mass or energy.

Since the properties of *evolutionary development* and *emergent behavior* are valid for a *complex system* as well, it seems that the primary distinction between a *system-of-*

systems and a *complex system* lies in the *operational, managerial, and geographical independencies* of the SoS components. The behaviors and interactions (if any) between these independent component systems combine to form the behavior of the overall SoS. For example, a commercial airliner can be viewed as a *complex system* with its own set of behaviors while the national air transportation system is a system-of-systems comprised with multiple commercial airliners, air traffic controllers, etc… The overall behavior of the national air transportation system is a result of the merging of the behaviors of the individual systems within the transportation system. The military is another example of a system-of-systems with the individual systems designed and managed/operated in such a way as to produce the desired/required emergent behavior (i.e. meeting strategic goals). Figure 26 below depicts the hierarchy of the overall military SoS, its component systems, and the component of those systems (subsystems).

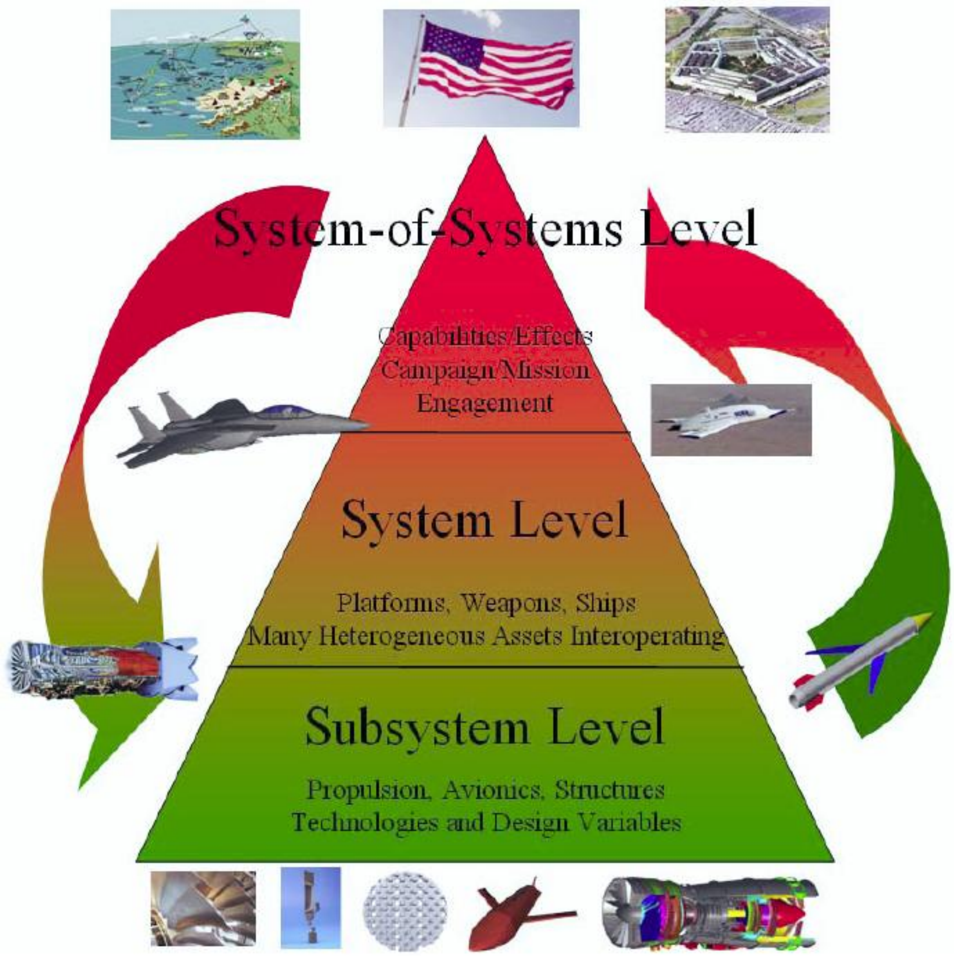


Figure 26: Military System-of-Systems Hierarchy [21]

Based on the figure above, modeling the effectiveness of one or more military assets within a given scenario/mission requires a modeling approach that can account for the relationships not just between a military system and its technology subsystems but also its interaction with the environment and other entities such as enemy systems and assets. Traditionally, such estimations have been obtained through the use of Empirical Relationship Models or Physics-based Simulations. However, the highly interactive nature of a military scenario/campaign model has lead to the use of Discrete Event Simulations in recent years.

As noted in Section 2.2.2.4, multiple approaches exist for modeling technology impact on system capabilities. However, as shown by the Air Force's development of the SEAS environment, agent-based models are particular suitable for this purpose.

5.3.1.1.2 Introduction to Agent-Based Modeling & Simulation

An agent-based model is a class of computational models for simulating the actions and interactions of autonomous agents in order to determine the combined or *emergent* behavior of the group as a whole. It is "built upon the premise that complex behavior emerges from the rules and interactions of the [agents] that compose the system" [74]. Each agent "individually assesses its situation and makes decisions on the basis of a set of [pre-determined] rules…,[and] may execute various behaviors appropriate for the system they represent" [23]. Bonabeau states:

> "ABM is, by its very nature, the canonical approach to modeling emergent phenomena: in ABM, one models and simulates the behavior of the system's constituent units (the agents) and their interactions, capturing emergence from the bottom up when the simulation is run" [23].

A common example application of an ABM is the modeling of the evacuation of a crowd of people from an enclosed area due to fire. Figure 27 provides a snapshot of a simulation conducted by Helbing, Farkas, and Vicsek [59]. The results of two separate scenarios are depicted by the figure. In Figure 27 (a), 200 people (yellow circles) are trying to leave a room as soon as possible. However, after 45 seconds, only 44 people have escape while 5 have been injured (green circle). Figure 27 (b) and (c) simulates the same scenario with the addition of a solid round column (black circle) near the exits that the escapees must maneuver around in order to get to the exit, with (b) capturing the simulation after 20 seconds and (c) after 45 seconds. Surprisingly, the addition of the column *improved* the evacuation process, with 72 escaped and none injured after 45 seconds [59]. This outcome is both unexpected and contrary to intuition but exemplifies the emergent behavior of interacting autonomous entities can only be captured by an agent-based model.

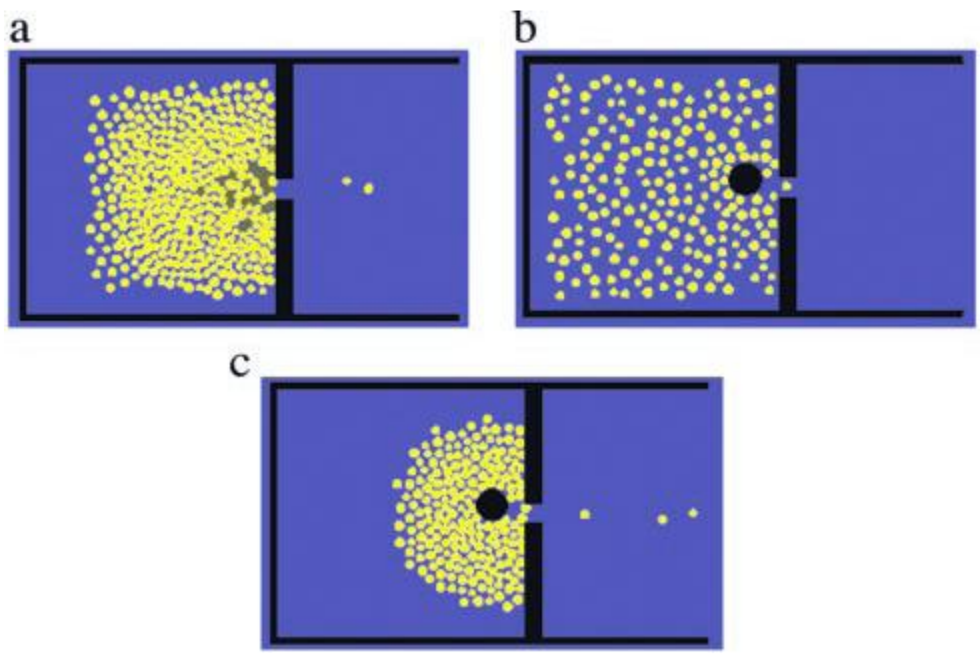


Figure 27: Fire Escape Agent-Based Simulation [23; 59]

The primary benefit of using an ABM&S is that it "captures [the] emergent phenomena" that emerge when autonomous entities interact with one another and their surrounding environment [23]. Within the context of this research, the emergent phenomena are the capability metrics associated with various military scenarios and the autonomous entities are the military systems and assets that interact with each other and with the scenario environment during the simulation. The behavior of the autonomous entities within the simulation can then be defined and modified using technology performance parameters. This allows for a quantitative linking between technology performance parameters and mission capability metrics. Probabilistic analyses of the technology parameters that affect agent behaviors will result in distributions of scenario capability metrics.

Regardless of the modeling approach used, the goal for this step is to create a parametric model that can be used to quantify the impact of technology performance parameters on system capability metrics. The parametric nature of this model will enable it to be coupled with a probabilistic analysis technique such as Monte Carlo simulations so that the impact of technology performance uncertainties can be aggregated into system capability variations. This information can then be used to assess the robustness of system capabilities against technology uncertainties.

5.3.1.2 Modeling Technology Development Impact on Program Budget and Schedule

As stated earlier, technology development can be broken down into a series of activities that have to be completed in order for the technology to reach full maturity. The uncertainties associated with each activity, particular the cost and time required for completion lead to potential variations in total development time and cost for the technology. These variations prevent an accurate estimation of total budget and schedule and could lead to longer and costlier than expected acquisition programs. As such, the cost and time uncertainties associated with each technology development activity need to be captured and correlated to variations in program budget and schedule requirements. Such an information will help acquisition DMs assess the robustness of the program budget and schedule against technology development uncertainties and allow them, if necessary, to take the appropriate steps to reduce the risk of exceeding either constraint.

A commonly utilized technique for visualizing the flow of project activities is the *Gantt Chart* originally developed by Henry K. Gantt as production control tool in 1917 [46]. In a *Gantt Chart*, the list of project activities (identified using industry standard methods such as *Work Breakdown Structures* (WBS) are typically listed down the left vertical axis while a timeline extends to the right (see Figure 28. Using this format, the time allocated and the degree completion for each activity can be visualized rapidly. Overall project development progress can be then assessed by examining the degree of completion for each activity vs. the time allocated for that activity to determine if the project is on schedule or now.

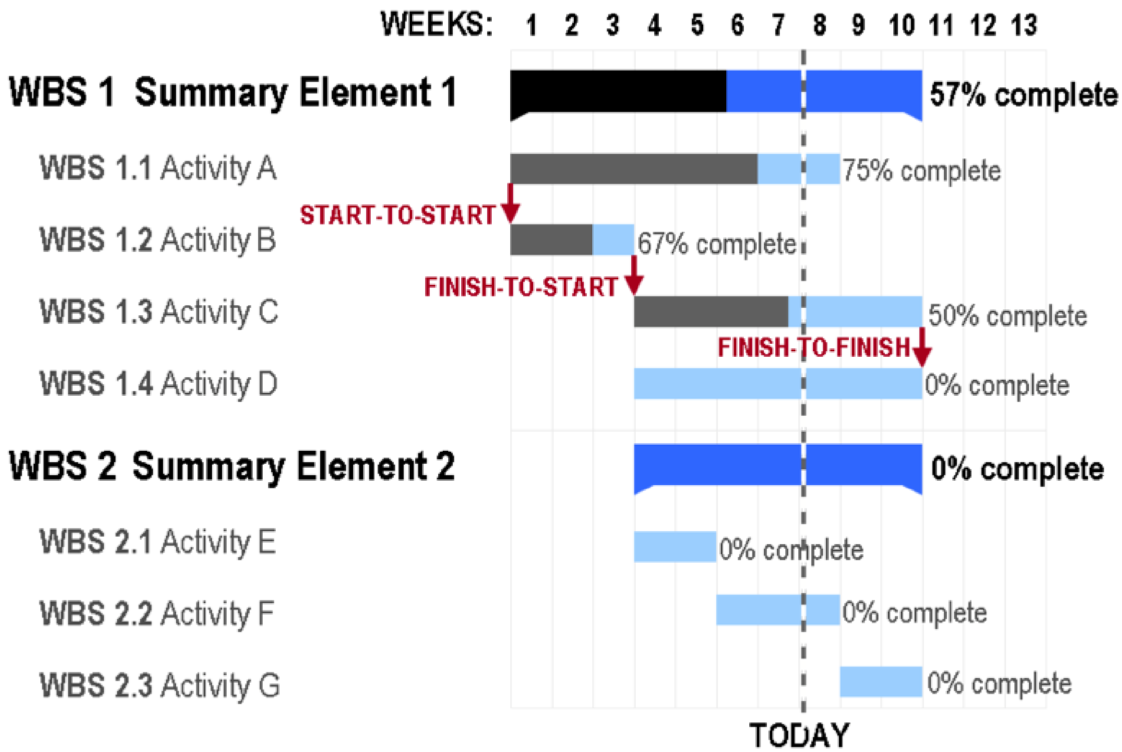


Figure 28: Example Gantt Chart [24]

While a Gantt chart is "an excellent technique for visualization of the time necessary for specific activities in a project," it requires a pre-estimation of activity timelines [85]. It also does not provide a visualization of the costs associated with each activity. Additional schedule/cost estimation methods are needed to generate the data for each activity's "time/cost box." Additionally, if uncertainties are assigned to each activity's "box," the chart can quickly become visually overwhelming and actually impede project management. As such, other methods for time/cost estimation have to be considered.

In general, project time/cost estimation techniques rely heavily on expert input. Estimations for the time and cost associated with specific project activities (or for the project in general) solicited from experts and used to determine overall project time and cost. To reduce the inherent bias of expert opinion, techniques that solicit data from multiple sources/experts like the Delphi Technique are used. However, these techniques suffer from the limitations noted in Chapter 2. In order to provide an objective and parametric modeling of the time and cost uncertainties associated technology development project activities, *Project Network Analysis*-based approaches are often employed [85; 86; 121].

Table 8: Common Cost/Time Estimating Methods and Concepts [100; 85]

Method	Description
Top-down techniques	Top-down techniques (also called aggregation techniques) are focused on estimating the costs or time incurred in large elements of the project first and then filtering the cost and time estimates down to components of the large elements.
Bottom-up techniques	Bottom-up techniques attempt to define the cost or time of the lowest level sub-components (or tasks) and then combine the low-level cost and time values to determine the cost or time for higher level components.
Analytical equations	Exact representations of the cost or time in terms of the contributing independent variables.
Parametric equations	Equations where parameters are used to control the relationship between the independent and dependent variables. These equations can take many forms and are often used as approximate representations of more complex analytical equations or processes (metamodels).
Regression equations	Regression equations involves gathering historical data on previous similar activities, and fitting a curve to the data, usually based on one variable (e.g. weight). The cost or time of similar activities or components may be estimated with the regressed equation.
Expert opinion	Estimations given by people knowledgeable in the field of study. The expert opinions can be of the overall cost or time, or of additional variables which affect the cost and time.
Analogy	Estimation of cost or time by comparing the project or project elements to other projects that have already been completed and have similar features.
Standard Costs and Times (Activity Based Costing)	Usually used for a bottom-up approach, standard costs and times (usually gained from observation) are associated with specific products and activities, and always used to represent the cost and time for completion of the products or activities when used as a part of an overall system or project plan.

5.3.1.2.1 Introduction to Project Network Analysis

Project network analysis is a "graphically oriented project management method that models the structure of the project" and is very useful for capturing the cost and time management aspects of technology development [85]. It's best known in the form Program Evaluation and Review Technique (PERT) and the Critical Path Method (CPM) developed in the 1950s [85]. These methods model technology development using a series of boxes (nodes) and arrows (arcs). In Activity on Arrow (AoA) methods, the arcs represent the activities and the nodes help with the flow of information. In Activity on Node (AoN) methods, the nodes represent the activities and the arcs are used to show the flow of the process. Both techniques "model the order of completion of activities and the possibility of parallel work efforts by visually representing the different paths through the project" [28]. This straightforward depiction of project activities and processes "allows for [a] simple calculation of the cost and time required for completion of the project," which is accomplished through the integration the costs and time associated with each completed task [85].

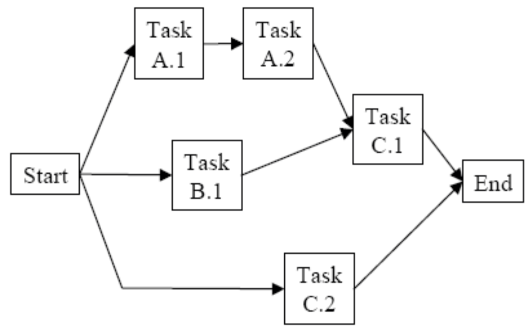


Figure 29: Example of an Activity on Node Project Network Model

Recent incarnations of this approach such as the Venture Evaluation and Review Technique (VERT) and Visual Slam with AweSim have incorporated probabilistic analysis techniques by "[requiring the user to input probabilistic distributions for cost and schedule (for each activity)" to generate "probabilistic results for the overall project cost and completion time" [85; 86]. Expert opinions on the assumptions of these distributions (shape function, range) can then be solicited to provide quantitative and probabilistic analysis of technology development time and cost distributions associated with technology projects. By soliciting SME input on these assumptions, some of the drawbacks of using models instead of expert opinion are mitigated.

5.3.1.2.1.1 Introduction to the Critical Path Method

The Critical Path Method is a method for "analyzing and managing a technology development project using a combination of critical path methods and probabilistic network analysis performed in VERT" [85; 19]. This method is centered around a process that requires obtaining cost-time tradeoff curves for the activities in the network and use VERT's probabilistic network analysis capabilities to generate the final cost and time distributions for the project [85]. The emphasis of this method is high-level decision-making by modeling the time and cost curves (i.e. distribution of values) associated with each project activity and calculating the time and cost curves for the project overall.

This method is useful if the critical (i.e. necessary) steps associated with a technology's development can be identified. However, it requires the range and distribution associated with each activity's completion time and cost value to be defined ahead of time. This is typically accomplished with the help of SMEs [3; 81; 85].

5.3.2 Step 6: Create Probabilistic Forecasting Environments

Once the technology performance and development models have been created, the next step is to couple these models with a probabilistic analysis technique in order to create probabilistic forecasting environments for generating requirements robustness assessment data. As stated earlier, Monte Carlo Simulations are commonly used to conduct uncertainty analyses in engineering industry and the design community [17; 39]. While the specific steps for conducting this analysis can vary depending on the specifics of each problem, the general process for conducting a Monte Carlo analysis consists of the following steps [61; 81]:

1. Define range and distribution shape (uniform, triangular, normal, etc…) for input parameters whose values are uncertain for a given

2. Generate a set of pre-determined number of samples using the input ranges and distributions defined in the previous step, using random or latin hypercube generation techniques.
3. Propagate samples through analysis environments (i.e. generate model output metric data for each sample).
4. Gather output metric data for sample dataset.
5. Extract relevant output statistical information.

In general, the larger the sampling size, the more realistic the output statistics are. However, a larger sampling size will require more computational resources. Thus a compromise has to be made between computational requirements and output accuracy and precision.

In order to reduce computational burden while still allowing for large MCS sampling sizes, several of the techniques examined in Chapter 3 utilize *Surrogate Models* in lieu for sample analysis propagation.

5.3.2.1 Introduction to Surrogate Models

Surrogate models are created by "careful observation of the analysis code behavior using a Design of Experiments (DoE)" [118]. DoEs are "purposeful manipulation of the significant variables, identified for the particular ranges of interest, with the goal of identifying the effects of each variable and the cross terms between the variables" [118]. These models mimic the behavior of the simulation model as closely as possible while being computationally cheap(er) to evaluate. They are typically used to "rapidly assess the results of a particular code, in a particular region of the design space, for conceptual design purposes" [118]. This technique is based on the following assumption:

> "In any given area of the design space, the variability of results can be attributed primarily to a handful of variables. While the other variables are necessary for the magnitude of the response, in nearly every case the vast majority of variables can be defaulted within the ranges being considered, significantly reducing the number of computational runs required for design space assessment. This concept, the Pareto Principle, allows designers in early stages of design to concentrate on the design variables that truly matter in the selected concept" [118].

Many types of Surrogate Models currently exist for various applications and assumptions, but the approaches based on regression analysis forecasting techniques discussed in Chapter 2 such as Response Surface Methodology of Artificial Neural Networks are quite popular [3; 74; 81; 85; 102]. Regardless of the technique selected, the desired product is a set of "equations that represent the behavior of [the] higher-fidelity code or tool with a high degree of accuracy" while requiring significantly less computational resources so that a probabilistic analysis of these relationships can be conducted using Monte Carlo simulations [119].

5.3.3 Summary

The objective of this phase is to create the probabilistic environments that will be used to quantify the impact of technology performance and development uncertainties on program capability, budget, and schedule metric metrics. The output distributions for these metric requirements can then be used to optimize portfolio solutions and support program robustness assessments.

During Step 5, technology performance impact and development activity models are created to in order to quantify the impact of candidate technologies on system. In Step 6 the forecasting models can then be coupled with a probabilistic analysis technique such as Monte Carlo Simulations to provide probabilistic forecasting environments for generating requirements robustness statistical data. Once these environments have been created, they can then be used in Phase III and Phase IV to support technology portfolio optimization and robustness evaluation.

Inputs

- Capability, budget, and schedule requirement and robustness metrics
- Technology impact descriptions (used to create technology impact model)

Techniques

- Technology Performance Impact Modeling Techniques
    - Empirical/Physics-based models couple of performance and capability metric relationships solicited from experts
    - Discrete Event Simulation techniques (e.g. event-based, agent-based)

- Project Network Analysis of technology development activities models
    - Activities models generated using expert opinions
- Surrogate Modeling and Design of Experiments techniques
- Monte Carlo Simulation

Outputs

- Probabilistic technology performance and development uncertainty analysis environments

5.4 Phase III: Alternatives Generation

In this phase, the probabilistic analysis elements created Step 6 are coupled with a Multi-Criteria Decision Making technique generate candidate technology portfolios that are optimal to program requirements robustness criteria. As noted previously, Multi-Objective Decision Making techniques are more appropriate for this application because of their ability to generate designs optimal to multiple objectives rather than ranking all possible solutions according to their attribute scores. However, if a previously down-selected set of solutions already exists, then this phase will not be necessary or is only needed to further reduce the number of options for the decision-maker. In either scenario, a Multi-Attribute Decision Making technique is more suitable.

For the proposed methodology, the author has assumed that no preexisting set of technology portfolios exist to be evaluated and ranked and thus the steps in this phase reflect those associated with identifying optimal technology portfolios and not ranking existing ones. Additionally, since it was observed during Chapter 2 that a Multi-Objective Genetic Algorithm is well-suited for this class of problems due to the discrete and combinatorial nature of technology portfolio optimization and has been successfully implemented by Raczynski in his implementation of the SOAR methodology, the proposed methodology will in general utilize a MOGA-based technology optimization selection approach [124]. As such, details of other multi-objective optimization techniques will not be provided. However, several are identified below:

The steps associated with a MOGA are:

- Step 7: Select Optimization Objectives
- Step 8: Define Fitness Function
- Step 9: Create Optimization Process
- Step 10: Generate Alternate Technology Portfolios

5.4.1 Step 7: Select Optimization Objectives

The first step in an optimization process is to select the objectives that will be optimized against. This can be the set (or subset) of program requirements or the set (or subset) of requirements robustness evaluation metrics associated with those requirements defined in Step 4. As stated, the purpose of this phase is to generate a set of alternate solutions that can be presented to the decision-maker for final down-select. As such, the selected objectives should reflect the needs and wishes of the decision-maker without over-constraining the problem (i.e. results in only one or few possible solutions due to tight constraints).

5.4.2 Step 8: Define Fitness Function

Once the optimization objectives have been identified and defined, the next step in a MOGA-based technology portfolio is to determine how technology portfolio fitness is determined. As stated previously, there are two general approaches to determining population member fitness; calculating using objective functions or assignment using Pareto-Rankings. The approach selected for a given proposed application depends on the needs and available resources for conducting optimization. For assessment with limited time and computational resources, fitness calculation using objective functions such as a *Weighted-Sum* approach is more appropriate as it is easier to implement and converges quicker than the *Pareto-Ranking* approach. However, objective function calculation based approaches such as *Weighted-Sum* require multiple iterations of optimization with varying weighting scenarios in order generate multiple candidate portfolios for evaluation for the decision-makers. A *Pareto-Ranking* approach, theoretically, will generate the entire Pareto optimal solutions set or a representative set on a single pass and does not require assigning weights to each objective.

5.4.3 Step 9: Create MOGA-based Optimization Process & Tool

Once fitness assignment/calculation functions have been established, the MOGA-based technology portfolio optimizer can be created. The optimization process this tool varies according to the problem at hand, but generally speaking a GA will consist of the following elements:

- Initial Population Setup

- Fitness Calculation/Assignment
- Selection
- Reproduction
- Mutation
- Convergence Check
- Iteration (if non-convergence)
- Output Results

5.4.4 Step 10: Generate Candidate Technology Portfolios

The final step in Phase III is to use the created MOGA-based optimizer to generate a set of technology portfolios that optimally meet program requirements and robustness criteria. If a *Pareto-Ranking* approach was selected, this will result in a set of non-dominating technology portfolios that lie along the Pareto Fronts of the optimization objectives (i.e. program requirements robustness metrics). If a *Weighted-Sum* approach was used, multiple iterations of the optimizer needs to be performed using different objective weighting scenarios in order to generate a set of alternate solutions for the decision-makers.

5.4.5 Summary

In this phase, the probabilistic analysis environments elements created in Phase II are coupled with a Multi-Objective Genetic Algorithm optimization scheme to generate a set of candidate program technology development portfolios for acquisition decision-makers during the AoA. This process consists of identifying the optimization objectives that will be used by the MOGA optimizer to generate solutions (Step 7), selecting a portfolio fitness assignment/calculation technique (Step 8), completing the MOGA-based process and optimizer tool (Step 9), and using the tool to generate alternative solutions (Step 10). The generated set of alternatives can then be presented to decision-makers in the next phase for evaluation and selection.

Inputs

- Probabilistic technology performance and development uncertainty analysis environments
- Program requirements and/or robustness criteria

Techniques

- Multi-Objective Genetic Algorithm and associated techniques
  - Fitness calculation techniques such as *Weighted Sum* and *Utility Theory* **or** fitness assignment using *Pareto-Ranking* techniques

Outputs

- Set of technology portfolios optimized against program capability, budget, and schedule requirements and robustness criteria

5.5 Phase IV: Decision Support

In the final phase of the proposed methodology, outputs from the previous three phases are embedded within a computer-based Decision Support System for supporting early phase acquisition decision-making activities. This computer-based DSS allows program managers and decision-makers to rapidly visualize the tradeoffs in program requirements robustness between candidate technology portfolios (for AoA support). These tradeoffs allow for a more informed selection of program technology alternatives early on in the acquisition lifecycle (i.e. during the Analysis of Alternatives).

Additionally, the DSS and the embedded analysis elements can be periodically with new technology performance and development uncertainty data and assumptions (as they become available) to provide an updated assessment of program requirements robustness. Such information provides vital information to critical program decisions such as risk management and mitigation strategy formulation.

This phase consists of two steps:

- Step 11: Create Decision Support System
- Step 12: Support Decision-Making

5.5.1 Step 11: Create Decision Support System

The purpose of creating a computer-based Decision Support System is to bring together various pieces of information that will provide the decision-maker with valuable insights that can be used to make informed and effective decisions. This requires a careful and structured integration of interactive quantitative, qualitative, and graphical elements that maximizes the amount of useful knowledge being presented without overwhelming the user and requires an understanding of *Visual Analytics* techniques.

5.5.1.1 Introduction to Visual Analytics

The National Visualization and Analytics Center defines *Visual Analytics* as "the science of analytical reasoning facilitated by interactive visual interfaces" [108]. The motivation behind this field of study comes from that fact that "our ability to collect data is increasing at a faster rate than our ability to analyze it" and often times decision-makers are presented with "overwhelming amounts of disparate, conflicting, and dynamic information" even though the relevant information on "exists in a few nuggets" [108]. Proper use of visual analytic tools will allow analysts and decision-makers to synthesize the relevant information and derive useful insight to support informed and effective decision-making.

Visual Analytics is a "multidisciplinary field" that includes the following focus areas" [108]

- *Analytical reasoning techniques* that enable users to obtain deep insights that directly support assessment, planning, and decision making
- *Visual representations and interaction techniques* that take advantage of the human eye's broad bandwidth pathway into the mind to allow users to see, explore, and understand large amounts of information at once
- *Data representations and transformations* that convert all types of conflicting and dynamic data in ways that support visualization and analysis

- Techniques to support *production, presentation, and dissemination* of the results of an analysis to communicate information in the appropriate context to a variety of audiences.

While a detailed discussion of each area is outside the scope of this research, the design and usage of decision support aides should adhere to these objectives and thus the remainder of this section will focus on how elements of a computer-based Decision Support System should be designed and integrated for support early phase acquisition decision-making activities. After all, “analytical presentations ultimately stand or fall depending on the quality, relevance, and integrity of their content” [154].

5.5.1.2 Design Considerations

The objective of using a computer-based DSS for the proposed method is to synthesize and present relevant program requirements robustness data in an informative yet intuitive manner. Acquisition decision-makers can then use this information to assist with critical program decisions such as technology portfolio selection and program risk assessment. In general, a computer-based DSS consists of two equally important components: a *graphical user interface (GUI) front-end* and *background analysis elements*.

5.5.1.2.1 GUI Front-End

A graphical user interface, is a type of human-computer interface (i.e. a way for humans to relay commands to computer) that uses visual elements like windows, menus, and icons that can be manipulated by a mouse and keyboards. Compared to *command line interfaces* (CLIs), which require the user to input "only text and are accessed solely by a keyboard… [GUIs] make computer operations more intuitive, and thus easier to learn and use"[87].

For the intended application, the GUI front-end should consist of the following elements:

- Interactive elements that allows analysts and decision-makers to change assumptions regarding requirements, robustness metrics, and any other relevant parameters that affect the results of the assessment
- Graphical displays that presents analysis outputs that presents relevant data in a format that is intuitive to analysts and decision-makers

Since the first intended use of the DSS is to support technology portfolio selection, the GUI should provide the user with the ability to compare the performance of different alternate technology portfolio solutions. After all, "the fundamental act in statistical reasoning is to answer the question 'Compared with what?'"[154]. This means allowing the user to select between candidate portfolio options or allowing them to input a technology combination themselves. A simple and effective approach to do this is to use provide the user with the ability to select elements from a list of options (i.e. portfolios or technologies) with a clear indication of the selected option or options. Common implementations included drop-lists, check boxes, and buttons.

For inputting quantitative parameters information such as constraint values and preference weightings, input boxes and/or slider bars can be used. These intuitive and easy-to-operate elements allows for quantitative assumptions and inputs to be altered rapidly without re-coding or modification of background analysis elements.

Finally, arguably the most important components of the GUI front-end are the output visuals that represent the results of the background analysis. As Edward Tufte explains, "often the most effective ways to describe, explore, and summarize a set of numbers is to look at a picture of those numbers" [156]. Computer-based Decision Support Systems provide the ability to sort through immense stockpiles of data and quickly assemble and display "one-time confections designed to serve immediate, local, unique purposes" that assist in the decision-making process [155]. Visualization is not merely a way of presenting data but of "understanding the relations and hidden properties" embedded within the data [124].

Typically, statistical data are shown using a probability density function (PDF) graph, which shows the probability of the metric being a certain value, or a cumulative distribution function (CDF) graph, which can be used to show what percentage of the results falls between two specific values. They provide the more direct and description way of showing robustness statics. For example, both the *variance* and *percentile difference* robustness assessment approaches rely on statistical parameters based on PDFs of relevant metrics (see 2.1).

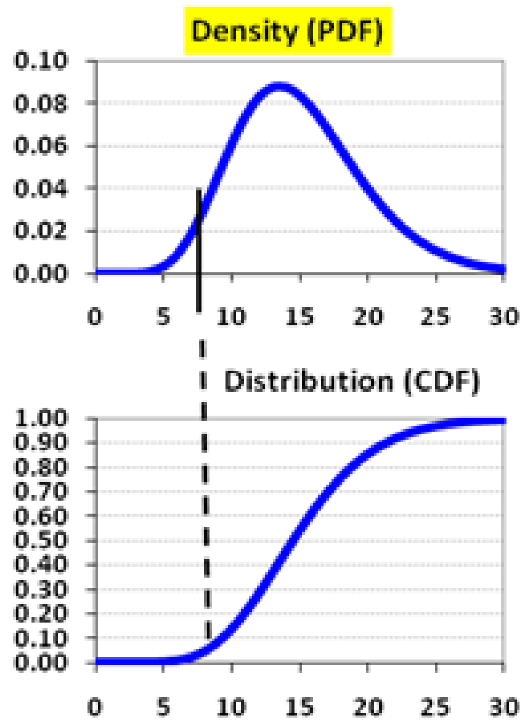


Figure 30: Example PDF and CDF Graphs

In additional to visuals of requirements robustness statistical data, other quantitative/qualitative/graphical information may be needed for decision-support. For example, for acquisition programs with a large number of metric requirements (which is probably all of them), it may be impractical to display robustness statistical for every metric requirement since such demonstration would most likely overwhelm the decision-maker/analyst. In these situations, it may be wiser to use a Multi-Attribute Decision Making technique such as OEC or TOPSIS to combine the requirement robustness statistics into a single manageable quantitative, qualitative, or graphical element that summarizes the results into a manageable format. However, it would be wise to maintain the ability, if so desired, to investigate the component contributors to the final "score" as such investigations could provide valuable insight that cannot be identified using the summary result.

Ultimately, the configuration and displays in the DSS's GUI front-end should be based on the questions being answered. According to Tufte, this question is: "What are the content reasoning tasks that this display is supposed to help with?" [154]. In this case, the content deals with the requirements robustness implications associated with the performance and development uncertainties for a given technology portfolio or a set of alternate technology portfolios.

5.5.1.2.2 Background Analysis Elements

As noted earlier, the data presented in the GUI front-end of the DSS is compiled from background analysis elements. Depending on the specific application, these elements can be simple databases (in which case table lookup techniques are used to compiled GUI front-end data), calculation elements (i.e. equations or expressions that generate data based on a set of inputs), or links to external entities that will provide the DSS with the necessary information. Regardless of the approach used, the objective is to "allow for tradeoffs to be made and assessed in real time" [124]. This means that the DSS needs to allow for decision input parameters and assumptions to be changed easily and have the background analysis elements update the data used by the visual outputs quickly. This "dynamic" tradeoff capability allows the analysts/decision-maker to not only perform tradeoffs between technology portfolio alternatives but also to perform sensitivity analysis of the output data to input assumptions (e.g. robustness "score" to requirement constraints). This provides insight in the "volatility the final plan has to an uncertain future" [124].

5.5.2 Step 12: Support Decision-Making

The 12th and final step of the proposed method is to use the computer-based DSS created in the previous step to support decision-making at critical program junctures (specifically during AoA and periodic program reviews such as Milestone Reviews). The process of making these decisions "is ultimately up to those involved in each application [of the proposed methodology]" [124]. The linkage between the program requirements and robustness metrics and program technology portfolio (or portfolios if during AoA) "allows those involved to not just see how much benefit one concept may provide over another but also to understand why such differences exist" [124]. Allowing program DMs to explore these relationships using the DSS will better help them understand the cost-benefits of program decisions, leading to a more informed program decision-making process and higher likelihood of future acquisition success.

5.5.2.1 Continuation throughout Acquisition Lifecycle

At this juncture, it should be clear that the proposed methodology is NOT intended to be a "one and done" process. Even though a majority of program technology development decisions are made early on in the acquisition lifecycle (i.e. pre-Milestone A), new circumstances later on in the program lifecycle (e.g. budget cuts, unanticipated variations in technology performance/development uncertainties, changing requirements, etc…) could require changes to program development and risk management strategies. The proposed method is designed be a living process that is continually updated with new data, assumptions, and requirements so that acquisition decision-makers can be updated on the current and potential future robustness of the program.

5.5.3 Summary

The objective of this fourth and final phase of the proposed method is to develop the decision-making tools that combine and condense the collected and generated data from the previous three phases into a format that is useful to the decision-maker. These tools present the relevant information in a visual and interactive manner and allow the decision-makers to make informed decisions regarding technology selection and/or development progress that will maximize program robustness against technology performance and development uncertainties and reduce the risk of program capability, budget, or schedule requirements failures.

Inputs

- Optimized technology portfolio alternatives
- Technology performance and development uncertainty analysis environments
    - Updated technology performance and development uncertainty estimations
- Program requirements and robustness evaluation criteria

Techniques

- Visualization techniques and interface design methodologies

Outputs

- Customized computer-based Decision Support System

5.6 ENTERPRISE Summary

As stated, the methodology introduced in this chapter is a general approach for addressing the need for requirements robustness assessment during early phase acquisition decision-making activities. This approach was formulated on the observation that while existing techniques did not sufficiently meet the needs for a acquisition requirements robustness assessment process, many of the elements are already being employed and thus can be used to synthesize a new technique that better meets the stated objectives. The result of this synthesis is the ENhanced TEchnology Robustness Prediction and RISk Evaluation (ENTERPRISE) method outlined in this chapter and summarized by Figure 31.

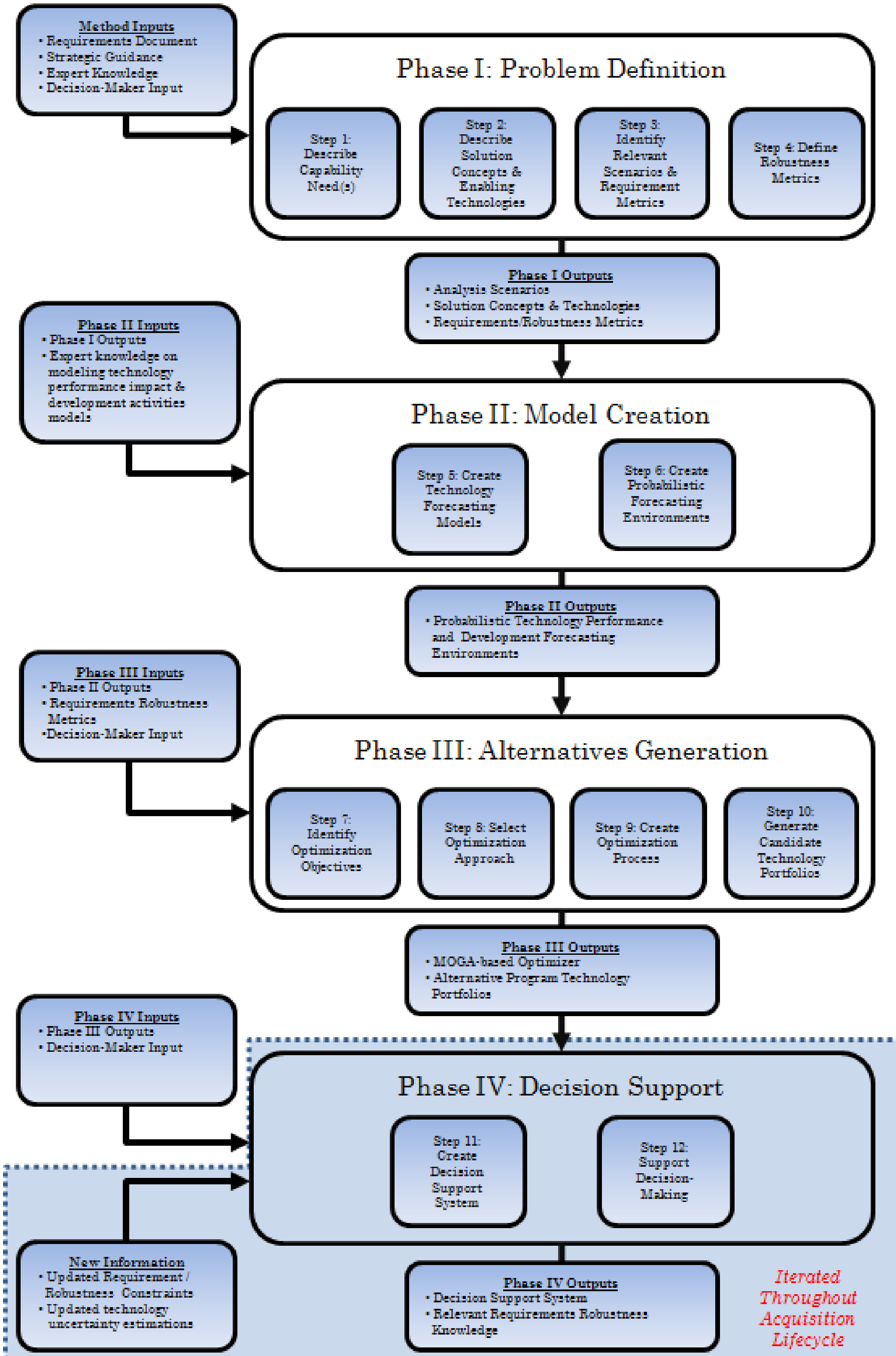


Figure 31: ENTERPRISE Methodology Overview

The ENTERPRISE method is built around the integrated use of the following components:

- Probabilistic Technology Performance and Development Forecasting Environments
- Multi-Objective Technology Portfolio Optimization Process
- Computer-based Decision Support System

The probabilistic technology forecasting environments combine multiple forecasting techniques to provide a probabilistic and quantitative estimation of the impact of technology performance and development uncertainties on program capability, budget, and schedule requirement metrics. The creation of these environments requires first the use of quantitative forecasting approaches, which in the past has relied on historical data and/or expert opinion. Unfortunately, the generally novel and immature nature of acquisition program technologies during early phases of the acquisition lifecycle limits the relevance and usefulness of these inputs. As such, there is a concerted effort to use computer modeling & simulation to generate forecasts (see Section 3.8) as powerful computer processors become more readily available. These models allow for quantitative objective forecasts.

The parametric nature of these forecasting models also allows them to be easily coupled with probabilistic analysis techniques (e.g. Monte Carlo Simulations). The result is a probabilistic forecasting environment that can be used to estimate the variations in forecast outputs based on uncertainty in forecast inputs. Input uncertainty is described using range and distribution functions and shapes and is typically defined using expert opinion. To reduce the computational requirements of this probabilistic analysis, Surrogate Modeling techniques based on regression analysis forecasting approaches such as Response Surface Methods or Artificial Neural Networks can be employed. These models significantly reduce the computational burden during probabilistic assessments without significantly reducing analysis fidelity.

In order to support program technology portfolio selection activities during pre Milestone A activities like the Analysis of Alternatives, the probabilistic forecasting environments are coupled with a Multi-Objective Genetic Algorithm to identify candidate portfolios that are optimal to decision-maker requirements and preferences. As demonstrated by Raczynski, the discrete and combinatorial nature of technology portfolio optimizations makes it a suitable candidate for Multi-Objective Genetic Algorithm optimization. Using this approach, technology portfolios that are optimal to multiple requirement metric robustness criteria can be identified without a full-factorial analysis of every single possible solution. The generated set of alternatives can then be presented to acquisition decision-makers for tradeoff studies and final down-select.

