An Integrated Cost and Performance Model to Inform Capability Selection During Early-Phase Systems Engineering: Case Analysis and Multi-Objective Optimization

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Dedication

The author wishes to dedicate this dissertation to his father, Dr. Raoul A. DeVilliers. As the former Dean of Mathematics and Science at Sacred Heart University, he always valued education and did his upmost to improve his university and the academic profession. He was an inspiration to the author to go after this degree, and the author wishes he could have lived to see it achieved.

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Abstract of Dissertation

An Integrated Cost and Performance Model to Inform Capability Selection During Early-Phase Systems Engineering: Case Analysis and Multi-Objective Optimization

Functionality and performance have been key elements of requirements generation for major systems, especially within the Department of Defense (DoD). However, rising cost growth rates and decreasing funding has led to legislation requiring DoD to factor cost into requirements selection and to keep within cost estimates much earlier in a system's life cycle. This paper presents a mixed methodology research effort that provides three main results. First, it provides descriptive statistical analysis of current cost growth causes within DoD system. Second, it provides new cases of programs that have conducted cost and technical analysis in their early lifecycle. Third, it provides a framework that supports a combined cost and performance estimation model with greater emphasis on cost to assess the impact of specific requirements selection for major hardware/software systems. This model is used within a synthesized process derived from new cases within DoD. It also uses Multi-Objective Optimization (MOO), specifically Linear Physical Programming (LPP), as a means to better define and assess the optimal selection of capabilities in the requirements generation phase rather than the design phase. Statistical hypothesis testing shows that this framework and the use of LPP provide more optimal material solutions than SME judgment or by simply optimizing for cost. The result is a repeatable, analytical process and model that can be used throughout a system's life cycle to concurrently assess cost and technical performance.

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List of Symbols

1. β– Concavity Factor within the Linear Physical Programming (LPP) algorithm. It ensures the correct sign of the slope of the line segments between LPP region boundaries.
2. F (x) – The general aggregate objective function based on the set of objective functions of a Multi-Objective Optimization (MOO) algorithm.
3. $f_ι$ – Function for a vector x of k design metrics and n optimization parameters.
4. g_i – The LPP scores of a soft class parameter or metric.
5. í – the ith parameter or metric to be evaluated within the LPP algorithm.
6. R_c – A set of rules that map capabilities to material components.
7. R_m – Set of rules that checks for the internal consistency of a set of material components selected to implement a set of capabilities.
8. R_p – Set of rules that generates performance values
9. R_v – Set of rules that maps performance metrics back to the selected capabilities
10. $\tilde{t}i$ – Regional boundary variable
11. x – Vector of the design metrics in the MOO algorithm.
12. $\tilde{Z}s$ – The difference in objective value between regional boundaries within LPP
13. Z^i - The LPP score for a i^{th} parameter or metric.
14. Z - The final LPP score considering soft class parameters or metrics.

Glossary of Terms

AAS: Advanced Airborne Sensor.

AATFB: Architecture and Analysis Team for Force Basing

AAV: Assault Amphibious Vehicle.

ABC: Activity Based Costing.

ACAT: Acquisition Category. Department of Defense acquisition programs are categorized to specify the level of oversight and documentation needed, normally based on the size of their budgets and level of complexity.

ACAT I: Acquisition Category I in the Department of Defense acquisition system denotes programs that have the highest level of oversight, normally due to surpassing specific budget levels.

ACCA: Army Center for Cost Analysis.

ACV: Amphibious Combat Vehicle.

AoA: Analysis of Alternatives.

AS: Acquisition Strategy. This is a required acquisition document with the DoDI 5000.01 which describes the acquisition approach and strategies for a program, such as the systems engineering, testing, and contracting strategies and planned program milestones and schedule.

AESA: Active Electronically Scanned Array.

AOF: Aggregate Objective Function. This is the final score of a MOO function.

APB/APBM: Acquisition Program Baseline/ Acquisition Program Baseline Memorandum. This document defines the threshold and objective targets for the key areas of cost, schedule, and performance for a program. Not meeting APBM thresholds by a certain percentage are grounds for high-level and/or congressional review of the program.

APUC: Average Procurement Unit Cost. This is reportable cost figure for DoD programs that equals the total procurement cost of a program divided by the total system quantity.

ASA (ALT): Assistant Secretary of the Army for Acquisition, Logistics and Technology.

ASD (A): Assistant Secretary of Defense for Acquisition.

BMUP: Block Modification Upgrade Program.

CAPE: Cost Analysis Performance Evaluation.

CARD: Cost Analysis Requirements Document.

CCI: Communications/Computing Infrastructure. This is one of three primary missions within Army Force Basing.

CD&I: Combat Development and Integration. This is the U.S. Marine Corps organization responsible for developing operational requirements for material acquisition programs.

CE: Cost Estimation.

CER: Cost Estimation Relationship.

CEBoK: Cost Estimation Body of Knowledge.

CoC: Counsel of Colonels.

COMOPTEVFOR: Commander Operational Test and Evaluation Force. This is a Navy organization for system operational testing.

COTS: Commercial Off-The-Shelf.

DAU: Defense Acquisition University.

DC SIAT: Deputy Commander for Systems Engineering, Interoperability, Architecture and Technology.

DoD: Department of Defense.

DoDI 5000.01: Department of Defense Instruction 5000.01 is the DoD document providing DoD-specific regulations and policies for material acquisition.

DRA: Design Readiness Assessment.

EFV: Expeditionary Fighting Vehicle.

EMD: Engineering and Manufacturing Development phase within the DoD acquisition process.

FAR: Federal Acquisition Regulation. This provides regulations concerning the processes, procedures and specific roles and responsibilities within the Federal government and its agencies for conducting material acquisitions.

FB: Force Basing.

FYDP: Five-Year Defense Plan. This is a program's budget for the current year and the following five years.

G-3: Operation Branch of Army Headquarters

G-5: Planning Branch of Army Headquarters

G-7: Integration Branch of Army Headquarters

IBD: Integrated Base Defense. This is one of three primary missions within Army Force Basing.

ICD: Initial Capabilities Document.

ICEAA: International Cost Estimating Analysis Association.

INCOSE: International Council of Systems Engineering.

ISR&T: Intelligence, Surveillance, Reconnaissance, and Targeting.

JROC: Joint Requirements Oversight Council.

KPP: Key Performance Parameter.

LCCA: Life Cycle Cost Analysis process.

LCCE: Life Cycle cost Estimate.

LPP: Linear Physical Programing.

LSA: Logical Systems Architecture.

LSRS: Littoral Surveillance Radar System.

MBSE: Model Based System Engineering.

MCSC: Marine Corps System Command.

MDD: Material Development Decision. This is a decision point within the DoD acquisition process where it is decided if a capability gap warrants a material development solution.

MEF: Mission Essential Function. This is a major set of capability requirements of the ACV program.

MOO: Multi-Objective Optimization.

MS: Milestone. This is a major event within program management where the status, current business case and continued need of a program is evaluated and decisions are made concerning program continuation.

MS A: Milestone A. This is a DoD acquisition process decision point at the end of the Material Solutions Analysis phase that determines if a program shall continue into the Technology Development (TD) Phase. Per WSARA, a program needs to have a cost estimate it will be held to during future program reporting.

MS B: Milestone B. This is a DoD acquisition process decision point at the end of the TD Phase that determines if a program shall continue into the Engineering and Manufacturing Development (EMD) phase.

MS C: Milestone C. This is a DoD acquisition process decision point at the end of the EMD Phase that determines if a program shall continue into the Production and Deployment (P&D) phase.

MSA: Material Solutions Analysis.

NAVAIR: Naval Air Systems Command.

O&S: Operations and Sustainability.

OCSE: Office of Chief Systems Engineer.

OUSD (AT&L): Office of the Under Secretary of Defense for Acquisition, Technology, and Logistics.

PARCA: Performance Assessment and Root Cause Analysis.

PDR: Preliminary Design Review.

PM: Program Manager.

POM: Project Objective Memorandum.

PP: Physical Programming.

RA: Reference Architecture.

RDT: Reference Architecture Development Team.

SAR: System Acquisition Report.

SE OPT: Systems Engineering Overarching Product Team.

SC: Soft Class; Category of measurement within LPP that indicates how well a parameter value falls within a certain region or class.

SME: Subject Matter Expert.

SPAWAR: Space and Naval Warfare Systems Command.

SoSE: System of Systems Engineering.

TACOM: Tank and Automotive Command.

SWaP: Space, Weight and Power.

TCO: Total Cost of Ownership.

TD: Technology Demonstration phase within the DoD acquisition process. This is meant to select and prove out technologies and processes for material acquisition programs

TDS: Technical Development Strategy.

Vice Chief of Staff of the Army: Position in charge of implementing needed requirement changes and approving funding changes to specific programs.

WBS: Work Breakdown Structure.

WSARA: Weapon System Acquisition Reform Act.

Chapter 1: Introduction

This research addresses the problem of more accurately estimating cost and technical performance of new, intensive hardware/software systems, especially as that understanding can be used to define the system capabilities and requirements that will be tackled by an acquisition program. To that end, it focuses on a portion of the overall system development process defined in terms of the Department of Defense (DoD) Defense Acquisition Process (DAP), from the Material Development Decision (MDD) and pre-Milestone A activities within DoD (Figure 1-1), and the system requirements and concept exploration phase in general. Many organizations, DoD in particular, are struggling to better define and provide guidance on how to choose system capabilities and meet both technical and business goals, such as cost and schedule, in an accurate manner that can lead to systems that are both capable and affordable. Unlike much of the requirements literature that focuses on the users' functional and performance needs as the key to requirements generation, this paper seeks to add cost as an integral part of the selection criteria of requirements and as part of the development of possible system concepts to satisfy selected capabilities.

This dissertation presents a framework and cost/technical performance model that is focused on the selection of system requirements early in the development phase that are informed by both the estimated technical performance and costs needed to reach desired capabilities. This framework links the selection of system capabilities to possible material implementation choices chosen using a multi-objective optimization (MOO) process. The material implementation choices are made within a system dynamics-like process meant to

reinforce the technical feasibility of the selection. It is also meant to recognize the complex

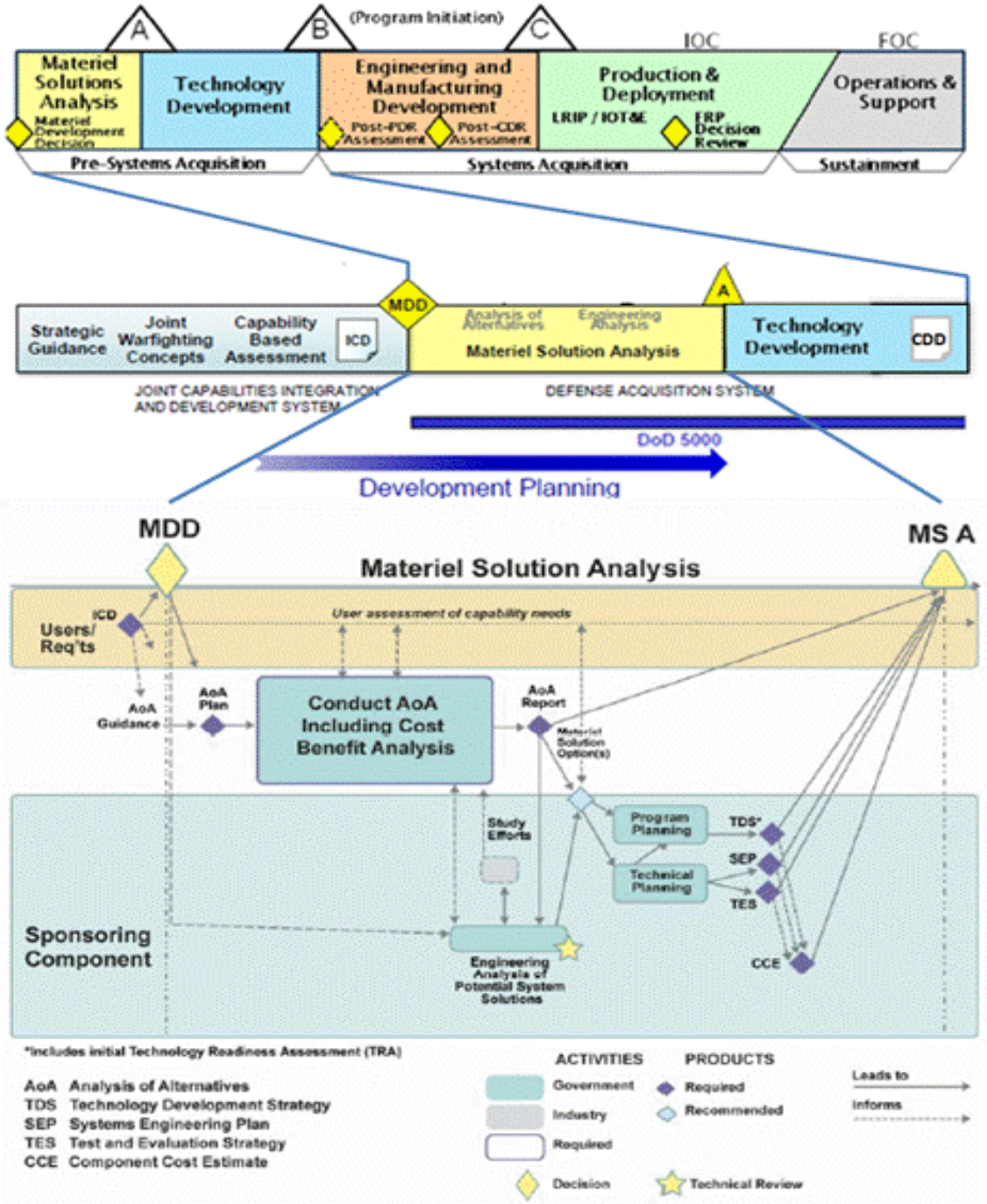

Figure 1-1. DoD Acquisition Phases with a Focus on Pre-Milestone A (Dahmann, Bhatti, and Kelley 2009)

relationships and feedback loops between the selection of material components and major system performance metrics and attributes, such as space, weight, and volume (SWaP). The material selection process is also designed to present selections that are technically feasible, based on known compatibility of components and the effects that attributes, such as SWaP, have on components and the system as a whole.

This work fits within the pre-MDD and Material Solutions Analysis (MSA) phase conducted before Milestone (MS) A within DoD. However, this framework is not limited to that early phase. It could also be used as part of an iterative, repeatable analytical process that refines the integrated cost and performance estimate and material implementation model.

The research reflected in this paper uses a mixed methods methodology. It applies to major system development across domains and organization within government and industry. However, it focuses on major weapon system development within DoD. This is for several reasons. First, DoD is required under federal statute, the Weapon System Acquisition Reform Act of 2009 (WSARA), to conduct greater system engineering analysis during the MS A and B phases of acquisition. Second, WSARA requires the integration of cost as part of requirements development and selection. Third, major DoD programs have been studied extensively concerning root causes of cost growth, as will be presented in the Background section of this paper. There was more data available to the authors for conducting the statistical analysis and verification of the model.

This paper is organized into the following chapters:

Chapter 2, Literature Review, provides a review concerning the identification of acquisition and cost growth problems within the context of the new Weapon System

Acquisition Reform Act of 2009 (WSARA) and directives within DoD. It also provides a review of the cost estimation (CE) techniques within the CE Body of Knowledge (CEBoK) and cost estimation research. This includes the use of system dynamics in cost estimation. Additionally, it reviews many of the methods available across the Multi-Criteria Decision Making (MCDM) field. This includes the use of MOO within design and recent work that has been using MOO during the pre-design, concept exploration phase. MOO features prominently in the framework proposed in this paper.

Chapter 3, Methodology, presents a review of the mixed methods approach taken in this research. The first section outlines the identification of relevant programs and cost growth causes though a quantitative statistical analysis of several cost growth root cause studies conducted both before and after WSARA. Various cost growth categorization frameworks from the literature are analyzed to pick one to be used in our research. This data helps define the goals and elements of the proposed framework and model. The next section outlines the use of a qualitative case development and analysis. As the literature review will show, there is no public documentation on how major DoD programs have successfully conducted Pre-Milestone A analysis. This limits the ability to develop an analysis framework based on empirical evidence. Finally, the third section reviews the various multi-objective optimization techniques useful in making decisions within our model, and the rational for the selection of the Linear Physical Programming (LPP) method.

Chapter 4, Research, presents the work outlined in Chapter 3, Methodology, in three main sections. The first section presented is the cost growth root cause analysis of major DoD Systems. This section presents a statistical analysis of various DoD weapon system

cost growth studies. It provides a quantitative review of several cost growth root cause studies conducted both before and after WSARA. This data helps define the goals and elements of the proposed framework and model.

The second section presents the case studies analysis. This section provides three new cases of programs that have conducted combined cost and technical assessment with successful results. This fills a gap in the current literature where no such cases exist to inform DoD policy makers. The cases are comparatively analyzed.

The third section provides a cost/technical performance model. This model integrates cost estimation using a bottom-up approach within a Work Breakdown Structure (WBS) and technical feasibility analysis. It presents the complexity of using known component data by conducting a correlation analysis of material component attributes, such as cost and SWaP. It also presents the method of using Linear Physical Programming (LPP) to assess optimal component selection against selected capability ranges. Finally, it includes a detailed view of the government and research model used in this research, to differentiate the work done in this research versus work done previously.

In Chapter 5, Research Results, the cost/technical performance model is assessed through the instantiation of our model using data from the Systems Engineering Overarching Product Team (SE OPT) case on eight different system concepts. The assessment results present both value comparisons between our model and SE OPT's cost and technical performance estimates, as well as statistical hypothesis testing, to determine how our model and the use of multi-objective optimization compared to the SE OPT case using SME assessments.

Chapter 6, Conclusions, summarizes the major points of our research and provides recommendations for future work.

Chapter 2: Literature Review

2.1 DoD Acquisition and WSARA.

There are several reports that discuss the issues of cost growth within DoD. Two reports, "DOD Must Balance Its Needs with Available Resources and Follow an Incremental Approach to Acquiring Weapon Systems" (GAO 2009) and "Better Weapon Program Outcomes Require Discipline, Accountability, and Fundamental Changes in the Acquisition Environment" (GAO 2008), discuss the lack of coordination between key DoD processes—requirements generation, budgeting, and acquisition—and that these processes need to be in synchronization. The reports also address the need for a portfolio approach. This becomes especially important because the number of systems/portfolio size is increasing much faster than the resources available. "From 1992 to 2007, the estimated acquisition costs needed to complete the major acquisition programs in DOD's portfolio increased almost 120 percent, while the funding provided for these programs only increased 57 percent, creating a fiscal bow wave that may be unsustainable" (GAO 2008). This situation led to further reports examining how the current requirements process could be changed. The GAO report "DOD WEAPON SYSTEMS: Missed Trade-off Opportunities During Requirements Reviews" (GAO 2011) pinpointed that the Analysis of Alternatives (AoA) currently provided the opportunity for deciding between different possible material solutions. By analyzing these alternatives and their technical maturity, better cost estimation for implementing specific capabilities could be developed. Hence, it recommended that the Joint Requirements Oversight Council (JROC) provide a process for requiring and reviewing the AoA results, with an aim at ensuring more detailed cost

analysis (GAO 2011). This echoed an earlier report calling for the selection of requirements to take into account cost and technology maturity (GAO 2003). It noted past system requirements focused on meeting user performance requirements with little concern of the life-cycle costs they may entail and the maturity of technology to achieve those performance goals (GAO 2003).

This led Congress to enact the Weapon System Reform Act of 2009 (Weapon System Acquisition Reform Act of 2009 2009). This law enacted several elements that addressed the handling of cost and requirements within the early phase of system development. These measures included standing up a Director of Systems Engineering to provide policy and guidance to the acquisition community for developmental planning, requiring independent cost estimates and root cause analysis of critical cost overruns by DoD program by the Performance Assessment and Root Cause Analysis (PARCA) Directorate within the Office of the Assistant Secretary of Defense for Acquisition and requiring an assessment of cost within the AoA process before MS A. These new requirements shifted to the left the required times for major activities, such as establishing a cost baseline at MS A rather than at the end of the technology demonstration phase (MS B), and moved the system's preliminary design review (PDR) before MS B (Kranz 2009). The end result is that a system needs to be better understood and its cost estimated much earlier in its developmental process.