The various approaches for forecasting technology performance and development, as well as generating optimal technology portfolios suggested in this chapter are summarized by the table below:

Table 9: ENTERPRISE Matrix of Alternatives

Problem	Potentential Techniques		
Forecasting Technology Performance	Empirical Models (with expert-defined performance-to-capability relationships)	Physics-based Model (with expert-defined performace-to-capability relationships)	Discrete Event Simulation (e.g. Agent-based M&S)
Forecasting Technology Development	Empirical Equations (based on previous or similar technology development efforts)	Expert Opinions (for overall technology time and cost estimations)	Project Network Analysis
Portfolio Optimization/Selection	MOGA (fitness calculation w/ composite objective function)	MOGA (fitness assignment using Pareto-Ranking)	MADM Techniques (for ranking existing pool of solutions)

To help streamline the decision-making process, the ENTERPRISE method prescribes the use of a computer-based Decision Support System. This interactive and graphical tools combines interactive and visual analysis elements with rapid background analysis components and allows for rapid tradeoffs and display the relevant information in graphical and intuitive formats. This allows analysts and decision-makers to quickly visualize the impact of technology portfolio alternatives and changing program assumptions and constraints (i.e. target levels for metric requirements, performance/development uncertainty assumptions, importance weighting of robustness criteria) on program requirements robustness metrics.

By combining elements of various existing techniques and methods, the ENTERPRISE approach is able to achieve a greater set of objectives. The primary of which is providing a probabilistic and quantitative assessment of acquisition program requirements robustness against technology performance uncertainties for supporting early phase acquisition decision-making. It should be noted, however, that in general a product requires multiple iteration of testing and refinement before a final, usable version is produced. Considering the complexity, breadth, and scope of defense acquisition, it is (most) likely that the ENTERPRISE method will need to be further refined before it is ready for “active duty.” Such testing and refinement would require applying the ENTERPRISE method on an acquisition program in early phases of development and use the output results and lessons learned to further refine the process. Since such an application is not possible for a Ph.D. thesis dissertation, the ENTERPRISE process will be implemented on a simplified, notional acquisition program and the results of this demonstration application will be used to identify further areas of research and refinement.

CHAPTER 6 – IMPLEMENTATION

In this chapter a **notional** application of the ENTERPRISE method process is provided. In addition to demonstrating how the ENTERPRISE process could be applied to a given acquisition problem and how the outputs of the method can be used to support critical acquisition decisions, this proof-of-concept is also used to identify implementation challenges and lessons-learned that can then used to identify future areas of research and method refinement that will close the gap between current assessment techniques and the desirable state or quantitative and probabilistic requirements robustness assessment for informed acquisition decision-making.

For this demonstration, the ENTERPRISE methodology is applied on a notional technology acquisition program for enabling Carrier-based Suppression of Enemy Air Defenses (SEAD) through the development of the Unmanned Combat Air Systems (UCAS) solution concept. The selections of both the capability program and the UCAS solution concept are based on discussions with members of the thesis committee, specifically Professor Dmitri Mavris and Ms. Kelly Cooper of the Office of Naval Research.

In order to keep the breadth and scope of this demonstration problem manageable and appropriate for a Ph.D. thesis, certain assumptions and simplifications of the process had to be made. These "shortcuts" will be identified as they are utilized during this implementation and the implications of using these shortcuts will be discussed and will also be used in combination with the challenges and lessons-learned along the way to identify future work.

6.1 Phase I: Problem Definition

During Phase I, the relevant terms, concepts, and any other vital information pertaining to the carrier-based SEAD capability and the UCAS enabling solution concept, including a notional evaluation scenario, program requirements, and robustness evaluation criteria, are identified/defined.

6.1.1 Step 1: Describe Capability Needs

The capability that is the motivating factor behind this notional application of the ENTERPRISE methodology is the C*arrier-based Suppression of Enemy Air Defenses*. This capability combines the need suppression of enemy air defense during military operations with the push for "sea-based approach to joint operations", or more commonly known as Seabasing [171].

6.1.1.1 Suppression of Enemy Air Defenses

The Department of Defense defines SEAD as an activity that "neutralizes, destroys, or temporarily degrades surface-based enemy air defenses by destructive and/or disruptive means" [166]. Typically, SEAD missions are performed by a variety of weapons platforms and munitions, including "long range bombers, helicopters, surface-to-surface missiles, precision guided munitions (PGMs), rockets, and 'dumb bombs'" [22]. However, several aircrafts currently in the U.S. military arsenal "have

[also] been designed or modified to increase their effectiveness against enemy air defenses and are typically thought of as SEAD assets" [22]. These aircrafts include:

- F-16 Fighting Falcon [163]
- EA-6B Prowler [173]
- F/A-18 Hornet [174]
- F-15E Strike Eagle [162]

According to a *Congressional Research Service Report*, the SEAD mission is of growing importance to DoD and Congress for at least three reasons [22]:

- While combat aircraft have played an important role in most U.S. conflicts since World War I, the last several conflicts (Bosnia in 1995, Kosovo in 1999, Iraq 1996-present, and Afghanistan in 2001) have emphasized the use of military aviation, suggesting that defense planners are finding airpower an increasingly practicable military tool.
- There appear to be very few countries capable of seriously challenging U.S. air forces in air-to-air combat. Since Operation Desert Storm, 100 percent of all U.S. combat aircraft losses have been due to enemy air defenses. No U.S. aircraft has been lost to an enemy aircraft since 1991 [150].
- Most countries will challenge U.S. airpower primarily with surface-based air defenses. DoD finds some air defenses difficult to suppress or destroy. Many analysts say that emerging air defense technologies and tactics will prove more threatening and more difficult to counter than current systems.

The "interrelated developments in enemy air defenses: the emergence and proliferation of a new generation of Russian [Surface-to-Air-Missiles (SAM) systems], and the application of new technologies, either in conjunction with these or with other air defense elements" as well as traditional shoulder-fired anti-aircraft missiles "continue to pose a problem" for today's (as well as tomorrow's) SEAD forces [22]. The newer generation of SAM systems, in particular, "are a concern for military planners due to their mobility, long range, high altitude, advance missile guidance, and sensitive radars" [22]. Clearly, the ability to disable or circumvent altogether existing and developing enemy air defense systems is critical to the ensuring U.S.'s ability to project military air power, now and in the future.

6.1.1.2 Seabasing

According to the Seabasing Joint Integrating Concept document:

> "Seabasing is described as the rapid deployment, assembly, command, projection, reconstitution, and re-employment of joint combat power from the sea, while providing continuous support, sustainment, and force protection to select expeditionary joint forces without reliance on land bases within the Joint Operations Area (JOA). These capabilities expand operational maneuver options, and facilitate assured access and entry from the sea" [169].

The advantages of *sea-based* assets over *land-based* ones include [169]:

- Complement overseas presence and forward basing strategy.

- Enable joint force access, complement existing basing, and enhance power projection. Seabasing provides commanders with greater flexibility to rapidly and effectively build and integrate joint capabilities during the early stages of operations particularly when the political situation restricts basing, overflight or US presence.
- Provide a dynamic, mobile, networked set of platforms from which selected joint forces can operate in relative safety, while reducing risk to vulnerable facilities ashore. It can also diminish the political implications of host government support for US forces by reducing insurgent ability to exploit our presence as a propaganda tool.

Clearly, a *Seabased* capability such as *Carrier-based Suppression of Enemy Air Defenses* will allow military commander to identify and defeat threats to U.S. air dominance in a rapid and portable fashion without being limited by geopolitical complications associated with traditional land missions.

In an actual application, a more thorough and rigorous description and identification of the capability need or needs motivating the assessment is probably desired. However, for the purposes of demonstrating the ENTEPRISE methodology, the author believes that the information provided regarding SEAD and Seabasing adequately describes and justifies the desire for a *Carrier-based SEAD* capability.

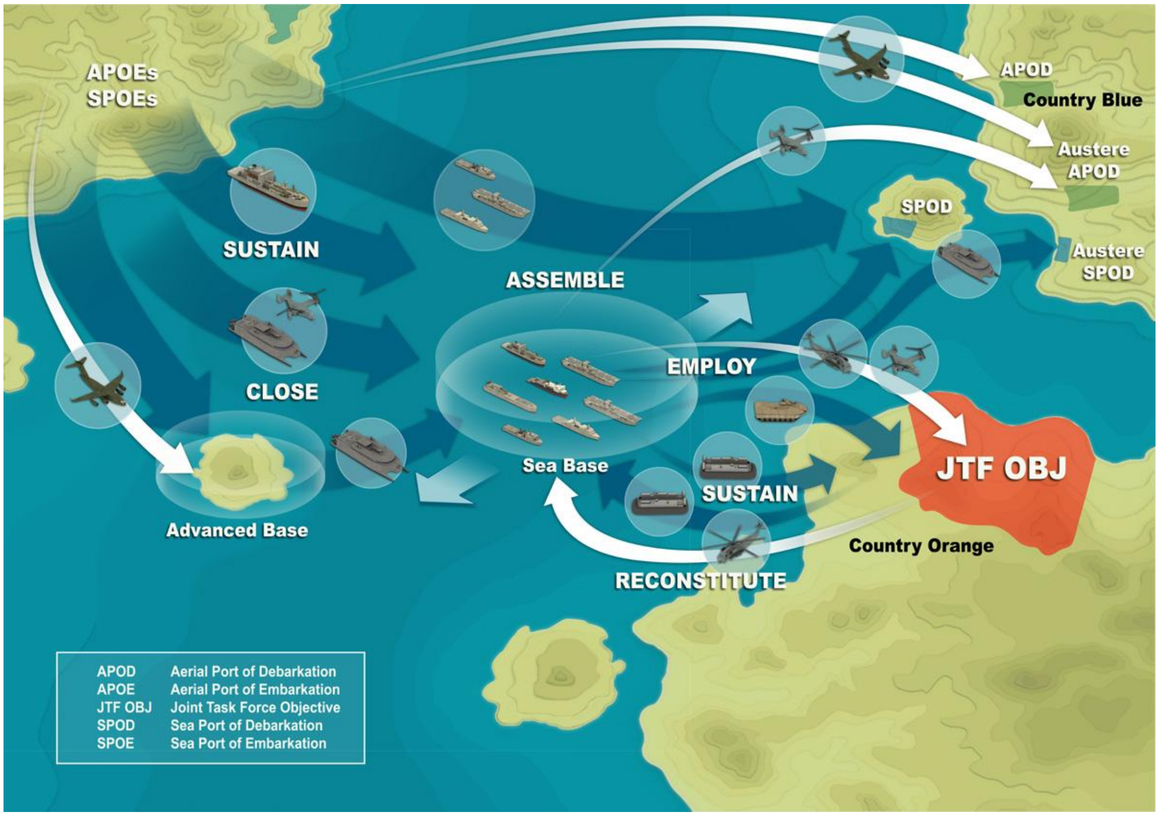


Figure 32: Conceptual Overview of Seabasing Capability [172]

6.1.2 Step 2: Describe Solution Concept(s) & Enabling Technologies

When performed as part of an ongoing DoD acquisition program, this step will require detailing every proposed concept solution to the capability need(s) identified in the previous step. However, for the purposes of this proof-of-concept demonstration, only one concept solution, the *Unmanned Combat Air System*, will be defined and carried through the remainder of the methodology. Because the *UCAS* is currently an ongoing program within the United State Navy, the author has taken steps to ensure that all of the information presented in the proceeding sections are open source and publicly available. Such a generalization of relevant program data decreases the fidelity of the assessment results of this ENTERPRISE application but eliminates ITAR/Information Security concerns. However, in order to assist in future/real world applications, the author will provide suggestions on how a real life application should be performed wherever possible to ensure highest analysis fidelity.

6.1.2.1 UCAS-D Program

The UCAS-D program is a U.S. Navy follow-up to the *Joint Unmanned Combat Air Systems (J-UCAS)* headed by the Defense Advanced Research Projects Agency (DARPA) and participated by the U.S. Navy and Air Force and was terminated in early 2006. According to DARPA's J-UCAS website:

> "The Joint Unmanned Combat Air Systems (J-UCAS) program is a joint DARPA/Air Force/Navy effort to demonstrate the technical feasibility, military utility and operational value for a networked system of high performance, weaponized unmanned air vehicles to effectively and affordably prosecute 21st century combat missions, including Suppression of Enemy Air Defenses (SEAD), surveillance, and precision strike within the emerging global command and control architecture" [164].

In 2007, the U.S. Navy initiated and awarded the UCAS-D program to Northrop Grumman in order to continue efforts of the J-UCAS program and "develop a strike fighter-sized unmanned air system that can carry out surveillance and precision strike missions" and "demonstrate that such an unmanned aircraft can be effectively and safely integrated into aircraft carrier-based launch and recovery operations" [6; 111]. Since SEAD was one of the intended missions of the original J-UCAS program, it is logical to assume that Carrier-based SEAD would be one of the intended missions of the UCAS-D program.

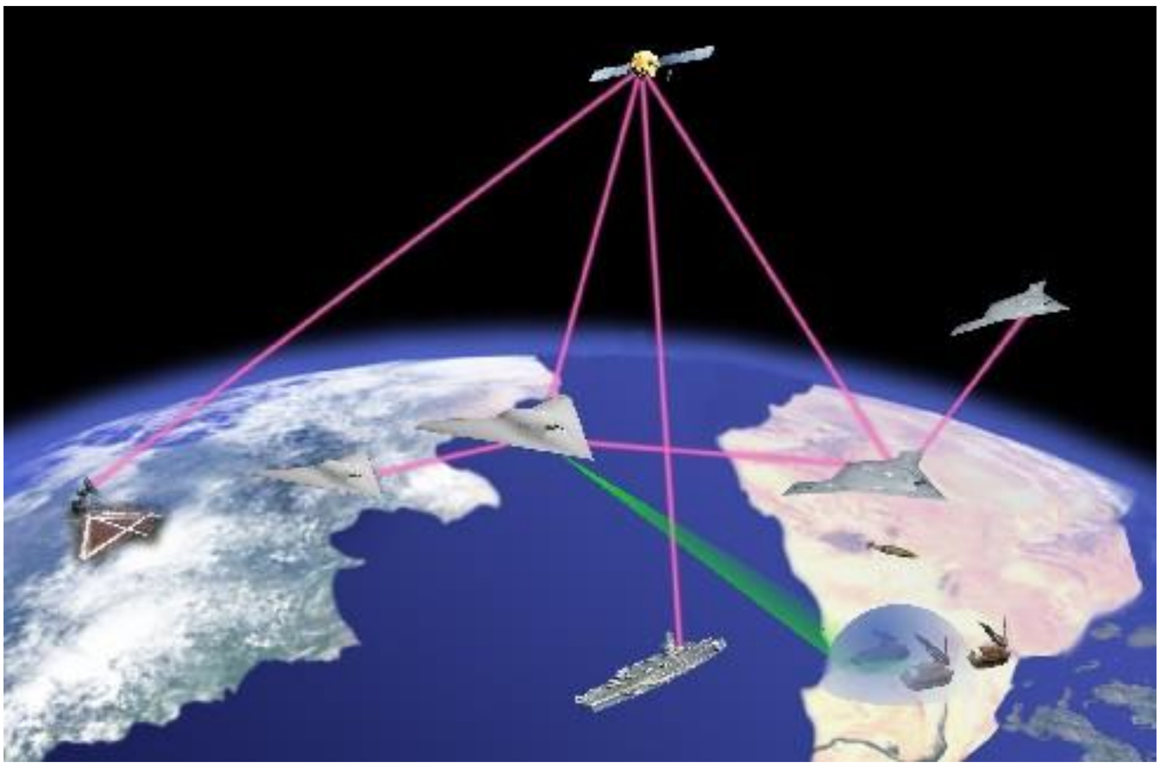


Figure 33: J-UCAS Program Conceptual Overview [164]

6.1.2.2 Baseline Vehicle

Currently, the Northrop Grumman X-47B (see Figure 34) is being developed for the UCAS-D program. As such, it will be used as the baseline conceptual solution with notional technologies being developed to enhance its performance and effectiveness for SEAD missions.

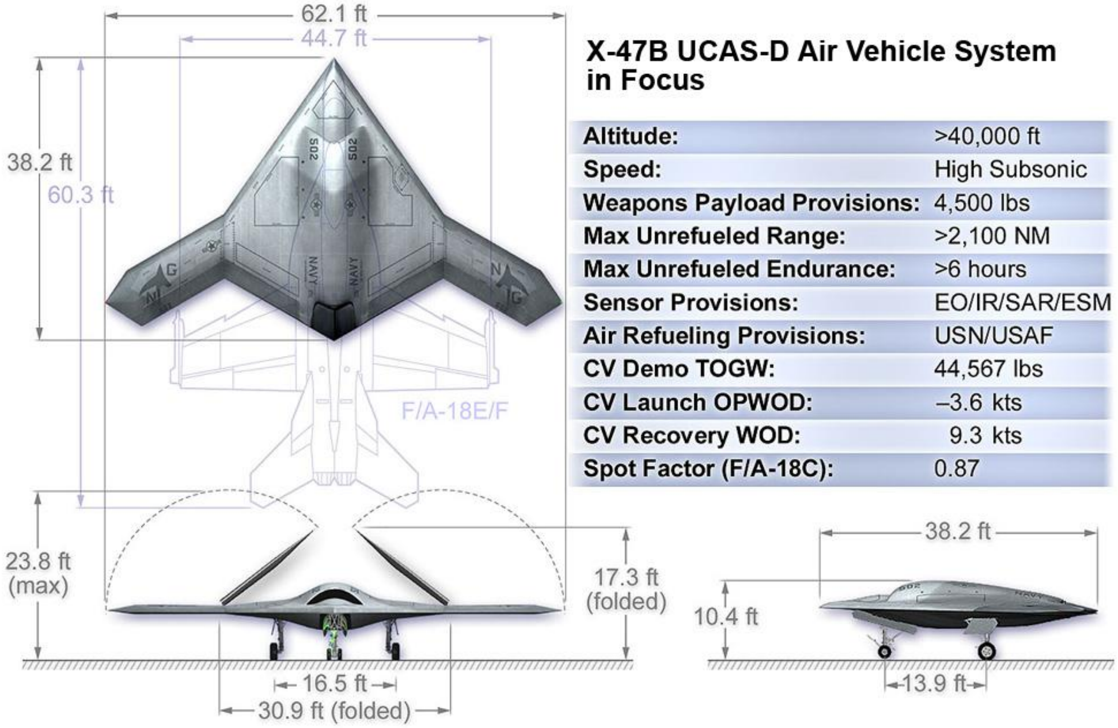


Figure 34: Northrop Grumman X-47B Overview

6.1.2.3 Notional UCAS-D Technologies

In order for the UCAS-D program to be success and produce the assets necessary for conducting successful Carrier-based SEAD missions in the future, enabling technologies have to be developed, implemented, and integrated into a single cohesive system. For this proof-of-concept demonstration, the author has defined eighteen candidate notional technologies that can be selected for development as part of the acquisition program. In the interest of preserving information non-sensitivity, these technologies have been defined using public domain data on existing and/or developing aircraft technologies and cover the following categories:

- Air Frame (AF)
- Propulsion (PR)
- Stealth (ST)
- Weapons (WP)
- Electronic Warfare (EW)
- Intelligence & Reconnaissance (IR)

Table 10 provides a brief description of each of the 18 notional technologies notionally identified for this proof-of-concept demonstration. Each technology is then discussed in more detail in the proceeding sections.

Table 10: Notional UCAS Enabling Technologies

Tech ID	Techn Name	Tech Description
AF-1	Advance Aircraft Wing Folding and Fuselage Telescoping	Advanced airframe folding and telescoping technology that allows more to be carried onboard a carrier
AF-2	Internal Cargo Bay Exapansion	Airframe technology that increases internal payload capacity
AF-3	High L/D Aeroconfiguration	Advanced airframe configuration that increases overall L/D of aircraft
AF-4	Embedded Fuel Pods	Embedded fuel pods that increase fuel capacity without negatively affecting vehicle stealthiness
AF-5	Efficient Transonic Planform	Aircraft planform configuration that decreases transonic drag
PR-1	Efficient Propulsion Installation	Efficient installation of vehicle propulsion that decreases drag due to engines
PR-2	Durable High Temp Core and Fuel Efficicient Turbine Engine	Advanced turbine engine that increases propulsive efficiency (less consumption) and output (more speed)
ST-1	Advanced Radar Absorption Materials	Advanced radar absorption material that significantly decreases vehicles radar footprint
ST-2	Advanced Stealth Planform Alignment	Planform alignment that deflect radar signals to reduce radar footprint
ST-3	Embedded Engines	Embedding engines into airframe decreases overall observability of aircraft
ST-4	Non-metallic Dielectric Airframe	Dielectric composities are more transparent to radar
WP-1	Long Range Air-to-ground Missile	Long-range air-to-ground missile
WP-2	Stealthy Air-to-ground Missile	Air-to-ground missile with stealth technology that reduces likelihood of being detected once fired
EW-1	Sensor Jamming	Jams enemy radars and sensor to reduce their effectiveness
EW-2	Missile Lock Inteference	Jams tracking/targeting sensors onboard enemies anti-aircraft missiles to reduce probability of missile hit
EW-3	Communications Jamming	Jams enemy communications to reduce enemy C2 capabilities
IR-1	Advanced Computer Guided Target Recognizition	Computer identification and assessment algorithms that significantly reduce time required to identy and
IR-2	Extended Range Sensors	Long range sensors that increase effective range of sensors

6.1.2.3.1 Technology AF-1: Advance Aircraft Wing Folding

Due to the limited deck space of aircraft carriers, wing folding is a common design feature of naval aircrafts. The addition of hinges to aircraft wings allows them to be folded up (or down depending on aircraft) so that each aircraft's deck footprint is reduced while parked onboard the aircraft carrier. The wings can then be returned to normal position when the aircraft is being prepped for launch. This technology was first introduced in World War II (see Figure 35) and has been in application ever since (see Figure 36) because of the significant increase in the aircraft capacity of carriers and thus the overall capability and versatility of the carrier. Including this technology in the UCAS program aircraft will allow additional number of UCAS assets available for carrier-based SEAD and thus potentially (and most likely) increase the likelihood of completing SEAD or any other missions successfully. Unfortunately, the time requires to unfold and lock the wings increases the amount of time it takes for prepare an aircraft with wing folding capabilities for launch.

Figure 35: Grumman Avengers with Wing Folding on USS Hornet (1945) [183]

Figure 36: An F/A-18 E/F Super Hornet With Folded Wings [75]

6.1.2.3.2 Technology AF-2: Internal Cargo Bay Expansion

Advanced stealth fighters such as the F-22 Raptor and the F-35 Lightning II carry munitions inside internal cargo bays to reduce their signature on enemy radars. Unfortunately, storing such weapons significantly reduces the payload capacity of the aircraft. This technology utilizes a revolutionary fuselage design and combines it with lightweight internal structures to increase the payload capacity of the aircraft. This allows Carrier-based SEAD UCAS assets to engage more assets before needing to return to the carrier and re-arm. The main drawback of this technology, albeit not directly related to the technology itself, is that regardless of how efficient the internal weapons bay is made, it is unlikely that the increase in payload capacity will be able to offset the loss of external payload capacity.

6.1.2.3.3 Technology AF-3: High L/D Aero-configuration

By increasing the lift-to-drag (L/D) ratio of the aircraft, this technology will increase the UCAS's aircraft operational range, endurance, and or persistence time depending on its mission. This reduces the amount of refueling that must be done during the mission. Unfortunately, high L/D configurations typically do not lend themselves to high speeds, thus reducing the operational and maximum speeds of UCAS assets if they are implemented.

6.1.2.3.4 Technology AF-4: Embedded Fuel Pods

To increase fuel capacity (and thus operational range), external fuel tank are typically attached to aircraft wings and/or right beside the fuselage (see Figure 37 below).

Figure 37: External Fuel Tank Attached Beneath F/A-18 Fuselage [33]

Embedded fuel pods, on the other hand are fuel tank that have been designed to conform to the main body of the aircraft. This not only serves to only reduce drag caused by the fuel pod, but also the radar cross section of the aircraft and making it less pervious to enemy detection. Similar to the previous technology (AF-3), this would increase the operational range and/or endurance of the UCAS while only slightly degrading its radar signature.

6.1.2.3.5 Technology AF-5: Efficient Transonic Planform

In the field of aerodynamics, it is common knowledge that there is a sharp increase in drag when transitioning from sub-sonic (less than Mach 1) to super-sonic (greater than Mach 1). This phenomenon is called *transonic drag* and is portrayed by the figure below (the physics or rather, aerodynamics of transonic drag are beyond the scope of this research and thus will not be discussed in detail):

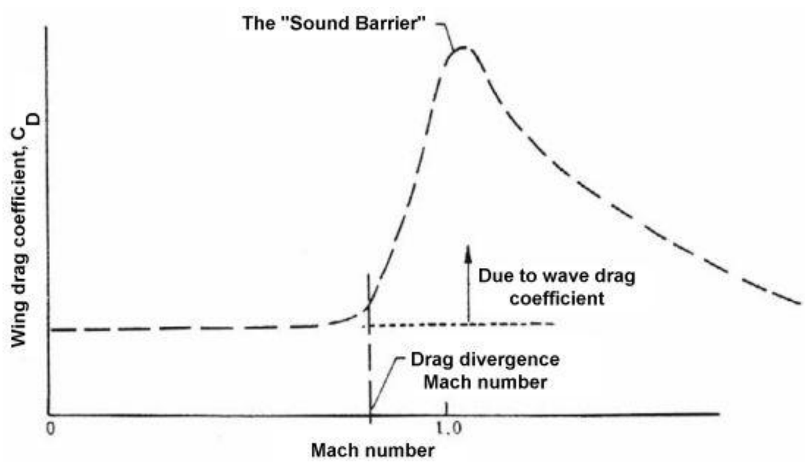


Figure 38: Drag Coefficient vs. Mach [136]

As can be seen in the figure above, when an aircraft is traveling near Mach 1 (Mach 0.8~1.2), the amount of drag it faces significantly increases. This makes it traveling at near sonic speeds (or transitioning from sub to supersonic speeds) difficult and fuel-consuming.

Transonic planform configurations, such as swept wings, help reduce the negative effects of transonic drag by angling the Mach cone (formed by shockwaves) away from the aircraft frame. This not only reduces the fuel consumption, but also the stresses on the airframe caused by the shockwaves. This allows the UCAS to be more fuel efficient when traveling at high subsonic speeds or transitioning to supersonic speeds. Unfortunately, such a planform is not efficient when the aircraft is traveling subsonically.

6.1.2.3.6 Technology PR-1: Efficient Propulsion Installation

Typically, the generated thrust from an aircraft's engine once it's installed, commonly referred to as *installed thrust,* is lower than its free-standing or *uninstalled thrust*. This is because of the interference to the engine's airflow intake as well as the uninstalled thrust being measure at standard sea level (where the air is denser than up in the atmosphere when the aircraft is in operation). Efficient propulsion installation reduces these negative impacts and decreases the drop in available engine thrust. This aids in not only UCAS fuel efficiency, but also maximum speed.

6.1.2.3.7 Technology PR-2: Durable High Temp Core and Fuel Efficient Turbine Engine

This technology utilizes advanced materials that allow higher engine combustion and turbine inlet temperatures (i.e. T4). Operating at higher T4 allows the engine to produce more thrust per unit fuel spent, which translates to an increase in net thrust for a given fuel consumption and thus overall engine efficiency. Figure 39 below shows the increase in overall engine thermal efficiency for increased T4 for seven different engines. Such a technology would enable the UCAS to have higher maximum speed and/or operational range.

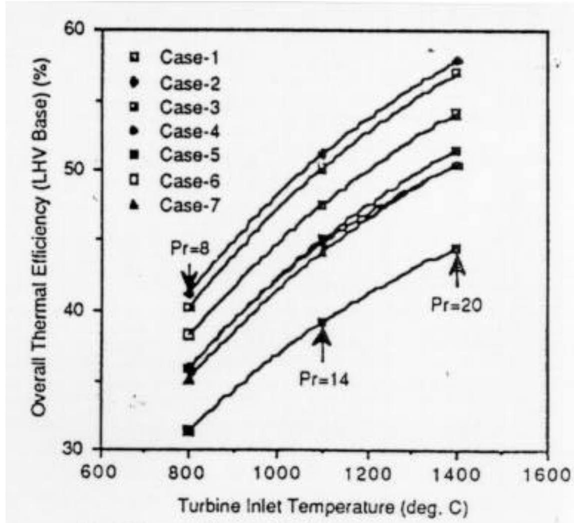


Figure 39: Overall Engine Thermal Efficiency vs. Turbine Inlet Temperature (T4) [56]

6.1.2.3.8 Technology ST-1: Advanced Radar Absorption Materials

Radar Absorbent Materials (RAMs), typically in the form of a specially created paint, are commonly used to reduce an aircraft's visibility to radar. When applied to part or all of an aircraft's exposed surface, RAMs can reduce aircraft radar cross section area absorbing part of all of the incoming radar waves emitted by enemy sensors (see Figure 40). Unfortunately, RAM absorption rates vary depending on the radar wavelength being absorbed and the composition of the RAM, so its effectiveness is reduced when multiple enemy radar wave lengths are present (this is why RAMs are only one of several methods used in combination to improve aircraft stealth).

Figure 40: Traditional Airframe vs. Radar Absorption Material Coating [187]

The use of radar absorbent paint on UCAS assets will, theoretically, help to reduce its radar visibility to enemy radars and thus enabling it to more effectively perform the SEAD mission.

6.1.2.3.9 Technology ST-2: Advanced Stealth Planform Alignment

Another method commonly used to reduce aircraft radar visibility is planform alignment. Generally speaking, planform alignment involves using a small number of surface orientations to deflect incoming radar waves to desired directions (i.e. away from enemy sensors) [88]. An example of this application is the F-22's leading and trailing edges, which have identical sweep angles (i.e. all leading edges have same angle and all trailing edges have the same angle) which minimize the amount of enemy radar reflection [142]. When applied, this technology will work in conjunction with other stealth technologies to reduce UCAS radar visibility.

6.1.2.3.10 Technology ST-3: Embedded Engines

Similar to embedded fuel pods technology, this technology embeds an aircraft's engine(s) into the airframe. By making the propulsive system of the aircraft, including everything from inlet duct to exhaust nozzles, conform to the overall planform of the aircraft, the radar signature of the aircraft can be (theoretically) significantly reduced. When applied in conjunction with other stealth technologies, this technology can potentially render the UCAS system virtually undetectable to enemy radars. Unfortunately, such a configuration would reduce the efficiency of the engine because of limited airflow, reduced T4, and nozzle shape.

6.1.2.3.11 Technology ST-4: Non-metallic Dielectric Airframe

Unlike traditional metals, non-metallic dielectric materials naturally disperse radar waves, which reduce the amount of waves reflected back to the emitting radar and thus reducing aircraft radar signature. By making the UCAS airframe out of this material, the susceptibility of UCAS aircrafts being detected by enemy radars is reduced and thus increasing probability of success.

6.1.2.3.12 Technology WP-1: Long Range Air-to-ground Missile

While reducing an aircraft's radar signature through the use of stealth technologies is an effective way of reducing friendly losses during SEAD missions, it is not the only method for circumventing enemy air defenses. Another method, albeit simplistic in nature, is to remain outside enemy radar/SAM effective ranges. The development of long/extended range air-to-ground missiles will allow UCAS assets to engage enemy air defense assets while remaining safely outside their ranges. Unfortunately, the higher amount of propellant required by these weapons reduces the number of missiles that can be carried at once by aircrafts. However, considering the high costs associated with military aircrafts, the reduction in available firepower is well worth the increase in aircraft survivability.

6.1.2.3.13 Technology WP-2: Stealthy Air-to-ground Missile

In addition to detecting and engaging enemy aircrafts, modern SAM installations are also capable of engaging smaller and (much) faster missiles fired from enemy aircrafts. This means that even if an aircraft is undetected (either through the use of stealth technologies and/or use of extended range weapons), the weapons it fires can still be intercepted before they can reach their intended targets. This technology applies some of the mentioned stealth technologies to the design of air-to-ground missiles so that they are less likely to be detected and intercepted by enemy air defenses, thus increasing probability of kill of enemy air defense installations.

6.1.2.3.14 Technology EW-1: Sensor Jamming

Another way of potential method for reducing enemy air defense capabilities is through the use of electronic warfare (EW) systems. Such systems involves "the use of [electromagnetic (EM)] energy, directed energy, or anti-radiation weapons" to degrade, neutralize, or destroy enemy combat capabilities [138]. This technology utilizes high energy EM waves to disrupt enemy radars operations and reduce their effective range. This allows UCAS systems to effectively operate closer to enemy sensors without being detected.

6.1.2.3.15 Technology EW-2: Missile Lock Interference

This technology works in a similar fashion as the previous technology, except it is specifically designed to jam the targeting and tracking radars on enemy air-to-air and surface-to-air missiles. Instead of wide area jamming (to confuse enemy sensors), this technology focuses jamming EM energy towards incoming enemy missiles launched towards the aircraft. When functioning according to specifications, this technology will allow UCAS assets to operate inside enemy SAM operation ranges and disable incoming missiles while accomplishing SEAD mission objectives.

6.1.2.3.16 Technology EW-3: Communications Jamming

Of the three EW technologies being examined for the notional UCAS program, communications jamming is perhaps the most mature/currently in use and several variants can be purchased commercially.

These devices send out high energy interference frequencies that hamper the ability of communication devices to send/receive properly. When active, these devices will disrupt the communications links between enemy air defense assets, which means that even if enemy radars have detected the UCAS aircraft, it cannot the relay the information to the command center and/or SAM sites or from the command center to anti-aircraft (AA) installations, thus rendering enemy air defenses useless.

6.1.2.3.17 Technology IR-1: Advanced Computer Guided Target Recognition

A successful engagement of enemy air defense installations requires not only capable sensors and weapons, but also rapid and accurate target recognition and assessment computing systems that can quickly confirm the identity of detected enemy targets as well as assess the results (i.e. was target hit? If so, has it been disabled/destroyed?) of an engagement. These computers can reduce the time between detection to engagement (i.e. firing missile at target) to confirmation of target kill. This reduction can have significant impact on the probability of success when engaging modern SAM systems that have the ability to rapidly deploy, fire, and then pack up and go back into hiding before they can be identified and engaged. These systems will enable UCAS aircrafts to rapidly engage SEAD mission critical targets without having to wait for an extended amount of time for target identification and kill confirmation.

6.1.2.3.18 Technology IR-2: Extended Range Sensors

The first step of a successful (or any) engagement is the detection of enemy targets. After all, one cannot engage a target that has not been detected. This technology utilizes advanced sensor technologies that increase the effective detection range UCAS enemy detection systems. The earlier (i.e. from farther away) detection of enemy targets allows UCAS assets to engage targets earlier, better plan an attack route, and/or avoid being fired upon. The increase in detection power will also improve the ability to detect hidden enemy targets (i.e. mobile SAM sites) and allow them to be engaged before they can "sneak away."

6.1.2.3.19 Compatibility and Current Maturity Level

Because of the laws of physics and certain limitations, it is likely that certain technologies will be incompatible with each other. For example, *High L/D Aeroconfiguration* and *Efficient Transonic Planform* are two technologies with opposite aircraft intentions. One aims to maximize the aspect ratio of the aircraft to increase L/D while the others encourage swept wings to minimize shock exposure.

Based on the author's own intuition and engineering knowledge, the compatibilities (or lack of) between the 18 UCAS-SEAD enabling technologies are described below:

Table 11: Compatibility Matrix of Notional UCAS-SEAD Technologies

	AF-1	AF-2	AF-3	AF-4	AF-5	PR-1	PR-2	ST-1	ST-2	ST-3	ST-4	WP-1	WP-2	EW-1	EW-2	EW-3	IR-1	IR-2
AF-1		Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y
AF-2			Y	N	Y	Y	Y	Y	Y	N	Y	N	Y	Y	Y	Y	Y	Y
AF-3				Y	N	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y
AF-4					Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
AF-5						Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
PR-1							Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y
PR-2								Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ST-1									Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ST-2										Y	Y	Y	Y	Y	Y	Y	Y	Y
ST-3											Y	Y	Y	Y	Y	Y	Y	Y
ST-4												Y	Y	Y	Y	Y	Y	Y
WP-1													N	Y	Y	Y	Y	Y
WP-2														Y	Y	Y	Y	Y
EW-1															Y	Y	Y	Y
EW-2																Y	Y	Y
EW-3																	Y	Y
IR-1																		Y
IR-2																		

In addition, because of the current reliance on TRL metrics throughout the acquisition lifecycle, the author has elected to define a "current" TRL for each technology. As will be demonstrated later on, this information will be useful throughout the course of this implementation. In addition, the data provided in this data can be used to compare the results of the ENTERPRISE methodology against the existing TRA process for providing acquisition decision-makers with an assessment of program robustness and potential risk areas.

Table 12: TRL Values for Notional UCAS-SEAD Technologies

Technology	Current TRL
Advance Aircraft Wing Folding and Fuselage Telescoping	***3***
Internal Cargo Bay Exapansion	***3***
High L/D Aeroconfiguration	***5***
Embedded Fuel Pods	***4***
Efficient Transonic Planform	***4***
Efficient Propulsion Installation	***5***
Durable High Temp Core and Fuel Efficicient Turbine Engine	***4***
Advanced Radar Absorption Materials	***3***
Advanced Stealth Planform Alignment	***4***
Embedded Engines	***4***
Non-metallic Dielectric Airframe	***3***
Long Range Air-to-ground Missile	***4***
Stealthy Air-to-ground Missile	***3***
Sensor Jamming	***5***
Missile Lock Inteference	***3***
Communications Jamming	***4***
Advanced Computer Guided Target Recognizition	***4***
Extended Range Sensors	***5***

6.1.3 Step 3: Identify Relevant Scenarios and Metric Requirement

Once the desired capability and solution concept have been identified and described, the next step is to identify and/or develop potential scenarios (i.e. missions) that can be used to evaluate the effectiveness of the UCAS concept (and its enable technologies) in fulfilling Carrier-based SEAD MoEs and requirements.

6.1.3.1 Notional Carrier-Based SEAD Scenario

For this proof-of-concept demonstration, a single notional analysis scenario will be used to measure system capability effectiveness (for real world applications will most likely require multiple scenarios to fully capture the full spectrum of missions relevant to the desired capability). This scenario will consist of the elements listed below:

- Blue forces (friendly)
    - An aircraft carrier will serve as the base of operations for launching, recovering, and re-loading UCAS aircrafts
    - A communications satellite that relays communications between carrier and UCAS assets when direct line-of-site (LOS) communications are not possible
    - An Airborne Early Warning and Control (AEW&C) system that serves to provide preliminary detection of enemy air targets and to support communications relay
    - Parametric number of UCAS assets that are launched, one at a time, from carrier to perform SEAD mission
- Red forces (enemy) consist of an Integrated Air Defense System (IADS) consisting of the following elements:
    - 10 radars capable of detecting and tracking multiple incoming aerial threats
    - 48 Surface-to-Air missile installations, arranged in clusters of 6 around 8 of the radars
    - Single airfield that can launch aircrafts to intercept incoming threats (for the demonstration problem, the author has elected to not include enemy aircrafts as part of the scenario to reduce modeling complexity)

- Single Command Center (CC) that received detections from radars and sends out commands to SAM sites to engage potential threats

The objective of this scenario is simple: detect, identify, and destroy all enemy targets in a localized region. Figure 41 below is a graphical depiction of the SEAD analysis scenario modeled using NetLogo, an ABM&S program that will be described in more detail during the M&S phase.

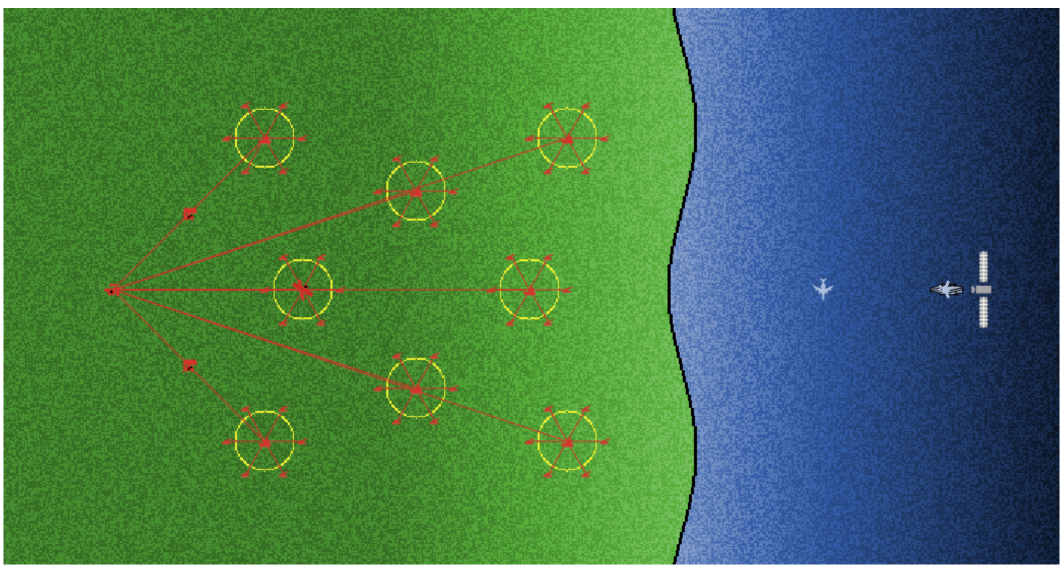


Figure 41: NetLogo Representation of Notional UCAS-SEAD Mission Scenario

6.1.3.2 Scenario Metrics

For the notional scenario described above, the author has selected the following Measures of Effectiveness that will be tracked and used for evaluating UCAS SEAD effectiveness:

Table 13: SEAD Scenario Metrics

Scenario Metric
Perc_Red_Killed_12hrs
Perc_Red_Killed_24hrs
Perc_Red_Killed_48hrs
Perc_Blue_Killed

These metrics were selected by the author with the assumption that friendly and enemy losses would be the most critical factors in assessing SEAD mission success follow by the amount of ammunition required to perform the mission. In real world applications, there will likely be many more metrics relevant to the warfighter and decision-makers.

6.1.3.3 Technology Development Metrics

In addition to effectiveness uncertainty, this method also aims to capture the development cost and schedule uncertainties associated with immature technologies. Because the current acquisition process technology development plan approval process is structured around the Technology Readiness Level metric, the author has elected to evaluate UCAS technologies using the following metrics:

Table 14: Technology Development Metrics

UCAS-SEAD Technology Development Metrics
Years to Reach TRL 6
Years to Reach TRL 7
Years to Reach TRL 9
$US to Reach TRL 6
$US to Reach TRL 7
$US to Reach TRL 9

In additional to reaching TRL 9, which represents a fully operational and field tested technology, TRL 6 and 7 were added because they are the required TRL threshold that every acquisition program technology must meet at Milestone B (TRL 6) and Milestone C (TRL 7). Combined with the seven scenario metrics, this set of thirteen metrics will be used to identify and assess the effectiveness (or lack thereof) and costs ($ and time) associated candidate UCAS program technology development portfolios. Again, in a real world application, the selection of program time and cost requirements would depend on the preferences and requirements of the decision-makers.