2.2 Cost Estimation.

The CE community has established a Cost Estimation Body of Knowledge (CEBoK) formed by the International Cost Estimating and Analysis Association (ICEAA) (ICEAA

2013), which reviews and outlines the concepts, methods, and application of CE. The commonly accepted methods are:

- Parametric Analysis. System parameters, such as weight or horsepower, are used within cost estimation relationships (CER) to produce a cost value.
- Analogy. This technique is used to estimate costs through comparison with similar systems or activities. This is a common approach during early phase engineering, which many times is faced with a lack of data.
- Engineering Bottoms-up Estimate. This method creates a WBS or cost element structure (CES) that treats the system or program as a series of decomposable products and activities, which each receive a cost. This method requires a large amount of data and is sometimes judged not to be appropriate for early conceptual and design phases (ICEAA, 2013), but is a method often used by businesses for cost proposals.
- Expert Judgment or Opinion. This method depends on opinions for domain experts to estimate costs or modify existing estimates based on their experience and knowledge.

Many studies have been conducted to review and propose cost estimation techniques within different domains. These include DoD weapon systems (Blickstein et al. 2012; Bolten et al. 2008), space systems (Younossi et al. 2008), aircraft systems (Younossi et al. 2005), and systems engineering and program management costs (Stem, Boito, & Younossi, 2006). As will be described in the Cost Growth Analysis section, these studies present a few different cost growth cause taxonomies (Table 3-1) (Blickstein et al. 2011;

Blickstein et al. 2012; Bolten et al. 2008), while many present lessons learned with domain-specific CERs and techniques (e.g. aircraft).

In reviewing other community bodies of knowledge, such as the Program Management Institute (2008) Project Management Body of Knowledge, Fourth Edition (PMBOK Guides) and the International Council of Systems Engineering (INCOSE) Systems Engineering Handbook (2011), the issue of integrating cost estimation with other systems engineering and program management activities may be systemic. Neither one of these references does much to address cost early in the program's lifecycle, either in the requirements generation phase or before decisions need to be made about starting the development effort.

The PMBOK was developed by the Project Management Institute (PMI) starting in 1983, and it is the basis for the Project Management Professional (PMP) Certification. Cost is addressed in the following sections: Section 3 – Project Management Processes and Section 7 – Project Cost Management. Requirements collection is needed to establish project scope and to develop a Work Breakdown Structure (WBS). Cost is not explicitly identified as a possible constraint to be considered. Cost estimation in the PMBOK process comes after project scope (Chapter 5.2), activities and schedule (Chapter 6), and WBS (Chapter 5.3) to the work package level, have been developed. This comes after requirements have already been developed within this process.

INCOSE SE Handbook (2011) is the main source for INCOSE Systems Engineering Professional Certifications. Relevant areas concerning cost are:

- Section 3.3 - Life-Cycle Stages. In 3.3.1 and 3.3.2 – Exploratory Research and Concept Stages address cost and schedule from a reference architecture. It does not mention culling requirements based on the cost.
- Section 3.4 - Life Cycle Approaches. In section 3.4.2, Incremental and Iterative Development (IID) may address the cost of implementing requirements (Spiral vs. Incremental approach) and section 3.4.3, Lean SE, addresses waste, with cost discussions as continual part of requirement generation with the customer.
- Section 4.1 Stakeholder Requirements Definition Process. Cost constraints are inputs, but cost estimates or various system concepts are not part of the process, and are not accomplished before the first System Requirements Document (SRD) draft.
- Section 4.2 - Requirements Analysis Process. While iterative, it does not explicitly mention cost as an input, output, or process activity. It does mention that good requirements, taken as a whole, should be affordable (4.2.2.2).
- Section 4.3 Architectural Design Process. Section 4.3.2 does address the need for the architecture to be affordable through iterative adjustment, although there is little explicit cost estimation activity explicitly mentioned, compared to performance. Section 4.3.2.8 focuses on addressing adjusting requirements from architecture and design analysis.

Within section 5, Project Processes, the handbook seems to put cost management as a project management function, rather than a systems engineering function, as depicted in figure 2-1 (International Council on Systems Engineering 2011).

There is a further problem that the link is not clear between the System architecting process within SE that can determine a cost estimate and the related cost activity of project planning. Also, section 5.7, Measurement Process, does not address the issue of cost measurement and coordinating the issue between the SE and PM teams, except possibly as an MOE (5.7.2.3). While the issue of affordability as part of MOEs is first mentioned in this section, it is not in the MOE discussion within Section 4. Finally, within Section 6.1, Acquisition Process, there is no mention of understanding the expected costs (procurement, development, and life cycle) following from the generated requirements.

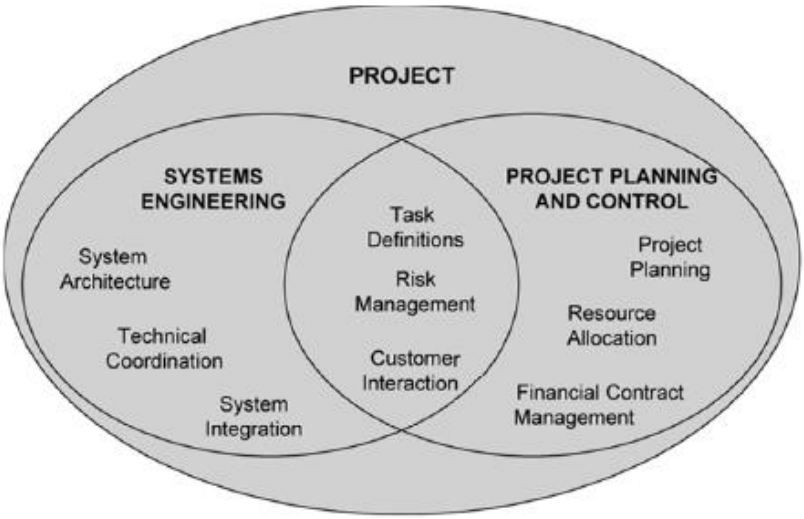

Figure 2-1. Division of Management and SE Processes within the INCOSE SE Handbook.

Between the Project Management and Systems Engineering bodies of knowledge references, cost is not addressed early in the acquisition process, especially the requirements generation and selection process. Arguably, the engineering processes and expertise that are needed to best calculate the possible cost of implementing specified requirements and system architecture are not clearly or explicitly involved in the cost estimation processes.

2.3 System Dynamics.

Another area of cost analysis is the application of system dynamics. (Forester 1961). System dynamics was developed by Jay Forrester (1961) from the MIT Sloan School of Management as a means to explain the complex behavior of systems, especially over time. In addition to cost estimation, it has been applied to many areas, notably global issues, such as population and pollution, and urban policy. In system dynamics, a system can be represented by variables that interact between each other in a looping, feedback fashion. A causal loop is a qualitative representation of a directed relationship between variables. The casual loops may be either reinforcing loops or balancing loops. This simply means that for a reinforcing loop, if the starting variable increases in value, then the ending variable also increases. For a balancing loop, the relationship is reciprocal.

While casual loops are a qualitative model of the relationship between variables, stocks and flows provide a quantitative modeling ability. Stocks are the variables that contain some quantity at any point in time. They increase or decrease based on the flows, the rate of change that determines how the stock may change in value over time.

What makes a system complex is the ability for variables to have several different causal loops that they interact with within the structure of the dynamic system. It is this structure, where variables may be impacted by several different forces, that makes the system complex and sometimes unpredictable.

A thorough review of system dynamics use in defense and cost analysis was conducted by R. G. Coyle. (Coyle, Exelby, and Holt 1999; Coyle 1992; Coyle 1996) There are several other examples available where system dynamics has been used. In the cost analysis context, the system dynamics literature is focused in long-term cost

modeling, especially total cost of ownership (TCO) or a life-cycle cost estimate (LCCE), as these estimates are impacted by external forces over a long period of time. Examples include cost management using activity-based costing (ABC) (Khataie, Segovia, and Bulgak 2011), software pricing (Rahmandad and Sibdari 2012), the operations and support costs (Coyle 2002; Purvis 2001), long-term development of new technologies for ships (Monga 2001), and estimating life-cycle cost improvements through improved reliability (Killingsworth, Speciale, and Martin 2010).

In addition to cost modeling, system dynamics has been used in general system design and requirements engineering. Loucopoulos and Prekas (2003) developed a framework that accounted for ontology modeling, goal modeling, process modeling, and scenarios generation, while others used system dynamics to influence the design of large systems, such as the coal conveyor belt system (Wolstenholme 1983). It has also been common to have system dynamics mixed with other methods, such as MOO (Coyle 1996; Duggan 2008). For instance, Duggan (2008) used system dynamics in conjunction with genetic algorithms for making policy decisions.

2.4 Multi-Criteria Decision Making.

In determining capabilities for a system and its possible system implementations that lead to a cost and technical performance estimate in the pre-MS A phase, there are very often trade-offs between competing capabilities and implementations. To determine the more optimal capabilities while weighing costs and constraints, MOO or multi-criteria decision making (MCDM) is required. We review the basic definitions and concepts of MCDM, and then review many of the techniques or methods available. This methods review includes the factors that differentiate one set of techniques from another, how to

categorize them, and then present them using our own categorization. Given that our research uses a derivative of Physical Programming developed by Achille Messac (1996), we review the current Physical Programming literature. We then review how some of the most well used MCSM techniques have been combined, and provide a brief overview of key application areas and the methods used.

2.4.1 Definitions.

Multi Criteria Decision Making (MCDM) is a field of Operations Research that goes by several names, to include Multi-Attribute Decision Making (MADM), Multi-Objective Decision Making (MODM), Multi-Objective Optimization (MOO), Multi-Criteria Optimization (MCO), and Multi-Criteria Decision Analysis (MCDA). Some distinguish the names according to whether the problem space has a set number of discrete options or alternatives to be evaluated, or a large number of discrete or continuous options or alternatives (Triantaphyllou et al 1998). In that case, MCDM is a superset term which breaks into the MODM or MOO areas for the continuous and large, discrete alternative discovery and selection, and MADM for the discrete, pre-defined alternative problems. For the discrete MADM area, some use the term MCDM interchangeably with MADM, and some also distinguish MCDM versus the term "Many-Criteria Decision Making" to differentiate problems where certain methods work well only with a small number of alternatives, sometimes no more than three to ten (Coello 2001, Garza-Fabre, Pulido, and Coello 2009). This is especially true for evolutionary algorithms, although pairwise comparison techniques, such as Analytical Hierarchal Process (AHP) can suffer as the number of n criteria becomes large because of the 2^n comparisons needed.

The typical MOO problem seeks to minimize F(x), the aggregate objective function (AOF) that is based on the set of objective functions, $f_i(x)$ for a vector **x** of k design metrics and *n* optimization parameters (Marler and Arora 2004).

$$\text{Minimize } \mathbf{F(x)} = [f_1(x), f_2(x), \ldots, f_k(x)]^T \quad (2.1)$$

$$\text{Where } \mathbf{x} = [x_1, x_2, \ldots, x_n] \quad (2.2)$$

$$\text{Inequality constraints: } g_l(x) = 0, \quad l = [1, 2, \ldots, m] \quad (2.3)$$

$$\text{Equality constraints: } h_l(x) = 0, \quad l = [1, 2, \ldots, e] \quad (2.4)$$

The design metrics may actually be composed of different types of variables, such as independent design variables or parameters (parameters under a designer's control), dependent variables or design attributes (derived from other variables), state variables, environmental variables, etc. The value of F(x) is based on how the objective functions are related together, sometimes through a preference value, such as weights, to form an AOF. Depending on the method used, F(x) may be either a scalar value or a vector.

2.4.2 Techniques.

Many say that there is no one best technique for conducting MCDM and its sub-areas, such as MOO (Ignizio 1983, Polatidis, Haralambopoulos and Munda 2006). However, each technique provides the ability to handle problems with certain characteristics. The following sections review the factors that help differentiate the methods, how the methods can be categorized, and then present these methods using that categorization.

2.4.2.1 Factors.

Discrete vs. Continuous. The decision-making context may provide a finite set of options whose criteria or attribute values vary. These are commonly called discrete problems. Korhonen, Moskowitz, and Wallenius (2006) provide several sub-

classifications of discrete problems. These include the number of alternatives, the number of criteria or attributes, and prior knowledge of the attribute values, alternatives, and attributes themselves. This creates 32 different combinations of problems. Common discrete problems in the literature, according to Korhonen, Moskowitz, and Wallenius (2006), include five different combinations of these sub-classification values:

1. Problems with a large number of known alternatives with a small number of criteria with known values.
2. Problems with a large number of known alternatives with a small number of criteria with uncertain values.
3. Problems with a small number of known alternatives with a large number of criteria with uncertain values.
4. Problems where the number of alternatives is very large, requiring the decision maker to either down-select to a smaller number of alternatives or search for more desirable alternatives.
5. Problems with a small number of alternatives, but the criteria to use are not known a priori. This results in the decision maker conducting pairwise comparisons of the alternatives in order to choose the criteria.

Continuous problems also have their own set of six sub-classifications, to include whether the alternatives are known a priori, the underlying models are linear versus non-linear, the variables are continuous versus integer, the relationships between variables are quantitative or not, and the number of variables and constraints are large or small. There are five common continuous problem types of continuous MCDM problems (Korhonen, Moskowitz, and Wallenius 2006).

1. The problems are based on a linear model with a small context of variables and constraints, where the number of criteria is small, and the variables are continuous with quantitative relationships between themselves.
2. The problems are based on a non-linear model with a small context of variables and constraints, where the number of criteria is small, and the variables are continuous with quantitative relationships between themselves.
3. The problems are based on a linear model with a small context of variables and constraints, where the number of criteria is small, and the variables are integer-based with quantitative relationships between themselves.
4. The problems are based on a linear model with a large context of variables and constraints, where the number of criteria may also be large, and the variables are continuous with quantitative relationships between themselves.
5. The problems are based on a linear model with a small context of variables and constraints, where the number of criteria is small, and the variables are continuous with some qualitative relationships between themselves.

Some methods work better on a small set of discrete options or alternatives to select. Methods that can handle a larger number of options or criteria, such as over 3, are sometimes called "Many-Objective Decision Making" methods (Lygoe, Cary and Fleming 2010).

Descriptive vs. Non-descriptive. Descriptive techniques use multivariate statistical methods, such as factor analysis and Principal Component Analysis (PCA) to reduce the number of attributes, and hence the dimensionality, of the problem. The goal is to provide a description of the inter-relatedness of the criteria and provide a graphical

representation that makes for easier decision-making, rather than going through the process of calculating sets of Pareto-optimal points. (Stewart, 1992). Zeleny (1982) calls this an example of a process-oriented approach to decision-making which aims for decision makers to understand the process of decision making based on the criteria involved and how they relate to the possible alternatives. Riabacke, Danielson, and Ekenberg (2012) also include others theories based on human psychology, such as Prospect Theory and Regret Theory, to help decision makers understand themselves and the decision making process. An example of a specific MCDM descriptive method is the Geometrical Analysis for Interactive Aid (GAIA) (Brans and Vinke 1985).

Preference Articulation. MCDM methods can be grouped according to how the preferences between objective functions are determined (Andersson 2000, Marler and Arora 2004). These include the a priori articulation of preferences, where the importance or goals of the objectives comes before running the MCDM method, progressive articulation of preferences, where the preferences between the objective functions is adjusted during the method execution, a posteriori articulation of preferences, where a solution is chosen from a set of possible optimal solutions after MCDM execution, and finally no articulation of preferences.

Type of Values Used. Deterministic, Stochastic, and Fuzzy values may be used by various methods can be used as a distinguishing feature (Triantaphyllou et al, 1998). There are numerous variations using fuzzy mathematics (Kahraman 2008), such as Fuzzy TOPSIS (Gao, Feng, and Yang 2008), Fuzzy Physical Programming, and Fuzzy AHP. Stochastic values are found in descriptive techniques, such as factor analysis, and are also found in the metaheuristic techniques called Simulated Annealing (Kirkpatrick et al,

1983). Deterministic, numerical values are found in most MOO and most MADM techniques.

Necessary and Sufficient for Pareto Optimality. The history of MCDM can be traced back to several sources, such as the work in Utility and Game Theory of von Neumann and Morgenstern (1944) and the work of Vilfredo Pareto (1896), both in the field of economics (Kiksalan, Wallenius, and Zionts 2013). Marler and Arora (2004) make it a point to distinguish if a method is necessary and/or sufficient for Pareto Optimality. As equation (2.1) has several factors, there is normally not a single answer that is best for all individual objective functions. There is a set of optimal points which make up the Pareto frontier, Pareto set, or Pareto Surface. These points are Pareto optimal or Pareto efficient. This simply means that there exists no other point where at least one objective function can be improved without worsening any other objective function. If a method can generate Pareto optimal points through manipulation of its parameters, then it provides necessary conditions for Pareto optimality. If the method always provides Pareto optimal points, then it provides sufficient conditions for Pareto optimality.

Finally, there are practical factors to the use of various methods, such as the ease to program the algorithms and the amount of computational power required. Again, Marler and Arora (2004) present these factors in their review of MOO techniques.

2.4.2.2 Categorization of Methods.

Based on the above factors, there are several different means in the literature to categorize the various MCDM/MOO methods that exist. Several papers use the factor of when a preference is know – a priori, postiori, interactive, and no preference (Andersson, 2000; Marler and Arora, 2004). Polatidis, Haralambopoulos and Munda (2006) assign

methods into the type of decision support models they provide, and the characteristics of those models. They construct four groups; Utility-based methods, outranking methods, programming methods (mathematical programming, continuous choices) and "other methods," such as like Novel Approach to Imprecise Assessment and Decision Environment (NAIADE), Flag Model, and the Stochastic Multiobjective Acceptability Analysis (SMAA) method. The Utility-based methods, which include MAUT, AHP, ANP, SAW and their derivatives, provide a single score for each option or alternative that may be chosen, where the criteria can all be compared with total compensation, there is no incomparability, and commensurability. Outranking methods provide a means of pairwise comparisons between alternatives, where only substantial differences in criteria values are applied, and incomparability and incommensurability are allowed. However, this paper does not delve into the review of evolutionary approaches. T. Stewart (1992) also provides a similar categorization, although he includes Goal Programming, Fuzzy Set Theory and Descriptive Methods.

For categorizing the numerous MCSM techniques within this review, we have developed the categorization depicted in Figure 2-2. While many reviews presented a structure based on preference articulation, there is repetition using that method. As will become clearer in the methodology section, it is important to distinguish methods that use weighting, as weighting brings several issues that should be avoided. Thirdly, distinguishing methods that provided a single scalar value, utility, or overall distance or difference measure makes the evaluation of optimality easier. Finally, there are important methods that are either do not generate numerical, Pareto-optimal points, such as MADM

outranking methods, or are based on natural phenomenon, such as Simulating Annealing, which can be easily group together.

Figure 2-2 presents a hierarchal categorization of MCDM methods or techniques. The first level of categorization is Descriptive vs. Non-Descriptive methods. Some descriptive methods have been mentioned in the section discussing MCDM factors and are meant for human decision maker interaction and elucidation. Since this research is looking for methods that require little decision maker interaction, focus will be given to non-descriptive methods. The non-descriptive methods are divided into four groups that are mostly, but not entirely, mutually exclusive. These are MOO, MADM, and Metaheuristic groups.

The MOO group contains both scalar and vector-based methods that are for problems which have quantitative criteria or attributes, and can cover both discrete and continuous (very large number) alternatives. These alternatives may or may not be known a priori. The scalar methods are those that the AOF, F(x), can be formed to produce a scalar value that can be either minimized or maximized. The scalar methods can be further subdivided into those methods which use weights against the individual objective functions, $f_i(x)$, of equation 2.1 and those that do not. The vector-based methods generate vector results for F(x). Some methods, such as rank-based genetic algorithms, actually use weights based on ranking the population points iteratively, one criteria at a time (Garza-Fabre, Pulido, and Coello 2009, Marler and Arora 2004).

Figure 2-2. Categorization of MCDM Methods.

The MADM methods are normally associated with a problem space comprised of a discrete number of alternatives defined a priori. Some of these methods, like ELECTRE and PROMETHEE, also do not find Pareto-optimal points, but decision maker preferences to rank alternatives. Again, this classification is not mutually exclusive within this categorization scheme, as TOPSIS is not just considered a MADM technique but a scalar MOO technique (Marler and Arora, 2004).

The other major classification is the Metaheuristic methods category. Metaheuristics use heuristics, search algorithms, to explore the solution space to find optimal solutions, especially in combinatorial problems. These solutions do not necessarily find a globally optimal solution (Baghel, Agrawal, and Silakari 2012). Many techniques in this area are inspired from the physical worlds, such as Simulated Annealing, which takes ideas from the area of thermodynamics.

2.4.2.3 Scalar Non Weight-based Methods.

Several of the following methods are based on variations of the following formula:

$$U = \sum_{i=1}^{k} w_i \, [f_i(x)]^p, \quad f_i(x) > 0 \; \forall i \tag{2.5}$$

$$U = \left\{ \sum_{i=1}^{k} w_i \left[f_i(x) - f_i^{\circ} \right]^p \right\}^{\frac{1}{p}}, \quad f_i(x) > 0 \; \forall i \tag{2.6}$$

where w_i is weight for the ith criteria or attribute, and f_i° is the optimal value of the ith objective function, and k is the number of objective functions. This optimal point may be a Utopia point, or an approximate value called an aspiration point, reference point, or target point (Marler and Arora 2004). The sum of all weights is normally equal to one. Also, as each objective function may have a different range of values, those objective values may

need to be normalized (Andersson 2000). How objective function values may be normalized is further discussed by Monat (2009).

Global Criteria methods are the simplest non-weighted methods that take the formulas 2.5 and 2.6 and set all weights, w_i , to 1. When w = 1 and p = 1, this becomes the "Objective Sum" method. According to Marler and Arora (2004), this provides a Pareto optimal solution. Also, since weights do not need to be determined a priori, this method and those based on it can be used with no preference articulation.

The Min-Max method (Lightner and Director 1981) is a technique that takes equation 2.5 and sets p = ∞. The basic formula for this method is:

$$\min_{x \in X} \max_i [f_i(x)] \tag{2.7}$$

where every objective function $f_i(x)$ is evaluated at point x. This makes this method similar to single criteria optimization, just done repetitively. It can achieve weak Pareto-optimal results and is sufficient for Pareto optimality (Marler and Arora 2004). It is not widely used in engineering design, and without changing the exponent p, it provides only one point of the Pareto-optimal set of points (Andersson 2000).

The e-Constraint method (Haimes, Lasdon and Wismer 1971) works by selecting one objective at a time, and setting the other objective functions as constraints. These constraint objective functions need to be less than or equal to a constant, e, established for each objective. This is a posteriori method, as it requires the decision maker to modify the e constraint values to form a Pareto set of point (Andersson 2000).

Goal Programming (Charnes and Cooper 1961, Charnes, Clower, and Kortanek 1967, and Ijiri 1965) is an a priori method that requires the decision maker to set goals for each objective in a multi-objective problem. The goal is then to minimize the total deviation

between the individual objective functions and their corresponding goals. Hence, it is similar to the Global Criteria method represented by (2.6). The philosophy of the method is that it may not be realistic to develop a value or utility function that accurately reflects the decision makers' preferences, but it can be expected that the decision maker has the ability to express goals or aspirations for each objective or attribute (Ignizio 1983). It is possible for objective functions to either overachieve or underachieve their goals (Augusto, Bennis, and Caro 2012). A variation of goal programming is Multigoal Programming (Zeleny 1982) where multiple goals for each objective function are provided and minimized. This helps minimize the problem of decision makers being able to generate meaningful goals. There are also interactive or progressive preference articulation variations called the interactive sequential goal programming and augmented goal programming (Ignizio 1983).

Some key advantages of goal programming are that it is easier to use compared to value or utility-based approaches for problems with large number of criteria, such as over ten criteria (Stewart 1992). It can also be used to down-select from a large set of alternatives (Stewart 1992). A key disadvantage of goal programming is the ability for the decision maker to come up with a priori goals at are feasible (Coello 2001, Hannan 1985, Stewart 1992). Also, this method does not guarantee generating Pareto-optimal points (Marler and Arora 2004).

2.4.2.4 Scalar Weight-based Methods.

Weight-based approaches are arguably the most prevalent methods used for both discrete and continuous MOO and MADM problems, especially the Simple Additive Weighting (SAW)/Weighted Sum Method (WSM) (Andersson 2000, Marler and Arora

2004, Marler and Arora 2010). Many of these methods are modification of the non-weighting techniques reviewed above. As the issue of developing the proper weights is very important, numerous methods have been developed to help establish those weights. These include AHP, ANP, and QFD. These are reviewed in the MADM section below. Riabacke, Danielson, and Ekenberg (2012) provide a review of the latest methods for prescriptive weight elicitation for weights-based methods. Marler and Arora (2004) provide information concerning the Pareto-optimality of these methods, which shall be discussed below.

The Weighted Global Criteria method is based on formulas (2.5) and (2.6) where the weights do not all equal one, and the exponent p can vary and does not have to equal one. Since p can vary, this method is also called the weighted exponential sum. If p = 1, then this becomes the Weighted Sum Method (WSM), also called the Simple Additive Weight (SAW) method.

The Weighted Min-Max (Weighted Tchebycheff) method is similar to the Weighted Global Criteria method depicted in formula (2.6), where the exponent p tends toward infinity. With a high p and varying the weights, this method provides the conditions necessary for Pareto-optimality (Marler and Arora 2004, Miettinen 1999). It is given by the following equations:

$$U = \max_i \{ w_i [f_i(x) - f_i^\circ] \} \tag{2.8}$$

$$U = \max_i \{ w_i [f_i(x) - f_i^\circ] \} + \rho \sum_{j=1}^{k} [f_j(x) - f_j^\circ] \tag{2.9}$$

The equation (2.9) is called the Augmented Weighted Tchebycheff method, where ρ is a small scalar provided by the decision maker.

Goal Programming has several different methods which include weights. Archimedean Goal Programming (Charnes and Copper, 1977) is a modification to goal programming where weights are given to the differences between each objective function and its goal. Preemptive or lexicographic Goal Programming (Charnes and Copper, 1977) ranks the objectives and their respective goals, and the deviations from the goals are minimized in that order. Zeleny (1982) showed that both Archimedean and Lexicographic Goal Programming may lead to non-Pareto optimal solutions. There are two methods related to Goal Programming that are also based on the Weighted Min-Max method above. Goal Attainment (Hwang and Md. Masud, 1979) is a computationally better performing method compared to general goal programming (Marler and Arora 2004). However, all these goal programming methods are not necessary or sufficient for Pareto-optimality (Marler and Arora 2004), which led to the creation of Reference Goal Programming (Ogryczak, 1994) that is also based on Weighted Min-Max.

Two other methods include the Exponential Weighted Criteria method (Athan and Papalambros 1996) and Weighted Product method (Gerasimov and Repko 1978). The Exponential Weighted Criteria method can capture points in a non-convex Pareto-optimal surface and provide necessary and sufficient Pareto optimality, while the Weighted Product method provides a means to use criteria at their native scale and not have to normalize them (Marler and Arora 2004).

As shown, the use of weights in MCDM and MOO is very widespread, with methods developed and used since the 1970s. Several authors have criticized the use of weights for several reasons. The first is the issue of subjectivity. Achille Messac (1996), in developing the Physical Programming method, presented a new method which does not

use weighting. He argued that the initial establishment of weights is very subjective, and the adjustment of weights by the decision maker after the execution of the aggregate objective functions is not straightforward. It is not clear what weights should be adjusted and by how much. This also presents the perception that weighting methods allow the decision maker to reach a pre-determined conclusion rather than a more objective choice. On a different note, Reilly and Doherty (1992) argued that decision makers or "Judges" may not have the required insight on how to establish corrected weighting amongst several criteria to lead to rankings and option selections that reflect the desires of the judges. "There is the distinct possibility that while people have reasonable self-insight on judgment tasks, they do not know how to express that insight. Or pointing the finger the other way round, while people do have insight we do not know how to measure it" (Reilly and Doherty, 1992, p. 305).

There is also the issue concerning what scales are used to normalize the attribute or criteria values even before weights are applied, and the means to scale weights. Monat (2009) provides a description of several different scales used in the literature for both criteria values and weights. For criteria, there is developing a "local scale" based on the minimum and maximum values of the criteria the current options under discussion. The scales normally go from 0 (the worst value) to 10 or 100 (for the best value), and other values are calculated as a proportional value between the min and max values. A "Global scale" is based on the decision maker's experience or expectations concerning the possible minimum and maximum values for a criteria, and not the values from the existing options. Weighting scales include simple category weights that indicate the decision makers' view of the proportion of the total weighting scale an attribute should

receive, importance weights that indicate the comparative importance between the various attributes or criteria, swing weights that show the importance of a criteria's swing from lowest to highest values compared to the related swing in values in the other criteria, and then weight adjustments due to the scale used.

The use of weights and the scales chosen for criteria values have interdependent effects, as outlined by Nitzsch and Weber (1993). For instance, Goodwin and Wright (2004) show that importance weights should not be used with local scales, especially with scales where the minimum and maximum range of values for a criteria are small. This is also discussed by Marler and Arora (2010) and Nitzsch and Weber (1993) who develop the subject in the context of Multi Attribute Utility Theory (MAUT). They present a Range Sensitivity Index (RSI) to aid in the development of weights in response to the criteria ranges. While this seems to be an aid in the use of weights, Monet found through a survey of the literature that decisions makers usually do not and cannot adjust the weights as needed to account for range, even when using RSI. Their recommendation was to use global scales in developing criteria ranges, which are normally not addressed or used in the literature (Monat 2009).

2.4.2.5 Vector-based Methods.

Vector-based methods provide an AOF whose result is a vector (size k) of individual objective function values. We examine two groups of methods, Lexicographic and Genetic Algorithms.

Lexicographic method provides optimal vectors by first sorting the objective functions a priori using decision maker preferences. It is sufficient for Pareto-optimality and is relatively simple to implement (Marler and Arora 2004). While the ordering of objectives

implies a priori articulation of preferences, objectives can be ordered randomly using no preference articulation and provide good results (Coello 2001). According to Andersson (2000), a disadvantage of the lexicographic method is that not all objectives may be considered as consideration of alternatives stop when they cannot be distinguished at a certain level. This method is more commonly used in combination with other methods, such as goal programming and genetic algorithms (Andresson 2000).

Genetic Algorithms (GA) were originally developed by John Holland (1975) to use the concepts of DNA, evolution, and natural selection. Objectives relate to genes, and the set of objectives within the multiobjective problem relate to the idea of chromosomes. An individual instantiation of a chromosome is a design point. The instantiations of multiple chromosomes with different objective values expressed by the genes form a population. Each iteration of the GA algorithm is called a generation. As a nature-inspired, metaheuristic method (Baghel, Agrawal, and Silakari 2012), it provides a globally Pareto-optimal vector answer to multi-objective problems (Marler and Arora 2004).

GAs are computationally complex (Marler and Arora 2004), as there are several ways to represent the genes and chromosomes, as well as different means to conduct the basic GA operations of selection, crossover, and mutation. Once an initial population is established, chromosomes must be selected. Coello (2001) provides a description of the use of MOO techniques that can be used to select chromosomes, to include the Weighted Sum, Goal Programming, Lexicographic, and Weighted Min-Max. There are also multi-objective GA algorithms for selection, to include the Vector Evaluated Genetic Algorithm (VEGA) (Schaffer 1985), Non-dominated Sorting Genetic Algorithm II (NSGA-II), Ranking (Garza-Fabre, Pulido and Coello 2009), Pareto-Set Filtering and Tournament

Selection (Coello 2001, Marler and Arora 2004). Hughes (2005) compares these selection methods and concludes that Multiple Single Objective Pareto Sampling (MSOPS) techniques are better than VEGA or NSGA-II methods when there are more than three objectives.

Selected chromosomes then need to be merged to form new chromosomes, thereby adding to the population in the crossover process. A mutation process can then be conducted to vary the chromosome encoding which introduces "diversity" into the population, thereby allowing the GA algorithm to further explorer the solution space and not converge to a few number of points (Augusto, Bennis, and Caro 2012).

2.4.2.6 MADM Methods.

MADM methods are those methods that are used for discrete problems where there are normally small numbers of alternatives or criteria, with variable values that can include qualitative as well as quantitative values used in the MOO techniques. The methods are grouped into Outranking methods, Analytical Hierarchal Process (AHP) family of methods, and TOPSIS, which is a popular method for deciding alternatives, although it can be used on MOO problems since it is based on the Global Criteria method.

Outranking methods, such as Elimination EtChoix Traduisant la REalite (ELECTRE) and Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE), compare alternatives in a pairwise fashion. Hence, they suffer in performance as the number of alternatives increases as there are 2^n comparisons that are necessary. These comparisons may lead to situations where the pair may not be comparable, or the comparison results may be inconsistent. For instance, A is better than B, B is better than C, and C is better than A (Stewart 1992).

The ELECTRE-based methods (Roy and Vincke 1981) is a family of methods that includes ELECTRE-I, II, II, IV, IS and TRE. The method uses concordance and discordance indices, where the decision maker considers weights that provide information for and against one alternative versus another. The leading alternatives have higher concordance index values while also smaller discordance index values. The ELECTRE methods are useful in down selecting alternatives to the top contenders, although the method may not necessarily lead to a top choice (Pohekar and Ramachandran 2004). The comparisons in ELECTRE can be descriptive to the decision maker when the number of alternatives is around six or less (Stewart 1992). The PROMETHEE method (Brans and Vincke 1985) is a pairwise comparison of alternatives, using six criteria. These criteria are weighted by the decision maker and are used to create a multi-criteria preference index. REGIME (Nijkamp, Hinloopen and Rietveld 1983) is also another pairwise ranking method. It works by first having the decision maker create an impact matrix that provides performance measure of each alternative. Then a set of weights is also generated to show the relative importance of the criteria to the decision maker. Like ELECTRE, it uses the idea of concordance and discordance to compare the alternatives. Criteria can be qualitative, but must be converted into a quantitative form.

Another very prominent pairwise comparison method is the Analytical Hierarchy Process (AHP) (Saaty 1980, Saaty 2008). This is not an outranking method, but a structured mechanism to generate the weights that can then be used in the Weighted Sum Method to determine the best alternative. In AHP, the decision makers need to categorize the criteria into a hierarchy of criteria for which a pairwise comparison is conducted between criteria at the same level. The comparisons are given a 1-9 scale value. Pairwise

comparisons are done between the criteria and between the alternatives. Hence, in this method, the alternatives need to be established a priori. Also, since there are 2^n comparisons per group of criteria, this method can take a great deal of time to accomplish.

On of the issues with AHP, as well as some other common methods, is rank reversal (Belton and Gear 1983, Stewart 1992, Zanakis et al 1998). Rank reversal is a phenomenon where the relative ranking between alternatives changes when new alternatives are introduced. When compared to the methods of Simple Additive Weighting, Exponential Weighting, TOPSIS and ELECTRE, AHP showed the second most effect to rank reversal, with ELECTRE being affected the most (Zanakis et al 1998). Stewart (1992) also asserts other issues to AHP. First, weights are developed without regard to the range of values of the related criteria. This is a general problem of weighting addressed by Nitzsch and Weber (1993). Second, the 1-9 scale used to assess criteria pairs is used as a ratio, implying that a pair that receives a 4 is twice as important as a pair that receives a 2, which is not the intent of the scale.

The last MADM method this review covers is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Hwang and Yoon 1981). It is a MOO method based on the Global Criteria formula (2.6). TOPSIS takes two measurements to judge the optimality of a point – its Euclidean distance from Ideal Point and the distance from the Negative Ideal point. The optimal points minimize the distance from the Ideal and maximize the Negative-Ideal distance.

TOPSIS can also use weighting to affect the distance measurement per attribute. Olsen (2004) examined the use of weights within TOPSIS. TOPSIS criteria need to be normalized, just as it is done in the common Simple Additive Weights method. Hence, it

is susceptible to the weighting and scale issues (local versus global scales) as other weighting methods. Another issue with TOPSIS is that it can suffer from rank reversal (Olsen 2004, Zanakis, Solomon, Wishart and Dublish 1998).

2.4.2.3 Metaheuristic Methods.

Metaheuristic methods use algorithms or procedures to explorer the solution space. The term was first used by Glover (1989) in the development of the Tabu Search technique. Some of these methods are inspired by nature, such as simulated annealing, particle swarms and the ant colony approach. Genetic algorithms are also considered a metaheuristic approach, although that method is covered in another section.

Tabu Search (Glover 1989) is a search technique that was originally developed to search beyond the local search space in combinatorial problems. The key to the Tabu Search is the storage of a set number of points already visited by the algorithm. As Pareto-optimal points are found, they are stored and if the search finds that point again, it is ignored. It is "tabu", and a new point is developed. Figure 2-3 is the algorithm of the Tabu Search.

In the Tabu algorithm of Figure 2-3, the set X are points or alternatives within the feasibility space and S is the set of points that should be considered in the search for Pareto optimal points. A point, s_k, is selected from S that is not a member of T, the Tabu list. If the current point is more optimal than the last point examined in a prior iteration, then the point s_k is added to the Tabu list. The algorithm will repeat until k, the counter, reaches a pre-determined number or there are no other points in S that are not already in the Tabu list.

The following methods are nature-inspired methods. Simulated Annealing (Kirkpatrick 1983) conducts random searches of possible optimal points while taking concepts from thermodynamics. With every iteration, the technique runs a probability function to decide if it should leave the local neighborhood. Once the decision of neighborhood is made, a new

SIMPLE TABU SEARCH

1. Select an initial $x \in X$ and let $x^* := x$. Set the iteration counter $k = 0$ and begin with T empty.
2. If $S(x) - T$ is empty, go to Step 4. Otherwise, set $k := k + 1$ and select $s_k \in S(x) - T$ such that $s_k(x) = \text{OPTIMUM}(s(x): s \in S(x) - T)$.
3. Let $x := s_k(x)$. If $c(x) < c(x^*)$, where x^* denotes the best solution currently found, let $x^* := x$.
4. If a chosen number of iterations has elapsed either in total or since x^* was last improved, or if $S(x) - T = \varnothing$ upon reaching this step directly from Step 2, stop. Otherwise, update T (as subsequently identified) and return to Step 2.

Figure 2-3. Original Tabu Search Algorithm from Glover (1989).

point is selected. It also keeps track of the last point it decides to keep. The decision on whether to keep the point is based on two factors. If the new point is considered to dominate the last held point, the new point is kept. If the new point is not more optimal, it may still be kept depending on the number of iterations the method has accomplished. Using the idea of annealing metals, metals are cooled slowly to improve their properties. In Simulated Annealing, the more the method iterates, the "cooler" it becomes and hence the less likely the algorithm will accept a worse solution than the one it already has. The probability used is based on the Boltzman distribution. The other two methods that are

nature-inspired, other than Genetic Algorithms, are the Particle Swarm method (Kennedy and Eberhart, 1995) and the Ant Colony Optimization method (Dorigo, 1992).

2.4.2.4 Method Combinations.

Many times, these techniques are used in combination to work problems. Called Hybrid methods, Andersson (2000) provided four categories of hybrids: Pipelining, Asynchronous, Hierarchal, and Additional Operator hybrids. Pipelining hybrids use different methods sequentially. For instance, genetic algorithms, lexicographic, and goal programming methods have already been mentioned as techniques used to down-selection are large field of alternatives. Asynchronous hybrids have multiple methods operating simultaneously on different parts of the solution space. Heirachal hybrids use different techniques at different levels of optimization. For instance, McAllister et al (2004) use Linear Physical Programming and goal programming at different levels. Finally, the Additional operators method embeds one techniques within another. Coello (2001) provides several examples of different MOO techniques used as a selection function within Genetic Algorithms.

The literature shows several common pairings of methods. One pairing is between AHP methods and TOPSIS. Sipahi and Timor (2010) provide statistics on the use of AHP-based methods with other MCDM techniques. Other literature showing the common use is "Vendor Evaluation Using Multi Criteria Decision Making Technique" by Elanchezhian, Ramnath, and Kesavan (2010) and an article by Trehan and Sharma (2012). Other methods are starting to be paired with physical programming. This includes AHP (Shad, Roghanian, and Mojibian 2014) and Quallity Functional Deployment (QFD) (Lai, Xie, and Tan 2006, Shad, Roghanian and Mojibian 2014).

2.4.3 Physical Programming

Physical Programming (Messac 1996) is a method derived from the design optimization area that seeks to avoid the use of weights by focusing on the specification of a series of continuous ranges crossing the spectrum from unacceptable to ideal for each objective. The name comes from the idea of the decision maker using physically meaningful values, and it should not be confused with linear programming.