6.1.4 Step 4: Define Robustness Metrics

The final step of Phase I is to define the metrics that will be used by decision-makers to assess program robustness. This typically involves the use of the *variance* or *percentile difference* robustness assessment techniques. However, the nature of acquisition requirements and the constraints typically placed on each requirement, the percentile of each output requirement variation distribution that falls within acceptable regions of the constraint will be used. These percentages are analogous to the probability of meeting specified constraint values for the program requirements listed Step 3 once technology performance and development uncertainties have been taken into account. The selection of the most optimal program technology development portfolio would be dependent on the each solution's ability to successfully meet capability, budget, and schedule metric constraints. In addition, these constraint values can be varied to assess program robustness against changing requirements. As previously discussed, changes in program requirements are not uncommon and can be caused by a variety of external factors such as congressional budget cuts and shifts in defense strategy.

6.2 Phase II: Model Creation

Phase I identified and defined the Carrier-based SEAD capability need, the notional UCAS solution concept (and notional enabling technologies), program capability, budget, and schedule requirement metrics, and a set of robustness evaluation criteria based on the probability of meeting specific constraints in these requirements even when technology performance and development uncertainties are taken into account. In this phase, this information is used to construct the M&S tools that will be used to perform both deterministic and probabilistic analyses for evaluating the uncertainties (and resulting risks) associated with the UCAS enabling technologies.

6.2.1 Step 5: Create Technology Forecasting Models

In this step, the parametric models that will be used to provide quantitative forecasts of technology impact on system capabilities and development budget and schedule are created. In general, unless existing models already exist, this requires utilizing a team of programmers guided by relevant subject experts to create the prediction models of appropriate and required analysis fidelity and complexity. However, since such a detailed modeling process was not possible during the course of this research, simplified but representative versions of such models were created and used for this demonstration application.

6.2.1.1 Modeling Impact of Technologies on UCAS Capabilities

As observed in Section 5.3.1.1.2, Agent-based Modeling & Simulation environments, a specialized version of Discrete Event Simulations, are an effective and desirable (as demonstrated by SEAS M&S environment and the FLAMES constructive simulation environment used by Biltgen for his implementation of the SOCRATES methodology) approach for modeling military campaigns and scenarios. The emergent behaviors of an ABM&S simulation describe the capabilities and effectiveness of the agent systems within the simulation. The behaviors and states of individual agents can be modified to reflect technology infusion and the resulting changes in simulation outputs can then be used to quantify the impact of system technologies on system effectiveness. Combined with a probabilistic analysis process such as Monte Carlo simulations, uncertainties in technology performance can then be translated to potential variations in system capability and effectiveness.

Typically, creating an Agent-based M&S is time consuming and requires significant inputs from SMEs regarding agent behaviors, states, and interactions. In addition, high fidelity ABM&S tools can be quite expensive and have steep learning curves (SEAS is free to government entities with a legitimate need but requires an above-average understanding of computer programming and algorithms). Fortunately, an existing ABM&S of a carrier-based SEAD scenario using UCAS already exists (created by Bagdatli and his team) and provided the author with the necessary analysis elements needed for this demonstration application of the ENTERPRISE methodology [15].

6.2.1.1.1 NetLogo UCAS-SEAD Agent-based Simulation Model

NetLogo is a commercially available tool that is free for academic applications and developed by Uri Wilensky [184]. It was used to create the existing J-UCAS created by Bagdatli and his team because of its availability (free) and not-as-steep learning curve. In addition, the program is can be made platform independent through the use of its JAVA classes.

For this demonstration, the original J-UCAS NetLogo model was modified for the needs of this assessment. While the details of the original model and changes made are beyond the scope of this text, the model and its principle components, in particular the entity agents and their behavioral rules are provided in the proceeding sections.

6.2.1.1.1.1 Environment

A coastal environment is modeled in NetLogo as the background environment for the demonstration UCAS-SEAD scenario (see Figure 41). Blue agents (i.e. friendly) will begin off shore with the *UCAS* agents aboard the *Carrier* agent, *AEWC* agent already airborne, and *Satellite* agent "in-orbit." Red (i.e. enemy) agents begin in active model searching for incoming air threats.

6.2.1.1.1.2 Friendly (Blue) Agents

The primary, active Blue agents in the UCAS-SEAD mission scenario are the *UCAS* agent and the *Carrier* agent that serves as their base of operations. In addition, there are two more Blue agents: *Satellite* and AEWC aircraft. Currently, these two agents do not actively participate in the mission because the UCAS assets communicate with each other and the carrier directly. If a higher fidelity/more realistic model is required for analysis, they can be programmed to serve as communication relays if necessary (i.e. non line-of-sigh). The author elected not to include this behavior as part of the model because of the complexity and programming know-how necessary to implement this behavior is beyond the scope of this research.

Carrier Agent

The behavior of the *Carrier* agent consists of the following:

- Launch *UCAS* agents at mission start
- Recover, refuel, re-arm, and re-launch *UCAS* agents

At the beginning of the mission, *UCAS* agents are launched, one at a time, from the *Carrier* agent. The amount of time between this initial launch is controlled by a parametric variable *input-Blue-time-to-launch-UCAVs*. Varying the value of this parameter allows the user to control the minimum number of seconds between launches. This is useful for simulating the impact of wing folding on launch operations.

The recovery (i.e. landing) of *UCAS* agents on the *Carrier* is assumed to be automatic once a returning *UCAS* is within a close proximity to the *Carrier* agent. Once an *UCAS* agent has landed, reloading (refueling and re-arming) begins. When an *UCAS* agent has completed the reloading process, it is placed into the carrier launch queue and launched when appropriate. The amount of time (in seconds) required for reloading an *UCAS* agent is determined by the parametric variable *input-Blue-UCAV-reload-time* and the amount time between re-launches is also determined by the *input-Blue-time-to-launch-UCAVs* variable.

UCAS Agents

Of all of the agent behaviors in the demonstration UCAS-SEAD model, the behavior of *Blue UCAS* agents is perhaps the most complex. *Blue UCAS* agents will perform one or more (or most likely, all) of the following functions throughout the mission:

- Launch from *Carrier*
- Seek out and engage enemy air defense assets without being destroyed
- Assess status (i.e. dead or alive?) of engaged enemies
- Return to *Carrier* to rearm and refuel

- Continue until scenario ends

The implementation details of *Blue UCAS* agent behavior is too complex and only serves to sidetrack the focus of this discussion. However, the author would like to high two specific behavior modules; UCAS kill-chain behavior and avoidance behavior.

UCAS Kill-Chain Behavior States

The Kill-Chain behavior states describe the process in which *Blue UCAS* agent search out and engaged Red agents. This process is summarized by the flowchart depicted by Figure 42.

The *Killchain* sequence starts with *Detect* state, during which the *UCAS* agent will survey all objects within its detection range and for each target that has not been labeled as detected, label it as detected and add it to the *to-be-identified* queue. The next action is *Identify*, during which an *UCAS* agent will set as its target the **closest target that is on the *to-be-identified*** queue (note that the queues mentioned in these chapters are not individual agent queues but common, shared queues used by the *UCAS* agents as a whole, which reduces redundancy). Assuming that the target to be identified is within the *UCAS* agent's detection range, the *identifying-time* will begin to countdown towards zero from an initial value set by the use and/or input file (*input-Blue-UCAV-time-to-id*). During the countdown, the *UCAS* agent must remain stay within its detection range to the target until the timer reaches zero, at which point the target is assumed to be identified correctly and then moved to the *to-be-tracked* queue.

The next state is *Track*, during which *UCAS* agents maintain a lock on the location (and if applicable, speed) of the target until the target can be engaged (i.e. awaiting engagement approval). Once the target has been tracked, it is then moved to the *to-be-engaged* queue. In its current state, the UCAS-SEAD model assume that as soon as a target has been identified, it can be fired upon so the *Track* state has no associated delays other than the fact that it is another step that much be completed before a target can be engaged (one more timestep between identify and engage). In future iterations, this state can be modified to implement decision-making time required for engagement approval and any other potential delays associated with engagement an identified target).

During the *Engage* state, an *UCAS* agent looks for the nearest target that is on the *to-be-engaged* queue and engages it (with an air-to-surface missile). The engaged target will be moved to the *to-be-assessed* queue and its color will be changed from red to black, indicating that it has been engaged but not yet assessed.

The last state is *Assess*, during which an *UCAS* agent attempts to assess whether or not an engaged target has been disable or destroyed. Similar to *Identify*, there is a countdown timer that must expire before the status of the target being assessed can be obtained. Once obtained, the target will either be turned to gray color (successful engagement) or turned back to red and put back on the *to-be-engaged* queue (failed engagement).

The state in which each *UCAS* agent is currently in depends on the status of the closes detected target to the agent. For example, if the closest target to an *UCAS* agent is on the *to-be-assessed* queue, the *UCAS* agent will switch to *Assess* state and assess the state of the target. While this target selection implementation is a simplistic (in the real world, there is likely a hierarchy of importance for different enemy target types), the author believes that it serves the purposes of this methodology demonstration.

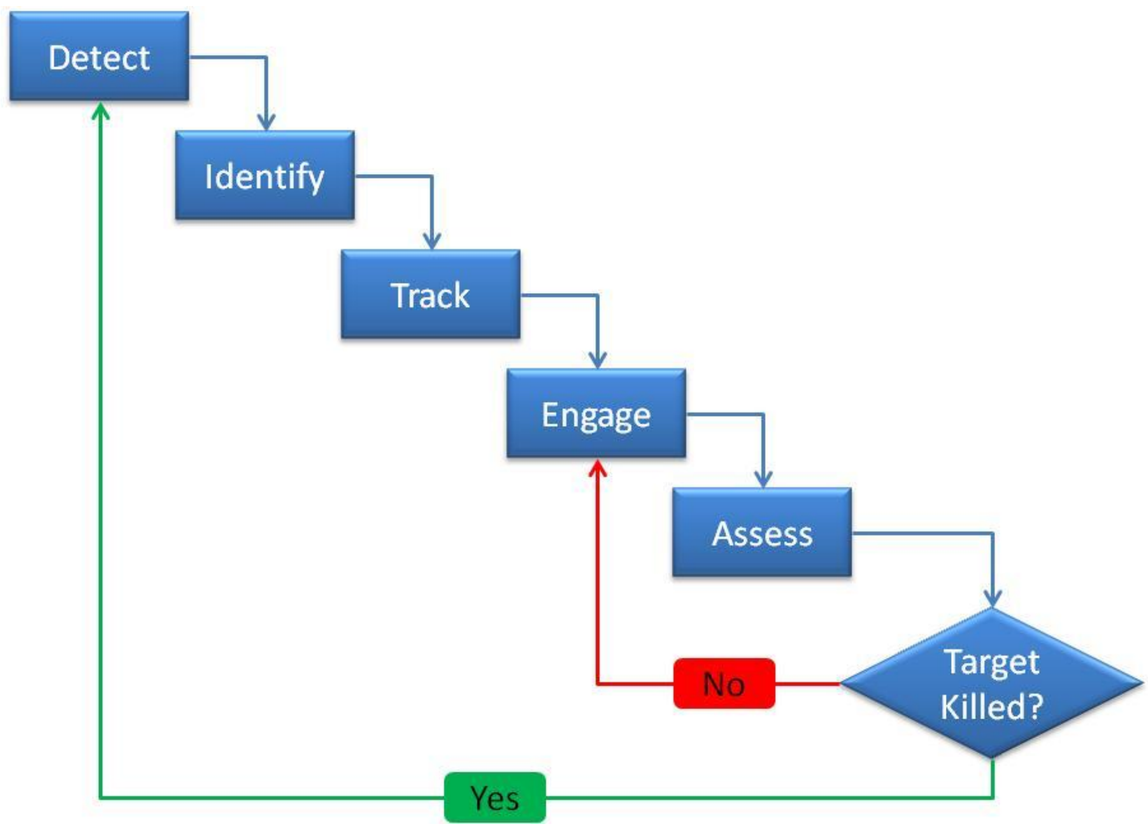


Figure 42: Blue UCAS Agent Killchain Behavior Flowchart

The other behavior the author would like to highlight is the *Avoid-enemies* behavior for *Blue UCAS* agents. During this action, *Blue UCAS* agents maneuver in such a way as to stay as far as from detected threats as possible while still within its shooting range (so just inside engagement range). This minimizes the likelihood of being detected and engaged by enemy anti-aircraft systems.

Satellite & AEWC Aircraft

As noted, the *Satellite* and *AEWC* aircrafts agent currently do not actively participate in the UCAS-SEAD mission. The implementation of the states and behaviors of these agents were not vital to this assessment and thus will be added to the list of future model improvements.

6.2.1.1.1.3 Enemy (Red) Agent

The enemy agents in the UCAS-SEAD scenario function together as an Integrated Air Defense System (IADS) and consist of the following agent types:

- Command Center
- Radars (regular and big)
- SAM sites
- Airfield

Command Center

The *Command Center* agent is the heart and soul of the enemy air defense system (EADS). When a *Radar* agent detects an incoming threat, it relays this information to the *Command Center*, who then assigns the nearest *SAM* agent to track and attack this threat. Once a threat has been eliminated, this information is then passed back to *Command Center*, which then stops trying to assign assets to engage the dead threat. The communication capabilities of *Red Command Center* are governed by *input-Red-pComm_success*, which describes the probability of success of communication between Red agents.

Radar

Red Radar agents detect incoming threats and relay this information the *Command Center*. For the selected scenario, there are **eight** *Red Radar* agents arranged to in such a way as to minimize the number of flight corridors that would allow UCAS assets to navigate through and engage high priority targets (e.g. airfields, command centers). Two parameters are used to adjust *Red Radar* behavior: *input-Red-Radar-pHit* and *input-Red-Radar-detect-range*. The first describes the probability of hit for *Red Radars* by Blue air-to-ground missiles and the second describes the operational detection range of *Red Radar*.

Because of the sensitive and difficult-to-obtain nature of the relationship between radar effectiveness and stealth technologies, the author implemented what he believes to be a simplistic yet logical detection algorithm for *Red Radars* against *Blue UCAS* agents. This simple algorithm adjusts the effective detection range of a *Red Radar* against a target. The adjustment (typically reduction) in radar range depends on the user-specifics RCS value of the incoming threat. Currently, Blue assets have RCS values between 0 and 10, so when an incoming threat has an RCS of 10, the effective range of *Red Radars* for that threat is 100% of its pre-determined range. For an RCS of 5, the effective range is 50% (effective range is linearly related to the value of the incoming threat's RCS divided by 10).

Big Radar

Red Big Radar agents currently do not have any functionality in the UCAS-SEAD model. However, in future model versions, they would serve as long range radars that can detect incoming threats from much further away. This information can then be relayed to the *Red Command Center*, who can then initiate appropriate responses such as launch intercept aircrafts or train *Red Radars* towards the direction of the incoming threat to maximize the track-ability of these threats so that SAMs may be fired at them.

SAM Site

Red SAM agents engage targets assigned to them by the *Red Command Center* agent, assuming that the assigned target is within their engagement range. If the assigned target is outside its engagement range, a *Red SAM* agent will wait until the target comes into range OR another target has been assigned to it (and if that target is within engagement range, it will fire an interceptor missile). *Red SAM* behavior is currently governed by two variables: *input-Red-SAM-pHit* and *input-Red-SAM-shoot-range*. The first variable describes the probability of hit of *Red SAMs* by Blue air-to-ground missiles when fired upon and the second establishes the engagement range of *Red SAMs*.

Airfield

The behavior of *Red Airfield* agent is simple: it serves as the base of operations for the Red aerial assets (i.e. helicopters, fighters, bombers, etc…) that are launched to meet incoming threats (i.e. Blue UCAS vehicles). For the purposes of the demonstration problem, the author has elected to not include Red aerial assets, so the *Red Airfield* agent simply serves as an additional target that *Blue UCAS* agent must eliminated as part of the SEAD mission.

6.2.1.1.1.4 Baseline Scenario

With the UCAS-SEAD model established, the last portion of this step prior to "baselining." This is the process is which the default, baseline values for each of the UCAS-SEAD model parameters are defined. For this notional demonstration, the author consulted only publicly available data on current state-of-the-art UCAS and air defense systems. The default values can be found in Table 15. It should be noted that the simulation is set to simulate ~48 hours at 10 second intervals.

For the Blue agents, specifically the *Blue UCAS* agents, the author used the publicly available data on the X-47B (see Figure 34) to determine the baseline parameter settings. In instances where public data could not be easily obtained, the author used his general knowledge and intuition to make an educated guess.

Identifying the baseline values for Red parameters was far less concise and straightforward than it was for the Blue parameters because of the wide variability in potential enemy anti-aircraft systems. For the UCAS-SEAD mission, the author has elected to establish the *Red Radar* and *Red SAM* agent behavior parameters based on the *SA-21 Growler* transportable SAM system developed by Russia (see Figure 43). According to publicly available data, the *SA-21* is capable of engaging multiple targets up to 400 km (~215 nm) with missile that travel at more than 9000 knots (~Mach 16 @ 40,000 ft) [130]. Clearly, Red assets calibrated to these performance settings would represent a serious challenge for any SEAD asset.

Figure 43: SA-21 Growler Mobile SAM Platform

The baseline values for the Blue agents are listed the table below. In addition to these values (these parameters are a subset of the available parameters that can be used to adjust simulation behavior), other Blue parameters such as default UCAS speed, range, endurance, etc… are based on public available data on the X-47B

Table 15: Baseline Parameter Values for UCAS-SEAD Model

Parameter	Baseline Value
sim-speed	2
ticks-to-run	17280
seed-val	702701
ref-Blue-speed	0.065
ref-Blue-detect-range	50
ref-Blue-shoot-range	15
ref-Blue-endurance	3600
input-Blue-IOL	5
input-num-Blue-UCAVs	8
input-Blue-pComm_success	1
input-Blue-CommRange	350
input-Blue-time-to-launch-UCAVs	600
input-Blue-UCAV-RCS	0.1
input-Blue-UCAV-pHit	1
input-Blue-UCAV-toughness	1
input-Blue-UCAV-detect-range-k_factor	1
input-Blue-UCAV-speed-k_factor	1
input-Blue-UCAV-endurance-k_factor	1
input-Blue-UCAV-fuel-consumption-k_factor	1
input-Blue-UCAV-max-turn_rate	1
input-Blue-UCAV-reload-time	2700
input-Blue-UCAV-time-to-assess	180
input-Blue-UCAV-time-to-id	300
input-Blue-UCAV-num-air-to-ground-missiles	2
input-Blue-air-to-ground-missile-range-k_factor	1
input-Red-SAM-RCS	10
input-Red-SAM-pHit	0.7
input-Red-SAM-missile-pKill	1
input-Red-SAM-toughness	1
input-Red-SAM-shoot-range	50
input-Red-SAM-speed	0.5
input-Red-SAM-endurance	150
input-Red-SAM-num-of-missiles	6
input-Red-Radar-RCS	10
input-Red-Radar-pHit	0.85
input-Red-Radar-toughness	1
input-Red-Radar-detect-range	100
input-Red-BigRadar-RCS	10
input-Red-BigRadar-pHit	1
input-Red-BigRadar-toughness	1
input-Red-Airbase-RCS	10
input-Red-Airbase-pHit	1
input-Red-Airbase-toughness	4
input-Red-Command-Center-RCS	10
input-Red-Command-Center-pHit	1
input-Red-Command-Center-toughness	3
input-Red-pComm_success	1

Using the baseline setting above, the author conduct a single seed value simulation and obtained the following values for the UCAS-SEAD scenario metrics:

Table 16: Baseline UCAS-SEAD Model Metric Outputs

Scenario Metric	Output
Perc_Red_Killed_12hrs	***10%***
Perc_Red_Killed_24hrs	***10%***
Perc_Red_Killed_48hrs	***10%***
Perc_Blue_Killed	***100%***

Looking at the table above, it is obvious that the mission is a complete failure with only 10% of Red assets destroyed and 100% of Blue UCAS assets lost. Clearly, technology infusion is (very) necessary if the warfighter wishes to complete the mission with better results (i.e. more Red killed, less Blue killed).

At this point, the UCAS-SEAD scenario model has been created and a baseline scenario based on available data on current state-of-the-art UCAS and air defense systems has been conducted. For real world application, the next step in the process is to verify/validate the model using real world performance data of these systems. However, since verification and validation (V&V) of the UCAS-SEAD ABM&S model would require resources not available to the author, this step will be skipped. This is only acceptable because this is a demonstration application. Real world implementations of the ENTERPRISE process should not skip model V&V activities because they strengthen the usability of analysis outputs by securing SME and decision-maker buy-in.

6.2.1.2 Modeling Technology Development Impact on Program Budget and Schedule

Ultimately, SMEs and technology project managers are responsible for the creation/identification of the development activities associated with each technology [85]. Previous development efforts for similar technology projects (or even for the current technology) being developed can provide an initial set of activities that can be modified to suit the specific development process for the technology in question. However, the development of each technology is unique so the creation of activities should be for the purpose of general technology maturation/uncertainty reduction. Since the objective of this research is to demonstrate how to utilize technology development activity models and NOT how to create the activities associated with each technology, the specifics of methods and techniques for identifying technology development/uncertainty reduction activities will not be described here. One concept for devising generic technology development activities is to use the TRL scale as the basis for the activities [85]. Other possible types of development activities are listed in Table 17.

Table 17: General Classes of Technology Development Activities [85]

Type of Activity	TRL Range	Basic Description
Paper Study	1-2	Purpose is to try to define the technology, the basics of how the technology might work, and the basic benefits and detriments of the technology. Use simple physics-based analysis and analogy with similar technologies to try to estimate performance.
System Study	Typically Low TRL	Focuses on a specific system or systems for application of the technology, identify the effect that the technology has at the system level. Show (at a basic level) how positive and negative effects of the technology roll up to affect the overall system performance.
Technology Response Exploration	2-3	The purpose of the technology control exploration is to reduce the uncertainty in low level technology responses. Tests are typically done at a small scale, and are usually experimental in nature. Typical experiments would vary certain basic design or experimental parameters and document the corresponding variation of the technology response level metrics.
Feasibility Study	2-3	The purpose of the feasibility study is to show if the technology, or some aspect of the technology, functions at all. Also explores the performance of the technology to see if initial estimates are close to actual test data.
Component-Level Test	4-5	Component level tests are typically used to show how larger components or aspects of the technology work together or function in a more realistic environment. The tests can be varied, with the focus either on realistic operating conditions for a single component, or simpler conditions in situations where multiple components are tested together.
Full Scale Technology Test	6	The purpose of the full scale technology test is to test the technology as a whole in an environment similar to the correct operating environment. All components should be at full scale, though design parameters need not be finalized.
Design Study	Any TRL	The purpose of the design study is to vary technology control variables to find the best combination of values for the performance/cost/etc of a technology. Design studies can be performed at different stages of the development process to continually refine the design of the technology through making use of validated models and test results.
Creation of Analysis Capability	Any TRL	The purpose of creating analysis capability or validating existing analysis capability is to provide the capability of predicting the performance of a technology, either at the technology control level, the technology response level, or the system response level.

As observed earlier, a Project Network Analysis-based technology development modeling approach coupled with time and cost estimations from technologies and SMEs has been demonstrated to be effective in providing probabilistic and quantitative analysis of technology development uncertainty impact on program budget and schedule (see Section 3.7). As such, this implementation of the ENTERPRISE methodology will utilize the process demonstrated by Largent for estimation project budget and schedule variations caused by technology development uncertainties [85].

Unfortunately, because of the notional nature of the proposed UCAS technologies, accurate and detailed network models with specific maturation activities and paths were not possible. Instead each technology's development is modeled by their progression through NASA's TRL metric. This is one of the techniques suggested by Largent for identifying generic technology development activities [85]. Using this technique, the development activities associated with a technology would be the transitions between its current TRL and the final TRL of interest. For example, a technology at currently TRL 3 would require the completion of the activities depicted Figure 44 below in order to reach TRL 9.

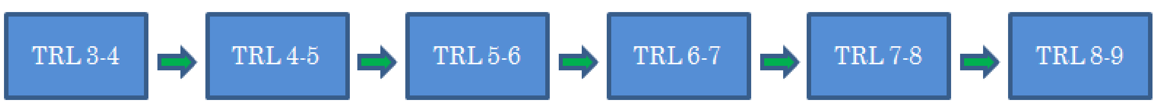


Figure 44: Notional Maturation Activities for a Technology at TRL 3

While this is a simplistic representation of technology development, it captures the essence of a network model and allows time and cost uncertainties for each activity to be defined and when coupled with a probabilistic analysis technique such as Monte Carlo Simulation, can be used to generate the output distributions for technology development budget and schedule. This information can then be used to estimate the impact on overall program budget and schedule.

Typically, the final stages of technology development and maturations requires and integration of the technologies on a test platform and eventual operational system. However, because of the notional nature of the proposed UCAS technologies, the author will that technology development projects are independent and that the time and costs associated with a set of technologies will be the sum of the costs and the maximum of the time estimations. Again, while simplistic, this implementation still allows for the demonstration of the appropriateness and utility of Project Network-based technology development models and their effectiveness in capturing the impact of technology time and cost uncertainties on acquisition program budget and schedule when pair a probabilistic analysis technique.

For this demonstration, the linear and independent nature of the technology development activities allowed the author to forgo highly-customizable but time-consuming to learn and implement network analysis modeling tools such as Simulink and instead used a simple spreadsheet program like Microsoft Excel. In addition, as will be demonstrated later, the compatibility of Excel with commercially and publicly available probabilistic analysis software packages such as Oracle Crystal Ball and ProbWorks still provided the probabilistic analysis capabilities desired by the ENTERPRISE methodology even for this notional demonstration [113; 117].

6.2.2 Step 6: Create Probabilistic Forecasting Environments

With the deterministic forecasting models complete, the next step is to establish the process and environment for probabilistically quantifying the impact of technology performance and development on UCAS capability, budget, and schedule requirements. As discussed previously, a commonly used approach for performing probabilistic analyses of parametric models is performing the Monte Carlo Simulations on the models. For this implementation of the ENTERPRISE methodology, the first two methods listed in Figure 10 will be used. The first method, in which a Monte Carlo Simulation is conducted on a computer-based model, will be applied for capturing technology development time and cost uncertainties. This method was selected from the three available options because it provided the most "realistic" results out of the three and the extremely fast calculation time associated with the Excel-based technology development network model make it possible to perform a large number of MCS run for a given case in a very short amount of time.

For probabilistically evaluating technology performance uncertainties, Method Two in Figure 10, which pairs MCS with rapid Meta or Surrogate models, was used. The reasoning behind this decisions is based on the fact that on average, a single NetLogo UCAS-SEAD simulation required anywhere from 2 to 15 minutes (and in occasion even longer) to run. This large variation in simulation time is caused by the fact that time it takes for the model to reach one of the three termination conditions, all blue (friendly) UCAS assets killed, all red (enemy) forces killed, or simulation time-limit reached, can vary depending on the combination of input parameters. Even on the lower end of simulation time, conducting even several hundred MC runs (a far smaller sample sizes than those used by past ASDL methods such as TIES and TDPM) for each technology infusion combination would require several hours, at a minimum, to generate output metric distribution data for a single UCAS-SEAD enabling technology combination. This means that the time required to identify optimal solutions using any of the identified technology selection/optimization could be days, weeks, or even months depending on number of desired solutions. Furthermore, this hampers the ability of a computer-based DSS to provide rapid responses to user inputs on technology portfolio selections, requirement constraints, or any other changes that would require a re-sampling of the model output.

The details of the probabilistic analysis environments created for UCAS-SEAD ENTERPRISE implementation are provided in the proceeding sections.

6.2.2.1 Probabilistic Technology Development Impact on Program Budget and Schedule Forecasting Environment

The process of creating the MCS-based analysis environment for capturing technology development time and cost uncertainties will be provided first as it is simple and more straightforward. As stated, this environment consists of performing MCS sampling runs on the actual technology development network model, which in this case is a Microsoft Excel spreadsheet. This spreadsheet was coupled with Oracle Crystal Ball, a "spreadsheet-based application suite for predictive modeling, forecasting, simulation, and optimization," was used to provide uncertainty analysis capabilities [113]. This Excel add-on's probabilistic analysis capabilities allow a MCS of the time and cost estimations for each technology's development activities to be conducted within Excel and can be set to automatically generate the subsequent total time and cost output distribution. The author's familiarity with this tool and its intuitive graphical user interface allows Monte Carlo Simulations of technology development uncertainties to be conducted rapidly and efficiently with almost no setbacks.

6.2.2.1.1 Development Activity Time and Cost Uncertainty Assumptions and Distributions

In order to probabilistically evaluate technology development time and cost uncertainties, Oracle Crystal Ball (and all MCS tools in general) requires the user to input assumptions for distribution range and shape (e.g. Normal, Beta, Triangle) for each uncertain variable (i.e. time and cost for each activity). Obviously, the range and shape function used to define each variable can have a major impact on output results. For real world applications, technologies and relevant SMEs would have to be consulted when defining these shape functions and ranges.

According to John, Beta distributions are generally seen as “suitable” in uncertainty/risk analysis because they provide “a wide variety of distributional shapes over a finite interval” [73]. However, one of the main disadvantages of defining parameter uncertainty using Beta distributions is the fact that they are not easily understood and “its parameters are not easily estimated” [73]. As such, several of the methods examined in Chapter 2 assigned Triangular distributions instead of Beta distributions to technology uncertainty variables [81; 85]. According to the author of these methods, this type of distribution was desirable because of the limited amount technology uncertainty data. Defining a Triangular distribution requires only establishing a minimum and maximum for the variable range and an "inspired guess" to the mode or most-likely value. Since the amount of SME and technologist input is limited/non-existent in this application, the author has elected to define the technology time and cost uncertainty functions using a Triangular distribution. Since technology performance uncertainty data is as equally lacking as time and cost data, the uncertainty distributions for those variables will also be defined using a Triangular distribution. For future applications, a structured process for defining these distribution and ranges using historical data and/or expert input would help improve the transparency and validity of uncertainty analysis results.

In order to assign the parameters for the Triangle distribution for each technology's activities, the author referred to the data in Table 18. According to Largent, the data in this table was compiled using development data from twelve major NASA programs [85]. While NASA technology development processes are not identical to acquisition technology development processes, similarity in the two can be assumed. Thus, the author elected to use these values as the basis for defining *low, high, and most-likely* parameters for each technology's TRL transition activities. However, instead using the same three distribution parameters for each TRL transition for each technology, the author shifted each parameter up or down according to his opinion of the difficult associated with that technology. For example, the TRL 4-5 transition time distribution for a "difficult" technology such as *Advanced Stealth Planform Alignment* would have higher *low, high*, and *most likely* values than something better understood like *Durable High Temp Core and Fuel Efficient Turbine Engine.*

Table 18: Sample Statistics for TRL Transition Time [114]

Transition From...	Average (Years)	Standard Deviation (Years)
TRL 1 to TRL 2	1.8	1.4
TRL 2 to TRL 3	1.4	1.5
TRL 3 to TRL 4	1.8	2
TRL 4 to TRL 5	1.6	1.2
TRL 5 to TRL 6	2.6	6.1
TRL 6 to TRL 7	2.1	2.5
TRL 7 to TRL 8	2.7	3.5
TRL 8 to TRL 9	2.2	3.1

Table 19 below compares the notional time estimation for each TRL transition created by the author for these two technologies (both assumed to currently be at TRL 4):

Table 19: TRL Transition Time Estimations for Two Notional UCAS-SEAD Technologies

	Durable High Temp Core and Fuel Efficicient Turbine Engine			Advanced Stealth Planform Alignment		
TRL Transition	**Low**	**High**	**Likely**	**Low**	**High**	**Likely**
TRL 1 to 2						
TRL 2 to 3						
TRL 3 to 4						
TRL 4 to 5	1.35	2.55	1.95	1.90	3.10	2.50
TRL 5 to 6	1.43	6.00	2.95	1.98	6.55	3.50
TRL 6 to 7	1.20	3.70	2.45	1.75	4.25	3.00
TRL 7 to 8	1.30	4.80	3.05	1.85	5.35	3.60
TRL 8 to 9	1.00	4.10	2.55	1.55	4.65	3.10

The TRL transition time estimates for each of the eighteen UCAS-SEAD enabling technologies can be found in Appendix B. Note that the transitions that occurred before the "current" TRL of each technology are not included for obvious reasons.

While the schedule data for TRL transitions was fairly easy to obtain, the cost data was not. Because of the severely limited availability of **complete** cost data for technology development programs (both commercial and government), the author elected to use a different approach for this methodology demonstration. Instead of defining *low, high*, and *most likely* values for the cost associated with the TRL transition of each technology, the author instead defined a *cost per year* for each TRL transition:

Table 20: Baseline TRL Transition Cost Estimates for Notional UCAS-SEAD Technologies

TRL Transition	Cost per Year ($k)
TRL 1 to 2	150
TRL 2 to 3	250
TRL 3 to 4	500
TRL 4 to 5	1000
TRL 5 to 6	3000
TRL 6 to 7	5000
TRL 7 to 8	8000
TRL 8 to 9	12000

The values in Table 19 were "adjusted" for each technology, again depending on the perceived difficulty of the technology, to establish the following cost estimation data for the TRL transition activity for each UCAS-SEAD technology using the following equation:

$$Transition\ Cost_{TRL\ i\ to\ TRL\ j} = \#\ of\ years_{\mathrm{TRL\ i\ to\ TRL\ j}} * (1 + adjustment\ factor) * cost\ per\ year_{TRL\ i\ to\ TRL\ j}$$

(25)

Where:

- $Transition\ Cost_{TRL\ i\ to\ TRL\ j}$ is the total cost to transition from TRL i to TRL j
- $\#\ of\ years_{TRL\ i\ to\ TRL\ j}$ is the estimated number of years to transition from TRL i to TRL j
- *adjustment factor* is the variable used to adjust the cost per year for the TRL transition (varies between technologies)
- $cost\ per\ year_{TRL\ i\ to\ TRL\ j}$ is found by looking up the corresponding TRL transition in Table 20

The cost adjustment factor for each technology was defined by the author and is listed below:

Table 21: TRL Transition Cost Adjustment Factors for Notional UCAS-SEAD Technologies

Technology	*Cost Adjustment Factor*
Advance Aircraft Wing Folding and Fuselage Telescoping	-0.2
Internal Cargo Bay Exapansion	-0.4
High L/D Aeroconfiguration	-0.45
Embedded Fuel Pods	0.5
Efficient Transonic Planform	0.55
Efficient Propulsion Installation	0
Durable High Temp Core and Fuel Efficicient Turbine Engine	0.35
Advanced Radar Absorption Materials	1.5
Advanced Stealth Planform Alignment	0.9
Embedded Engines	0.15
Non-metallic Dielectric Airframe	1.25
Long Range Air-to-ground Missile	-0.45
Stealthy Air-to-ground Missile	0.75
Sensor Jamming	-0.15
Missile Lock Inteference	0.5
Communications Jamming	-0.65
Advanced Computer Guided Target Recognizition	0.2
Extended Range Sensors	0.4

Once the assumptions regarding each technology time and cost uncertainty variable was defined, a MCS could then be conducted using Oracle Crystal Ball. Table 22 summarizes the results of a 10,000 case MCS conducted on each of the eighteen proposed UCAS-SEAD technology. The value for each TRL time and cost metric listed in this table represents the mean of the generated output distributions. Depending on the needs of the decision-makers, these values can be changed to reflect specific percentiles of the distribution (i.e. 50%, 70%, etc…)

Table 22: Development Schedule and Cost Monte Carlo Simulation Output Summary for Notional UCAS-SEAD Technologies

	Years to			Cost ($M) to		
Technology	**TRL 6**	**TRL 7**	**TRL 9**	**TRL 6**	**TRL 7**	**TRL 9**
AF-1	5.93	7.83	12.33	8.80	16.40	51.60
AF-2	4.98	6.68	10.79	7.24	14.05	46.09
AF-3	2.14	3.80	7.80	5.14	11.76	42.97
AF-4	5.72	8.31	14.19	10.36	20.73	66.98
AF-5	5.80	8.46	14.46	10.48	21.10	68.32
PR-1	2.98	4.93	9.52	7.15	14.96	50.89
PR-2	5.42	7.87	13.46	9.87	19.67	63.61
ST-1	10.99	14.59	22.48	14.83	29.22	91.51
ST-2	6.49	9.49	16.19	11.58	23.59	76.35
ST-3	5.00	7.26	12.46	9.20	18.23	59.02
ST-4	10.24	13.59	20.98	13.91	27.35	85.65
WP-1	3.31	4.96	8.96	6.10	12.69	43.91
WP-2	8.76	11.62	18.02	12.17	23.61	74.02
EW-1	2.96	4.91	9.51	7.10	14.90	50.89
EW-2	8.01	10.62	16.52	11.26	21.71	68.12
EW-3	2.80	4.25	7.85	5.20	10.99	39.04
IR-1	5.11	7.40	12.71	9.38	18.56	60.26
IR-2	3.52	6.01	11.71	8.44	18.42	63.20

6.2.2.2 Probabilistic Technology Impact on UCAS Capability Forecasting Environment

As discussed previously, the probabilistic technology impact on UCAS capability forecasting environment would couple MCS with surrogates of the NetLogo ABM&S in order to reduce analysis runtime. The process for creating this environment will be described in this section, but first the assumptions for performance uncertainties must be defined.

6.2.2.2.1 Technology Performance Uncertainty Assumptions and Distributions

Similar to the probabilistic technology development uncertainty analysis process, the performance uncertainties associated with each UCAS-SEAD technology will be described using Triangular distributions due to the lack of expert input and creditable data. As noted in Section 6.2.1.1.1.4, the impact of each technology will be simulated by adjusting a specific set of UCAS-SEAD NetLogo model input parameters associated with that technology. Such implementations were demonstrated by Biltgen, Largent, and Kirby in their method implementations.

Once again, the lack of SME input and actual data, technology impact on NetLogo input parameters were notionally defined by the author using Technology Impact Matrices (TIMs). These TIMs define the changes (if any) to the NetLogo model parameters for each technology. Two examples of the TIMs created for this implementation are listed in Table 24 (please refer to Appendix C for the entire set of TIMs created for this demonstration application). For this demonstration, only 18 of the variables listed in Table 15 were impacted by technologies. Also, for easier implementation, these impacts are assumed to be additive in nature.

Table 23: NetLogo Model Parameters Impacted By Notional UCAS-SEAD Technologies

Parameter	Description
input-num-Blue-UCAVs	Number of Blue UCAS assets aboard carrier
input-Blue-time-to-launch-UCAVs	Minimum amount of time (s) between UCAS carrier launches
input-Blue-UCAV-RCS	Notional Radar Cross Section of UCAS assets
input-Blue-UCAV-pHit	Probability of hit of UCAS assets by Red SAMs when fired upon
input-Blue-UCAV-speed-k_factor	UCAS asset speed k-factor
input-Blue-UCAV-endurance-k_factor	UCAS asset endurance/range k-factor
input-Blue-UCAV-fuel-consumption-k_factor	UCAS asset fuel consumption k-factor
input-Blue-UCAV-reload-time	Time (s) required to rearm and refuel UCAS assets onboard carrier
input-Blue-UCAV-time-to-assess	Time (s) required by UCAS assets to assess operability of engaged targets
input-Blue-UCAV-time-to-id	Time (s) required by UCAS assets to identify detected potential threats
input-Blue-UCAV-detect-range-k_factor	UCAS asset sensor detection range k-factor
input-Blue-UCAV-num-air-to-ground-missiles	Number of air-to-ground missile onboad UCAS asset
input-Blue-air-to-ground-missile-range-k_factor	Blue air-to-ground missile range k-factor
input-Red-SAM-pHit	Probability of hit for Red SAMs by Blue air-to-ground missiles when fired upon
input-Red-SAM-shoot-range	Engagement range of Red SAMs
input-Red-Radar-pHit	Probability of hit for Red Radarss by Blue air-to-ground missiles when fired upon
input-Red-Radar-detect-range	Detection range of Red Radars
input-Red-pComm_success	Probability of success for communcation between Red agents

Table 24: TIM for Notional Technologies AF-1 and AF-2

	Airframe Tech 1: Advance Aircraft Wing Folding and Fuselage Telescoping			Airframe Tech 2: Increased Internal Cargo Bay		
Parameter	***Low***	***High***	***Likely***	***Low***	***High***	***Likely***
input-num-Blue-UCAVs	4	8	6			
input-Blue-time-to-launch-UCAVs	300	900	750			
input-Blue-UCAV-RCS (%)						
input-Blue-UCAV-pHit						
input-Blue-UCAV-speed-k_factor						
input-Blue-UCAV-endurance-k_factor						
input-Blue-UCAV-fuel-consumption-k_factor				0.25	0.75	0.5
input-Blue-UCAV-reload-time (%)				10	30	20
input-Blue-UCAV-time-to-assess (%)						
input-Blue-UCAV-time-to-id (%)						
input-Blue-UCAV-detect-range-k_factor						
input-Blue-UCAV-num-air-to-ground-missiles				2	4	2
input-Blue-air-to-ground-missile-range-k_factor						
input-Red-SAM-pHit						
input-Red-SAM-shoot-range (%)						
input-Red-Radar-pHit						
input-Red-Radar-detect-range (%)						
input-Red-pComm_success						

In order to reduce the computation burden associated with the probabilistic UCAS capability forecasting environment, surrogate models of the UCAS-SEAD models are needed.

6.2.2.2.2 Surrogate Model Generation

As discussed in Section 5.3.2.1, multiple surrogate modeling approaches are available depending on the specific needs and nature of the model(s) being surrogated. The general process for creating surrogates is as follows:

- Identify inputs parameters and output metrics of interest
- Define potential range of values for each input parameter (i.e. low and high limits)
- Map values to a Design of Experiments
- Generate regression data using DoE
- Create Surrogate Models using regression data
- Verify Surrogate "goodness of fit"

For their investigations, Bagdatli and his team elected to use the Artificial Neural Networks approach because of its ability to handle non-continuous design spaces and discrete output metrics [15]. Follow-up discussions with Bagdatli led the author to also select the ANN approach since has already been demonstrated to be effective in capturing the behavior of the NetLogo J-UCAS model (of which the current UCAS-SEAD model is a derivative of) [15].

Unfortunately, the *stochastic* nature of the UCAS-SEAD ABM&S model requires additional steps to be taken in order to create ANNs that adequately capture the behavior of the model.

6.2.2.2.2.1 Capturing UCAS-SEAD Model Stochastic Behavior

In a deterministic model or process, there is only one possible outcome for a given set of inputs. Thus repeated runs of a deterministic model will always generate the same results for a given set of inputs. However, Discrete Event Simulations like ABM&S typically have indeterminacy in its evolution which results in variations in simulation outputs. These indeterminacies are caused by probabilistic parameters typical to this approach. For example, within the UCAS-SEAD model several of the parameters are probabilistic in nature:

- Probability of Detection (Red and Blue)
- Probability of Hit (Red and Blue)
- Probability of Kill when Hit

During the course of a given simulation, the results of the "random dice rolls" or random number generation that occur when one these parameters are taken into consideration for an event occurrence (e.g. probability of Blue UCAS being detected by Red Radar once inside Red Radar detection range) can differ when the model is initialized with a different *random seed*. As such, the eventual outcome of the simulation can different between different random seed assignments, creation a distribution of outputs for a given set of inputs. In order to capture the stochastic behavior of the UCAS-SEAD model, the generated ANNs must be able to account for this randomness behavior when predicting simulation results.