Unlike other methods, the objective values do not need to be normalized. The objective functions are formulated to generate spline curves that cross the boundary points between ranges, and the objective functions for all metrics generate the same value at their respective range boundary values. This method is a minimization function, although it can handle criteria that need to be either minimized, maximized, or stay close to a specific value or range. Also, the criteria of Physical Programming can be any kind of variable – dependent vaiables, independent variables, design variable, and constraints (Messac 1996).

According to Marler and Arora (2004), Physical Programming is both necessary and sufficient for Pareto-optimality. It is also very expressive in terms of specifying user preferences, although calculating the AOF can be complicated. While they list this method as being applicable for both a priori and posteriori preference articulation, it has also been shown to be useful for progressive or interactive preference articulation (Tappeta, Renaud, Messac, and Sundararaj 2000).

2.4.3.1 Background

As seen in Figure 2-4 (Messac and Wilson 1998; Mullur, Mattson, and Messac 2003), PP classifies its design metrics or parameters into hard and soft classes. Hard classes are

simply binary membership functions. The parameter value is either less than, greater than, or equal to a certain defined value or between two defined values. Optimization occurs only with the soft classes. Soft classes measure how well a parameter value falls within a particular region within the class. The regions are defined by boundary values between the regions (t_{is}, $1 \leq s \leq 5$ for classes S-1 and S-2, and $\tilde{t}_{is}^{+}$: $1 \leq s \leq 5$ and $\tilde{t}_{is}^{-}$: $1 \leq s \leq 5$ for classes S-3 and S-4). These regions are described in the following list, where g_i is the value of parameter *i*:

- Unacceptable range (region 6), where ($\tilde{t}_{i5}^{+} \leq g_i$)
- Highly undesirable range (region 5), where $\tilde{t}_{i4}^{+} \leq g_i \leq \tilde{t}_{i5}^{+}$
- Undesirable range (region 4), where $\tilde{t}_{i3}^{+} \leq g_i \leq \tilde{t}_{i4}^{+}$
- Tolerable range (region 3), where $\tilde{t}_{i2}^{+} \leq g_i \leq \tilde{t}_{i3}^{+}$
- Desirable range (region 2), where $\tilde{t}_{i1}^{+} \leq g_i \leq \tilde{t}_{i2}^{+}$
- Highly desirable range (region 1), where $g_i \leq \tilde{t}_{i1}^{+}$

As you move across the regions, from highly desirable to highly undesirable, the value of the objective function, $\check{Z}^s$, grows exponentially, based on the number of soft criteria parameters, n_{sc}. The difference in objective value between region boundaries $\tilde{t}_{is}^{+}, \tilde{t}_{i(s-1)}^{+}$ is $\tilde{Z}^s$

$$\tilde{Z}^s = \beta(n_{sc})\tilde{Z}^{s-1} \qquad (2 \leq s \leq 5) \tag{2.10}$$

where β is a concavity factor. As part of the design, $\check{Z}^s$ at $\tilde{t}_{is}^{+}$ for any parameter *i* is the same. For each parameter, the farther away the parameter g_i moves toward the undesirable form of inter-criteria preference.

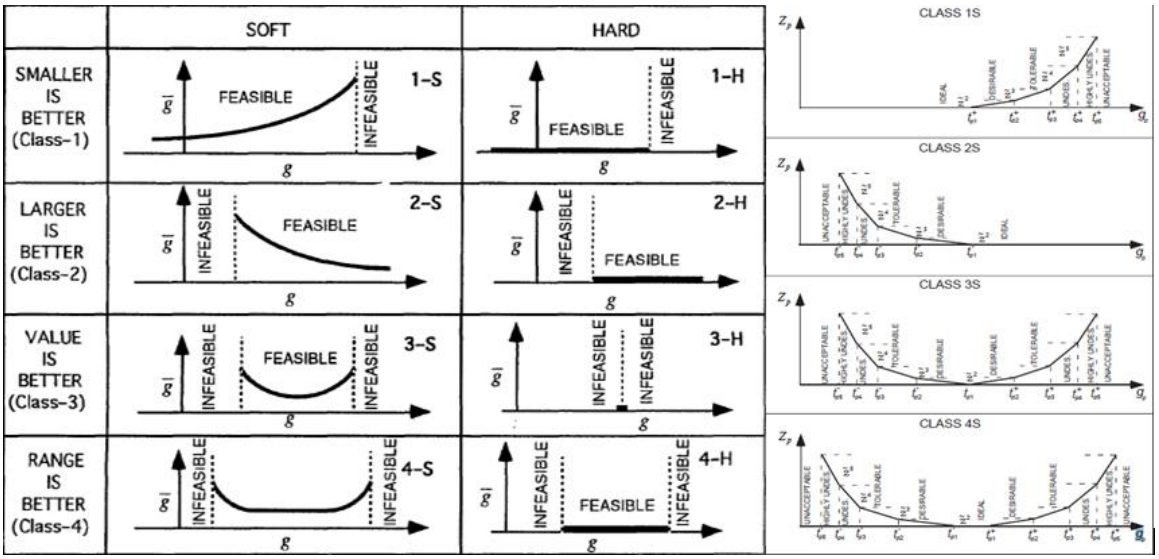

Figure 2-4. PP and LPP Classes and Region Depictions (Ma and Dong 2008).

PP forms a spline curve through the points $(\tilde{t}_{is}^{+}, \tilde{Z}^{s})$ (Messac 1996). The creation of this spline and the calculations for finding Z^{i} make PP difficult to implement. An easier version of the objective functions come from Linear Physical Programming (LPP). LPP replaces the spline curve with line segments between the region boundary points, as seen in Figure 2-4 (Ma and Dong 2008). The calculations to find *Z* are as follows, which contain slight differences from the PP equations:

$$Z^{S} = Z_i(t_{is}^{+}) = Z_i(t_{is}^{-}) \quad \forall i; \quad (2 \le s \le 5); \; Z^{1} = 0; \; Z^{2} = 0.1 \tag{2.11}$$

$$\check{Z}^{s} = Z^{s} - Z^{s-1}; \; (2 \le s \le 5) \tag{2.12}$$

$$\tilde{Z}^{s} = \beta(n_{sc})\tilde{Z}^{s-1} \quad (3 \le s \le 5); \; n_{sc} > 1; \; \beta > 1 \tag{2.13}$$

Part of the requirement of PP and LPP is that the graph stays convex. The following equations are used to check convexity for all parameters:

$$\tilde{t}_{is}^{+} = t_{is}^{+} - t_{i(s-1)}^{+}; \quad \tilde{t}_{is}^{-} = t_{is}^{-} - t_{i(s-1)}^{-}; \tag{2.14}$$

$$w_{is}^{+} = \frac{\tilde{Z}^{s}}{\tilde{t}_{is}^{+}}; \; w_{is}^{+} = \frac{\widetilde{\tilde{Z}^{s}}}{\tilde{t}_{is}^{+}}; \; (2 \le s \le 5), \tag{2.15}$$

which is the slope of the *s* region.

$$\widetilde{w}_{min} = min\{w_{is}^{+}; w_{is}^{-}\} > 0;\ (2 \le s \le 5) \quad i\text{: parameter} \tag{2.16}$$

where

$$\widetilde{w}_{is}^{+} = w_{is}^{+} - w_{i(s-1)}^{+} \tag{2.17}$$

$$\widetilde{w}_{is}^{-} = w_{is}^{+} - w_{i(s-1)}^{+} \tag{2.18}$$

$$w_{is}^{+} = w_{i1}^{-} = 0 \tag{2.19}$$

The preference function is then merely solving for a linear function at g_i, the parameter value.

$$Z^{i} = Z^{is} + (g_i - t_{is}^{+})w_{is}^{+} \quad (t_{is}^{+} < g_i \le t_{i(s+1)}^{+}) \tag{2.20}$$

Once Z^i has been calculated for all parameters *i*, $1 \le i \le n_{sc}$, the PP AOF, Z, can be taken:

$$Z = \frac{1}{n_{sc}} log\left(\sum_{i=1}^{n_{sc}} Z^{i}\right) \tag{2.21}$$

2.4.3.2 Methodologies.

In addition to the original Physical Programming method, several variations now exist. Linear Physical Programming (LPP) replaces the spline curves with piecewise linear functions (Messac, Gupta, and Akbulut 1996), making the calculation and use of PP much easier. A form of Physical Programming for progressive preference articulation was developed by Tappeta et al (2000). There is a Fuzzy version of Physical Programming developed by Tian, Huang, and Guan (2002). Also, Global Physical Programming, a version that uses Genetic Algorithms to do the point searching as the optimizer, was developed by Sanchis et al (2010). Off all the variant, LPP is by far the most popular in the literature, with 37 publications out of a total of 43 (Ilgin and Gupta, 2014).

2.4.4 Applications.

Many say that there is no one best technique for conducting MCDM and its sub-areas, such as MOO (Polatidis, Haralambopoulos and Munda 2006). Korhonen, Moskowitz, and Wallenius (2006) provide a framework to determine the use of discrete or continuous methods in addition to describing the characteristics of those problem spaces. They also provide a good example of using factors to choose among MCDM methods, such as the need to use qualitative or quantitative data, preference articulation by the decision maker, the need to establish weights, the need to handle uncertainty in the data, and practical considerations, such as the ease of use of the method. However, another means to judge the appropriateness of a given method is to view if it has been used in a relevant application area. This section does a quick review of key application areas found in the literature.

2.4.4.1 Design Optimization.

Many of the papers reviewed dealt with using MOO for design choices. Examples using LPP include a high-speed civil transport (HSCT) (Messac and Hattis 1996), water distribution networks (Jamieson 2007), turbine design (Zhang 2010), and conducting portfolio choices (Messac, Martinez, and Simpson 2002). Mcallister, Simpson, Lewis, and Messac (2006) use LPP in conjunction with Goal Programming in designing a system within the Multidisciplinary design optimization (MDO) domain using the Collaborative Optimization (CO) framework developed by Braun and Kroo. Goal programming is used within both the system and subsystem level to set goals, and the CO framework is used to define variables that link the various subsystems to the overall system criteria.

2.4.4.2 Concept Exploration.

Recent literature is starting to address more the use of MOO during the conceptual and pre-design stages. Curtis et al. (2013) provide a MOO strategy that explores the design space beyond the initial definitions of the problem dynamically, in a "divergent" fashion. In their concept called formulation space exploration, where the problem can be redefined dynamically to identify new requirements and preferences. They also present metrics to assess the new concepts as they are developed. Guenov et al. (2010) proposed a multi-disciplinary design framework using a workflow management process, along with the use of MOO, sensitivity analysis, and modeling the effects of uncertainty in the problem model. Huang, Liu, Li, Xue, and Wang (2012) present new evaluation methods for conceptual design selection using computational intelligence techniques using LPP as well as several other methods.

2.4.4.3 Energy Planning.

Polatidis, Haralambopoulos and Munda (2006) and Pohekar and Ramachandran (2004) review energy planning in their article "Selecting an Appropriate Multi-Criteria Decision Analysis Technique for Renewable Energy Planning". The overall conclusion for that area is that outranking techniques, which provide a general ranking of a discrete set of alternatives, and allows for in comparability because of a lack in available data, seemed more appropriate for this sector that utility-based methods that required enough data to construct weights and compare factors. However, these results are limited in that they did not evaluate continuous, mathematical programming methods or mention evolutionary methods, and they also conclude that there was no perfect method based on their evaluation criteria.

2.4.4.5 Project Alternatives.

Gao, Feng, and Yang (2008) reference several techniques that have been used in information system selection. These include Buss (1983) using ranking methods, Lucas (1976) using scoring, Badri and Davis (2001) using mathematical programming, and AHP and ANP methods (Lee and Kim 2000, Lai, Wong, and Cheung 2002). TOPSIS was used recently within an AOA for selection technology (Georgiadis, Mazzuchi, and Sarkani, 2013), while Gao, Feng, and Yang (2008) used a variation of TOPSIS, called Fuzzy TOPSIS, to conduct an information system project selection. MADM techniques, to include SAW and TOPSIS were evaluated by Chang (2005).

2.5 Current Gaps in the Literature.

While the general events for DoD weapon system requirements formulation and alternatives development for MS A are defined, there are no specific guidance or examples of how this work can or has been done. In discussions with the Deputy Director for SE Policy and Guidance, Office of the Deputy Assistant Secretary of Defense, Systems Engineering, there are no public cases that provide details of programs that have conducted the integrated cost and technical analysis required by WSARA (Sedmak, personal communications, 2012). A literature search did not yield any cases.

There has been modeling and simulation research within the design area that has used surrogate modeling and probabilistic models to estimate the technical performance using chosen material components (Biltgen, Ender, and Mavris 2006; Ender 2006; Ender et al. 2010; Reddy, Fertig, and McCormick 2006). By choosing components, these models can aggregate attributes, such as weight, and through surrogate model development, create relationships between these attributes and performance metrics. However, these efforts

have not provided a method to link user capabilities to the component selection or the automation of picking multiple components within a component type. Currently, the selection of components that affects a system's cost and performance is conducted via interaction with the designer (Yukish, Stump, and Lego 2007).

Chapter 3: Methodology

As the final processes for developmental planning are not yet well defined by DoD, the research took a mixed methodology approach, incorporating both quantitative and qualitative approaches provide the basis for the model and the statistical experimentation to show its effectiveness. To build a model and processes to integrate cost and performance estimation, we needed to understand what types of systems and programs related to specific cost growth causes. This would provide the scope of programs that would be applicable for this research and benefit from it. We conducted a descriptive statistical analysis of the types of programs and their corresponding cost growth causes from pre and post WSARA studies. This presupposes a means to categorize the causes for that growth. However, there are several approaches to categorizing cost growth causes that are used in the literature. We analyzed the different category structures in the literature that can be used to normalize the data across various root cause analyses.

Second, most cost growth cases were conducted pre-WSARA. We presented three new cases of programs conducting in-depth systems engineering and cost analysis as required by WSARA. This helped us better understand how various programs shown as relevant from our cost growth statistical analysis conducted their pre-MS A activities. This included their processes, techniques, and teams used to address the need for established technical and cost baselines by MS-A/concept exploration phase.

Finally, we assessed the methodology to construct the technical/cost model. We focused on the types of MOO techniques available that can be used to balance the inter-related factors of cost, SWaP, and various performance measures that result from the

mapping of capabilities to material components. The overall framework is depicted in Figure 3-1.

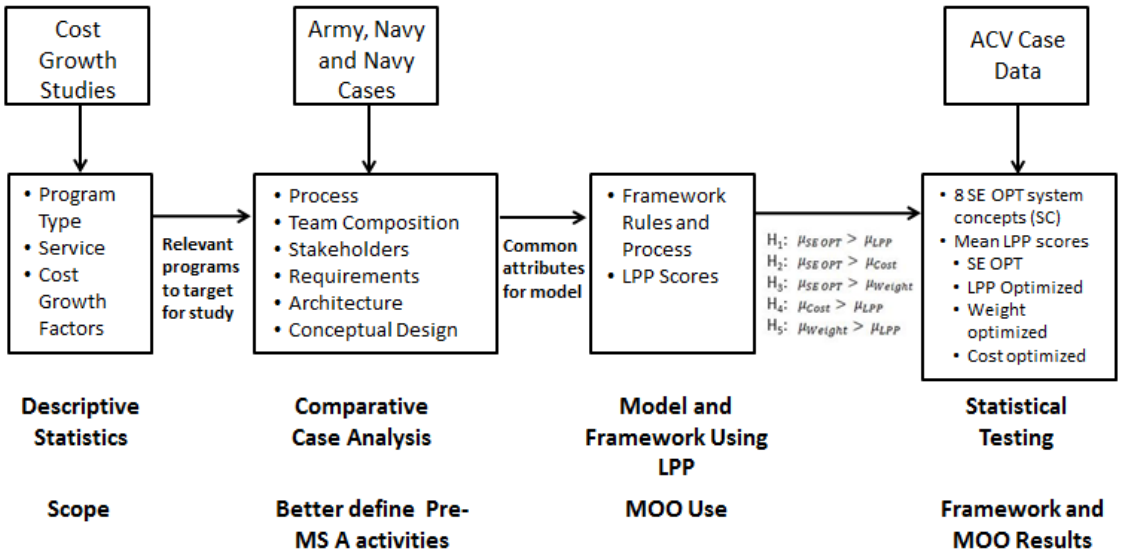

Figure 3-1. Methodology and Theoretical Framework

3.1 Cost Growth Root Cause Analysis.

To understand the types and sources of systems that experience different categories of cost growth that can be addressed by our cost/performance model, we went to various root cause analysis documents. These included a statistical analysis of several defense programs (Bolten et al. 2008), aviation platforms (Bronson et al. 2010; Fox et al. 2011; Younossi et al. 2005), and programs that had gone through major congressional review for critical cost growth increases (Blickstein et al. 2011; Blickstein et al. 2012). Many of these documents come from the Performance Assessment and Root Cause Analysis (PARCA) organization within the Office of the Under Secretary of Defense for Acquisition, Technology, and Logistics (OUSD (AT&L)). The systems analyzed all had significant (>15%) variance from their baseline. Hence, the analysis provides an understanding of the

correlation of different system types to root causes and the correlation of root causes with each other.

The literature presents several methods of categorizing cost growth causes. Table 3-1 presents the major categories, while many references present their own cost growth categories. All DoD major acquisition defense programs (MDAPs) provide System Acquisition Reports (SARs) that present a status of their current cost against an established baseline. SARs are also required if the program breaks its cost threshold by 15% (a significant breach) or 25% (a critical breach). A critical breach results in a major review by the DoD Acquisition Executive and Congress and may lead to the program's termination.

Table 3-1. Major Categories of Cost Growth Causes

SAR	RAND 2008	WSARA
• Estimating • Quantity • Schedule • Support • Economic • Engineering • Other	Estimation and Planning Errors • Cost Estimation • Schedule Estimation • Technical issues Decisions • Requirements • Affordability • Quantity • Schedule • Program transfers Financial • Exchange Rate • Inflation Miscellaneous • Error corrections • Unidentified variances • External events	Baseline Issues • Unrealistic estimates for cost or schedule • Immature technology; excessive manufacturing and integration risk • Unrealistic performance expectations Execution Issues • Changes in procurement quantities • Inadequate funding • Unanticipated technical or engineering issues • Poor performance of government or contractor personnel • Other

The SAR has the following categories in which cost variances are listed and explained: estimation, quantity, schedule, support, economic, engineering, and other. However, there are several reasons why SARs are problematic for analysis. These include

the training of the SAR writers, the mixing of cause and effect in allocating costs to the correct cause, reporting inconsistently over time and between programs, limiting SARs to major programs, changing cost estimates and requirements over time, and not explaining programmatic context for the cost growth (Bolten et al. 2008). The RAND 2008 report (Bolten et al. 2008) created its own category using four subgroups: errors, decisions, financial, and miscellaneous. WSARA established a new category structure for cost growth causes which seems commonly used in recent cost analysis papers.

To use both the data from the RAND 2008 study and more current cost growth root cause analysis reports, we chose the RAND 2008 taxonomy, rather than the more current WSARA taxonomy or the original SARs. First, the RAND study does not state in detail how they analyzed the individual SARs and reassigned cost data into their own taxonomy. They did present a detailed matrix that showed a complicated many-to-many relationship between their taxonomy and the SAR. Hence, trying to conduct our own study using SAR data could introduce different interpretations that would affect any statistical analysis. Second, the WSARA taxonomy has a major category not addressed in the RAND study—poor government or contractor performance. It would be very hard, if not impossible, to backfit that category into the RAND study. Third, the RAND study had a more detailed breakout that included distinguishing cost from schedule estimate errors. As we will show, we believe it is a mistake to lump these two types of errors together.

With the in-depth root cause analysis from PARCA of individual and small groups of systems using the WSARA model, we were able to work from that model back to the RAND taxonomy. Our mapping between the two taxonomies is shown in Table 3-2. The majority of systems with root cause analysis data came from the RAND 2008 study,

which had specific criteria as to the systems it included. Some of these criteria required that these programs be reasonably current, with a MS B decision after 1980, and were well established by having a sizable amount of procurement budgeted up through the year of the study and not having been cancelled early in procurement. The programs had to have established estimates for costs and procurement quantity. Also, being an Air Force study, included programs were consistent with the complexity of existing Air Force programs. This resulted in ships and submarines not being included. To stay consistent in our review, we did not include cost analysis that did not fit these criteria. Hence, we did not include the Guided Missile Destroyer DDG 1000 (Blickstein et al. 2011) or Future Combat System (FCS) (Pernin et al. 2012) programs. Unlike the RAND study, other papers explicitly placed programs into specific cause categories without trying to break out costs per category.

Table 3-2. Mapping between WSARA and RAND Cost Growth Cause Categories.

	RAND Study of 2008												
	Estimation and Planning Errors			Decisions					Financial		Miscellaneous		
WSARA	Cost Estimation	Schedule Estimation	Technical Issues	Require-ments	Afford-ability	Quantity	Schedule	Program Transfers	Exchange Rate	Inflation	Error Corrections	Unident. Variances	External Events
Unrealistic estimates for cost or schedule	X	X											
Immature technology; excessive manufacturing and integration risk			X								X		
Unrealistic performance expectations				X			X						
Changes in procurement quantities						X							
Inadequate funding					X								
Unanticipated technical or engineering issues			X										
Poor performance of government or contractor personnel							X	X			X		
Other									X	X		X	X

To address the differences in expressing the assignment of programs to root causes (cost growth per cause category versus explicit assignment to a category), this analysis converts cost growth percentages to a member assignment of a cost growth category, such

as quantity change. As the DoD judges a total 15% cost increase as significant for SAR reporting purposes, any cost growth of over 7.5% associated with any single cost growth cause results in the program's membership with that cause type.

3.2 Pre-Design Case Development and Analysis.

Post-WSARA developmental phase case studies of DoD systems are virtually non-existent in the literature or in internal forums known by the Systems Engineering Office of the Secretary of Defense (OSD) (Sedmak, personal communications, 2012). Since WSARA was passed only recently in 2009, there are few frameworks on which to build techniques and models to guide pre-MS A activities.

As present by Robert K. Yin (2009), case studies are an appropriate method for our research problem. It is "preferred in examining contemporary events, but when the relevant behaviors cannot be manipulated" (Yin 2009, 11). It serves to help understand the events within different contexts where there may be more variables than can be addressed in other data collection methods. Pre-MS A activities undertaken by different programs under different constraints fit this description. According to Yin, this method can provide several benefits. It serves well to answer the questions of "how" and "why". It can provide generalizable results, and has been useful as an exploratory stage before using other research methods. Additionally, case studies can include quantitative data which can be useful in a mixed-methods approach (Yin 2009).

Friedman and Sage (2004) describe the case study methodology as it applies to systems engineering, and refer to Yin's work in developing their proposed framework for systems engineering case studies. This research uses Friedman and Sage (2004) and Yin (2009) as a foundation on conducting this portion of the research. Yin (2009) lists five

components important to a case study design: the studies questions, propositions, units of analysis, the logic linking the data to the study's propositions, and criteria for interpreting the findings. Yin also stresses that these components need to be supported by a basic theoretical foundation on which to start the data collection and define these five components (Yin 2009, 35).

For this portion of our research, the research question for the case analysis is how existing efforts by DoD material development offices have been conducted to accurately determine cost and affordable requirements. As such, this is an exploratory case study where We also have these sub-questions that align with our main research question: what are the common attributes that we could find among these efforts? How is cost estimation conducted within these cases? How are requirements stakeholders involved in the cost estimation and technical analysis process to evolve requirement? We also had several propositions. First, based on the literature review, pre-MS A activity will demonstrate system dynamics elements of iteration with feedback loops, both in the processes used as well as developing the cost and technical attributes of the program in question. Second, as we are concerned with how this activity is done, we propose that it is important to determine the tools used. Third, as cost estimates have been seen to be affected by both government and industry desires to gain positive decisions to go forward (Gardener and Moffat 2008), the governance structure is an important consideration. Fourth, we propose that the programs to include should conform to the types of programs with relevant cost growth causes determined from our cost growth analysis. Finally, we propose that the team composition performing the case activities are important to discover, based on the responsibility domain of the Friedman and Sage (2004) framework.

The unit of analysis defines the focus of the case study. For our cases, we used multiple embedded units of analysis that fall within the overall context of individual teams within DoD material development programs that are engaging in Pre-MS A cost and requirement development activities. Within this context, our units of analysis include the overall team process, the tools used to support the analysis process, the formation of requirements, the governance structure under which the teams perform, and the stakeholders that are directly involved with the teams in their estimation and requirement development activities. Depending on the information available for the specific case, we could not include all units of analysis for all cases.

Friedman and Sage (2004) list five techniques for conducting what Yin calls the logic linking the data to the study's propositions. This is the analysis of the case studies. We use the technique of cross-case analysis and synthesis. Friedman and Sage (2004) indicate that comparative case study analysis can be effective for analyzing similar types of cases. These cases shall be used to find commonality and disparities among the processes, tools, cost analysis methodology, team structure, governance, and lessons learned from these current developmental phase efforts.

Both Friedman and Sage (2004) and Yin (2009) discuss the issues of designing a quality case study, which include the four areas of construct validity, internal validity, external validity, and reliability. Addressing these areas helped guide the design of the case study portion of our research. Construct validity is "identifying correct operational measures for the concepts being studied" during the data collection and drafting of the study (Yin 2009). We attempted to access multiple sources of evidence, as depicted in Table 4-2. We also submitted the case study for review to the source program offices.

Internal validity is most concerned with avoiding researcher bias. According to Yin (2009), this is applicable to explanatory and causal studies only. Our case studies are exploratory, as we are researching a relatively new phenomenon where no new case studies exist. However, it is still a concern. The author has the most direct and prolonged experience with the SE OPT ACV case. This case study could almost have been a single-case study where the SE OPT case was considered a revelatory case (one where researchers have not had access to such a case before). However, a multiple case study allows for pattern matching against our theoretical framework, and replicating those findings in other cases. It also allows for greater external validity to show a generalizability of the results. The multiple cases in this study are meant to use literal replication logic (Yin, 2009) where we are expecting similar results within our units of analysis among the different cases.

3.3 Multi-Objective Optimization Techniques.

As we will describe in detail in Chapter 4, our framework and model map capabilities to material components. That selection is based on the use of Multi-Objective Optimization (MOO) to select components based on a variety of metrics associated with the components. Marla and Arora (2004) and Andersson (2000) provide a thorough review of different types of MOO algorithms that are useful in engineering. The typical MOO problem seeks to minimize F(x), the aggregate objective function (AOF) that is based on the set of objective functions, $f_i(\mathrm{x})$ for a vector **x** of k design metrics and *n* optimization parameters.

$$\text{Minimize } \mathbf{F(x)} = [f_1(\mathrm{x}), f_2(\mathrm{x}), \ldots, f_k(\mathrm{x})]^{\mathrm{T}} \tag{3.1}$$

$$\mathbf{x} = x_1, x_2, ..., x_n \tag{3.2}$$

The design metrics may actually be composed of different types of variables, such as independent design variables or parameters (parameters under a designer's control), dependent variables or design attributes (derived from other variables), state variables, environmental variables, etc. The value of F(x) is based on how the objective functions are related together, sometimes through a preference value, such as weights, to form an AOF.

MOO methods can be grouped according to how the preferences between objective functions are determined (Andersson 2000; Marler and Arora 2004). These include the a priori articulation of preferences, where the importance or goals of the objectives comes before running the MOO method, progressive articulation of preferences, where the preferences between the objective functions is adjusted during the method execution, a posteriori articulation of preferences, where a solution is chosen from a set of possible optimal solutions after MOO execution, and finally no articulation of preferences.

The cases we have reviewed show that we require a method that can handle a priori, a posteriori, and progressive articulation of preferences due to when the requirements are known. The method selected was LPP, a derivative of PP (Ilgin and Gupta 2012; Messac 1996). In addition to the ability for PP to be used with different articulation preferences (Marler and Arora 2004; Tappeta et al. 2000), it has several other benefits. Unlike the commonly used weighting method, which requires subjective weights to be applied and then adjusted to suit the decision maker, PP and LPP avoid the use of weights through the specification of different desirability regions for each parameter (Marler & Arora 2004; Messac and Wilson 1998; Messac 1996). PP does not distinguish between independent and dependent variables, objective attributes, constraints, or goals. All these parameters are treated as design metrics that can be optimized against each other (Andersson 2000;

Marler and Arora 2004). Also, the PP algorithm is sufficient to produce Pareto-optimal results (Marler and Arora 2004). Finally, the AOF used in PP, a log of the sum of the individual parameter objective functions, does not require adjustments using weights or other modifications (Chen et al. 2000).

Using the LPP method and the SE OPT case data, we can run statistical hypothesis testing to verify that our framework improves on average the system selection and APUC costs calculated using MS Excel spreadsheets to implement our framework. We calculate LPP scores for four sets of data. Each set will have eight values, which are the LPP values for each SE OPT system concept. The four sets include the original system concepts with component selection from the SE OPT team. The other three sets vary the system selection based on selecting components optimizing for weight, cost, and the overall LPP score of the components themselves using key component metrics.

The following are the hypothesis test we will run using Paired t-test against the existing SE OPT case data:

1. H_0: $\mu_{SE\ OPT} \leq \mu_{LPP}$ (3.3)

   H_A: $\mu_{SE\ OPT} > \mu_{LPP}$ (3.4)

2. H_0: $\mu_{SE\ OPT} \leq \mu_{Cost}$ (3.5)

   H_A: $\mu_{SE\ OPT} > \mu_{Cost}$ (3.6)

3. H_0: $\mu_{SE\ OPT} \leq \mu_{Weight}$ (3.7)

   H_A: $\mu_{SE\ OPT} > \mu_{Weight}$ (3.8)

The first hypothesis test, represented by equations (3.3 and 3.4), is a one-tailed test. The alternate hypothesis is that the SE OPT mean of the LPP scores for the 8 system concepts is greater than the mean using our LPP model to choose components to satisfy

the capability requirements. As LPP is a minimization algorithm, a greater mean indicates a worse result. For the second (3.5 and 3.6) and third (3.7 and 3.8) hypothesis tests, we want to see if the results of using simple attributes of cost and weight provide results which are also better than the SE OPT results, so these tests are one-tailed also.

We also have the following tests to compare our LPP component selection method within our model with simple methods of trying to minimize cost or weight. Just like hypothesis test # 1, hypothesis test #4 conducts a one-tailed test (formulas 3.9 and 3.10). The alternate hypothesis checks to see if the mean of the scores for the eight system concepts using cost as a component selection factor is greater than the mean of the system concept LPP scores using LPP as the component selection method. If we cannot reject the null hypothesis, then our LPP method did not perform statistically better than using cost. Hypothesis test #5 (3.11 and 3.12) is set the same way, except it examine the use of weight rather than cost.

4. H_0: $\mu_{Cost} \leq \mu_{LPP}$ (3.9)

   H_A: $\mu_{Cost} > \mu_{LPP}$ (3.10)

5. H_0: $\mu_{Weight} \leq \mu_{LPP}$ (3.11)

   H_A: $\mu_{Weight} > \mu_{LPP}$ (3.12)

Chapter 4: Research Results

Using the methodology described in Chapter 3, the research provided three main products. First, it produced a statistical analysis determining correlations between different cost growth causes and attributes of the systems under analysis. Various cost growth analysis studies were mined for data, and systems were allocated into specific groups, to include significant cost growth causes, type of system, and Service source. This provided data concerning relevant cost growth causes which our model should address and what types and sources of systems are affected. Second, we provide three new cases to address the question regarding how relatively new programs are attempting to meet WSARA Pre-MS A requirements. We conduct a new comparative case analysis using the United States Air Force Early Systems Engineering Guidebook as basis for key concepts to address. Finally, using the comparative case analysis results, we constructed an integrated cost and performance model and framework using system dynamics and show the application of Linear Physical Programming, a Multi-Objective Optimization (MOO) approach, for making decisions which the model.

4.1 Cost Growth Statistical Analysis.

To understand the types and sources of systems that experience different categories of cost growth that can be addressed by our cost/performance model, we went to various root cause analysis documents. These included a statistical analysis of several defense programs (Bolten et al., 2008), aviation platforms (Bronson et al. 2010; Fox et al. 2011; Younossi et al. 2005), and programs that had gone through major congressional review for critical cost growth increases (Blickstein et al. 2011; Blickstein et al. 2012). Many of these

documents come from the Performance Assessment and Root Cause Analysis (PARCA) organization within the Office of the Assistant Secretary of Defense for Acquisition, Technology, and Logistics (ASD (A)). The systems analyzed all had significant (>15%) variance from their baseline. Hence, the analysis provides an understanding of the correlation of different system types to root causes and the correlation of root causes with each other.

As explained in Chapter 3, Methodology, we chose the RAND 2008 taxonomy (Bolten et al. 2008), rather than the more current WSARA taxonomy or the original SARs. With the in-depth root cause analysis from PARCA of individual and small groups of systems using the WSARA model, we were able to work from that model back to the RAND taxonomy. We followed the specific criteria used in that study to select the system. These criteria included that these programs be reasonably current, with a MS B decision after 1980, and were well established by having a sizable amount of procurement budgeted up through the year of the study and not having been cancelled early in procurement. The programs had to have established estimates for costs and procurement quantity. Also, being an Air Force study, included programs were consistent with the complexity of existing Air Force programs. This resulted in ships and submarines not being included. To stay consistent in our review, we did not include cost analysis that did not fit these criteria. Hence, we did not include the Guided Missile Destroyer DDG 1000 (Blickstein et al. 2011) or Future Combat System (FCS) (Pernin et al. 2012) programs. Unlike the RAND study, other papers explicitly placed programs into specific cause categories without trying to break out costs per category.

To address the differences in expressing the assignment of programs to root causes

(cost growth per cause category versus explicit assignment to a category), this analysis converts cost growth percentages to a member assignment to a cost growth category, such as quantity change. As the DoD judges a total 15% cost increase as significant for SAR reporting purposes, any cost growth of over 7.5% associated with any single cost growth cause results in the program's membership with that cause type.

The resulting data is summarized in Table 4-1, which provides basic descriptive statistics of the cost growth per service and type of system. The table presents descriptive statistics not provided before, which include new root cause analysis data. It shows the conditional probabilities of a particular cost growth cause, given the presence of a military service, system type, or an additional and present cost growth cause.

From Table 4-1, several key patterns emerge. Whether looking at programs as grouped by service, system type, or the presence of cost growth causes given the presence of another, a key linkage is found between cost estimate errors and requirements errors and growth. While some of the statistics suffer from lower numbers of examples, the linkage between cost estimate errors and requirements errors was found using cluster analysis. The dendritic (Figure 4-1) shows the linkage between the two concepts.

Notably, cost estimate and schedule estimate errors do not frequently occur together. Schedule estimate errors occur with at least a 7.5% cost growth impact only 8% of the time in the presence of cost estimate errors that also have at least a 7.5 % cost growth impact. Hence, the combining of cost estimate and schedule estimate errors as a single category in the WSARA model is not supported with our current data

4.2 Pre-Design Case Development and Analysis.

This section presents three new cases for a comparative case analysis. These cases are

from programs initiated after the passing of WSARA. The cases are the SE OPT effort

Table 4-1. Cost Growth Descriptive Statistics.

40 Programs		Total Programs	Percent of Programs Reviewed	Mean, Dev Growth % per Program	Std Dev, Dev Growth % per Program	Cost Estimates	Schedule estimate	Technical issues	Requirements	Affordability	Quantity	Schedule changes	Inter-program transfers	Exchange rate	Inflation	Error correction	Unidentified	External events
Service																		
	Air Force (1)	17	42.5%	35.7%	41.6%	0.53	0.06	0.06	0.47	0.12	0.18	0.41	0.18	0.00	0.00	0.00	0.00	0.06
	Army	15	37.5%	56.2%	58.5%	0.73	0.07	0.20	0.67	0.13	0.20	0.20	0.20	0.00	0.07	0.07	0.07	0.00
	Navy	6	15.0%	46.0%	58.1%	0.67	0.00	0.00	0.33	0.00	0.17	0.00	0.17	0.00	0.00	0.00	0.00	0.17
	Joint	1	2.5%	N/A	N/A	1.00	1.00	1.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
Type																		
	Aircraft	12	30.0%	49.1%	56.7%	0.75	0.08	0.17	0.58	0.08	0.17	0.25	0.25	0.00	0.00	0.08	0.08	0.00
	AIS	5	12.5%	72.2%	36.7%	1.00	0.00	0.00	0.60	0.00	0.40	0.40	0.20	0.00	0.00	0.00	0.00	0.20
	Comm	2	5.0%	53.4%	46.6%	0.50	0.00	0.00	1.00	0.50	0.50	0.50	0.50	0.00	0.50	0.00	0.00	0.00
	Embedded System	4	10.0%	18.7%	17.5%	0.25	0.25	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00
	Launch Vehicle	2	5.0%	229.9%	306.6%	0.50	0.00	0.00	0.50	0.00	0.50	0.50	0.50	0.00	0.00	0.00	0.00	0.50
	Missile	6	15.0%	40.1%	68.1%	0.50	0.17	0.17	0.67	0.00	0.00	0.17	0.17	0.00	0.00	0.00	0.00	0.00
	Munition	4	10.0%	53.5%	67.8%	0.50	0.00	0.00	0.50	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Satellite	1	2.5%	16.5%	29.7%	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Vehicle	2	5.0%	16.5%	29.7%	0.50	0.00	0.50	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Weapon	1	2.5%	N/A	N/A	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
Percentage of programs with significant issue																		
	Cost Estimates	25	62.5%	18.0%	28.5%		0.08	0.16	0.64	0.08	0.28	0.32	0.28	0.00	0.04	0.08	0.04	0.08
	Schedule estimate	3	7.5%	1.0%	3.4%	0.67		0.33	0.33	0.00	0.33	0.00	0.00	0.00	0.00	0.33	0.00	0.00
	Technical issues	5	12.5%	0.6%	2.1%	0.80	0.20		0.60	0.20	0.60	0.00	0.00	0.00	0.00	0.40	0.20	0.00
	Requirements	21	52.5%	17.5%	22.8%	0.76	0.05	0.14		0.10	0.33	0.29	0.19	0.00	0.05	0.05	0.05	0.10
	Affordability	4	10.0%	-1.9%	8.1%	0.50	0.00	0.50	0.50		0.75	0.25	0.00	0.00	0.00	0.25	0.25	0.00
	Quantity	8	20.0%	4.3%	14.5%	0.88	0.13	0.38	0.88	0.38		0.25	0.13	0.00	0.00	0.25	0.13	0.25
	Schedule changes	10	25.0%	6.0%	11.5%	0.80	0.00	0.00	0.60	0.10	0.20		0.50	0.00	0.00	0.00	0.00	0.10
	Inter-program transfers	7	17.5%	4.8%	16.1%	1.00	0.00	0.00	0.57	0.00	0.14	0.71		0.00	0.14	0.00	0.00	0.14
	Exchange rate	0	0.0%	0.1%	0.5%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
	Inflation	1	2.5%	0.9%	3.3%	1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00		0.00	0.00	0.00
	Error correction	2	5.0%	-0.5%	3.2%	1.00	0.50	1.00	0.50	0.50	1.00	0.00	0.00	0.00	0.00		0.00	0.00
	Unidentified	1	2.5%	-0.3%	2.1%	1.00	0.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00		0.00
	External events	2	5.0%	6.0%	35.2%	1.00	0.00	0.00	1.00	0.00	1.00	0.50	0.50	0.00	0.00	0.00	0.00	

(1) For Air Force Mean and Std Dev, one outlier (Titan IV) was removed.

Descriptive Statistics

Conditional Probability - Probability of cost growth type (horizontal list) given membership in a particular category (vertical list)

analyzing the Amphibious Combat Vehicle (ACV) and Assault Amphibious Vehicle (AAV) Upgrade, the Advanced Airborne Sensor (AAS) based on the Littoral Surveillance Radar System (LSRS), and the Army Reference Architecture for Force Basing, formerly know as Force Basing Portfolio Management. These cases represent three of the four major Armed Services and a mix of combat vehicle, aviation, and portfolio programs. All have a mix of hardware and software development, aligning with the characteristics of the majority of systems found to have cost overruns and requirements issues from our review of the cost growth literature.