The simplest (and most imprecise) approach for capturing for the stochastic nature of the UCAS-SEAD model is with Surrogate Models is to regress against the mean value of the output metric distributions for a given set of inputs conducted with different random seed value assignments. However, with the exception of Normal and Uniform distributions, distribution functions are generally described using the mode and not mean value (along with other parameters). In addition, additional parameters are necessary to properly describe the distribution (e.g. standard deviation for Uniform distributions). As such, the distributions of metric outputs need to be first examined before a proper surrogate approach can be selected.

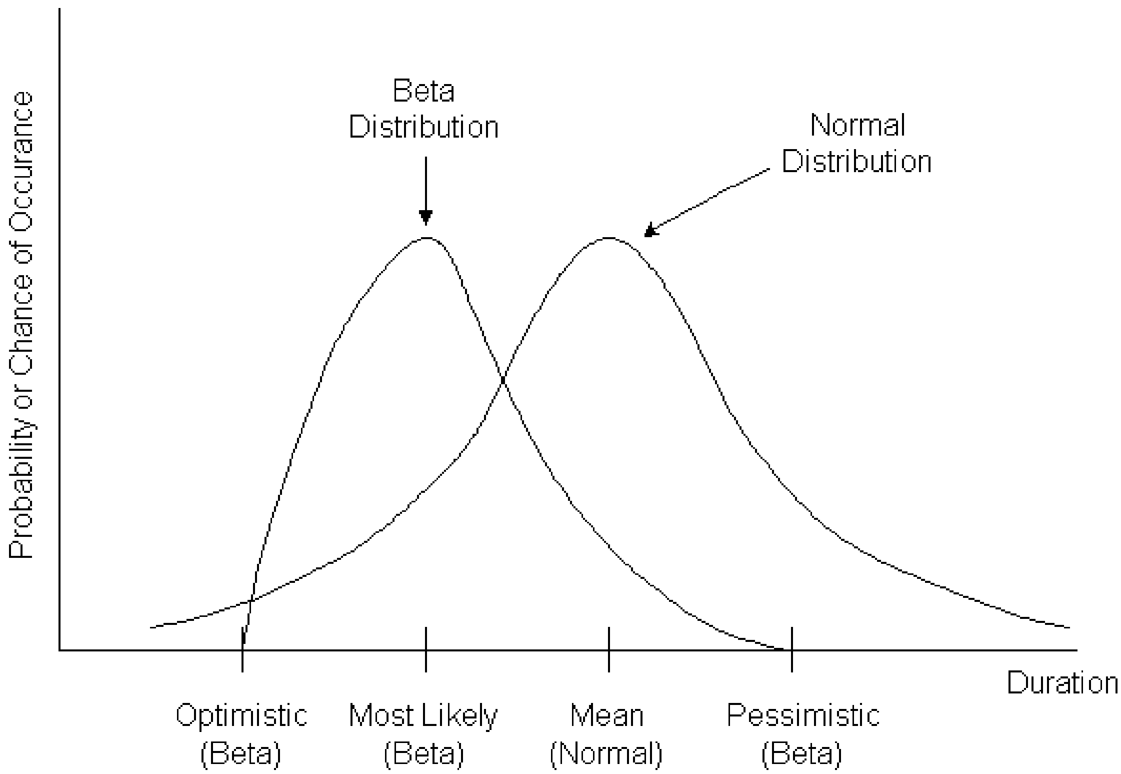


Figure 45: Comparisons Between Normal and Beta Distribution and the Parameters Commonly Used to Describe Them [62]

For the UCAS-SEAD ENTERPRISE implementation, two hundred repetitions of a single set of input parameters were conducted using different seeds and the results for the *% Red Killed @ 24 Hours* and *% Red Killed @ 48 Hours* metric are plotted below:

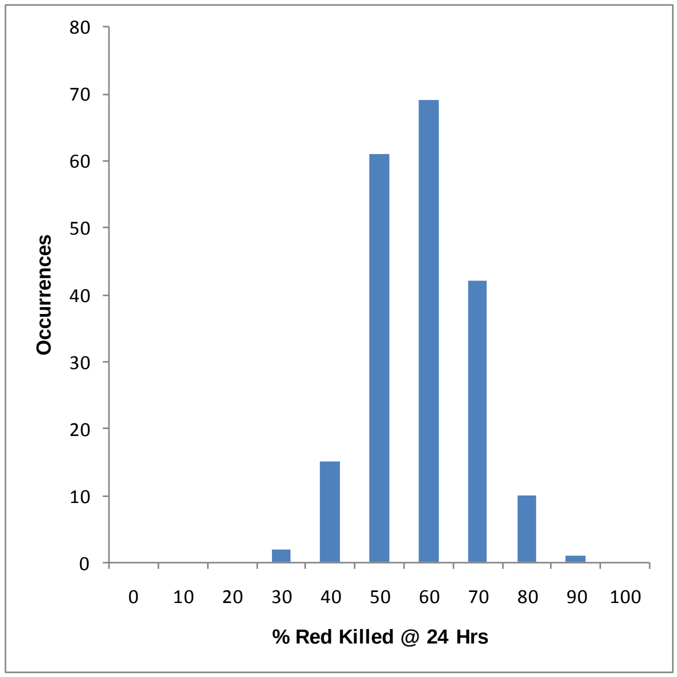


Figure 46: Distribution of *% Red Killed @ 24 Hrs* for a Given Set of UCAS-SEAD Parameters Repeated for 200 Random Seed Values

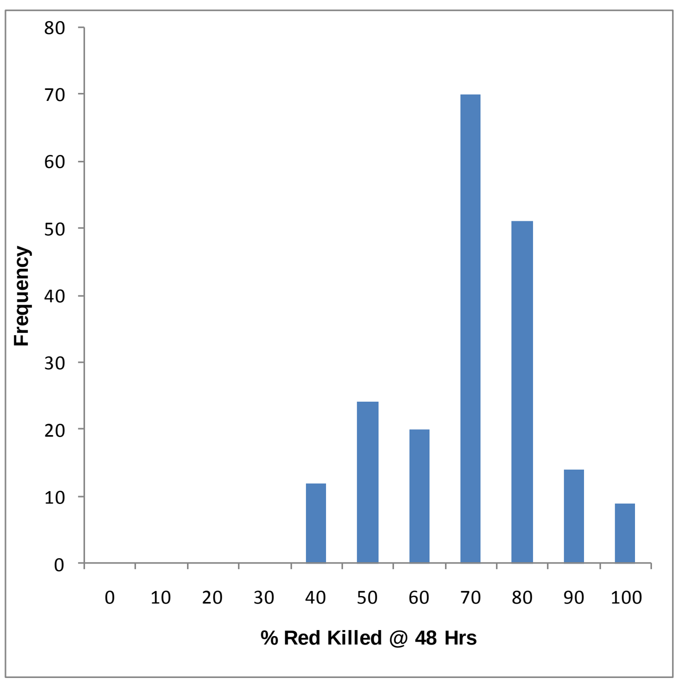


Figure 47: Distribution of *% Red Killed @ 48 Hrs* for a Given Set of UCAS-SEAD Parameters Repeated for 200 Random Seed Values

Base on the author's opinion, the distributions provided in these figures above most closely resemble a Beta or Normal distribution. However, as will be shown in the next section, the limited amount of data that could be generated using the computations resources available for this application allowed for only ten repetitions for each DoE case. Extracting the necessary statistical parameters (e.g. mode, low, high, etc…) needed to describe a Beta distribution, or even its simpler relative, Triangular distribution, is not possible. As such, the author has elected to extract the mean and standard deviation values for metric output distributions for each DoE case and create ANNs of these values for predicting the behavior of the UCAS-SEAD ABM&S output capability metric behaviors. In future applications where (hopefully) additional computational resources are available, the number of repetitions per DoE should be increased to allow for a better prediction of model behavior using SMs.

In order to determine the performance in capturing model stochastic behavior, a Student-T test on the single DoE case, multi random seed experiment results was conducted. The results, in terms of accuracy tolerance and confidence level, associated with 10 repetitions are summarized below:

Table 25: Student T-Test Results for Notional UCAS-SEAD NetLogo Model

	%_Red_Killed _12hrs	**%_Red_Killed _24hrs**	**%_Red_Killed _48hrs**	**%_Blue_Killed**
Mean	34.53	54.34	66.10	97.56
Std. Dev.	6.12	10.54	14.70	7.99
Accuracy Tolerance	0.1	0.1	0.1	0.1
Confidence	0.9	0.9	0.85	0.8

Based on these results, the author believes that capturing model stochastic behavior using only 10 random seed iterations is sufficient for this demonstration application. However, in future application where high analysis fidelity and model prediction accuracy is desired, additional seed iterations are suggested. It should be noted that it too approximately 24 hours for the author's personal computer to conduct these 200 cases. Clearly the computation requirements needed to generate sufficient data for accurately capturing stochastic model behavior can be quite large. Coupled with the requirements needed to capture deterministic model behavior (next section), the amount of required computing resources far exceeds those available to the author. Clearly, a compromise is needed between the need to capture stochastic and deterministic behaviors. For future applications, a more structured process for doing this AND for identifying and capturing the stochastic behavior of the model (if one exists) would make the ENTERPRISE method easier to implement.

6.2.2.2.2.2 Selecting Design of Experiments

With the regression strategy in place, the next step is to select the Design of Experiments that will be used to generate the ANN regression data (i.e. mean and standard deviation values for each scenario metric. Figure 48 summarizes the advantages and disadvantages of four popular types of DoEs commonly used by the engineering and design community: *Full-Factorial, Box-Behnken, Latin Hyper Cube,* and *Face-centered Central Composite.* For the UCAS-SEAD ANNs, the author elected to use a Latin Hyper Cube (LHC) DoE. This selection was made because of two main reasons:

* *Higher order approximations:* It is possible (and highly likely) that the relationships between UCAS-SEAD scenario metrics and model parameters exceed 2nd order polynomial (a LHC DoE is better suited for higher order approximations).

* *Higher accuracy when predicting interior design points:* This is desirable because in all likelihood, the true impact of technologies on model parameters will not be at either extreme but somewhere in between so sacrificing accuracy at the extremes for improved predictability in the interior is acceptable.

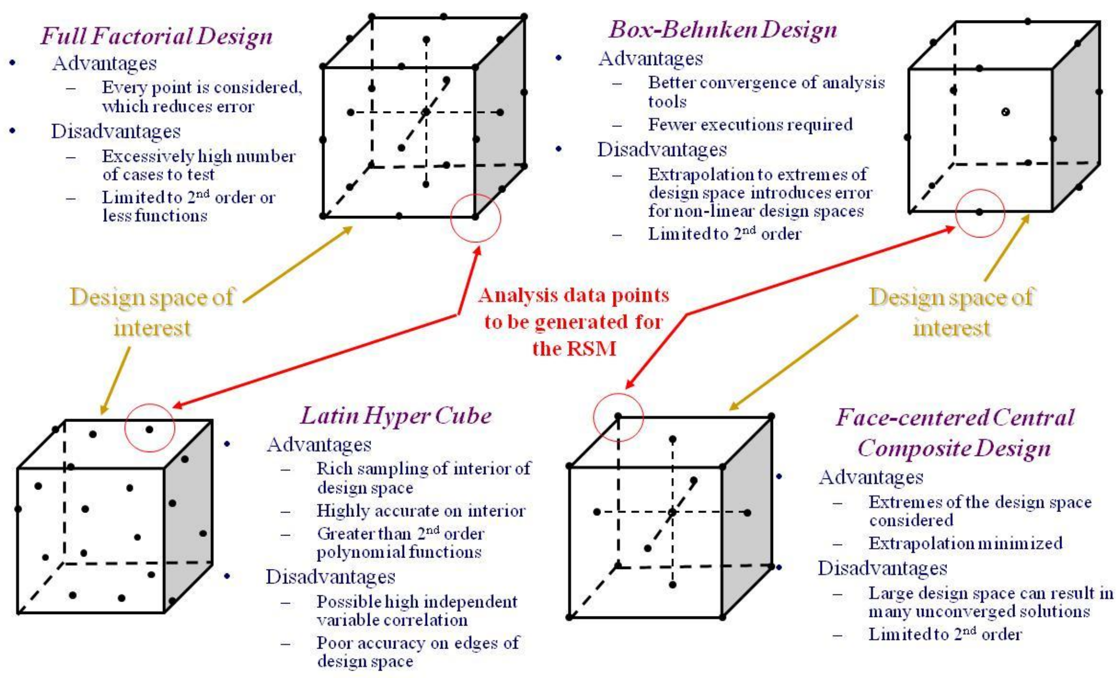


Figure 48: Advantages and Disadvantages of Four Common Types of DoEs [80]

The MATLAB routine *lhsdesign* was used to generate a normalized (-1 to 1) 18-variable Latin Hyper Cube DoE. Combining the normalized values in the generated LHC DoE with the parameter ranges established in the previous section resulted in actual set of DoE runs that will be simulated to generate the ANN data. Before the details of conducting these runs are provided, the author will first provide a brief discussion on the selection of the size of the LHC DoE (5,000) used to generate the UCAS-SEAD ANNs as that will be used later on.

6.2.2.2.2.3 Determining DoE Size

Logically, the accuracy and precision of a Surrogate Model increases as the number of data points used to create it increases. However, as discussed previously, the computation cost of conducting a large number of cases for creating SMs can make this entire process impractical. Thus a balance must be made between SM accuracy and computational cost.

To examine the benefits gained/computational resources required for using a large DoE to generate the UCAS-SEAD ANNs, the author compared the performance of ANNs generated by six Latin Hyper Cube DoEs with different sizes: 1500, 2000, 3500, 5000, 7000, and 10,000 cases. For this study, the author compared the performance for the ANN generated for the red targets killed 4 hours into the simulation. The performance (i.e. accuracy and precision) of the generated ANNs, typically measured using the ANN's *R^2 Training*, *R^2 Validation, Model Fit Error (MFE) Mean* and *Standard Deviation*, and *Model Representation Error (MRE) Mean* and *Standard Deviation* values, are summarized below. The results of this tradestudy are summarized in Table 26 below:

Table 26: ANN Prediction Accuracy vs. DoE Size for Notional NetLogo Model

DoE Size	R2 Training	R2 Validation	MFE Mean	MFE Std. Dev.	MRE Mean	MRE Std. Dev.
1500	0.79958	0.77687	-0.10423	6.4664	-0.25718	7.9665
3500	0.84841	0.80412	0.081316	6.7927	-0.23157	6.8271
5000	0.87345	0.83085	0.0031187	5.3927	0.022797	6.0671
7000	0.86862	0.84704	0.044293	5.4336	-0.098056	6.0366
10,000	0.86463	0.8537	0.012131	5.1244	0.098618	5.3429

Looking at the table above, it is clear that above a DoE size of 5000, the improvement in ANN accuracy metrics are minimal. Based on this observation, the author elected to use a 5,000 case LHC DoE to generate the ANNs for the UCAS-SEAD scenario analysis metrics.

6.2.2.2.2.4 Regression Data Generation

With the DoE size and number of seed iterations established, the next step is to generate the data needed to create the ANNs. As previously states, the average time to conduct a single UCAS-SEAD simulation ranged from 2-15 minutes. For a **single** seed iteration of the 5,000 case LHC DoE this translates to an analysis run-time between 7-52 days! Fortunately, the author had (some) access to additional computing resources that allowed the generation of 10 seed iterations over the span of a several weeks.

Fortunately, the author had access to Centerlink, a program developed by Phoenix Integration that automatically parcels out one or multiple sets of analysis studies to a pre-defined set of computers called a cluster. It also automatically collects and compiles the results of these studies into a single repository. This program allows a single user to setup, distribute, and collect data from hundred, thousands, or even higher number of studies conducted on multiple computers located in different locations from a single access point (e.g. Centerlink web portal or server computer). This automated process is much more efficient than the traditional sneaker-net where the studies have to be manually loaded, conducted, and results collected each computer on the cluster. Automating this process also reduces the likelihood of human error during the data generation process (e.g. forgetting to run some cases, overwriting data, etc…).

In order for Centerlink to distribute the NetLogo UCAS-SEAD scenario analysis study, it must first be wrapped into a ModelCenter file. The remainder of this section will detail the wrapping of the UCAS-SEAD model into ModelCenter and the use of this wrapped model by Centerlink to run the 50,000 simulations for ANN generation.

ModelCenter, another product from Phoenix Integrations, is a "graphical environment for process integration and design automation" [116]. It allows the user to import different types of analysis tools (e.g. MATLAB code, Excel Spreadsheet, etc…) and integrate them into a single analysis environment with interconnected inputs and outputs. Importing the NetLogo UCAS-SEAD environment required the use of a ModelCenter *fileWrapper*, which is a ModelCenter run script that can be used to instruct ModelCenter to automatically create an input file, execute one or more commands (i.e. executable files), and parse the outputs. Once a *fileWrapper* has been created, the user can modify analysis parameters from the ModelCenter GUI, hit "run," and wait for the results to be generated and parsed.

According to Phoenix Integration's website, Centerlink accelerates design simulations and running integrated processes through the use a an unique grid computing server that takes advantage of idle computing resources [115]. To accelerate the data generation process (for creating UCAS-SEAD ANNs), the author utilized ASDL's Centerlink capabilities to utilize a cluster of sixteen node computers, each similar in computer power as the author's. This coupling of ModelCenter and Centerlink allowed up to sixteen NetLogo UCAS-SEAD simulations to be continued in parallel at a time, thus significantly reducing the actual time required to generate ANN data points. Unfortunately, not all sixteen node computers were available during data generation (priority typically given to research projects over individual thesis data generation) and why only 10 seed iterations could be conducted in the span of several weeks.

6.2.2.2.2.5 ANN Creation

Once the regression data has been collected and compiled, the means and standard deviations of the 5,000 case LHC DoE were calculated so that ANNs for predicting these values could be created. Since a reproduction of a data table with 5,000 rows and 25 columns (18 columns for the 18 DoE parameters and 7 columns for each of the UCAS-SEAD scenario metrics identified in Step 3) is impractical, the processed results of the data generation process are not included in this work.

For the creation of ANN SMs of UCAS-SEAD scenario metrics, multiple options were available to the author including JMP by the SAS Institute, MATLAB, and Microsoft Excel each with ANN generation capabilities. The author elected to use the MATLAB-based Basic Regression Analysis for Integrated Neural Networks (BRAINN) tool developed by Carl Johnson and Jeff Schutte at ASDL because of the additional capabilities it provided over JMP and Excel ANN generation capabilities, familiarity of the author with the tool from past projects, and easy access to tool developers in the event of operational emergencies.

BRAINN is a GUI-based program that allows for the "automated generation of neural network regressions" built on top of MATLAB's Neural Net Toolbox, which has a "large degree of flexibility" for ANN-generation [72]. This tools allows for the "maximum utilization of this flexibility while maintaining compatibility with JMP" [72]. Figure 49 below provides a snapshot of the BRAINN GUI:

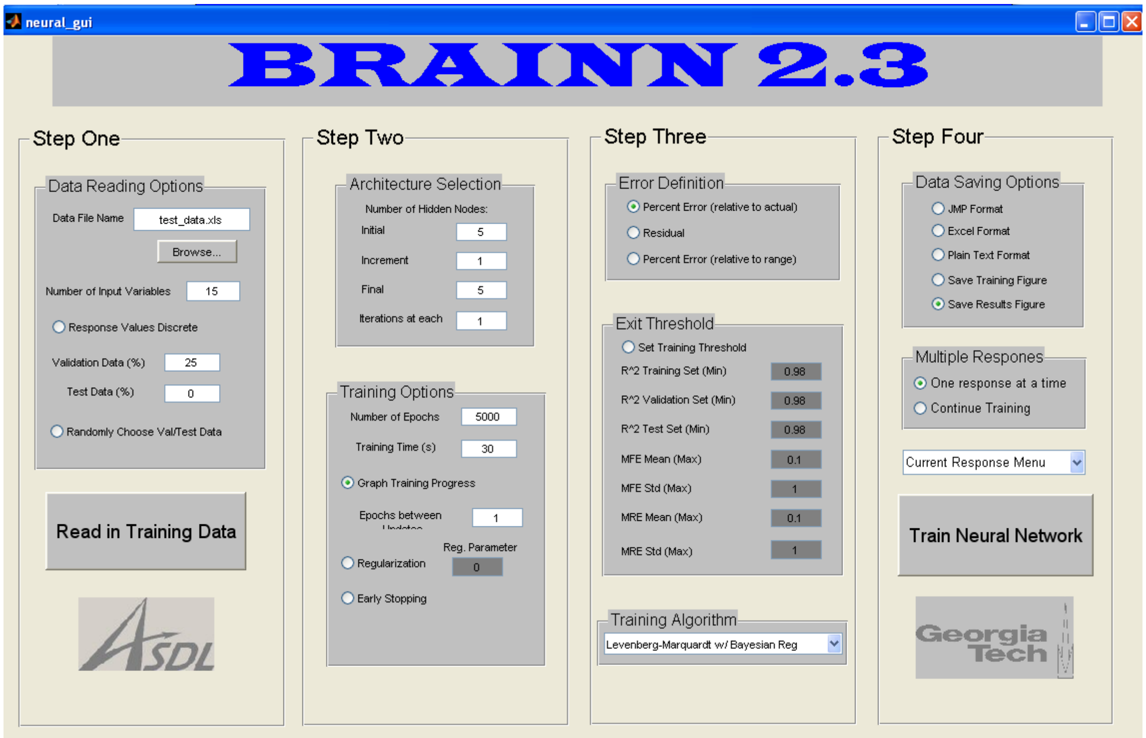


Figure 49: BRAINN GUI Snapshot

Using BRAINN with the regression parameters listed in Table 27, the author created 2 ANNs for predicting the behavior of each of the seven UCAS-SEAD scenario metrics (1 for mean, 1 for standard deviation).

Table 27: BRAINN Parameters

ANN Generation Parameter	Value
% of Dataset for Validation	*20*
Hidden Node Iteration Initial	*10*
Hidden Node Iteration Final	*50*
Hidden Node Iteration Increment	*2*
Hidden Node Iteration	*2*
Training Time Limit (s)	*3600*
Early Stopping	*Yes*
Training Algorithm	*Train-BR*

The number of hidden nodes used to create each generated ANN is listed below:

Table 28: Number of Hidden Nodes Used For Notional UCAS-SEAD Metric Prediction ANN

Prediction Metric	# of Hidden Nodes
Mean %Red Killed @ 12 hours	40
Mean %Red Killed @ 24 hours	18
Mean %Red Killed @ 48 hours	14
Mean %Blue Killed Total	24
Std.Dev %Red Killed @ 12 hours	32
Std.Dev %Red Killed @ 24 hours	52
Std.Dev %Red Killed @ 48 hours	10
Std.Dev %Blue Killed Total	12

6.2.2.2.2.6 ANN Validation

When using Surrogate Models instead of actual analysis tools to predict analysis output metrics, it is important to evaluate the accuracy and precision of the generated SMs against the original model/tools used to generate them. For ANN creation, Schutte and Johnson includes the following "goodness of fit" metrics for each ANN generated using BRAINN:

- *R^2 Training & Actual by Predicted Plot*
- *R^2 Validation & Actual by Residual Plot*
- *Model Fit Error Distribution*
- *Model Representation Error Distribution*

The full summary figures for each metric ANN can be found in Appendix D.

<u>R^2 Training & Actual by Predicted Plot</u>

R^2 refers to the *coefficient of determination* and describes the proportion of variability in a data set that is accounted for by the statistical model (in this case, ANN) [144]. For example, an R^2 value of 1.0 corresponds to a perfect fit (i.e. model predicts behaviors 100% of the time). According the *ASDL RSM Background* material, as a rule of thumb an "R^2 value greater than [0.90] represents a good model fit" [80]. In ANN generation, R^2 Training refers to the ANN SM behavior when predicting the metrics for the cases used to generate the ANN SM itself (as opposed to predicting the metrics for the validation cases, which were not used to generate the ANN SM and is described in the next section). The R^2 Training values for the UCAS-SEAD ANN are listed below:

Table 29: R-squared Training Values for Notional UCAS-SEAD Metric ANNs

UCAS-SEAD Metric	R-square Training
Mean Perc_Red_Killed_12hrs	0.975
Mean Perc_Red_Killed_24hrs	0.962
Mean Perc_Red_Killed_48hrs	0.959
Mean Perc_Blue_Killed	0.976
Std Dev Perc_Red_Killed_12hrs	0.666
Std Dev Perc_Red_Killed_24hrs	0.726
Std Dev Perc_Red_Killed_48hrs	0.684
Std Dev Perc_Blue_Killed	0.598

Looking at the table above, it appears that Mean ANNs were all extremely effective in predicting the behavior of the training data while the Std Dev ANNs did not fare as well. These R^2 Training values are still within acceptable bounds for the purposes of this demonstration.

The R^2 Training for an ANN is typically shown beside the *Actual by Predicted* plot, which plots the actual vs. predicted values of the metric. An indication of a good fit is an "even distribution of the data along the perfect fit lines" (see Figure 50) [80]. The R^2 Training and *Actual by Predicted* plot for each metric ANN are listed in Appendix D and conform (albeit with wider margin than desired) to the guidelines and thus are deemed acceptable for this process demonstration.

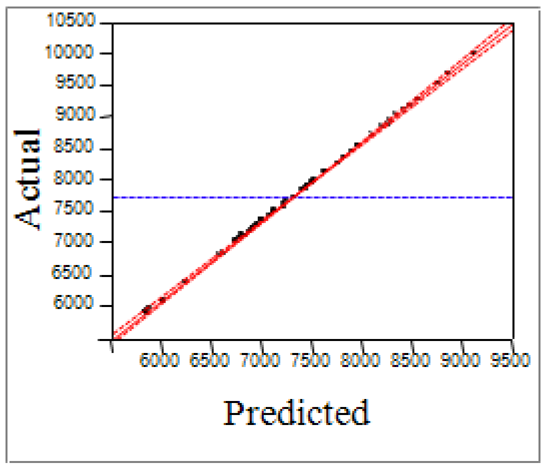


Figure 50: Example Actual by Predicted Plot [80]

<u>R^2 Validation & Residual Plot</u>

In addition to measuring the R^2 value for the training data set, BRAINN also tests the R^2 for a separate validation data set. This allows the performance of the generated ANNs to be tested against data points that were not used to create them. The R^2 Validation values for the UCAS-SEAD metric ANNs are:

Table 30: R-squared Validation Values for Notional UCAS-SEAD Metric ANNs

UCAS-SEAD Metric	R-square Validation
Mean Perc_Red_Killed_12hrs	0.941
Mean Perc_Red_Killed_24hrs	0.914
Mean Perc_Red_Killed_48hrs	0.918
Mean Perc_Blue_Killed	0.955
Std Dev Perc_Red_Killed_12hrs	0.554
Std Dev Perc_Red_Killed_24hrs	0.656
Std Dev Perc_Red_Killed_48hrs	0.605
Std Dev Perc_Blue_Killed	0.444

Again, because of the intent of this application is to demonstrate the ENTERPRISE methodology process and not in support of actual acquisition program decisions, the remaining R^2 Validation values are deemed acceptable. It should be noted that the performance of the Std Dev % Blue Killed is faring worse than some of the other metrics is most likely due to its worse Student-T testing results (see Table 25).

Like R^2 Training, R^2 Validation is typically paired with a visual representation. In this case, this representation takes the form of a *Residual by Predicted* plot. According to Kirby, the residual is "the error in the fitted model which represents the difference between the actual value of each observation (data point) and the value predicted by the fitted model" and is typically calculated using the equation below [80]:

$$residual = actual - predicted \tag{26}$$

Unlike the *Actual by Predicted* plot where a conformation to the *Perfect Fit Line* is desired, a good residual plot "displays the error in a random pattern" that resembles a "shotgun" appearance (see Figure 51) [80].

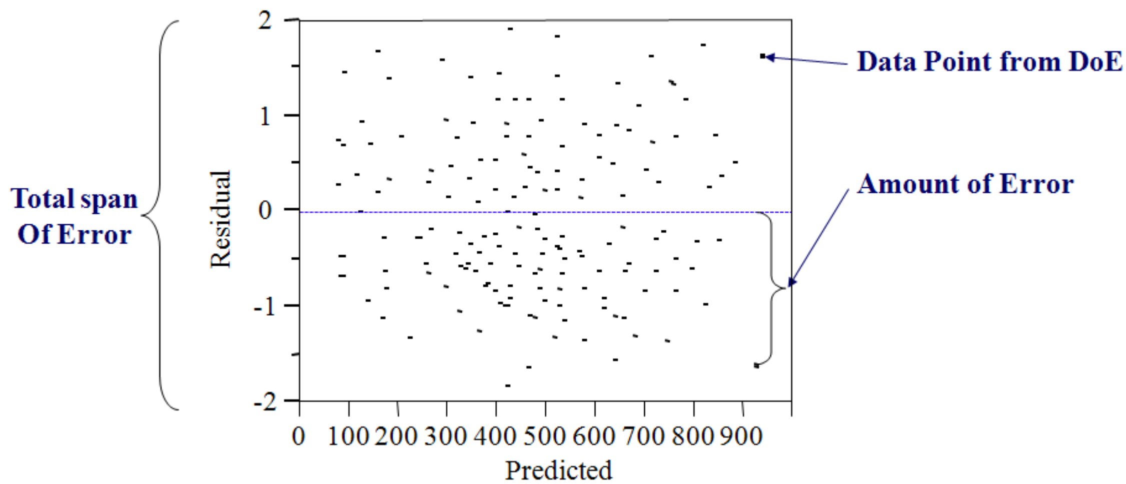


Figure 51: Example Residual by Predicted Plot [80]

The *Residual by Predicted* plots for the UCAS-SEAD metric ANNs are provided in Appendix D. Note that in this case the residual is calculated using the following equation:

$$\frac{residual = actual - predicted}{range}$$

(27)

Where *range* is the difference between the maximum and minimum **actual** values of each metric (thus the calculated residual value is relative value to the entire range of detected values instead of being an absolute value).

The *Residual by Predicted* plots in Appendix D all appear to show this pattern (or technically, lack of a pattern) and thus indicate that model behavior is being captured by the ANNs, albeit not as good as could be due to inability to conduct sufficient DoE iterations.

<u>Model Fit Error</u>

The R^2 value, by itself, is insufficient for evaluating a SM's accuracy. While the R^2 value describes how much of the behavior is described by the SM, it does not describe the deviation (i.e. error) of the model. Thus in addition to R^2, the Model Fit Error and Model Representation Error distribution metrics associated with the generated ANNs will be used to assess ANN validity. This section will highlight the MFEs associated with the UCAS-SEAD ANNs and the next section will highlight the MREs.

The MFE distribution, typically in the form of a histogram, "shows the magnitude and shape of the error" [80] associated with the model when predicted the training data. As a rule of thumb, the MFE is considered "excellent" if it is in the shape of a normal distribution with a mean of 0 and a standard deviation less than 1.0. Again, please refer to Appendix D for the MFE distribution plots.

Table 31: Model Fit Error Statistics for Notional UCAS-SEAD Metric ANNs

UCAS-SEAD Metric	MFE Mean	MFE Std.Dev
Mean Perc_Red_Killed_12hrs	-0.009	3.860
Mean Perc_Red_Killed_24hrs	0.050	4.787
Mean Perc_Red_Killed_48hrs	0.000	4.964
Mean Perc_Blue_Killed	-0.005	6.118
Std Dev Perc_Red_Killed_12hrs	-0.069	4.512
Std Dev Perc_Red_Killed_24hrs	0.027	5.746
Std Dev Perc_Red_Killed_48hrs	0.109	6.455
Std Dev Perc_Blue_Killed	0.373	6.024

Looking at the Table 31, it is clear that the MFE statistics cannot be classified "excellent." While the mean values are centered around zero, the standard deviations range from 2.5 to 6.5. However, looking at the histogram provided in Appendix D, the MFE distribution all take on the shape of a Normal Distribution. This means that the source of the error is most likely due to the fact that not enough seed repetitions could be run to capture the stochastic nature of the UCAS-SEAD model. It is likely that with additional seed interaction runs these errors will be reduced. For this demonstration, they are deemed tolerable.

Model Representation Error

The MRE is similar in concept to the MFE except it measures the error residuals for the validation data set instead of the training set. As is the case with R^2 Validation, the MRE values for a SM tend to be higher than its MFE counterparts. The MRE statics for the UCAS-SEAD metric ANNs are summarized below:

Table 32: Model Representation Error Statistics Values for UCAS-SEAD Metric ANNs

UCAS-SEAD Metric	MRE Mean	MRE Std. Dev
Mean Perc_Red_Killed_12hrs	-0.058	5.776
Mean Perc_Red_Killed_24hrs	0.019	6.951
Mean Perc_Red_Killed_48hrs	0.072	6.768
Mean Perc_Blue_Killed	-0.191	8.252
Std Dev Perc_Red_Killed_12hrs	-0.304	5.336
Std Dev Perc_Red_Killed_24hrs	-0.090	6.617
Std Dev Perc_Red_Killed_48hrs	0.152	7.128
Std Dev Perc_Blue_Killed	0.065	7.587

The values in the table above display a similar pattern to the MFE value in the previous section with the mean values centering around zero. However, as expected, the standard deviation values are higher for this test. As with the MFE, the general rule of them is 0 and 1 for mean and standard deviation, respectively. Since the increase in error is not significant from the author deems these mean and standard deviation values acceptable.

Looking at the goodness of fit summary figures in Appendix D, it is clear that even though the metrics are not within the standard ranges for an “excellent” fit, they are sufficiently close and do not exhibit any patterns that would otherwise indicate bad fits (e.g. non-shotgun *Residual by Predicted*, MFE/MRE not in the shape of a Normal Distribution). Combined with the fact that the current emphasis is on method demonstration and not actual detailed analysis, the generated UCAS-SEAD ANNs are deemed acceptable to use (for this example application.

Because of the ability of BRAINN to generate ANN prediction equations formats compatible with MATLAB and Excel, the generated ANN prediction equations were exported to these environments to produce two probability technology performance analysis environments. The MATLAB based environment will be used in the next section during for identifying optimal solutions for UCAS-SEAD technologies (along with the analysis results obtained from the technology development model). The second environment will be part of the computer-based DSS created in Phase IV to support rapid assessments of program robustness.

6.3 Phase III: Alternatives Generation

In this phase, the technology uncertainty analysis environments created in the Phase II integrated into a technology portfolio optimization tool based on a Multi-Objective Genetic Algorithm. The created MOGA tool is then used to generate several alternate portfolio solutions for meeting program robustness criteria. This provides acquisition PMs and DMs with a starting point or initial "guess" as to what which combination of technologies will provide the program with most robustness to performance, development, and requirements uncertainties. Tradeoffs in these areas can then be performed using the computer-based DSS created in the next phase.

6.3.1 Step 7: Select Optimization Objectives

As stated in Section 5.2.5, for this ENTERPRISE application, program robustness will be measured by the probabilities of success for meeting target capability, budget, and schedule constraint values based on the output metric distribution functions calculated using the analysis environments created in Step 7. The objectives for optimization would then, the calculated probability of success for success for meeting each metric requirement target/constraint for each population member, with a desire to maximize each of these objectives. In order to reduce implementation complexity and optimization run time, the author elected to only use a subset (4) of the 10 requirements indentified in Step 3. This "relaxed" set of optimization objectives still allows for robust technology portfolios to be identified but requires less time to converge. In addition, because of the notional nature of this application, this reduction meant that the author did not have to fabricate as many notional constraints. Improperly formulated constraints could result in solutions that do not reflect decision-maker requirements and preferences. In real world applications, these constraints would be determined by people with a far deeper knowledge of the problem (e.g. analysts, warfighters).

Table 33: Optimization Objectives for Notional UCAS-SEAD Technology Portfolio

UCAS-SEAD Metric Requirement	MOGA Objective
Perc_Red_Killed_24hrs	% of Output Distn. >= Constraint
Perc_Blue_Killed	% of Output Distn. <= Constraint
Time_to_TRL_9	% of Output Distn. <= Constraint
Cost_to_TRL_9	% of Output Distn. <= Constraint

To ensure comprehensive analysis of robustness of all requirements, the other requirements robustness criteria can then be brought into play, if so desired, using the computer-based Decision Support system in Phase IV in the final down-select of notional UCAS-SEAD technology development portfolio.

6.3.2 Step 8: Define Fitness Function(s)

The most critical aspect of a GA-based optimization is the calculation or assignment of population member fitness. As discussed previously, multiple MOGA implementations exist (see Table 4) with each approach having its benefits and drawbacks that should be taken into consideration when selecting the approach most appropriate for a given ENTERPRISE implementation. For this notional application, the author elected to calculate member fitness using a *Weighted Sum* approach that combines each of the four objectives listed in Step 8 into a single hybrid objective function. This approach was the most straightforward implantation and required far less computer coding acumen than *Pareto Ranking* approaches. In order to compensate for the fact that this approach only produces a single solution per optimization, the author will use multiple objective weighting scenarios to generate multiple technology portfolios for evaluation in Phase IV.

The hybrid fitness function that will be used for this optimization is as follows:

$$fitness = \sum_{i=1}^{n} W_i * Objective_{i,normalized}$$

(28)

Where:

- W_i is the importance value assigned to metric i
- $Objective_{i,normalized}$ is the normalized value of objective i for the given population member

- n is the number of metrics ($n=4$ for this demonstration

The normalized objective function values for two UCAS-SEAD scenario metrics are calculated using the following equations:

$$Objective_{\%\_Red\_Killed\_24hrs} \begin{cases} = 1 \; if \; R_{\%\_Red\_Killed\_24hrs\_high} < Target_{\%\_Red\_Killed\_24hrs} \\ = 0 \; if \; R_{\%\_Red\_Killed\_24hrs\_low} > Target_{\%\_Red\_Killed\_24hrs} \\ else = \frac{(R_{\%\_Red\_Killed\_24hrs\_high} - Target_{\%\_Red\_Killed\_24hrs})}{(R_{\%\_Red\_Killed\_24hrs\_high} - R_{\%\_Red\_Killed\_24hrs\_low})} \end{cases}$$

(29)

$$Objective_{\%\_Blue\_Killed} \begin{cases} = 0 \; if \; R_{\%\_Blue\_Killed\_low} > Target_{\%\_Blue\_Killed} \\ = 1 \; if \; R_{\%\_Blue\_Killed\_high} < Target_{\%\_Blue\_Killed} \\ else = \frac{(Target_{\%\_Blue\_Killed} - R_{\%\_Blue\_Killed\_low})}{(R_{\%\_Blue\_Killed\_high} - R_{\%\_Blue\_Killed\_low})} \end{cases}$$

(30)

Where:

- $Target_{\%\_Red\_Killed\_24hrs}$ and $Target_{\%\_Blue\_Killed}$ are listed in Table 33
- $R_{\%\_Red\_Killed\_24hrs\_high}$ is calculated by finding the mean output value of a 10,000 case MCS run for $ANN_{Mean\_\%\_Red\_killed\_24hrs}$ and adding the mean output value of a 10,000 case MCS run for $ANN_{StdDev\_\%\_Red\_killed\_24hrs}$
- $R_{\%\_Red\_Killed\_24hrs\_low}$ is calculated by finding the mean output value of a 10,000 case MCS run for $ANN_{Mean\_\%\_Red\_killed\_24hrs}$ and subtracting the mean output value of a 10,000 case MCS run for $ANN_{StdDev\_\%\_Red\_killed\_24hrs}$
- $R_{\%\_Blue\_Killed\_high}$ and $R_{\%\_Blue\_Killed\_low}$ are calculated in a similar fashion

Using these two functions, the objective function values for *%_Red_Killed_24hrs* and *%_Blue_Killed* will range from 0 (no portion of MC output distribution intersects with target metric value range) to 1 (all of MC output distribution intersects with target metric value range) (i.e. the higher the better).

The *Time to TRL 9* and *Cost to TRL 9* objective functions are calculated using the equations below:

$$Objective_{Time\_to\_TRL\_9} = \frac{R_{Time\_to\_TRL\_9}}{Target_{Time\ to\ TRL\ 9}} \quad \textbf{(31)}$$

$$Objective_{Cost\_to\_TRL\_9} = \frac{R_{Cost\_to\_TRL\_9}}{Target_{Cost\ to\ TRL\ 9}} \quad \textbf{(32)}$$

Where:

- $R_{Yrs\_to\_TRL\_9}$ is calculated by taking the mean value of the output distribution for a 10,000 case MCS on the *Yrs_to_TRL_9* metric calculated from the Excel-based probabilistic technology development uncertainty environment created in Step 7
- $R_{Cost\_to\_TRL\_9}$ is calculated in a similar fashion

Once calculated, each objective is then normalized. For the UCAS-SEAD scenario metrics, the following normalization equation was used:

$$Objective_{\%\_Red\_Killed\_24hrs\_normalized} = \frac{Objective_{\%\_Red\_Killed\_24hrs}}{Objective_{\%\_Red\_Killed\_24hrs\_high} - Objective_{\%\_Red\_Killed\_24hrs\_low}}$$

(33)

$$Objective_{\%\_Blue\_Killed\_normalized} = \frac{Objective_{\%\_Blue\_Killed}}{Objective_{\%\_Blue\_Killed\_high} - Objective_{\%\_Blue\_Killed\_low}}$$

(34)

Where:

- $Objective_{\%\_Red\_Killed\_24hrs\_low}$ is the lowest observed $Objective_{\%\_Red\_Killed\_24hrs}$ for the current population
- $Objective_{\%\_Red\_Killed\_24hrs\_high}$ is the highest observed $Objective_{\%\_Red\_Killed\_24hrs}$ for the current population
- $Objective_{\%\_Blue\_Killed\_low}$ and $Objective_{\%\_Blue\_Killed\_high}$ are calculated in a similar fashion

For the normalized objective values for *Time_to_TRL_9* and *Cost_to_TRL_9*, the following two equations are used:

$$Objective_{Time\_to\_TRL\_9\_normalized} = 1 - \frac{Objective_{Time\_to\_TRL\_9}}{Objective_{Time\_to\_TRL\_9\_high} - Objective_{Time\_to\_TRL\_9\_low}}$$

(35)

$$Objective_{Cost\_to\_TRL\_9\_normalized} = 1 - \frac{Objective_{Cost\_to\_TRL\_9}}{Objective_{Cost\_to\_TRL\_9\_high} - Objective_{Cost\_to\_TRL\_9\_\_low}}$$

(36)

These equations produce normalized objective values for the four objective functions from 0 to 1. The higher a member's normalized objective values, the better they compare overall against the rest of the population.

It should be noted that while this MOGA approach is simpler and more straightforward to implement than approaches based on Pareto dominance, it has certain limitations that can make it an inappropriate selection for real world applications. The biggest drawback of this approach is the sensitivity of the results to the weighting scenarios used. If the scenarios used do not accurately reflect decision-maker preferences, then the generated solutions will not be optimal. Pareto dominance-based approaches do not suffer from this problem. However, weighted-sum approach does allow for emphasis to be placed on certain objectives over others while Pareto dominance approaches generally assume equal emphasis. In general it is likely that decision-makers will favor certain requirements over others.