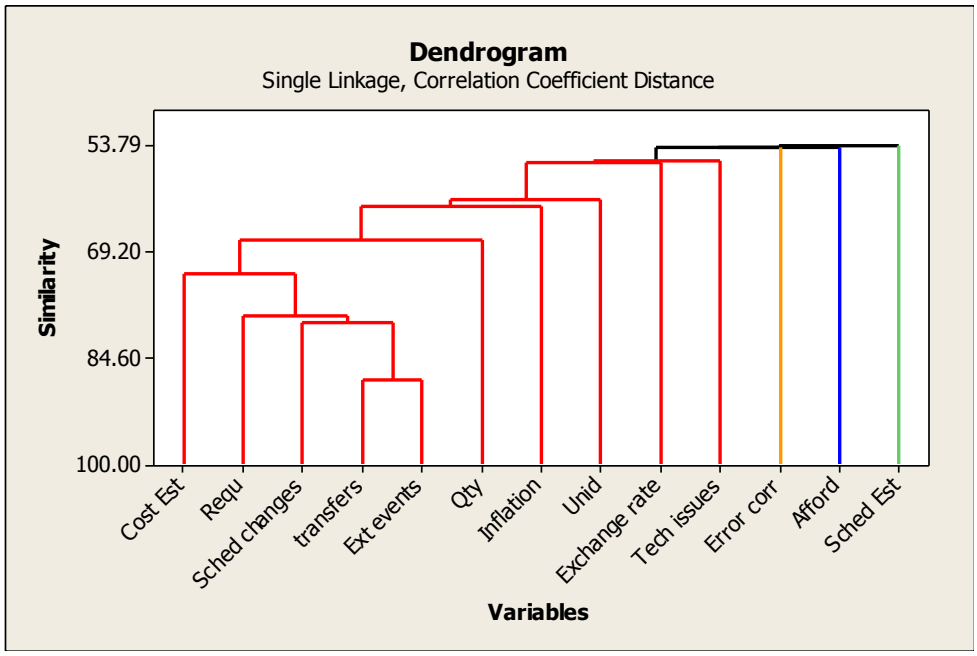

Figure 4-1. Dendritic Showing Clustering of Related Cost Growth Causes.

Friedman and Sage (2004) indicate that comparative case study analysis can be effective for analyzing similar types of cases. These cases are used to find commonality and disparities among the processes, tools, cost analysis methodology, team structure, governance, and lessons learned from these current developmental phase efforts. The cases each had different amounts of background data, based on the background of the program. For example, the AAS Program, having started as a classified program, was restricted in the amount of data that could be provided via a detailed security review. However, each provided enough data for a comparative assessment.

Friedman and Sage (2004) and Yin (2009) list six possible sources of data for developing cases. These are documentation, archival records, interviews, direct observation, participant observation, and physical artifact observation. Table 4-2 provides a description of the sources of information used to develop each case. As the author had

the most data and experience dealing with the SE OPT case, it was used more as a revelatory case, as explained in the Chapter 3, Methodology.

Table 4-2. Case Data Sources.

Cases	Documentation	Archival Records	Interviews	Direct Observation	Participant Observations	Physical Artifact Observation
Amphibious Combat Vehicle	All analysis tools and data	Market research data, Cost records	N/A	Author direct participation in ACV activities	N/A	N/A
Advanced Airborne Sensor	AAS program articles	N/A	Former PM and APM for Engineering	N/A	Former PM and APM for Engineering	N/A
Army Force Basing	Unpublished white papers and presentations	Charter	Force Basing Branch Chief and staff	N/A	Force Basing Branch Chief and staff	N/A

4.2.1 SE OPT and the Amphibious Combat Vehicle.

Amphibious assault remains one of the signature missions of the U.S. Marine Corps. Accordingly, the Marine Corps had been in the process of conducting the research, development, and acquisition of a new amphibious vehicle, the Expeditionary Fighting Vehicle (EFV), to replace its current amphibious vehicle, the Assault Amphibious Vehicle. On 6 January 2011, the Secretary of Defense announced the termination of the EFV Program. This decision was based on concerns that the EFV, because of its projected procurement and life-cycle costs, was unaffordable (SE OPT 2012d).

Upon cancellation of the EFV Program, senior Marine Corps leadership immediately began consideration of a new vehicle concept termed the Amphibious Combat Vehicle (ACV) (SE OPT 2012d). In an effort to ensure that the Marine Corps does not specify operational requirements that lead to another unaffordable vehicle, the Marine Corps Systems Command (MCSC), under the Deputy Commander for Systems Integration and Technology (DC SIAT), established a select group of engineers, logisticians, cost estimators, and acquisition professionals to form the SE OPT. The SEOPT was charged with working with the Marine Corps' requirements community to produce various vehicle

performance options, development and procurement schedules, and accompanying cost estimates for vehicle system concepts (SCs). The desired end state of the process was to produce engineering and cost informed requirements for MS A.

This case was developed mainly through the analysis of the library of analysis documents, tools, spreadsheets, and presentations that were made available to the authors (SE OPT 2012a; SE OPT 2012b; SE OPT 2012c; SE OPT 2012d; SE OPT 2012e). These documents included schedules and taskings, background vehicle analysis, external analysis results from organizations supporting the SE OPT, Microsoft Project schedules, lessons learned statements, and copies of the tools and their results discussed within this case. Additionally, numerous interviews, email exchanges, and in-depth involvement at SE OPT meetings provided further data and understanding.

4.2.1.1 Processes.

Over a nine-month period, the SE OPT established an iterative process coordinated with the Marine Corps' requirement organization, Combat Development and Integration (CD&I). With CD&I, the SE OPT produced various vehicle concepts with accompanying technical performance characteristics, implementation schedules, and LCCEs. The process also analyzed variations in capability options, programmatic variables, and material choices to identify the desired capability options for the ACV concepts. The SE OPT analyzed and completed four such spiral assessments of ten SCs.

The SE OPT process, depicted in Figure 4-2, was an iterative process wherein SE OPT members worked collaboratively with CD&I to establish the initial capabilities and parameters to be considered. This included the mission essential functions (MEFs) of move, shoot, communicate, carry, and protect, as well as various logistics functions,

including supportability, transportability, training, and acquisition variables, such as acquisition schedules and objectives (number of vehicles required). The SE OPT then conducted extensive market research to identify the available material options that could translate these capabilities into an actual vehicle. Procurement and development costs were calculated using historical data to establish CERs from the component costs, as well as vehicle technical attributes such as range, maximum speed, reserve buoyancy, and other aspects agreed upon by both the SE OPT and CD&I. These costs and attributes, as well as estimated schedules, reliability, and related acquisition assumptions, were used to create an LCCE. Along the way, CD&I was involved so they could remain informed as to the most significant cost drivers and impacts from their choice of capabilities.

Once the estimates were prepared, they were presented to CD&I. CD&I determined if the cost and capabilities of the SC were acceptable. If not, an updated set of SC capabilities was identified by CD&I and analyzed by the SE OPT. The SE OPT was cost agnostic and provided a technical analysis of each SC and all of its associated costs, based on the CD&I selected capabilities. The SE OPT functioned as an "honest broker" of ACV costs with respect to the identified capabilities.

In addition to the SC capabilities, other factors influenced the life-cycle cost of a vehicle. These included programmatic aspects, such as acquisition strategy, development strategy, selection process, number of years in production, total number of vehicles, and support strategy. The SE OPT analysis required the assessment of these and other factors well ahead of the typical acquisition timeline, providing a higher fidelity and more accurate cost and schedule estimate, thus reducing ACV implementation risk (SE OPT 2012d).

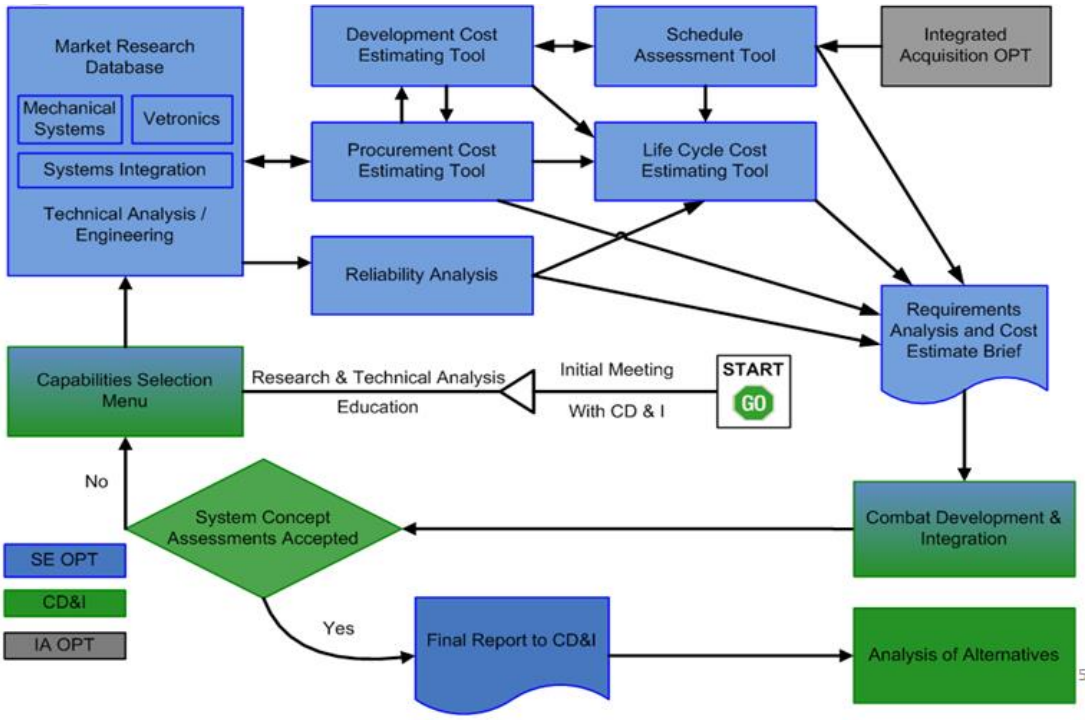

Figure 4-2. SE OPT Iterative Process.

The SE OPT generated procurement, development, and life-cycle cost estimates for 11 different vehicle concepts during four distinct iterations of the SE OPT process, as depicted in Figure 4-3. At the conclusion of the analysis, the SE OPT provided the technical performance and cost estimation data of eleven SCs to CD&I for review. CD&I then chose four SCs to be entered into the ACV AoA. Throughout the process, CD&I representatives became increasingly informed on how different capability choices impacted cost estimates and, at times, schedules. In addition, a Red Team was formed to review the SE OPT tools and processes. While minor adjustments were made, the processes and tools remained essentially intact.

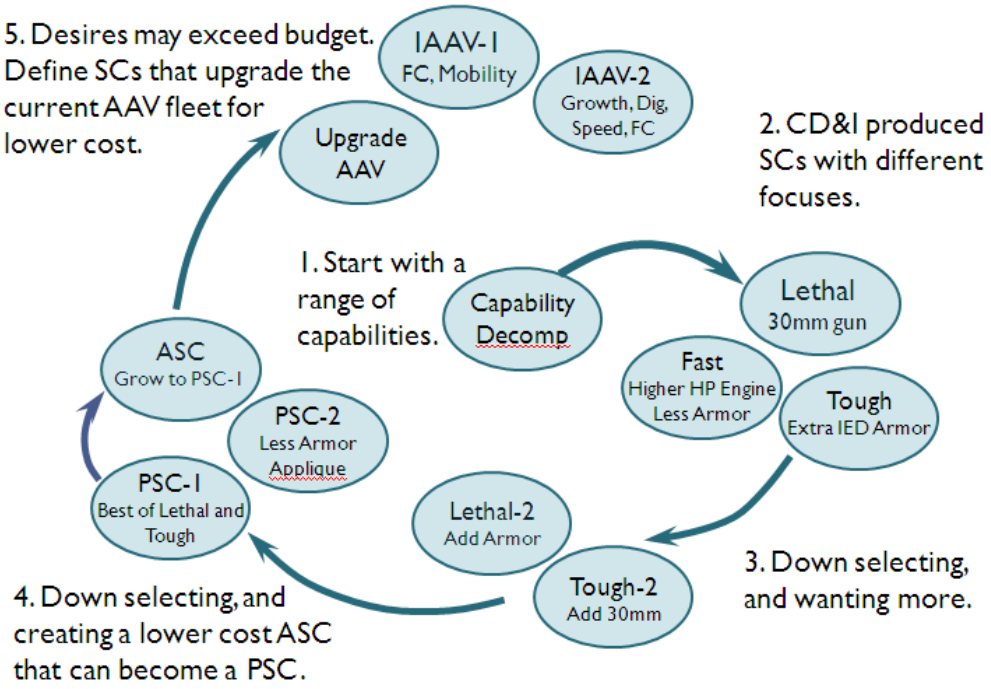

Figure 4-3. Iterative Creation of System Concepts

4.2.1.2 Team Composition

The SE OPT was composed of a relatively small core group of experienced engineers, logisticians, cost estimators, and acquisition professionals numbering around 12 people (SE OPT 2012d). This core group was augmented by various SMEs, as required, including professionals from the Naval Surface Warfare Center, Carderock, Naval Surface Warfare Center, Dahlgren, Space and Naval Warfare Systems Command (SPAWAR)-Atlantic and Pacific, the Tank and Automotive Command (TACOM), Defense Acquisition University (DAU), and numerous others. They provided expertise and data in support of market research, tool development, and processes and also provided membership for Red Team reviews.

The entire team met daily, and each member had situational awareness of the members' assignments, needs of the other team members, and task status. A lesson

learned was that it was important to establish both a daily rhythm along with single-person responsibility and accountability for task accomplishment (SE OPT 2012d).

4.2.1.3 Tools.

The SE OPT developed various tools and methodologies to produce the cost estimation and vehicle attribute information to support the SE OPT process (SE OPT 2012c). These tools and methodologies included the Capability Decomposition Tool, the Market Research Database, the Procurement Cost Tool, the Development Cost Tool, the reliability estimation process, the schedule analysis process, and the LCCE Tool.

The purpose of the Capability Selection Tool was to provide DC CD&I and the SE OPT a consistent, repeatable framework to capture various potential ACV alternatives. Given the complex, often overlapping relationship of subsystem integration from a cost perspective, it was determined that each ACV alternative would be captured as a "whole system." During development of the tool, representatives from both CD&I (Fires and Maneuver Integration Division) and the SE OPT reviewed the tool for a common understanding, making changes and clarifications where required.

Capabilities were organized within MEFs and other critical functions common to ground combat vehicles. These functions included move, shoot, communicate, protect, and carry, as well as mission performance, transportability, sustainment, and training. Within each of these functional areas, subordinate system attributes were grouped together. Each attribute was then given an incremental range of capabilities that could have a measurable cost impact. The range of capabilities for each attribute was predominantly derived from existing U.S. ground combat platforms, both tracked and wheeled (SE OPT 2012d).

The Market Research Database was a Microsoft Excel file containing the cost and attribute data for various components, organized using a modified EFV WBS. Each component had a low, most likely, and high range of values. Each Excel page was a level 3 WBS subsystem collection of components. Within each page, there was a breakout of WBS level 4 components. Each level 4 component had one or more candidates of available components on the market. A separate Market Research Database file was created for each SC.

The market research non-cost data included weight, horsepower, hydraulic power, electrical power, and Design Readiness Assessment (DRA) values (SE OPT 2012b). These values would be needed to calculate vehicle attributes in the Procurement Cost Tool that are important to estimate vehicle performance and judge whether CD&I capability selections were met and if technical factors, like power, were not being met. For instance, the electrical power consumption of various components may exceed the electrical power production of the engine. This would require changes in component selection in the Market Research Database and a change in the values passed on to the Procurement and Development Cost tools. Inspecting the market research files, the system entries contained cost, weight, and horsepower data, but other attributes, such as electrical power generation and consumption, were lacking.

Once the system's capabilities were selected, a mapping between the capabilities and the possible material composition of the vehicle was documented in the Procurement Cost Tool. The Procurement Tool was a Microsoft Excel file that provided the user with a "Ford.com" view of selecting a base vehicle that would meet water speed and direct fire protection capabilities and then allow the selection of optional equipment. Eighteen

subsystems and various components provided the ranges of cost, weight, and power estimates based on the market research of similar components.

The tool was used iteratively to refine the SC composition until CD&I capability selections could be fulfilled, as much as possible. For instance, if a particular armor was chosen that brought the weight to a point that the engine was underpowered to satisfy the selected speed capability, then a new class of engine would need to be selected (SE OPT 2012d). That in turn might change the fuel consumption, increasing the fuel tank size needed to reach specific ranges. Increased fuel tank size would increase the weight again. Such analysis continued until a stable selection of components was chosen. This example demonstrates the need to conduct cost estimation concurrent with technical performance prediction of the SC.

The Development Cost Tool is a matrix of WBS components and activities versus parametric CERs and SME opinion values that provided estimated recurring and non-recurring engineering costs. The CERs had a direct relationship to the first vehicle procurement cost of the components selected in the Procurement Tool. As capability requirements and potential material solutions are varied, the development cost estimates changed in response to the adjusted material solution hardware costs. The Development Cost Tool also accounted for values such as systems engineering and program management (SE/PM) costs, software development, integration, testing, certification, and reliability efforts. Other studies have shown that costs, such as SE/PM support, can be estimated from procurement costs (Stem et al. 2006).

Some components had been already designed for use in amphibious vehicles; others had been used in other vehicles but not in a marine environment; and others would need

redesign. This would affect the development cost. Hence, the SE OPT developed a development cost weighting factor (DRA) (SE OPT 2012b). The DRA weighted several factors to determine any impact to the developmental cost of the component. The DRA factors included component maturity, complexity, applicability, interfaces, testing, cost, schedule, performance, and reliability.

The SE OPT developed program schedules by analyzing necessary programmatic and development activities throughout the life cycle of each SC. The initial input was a program schedule provided by the Integrated Acquisition OPT. This schedule was further refined to meet the technical needs, test requirements, production quantity, and production duration for each SC. This schedule refinement resulted in the development of 27 cost scenarios for various development and production strategies of each SC (three acquisition objectives, three schedule variations, and three production timeframes). This data was then provided to the LCCE Tool as part of the input required to develop the average procurement unit cost (APUC) and LCCEs.

The LCCE Tool provided cost estimates in five major areas using the data input into the model from the other tools and analysis, contractor and government personnel pay scales, analogous facilities, spares, contractor profit, and burden rates. These five areas are final procurement costs and APUCs, research and development costs, military construction (MILCON) cost, operations and supportability (O&S) costs, and disposal costs. The O&S costs included the following elements: unit manpower, unit operations, maintenance costs for all three standard levels of DoD vehicle maintenance, sustaining support, system improvements/technical refresh, and indirect sustainment.

4.2.1.4 Cost Analysis Methodology.

The SE OPT conducted an initial cost analysis to determine how the current EFV could be reduced or modified in terms of design or capability to meet the Marine Corps' goal of acquiring an ACV capability at a lower cost than the EFV. The SE OPT analysis included developing an initial baseline of cost concepts and terms. It then explored two major preconceptions coming from different EFV/ACV stakeholders.

The first preconception was that the removal of high water speed requirements and its associated components would substantially reduce the ACV APUC to meet possible Marine Corps cost targets (SE OPT 2012d). These targets had not been formally defined, but CD&I had mentioned a $10−12 million APUC figure.

The second preconception was that a Capability Production Document (CPD)-to-design trace would allow the SE OPT to quickly identify cost drivers and be able to delete those capabilities and their associated costs. The result was that the components of the system were too interdependent to simple remove and lower the overall vehicle cost to the extent desired. The SE OPT then explored a bottoms-up approach for a rough cost of different ACV concepts. The bottoms-up analysis was conducted before the formal SCs had been defined by CD&I and analyzed by the SE OPT. The results of this analysis gave an initial cost range for possible SCs.

4.2.1.5 Governance.

While the SE OPT membership came predominantly from the Program Manager (PM) Advanced Amphibious Assault (AAA), the SE OPT Lead reported to the Deputy Commander, SIAT, MCSC. Hence, the SE OPT effort was free to develop an independent CE of the vehicle SCs. The estimates were accepted by the DoD CAPE (Cost Analysis and Performance Evaluation) Office that is required to perform its own assessment of new

program costs. The SE OPT was awarded the 2011 Dr. Etter Chief Scientist and Engineer Award for "the most comprehensive evaluation of cost and performance that has been accomplished on any Marine Corps weapon system development to date" (Marine Corps Systems Command 2012).

4.2.2 Advanced Airborne Sensor.

The AAS is a Navy ACAT 1D sensor program developed to replace the LSRS, a formerly classified program that provided very detailed radar tracking of ground and sea entities, to include vehicles and people. As a black program, being hosted on a P-3C Orion aircraft may not have been a cost concern, but expanding the system would be cost prohibitive if it required its own aircraft platform. The AAS Program was created to move the LSRS Program from a black program to an unclassified DoD program that would be designed as a sensor package to existing aircraft. The information for this case came from interviews with Capt. Scott Anderson (Ret.), the former LSRS Program Manager, and John Gensure, the AAS Deputy Assistant Program Manager System Engineering (DAPMSE), overseeing the AAS SE development effort. The official responses to questions came as a written response reviewed and approved by the program's security office (Gensure 2013).

4.2.2.1 Background.

The Advanced Sensor Technologies (AST) is the program office responsible for the development of the LSRS and the AAS under the Program Executive Office Aircraft (PEO(A)). For requirements generation, such as the Capability Design Document (CDD) due at the end of the technology demonstration phase and the CPD due before the engineering and manufacturing demonstration (EMD) phase, and resource

sponsorship, the program office looked to the Deputy Chief of Naval Operations for the Integration of Capabilities and Resources (N8). Other agencies involved are the Naval Air Systems Command (NAVAIR), Commander Patrol and Reconnaissance Group for Operations and Logistics, the Commander Operational Test and Evaluation Force (COMOPTEVFOR) for operational testing, and the development team of Raytheon and Boeing.

The LSRS is an active electronically scanned array (AESA) radar system hosted on a modified U.S. Navy P-3C Block Mod Upgrade Program (BMUP) aircraft. The LSRS aircraft provides Component Commanders with highly accurate battlespace situational awareness as an integrated intelligence, surveillance, reconnaissance, and targeting (ISR&T) asset.

The AAS is an evolutionary spiral to the currently deployed LSRS and will be hosted on the P-8A, the Navy's Multi-Mission Maritime Aircraft (MMA). Like LSRS, AAS provides an airborne, high-resolution, near-real-time radar surveillance system. Employment will also increase the Component Commanders' warfighting effectiveness by ensuring a situational awareness advantage, achieving information dominance throughout all campaign phases and providing on-demand, actionable sensor data to support precision targeting against threats at sea and on land. By maximizing the incorporation of commercial off-the-shelf (COTS) technologies, AAS aims to be highly supportable, maintainable, scalable, and upgradeable, with the goal of reduced unit production and life-cycle costs.

4.2.2.2 Processes.

In developing the AAS requirements, the AAS Program utilized a feedback loop between three major elements. The first was the draft CDD development. Given the well-known background of the LSRS Program, the AAS requirements and resource sponsor (N8) leveraged Integrated Capabilities Documents (ICDs), the LSRS Operational Requirements Document (ORD), and Fleet input to develop the AAS Key Performance Parameters (KPPs). The second key element in the feedback loop was the researching of current technology. With a focus on using COTS components and available technology, N8 solicited inputs from the AST Program Office and AAS Integrated Product Team (IPT) to understand the industry technology base and actual LSRS operational capabilities demonstrated in the Fleet. The third element was the cost estimation effort. Early in the AAS technology development phase, the AAS IPT generated a Cost Analysis Requirements Document (CARD). The CARD included programmatic information, such as the acquisition strategy and schedule for the program, as well as an AAS "Government Candidate Design." The candidate design scoped a notional design for the AAS system that the AAS Cost Team utilized to develop an associated notional CE for the development and procurement of the AAS system. Draft changes to the AAS CDD became draft changes to the AAS CARD, Government Candidate Design, and associated CE, and then the updated CE was fed back to the requirements agency in a feedback loop to inform the CDD development process.

The AAS Program Office also took an evolutionary approach to system development to meet AAS performance requirements. The design incorporated upgradeable COTS components and an open architecture approach to support future

growth. The focus on design-to-cost resulted in achieving a goal of a low-cost, evolutionary system design.

4.2.2.3 Team Composition.

The AAS development was managed at the same program office as the LSRS, and the same prime developers as LSRS, Boeing and Raytheon. AAS therefore started with a solid knowledge foundation in its team. At the commencement of the AAS technology demonstration phase, an integrated Government/contractor team was established to generate the AAS CARD, Government Candidate Design, and CE. The team consisted of Government personnel and contractor SMEs in all required disciplines, including technical design, supportability, and cost. The team was maintained throughout the CDD development process and program execution, and it met on a continual basis during program execution. Throughout system development, it provided feedback to the requirement agency (N8) regarding CPD development, design to cost, and should cost initiatives.

4.2.2.4 Cost Analysis Methodology.

The cost analysts in the Government team worked in conjunction with its engineers, system SMEs, and logisticians in development of its CEs. The exact techniques used by the team were not released by the program office. However, the team had as its basis the cost data from the LSRS Program. The historical O&S cost data included the depot-level maintenance, repair, sparing, and software maintenance. Additionally, the development of the CARD required addressing the programmatic aspects of the program in addition to the technical costs, including the costs of commercial technology that may be used. The AAS CARD and associated CE included the entire TOC for the AAS system. All

phases of the program (technology development, engineering and manufacturing development, procurement, O&S, and disposal) were included in the AAS CE that supported the CDD development process.

4.2.2.5 Governance.

The AAS Program has a governance structure of a typical DoD ACAT 1 program. The team conducting the cost and technical analysis is part of the program office or the prime developers. As such, AAS would require independent cost analysis by the CAPE. As a program, however, they have been recognized for improving life-cycle cost and acquisition management techniques (Defense AT&L Staff 2007).

4.2.3 Army Force Basing.

While developmental planning applies to all areas of Army acquisition, one area that is conducting the development of new developmental planning processes, techniques, and tools is Force Basing (FB). Within the Office of System of Systems Engineering (SoSE), Assistant Secretary of the Army (Acquisition, Logistics, and Technology) (ASA(ALT)), the Architecture and Analysis Team for Force Basing (AATFB) conducts Reference Architecture (RA) development for the three areas of Integrated Base Defense (IBD), Communications/Computing Infrastructure (CCI), and Base Infrastructure (BI). Information for this case was gathered via an interview with Ms. Karen Short, the Branch Chief for Force Basing, Formations Architecture, in SoSE, organization under ASA(ALT). The interview also included Vic Robertson, the Lead Integrator for Force Basing under Ms. Short, and Jeff Jones, a support contractor who has helped lead the development of the first RA for IBD. They also provided documentation that provided a review of their effort, methodology, and products and examples of their use.

4.2.3.1 Background.

The AATFB is the execution arm for Army developmental planning on behalf of ASA(ALT) Office of the Chief Systems Engineer (OCSE). ASA(ALT)/OCSE has identified the seven developmental planning mission functions. These are system architecture development, trade space analysis, baseline program concept development, business case analysis, initial technology review and roadmapping, acquisition strategy and integrated master schedule (IMS) development, and program governance.

4.2.3.2 Processes.

The AATFB implements developmental planning and supports the seven planning functions by executing the RA development process, formerly known as the portfolio development process. The idea of a portfolio is critical, as the RA is meant to be applied to numerous related programs of record in the three mission areas of IBD, CCI, and BI. This process, which is aligned with the AATFB Charter, consists of RA design and RA management. The RA development process is a system of systems (SoS) engineering approach employing developmental planning principles and model-based SE (MBSE) techniques to reliably produce an RA that is well supported by analysis and ready for use by various customers.

The RA design process has four major subprocesses: RA definition, system data collection, use case development, and RA analysis and design (RAD). Each one is necessary to produce an initial RA. The following are more detailed descriptions of these four processes.

- RA Definition. Given the requirement for an RA, the RA definition process clearly defines the scope and the deliverables, assembles the RA Development

Team (RDT), identifies stakeholders, identifies authoritative references, establishes team schedule and battle rhythm, and produces several artifacts that the team agrees represent the RA.

- System Data. Given the scope and Logical Systems Architecture (LSA), the RDT must catalogue all possible systems available to satisfy required capabilities within the system categories of the LSA.
- Use Case Development. The use case development process includes requirements analysis, operational analysis, and use case preparation. Use cases are system agnostic vignettes selected in concert with requirements generators to expose required capabilities in an operational context. When completed, the requirements generators and the core RDT understand the restated required capabilities (RCs) and their prioritization.
- RA Analysis and Design. RAD is the final step in the RA design process. Here, the system data and use cases come together with rigorous analysis to determine the combination of systems that best satisfies the RCs.

In the end, after analyzing requirements across programs of record and understanding the large variety of possible material solutions, the AATFB (specifically, the Force Basing Branch), produces an RA for a particular mission area (Figure 4-4). This RA is composed of information gained across the current programs. With this information, the RA can then be applied to specific programs, such as the Ft. Belvoir IBD upgrade (Short, Robertson, and Jones 2013). The product of this specific application is an implementation architecture, which is a subset of the RA.

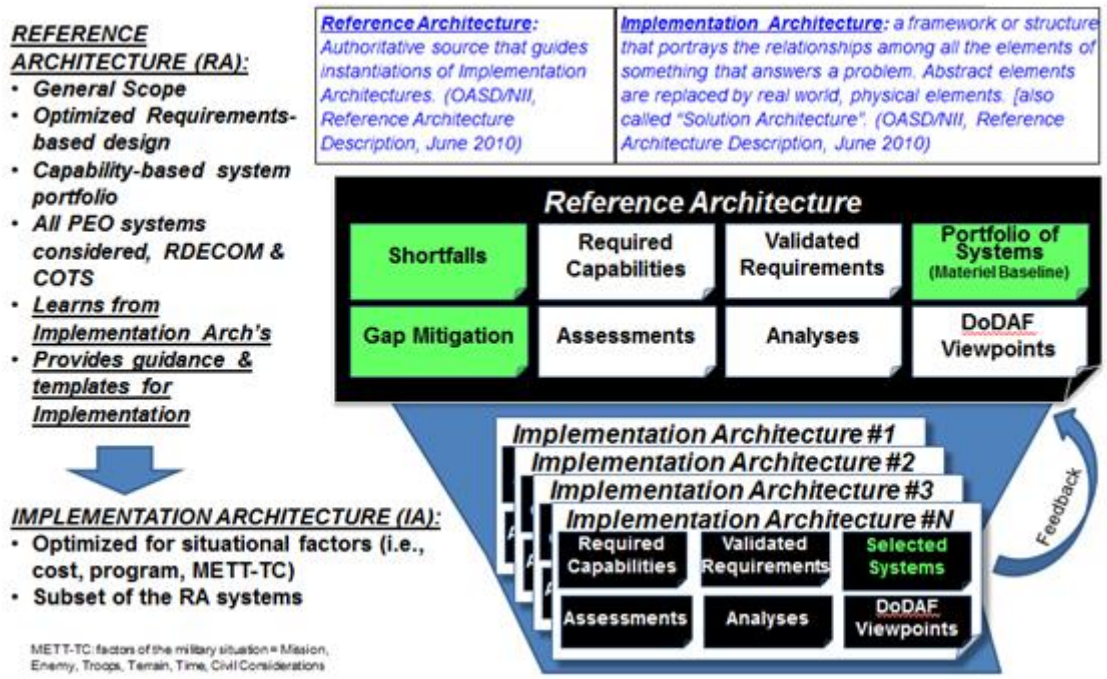

Figure 4-4. Reference and Implementation Architecture Relationships (Jones, 2013)

In the analysis of existing material options, the RDT makes material decisions, down-selecting from available systems and components for satisfying requirements that become part of the RA. Arguably, this may reduce flexibility for the RA user. However, it simplifies the process for a program to make initial architectural and design choices. They do not need to undertake that analysis themselves. More importantly, it allows all stakeholders to understand better the overall problem they are trying to solve with a material solution up front in the life cycle. An important point of RAs in conjunction with the governance structure is that they are designed to be executed in the near-term and help in the Program Objective Memorandum (POM) process. As seen in Figure 4-5, the RAs are used to calculate budgets across the Five-Year Defense Plan (FYDP) and

are updated yearly based on changes to technology and the programmatic situation of the programs, such as new or shifting requirement priorities.

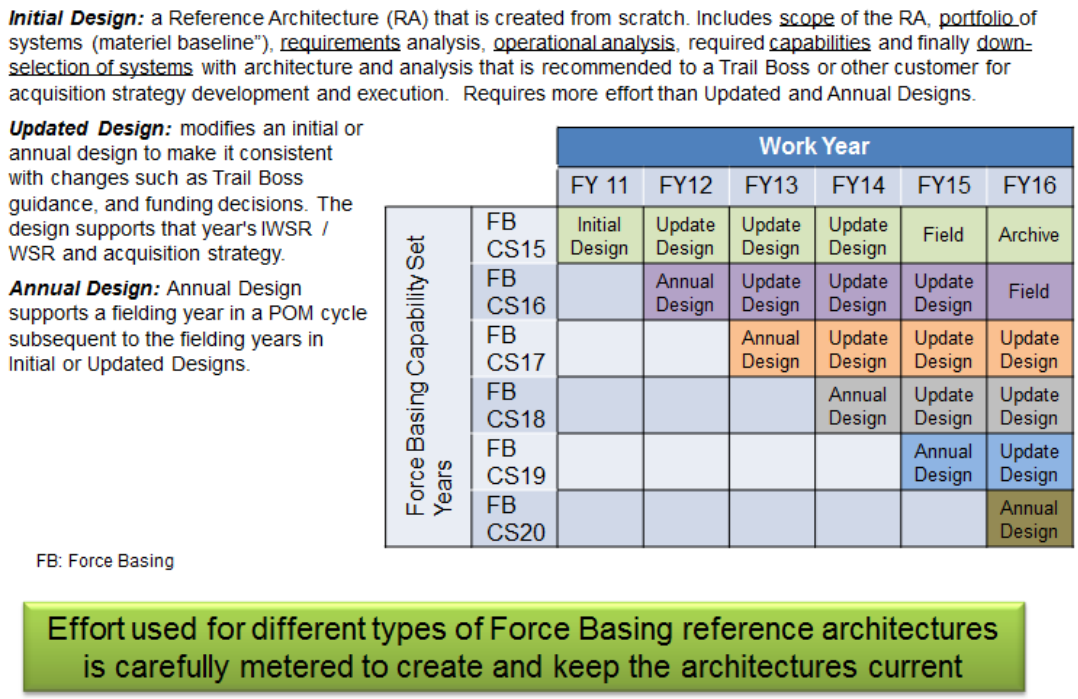

Figure 4-5. Evolution of RAs and the POM Process (Short 2013)

In the end, the RA process is not a one-time event but a recurring process that treats program implementation within an SoS context in a controlled manner.

4.2.3.3 Team Composition.

According to the Force Basing leadership, the core team that develops the RA spans 8−12 people (Short, Robertson, and Jones 2013). These people brought a variety of skills to the table, to include system and base subject matter expertise, defense acquisition, systems engineering, and logistics. Additional people, such as experts from individual program offices, base representatives, Army requirements representatives, and cost analysts assist the core group as necessary. Key people that aided RA efforts include the major representatives from Army Headquarters (G-3 (Operation), G-5 (Planning), and G-7

(Integration)), the Army requirements command (TRADOC), and the Vice Chief of Staff of the Army to implement needed requirements changes and approve funding changes to specific programs, as identified by a member of the governance structure, the Trail Boss.

4.2.3.4 Cost Analysis Methodology.

Cost analysis is part of the RA development process, picking specific systems or components from a number of options to satisfy known requirements (Jones 2013). The RA effort has cost analysts who obtain cost data on systems, working with the Army Center for Cost Analysis (ACCA). The cost analysts use available and approved tools, such as ASCEIT. The ACCA certifies the data used in the RA development. It is then placed in a central database for future use in assessing program costs and re-evaluating chosen RA systems and components.

Additionally, the RA group works collaboratively with programs of record to understand the specific requirements and assess where costs can be saved, such as reuse of existing systems and components. For example, working with the Ft. Belvoir case study identified $44 million in RA capabilities not applicable to Ft. Belvoir. Additionally, identifying reusable capabilities and materials resulted in a $32.9 million savings. Overall, IBD effort went from a $160.3 million effort based on the RA to $83.4 million with the additional coordination and review (Short 2013).

The RA Team focused on the approved requirements and capabilities needed for the program of record and then focused on cost. Cost data was collected from various efforts and then used to form Candidate Capability Packages. These are possible implementation choices for the RA where cost is used to make choices when decisions are needed between alternatives.

4.2.3.5 Governance.

While technically the RA process can decrease time for individual programs to develop an architecture and general design, it may not be effective if left as a voluntary option for individual Program Managers (PMs). Peer PMs may find it hard to coordinate schedules or project funding. The need to satisfy specific requirements using a pre-defined timetable may also hinder changes. For these reasons, the RA development process has a strong governance structure that, like RA development, also looks across systems and programs. The technical is combined with the programmatic for an integrated solution.

Key to the governance of the portfolio of programs of record in the mission area and the application of the RA is the Trail Boss. Each mission area has a Trail Boss, who is a PM and is empowered to enforce SoS acquisition strategies on the individual programs by the Army Acquisition Executive (AAE). Each Trail Boss co-chairs the Force Basing Council of Colonels (CoC) with the ASA(ALT) Deputy for Acquisition and Systems Management (DASM). The Trail Bosses, in coordination with the PMs of the component systems, have used the RA process to jump-start the acquisition and design effort by finding parts of the architecture that could be used. The decision to use a particular part of the RA for a program of record could be both technical and programmatic. For instance, not having enough funding may preclude implementation of a portion during a specific fiscal year. This leads to the Trail Boss implementing an acquisition strategy across programs, requiring the modification of individual program acquisition strategies, which state the cost, schedule, performance targets, and contracting methods for a program. Hence, the Trail Boss has control over the evolutionary development of systems by

picking which requirements may be implemented in a particular system from an SoS perspective.

4.2.4 Case Comparisons.

These three cases present many similarities, yet some differences, in key areas such as the development and management of system data and requirements, their cost analysis methodology, system concept production, and the process governance. The major points of the cases are provided in Table 4-3.

4.2.4.1 Database and Architecture.

Each case made a large effort to not only gather but also maintain data concerning components and material that may be required in developing SCs or "capability packages" for their programs. While the Air Force Early Phase SE Guidelines (2008) point to the need to develop architectural products, the SE OPT and FB cases went beyond architectures. They both collected supersets of data, especially in the realm of material systems and components. Not only was the inter-relation of components collected, but also key data such as cost and SWaP. This data was also normalized to a specific fiscal year value in the SE OPT case.

With the SE OPT and FB cases, each looked at finding the best fit of components based on their requirements and component cost. While FB did this early in their process in creating an RA and then using that downselected list to select needed components, the SE OPT kept all alternatives and then selected components as needed for each system concept analysis. However, each had to use a process to select from a list of available components or systems to a final selection.

4.2.4.2 Requirements Analysis.

All three cases used an iterative feedback system in generating cost and technology informed requirements. For the SE OPT and AAS cases, they both benefitted from prior

Table 4-3. Cross-Case Analysis Summary

Area	SE OPT	AAS	Force Basing
Background	USMC Amphibious Vehicle. Purpose was to determine affordable requirements Pre-MS A and field a technically mature system quickly.	Navy Aviation-based sensor package. Move from an aircraft platform to an aviation package.	Army portfolio of base systems. Developed to implements a process to conduct Pre-MS A engineering.
Process	Iterative process of system concept and cost development. Mapped capabilities to material solutions.	Utilized three feedback loops ; developing requirements between stakeholders, assessing technology, and conducting cost estimation.	Developed a reference architecture mapping requirements to the best material solutions. Applied RA to specific programs.
Team Structure	10-12 core, multi-disciplinary personnel, with external SMEs as needed.	"Small" undefined number of personnel, integrated within the program office.	8-12 core, multi-disciplinary personnel, with external SMEs as needed.
Iterations	Conducted four refining iterations. Also iterated within the process of defining possible material solutions.	Multiple iterations assessing evolving and new technologies. Used evolving COTS technology to meet capabilities and bring down costs.	Iterations through data gathering and analysis process to form RA. Iterate yearly to select aspects to implement
Require-ments	Needed to settle on new requirements set. Requirements organization very involved with material developer.	Operational requirements defined. Deep involvement with requirements organization	Sourced requirements from existing programs. Priori-tized requirements to implement based on programmatics
Data/ Architecture	Market survey database of possible components collected. Vehicle architecture well established	Data collection of current and new technologies, with their capabilities and costs. Architecture established previously via R&D.	Data collection of current and new technologies and systems. Down-selection of systems to those to best satisfy requirements.
Tools	Database of possible components and their attributes. Integrated cost and performance model	Various tools were used, to include database of technologies and cost estimation tools.	Database of components and systems, architectural products, requirements, and cost models (ACEIT).
Cost Analysis	Multiple methods within an integrated cost/performance MS Excel tool.	Interative use of the DoD CARD and combined cost/ engineering team.	Cost input from individual programs/systems, and validated by separate cost office (
Governance	Leadership and reporting chain outside the PM for Advanced Amphibious Vehicles.	Leadership contained within the AAS PM Office.	Analysis team outside the PMs. "Trail Boss" established to lead multiple PMs in SoS activities.

knowledge of related programs, which eased the analysis of the new systems. In the case of FB, looking at portfolios of systems in forming an RA, their effort encompassed more of a data collection effort. However, they exercised this process in different phases of development. The SE OPT conducted its effort in the pre-MS A phases about which we are most concerned. AAS's description of its process focused on the technology demonstration phase leading to MS B. The FB effort presented a continuous process where the RA, the selected components, and the budgeting for implementation were updated at least yearly so the Trail Boss could decide on which existing requirements would be implemented.