For future applications, it is important to taken into account the specific optimization needs of the problem and the amount of resources available for generating candidate technology portfolio solutions when selecting a MOGA approach.

6.3.3 Step 9: Create Technology Portfolio Optimizer

Once the fitness calculation procedure and equations have been defined, the final step in creating the optimization too for this implantation, which is named the *UCAS-SEAD Technology Portfolio Optimization Tool (UCAS-SEAD TPOT)* and coded using MATLAB, involves defining the remainder of the GA optimization procedures such as population setup, selection, reproduction, mutation, and convergence. Details of each of these procedures are described in this section. The general process overview for the UCAS-SEAD TPOT is shown in the figure below:

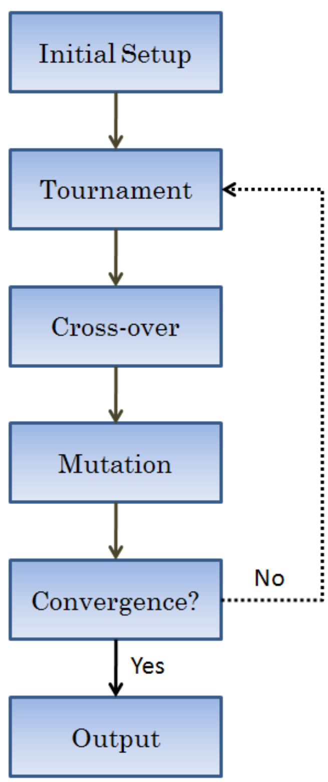


Figure 52: UCAS-SEAD Genetic Algorithm Process Overview

6.3.3.1 Initial Population Setup

The first step in a GA process is defining the initial population. This involves not only defining the population size but also each member's chromosome string. Since the objective of this GA process is to identify the technology combination or combinations that best meet UCAS-SEAD requirements, each member's chromosome string will represent a single technology combination. Thus at the end of the GA process, the final population will (theoretically) consist of only the "fittest" or most optimal technology combinations.

6.3.3.1.1 Binary Chromosome String

For the UCAS-SEAD demonstration, an 18-bit binary chromosome string is used to represent each population member. The value of each bit, or *gene*, describes whether or not each of the eighteen UCAS-SEAD enabling technologies is included ("1" for inclusion, "0" for exclusion). For example, a technology combination consisting of technologies AF-1, AF-4, PR-1, ST-2, and IR-1 will have the following chromosome string:

Table 34: UCAS- Binary Chromosome String Notional UCAS-SEAD MOGA Implementation

Bit #	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Value	*1*	*0*	*0*	*1*	*0*	*1*	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*0*

6.3.3.1.2 Initial Population Generation

Once the binary chromosome string structure has been defined, the next step is randomly generate X number of chromosomes, with X being the pre-determined population size (e.g. 1000). However, because of the incompatibilities associated with certain technologies (see Table 11), each generated chromosome must be checked for compatibility issues and discarded if compatibility rules are broken. Thus the generation process is only complete when X number of **valid** technology combinations has been generated.

In order to increase the diversity of the initial population across the available design space (i.e. technology combinations), the UCAS-SEAD GA tool is set up to generate **unique** chromosome strings for the initial population. This means that if the population size is set to 500, then 500 **different** technology combinations are generated for the initial population. This is done by comparing each newly generated (and valid) combination with other generated combinations.

The MATLAB code for the initial population setup can be found in *popSetup.m*, *generateValidTechCombo.m*, and *checkTechComp.m*.

6.3.3.2 Tournament Selection

The first "genetic" process in a GA, once the initial population has been established, is *Selection*. During *Selection*, the "fitness" values of population members are established and "fit" members are selected for continuation to the next genetic process, *Reproduction*. For the UCAS-SEAD proof-of-concept demonstration, the author has elected to implement *Tournament Selection* for this process. The remainder of this section will outline the implementation of this method. In additional, specifics regarding other *Selection* methods such as *roulette-wheel selection* and *stochastic universal sampling* are outside the scope of this work and thus are not discussed so please refer to referenced materials for additional information on these methods.

The fundamental governing principle behind *Tournament Selection* is quite simple: select two or more population members, compare their fitness values, and create a copy the "fittest" member's chromosomes in the *Post-Tournament Population*. This process is then repeated until the size of the *Post-Tournament Population* is equal to the initial population size. At this point, the modified population is ready for *Reproduction*.

It should be obvious to the reader that the size of each tournament (i.e. number of population members selected) can have a major impact on the *Selection* process. The likelihood that the "most-fit" members of the population are selected and copied into the *Post-Tournament Population* increases as tournament size increases. However, as tournament sizes increase, so does the computational burden. In addition, simply copying the most fit members of the entire population every time will severely limit the genetic diversity of the population and could actually hurt the optimization process by prematurely eliminating gene combinations. As such, the UCAS-SEAD TPOT allows the user to define the tournament size (as a % of the entire population) so that the balance between genetic diversity and computational burden can be adjusted depending on user wishes and requirements.

For calculating the fitness, the generated ANN equations for *%_Red_Killed_24hrs* and *%_Blue_Killed* were imported into MATLAB so that a MCS can be conducted on these two metrics for each population member. To reduce computational burden, the *Time_to_TRL_9* and *Cost_to_TRL_9* metrics for each technology were calculated ahead of time and the means of each metric output distribution were saved as Excel tables and imported into MATLAB. This offline calculation was possible because of the independent and additive nature of technology time and cost.

Also, since this MOGA implementation requires pre-defined weights for each metric, the weighting values for each metric are put into an Excel table (*Metrics_Weights.csv)* ahead of time and extracted by the UCAS-SEAD TPOT as needed.

6.3.3.2.1 Elitist Selection

Even with a large tournament size, it is still possible that the "most-fit" members of a given population do not survive an iteration of the GA process. This typically occurs during *Reproduction* or *Mutation* where gene combinations are altered. In certain instances this could decrease the likelihood that the most optimal gene combinations are found or drastically increase the number of iterations required to identify such combinations. To alleviate these concerns, the UCAS-SEAD TPOT couples the *Tournament Selection* process with *Elitist Selection* during the *Selection* phase.

Elitist selection is "a variant of the general process of constructing a new population in the genetic algorithm…[and] allows some of the ["most-fit" members] from the current generation to carry over to the [next generation], unaltered" [148]. By preserving a small amount of the "most-fit" members of the population and not allowing them to be modified or altered during *Reproduction* or *Mutation*, *Elitist Selection* "prevents the random destruction by crossover or mutation operators of individuals with good genetics" and has shown to be "very successful"[179]. However, it should be noted that if the number of population members selected using *Elitist* Selection "should not be too high, otherwise the population will tend to degenerate" and result in less-than-optimal solutions [179].

As is the case with *tournament size*, the UCAS-SEAD TPOT allows the user to define the percentage of the population (according to fitness) that is elitist-selected to allow for a balance between genetic diversity and optimization performance.

6.3.3.2.2 Time-Saving Features

It should be noted that even with the rapid calculations afforded by ANN equations the number of calculations needed to probabilistically assess a population of technology combinations can still be quite daunting. For example, a population of 1,000 members, each with 7 output metrics that require 10,000 runs to calculate, will require 1000x7x10,000 = 70,000,000 ANN equation calls *per iteration* of the GA *Tournament Selection* process. Even with each equation call requiring only ~0.001 seconds to complete, this would still require approximately 19.4 hours, and that is only for a single iteration! As such, the UCAS-SEAD TPOT implements the following time-saving features that significantly reduced the amount of time required to complete the selection process:

- Parallel Computing
- Results Saving

6.3.3.2.2.1 Parallel Computing

To reduce runtime, UCAS-SEAD TPOT takes advantage of multiple cores typical of modern computers by performing multiple metric ANN equation calculations in parallel through the use of the *matlabpool* function. This function allows a pool of "worker sessions" to be initialized and used to perform functions independently (the size of the pool depends on the number of available cores). Since the sessions are in parallel, the same number of functions can be performed in far less time. For the UCAS-SEAD demonstration problem, the author was able to reduce the GA optimization run-time by two-thirds when running the UCAS-SEAD TPOT on his quad-core computer.

6.3.3.2.2.2 Results Saving

In addition to utilizing MATLAB's parallel computing capabilities, the UCAS-SEAD TPOT further reduces computational burden by storing the calculated metric values each time a new gene combination is tested. This way, each unique gene combination is only tested only throughout the entire GA process. While this time-saving device does not reduce computation burden in the first iterations of the GA process (because the initial population is unique and thus no repeats), fewer and fewer function calls in subsequent iterations because most optimal combinations will slowly become more and more prevalent in the population (i.e. more and more duplicates of the same gene combination). As shown in Table 35, saving the output metrics and re-using them instead of conducting a new MC simulation for each repeated technology combination can **significantly** reduce the number of functional calls (i.e. MC simulation of output metrics). Note that the initial population size was set to 1,000.

Table 35: Reduction in Number of Function Calls Afforded by Results-Saving in UCAS-SEAD TPOT

GA Iteration	Unique Combinations Tested
1	1000
2	396
3	122
4	49
5	18
6	21
7	27
8	14
9	13
10	18
11	15
12	14
13	18
14	26
15	13
16	15
17	25
18	22
19	13
20	16
21	18
22	13

6.3.3.3 Cross-over Reproduction

Typically in a GA process, *Selection* is followed by *Cross-over Reproduction*. During this step, population members are paired up and their genes are “crossed” to produce two new (i.e. children) gene combinations. Since only the most “fit” population members are selected during *Selection*, this step will (theoretically) result in a population of children that possess the good characteristics (i.e. genes) from both parents and thus further improving its survival rate (i.e. higher fitness value) in subsequent GA iterations.

Currently, the UCAS-SEAD TPOT first randomly decides whether or not a randomly selected pair of population members will “mate,” with the probability of *Cross-over* pre-determined by the user. If selected for *Cross-over*, a *two-point Cross-over* is performed. This process “swaps” the genes of the two parent chromosomes between to two randomly selected points along the chromosomes and results in two child chromosomes that are different from but possess many of the characteristics of their parents (see Figure 53). The process is repeated until the size of the child population is the same as the parent population.

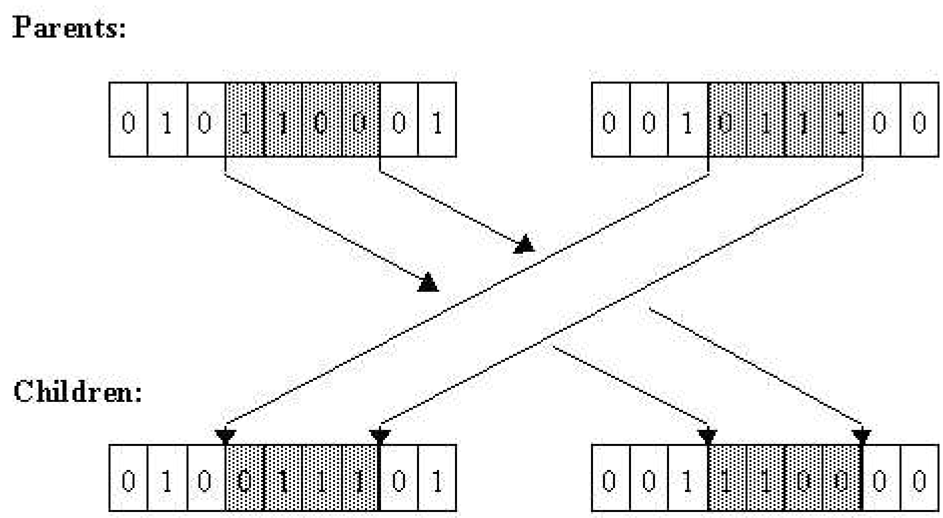


Figure 53: Depiction of Two-Point Cross-over Reproduction [58]

During the course of *Cross-over Reproduction*, it is possible (and very likely) that a resulting technology combination violates one or more of the technology compatibility rules defined by Table 11. In such instances, the invalid chromosome must be discarded and replaced with a valid one.

To ensure that the output child population from *Cross-Over Reproduction* does not contain any invalid gene combinations, the UCAS-SEAD TPOT checks the validity of each child chromosome. If one or both of the children chromosomes are invalid, the reproduction procedure for the two parent chromosomes are repeated until two valid children chromosomes are produced. This is a straightforward and easy to understand way of ensuring sufficient Cross-Over in the population.

6.3.3.4 Gene Mutation

The third and final "genetic" process used by the UCAS-SEAD TPOT is *Mutation*. Biologically speaking, a *mutation* is a sudden departure from the parent type in one or more heritable characteristics, caused by a change in a gene or a chromosome. For the problem at hand, this means that one or more technology inclusions described by the chromosome is switched (i.e. from "1", or "on", to "0" or "off"). The idea here is that random mutations could yield a genetic combination that is superior but would not be attained through *Tournament Selection* or *Cross-over Reproduction*.

Currently, the UCAS-SEAD TPOT implements a *sing-point Mutation*. This means that if a population member is selected for *Mutation* (probability of mutation pre-determined by user), then the value of random gene in the selected member's chromosome is reversed from "0" to "1" or vice-versa. If the mutated output is invalid, another gene is selected for mutation and this repeats until a valid mutation is found. This ensures that mutations occur according to the user-define frequency.

6.3.3.5 Termination Conditions and Iterations

Once the three primary "genetic" processes have been performed, the UCAS-SEAD TPOT checks to see if one or more of the following termination conditions have been met:

- Most "fit" member(s) of a population remains constant for a pre-determined number of consecutive generations

- Maximum number of generations (i.e. iterations)

6.3.3.5.1 Repetition of Most-Fit Chromosome(s) in Consecutive Generations

Typically, a GA optimization is considered "finished" if the maximum fitness value of a population remains the same for a pre-determined consecutive number of generations. This is based on the reasoning that a repetition in maximum fitness value for multiple consecutive generations corresponds to the presence of the *global optimum* in the population and since the *global optimum* is by definition the most "fit" chromosome possible and thus no additional iterations are necessary. By requiring the same maximum fitness value to be repeated for multiple consecutive generations before termination, the likelihood that a *local optimum* is mistaken for the *global optimum* is reduced. The higher number of consecutive generations required before termination, the more likely that the final solution is the *global optimum* and not a *local optimum*.

For the UCAS-SEAD problem, the UCAS-SEAD TPOT terminates if the **same chromosome**, not maximum fitness value, has been repeated for a user-defined number of generations. This deviation from the tradition termination condition was necessary because fitness calculation in the UCAS-SEAD TPOT depends on the observed range of metrics in a given population. This dependence on observed metric ranges for each generation can result in variations (typically slight) in the calculated fitness of a given gene combination from one generation to the next. This can cause the optimization process to run for many generations past the traditional stopping point because the difference in fitness value for the same chromosome will be interpreted by the process as belonging to different gene combinations. In rare instances, this can cause the optimization to run indefinitely despite the presence of the *global optimum*. In such instances, a second termination condition is necessary.

The number of repetitions prior to termination depends on the problem and the aversion to mistaking a *local optimum* for the *global optimum*. By requiring a high number of repetitions before termination, the likelihood of *sub-optimization* is reduced. However, a higher number of repetitions translate to a higher computational burden and thus longer run-time. As such, the UCAS-SEAD TPOT allows the user to define the repetition tolerance to better meet his/her requirements on the balance between solution optimality and schedule/resource limitations.

6.3.3.5.2 Maximum Number of Generations

To prevent the GA optimization process from running indefinitely, the UCAS-SEAD TPOT is set to stop after a pre-determined, user-defined number of iterations. This value should be set large enough to allow the GA-process to find the optimal solution (or solutions in some cases) but not so large that unnecessary generations are processed (caused by the reasons given in the previous section). Once again, the UCAS-SEAD TPOT is implemented to allow this termination to be defined by the user to better match his/her optimization requirements.

6.3.3.6 Outputs

In addition to outputting the final "most fit" technology combination(s), the UCAS-SEAD also outputs the additional information listed in Table 36 for iteration/generation of the optimization process. This additional data provides the user with insight into the optimization process and helps with identifying potential issues and emerging patterns so that if future optimizations can be better tailored for the problem at hand.

Table 36: List UCAS-SEAD TPOT Outputs

Max. Fitness Value
Average Fitness Value
Max Fitness Repetitions (termination condition)
Number of Metric New Combinations Tested
of Cross-overs
of Adoptions
of Mutations
Computation Time for Generation (s)
Gene Combination of Most Fit Member
Metric Ouput of Most Fit Member

6.3.4 Step 10: Generate Candidate Technology Portfolios

With the UCAS-SEAD TPOT created, the final step in Phase III is to generate the set of alternative technology portfolio solutions that will be presented to the decision-makers in the Phase IV for assessment. For this demonstration, the author placed the following constraints on the four MOGA objectives (again, constraint values fabricated by author for demonstration purposes):

Table 37: Objective Constraints for Notional UCAS-SEAD MOGA Implementation

UCAS-SEAD Requirement	MOGA Objective
Perc_Red_Killed_24hrs	>90%
Perc_Blue_Killed	<5%
Time to TRL 9	<15 Yrs
Cost to TRL 9	<$200M

For generating a represent set of solutions represent potential range of decision-maker preferences for each metric requirement generate the author utilized the following five sets of weighting scenarios:

Table 38: Weighting Scenarios for Notional UCAS-SEAD MOGA Implementation

Metric Requirement	Set 1	Set 2	Set 3	Set 4	Set 5
Perc_Red_Killed_24hrs	1	1	3	6	3
Perc_Blue_Killed	1	1	3	3	6
Time to TRL 9	1	3	1	1	1
Cost to TRL 9	1	3	1	1	1

The logic behind these five sets of weighting scenarios is as follows:

- Set 1 represents scenario where no objective is preferred over other objectives
- Set 2 represents scenario where budget and schedule constraints are more emphasized equally more than capability constraints
- Set 3 represents scenario where capability metrics are emphasized equally more than budget and schedule constraints
- Set 4 represents scenario where defeat of enemy defenses take priority above all other requirements

- Set 5 represents scenario where emphasis is placed on minimizing UCAS losses

Using the optimization parameters listed in Table 39, the UCAS-SEAD TPOT was used to identify the "optimal" technology portfolio for each of the five weighting scenarios listed above and reproduced in Table 40.

Table 39: General GA Parameters for Notional UCAS-SEAD MOGA Implementation

MOGA Optimization Parameters	Value
Population	1000
Tournament Size	5%
Elitist Selection Size	2% (of population)
Probability of Cross-over	70%
Probability of Mutation	20%
Termination Condition: **# of Consecutive Generations with Identical Most-Fit Chromosome**	10
Termination Condition: **Max. # of Generations**	100

Table 40: Generated Technology Portfolio Alternatives for Notional UCAS-SEAD MOGA Implementation

Technology	Set 1	Set 2	Set 3	Set 4	Set 5
Advance Aircraft Wing Folding and Fuselage Telescoping				x	
Internal Cargo Bay Expansion					
High L/D Aeroconfiguration					
Embedded Fuel Pods					
Efficient Transonic Planform					
Efficient Propulsion Installation					
Durable High Temp Core and Fuel Efficicient Turbine Engine					
Advanced Radar Absorption Materials					
Advanced Stealth Planform Alignment					x
Embedded Engines					
Non-metallic Dielectric Airframe					
Long Range Air-to-ground Missile	x		x	x	x
Stealthy Air-to-ground Missile					
Sensor Jamming	x		x	x	x
Missile Lock Interference					
Communications Jamming					
Advanced Computer Guided Target Recognizition					
Extended Range Sensors					

Looking at the figure above, one immediate trend is the persistence of *Long Range Air-to-ground Missile* and *Sensor Jamming* technologies. These two technologies appear in four out of the five weight scenarios. Logically, the selection of these two technologies makes sense. The *Long Range Air-to-ground Missile* technology extends the engagement range of UCAS assets, which allows them to engage enemy targets from further out which positively impacts their *% Red Killed @ 24hrs* metric. In addition, because of the larger engagement radius, UCAS assets have a better chance of staying outside enemy SAM detection and engagement zones. This helps to reduce *% Blue killed* metric. The *Sensor Jamming* technology, which reduces enemy radar and SAM detection range, has a similar impact.

In Set 2, no technologies were selected. This is because the *Time_to_TRL_9* and *Cost_to_TRL_9* metrics were heavily emphasized over the other two metrics. Even though with this "portfolio", which results in ALL UCAS assets killed and ZERO red targets destroyed, the improvement in time and cost over other candidates could not be overcome (this portfolio required zero dollars and zero years to develop).

For Set 4, the *Advance Aircraft Wing Folding and Fuselage Telescoping* technology was also added to the two technologies mentioned above. In this scenario, emphasis was placed mostly on *% Red Killed 24hrs*, followed by *% Blue Killed*, and the two time and cost metrics were equally non-emphasized. The addition of this technology appears to be logical because this technology increases the number of UCAS assets available in the scenario, which meant that more UCAS assets were operating simultaneously to perform the SEAD mission. Combined with the noted benefits of the *Long Range Air-to-ground Missile* and *Sensor Jamming* technologies, this is a logical selection of technologies for this scenario.

For the final scenario, the *Advance Aircraft Wing Folding and Fuselage Telescoping* technology was replaced with *Advanced Stealth Planform Alignment*. This technology reduces UCAS visibility, leading to an improvement in *% Blue Killed*. While the time and cost impacts of this time-consuming and expensive technology are significant, the heavy emphasis placed on UCAS survivability makes the selection of a stealth technology a logical choice. The selection of this technology over the other stealth technologies is most likely caused by the variations in performance and development uncertainties assumed for the other technologies.

At this point, the alternate UCAS-SEAD technologies have been generated. In the next phase, these solutions and their associated robustness evaluation results will be presented to the decision-maker in a computer-based Decision Support System so that the notional UCAS-SEAD program technology portfolio can be finalized (and then infused with new data to simulate an updated assessment of program robustness evaluation).

6.3.4.1 Sensitivity Study

Often times, it is a good idea to perform sensitivity study using the optimizer. The results of this study can provide additional insights into the solution space and could potential alter the perceived “goodness” of the solutions. Since this is a notional application of the ENTERPRISE process, The process demonstrated in this section is a just notional representation using the UCAS-SEAD TPOT. Sensitivity studies conducted for real world application should be more encompassing.

In step 10, five weighting scenarios were used by the UCAS-SEAD TPOT to generate a representative optimal solution set. Each scenario represents a different compromise between the four optimization objectives for the problem. To gain more insight into the solution space, this study will examine the solutions generated when only emphasis is placed on a single objective and thus become a uni-modal optimization problem. The solutions generated using these uni-criterion weighting scenarios, in theory, should be the best possible solution for meeting that criterion, or the ideal case that is not constrained by other criteria. These results can then be compared to the solutions generated in Step 10.

To start, the following four weighting scenarios were fed into the UCAS-SEAD TPOT:

Table 41: Weighting Scenarios for Notional UCAS-SEAD Metric Sensitivity Study

Metric Requirement	Set 1	Set 2	Set 3	Set 4
Perc_Red_Killed_24hrs	1	0	0	0
Perc_Blue_Killed	0	1	0	0
Time to TRL 9	0	0	1	0
Cost to TRL 9	0	0	0	1

These weighting scenarios were placed on the following, less restrictive objective functions for the four UCAS-SEAD metrics:

Table 42: Objective Constraints for Notional UCAS-SEAD Sensitivity Study

UCAS-SEAD Requirement	MOGA Objective
Perc_Red_Killed_24hrs	>75%
Perc_Blue_Killed	<<25%
Time to TRL 9	<15 Yrs
Cost to TRL 9	<$200M

For the first two weighting scenarios, the optimizer ran until the *maximum number of iterations allowed* termination condition was reached. This means that a solution did not repeat as the most-fit member of the population for ten straight generations within 100 iterations of the MOGA process. Since increasing the maximum number of iterations to 500 had the same results and changing the value of the importance from 1 to 3 to 9 did not alter the outcome, it is clear that when emphasis is placed on either the *Perc_Red_Killed_24hrs* or the *Perc_Blue_Killed* objective functions, multiple solutions are equally optimal and can only be distinguished from each other when additional criteria/objective functions are used can a definitive optimal subset be identified. For the 3rd and 4th weighting scenarios, as expected, optimal solutions were identified and the solution for both scenarios was a null technology combination. Obviously, when only time or cost considerations are taken into account, no technology development is the best solution.

In an attempt to see if more restrictive objective constraints would allow for a single optimal solution to be identified for each of the first two weighting scenarios, the objective constraints for *Perc_Red_Killed_24hrs* or the *Perc_Blue_Killed* objectives from Table 37 were fed into the UCAS-SEAD TPOT. The results were the same as the previous study as neither scenario resulted in a single definitive optimal solution being identified. Based on this analysis, one can draw the conclusion that the only reason these two objectives cannot be met with the available set of technologies, regardless of how strict the constraints placed on them are, is when there are cost and time limitations placed on the development of these technologies. As such, it will be up to the decision-makers to determine how much capability they are willing to sacrifice in order to keep cost and time requirements down.

6.4 Phase IV: Decision Support

In the final phase of this demonstration implementation, outputs from the previous three phases are used in combination to create a computer-based Decision Support System that will allow a notional decision-maker (i.e. the author) to assess the tradeoffs between alternative UCAS-SEAD technology portfolios and evaluate the robustness of each solution against technology performance and development uncertainties. The DSS can then be updated later on with new technology uncertainty data and/or changes in program requirements to provide a refreshed analysis of program robustness.

6.4.1 Step 11: Create Interactive Decision-Support System Tool

For the UCAS-SEAD ENTERPRISE application, the author developed the computer-based DSS using Microsoft Excel. This tool, named the UCAS-SEAD Decision Support Tool (UCAS-SEAD DST), links together the analytical elements created in Phase II with an interactive and visual front-end. The integration allows not only rapid visualizations of tradeoffs between candidate UCAS-SEAD technology portfolio solutions, but also the impact of changing program requirements on robustness measures. The tool can also be infused with new assumptions regarding technology performance and development uncertainties to provide an updated assessment of current program robustness. The results of these evaluations help inform acquisition decision-makers of the potential risks associated with candidate solutions during the AoA and the current technology portfolio during subsequent program reviews. In the remainder of this section, the author will identify and describe primary elements of the UCAS-SEAD DST. In the next step, the UCAS-SEAD DST will be used to make several notional decisions.

The UCAS-SEAD DST has a simple but fully functional (i.e. interactive) GUI front-end containing the following elements:

- *Inputs and Assumptions*
- *Outputs and Visuals*

A snapshot of the entire GUI front-end for the UCAS-SEAD DST is provided in Figure 54. The elements depicted in the figure will be discussed separately in the proceeding sections.

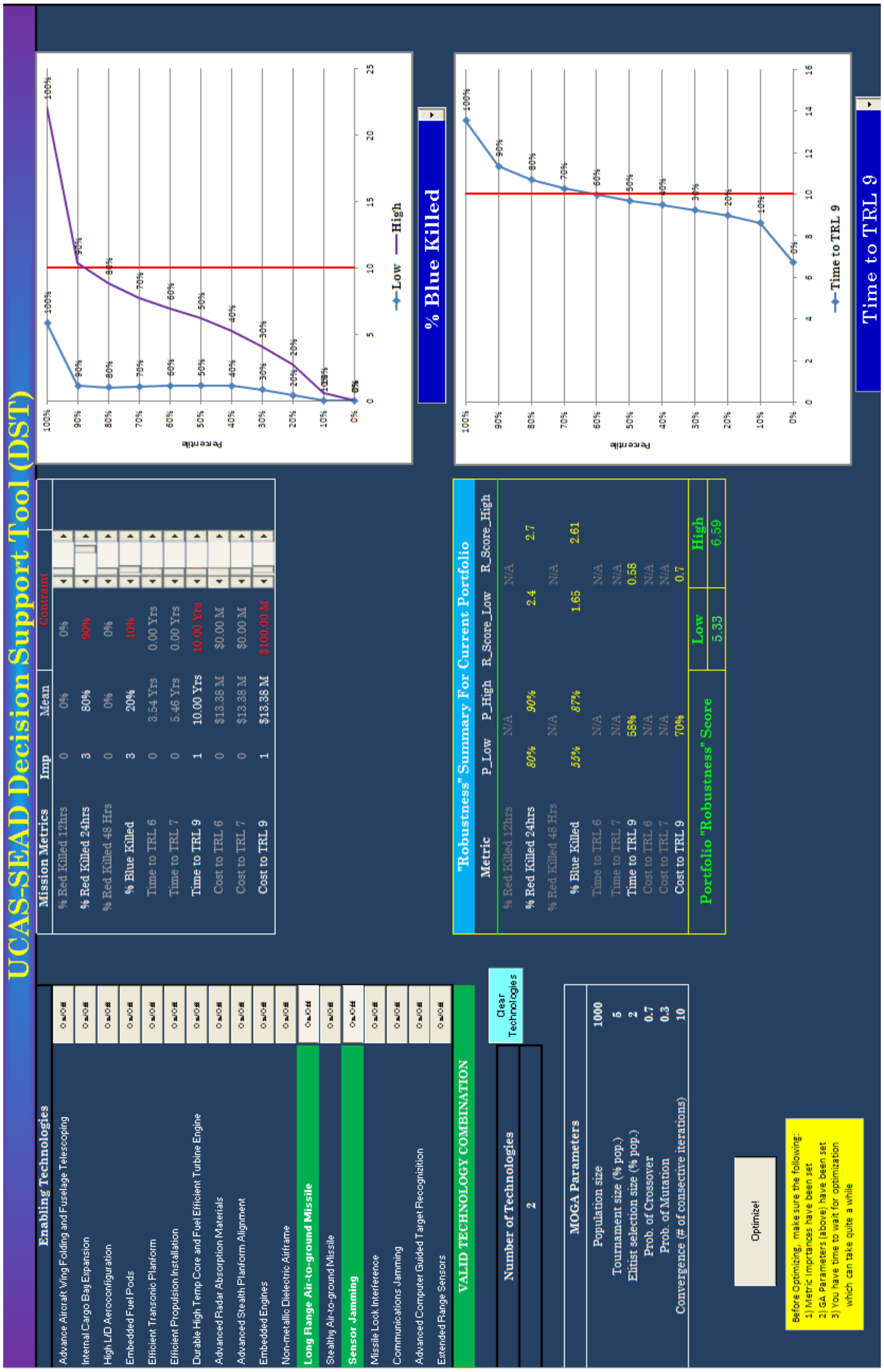


Figure 54: GUI Front-end of Notional UCAS-SEAD Decision Support Tool

It should be noted that the current design of the UCAS-SEAD DST is based on the operational and visual preferences of the author, who will also act at the notional decision-maker for the next step. When designing the layout and configuration (interactive control elements, visual display types, etc…), it is important to keep in mind the intended decision supporting role and the intended users of the DSS tool. Creating an effective DSS requires coupling these requirements with *Visual Analytics* and *normative Decision Theory* techniques that maximize the usefulness of the displays and controls to the users. While such a detailed DSS design process is beyond the scope of this work, future applications, especially those intended to support real acquisition program decisions, should take this into consideration to ensure that the program requirements robustness assessment results are effectively conveyed to acquisition decision-makers.

6.4.1.1 Inputs and Assumptions

The *Inputs and Assumptions* portion of the GUI front-end can be broken up into three primary elements; *Technology Selection* (Figure 57), *Metric Importance & Constraint Definition,* and *MOGA Optimization Setup* (Figure 56).

The *Technology Selection* element (see Figure 57) allows the user to select the technologies whose combined impact on the mission and technology development metrics will be probabilistically evaluated. Next to each technology name is an "On/Off" button that when depressed, will automatically apply the estimate range of impacts associated with that technology on the mission parameters (which will be used by the ANN predictive equations to calculate output metrics). To prevent incompatible technologies from being selected the background color of the selected incompatible technologies will change from green to red (see Figure 58). This helps to notify the user that an invalid portfolio has been selected and prevents it from being considered as legitimate alternative. In addition, there is a "Clear Technologies" button that will "wipe the slate clean" and unselects all technologies. This is a convenience addition that saves the user from having to unselect each technology manually.

The *Metric Importance & Constraint Definition* interactive element allows the user to specify weighting scenarios and constraints for each metric requirement. The constraint/target values for each requirement is used to visually identify the percentage of the metric output distributions, calculated from a MCS of the selected technologies and their associated performance and development uncertainties, fall within acceptable limits. These percentage values are used, in combination with the metric weights, to help assess the overall "robustness" of the selected scenarios.

And finally, the *MOGA Optimization Parameters* element displays the GA-based optimization parameters that can be used to re-run the UCAS-SEAD TPOT created in Step 7. An Excel macro has been created to link the MATLAB code for the UCAS-SEAD TPOT to the UCAS-SEAD DST so that the optimization can be initiated directly from the UCAS-SEAD DST. Re-running the optimization tool may be necessary if the requirements importance values and/or constraints change drastically and the current optimization results are no longer invalid. Instead of manually altering the technology portfolio combination, the user can use this feature to re-run the UCAS-SEAD TPOT to identify the new optimal solution(s). Note however that this feature can take a lot of time to run (as was the case with the original optimization back in Step 8) so care should be taken to ensure that re-optimization is necessary and all the parameters are properly defined.

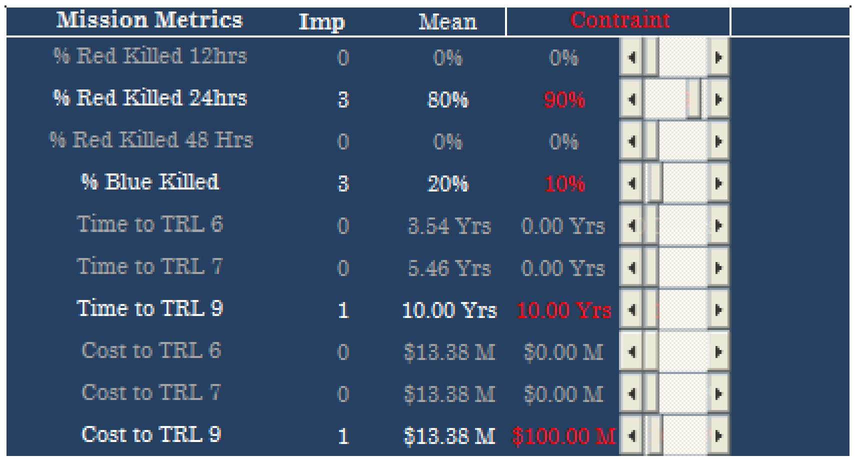


Figure 55: UCAS-SEAD DST Metric Importance & Constraint Definition Element

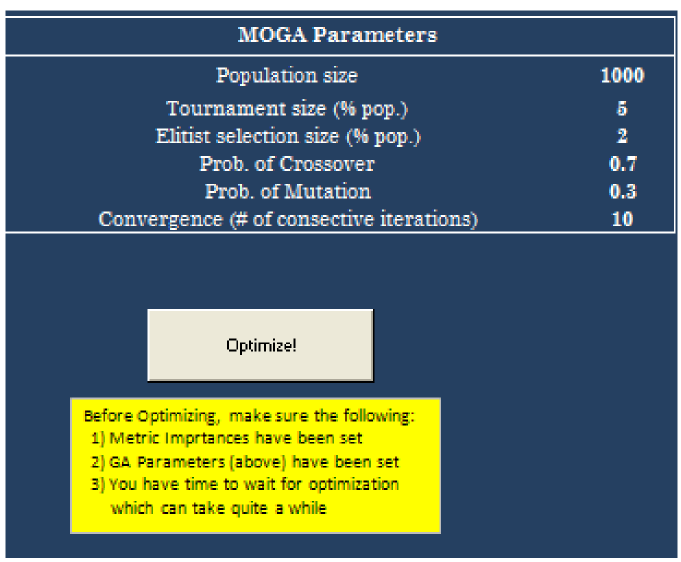


Figure 56: UCAS-SEAD DST GA Optimization Element

Figure 57: UCAS-SEAD DST Technology Selection Element

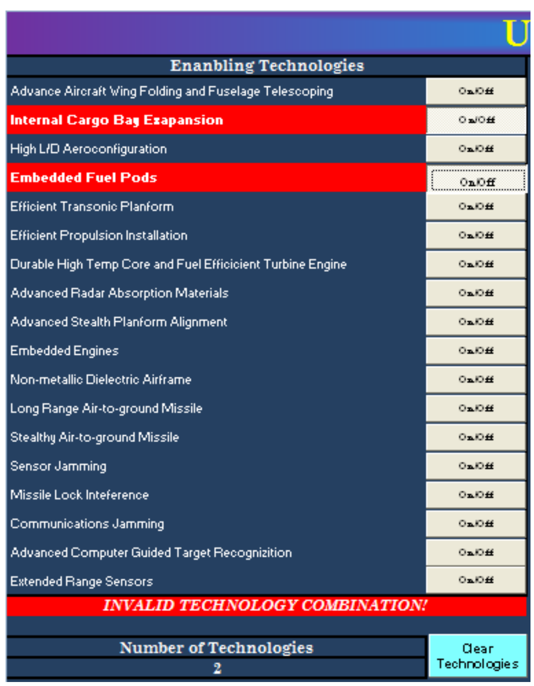


Figure 58: Highlighting of Incompatible Technologies in UCAS-SEAD DST

6.4.1.2 Outputs and Visuals

The *Outputs and Visuals* portion of the GUI consists of the following elements:

- *Program Metric Distribution Graphs*
- *Program "Robustness" Calculation*

The *Program Metric Output Distribution Graphs* element consists of two graphs that plot the percentile data, in increments of 10%, for the UCAS-SEAD program metrics (the process for calculating the percentile data for each metric are not currently relevant but will be discussed Section 6.4.1.3). These graphs display the cumulative distribution functions resulting from Monte Carlo simulation analysis conducted on each metric. To account for the stochastic nature of the technology performance model, two distributions are plotted for each capability metric. The "Low" curve represents the predicted *mean minus* predicted *standard deviation* value at the percentiles while the "High" curve is the *mean plus standard deviation* for a given percentile. The range between the upper and lower percentile values for a given metric describes the variations in metric output caused by the stochastic nature of the technology performance model.

To assist the decision-makers in identifying the percentile corresponding to a specific metric value (i.e. what percentage of the MC output data fall at or below a specific value), a vertical *metric constraint line* is plotted along with the metric CDF. The value of the *constrain line*, which is constant for every percentile data, is set in the *Metric Importance & Constraint Definition* element and can be used to find the probability that a an output metric will be at or below a specific value. This information can then be used to determine the probability that a given metric will be fall within an acceptable range. For the capability metrics, the points where the constraint line cross the "Low" and "High" curves represent the range for the probability of meeting a specific constraint ~65% (assuming a Normal or near-Normal distribution behavior of stochastic model outputs). This provides a simplistic but intuitive capturing of the potential variations in system effectiveness metrics associated with the stochastic nature of the UCAS-SEAD ABM&S model. As mentioned previously, a real world application of the ENTERPRISE methodology would require a higher fidelity investigation and representation of the stochastic behavior of a DES model (e.g. use Beta distributions or higher number of standard deviations).

Because of the high number of program potential metrics used to assess program robustness (10), the UCAS-SEAD DST currently only displays the output CDF and constraint line for two metrics (one mission and one development). The output metric data displayed in each graph can be changed by using the scrollbars beneath each graph. This prevents the decision-makers from being overwhelmed by a myriad of metric CDFs and constraint lines and leads to a more efficient understanding and absorption of the results.

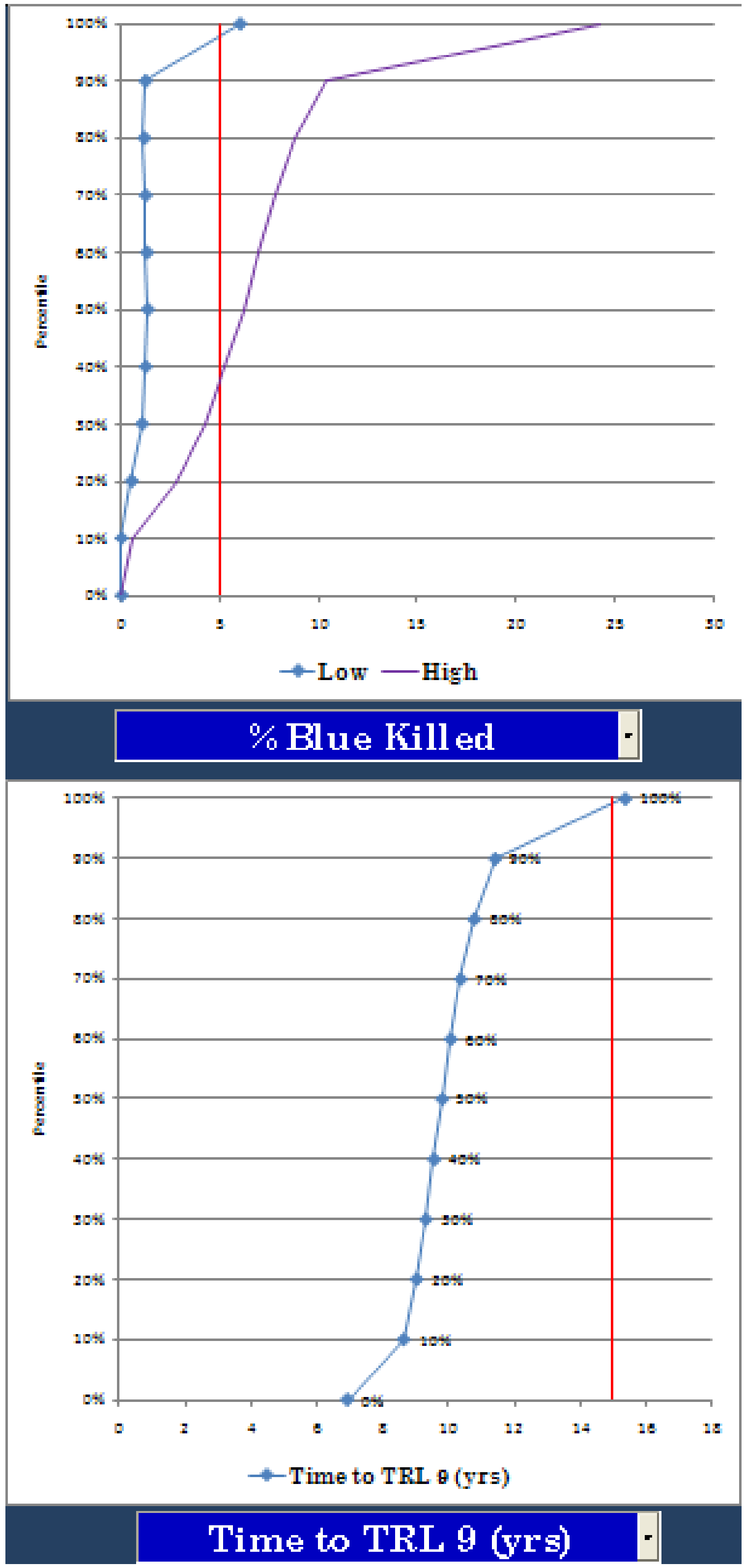


Figure 59: UCAS-SEAD DST Metric Output Distribution Graphs

As mentioned, the constraint line for each metric can defined and adjusted by using the *Metric Importance & Constraint Definition* element. Using these constraint lines, the probability (or probabilities for capability metrics) for meeting each constraint can be visually identified. This information can then be inputted into the *Program "Robustness" Calculation* output element. For this demonstration, the author used a simple but intuitive measure of program "robustness":

$$Robustness = \sum_{i=1}^{N} W_{i*}P_i$$

(37)

Where:

- N is the total number of metrics used for robustness calculation
- W_i is the weight assigned to metric i
- P_i is the probability of successfully meeting the constraint for metric i

Since there are two P_i's for the capability metrics, a low and high "Robustness" score is calculated. Again, while simplistic, this implementation allows for a straightforward and intuitive evaluation of program robustness against technology and requirements uncertainties.

"Robustness" Summary For Current Portfolio				
Metric	P_Low	P_High	R_Score_Low	R_Score_High
% Red Killed 12hrs	N/A		N/A	
% Red Killed 24hrs	*80%*	*90%*	2.4	2.7
% Red Killed 48 Hrs	N/A		N/A	
% Blue Killed	*55%*	*87%*	1.65	2.61
Time to TRL 6	N/A		N/A	
Time to TRL 7	N/A		N/A	
Time to TRL 9	58%		0.58	
Cost to TRL 6	N/A		N/A	
Cost to TRL 7	N/A		N/A	
Cost to TRL 9	70%		0.7	
Portfolio "Robustness" Score			Low	High
			5.33	6.59

Figure 60: UCAS-SEAD DST Portfolio "Robustness" Calculation Element

It should be noted that the probability values used by the UCAS-SEAD DST are *marginal probabilities* that describe the probability of each metric requirement robustness criteria. These probabilities assume that the distribution of each criterion's probability values is independent of each other. However, as noted by Bandte, analysis outputs generated by same process represent "a common system and are thus interdependent" and output probabilities are better described used *joint probabilities*.

6.4.1.2.1 Introduction to Joint Probability Theory

Generally defined, a joint probability is the probability of two or more events will happen *concurrently*. For the problem at hand, this means the probability of a given technology portfolio combination meeting all of the requirements robustness criteria simultaneously. A comparison between two notional criteria, X and Y and their marginal and joint probabilities is provided in Figure 61.

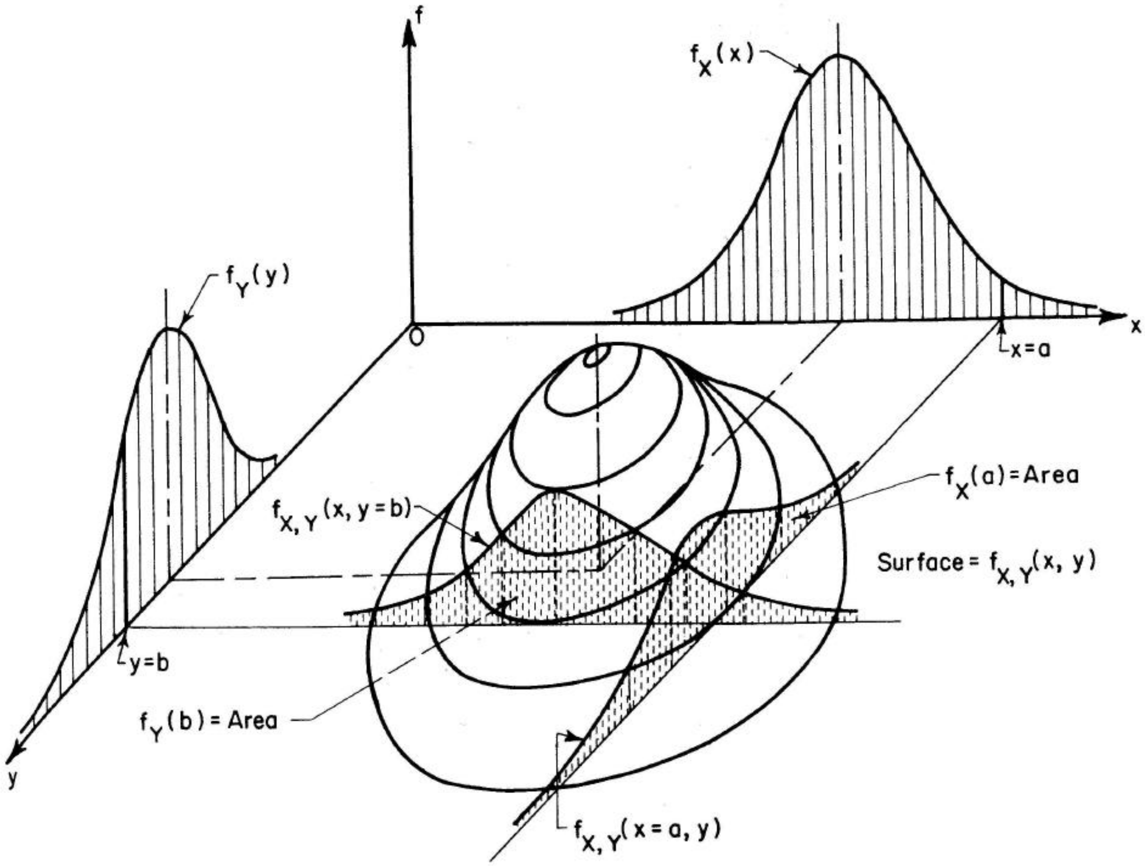


Figure 61: Example Marginal and Joint PDF of Continuous Criteria X and Y [9]

According to Bandte, decisions involving multiple, interdependent criteria require should utilize a joint probabilistic formulation since "marginal, or univariate, distribution for each criterion does not indicate the likelihood of any other criterion" [17]. Such a formulation can be accomplished using either a *Joint Probability Model* or an *Empirical Distribution Function* [17].

Joint Probability Model

A joint probability model is "an explicit formulation of a parametric joint probability density (or cumulative) distribution function that can be used as an algorithm to compute joint probabilities" [17]. Unlike the empirical distribution function, which is calculates joint probabilities using sample data, this approach can utilize parametric univariate criterion distributions generated using tradition probabilistic design processes. This is done by first identifying or assumption a PDF for each criterion and then correlate them using correlation parameters and or functions.

Typically, explicit formulations of a joint PDF are based on the joint Normal Distribution [17]. The equation below is an example of a bivariate Normal-Distribution PDF for criteria *X* and *Y*:

$$f_{XY}(x,y)=\frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}}\exp\left(\frac{1}{2\rho^2-2}\left(\left(\frac{x-\mu_X}{\sigma_X}\right)^2-2\rho\frac{x-\mu_X}{\sigma_X}\frac{y-\mu_Y}{\sigma_Y}+\left(\frac{y-\mu_Y}{\sigma_Y}\right)^2\right)\right)$$

(38) [17]

Where:

- μ_X and μ_Y are estimated mean values for criteria *X* and *Y*
- σ_X and σ_Y are the estimated standard deviations for criteria *X* and *Y*
- ρ is the correlation coefficient between criteria *X* and *Y*

In addition to the bivariate Normal Distribution provided above, other commonly used explicit joint probabilistic PDF formulations include the Normal-Lognormal and Lognormal joint distributions [47].

According to Bandte, this approach is advantageous when there is limited information or modeling/simulation is available. In such instances, expert knowledge can be used to provide "educated guesses" for the parameters needed to describe the joint probability model such as the mean, standard deviation, and correlation coefficient values in the equation above. The main disadvantage of this approach is that as the number of criteria increases, the computational burden required to calculate the joint probabilities become prohibitive.

Empirical Distribution Function

The second approach for creating joint probabilistic formulation is based on the use of empirically collected data samples to generate the joint probability values. Using this approach, the joint probability of criteria X and Y is calculated by examining the collect data samples and determining what percentage of the samples match both criteria. Since this approach relies only on examining available sample data, no assumptions regarding univariate PDFs or numerical integrations are required and thus it does not suffer from the limitations associated with explicit joint probability formulations. However, it does require the ability to collect or generate sample data. For problems involving large number of criteria, the size of the sample data necessary for accurate joint probabilistic distribution predictions can be quite large and thus computationally expensive.

For the notional implantation of the ENTERPRISE method, it would appear that the *Empirical Distribution Function* is more appropriate because of the existing of probabilistic forecasting environments that can be used to generate a large amount of sample data. Unfortunately, limitations with Excel's statistical analysis capabilities made implementation of either option difficult. As such, the UCAS-SEAD DST provides only the marginal probabilities. Since the objectives of this application are to demonstrate a notional implementation of the ENTERPRISE methodology and to identify limitations and shortcomings to be addressed by future work, this was deemed acceptable. However, for future ENTERPRISE applications, joint probabilistic formulations should be utilized using a more capable statistical analysis tool.

6.4.1.3 Background Data Analysis Elements

Since a detailed description of the background data analysis elements of the UCAS-SEAD DST are beyond the scope of this work and will shift the focus from the implementation of the ENTERPRISE method to the implementation of the notional UCAS-SEAD DST, the author will only provide an overview of the use of the Oracle Crystal Ball Excel add-in for conducting the Monte Carlo simulations needed to generate the output metric data displayed by the GUI Front-End. Please refer to Oracle's Crystal Ball website for a detailed description of the add-in and it's analytical capabilities [113].

Oracle Crystal Ball is used by the UCAS-SEAD DST to conduct Monte Carlo simulations on the mission and development metrics and generate the output distribution functions (and vital statistics like percentile ranges) that is displayed on the GUI Front-End. Similar to the analysis conducted in Phase III, the input parameters are assigned triangle distributions and a user-defined number samples are taken for each input parameter distribution to generate output distribution. Because this analysis relies on the estimated impact, time, and cost associated with each technology, the TIM, TCM, and technology development cost and schedule tables defined and used in earlier phases are imported into the tool and used to define the Monte Carlo simulation parameters. The calculations of the metrics are done in three separate worksheets: The *Mission Metric Analysis* worksheet, *Technology Development Schedule Analysis* worksheet, and the *Technology Development Cost Analysis* worksheet.

Within the *Mission Metrics Analysis* worksheet (see Figure 64), the low, high, and most-likely values for each parameter corresponding to the selected technologies are calculated using data from the TIM (located in the *TIM* worksheet). These values are then used by the ANN metric prediction equations (located in the *ANN Equation* worksheet) to estimate the metric outputs displayed in the *Mission Metric Analysis* worksheet. During a MC simulation, Oracle Crystal Ball will automatically generate a randomly selected value for each parameter (within its defined distribution), record the resulting outputs, and generate the output distribution statistics (i.e. CDF percentiles). The output data can then be used to generate the *metric CDF* graphs.

Estimated Time for ALL Selected Technology Combination to Reach Specified TRL (Years)	
Time to TRL 6	11.16
Time to TRL 7	14.68
Time to TRL 9	22.32

	Forecast Name	Time to TRL 6	Forecast Name	Time to TRL 7	Forecast Name	Time to TRL 9
Percentiles (10% at a time)	0%	1.78	0%	3.14	0.00	7.61
	10%	2.81	10%	4.50	0.10	8.66
	20%	3.04	20%	4.84	0.20	9.05
	30%	3.24	30%	5.05	0.30	9.34
	40%	3.40	40%	5.24	0.40	9.57
	50%	3.60	50%	5.41	0.50	9.83
	60%	3.80	60%	5.62	0.60	10.08
	70%	4.02	70%	5.84	0.70	10.44
	80%	4.22	80%	6.14	0.80	10.83
	90%	4.52	90%	6.47	0.90	11.49
	100%	5.46	100%	8.21	1.00	13.61
Output Statistics	Trials	1,000	Trials	1,000	Trials	1,000
	Mean	3.63	Mean	5.48	Mean	9.97
	Median	3.60	Median	5.41	Median	9.83
	Standard Deviation	0.66	Standard Deviation	0.76	Standard Deviation	1.08
	Minimum	1.78	Minimum	3.14	Minimum	7.61
	Maximum	5.46	Maximum	8.21	Maximum	13.61

Make Sure Schedule Data Matches Those in Technology List.xlsx

Don't Add/Remove Rows or ProbWorks/Crystal Ball Cell Pointers Will have to be Re-set

Active?	No	No	No	Yes	No	Yes	No	No	No
Current TRL	*3*	*3*	*5*	*4*	*4*	*5*	*4*	*3*	*4*
Technology	AF-1	AF-2	AF-3	*AF-4*	AF-5	PR-1	PR-2	ST-1	ST-2
TRL 1 to 2 Transition									
TRL 2 to 3 Transition									
TRL 3 to 4 Transition	1.63	1.91						3.91	
TRL 4 to 5 Transition	1.47	1.55		*2.58*	2.66		1.75	3.38	3.05
TRL 5 to 6 Transition	2.63	3.32	2.46	*4.44*	3.85	1.15	2.96	4.36	3.99
TRL 6 to 7 Transition	1.73	1.88	1.70	*2.36*	2.83	1.90	2.05	2.79	3.08
TRL 7 to 8 Transition	2.83	1.87	2.67	*4.49*	4.11	3.72	3.16	4.20	4.05
TRL 8 to 9 Transition	2.30	1.51	1.66	*2.34*	2.04	0.77	1.43	3.42	2.87
Time to TRL 6	*0.00*	*0.00*	*0.00*	*7.02*	*0.00*	*1.15*	*0.00*	*0.00*	*0.00*
Time to TRL 7	*0.00*	*0.00*	*0.00*	*9.38*	*0.00*	*3.05*	*0.00*	*0.00*	*0.00*
Time to TRL 9	*0.00*	*0.00*	*0.00*	*16.22*	*0.00*	*7.54*	*0.00*	*0.00*	*0.00*

Figure 62: UCAS-SEAD DST Technology Development Schedule Analysis Worksheet

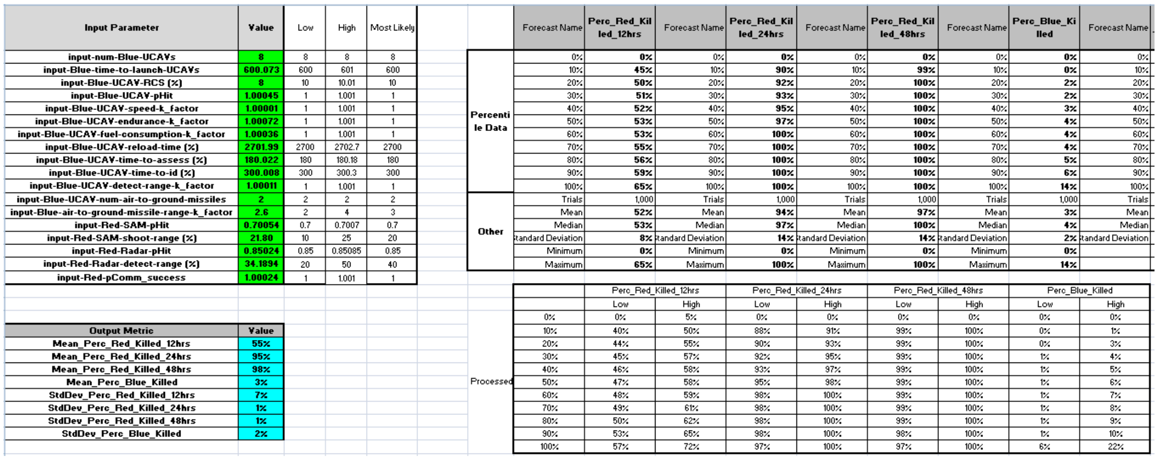
Estimated Cost for ALL Selected Technology Combination to Reach Specified TRL ($M)	
Cost to TRL 6	$30.92
Cost to TRL 7	$62.09
Cost to TRL 9	$206.82

Baseline Cost/Year	
TRL Transition	Cost per Year ($k)
TRL 1 to 2	150
TRL 2 to 3	250
TRL 3 to 4	500
TRL 4 to 5	1000
TRL 5 to 6	3000
TRL 6 to 7	5000
TRL 7 to 8	8000
TRL 8 to 9	12000

	Forecast Name	Cost to TRL 6	Forecast Name	Cost to TRL 7	Forecast Name	Cost to TRL 9
Percentiles (10% at a time)	0%	$5.82	0%	$16.34	0.00	$64.80
	10%	$10.00	10%	$22.99	0.10	$83.15
	20%	$10.98	20%	$24.68	0.20	$87.05
	30%	$11.85	30%	$25.93	0.30	$90.05
	40%	$12.44	40%	$26.93	0.40	$92.52
	50%	$13.10	50%	$27.74	0.50	$94.84
	60%	$13.94	60%	$28.75	0.60	$97.16
	70%	$14.71	70%	$29.75	0.70	$99.58
	80%	$15.69	80%	$30.91	0.80	$102.80
	90%	$16.91	90%	$32.42	0.90	$107.23
	100%	$21.24	100%	$37.67	1.00	$120.71
Output Statistics	Trials	1,000	Trials	1,000	Trials	1,000
	Mean	$13.31	Mean	$27.80	Mean	$94.97
	Median	$13.12	Median	$27.75	Median	$94.84
	Standard Deviation	$2.69	Standard Deviation	$3.58	Standard Deviation	$9.19
	Minimum	$5.82	Minimum	$16.34	Minimum	$64.80
	Maximum	$21.24	Maximum	$37.67	Maximum	$120.71

Active?	No	No	No	Yes	No	Yes	No	No	No	No	Yes	No	No
Cost Correction Factor	*-0.2*	*-0.4*	*-0.45*	*0.5*	*0.55*	*0*	*0.35*	*1.5*	*0.9*	*0.15*	*1.25*	*-0.45*	*0.75*
Technology	AF-1	AF-2	AF-3	*AF-4*	AF-5	PR-1	PR-2	ST-1	ST-2	ST-3	ST-4	WP-1	WP-2
TRL 1 to 2 Transition													
TRL 2 to 3 Transition													
TRL 3 to 4 Transition	652.22	762.97						1565.31			1271.77		990.40
TRL 4 to 5 Transition	1178.49	1240.72		2065.16	2131.63		1396.29	2700.01	2440.60	1540.36	2486.66	877.95	2191.62
TRL 5 to 6 Transition	6307.54	7973.25	5915.06	10652.51	9242.48	2750.64	7103.72	10472.93	9568.08	6557.67	11690.33	5860.35	9624.09
TRL 6 to 7 Transition	6911.22	7508.05	6789.56	9450.73	11310.12	7615.34	8199.47	11158.83	12315.95	7086.68	14103.46	7701.14	14128.5
TRL 7 to 8 Transition	18124.67	11983.94	17100.10	28734.61	26304.37	23836.30	20224.24	26886.63	25936.14	13718.95	22144.31	13253.22	20254.9
TRL 8 to 9 Transition	22127.55	14535.81	15973.61	22505.26	19553.10	7381.13	13690.10	32842.62	27566.64	17500.63	40127.78	23663.82	30948.0
Cost to TRL 6 ($k)	*0.0*	*0.0*	*0.0*	*12717.7*	*0.0*	*2750.6*	*0.0*	*0.0*	*0.0*	*0.0*	*15448.8*	*0.0*	*0.0*
Cost to TRL 7 ($k)	*0.0*	*0.0*	*0.0*	*22168.4*	*0.0*	*10366.0*	*0.0*	*0.0*	*0.0*	*0.0*	*29552.2*	*0.0*	*0.0*
Cost to TRL 9 ($k)	*0.0*	*0.0*	*0.0*	*73408.3*	*0.0*	*41583.4*	*0.0*	*0.0*	*0.0*	*0.0*	*91824.3*	*0.0*	*0.0*

Figure 63: UCAS-SEAD DST Technology Development Cost Analysis Worksheet



Input Parameter	Value	Low	High	Most Likely
input-num-Blue-UCAVs	8	8	8	8
input-Blue-time-to-launch-UCAVs	600.073	600	601	600
input-Blue-UCAV-RCS (%)	8	10	10.01	10
input-Blue-UCAV-pHit	1.00045	1	1.001	1
input-Blue-UCAV-speed-k_factor	1.00001	1	1.001	1
input-Blue-UCAV-endurance-k_factor	1.00072	1	1.001	1
input-Blue-UCAV-fuel-consumption-k_factor	1.00036	1	1.001	1
input-Blue-UCAV-reload-time (%)	2701.99	2700	2702.7	2700
input-Blue-UCAV-time-to-assess (%)	180.022	180	180.18	180
input-Blue-UCAV-time-to-id (%)	300.008	300	300.3	300
input-Blue-UCAV-detect-range-k_factor	1.00011	1	1.001	1
input-Blue-UCAV-num-air-to-ground-missiles	2	2	2	2
input-Blue-air-to-ground-missile-range-k_factor	2.6	2	4	3
input-Red-SAM-pHit	0.70054	0.7	0.7007	0.7
input-Red-SAM-shoot-range (%)	21.80	10	25	20
input-Red-Radar-pHit	0.85024	0.85	0.85085	0.85
input-Red-Radar-detect-range (%)	34.1894	20	50	40
input-Red-pComm_success	1.00024	1	1.001	1

Output Metric	Value
Mean_Perc_Red_Killed_12hrs	55%
Mean_Perc_Red_Killed_24hrs	95%
Mean_Perc_Red_Killed_48hrs	98%
Mean_Perc_Blue_Killed	3%
StdDev_Perc_Red_Killed_12hrs	7%
StdDev_Perc_Red_Killed_24hrs	1%
StdDev_Perc_Red_Killed_48hrs	1%
StdDev_Perc_Blue_Killed	2%

	Forecast Name	Perc_Red_Killed_12hrs	Forecast Name	Perc_Red_Killed_24hrs	Forecast Name	Perc_Red_Killed_48hrs	Forecast Name	Perc_Blue_Killed	Forecast Name
Percentile Data	0%	0%	0%	0%	0%	0%	0%	0%	0%
	10%	45%	10%	90%	10%	99%	10%	0%	10%
	20%	50%	20%	92%	20%	100%	20%	2%	20%
	30%	51%	30%	93%	30%	100%	30%	2%	30%
	40%	52%	40%	95%	40%	100%	40%	3%	40%
	50%	53%	50%	97%	50%	100%	50%	4%	50%
	60%	53%	60%	100%	60%	100%	60%	4%	60%
	70%	55%	70%	100%	70%	100%	70%	4%	70%
	80%	56%	80%	100%	80%	100%	80%	5%	80%
	90%	59%	90%	100%	90%	100%	90%	6%	90%
	100%	65%	100%	100%	100%	100%	100%	14%	100%
Other	Trials	1,000	Trials	1,000	Trials	1,000	Trials	1,000	Trials
	Mean	52%	Mean	94%	Mean	97%	Mean	3%	Mean
	Median	53%	Median	97%	Median	100%	Median	4%	Median
	Standard Deviation	8%	Standard Deviation	14%	Standard Deviation	14%	Standard Deviation	2%	Standard Deviation
	Minimum	0%	Minimum	0%	Minimum	0%	Minimum	0%	
	Maximum	65%	Maximum	100%	Maximum	100%	Maximum	14%	

		Perc_Red_Killed_12hrs		Perc_Red_Killed_24hrs		Perc_Red_Killed_48hrs		Perc_Blue_Killed	
		Low	High	Low	High	Low	High	Low	High
Processed	0%	0%	5%	0%	0%	0%	0%	0%	0%
	10%	40%	50%	88%	91%	99%	100%	0%	1%
	20%	44%	55%	90%	93%	99%	100%	0%	3%
	30%	45%	57%	92%	95%	99%	100%	1%	4%
	40%	46%	58%	93%	97%	99%	100%	1%	5%
	50%	47%	58%	95%	98%	99%	100%	1%	6%
	60%	48%	59%	98%	100%	99%	100%	1%	7%
	70%	49%	61%	98%	100%	99%	100%	1%	8%
	80%	50%	62%	98%	100%	99%	100%	1%	9%
	90%	53%	65%	98%	100%	98%	100%	1%	10%
	100%	57%	72%	97%	100%	97%	100%	6%	22%

Figure 64: UCAS-SEAD DST Mission Metrics Analysis Worksheet

6.4.1.4 Operational Procedures

Using the UCAS-SEAD DST to conduct probabilistic analysis on candidate UCAS-SEAD technology development portfolios consists of the following several simple and intuitive steps:

1) Selected technologies portfolio (making sure not to select incompatible technologies)
2) Define metric weights and constraint values
3) Initial MCS using Crystal Ball
4) Visually inspect CDF/constraint line graph and record probabilities of meeting constraints
5) Assess portfolio "robustness"
6) If necessary, define GA optimization parameters and run UCAS-SEAD TPOT to identify optimal solution according to current requirement metric preferences and importance

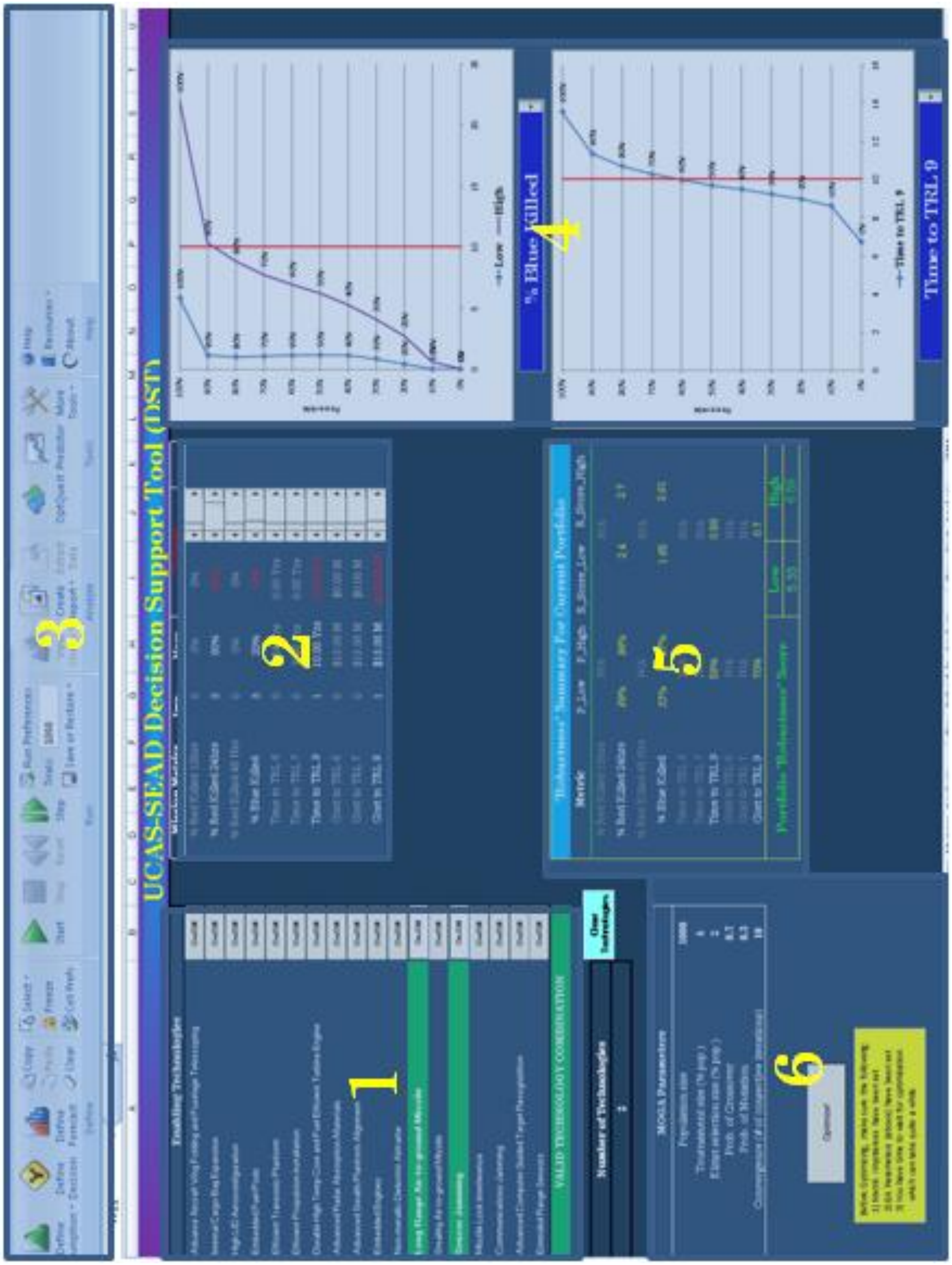


Figure 65: UCAS-SEAD DST Operation Process Overview

6.4.2 Step 12: Support Decision-Making

In the final step of this notional ENTERPRISE application, the UCAS-SEAD DST is used to support two notional decision points in the UCAS program development. The first decision point is to assist in the down-select of program technology development portfolio and the second is to update program robustness assessment at a subsequent program review.

6.4.2.1 Finalize UCAS-SEAD Technology Portfolio

During Step 9, the UCAS-SEAD TPOT was used to probabilistically evaluate and select an optimized technology portfolio according to the notional metric weighting schemes listed in Table 38. This produced the set of alternatives listed in Table 40. For final UCAS program technology portfolio down-select, the "robustness" of each of these scenarios is assessed using the UCAS-SEAD DST and the results are used to select the final UCAS-SEAD portfolio. For this application, a notional weighting scenario and set of constraint values were fabricated by the author the portfolio down-select. Note that these metric weights values do not reflect those used by the UCAS-SEAD TPOT in the previous step. This was purposely done to demonstrate the ability of a computer-based DSS to capture changing decision-maker requirements and rapidly produce the impacts of these changing requirements on assessment results.

Table 43: Metric Weighting and Constraint Values Used for Notional UCAS Program Technology Portfolio Down-selection

Mission Metrics	Importance	Contraint
% Red Killed 24hrs	2	>90%
% Blue Killed	6	<5%
Time to TRL 9	1	<15 Yrs
Cost to TRL 9	1	<$200M

Using the UCAS-SEAD DST, the probabilities for meeting metric constraint and "robustness" scores for each alternate portfolio were calculated and the results are reproduced below:

Table 44: Calculated Robustness Scores for Notional UCAS-SEAD Technology Portfolios Alternatives

Alternative	% Red Killed 24hrs		% Blue Killed		Time to TRL 9	Cost to TRL 9	R_Low	R_High	R_Avg
	Low	High	Low	High					
One	80%	90%	38%	95%	99%	100%	**5.87**	**9.49**	**7.68**
Two	0%	0%	0%	0%	100%	100%	**2**	**2**	**2**
Three	90%	90%	50%	95%	92%	100%	**6.72**	**9.42**	**8.07**
Four	91%	91%	93%	95%	20%	94%	**8.54**	**8.66**	**8.6**

Note in the table above, Alternative 1 corresponds to Solution set 1 from Table 40, Alternative 2 corresponds to Solution set 2, Alternative 3 corresponds to Solution set 4, and Alternative 4 corresponds to Solution set 5. This shift was done because Solution sets 1 and 3 outputted by the UCAS-SEAD TPOT were the same and thus it was unnecessary to repeat the same analysis for two identical alternative solutions.

It should be noted that while the results in Table 44 provides sufficient information for comparing between the robustness scores between the alternative solutions for an analyst (such as the author) with more intimate knowledge of the problem, a more graphical and visually intuitive representation is needed to demonstrate tradeoffs and contrasts between the alternative portfolio solutions. As such, the summary results are plotted in radar diagrams that visually demonstrate the performance of each alternative across each of the four robustness criteria. Figure 66 on the next page depicts the radar diagram comparing the un-weighted average robustness score for the four alternatives while Figure 67 contrasts the weighted averaged robustness scores.

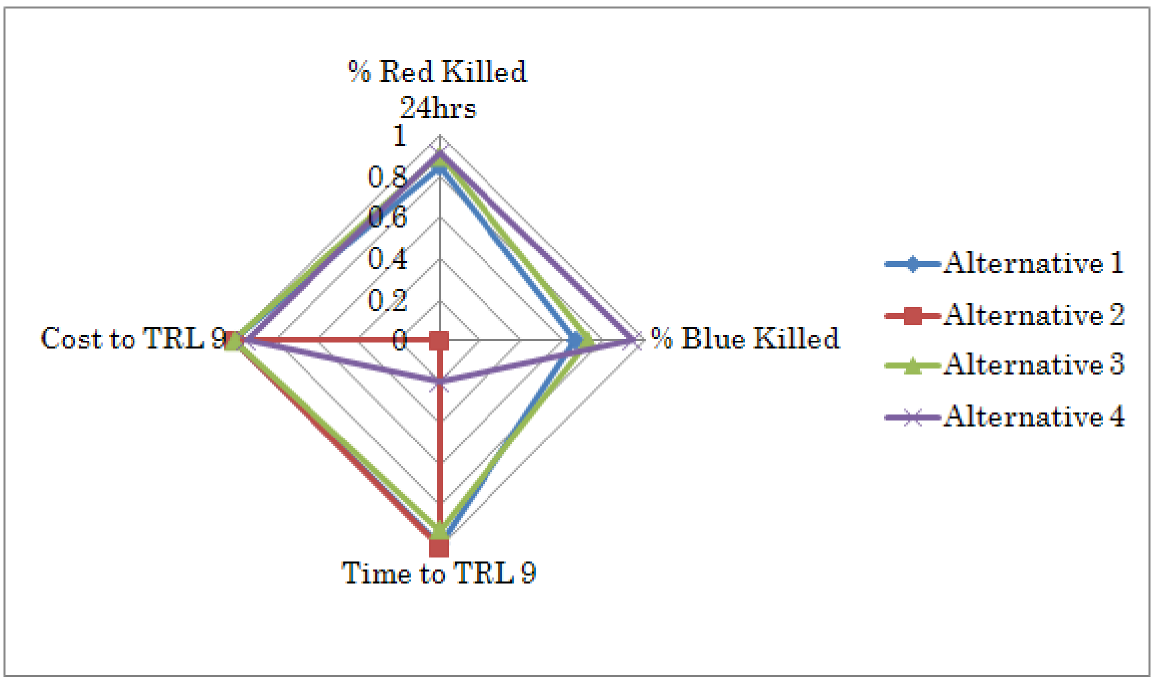


Figure 66: Radar Diagram Comparing the *Unweighted* Average Robustness Scores of Notional UCAS-SEAD Technology Portfolio Alternatives

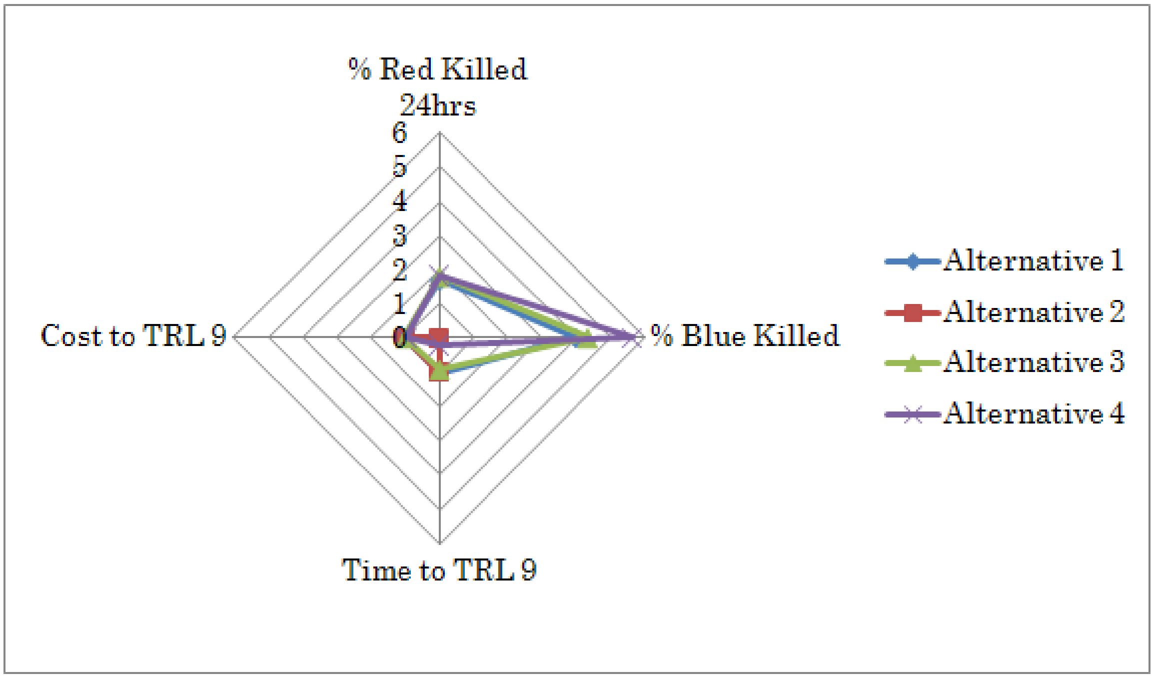


Figure 67: Radar Diagram Comparing the *Weighted* Average Robustness Scores of Notional UCAS-SEAD Technology Portfolio Alternatives

Looking at the figures on the previous page, it would appear that Alternatives 1 and 3 are clearly the two best solutions when equal emphasis is placed on the metric requirements. However, when weighted importance values are taken into account, the "distance" between these two alternatives and Alternative 4 becomes much closer. In fact, when looking at the *R_Avg* values from Table 44, it would appear that Alternative 4 becomes the best solution (i.e. highest *R_Avg*) once metric weights are taken into account. Radar diagrams for *R_Low* and *R_High* values can also be generated to the variations in robustness for the four alternatives.

Looking at figures on the previous page and Table 44, if *R_Avg* is used as the OEC for evaluating the "goodness" of each alternative, then Alternative 4, which consists of *Sensor Jamming*, *Long Range Air-to-ground missiles*, and *Advanced Stealth*

Planform Alignment technologies, is the best meet decision-maker requirements and preferences. Obviously, the rankings may change if *R_Low* or *R_High* is used instead. For the notional UCAS-SEAD program, the author elected to use *R_Avg* as the OEC and thus Alternative 4 is selected as the final technology portfolio.

The author would like to add that the radar diagrams were not part of the UCAS-SEAD DST because of space limitations of the GUI front-end. However, future iterations of this tool should include such visualizations because of their ability to provide intuitive and visual comparisons between alternatives to the analyst/decision-maker.

6.4.2.1.1 Sensitivity Analysis

As noted in previously, one of the key analytical capabilities provided by a computer-based Decision Support System is the ability to perform rapid tradeoffs and sensitivity studies. Such studies can be used to demonstrate the variations in the "goodness" of each candidate technology portfolios across changing requirement constraints and weights change and provide valuable insight to analysts and decision-makers. In this section, a notional sensitivity study will be conducted by varying constraints for the four UCAS-SEAD metric requirements and show the changes (if any) in the desirability of the candidate portfolios generated from Step 10. Since many potential weighting scenarios are possible, a notional representative set will be used to provide a notional sensitivity analysis of portfolio robustness against changing requirements.

To test for sensitivity against changing decision-maker preferences, the weighted importance of each portfolio is first varied based on the values in the follow table:

Table 45: Weighting Scenarios Used for Notional UCAS-SEAD Requirements Sensitivity Study

	Metric Requirement			
Weighting Scenarios	**Perc_Red_ Killed_24hr**	**Perc_Blue _Killed**	**Time to TRL 9**	**Cost to TRL 9**
Set 1	2	6	1	1
Set 2	2	4	1	1
Set 3	2	2	1	1
Set 4	4	2	1	1
Set 5	6	2	1	1
Set 6	2	6	2	2
Set 7	2	4	2	2
Set 8	2	2	2	2
Set 9	4	2	2	2
Set 10	6	2	2	2
Set 11	2	6	4	4
Set 12	2	4	4	4
Set 13	2	2	4	4
Set 14	4	2	4	4
Set 15	6	2	4	4
Set 16	2	6	6	6
Set 17	2	4	6	6
Set 18	2	2	6	6
Set 19	4	2	6	6
Set 20	6	2	6	6
Set 21	1	1	2	2
Set 22	1	1	4	4
Set 23	1	1	6	6

The first five scenarios reflect a gradual shifting of emphasis from *Perc_Blue_Killed* to *Perc_Red_Killed_24hrs* capability metric requirements with minimal emphasis on the *Time_to_TRL_9* and *Cost_to_TRL_9* development budget and schedule metrics (note: the first scenario is the same weighting scenario used in the previous section).

Scenarios 6-10 is similar to the first five scenarios except emphasis on development metrics has been increased from 1 to 2 to represented increased emphasis on development budget and schedule. This pattern is increases in Scenarios 11-15 and 16-20 with increasing emphasis on these two metrics. Finally, the last three scenarios places equally (low) importance on the two capability metrics while the time and cost metrics are increased together. Note that in this study the two development time and cost metrics are increased together rather than independently to simplify the process under the assumption that decision-maker are likely to place equal emphasis on budget and schedule. For applications where this is not true, these metrics should be varied independently.

The resulting values for *R_Low, R_High*, and their average for each alternate technology portfolio for each of the 23 scenarios listed above are provided below:

Table 46: Results for Notional UCAS-SEAD Requirements Sensitivity Study

	Technology Portfolio Alternatives											
Weighting Scenarios	Alternative 1			Alternative 2			Alternative 3			Alternative 4		
	Low	High	Avg.	Low	High	Avg.	Low	High	Avg.	Low	High	Avg.
Set 1	5.88	9.32	7.60	2	2	2.00	6.78	9.42	8.10	8.52	8.7	8.61
Set 2	5.12	7.48	6.30	2	2	2.00	5.76	7.52	6.64	6.66	6.78	6.72
Set 3	4.36	5.64	5.00	2	2	2.00	4.74	5.62	5.18	4.8	4.86	4.83
Set 4	5.96	7.44	6.70	2	2	2.00	6.54	7.42	6.98	6.6	6.66	6.63
Set 5	7.56	9.24	8.40	2	2	2.00	8.34	9.22	8.78	8.4	8.46	8.43
Set 6	7.88	11.32	9.60	4	4	4.00	8.7	11.34	10.02	9.66	9.84	9.75
Set 7	7.12	9.48	8.30	4	4	4.00	7.68	9.44	8.56	7.8	7.92	7.86
Set 8	6.36	7.64	7.00	4	4	4.00	6.66	7.54	7.10	5.94	6	5.97
Set 9	7.96	9.44	8.70	4	4	4.00	8.46	9.34	8.90	7.74	7.8	7.77
Set 10	9.56	11.24	10.40	4	4	4.00	10.26	11.14	10.70	9.54	9.6	9.57
Set 11	11.88	15.32	13.60	8	8	8.00	12.54	15.18	13.86	11.94	12.12	12.03
Set 12	11.12	13.48	12.30	8	8	8.00	11.52	13.28	12.40	10.08	10.2	10.14
Set 13	10.36	11.64	11.00	8	8	8.00	10.5	11.38	10.94	8.22	8.28	8.25
Set 14	11.96	13.44	12.70	8	8	8.00	12.3	13.18	12.74	10.02	10.08	10.05
Set 15	13.56	15.24	14.40	8	8	8.00	14.1	14.98	14.54	11.82	11.88	11.85
Set 16	15.88	19.32	17.60	12	12	12.00	16.38	19.02	17.70	14.22	14.4	14.31
Set 17	15.12	17.48	16.30	12	12	12.00	15.36	17.12	16.24	12.36	12.48	12.42
Set 18	14.36	15.64	15.00	12	12	12.00	14.34	15.22	14.78	10.5	10.56	10.53
Set 19	15.96	17.44	16.70	12	12	12.00	16.14	17.02	16.58	12.3	12.36	12.33
Set 20	17.56	19.24	18.40	12	12	12.00	17.94	18.82	18.38	14.1	14.16	14.13
Set 21	5.18	5.82	5.50	4	4	4.00	5.25	5.69	5.47	4.11	4.14	4.13
Set 22	9.18	9.82	9.50	8	8	8.00	9.09	9.53	9.31	6.39	6.42	6.41
Set 23	13.18	13.82	13.50	12	12	12.00	12.93	13.37	13.15	8.67	8.7	8.69

Looking at the table above, the following observations were made:

- The *Robustness* scores for Portfolio Alternative 2 (corresponding to zero technologies selected) only changes with the weighted importance of the two development metrics. This makes sense since implementation of solution 2 would lead to completely failure of both of the capability metrics. The other observations will be made without examining **Alternative 2 since it is an academic solution that would not be selected under any realistic acquisition scenario.**
- As the development and cost metrics became more and more important (i.e. higher weight values), Portfolio Alternative 1 (corresponding to portfolio

consisting of *Long Range Sensors and Long Range Air-to-Ground Missiles)* became more attractive (i.e. higher robustness) compared to the other solutions. This is likely due to the fact that compared to Alternatives 3 and 4 both include a 3rd technology on top of the two technologies in Alternative 1, will likely cost more and take longer to develop. Thus, **Alternative 1 is the best alternative when development cost and budget robustness are emphasized.** Figure 68 below provides a comparison of the average *robustness* scores for four weighting scenarios with identical weights on the two capability metrics and increasing weights on the development metrics.

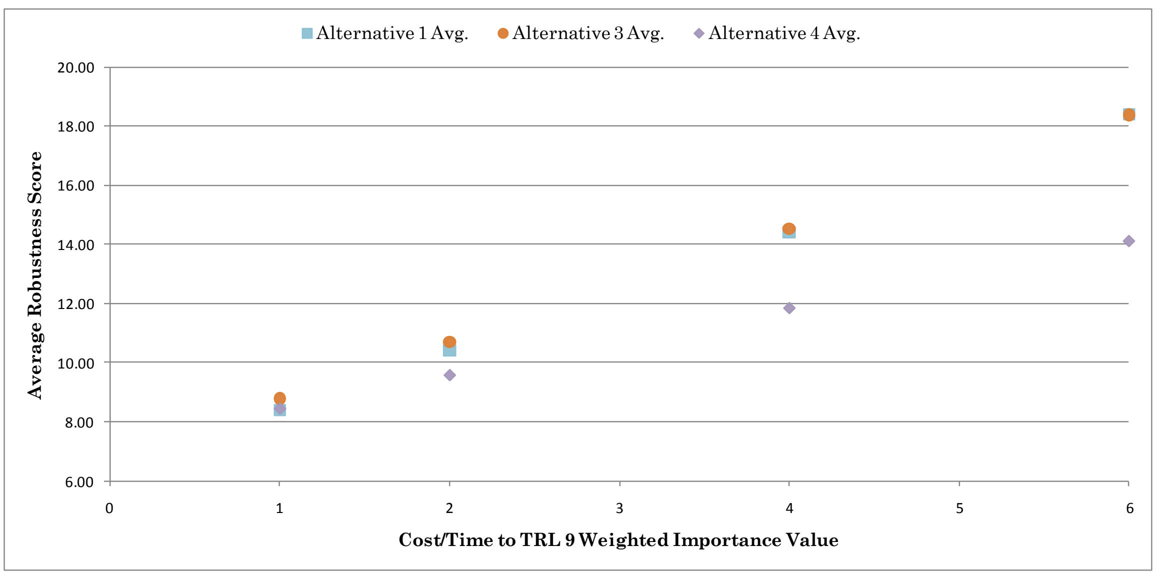


Figure 68: Comparison of Average Robustness Scores for Fixed Capability Metric Weights and Varying Development Metric Weights for Notional UCAS-SEAD Technology Portfolio Alternatives

- **As emphasis switched from *Perc_Blue_Killed* to *Perc_Red_Killed_24hrs*, Alternatives 1 and Alternative 3 became**

more attractive than Alternative 4. This is likely due to the fact that third technology included in Alternative 4, which is the *Advance Stealth Planform Alignment*, is still in early development and require a considerable amount of time and resources to mature compared to the other two solutions. Only when sufficient emphasis is placed on *Perc_Blue_Killed* would this technology (or the other stealth technologies that would enhance UCAS survivability) be the optimal solution. Thus, **Alternative 4 is the best alternative only when emphasis is placed on "force protection" metric requirement robustness.** Figure 69 below provides a comparison of the average *robustness scores* for the 3 candidate portfolios for Weighting Scenarios 1 to 5 (i.e. emphasis switching from *Perc_Blue_Killed* to *Perc_Red_Killed_24hrs*.

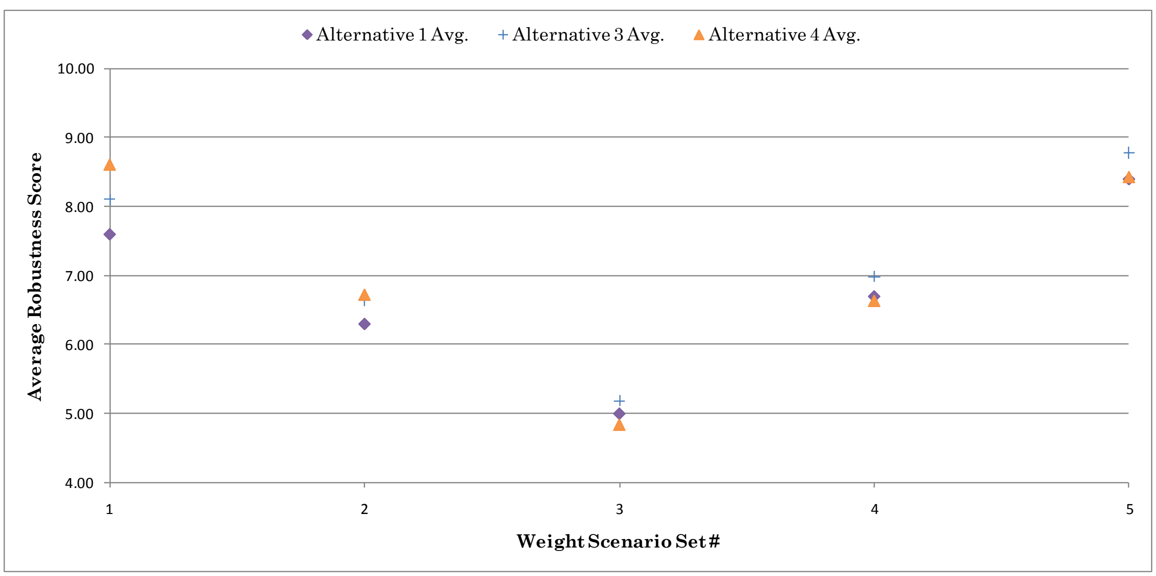


Figure 69: Comparison of Average Robustness Scores as Emphasis Switches from *Perc_Blue_Killed* to *Perc_Red_Killed_24hrs* for Notional UCAS-SEAD Technology Portfolio Alternatives

- When comparing the scores between Alternative 1 and Alternative 3, one can see that there is minimal gain in the robustness of the requirements with the inclusion of the *Advanced Wing Folding and Telescoping* technology. This alternative would likely to only be preferred over the other alternatives when higher emphasis is placed on shorting the mission timeframe since it allows for more UCAS assets to be employed at one time. Thus, **Alternative 3 provides minimal benefit over Alternative 1 at a cost of having to developed an extra technology.** Figure 70 compares the average *robustness score* between the two portfolios across the 23 weighting scenarios. Note the minimal gains in robustness provided by Alternative 3 and in some instances (when development and cost metrics are highly emphasizes), the better performance of Alternative 1.

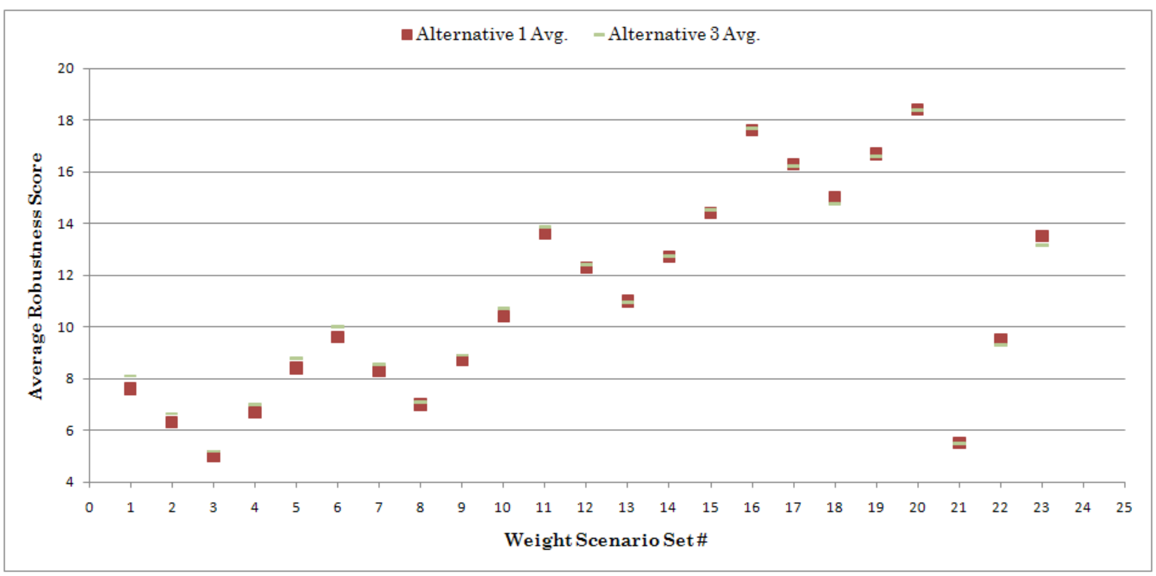


Figure 70: Comparison of Average Robustness Scores between Notional UCAS-SEAD Technology Portfolio Alternatives 1 and 3

- Alternative 4 typically has the smallest variation between the *R_Low* and *R_High* values associated with the stochastic behavior of the agent-based UCAS-SEAD model. Thus, **selection of Alternative 4 results in capability requirement metrics that are least sensitive (i.e. most robust) to the stochastic behavior of the technology performance impact forecasting model.** Figure 71 below compares the low and high *robustness scores* for each of the three alternatives across the 23 weighting scenarios. Note the close proximity between the low and high scores for Alternative 4 when compared against the other alternatives

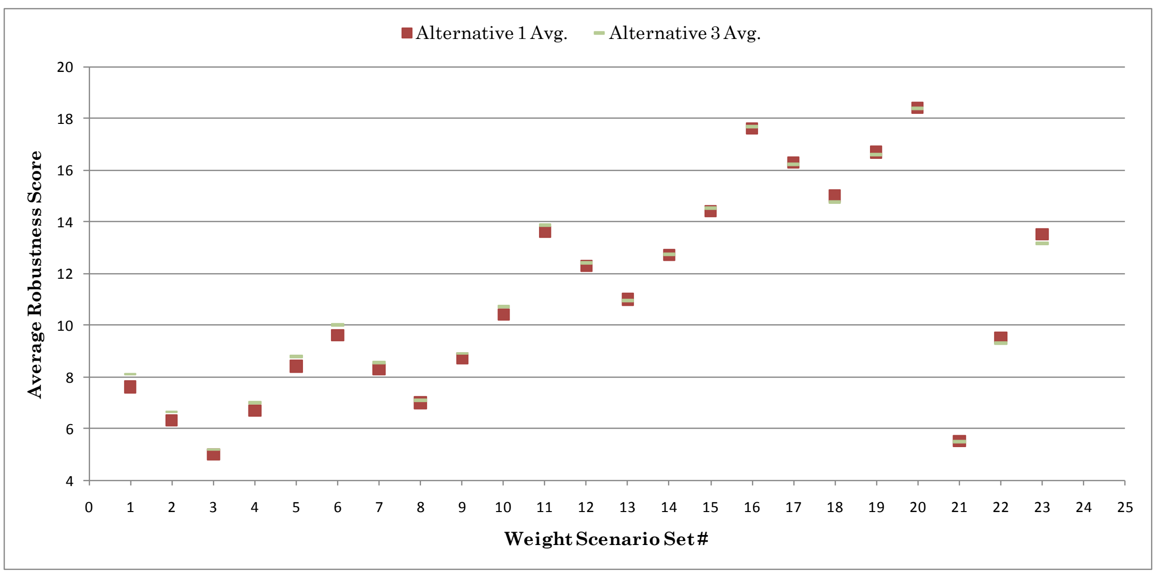


Figure 71: Comparison of Low and High Robustness Scores Notional UCAS-SEAD Technology Portfolio Alternatives 1 and 3

It should be obvious that identifying trends using the table above would most likely overwhelm the decision-maker and is a task that should be left to the analysts.

Ideally, the results above would be converted to a more intuitive and graphical format such as *Scatter* or *Pareto* plots, but because of the limited graphical capabilities within Excel, this was not possible and thus required the user to manually plot the results and examine the trends. For example, the results data from Table 46 could be imported into *JMP*, a statistical analysis software package developed by the SAS Institute and *Pareto* plots can be generated to show the relative impact of each metric weight value on the robustness scores (note *Cost_to_TRL_9_Weight* is not shown because for the weighting scenarios used it always has the same value as *Time_to_TRL_9_Weight*):

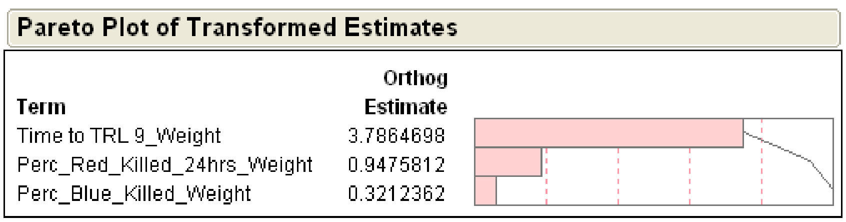


Figure 72: Pareto Plot of Notional UCAS-SEAD Technology Portfolio Alternative 1 R_Low Score

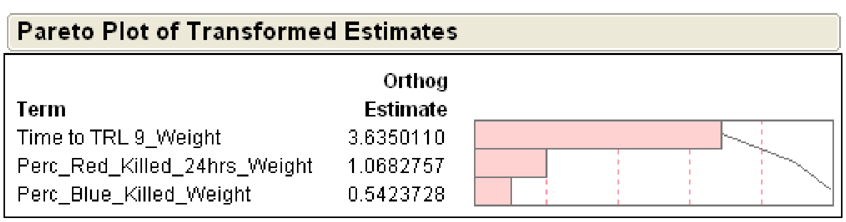


Figure 73: Pareto Plot of Notional UCAS-SEAD Technology Portfolio Alternative 3 R_Low Score

Pareto Plot of Transformed Estimates

Term	Orthog Estimate
Time to TRL 9_Weight	2.1582878
Perc_Blue_Killed_Weight	1.3327302
Perc_Red_Killed_24hrs_Weight	0.9786059

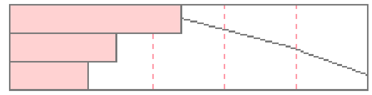


Figure 74: Pareto Plot of Notional UCAS-SEAD Technology Portfolio Alternative 4 R_Low Score

Pareto Plot of Transformed Estimates

Term	Orthog Estimate
Time to TRL 9_Weight	3.7864698
Perc_Blue_Killed_Weight	1.1914322
Perc_Red_Killed_24hrs_Weight	0.8862126

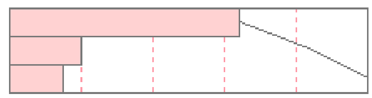


Figure 75: Pareto Plot of Notional UCAS-SEAD Technology Portfolio Alternative 1 R_High Score

Pareto Plot of Transformed Estimates

Term	Orthog Estimate
Time to TRL 9_Weight	3.6350110
Perc_Blue_Killed_Weight	1.2514214
Perc_Red_Killed_24hrs_Weight	0.8825359

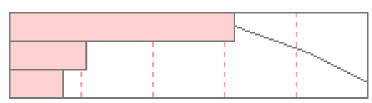


Figure 76: Pareto Plot of Notional UCAS-SEAD Technology Portfolio Alternative 3 R_High Score

Pareto Plot of Transformed Estimates

Term	Orthog Estimate
Time to TRL 9_Weight	2.1582878
Perc_Blue_Killed_Weight	1.3810745
Perc_Red_Killed_24hrs_Weight	0.9659418

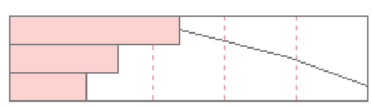


Figure 77: Pareto Plot of Notional UCAS-SEAD Technology Portfolio Alternative 4 R_High Score

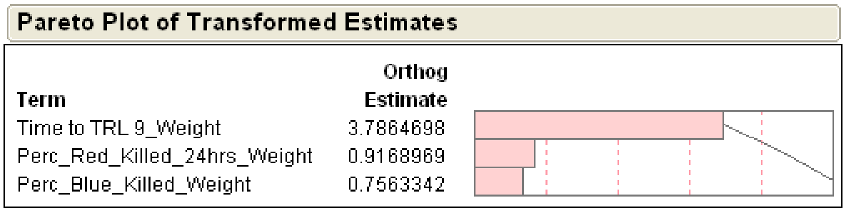


Figure 78: Pareto Plot of Notional UCAS-SEAD Technology Portfolio Alternative 1 R_Avg Score

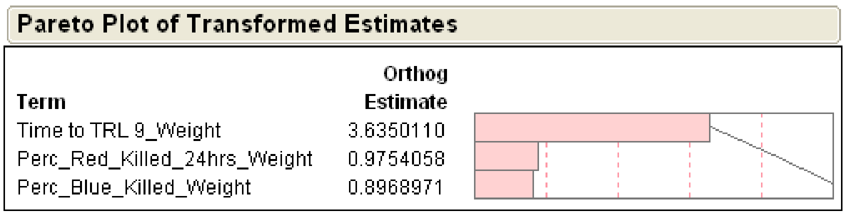


Figure 79: Pareto Plot of Notional UCAS-SEAD Technology Portfolio Alternative 3 R_Avg Score

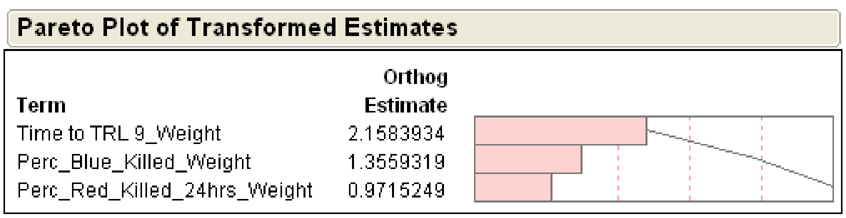


Figure 80: Pareto Plot of Notional UCAS-SEAD Technology Portfolio Alternative 4 R_Avg Score

Looking at the figures in the previous two pages, it is clear that the *Time_to_TRL_9_Weight* (and *Cost_to_TRL_9_Weight* implicitly) has the biggest impact on the robustness scores of the three alternatives. JMP also provides the ability to produce a *Prediction Profiler* using these results that provides the user with the ability to quickly evaluate the change in alternative robustness scores caused by changing metric weighting values.

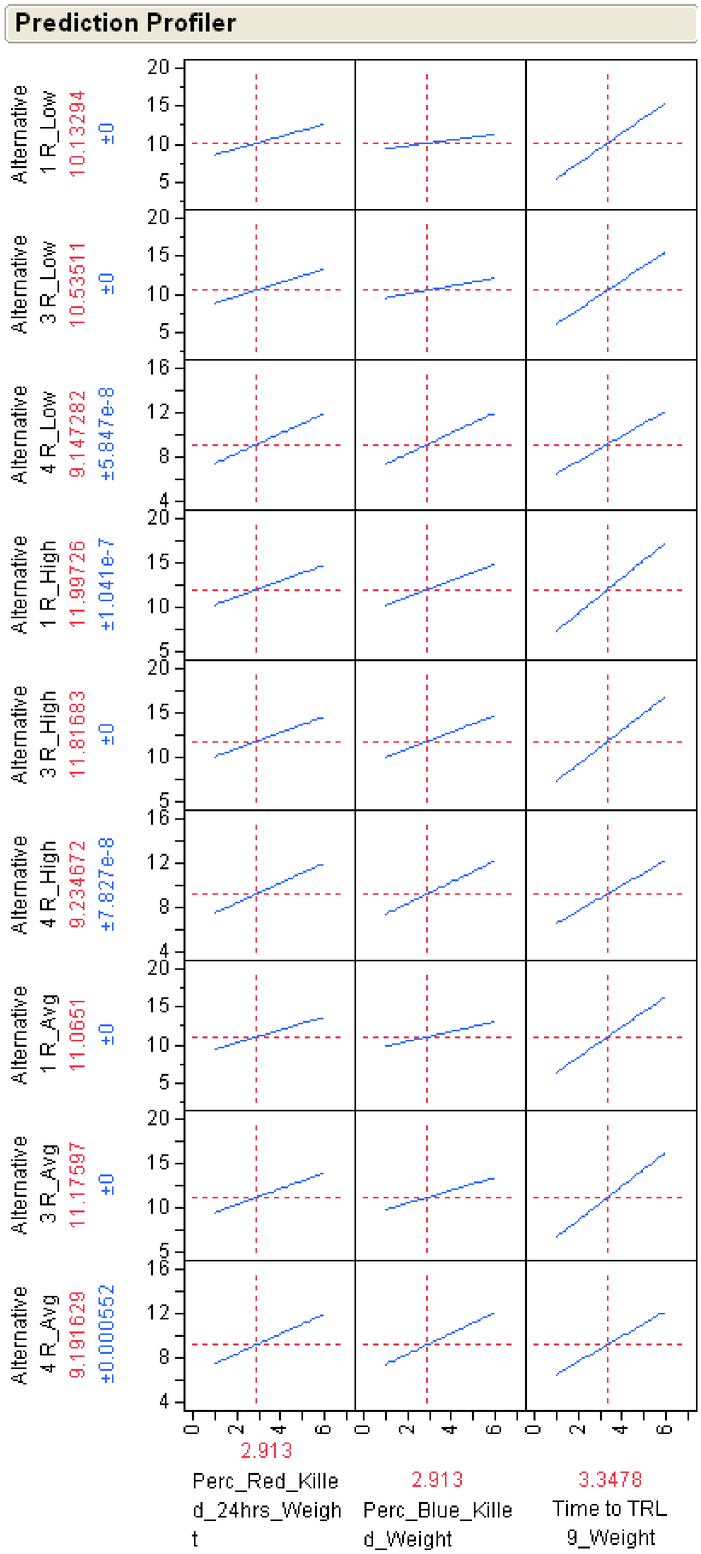


Figure 81: Snapshot of Interactive Prediction Profiler for Notional UCAS-SEAD Technology Portfolio Alternatives Robustness Scores

It should be noted that since the metric constraint values were fixed for this analysis, the generated sensitivity study results only apply *for the given set of metric constraints*. Pareto plots generated using a different set of metric constraints could have different results. Ideally, one would want to simultaneous vary metric constraints AND weighted importance values (and other relevant inputs for robustness calculation) so that a full-spectrum sensitivity analysis on alternative robustness can be conducted. Since the purpose of this study is to demonstrate the usefulness of a computer-based DSS in identifying relevant trends in the data for decision-makers, this task will be left for future implementations.

In addition to drawing conclusions regarding the sensitivity of alternative robustness scores, an obvious conclusion based on this study is the importance of statistical analysis to generating useful visual representations for informing the user/analyst/decision-maker. Limitations with Excel's statistical analysis capabilities required the author to export the data into JMP. For future applications, more thought should be given to anticipating the types of analysis that will be conducted using the DSS and an appropriate framework should be used to develop the DSS. For this application, Excel was selected because of it portability and ease of use but its limited capabilities limited the usefulness of the UCAS-SEAD DST in the end.

6.4.2.2 Update UCAS-SEAD Program Metrics

In this section, the UCAS-SEAD DST is used to update program "robustness" assessment results during a notional review. This is to demonstrate how the UCAS-SEAD DST and the ENTERPRISE methodology in generate can be iterated throughout the acquisition lifecycle to provide decision-makers with an assessment of program "robustness" that can then be used to make critical program decisions once technology development has commenced.

For this application, the author will assume that a period of five years has passed since the initial selection of the UCAS-SEAD technology and both technologies have been matured to TRL 6 at a total cost of $35 Million. Since the technologies have increased in maturity since the initial selection during the AoA, updated Technology Impact Matrices as well as development time and schedule estimates for each technology are required. Once again, the author will fabricate this data for this methodology demonstration, but in real world applications, such information would come from the technologists and relevant experts. The updated impact, cost, and schedule estimations for the three selected technologies are listed in the proceeding pages. Note that because all three technologies are at TRL 6, only the estimations for transition activities from TRL 6 to TRL 9 have changed. In addition, since the cost estimations are based on the schedule estimations in the notional UCAS-SEAD technology development models, changes in schedule estimations will automatically result in cost estimation changes as well.

Table 47: Updated TIM for Notional UCAS-SEAD Advanced Stealth Planform Alignment (ST-2) Technology

Parameter	*Low*	*High*	*Likely*
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)	-60%	-85%	-75%
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 48: Updated TIM for Notional UCAS-SEAD Long Range Air-to-ground Missile (WP-1) Technology

Parameter	*Low*	*High*	*Likely*
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor	1	2.5	2
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 49: Updated TIM for Notional UCAS-SEAD Sensor Jamming (EW-1) Technology

Parameter	*Low*	*High*	*Likely*
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)	-55%	-75%	-65%
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)	-55%	-75%	-65%
input-Red-pComm_success			

Table 50: Updated Maturation Activities Schedule Estimates for Notional UCAS-SEAD Advanced Stealth Planform Technology

Moving From (Yrs)	Low	High	Likely
TRL 6 to 7	2.00	4.50	3.00
TRL 7 to 8	2.25	5.50	4.00
TRL 8 to 9	2.00	5.00	3.50

Table 51: Updated Maturation Activities Schedule Estimates for Notional UCAS-SEAD Long Range Air-to-ground Missile Technology

Moving From (Yrs)	Low	High	Likely
TRL 6 to 7	1.25	2.75	2.00
TRL 7 to 8	1.50	3.00	2.25
TRL 8 to 9	1.00	3.00	2.00

Table 52: Updated Maturation Activities Schedule Estimates for Notional UCAS-SEAD Sensor Jamming Technology

Moving From (Yrs)	Low	High	Likely
TRL 6 to 7	0.50	3.00	2.00
TRL 7 to 8	1.00	5.00	3.00
TRL 8 to 9	1.00	4.00	2.50

Using these new uncertainty assumptions, a new set of program "robustness" metrics were generated:

Table 53: Updated Robustness Scores for Notional UCAS-SEAD Technology Portfolio

	% Red Killed 24hrs		% Blue Killed		Time to TRL 9	Cost to TRL 9	R_Low	R_High	R_Avg
	Low	High	Low	High					
Initial	91%	91%	93%	95%	20%	94%	**8.54**	**8.66**	**8.6**
Current	100%	100%	100%	100%	30%	55%	**8.85**	**8.85**	**8.85**

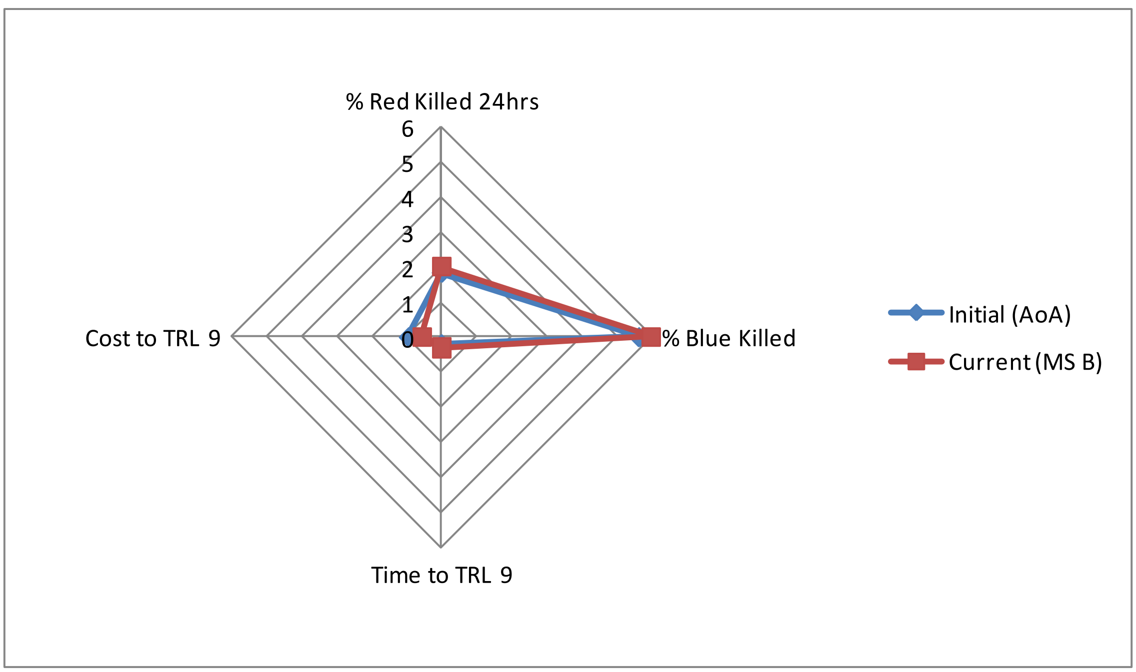


Figure 82: Radar Diagram Comparing Initial and Current Average Robustness for Notional UCAS-SEAD Technology Portfolio

Looking at Figure 82 and comparing Table 44 Table 53, it appears that the *R_Avg* score of the selected UCAS-SEAD technology portfolio has decreased slightly. **While the probability of meeting program schedule has increased to 30% (still unacceptably low), the probability of meeting program budget has dropped to 55%.** It appears that the costs required to mature the technologies to TRL 6 exceed conservative estimates and has reduced the robustness of program budget against technology development uncertainties and increase the risks of budget overruns.

At this point, it is up to the decision-makers and the Program Managers to decide on the best course of action to manage and/or mitigate this decrease in program robustness (which translates to an overall increase in program risk). For example, additional sensitivity studies can be conducted to determine the sensitivity of requirements robustness to external factors. However, since this is only a demonstration application using notional data, such analyses are beyond the intended purposes of this work. As such, this concludes the demonstration application of the ENTERPRISE method on a notional acquisition program.

6.5 Summary

In order to test the three research Hypotheses and assess method performance, the ENTERPRISE methodology was tested on a notional program for acquiring *Carried-based Suppression of Enemy Air Defenses* capability through the development of an *Unmanned Combat Aircraft System* (UCAS) and associated technology elements. For this example problem, program robustness was measured using the probability of meeting target constraints for two capability metrics and two time and cost metrics. Thanks to Bagdatli and his team, an existing and usable Agent-based model created using NetLogo for capturing UCAS technology performance on Carrier-based SEAD was available (with some modifications) and thus did not require the author to create a new technology performance impact model. As noted in Section 2.2.2.4.3, such models typically take the form of a Discrete Event Simulation. In the absence or inability to create such a model, existing Empirical and Physics-based models can be used but would require additional inputs from experts in order to establish the relationship between technology/system performance and system effective/capability.

Because of the notional nature of the identified UCAS technologies, creating a high-fidelity Project Network-based model of each technology's development was not possible. Instead, the author created a simple linear technology development model that consisted of each of the nine TRL transitions. Published NASA data on the average and standard deviation values for each transition were then used to establish the time and cost associated with each technology's development activities.

In order to provide a probabilistic analysis of the performance impact and development time and cost uncertainties associated with proposed UCAS technologies these models were coupled with Oracle Crystal Ball, an Excel-based probabilistic analysis package that allowed MCS to be setup and conducted easily and intuitively. However, because of the time requirements associated with the NetLogo model, it was decided that surrogates for predicting UCAS-SEAD output metrics would be used during the MCS. Normally, Surrogate Model creation requires regression against the results of a single set of runs described by a Design of Experiments. However, because of the stochastic nature of the UCAS-SEAD model, multiple repetitions for each DoE run had to be conducted and Surrogates for the mean and standard deviation values were created. Combined, these two values could be used to adequate predict the behavior of the UCAS-SEAD model against varying input parameters and stochastic effects.

Once the probabilistic analysis environments were created, they were embedded within a MOGA-based optimizer so that optimal technology portfolio solutions could be generated. Since this application of the ENTERPRISE methodology was academic and not in support of an actual acquisition program, a simplistic and straightforward method of calculating portfolio fitness using a *Weighted-Sum* approach was used. This approach for determining portfolio fitness required far less coding but required multiple metric weighting scenarios to be used in order to create multiple technology portfolio alternatives. Once again, for a real world application, a *Pareto Ranking* based approach to fitness determination is preferred for creating optimal solution alternatives.

Using the UCAS-SEAD TPOT tool, four technology portfolio alternatives, each reflecting a different weighting scenario, were created. These four alternatives were then assessed using a computer-based Decision Support System. This DSS, the UCAS-SEAD DST, allowed the user to input technology combinations, weighted preferences for each capability, budget, and schedule metric requirements, and, using Oracle Crystal Ball, conducted a MCS of the uncertainties associated with the selected technology combination to estimate the probability for meeting each metric constraint. These probabilities are then used to calculate a generic "robustness" score that takes into account decision-maker's preference for each metric requirement and the probability the selected technology combination will meet each metric requirement constraint.

Based on the results tradeoff study between the five generated solutions, it was decided that a technology portfolio consisting of *Long Range Air-to-ground Missile*, *Sensor Jamming*, and *Advanced Stealth Planform* technologies allowed program requirements to be most robust against technology performance and development uncertainties. However, a follow-up evaluation of program robustness using "updated" technology data (fabricated by the author) revealed that initial constraints set for program budget and cost were too restrictive. In order to reduce the risk going over budget/schedule, changes are necessary (the decisions that needed to be made or should be made for reducing these risks are outside the scope of this research).

Despite the notional nature of this proof-of-concept demonstration, it is still possible to draw conclusions and identify lessons-learned that can be used to refine then ENTERPRISE process for future applications. Discussions of these topics will be provided in the concluding chapter of this thesis.

CHAPTER 7 - CONCLUSIONS

The focus of this thesis is on the formulation of a conceptual approach for assessing acquisition requirements robustness against technology performance and development uncertainties. As noted in Chapter 1, such uncertainties have plagues recent acquisition programs and have led to significant budget and schedule overruns (or in the case of the *Comanche*, outright cancellation) and negatively impacting the overall robustness of acquisition programs. Using the current TRA process, Program Managers and decision-makers can only make a subjective and qualitative estimation of program requirements robustness based on the assumption that higher TRL meant lower uncertainty and thus there will be a better chance that the program will be robust against technology uncertainties. As such, a new process was needed that provided a more informed assessment of program "robustness." The results of such an assessment would enable a more informed selection of technology development portfolio during the Analysis of Alternatives phase of the acquisition lifecycle as well as improving program risk mitigation strategy formulation. Because of the complex nature of defense acquisition, the objective was to formulate a general approach for providing such an assessment that, with future research and refinements will provide the analytical capabilities needed by acquisition decision-makers.

In Chapter 2, relevant background information was provided. This investigation included examination of materials relating to statistical robustness assessment, qualitative and quantitative technology forecasting, multi-criteria decision-making, and decision-support approaches and techniques. In Chapter 3, current implementations of these approaches and techniques within the aerospace and acquisition communities were evaluated. Based on the results of this benchmarking, it was concluded that a new approach that combined elements of the existing approaches could be formulated to provide the necessary requirements robustness assessment needed to support early phase defense acquisition decision-making. Chapter 4 provided the formulation details for Hypotheses for addressing the Research Questions posed in Chapter 1. These Hypotheses were constructed using the observations and conclusions made in Chapters 2 and 3

In Chapter 5, the ENhanced TEchnology Robustness Prediction and RISk Evaluation (ENTERPRISE) method was formulated to provide acquisition decision-makers with a probabilistic and quantitative process for assessing program robustness against technology performance and development uncertainties. By coupling parametric and quantitative models of technology performance impact and development forecasting models with a Monte Carlo Simulation probabilistic analysis technique, variations in metric requirements could be established and used to assess program robustness. Furthermore, by embedding these analysis elements into a MOGA-based technology optimization tool, candidate solutions for meeting program robustness requirements could be identified. These solutions could then be compared against one another so that the portfolio that best meets decision-maker requirements and "robustness" criteria can be selected for development. Using the computer-based DSS, the assessment results can be updated with new data such as updated technology performance and/or development uncertainty assumptions and estimations or changing program requirements caused by external events such as congressional budget cuts and changes in defense strategy. The new results would provide decision-makers with an updated assessment of program robustness and allow them to formulate future program development and risk management strategies.

7.1 Hypotheses Resolution

Because of the notional nature of the UCAS-SEAD proof-of-concept problem, the results from Chapter 6 cannot provide an absolute confirmation or invalidation of the Hypotheses constructed for this thesis. As such, the intent is to test the Hypotheses and speculate on their validity using the results from the notional application. The results of these tests can then be used in the future to conduct true confirmation/rejection tests of these Hypotheses.

Confirmation of Hypothesis I requires demonstrating that the outputs of a probabilistic and quantitative analysis of technology performance impact and development activities models provided a more informed assessment of requirements robustness against technology performance and development uncertainties. As demonstrated by the notional application, the probabilities of meeting program capability, budget, and schedule requirement constraints were calculated using the results of a probabilistic analysis on technology performance impact and development activities models. These probabilities provided an estimation of the likelihood of requirements success *despite* technology performance and uncertainties and thus provided decision-makers with a measure of requirements robustness against such uncertainties. Using the current TRA process, which is based on the TRL metric, no estimation, qualitative or quantitative, of the impacts of technology performance and developments on program requirements is possible. Thus no measurable degree of program or requirements robustness can be provided for decision-makers. Demonstration of this capability in the future for a real-world application will verify the validity of this Hypothesis.

In order to prove Hypothesis II, one or more of the optimal solutions identified by a MOGA-based technology portfolio optimizer had to adequately meet or even exceed identified decision-maker robustness criteria. For the demonstration problem, the identified combination of *Long Range Air-to-ground Missile*, *Sensor Jamming*, and *Advanced Stealth Planform Alignment* technology provided acceptable requirements robustness against technology uncertainties. The analysis results of the probabilities of success for meeting program requirements constraints show that this particular combination of technologies (one of four outputted by the UCAS-SEAD TPOT) results in a system that had a very high chance of meeting capability requirements but not so good chances of meeting program budget and schedule. However, because optimization emphasis was placed on capability metric requirements over program budget/schedule requirements, this was expected and supports Hypothesis II.

In order to speculate on the validity of Hypothesis III, the author had to show that the use of a computer-based Decision Support System lead to more informed acquisition decisions. During Phase IV of the demonstration ENTERPRISE application, the UCAS-SEAD DST allowed the decision-maker to rapidly assess the tradeoffs in probabilities of meeting requirement constraints and generic "robustness scores" for candidate portfolios by changing metric constraints. The results of these tradeoffs allowed the selection of the two UCAS-SEAD program technologies to be justified using quantitative and objective data. Without the use of the UCAS-SEAD DST, such rapid and interactive assessment would not be possible. In addition, during the notional program review, the UCAS-SEAD DST results clearly showed the relatively high probability of program budget and schedule overruns. Using the TRA, no such knowledge would have been provided to the decision-makers and since both technologies were at TRL 6, the program would have moved beyond Milestone B of the acquisition process. The leads the author to believe that true confirmation of this Hypothesis can be obtained by applying the ENTERPRISE process along-side the TRA process for an on-going acquisition program.

7.2 Method Sensitivity

Although the ENTERPRISE mythology has been shown to notionally meet the needs for early-acquisition assessment of requirements robustness against technology performance and development uncertainties, questions can still arrive as to the sensitivity of the process to changes in resources available and techniques used for each specific application. This section attempts to address some of these sensitivity questions.

7.2.1 Limited Expert Input

In order to conduct a probabilistic analysis of technology performance impact and development activities times and costs, estimations of the uncertainties around these values need to be obtained from experts. Logically, if a technology is being developed or being considered for development, there should exist at least one or more persons that are familiar enough with the technology to provide even rough estimations regarding the impact and development activities, times, and costs of that technology. If the technology is a continuation or derivative of existing technologies (matured or under development), then experts and existing data from those technologies should be consulted as well. If, for whatever realistic reason, no experts exist for a given technology, then all efforts should be put into identifying, training, or whatever means necessary to create one or more experts who are familiar enough with the technology to provide reasonable assumptions on its performance and development uncertainties.

7.2.2 Limited Analysis Capability

At the heart of the ENTERPRISE method is the ability to quantify the impact of technology performance and development activities on program capability, budget, and schedule requirements using parametric models that can be coupled with a Monte Carlo Simulation. In the absence of such models, the first priority would of course be identifying potential ways to create these models or modify, if available, existing models to suit analysis purposes. For example, if an empirical or physics-based model exists to calculate the performance measures associated with a system (e.g. speed, weight, turning radius) infused with a set of enabling technologies, then focus should be placed on quantifying/qualifying the relationship between these measures and capability metrics. The most effective and logical way to do this is by soliciting expert knowledge or by examining past data of similar systems with similar capability requirements. If creation of parametric models of any kind is not possible, then qualitative relationships between technologies and requirement metrics should be established and used instead. However, as noted during the examination of Raczynski's SOAR methodology, these relationships do not lend themselves very well to probabilistic uncertainty analysis and would instead require Possibility Theory or Fuzzy Logic techniques to be used instead. While not as quantitative and objective, application of these techniques during an ENTERPRISE application would still provide far more informative results than existing acquisition technology uncertainty analysis processes.

7.2.3 Limited Decision-Maker Input

Another key assumption in the ENTERPRISE methodology is the availability of decision-maker input. Throughout the application process, decision-maker inputs, requirements, and preferences are used to identify robustness evaluation metrics (Phase I and Phase IV), identify optimization objectives (Phase III if using multi-objective optimization techniques), assign weights/importance values to each metric (Phase III if using weighting objective functions for optimization or MADM techniques for selection and Phase IV), and evaluate portfolio robustness. If this level of decision-maker involvement is not possible, then assumptions on their wishes and preferences have to be made. Obviously, this could result in reduced or complete lack of decision-maker buy-in at the end if the assumptions are completely wrong. However, in most realistic scenarios, even if the decision-makers themselves are not readily available there will be persons (aids, assistants, second-in-commands, etc…) that can be used to approximate decisions-maker feedback. In these situations, it would be wiser to widen the scope a bit (e.g. include additional requirements/robustness metrics, multiple constraint values, etc…) in the hopes that the actual decision-makers' inputs/feedbacks are captured. Additionally, one of the main reasons for using a computer-based Decision Support System is because it's interactive and rapid analysis features allows assumption on requirements/weights/constraints/etc… to be updated and results re-generated quickly and efficiently. This prevents having to reschedule additional meetings with decision-makers because additional analysis time is necessary.

7.3 Contributions

As noted, there is a significant gap between the DoD's current approach for assessing program robustness and risk using the Technology Readiness Level and a probabilistic and quantitative assessment of acquisition program requirements. According to Dr. Cynthia Dion-Schwarz, Associate Director of the Network Technologies group within the Office of the Under Secretary of Defense for Acquisitions, Technologies, and Logistics, "the TRL value does not indicate that the technology is right for the job or that application of the technology will result in successful development of the [program and the system]" [36]. The proposed ENTERPRISE methodology is a first attempt at providing the answers to these questions. It provides a structured process for integrating various forecasting, multi-criteria decision-making, and decision-support techniques to provide a probabilistic and quantitative technology performance impact and development forecasting models to generate the statistical data needed to quantitatively predict requirements robustness. The results of the robustness assessment indicates to the decision-makers whether or not the technology or set of technologies being developed for the program will result in system capabilities and program budget and schedule that meet decision-maker requirements and preferences. In addition, the generic and modular nature of the steps within this process allows it to be versatile against a wide spectrum of acquisition program. For example, as newer, better, quicker, cheaper, and/or higher fidelity models become available for a given acquisition program, they can be swapped into the process to provide a higher fidelity assessment. With additional improvements and refinements, the ENTERPRISE methodology can potentially replace the current TRA process for addressing these and other additional program robustness and risk assessment questions:

- *How robust is the program to*
    - *Changes in technology portfolio (e.g. more/less technologies being developed)?*
    - *Changes in program requirements (i.e. capability, budget, and/or schedule requirements and constraints)?*
- *What is the likelihood that the final product (i.e. system) will meet expectations? What about failing to meet expectations?*
    - *What is the expected range of system performance and effectiveness?*

- *What is the expected range of program budget and schedule?*
- *What is the probability that one or more program expectations (i.e. requirements) will not be met?*

The author also demonstrated the significant and positive impact that distributed and parallel computing technologies can have when conducting time-consuming probabilistic analyses such as Monte Carlo Simulations. Implementation of these technologies allowed a much higher number of random samples to be taken during the MC simulations, which according to the principle behind MC simulations will result in a more accurate representation of the output distributions.

Another contribution was made in the use of Surrogate Models to describe the behavior of stochastic models such like the agent-based NetLogo UCAS-SEAD model used for the ENTERPRISE implementation. In the past, regressing against the mean value of output distributions for a single set of cases repeated at multiple random-seeds, or regressed against the multiple sets of data, was assumed to be sufficient to capture the stochastic behaviors of the model. However, as demonstrated in Section 6.2.2.2.2.1, the variations caused by the stochastic nature of the model can have significant impact on simulation outputs. To account for these variations, the author elected to assume a near-Normal distribution for simulation outputs and created surrogates for predicting the mean *and* standard deviation values. This allowed a range of potential simulation outputs to be described within a certain tolerance (for pure Normal distribution, ~ 2/3rds of the values within +/- 1 standard deviation). This information was then taken into account by the MOGA-based technology portfolio optimizer and the computer-based Decision Support

System so that the group of technologies that was robust against not only the performance and development uncertainties associated of each technology, but also the stochastic uncertainties associated with the model.

The significant increase in computational power afforded by parallel computing capabilities within MATLAB also enabled the author to implement a probabilistic, Multi-Objective Genetic Algorithm optimization scheme rather than a deterministic one. This meant that the calculated fitness value of each population member better takes into account the uncertainty associated with each technology combination and the optimized result has a higher probability of meeting defined constraints and requirements despite its uncertainties.

Lastly, the author demonstrated how the program requirements/robustness metrics can be updated rapidly and visually using a Decision Support System and used to support decision-making throughout the acquisition process. Using the UCAS-SEAD DST to assess the risks to program metric requirements stemming from technology impact, cost, and schedule uncertainty and use the results to first finalize the UCAS program technology portfolio according to the risks (Section 6.4.2.1) and then update program risk levels during a subsequent program review (Section 6.4.2.2). Considering the significant upfront investment of time and money needed to conduct the ENTERPRISE methodology for a real world acquisition program, this rapid updating of program risk implications further speaks to the utility of the ENTERPRISE methodology and its output products.

7.4 Limitations and Recommendations for Future Work

During the course of this research, in particular during demonstration application of the ENTERPRISE process, many simplifications and assumptions were made that affected the validity and usability of the results. However, without these simplifications it would not have been possible to demonstrate the ENTERPRISE process within the time frame and research breadth and scope appropriate for a Ph.D. thesis. This section will list these limitations and provide recommendations for future work addressing them.

Use of Notional/Fabricated Technology Data

Because of the sensitive nature of acquisition technology problems, notional data was used for defining technology performance impacts and development activity times and costs. Since this data was fabricated primarily by the author, a process for gathering and collecting such information was not discussed nor provided. Since the validity of any analysis result depends on the validity of the data inputted into the process (e.g. technology impact, cost, and schedule parameter distribution estimations), future applications should utilize established data gathering techniques that can efficiently obtain relevant from Subject Matter Experts. An example would be the Technology Audit Sheets used by the TMAT process for collecting expert opinions on technology performance uncertainty distributions and ranges.

Use of Generic/Un-validated Technology Forecasting Models

Because of the existence of a usable model for capturing UCAS technology performance impacts on SEAD capability metrics, the process of creating and validating a technology performance impact model was not investigated. However, the verification & validation of models, especially those with non-linear and non-mathematical formulations such as an Agent-based model, is important in obtaining SME and decision-maker buy-in on analysis results. If accuracy of the technology impact models is in doubt, the output analyses generated by these models will be as well. As such, future iterations of the ENTERPRISE process should demonstrate a process for validating or at least verifying the accuracy/usability of the technology performance impact models. The same could be said for the technology development time and cost models.

In line with the previous item, potential process for identifying technology development activities and other appropriate methods for modeling them should be investigated. Because of the notional nature of the UCAS-SEAD technologies and the lack of relevant expert input, TRL transitions were used as technology development activities. While the use of these generic activities were sufficient for method demonstration purposes, real world applications would likely require a more in-depth analysis involving the specific activities associated with each technology's development. These higher-fidelity analyses would better capture the uncertainties specific to each technology's development.

Limited Capturing of Stochastic Behavior of Agent-based Model

Another potential area for improvement is the investigation of methods for surrogating the stochastic behavior of agent-based/discrete event simulation models. In the UCAS-SEAD demonstration, the limited number of data allowed only for a regression against the mean and standard deviation values of output metric distribution. While these parameters are adequate for demonstration purposes, a higher-fidelity capturing is desirable. For example, regressions against two or even three standard deviations would allow for a greater percentage of the variations of the model associated with its stochastic behavior to be captured. Furthermore, the assumption of a Normal distribution for metric distributions was acceptable for this particular agent-based model but for other models a Beta or other distribution functions might their stochastic behavior. A structured and rigorous process for creating surrogates for describing such behavior would provide tremendous benefits not only to acquisition decision-making, but to the modeling & simulation community in general.

Use of Weighted-Sum MOGA Approach

Because of the difficulties in implementing a Pareto Dominance-based MOGA for, a weight-sum MOGA approach was implemented for the demonstration application. While this approach is simpler and more straightforward to implement, it is not suited for non-convex solution spaces and requires a pre-determine set of weights to be defined for each optimization objective. The sensitivity of the generated solutions to these weighting scenarios could result in sub-optimal technology portfolios if the scenarios do not perfect match decision-maker preferences. Future applications of the ENTERPRISE methodology should consider using one of the Pareto Dominance-based MOGA listed in Table 4 (or develop a new approach) when generation technology portfolio alternatives. These approaches ensure that the technology portfolio alternatives generated and presented to the decision-makers are, at a minimum, a representative subset of the Pareto optimal solution set that best meets their requirements and preferences.

Limited Statistical Analysis Capabilities of Current Decision Support System

The demonstrated ENTERPRISE implementation utilized a Decision Support System built using Microsoft Excel. This was based on the author's familiarity with the software and its portability. However, as shown repeatedly in during Steps 11 and 12, limited statistical and visual analytical capabilities associated with Excel reduced the effectiveness of the UCAS-SEAD DST.

As noted in Section 6.4.1.2.1, joint probabilistic decision-making formulations are more appropriate for multi-variate probabilistic analysis problems such as the one demonstrated in Chapter 6. However, because of the limited capabilities of Excel and the academic version of Oracle Crystal Ball, the author had to resort to using marginal probabilities for assessing the "goodness" of candidate technology portfolios. To ensure highest probability of selecting the "best" and most optimal solution, future applications of the ENTERPRISE process should utilize an environment better suited for conducting joint probabilistic analyses. An example of such an environment is the JMP statistical analysis package developed by the SAS Institute.

Limitations with Excel also hampered the ability to conduct sensitivity studies using the UCAS-SEAD DST. Evaluating the sensitivity of the robustness of candidate solutions to changing requirements required manual iterations of inputting parameters and recording solutions. The use of CDF plots and data table may be acceptable when conducting a detailed analysis of requirements robustness sensitivities, they are probably inappropriate for a decision support tool meant to assist decision-makers. More visually intuitive representations of such data based on normative decision theory and visual analytics techniques should be considered when creating computer-based Decision Support Systems for future ENTERPRISE applications.

Finally, since the objective of the current *capabilities-based* acquisition policy is to provide overall force robustness, a logical evolution for the ENTERPRISE methodology would be to bring in additional elements that allow for assessing the robustness of the requirements and technologies against changing enemy behaviors, environments, and tactics.

7.5 Final Remarks

The prime directive of this research is to provide narrow the gap between the current Technology Readiness Assessment process and a probabilistic and quantitative assessment of program requirements robustness for support early phase acquisition decisions. Even though the simplifications made during the course of this research made the results notional and academic, the provided framework and proposed ENTERPRISE methodology meets this objective and serves as a roadmap towards the development of a more refined and useful acquisition requirements robustness assessment process.

Finally, the author would like to point out that in general, the decisions made during critical acquisition program junctures consist of more than just selecting the technologies to develop or estimating the likelihood of meeting program requirements. Other decisions such as resource allocation, program development planning, and program risk management strategy formulation are all part of the decisions that are made early on and throughout the entire acquisition lifecycle. As such, the results of the ENTERPRISE process need be combined the results of other acquisition decision support activities in order to ensure a truly *capable* and *robust* United States military.

Appendix A - DoD TRL Definitions

The DoD's TRL definitions for hardware, software, and manufacturing technologies are listed in the tables below.

Table 54: Hardware TRL Definitions

TRL	Definition	Description
1	Basic principles observed and reported	Lowest level of technology readiness. Scientific research begins to be translated into applied research and development. Examples might include paper studies of a technology's basic properties.
2	Technology concept and/or application formulated	Invention begins. Once basic principles are observed, practical applications can be invented. Applications are speculative and there may be no proof or detailed analysis to support the assumptions. Examples are limited to analytic studies.
3	Analytical and experimental critical functions and/or characteristic proof-of-concept	Active research and development is initiated. This includes analytical studies and laboratory studies to physically validate analytical predictions of separate elements of the technology. Examples include components that are not yet integrated or representative.
4	Component and/or breadboard validation in laboratory environment	Basic technological components are integrated to establish that they will work together. This is relatively "low fidelity" compared to the eventual system. Examples include integration of "ad hoc" hardware in the laboratory.
5	Component and/or breadboard validation in relevant environment	Fidelity of breadboard technology increases significantly. The basic technological components are integrated with reasonably realistic supporting elements so it can be tested in a simulated environment. Examples include "high fidelity" laboratory integration of components.

6	System/subsystem model or prototype demonstration in a relevant environment	Representative model or prototype system, which is well beyond that of TRL 5, is tested in a relevant environment. Represents a major step up in a technology's demonstrated readiness. Examples include testing a prototype in a high-fidelity laboratory environment or in simulated operational environment.
7	System prototype demonstration in an operational environment	Prototype near, or at, planned operational system. Represents a major step up from TRL 6, requiring demonstration of an actual system prototype in an operational environment such as an aircraft, vehicle, or space. Examples include testing the prototype in a test bed aircraft.
8	Actual system completed and qualified through test and demonstration	Technology has been proven to work in its final form and under expected conditions. In almost all cases, this TRL represents the end of true system development. Examples include developmental test and evaluation of the system in its intended weapon system to determine if it meets design specifications.
9	Actual system proven through successful mission operations	Actual application of the technology in its final form and under mission conditions, such as those encountered in operational test and evaluation. Examples include using the system under operational mission conditions.

Appendix B - Notional TRL Transition Time Estimates for UCAS-SEAD Enabling Technologies

Table 55: Technology AF-1 TRL Transition Time Estimates

AF-1: Advance Aircraft Wing Folding and Fuselage Telescoping			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4	0.60	2.60	1.60
TRL 4 to 5	0.80	2.00	1.40
TRL 5 to 6	0.88	5.45	2.40
TRL 6 to 7	0.65	3.15	1.90
TRL 7 to 8	0.75	4.25	2.50
TRL 8 to 9	0.45	3.55	2.00

Table 56: Technology AF-2 TRL Transition Time Estimates

AF-1: Advance Aircraft Wing Folding and Fuselage Telescoping			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4	0.60	2.60	1.60
TRL 4 to 5	0.80	2.00	1.40
TRL 5 to 6	0.88	5.45	2.40
TRL 6 to 7	0.65	3.15	1.90
TRL 7 to 8	0.75	4.25	2.50
TRL 8 to 9	0.45	3.55	2.00

Table 57: Technology AF-3 TRL Transition Time Estimates

AF-3: High L/D Aeroconfiguration			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5			
TRL 5 to 6	0.63	3.68	2.15
TRL 6 to 7	1.03	2.28	1.65
TRL 7 to 8	1.38	3.13	2.25
TRL 8 to 9	0.98	2.53	1.75

Table 58: Technology AF-4 TRL Transition Time Estimates

AF-4: Embedded Fuel Pods			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5	1.50	2.70	2.10
TRL 5 to 6	1.58	6.15	3.10
TRL 6 to 7	1.35	3.85	2.60
TRL 7 to 8	1.45	4.95	3.20
TRL 8 to 9	1.15	4.25	2.70

Table 59: Technology AF-5 TRL Transition Time Estimates

AF-5: Efficient Transonic Planform			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5	1.55	2.75	2.15
TRL 5 to 6	1.63	6.20	3.15
TRL 6 to 7	1.40	3.90	2.65
TRL 7 to 8	1.50	5.00	3.25
TRL 8 to 9	1.20	4.30	2.75

Table 60: Technology PR-1 TRL Transition Time Estimates

PR-1: Efficient Propulsion Installation			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5			
TRL 5 to 6	0.93	5.50	2.45
TRL 6 to 7	0.70	3.20	1.95
TRL 7 to 8	0.80	4.30	2.55
TRL 8 to 9	0.50	3.60	2.05

Table 61: Technology PR-2 TRL Transition Time Estimates

PR-2: Durable High Temp Core and Fuel Efficicient Turbine Engine			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5	1.35	2.55	1.95
TRL 5 to 6	1.43	6.00	2.95
TRL 6 to 7	1.20	3.70	2.45
TRL 7 to 8	1.30	4.80	3.05
TRL 8 to 9	1.00	4.10	2.55

Table 62: Technology ST-1 TRL Transition Time Estimates

ST-1: Advanced Radar Absorption Materials			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4	2.30	4.30	3.30
TRL 4 to 5	2.50	3.70	3.10
TRL 5 to 6	2.58	7.15	4.10
TRL 6 to 7	2.35	4.85	3.60
TRL 7 to 8	2.45	5.95	4.20
TRL 8 to 9	2.15	5.25	3.70

Table 63: Technology ST-2 TRL Transition Time Estimates

ST-2: Advanced Stealth Planform Alignment			
TRL Transition	Low	High	Likely
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5	1.90	3.10	2.50
TRL 5 to 6	1.98	6.55	3.50
TRL 6 to 7	1.75	4.25	3.00
TRL 7 to 8	1.85	5.35	3.60
TRL 8 to 9	1.55	4.65	3.10

Table 64: Technology ST-3 TRL Transition Time Estimates

ST-3: Embedded Engines			
TRL Transition	Low	High	Likely
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5	1.15	2.35	1.75
TRL 5 to 6	1.23	5.80	2.75
TRL 6 to 7	1.00	3.50	2.25
TRL 7 to 8	1.10	4.60	2.85
TRL 8 to 9	0.80	3.90	2.35

Table 65: Technology ST-4 TRL Transition Time Estimates

ST-4: Non-metallic Dielectric Airframe			
TRL Transition	Low	High	Likely
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4	2.05	4.05	3.05
TRL 4 to 5	2.25	3.45	2.85
TRL 5 to 6	2.33	6.90	3.85
TRL 6 to 7	2.10	4.60	3.35
TRL 7 to 8	2.20	5.70	3.95
TRL 8 to 9	1.90	5.00	3.45

Table 66: Technology WP-1 TRL Transition Time Estimates

WP-1: Long Range Air-to-ground Missile			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5	0.85	1.45	1.15
TRL 5 to 6	0.63	3.68	2.15
TRL 6 to 7	1.03	2.28	1.65
TRL 7 to 8	1.38	3.13	2.25
TRL 8 to 9	0.98	2.53	1.75

Table 67: Technology WP-2 TRL Transition Time Estimates

WP-2: Stealthy Air-to-ground Missile			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4	1.55	3.55	2.55
TRL 4 to 5	1.75	2.95	2.35
TRL 5 to 6	1.83	6.40	3.35
TRL 6 to 7	1.60	4.10	2.85
TRL 7 to 8	1.70	5.20	3.45
TRL 8 to 9	1.40	4.50	2.95

Table 68: Technology EW-1 TRL Transition Time Estimates

EW-1: Sensor Jamming			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5			
TRL 5 to 6	0.93	5.50	2.45
TRL 6 to 7	0.70	3.20	1.95
TRL 7 to 8	0.80	4.30	2.55
TRL 8 to 9	0.50	3.60	2.05

Table 69: Technology EW-2 TRL Transition Time Estimates

EW-2: Missile Lock Inteference			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4	1.30	3.30	2.30
TRL 4 to 5	1.50	2.70	2.10
TRL 5 to 6	1.58	6.15	3.10
TRL 6 to 7	1.35	3.85	2.60
TRL 7 to 8	1.45	4.95	3.20
TRL 8 to 9	1.15	4.25	2.70

Table 70: Technology EW-3 TRL Transition Time Estimates

EW-3: Communications Jamming			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5	0.71	1.19	0.95
TRL 5 to 6	0.43	3.17	1.95
TRL 6 to 7	0.95	1.95	1.45
TRL 7 to 8	1.35	2.75	2.05
TRL 8 to 9	0.93	2.17	1.55

Table 71: Technology IR-1 TRL Transition Time Estimates

IR-1: Advanced Computer Guided Target Recognizition			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5	1.20	2.40	1.80
TRL 5 to 6	1.28	5.85	2.80
TRL 6 to 7	1.05	3.55	2.30
TRL 7 to 8	1.15	4.65	2.90
TRL 8 to 9	0.85	3.95	2.40

Table 72: Technology IR-2 TRL Transition Time Estimates

IR-2: Extended Range Sensors			
TRL Transition	**Low**	**High**	**Likely**
TRL 1 to 2			
TRL 2 to 3			
TRL 3 to 4			
TRL 4 to 5			
TRL 5 to 6	1.48	6.05	3.00
TRL 6 to 7	1.25	3.75	2.50
TRL 7 to 8	1.35	4.85	3.10
TRL 8 to 9	1.05	4.15	2.60

Appendix C - UCAS-SEAD Technology Impact Matrices

Table 73: Technology AF-1 TIM

	Airframe Tech 1: Advance Aircraft Wing Folding and Fuselage Telescoping		
Parameter	***Low***	***High***	***Likely***
input-num-Blue-UCAVs	4	8	6
input-Blue-time-to-launch-UCAVs	300	900	750
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 74: Technology AF-2 TIM

Parameter	Airframe Tech 2: Increased Internal Cargo Bay		
	Low	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor	0.25	0.75	0.5
input-Blue-UCAV-reload-time (%)	10	30	20
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles	2	4	2
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 75: Technology AF-3 TIM

Parameter	Airframe Tech 3: High L/D Aeroconfiguration		
	Low	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor	-0.05	-0.15	-0.1
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 76: Technology AF-4 TIM

Parameter	Airframe Tech 4: Embedded Fuel Pods		
	Low	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor	0.15	0.4	0.25
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)	10	20	20
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 77: Technology AF-5 TIM

Parameter	Airframe Tech 5: Efficient Transonic Planform		
	Low	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor	0.1	0.2	0.1
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor	-0.05	-0.2	-0.1
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			

Table 78: Technology PR-1 TIM

Parameter	Propulsion Tech 1: Efficient Propulsion Installation		
	Low	*High*	*Likely*
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor	-0.1	-0.25	-0.15
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 79: Technology PR-2 TIM

Parameter	Propulsion Tech 2: Durable High Temp Core and Fuel Efficicient Turbine Engine		
	Low	*High*	*Likely*
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor	0.3	0.8	0.6
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor	-0.1	-0.3	-0.2
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 80: Technology ST-1 TIM

Parameter	Stealth Tech 1: Advanced Radar Absorption Materials		
	Low	*High*	*Likely*
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)	-30	-80	-65
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 81: Technology ST-2 TIM

Parameter	Stealth Tech 2: Advanced Stealth Planform Alignment		
	Low	*High*	*Likely*
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)	-60	-95	-80
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 82: Technology ST-3 TIM

Parameter	Stealth Tech 3: Embedded Engines & Payload Hardpoints		
	Low	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)	-30	-70	-50
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor	-0.2	-0.4	-0.3
input-Blue-UCAV-endurance-k_factor	-0.1	-0.2	-0.15
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 83: Technology ST-4 TIM

Parameter	Steach Tech 4: Non-metallic Dielectric Airframe		
	Low	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)	-25	-65	-40
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor	0.1	0.2	0.15
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 84: Technology WP-1 TIM

	Weapon Tech 1: Long Range Air-to-ground Missile		
Parameter	***Low***	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor	1	3	2
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 85: Technology WP-2 TIM

	Weapon Tech 2: Stealthy Air-to-ground Missile		
Parameter	***Low***	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit	0.2	0.29	0.25
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit	0.1	0.14	0.14
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 86: Technology EW-1 TIM

	Elec. Warfare Tech 1: Sensor Jamming		
Parameter	***Low***	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)	-50	-80	-60
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)	-50	-80	-60
input-Red-pComm_success			

Table 87: Technology EW-2 TIM

	Elec. Warfare Tech 2: Missile Lock Inteference		
Parameter	***Low***	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit	-0.5	-0.9	-0.7
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 88: Technology EW-3 TIM

Parameter	Elec. Warfare Tech 3: Communications Jamming		
	Low	**High**	**Likely**
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success	-0.5	-0.9	-0.7

Table 89: Technology IR-1 TIM

Parameter	ISR Tech 1: Advanced Computer Guided Target Recognizition		
	Low	**High**	**Likely**
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)	-50	-80	-65
input-Blue-UCAV-time-to-id (%)	-50	-80	-65
input-Blue-UCAV-detect-range-k_factor			
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Table 90: Technology IR-2 TIM

	ISR Tech 2: Extended Range Sensors		
Parameter	***Low***	***High***	***Likely***
input-num-Blue-UCAVs			
input-Blue-time-to-launch-UCAVs			
input-Blue-UCAV-RCS (%)			
input-Blue-UCAV-pHit			
input-Blue-UCAV-speed-k_factor			
input-Blue-UCAV-endurance-k_factor			
input-Blue-UCAV-fuel-consumption-k_factor			
input-Blue-UCAV-reload-time (%)			
input-Blue-UCAV-time-to-assess (%)			
input-Blue-UCAV-time-to-id (%)			
input-Blue-UCAV-detect-range-k_factor	0.75	2	1.25
input-Blue-UCAV-num-air-to-ground-missiles			
input-Blue-air-to-ground-missile-range-k_factor			
input-Red-SAM-pHit			
input-Red-SAM-shoot-range (%)			
input-Red-Radar-pHit			
input-Red-Radar-detect-range (%)			
input-Red-pComm_success			

Appendix D - UCAS-SEAD Metric ANN Goodness of Fit Summary Figures

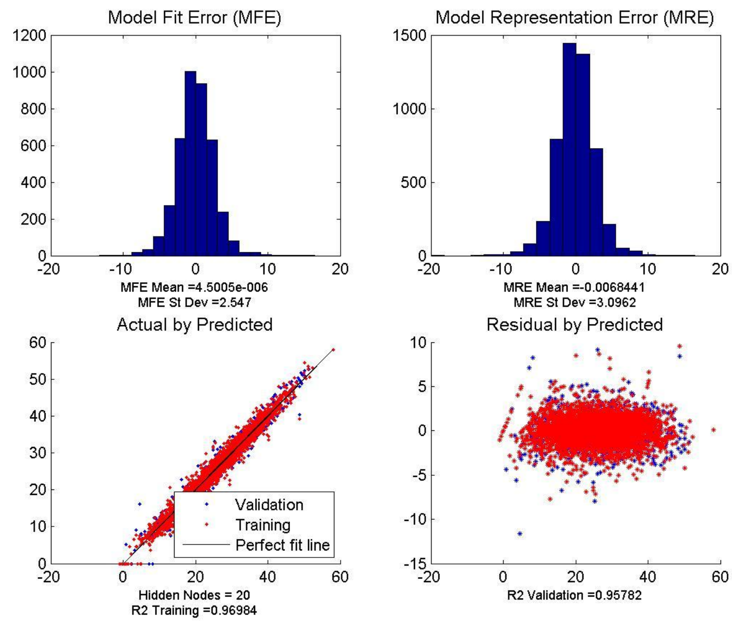


Figure 83: Goodness of Fit Summary for Mean Perc_Red_Killed_@4Hrs

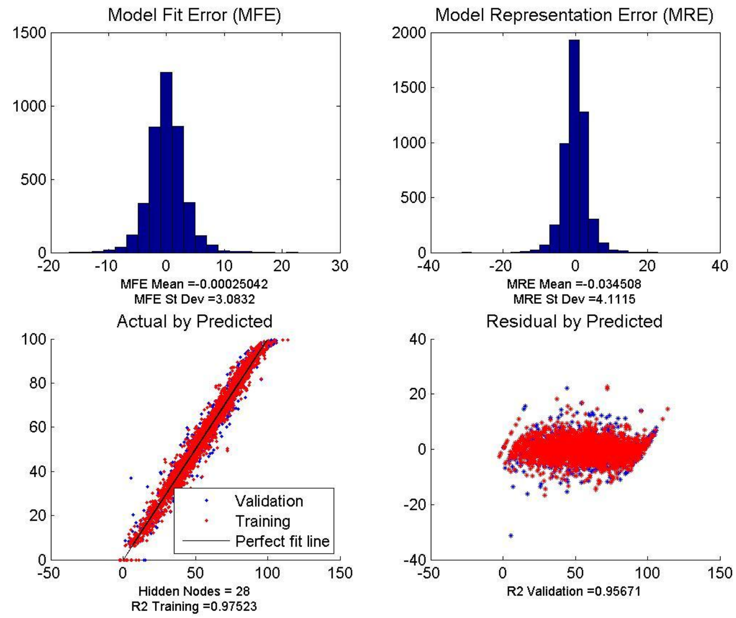


Figure 84: Goodness of Fit Summary for Mean Perc_Red_Killed_@8Hrs

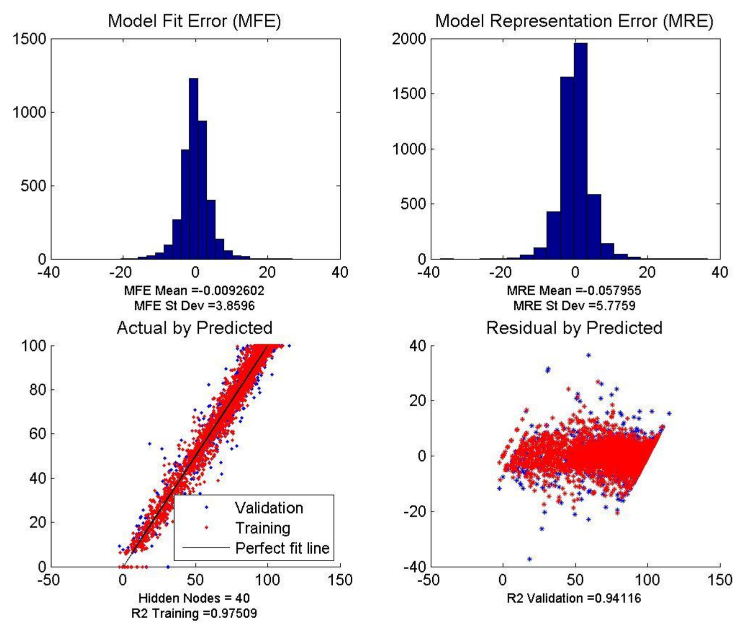


Figure 85: Goodness of Fit Summary for Mean Perc_Red_Killed_@12Hrs

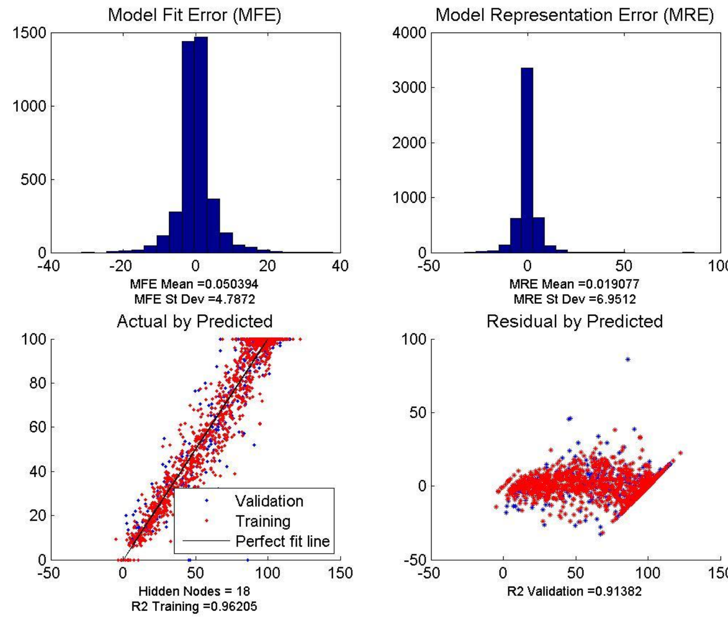


Figure 86: Goodness of Fit Summary for Mean Perc_Red_Killed_@24Hrs

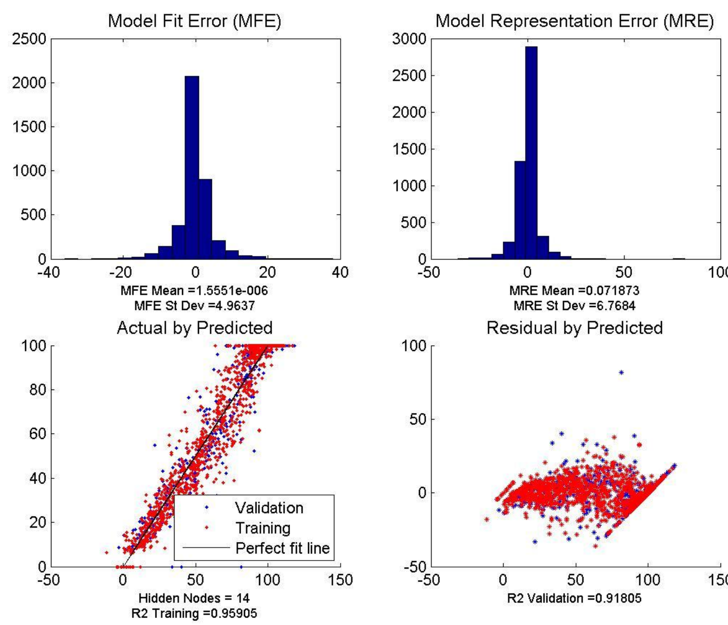


Figure 87: Goodness of Fit Summary for Mean Perc_Red_Killed_@48Hrs

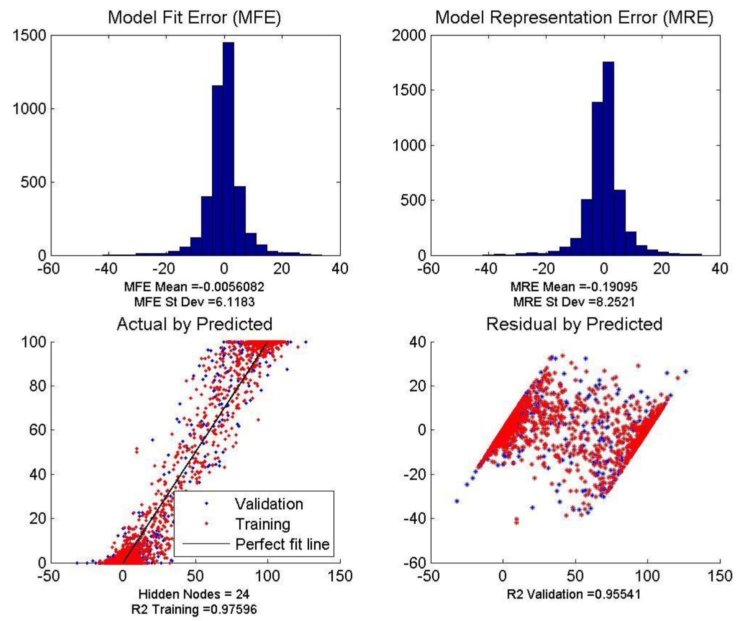


Figure 88: Goodness of Fit Summary for Mean Perc_Blue_Killed

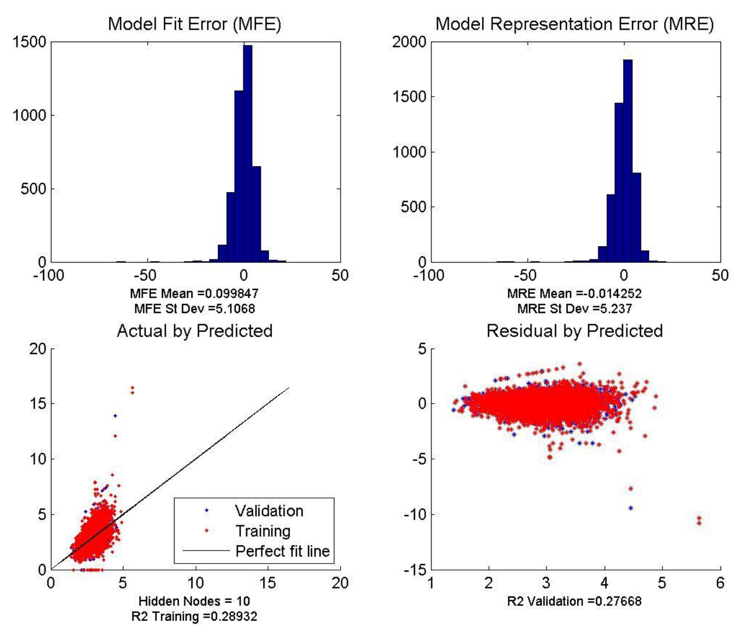


Figure 89: Goodness of Fit Summary for Std Dev Perc_Red_Killed_@4Hrs

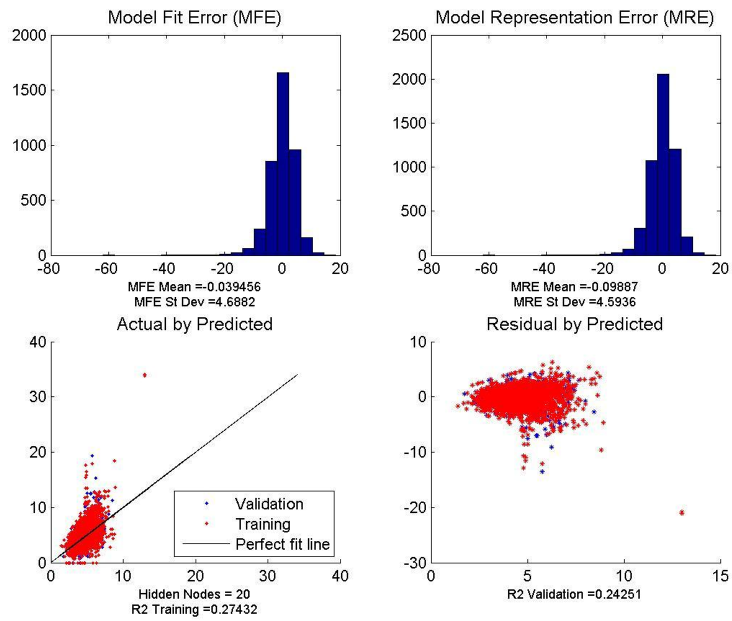


Figure 90: Goodness of Fit Summary for Std Dev Perc_Red_Killed_@8Hrs

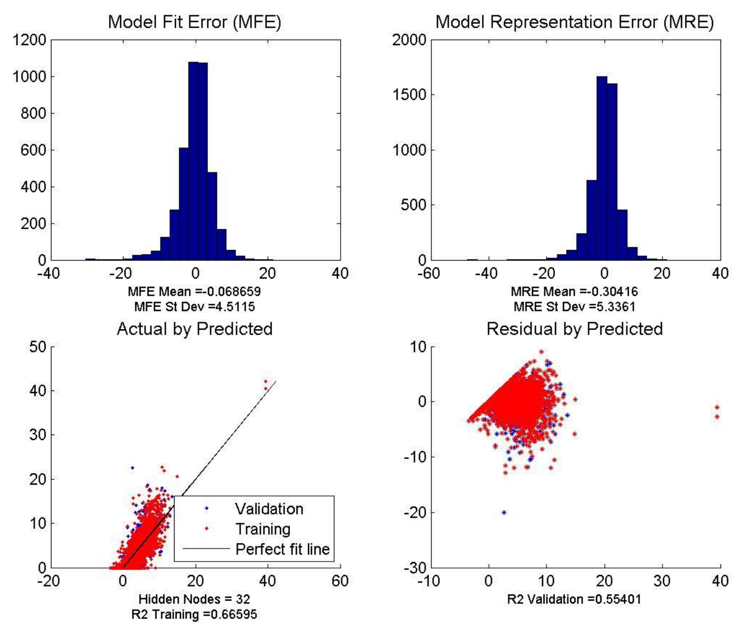


Figure 91: Goodness of Fit Summary for Std Dev Perc_Red_Killed_@12Hrs

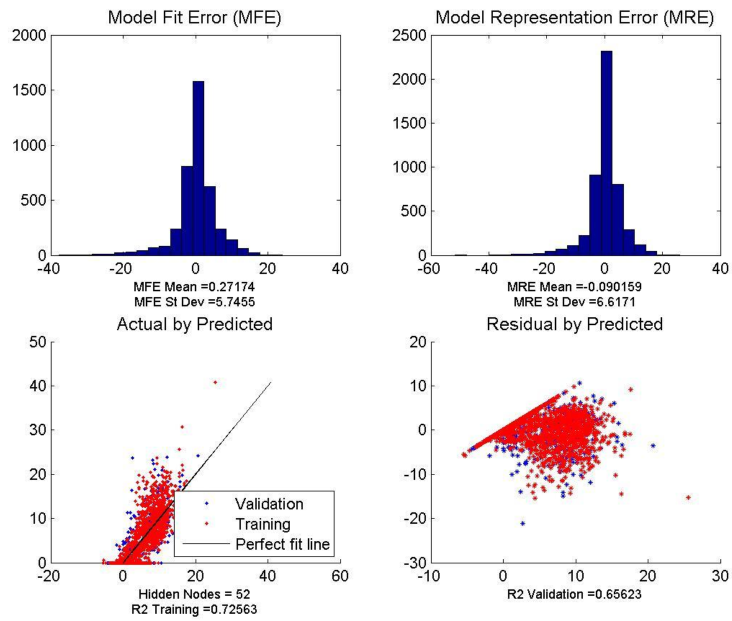


Figure 92: Goodness of Fit Summary for Std Dev Perc_Red_Killed_@24Hrs

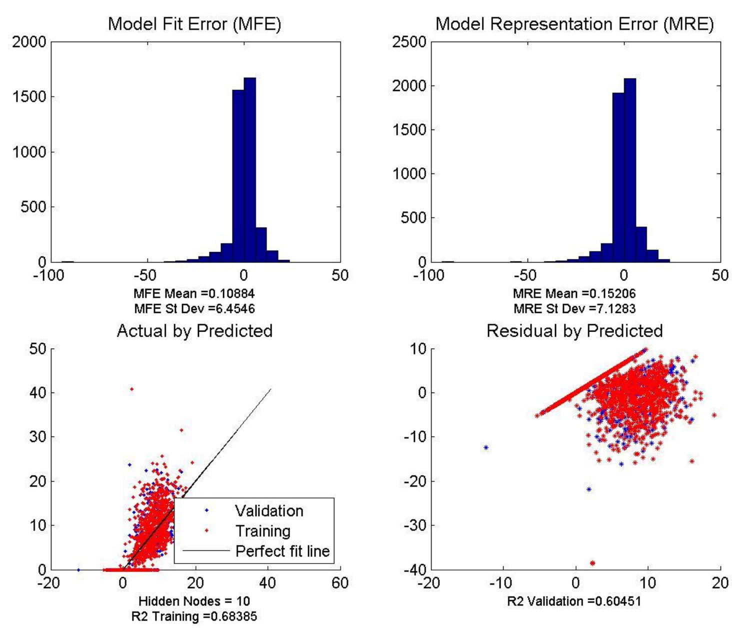


Figure 93: Goodness of Fit Summary for Std Dev Perc_Red_Killed_@48Hrs

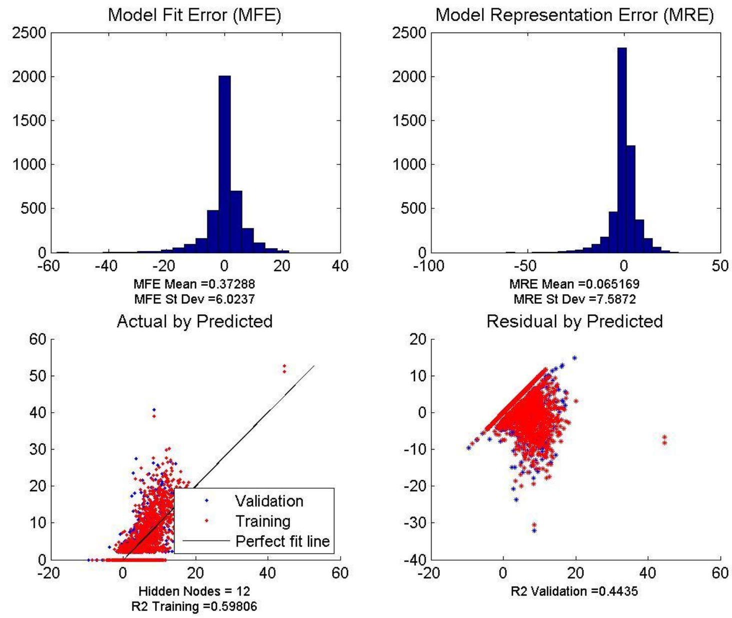


Figure 94: Goodness of Fit Summary for Std Dev Perc_Blue_Killed

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