There were also disparities in the approaches each took in this area, as each case had a different background. The AAS case used a COTS-based, open architecture design so that the system could evolve over time within its smaller form factor that could be placed on a non-dedicated aircraft. Hence, it could respond to both changing technology and requirements. In the case of the ACV, this was a new vehicle, albeit derived from the cancelled EFV Program. The Marine Corps needed to ensure it accepted requirements that it could afford in the long run, vice see another major vehicle cancellation. Being a hardware-intensive design, it seemed less flexible to future changes, although the PSC-1 and ASC SCs were conceived to provide additional hardware protection or future hardware upgrades. The FB case took existing requirements and looked at how to time-phase their implementation based on both technical and programmatic considerations. Hence, each had requirements flexibility built into their process, taking factors such as cost, schedule, and affordability into account. For the SE OPT and FB, what requirements would be accepted was not simply an issue of user need but programmatic realities.

All cases also worked closely with their stakeholders to include their requirements organizations. As they exercised their iterative processes of defining possible requirements, SCs, or capability packages, they all reported a gain in understanding of the requirements and their interdependencies. As a result, the AAS Program stated that once their requirements and key performance parameters were established, they remained stable throughout the program.

4.2.4.3 Team Composition.

All three cases had a similar team structure. All three used multi-disciplinary groups, including cost analysts, who worked together in an iterative process to assess the cost and technical capabilities of components and proposed designs. The SE OPT and FB cases used core groups of 8−12 people, while augmenting them with outside personnel as needed to answer questions as they arose. The groups were composed of a mix of system engineers, system and operational area SMEs, cost analysts, acquisition experts, and logisticians. In all cases, the groups met regularly and stayed involved in their programs, especially in the AAS case.

4.2.4.4 Cost Analysis Methodology.

All three cases had several characteristics in common. First, each case collected information on individual components, including vehicle components, systems usable for base infrastructure, or current COTS technology. That information was collected, stored, and, in the case of AAS and FB, updated regularly. This component data was then used to create cost estimates centered around various system or design concepts or "capability packages." In the case of the SE OPT, it was very specific in the use of a bottoms-up approach that used a standard WBS to fill in vehicle components and other cost activities.

All three cases also used programmatic data to help develop CEs. While the AAS started developing a CARD after MS A to address programmatics, such as the acquisition strategy, the SE OPT case worked within its IPT structure to develop CARD-like data to create the essence of CARD data and schedules before MS A.

Finally, both the SE OPT and FB cases reported that while the building of the cost and performance model or RA may take significant time, its ability to produce analysis results can be fast. For instance, FB took approximately one year to establish its RAs for its three mission areas. However, the analysis for the Ft. Belvoir basing program took three days. The SE OPT also showed that once it had determined its processes and tools during its first six months, analyzing new system concepts could be completed in approximately one to two weeks, if not shorter.

4.2.4.5 Governance.

If there was one area in which there was little similarity between the cases, it was governance. It spanned from the AAS Program, in which the personnel and leadership were contained within the same program office, to the FB RA effort, which resided outside the programs of record but whose governance was provided by Trail Bosses assigned broad acquisition authority by ASA(ALT).

4.3 Integrated Cost-Performance Model.

Based on the cost growth data analysis and the case studies, we developed a model to incorporate the issues brought forward by that research (Table 4-4). This included focusing on creating better cost estimates that encompassed a greater understanding of the requirements and their interplay with each other. From the case studies, this greater understanding included the following major points:

1. In-depth data capture of possible components and attributes, to include cost, SWaP, and other attributes that may be common across groups of components.
2. The ability to define the range of capabilities based on analysis of existing systems that could be chosen through a collaborative team from the program office and requirements personnel.
3. An interactive feedback process that included the review of the interplay of programmatic data, the assembly of possible SCs, and cost data.

   Develop an understanding of system performance based on the selection of known or possible components. This includes either understanding the performance brought by individual components or constructing relationships or "surrogate models" by which aggregate system performance, such as the speed of a vehicle, can be estimated using aggregate measures, such as total vehicle weight or horsepower.

To that end, a simple causal model (Figure 4-6) was developed that spans the pre-MS A activities of assembling possible capabilities of the system and associating them with possible material components, calculating aggregate metrics which may have impact on overall system performance, calculating the performance metrics useful to satisfying capabilities, and assessing the calculated APUC and LCCE costs along with how the current selection met the capability selection.

The system dynamics-like causal model is appropriate, as major component attributes can easily conflict with each other in complex ways that produce feedback loops. For instance, increasing system weight can negatively impact system speed. However, increased engine power may increase speed yet increase system weight.

Table 4-4. Research Results to Framework Mapping.

Framework Areas	Background/ Cost Growth Analysis	SE OPT	AAS	Force Basing
System Dynamic Approach	Used for requirements, design, and cost estimation	iteration and Feedback in process and procurement tool	Feedback loops for requirements, technology assessment, and cost	Iterative assessment and feedback using cost and programmatic data
Capability Choices	GAO reports advocating requirements selection with cost estimation	Capability Decomposition Tool - choose capabilities holistically	Assess new technologies to implement cost effective, evolutionary improvements	Annual assessment by Trail Boss for RA implementation decisions
Material Attributes Database		Market Research database, any component that could be linked to capability	New technology data collection	Database of existing systems, both those in and out of the final RA's
Material Choices Stock		Selection of components in Procurement Tool can vary iteratively	Evolving selection of materials and technologies to increase capabilities and lower cost	Database holds decision rationale for including or exclusing systems from RA's
WBS Use	Blanchard LCCE methodology	WBS use across all tools		Categorize material data
Capability to Material Mapping	GAO reports advocating portfolio management. Understanding needed between requirements and possible material costs	Mapping between Capability Decomposition Tool and Procurement Tool	Link capability to new technology via continuous technology assessments	Maps program requirements to existing systems to form RA's
Performance Modeling	MOO design applications. Applicable to programs of all Services and types (Air, Ground, AIS, etc.)	Procurement Tool calculations given material component selections	Assessment of new technologies to increase capabilities	Conduct trade-off analysis on possible components of RA's
Integrate Material and Development Cost Stock	System Dynamics cost estimation references	Procurement and development cost tools	CARD reassessed as new technologies look to be implemented	Cost estimates integrated into yearly budget planning
Integrate APUC and LCCE Cost Stock	System Dynamics cost estimation references	LCCE Tool - estimates impacted automatically with new material selections.	Assess cost while assessing new technologies by updating CARD	Cost estimates integrated into yearly budget planning
Multi-Objective Optimization	MOO design applications, Pre-design applications	Multiple criteria used to assess performance, perform trade-offs.		Multi-criterion selection process to choose systems for RA's
Acquisition Strategy		Input into LCCE and Schedule tools to affect cost calculations	Input into the CARD, which is reassessed as new technologies are introduce	Individual program acquisition strategies subordinated to SoS acquisition strategy by Trail Boss
Program Schedule	Schedule errors are a separate category for cost growth - low correlation with requirements errors	Schedule Tool inputs to LCCE and APUC cost estimations	Schedule input into the CARD	Trail Boss uses Program Schedules to determine RA implementation.

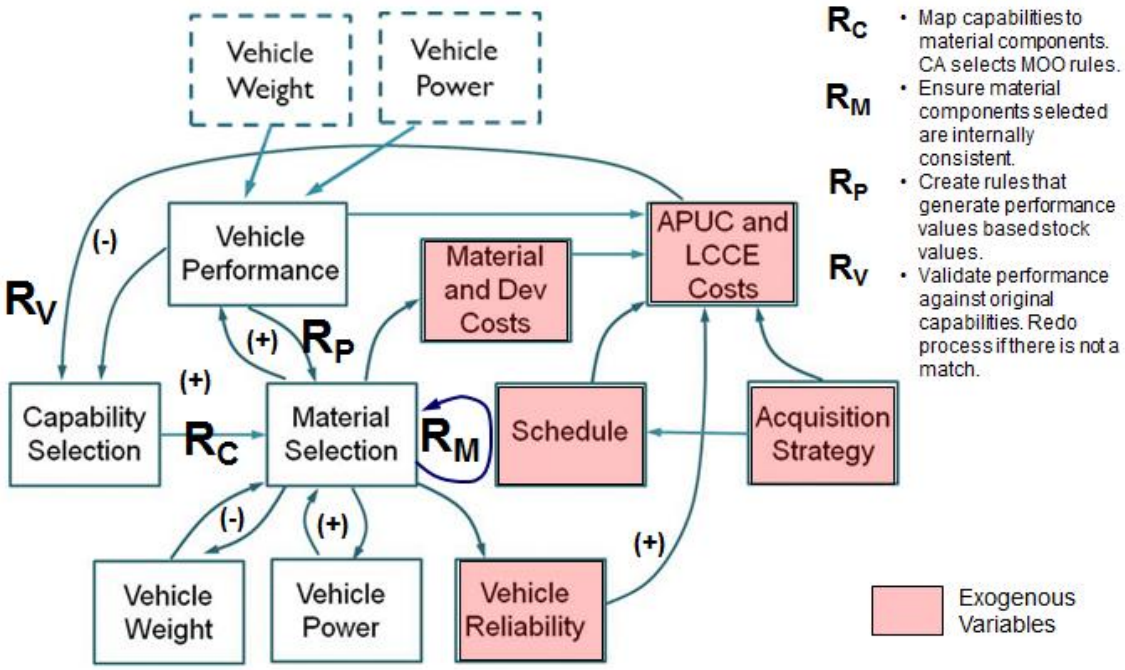

Figure 4-6. Combined Cost/Technical Performance Causal Model.

Hence, as possible components are assessed to provide possible capability solutions, the impact needs to be assessed iteratively.

This problem becomes more complex once individual components are introduced to provide the capability solutions and hence provide system cost and performance estimates. As individual components may vary and not show correlation between attributes like weight, cost, and power, it makes it much harder to create simple relationships to predict the cost and performance.

Making decisions concerning conflicting attributes or system objectives is the province of MOO. However, examples of MOO in the literature provide non-complex rules for optimization. Hence, we have combined the feedback model with MOO to assess how well the component selection has worked to meet cost and performance targets. This model uses the Linear Physical Programming (LPP) method, a variant of Physical

Programming (PP), as part of the component selection process, as well as assessing the SCs produced to meet specific capabilities.

4.3.1 MOO and Physical Programming.

The cases we have reviewed show that we require a method that can handle a priori, a posteriori, and progressive articulation of preferences due to when the requirements are known. The method selected was LPP, a derivative of PP (Ilgin and Gupta 2012; Messac 1996). In addition to the ability for PP to be used with different articulation preferences (Marler and Arora 2004; Tappeta et al. 2000), it has several other benefits. Unlike the commonly used weighting method, which requires subjective weights to be applied and then adjusted to suit the decision maker, PP and LPP avoid the use of weights through the specification of different desirability regions for each parameter (Marler and Arora 2004; Messac and Wilson 1998; Messac 1996). PP does not distinguish between independent and dependent variables, objective attributes, constraints, or goals. All these parameters are treated as design metrics that can be optimized against each other (J. Andersson 2000; Marler and Arora 2004). Also, the PP algorithm is sufficient to produce Pareto-optimal results (Marler and Arora 2004). Finally, the AOF used in PP, a log of the sum of the individual parameter objective functions, does not require adjustments using weights or other modifications (Chen et al. 2000).

As seen in Figure 4-7 (Messac and Wilson 1998; Mullur, Mattson, and Messac 2003), PP classifies its design metrics or parameters into hard and soft classes. Hard classes are simply binary membership functions. The parameter value is either less than, greater than, or equal to a certain defined value or between two defined values. Optimization occurs only with the soft classes. Soft classes measure how well a parameter value falls within a

particular region within the class. The regions are defined by boundary values between the regions (t_{is}, $1 \leq s \leq 5$ for classes S-1 and S-2, and $\tilde{t}_{is}^{+}$: $1 \leq s \leq 5$ and $\tilde{t}_{is}^{-}$: $1 \leq s \leq 5$ for classes S-3 and S-4). These regions are described in the following list, where g_i is the value of parameter *i*:

- Unacceptable range (region 6), where ($\tilde{t}_{i5}^{+} \leq g_i$)
- Highly undesirable range (region 5), where $\tilde{t}_{i4}^{+} \leq g_i \leq \tilde{t}_{i5}^{+}$
- Undesirable range (region 4), where $\tilde{t}_{i3}^{+} \leq g_{\square} \leq \tilde{t}_{i4}^{+}$
- Tolerable range (region 3), where $\tilde{t}_{i2}^{+} \leq g_i \leq \tilde{t}_{i3}^{+}$
- Desirable range (region 2), where $\tilde{t}_{i1}^{+} \leq g_i \leq \tilde{t}_{i2}^{+}$
- Highly desirable range (region 1), where $g_i \leq \tilde{t}_{i1}^{+}$

As you move across the regions, from highly desirable to highly undesirable, the value of the objective function, $\check{Z}^s$, grows exponentially, based on the number of soft criteria parameters, n_{sc}. The difference in objective value between region boundaries $\tilde{t}_{is}^{+}$, $\tilde{t}_{i(s-1)}^{+}$ is $\tilde{Z}^s$

$$\tilde{Z}^s = \beta(n_{sc})\tilde{Z}^{s-1} \qquad (2 \leq s \leq 5) \tag{4.1}$$

where β is a concavity factor. As part of the design, $\check{Z}^s$ at $\tilde{t}_{is}^{+}$ for any parameter *i* is the same. For each parameter, the farther away the parameter g_i moves toward the undesirable form of inter-criteria preference.

The calculations to find *Z* are as follows, which contain slight differences from the PP equations:

$$Z^S = Z_i(t_{is}^{+}) = Z_i(t_{is}^{-}) \qquad \forall i; \quad (2 \leq s \leq 5); \; Z^1 = 0; \; Z^2 = 0.1 \tag{4.2}$$

$$\check{Z}^s = Z^s - Z^{s-1}; \; (2 \leq s \leq 5) \tag{4.3}$$

$$\tilde{Z}^s = \beta(n_{sc})\tilde{Z}^{s-1} \quad (3 \le s \le 5);\ n_{sc} > 1;\ \beta > 1 \tag{4.4}$$

Part of the requirement of PP and LPP is that the graph stays convex. The following equations are used to check convexity for all parameters:

$$\tilde{t}_{is}^{+} = t_{is}^{+} - t_{i(s-1)}^{+}; \quad \tilde{t}_{is}^{-} = t_{is}^{-} - t_{i(s-1)}^{-}; \tag{4.5}$$

$$w_{is}^{+} = \frac{\tilde{Z}^s}{\tilde{t}_{is}^{+}};\ w_{is}^{+} = \frac{\widetilde{\tilde{Z}^s}}{\tilde{t}_{is}^{+}};\ (2 \le s \le 5), \tag{4.6}$$

which is the slope of the *s* region.

$$\tilde{w}_{min} = min\{w_{is}^{+}; w_{is}^{-}\} > 0;\ (2 \le s \le 5) \quad i\text{: parameter} \tag{4.7}$$

where

$$\tilde{w}_{is}^{+} = w_{is}^{+} - w_{i(s-1)}^{+} \tag{4.8}$$

$$\tilde{w}_{is}^{-} = w_{is}^{+} - w_{i(s-1)}^{+} \tag{4.9}$$

$$w_{is}^{+} = w_{i1}^{-} = 0 \tag{4.10}$$

The preference function is then merely solving for a linear function at g_i, the parameter value.

$$Z^i = Z^{is} + (g_i - t_{is}^{+})w_{is}^{+} \quad (t_{is}^{+} < g_i \le t_{i(s+1)}^{+}) \tag{4.11}$$

Once Z^i has been calculated for all parameters *i*, $1 \le i \le n_{sc}$, the PP AOF, Z, can be taken:

$$Z = \frac{1}{n_{sc}} log\left(\sum_{i=1}^{n_{sc}} Z^i\right) \tag{4.12}$$

4.3.2 Framework Process.

The application of this model and framework are domain-dependent. The data needed for a ground vehicle may be different from an aircraft, although certain attributes should be common, such as component cost, weight, power production or consumption, technology readiness level (TRL), and spatial dimensions. This model can accommodate

domain and component specific attributes in addition to the common attributes mentioned above, such as engine fuel efficiency. However, the framework process applies to all domains.

To implement this framework, the following steps are taken:

1. Component/System Database Development. The components that may be needed to implement the user capabilities within a domain are collected in a database. Each component entry shall have associated attributes entered, such as SWaP, cost, and any attribute that serves to distinguish components of a similar type.
2. Capability Development. User capabilities, as much as possible, would be defined as a spread of continuous values that define a continuum of possible capability targets, for instance, maximum land speed. The range of values of capabilities could be derived through market research of existing, related systems, as well as new user-desired capabilities.

   In the best case, capability ranges per metric would map to the five boundary values used to define the preference ranges used with LPP (Ideal, Highly desirable, Desirable, Tolerable, Undesirable, and Unacceptable). If the capability ranges are defined as threshold and objective values, as is often the case in requirements documents, then the threshold and objective values can be mapped to LPP boundary values t_1 and t_5, and values t_2, t_3, and t_4 can be calculated easily.
3. LPP Case Assignment. Once the capabilities are defined, they are reviewed to see if they provide a numerical spread of possible values. Using the PP/LPP

methodology, possible capability values are mapped to the boundary values of the relevant case, such as S-1 "smaller is better." The total number of capabilities that can be assigned to a PP/LPP case is captured for future processing.

4. WBS Development. Several sources point to the need for WBS construction for cost estimation and system definition (ICEAA 2013; Blanchard 2004). Within a domain, a WBS is constructed to define the needed types of components for a system. The WBS element should be related to the components in the component database.
5. R_C Rules Development and Execution. These rules map the capabilities within a specific domain to possible material solutions that align to a WBS element. The material selections may include multiple possibilities for a particular component type, such as an engine. The rules could also be used to assign components en mass to support a base vehicle approach, such as what was done for the SE OPT analysis. In that case, the selection of specific max water speed and armor protection capability values led to a specific base vehicle with predefined components.
6. Material Selection. Using the set of possible components developed in step 5 using the R_C rules, WBS elements that have more than one choice of component are assessed using LPP. The component choices in each WBS element are provided an LPP score. Each attribute of a component type becomes an LPP design metric, with a specific LPP soft case assigned. Values are assigned to the boundary values of the LPP soft cases for each metric using

the mean and standard deviations of the attribute values across the selected possible components. For the soft cases, the middle boundary value (t_{i3}^{+} for the S-1 and S-2 cases) equals the mean of the metric. For case S-1, for example: using the mean μ_i and standard deviation σ_i for attribute i, $t_{i1}^{+} = \mu_i - 2\sigma_i$, $t_{i2}^{+} = \mu_i - \sigma_i$, $t_{i3}^{+} = \mu_i$, $t_{i4}^{+} = \mu_i + \sigma_i$, $t_{i5}^{+} = \mu_i + 2\sigma_i$.

The LPP scores for the individual components are then used to rank the components within each WBS element, and the top scoring components within each WBS element are selected. The component selection is recorded. If this step is revisited in an iteration, new components will be selected by going down the component list per WBS element using the LPP ordering. The new combination of components is compared to previous component selections. If the new component set perfectly matches a previous component selection, then this step is repeated until a unique set of components are selected.

7. R_M Rules Development and Execution. Once components are chosen and entered into the WBS element, these rules check for known interoperability issues, such as incompatibility between components or the need to have certain components given the aggregate attributes of the system, such as weight. If the rules are violated, the process goes back to step 6 to pick a new component in order to resolve the interoperability issue.
8. R_P Rules Development and System Performance Calculations. These rules are the performance relationships between the system attributes, component selections with their specific attribute values, and the performance metrics of the system.

9. R_V Rules Development and Execution. These rules provide a check between the performance metrics of the system within the domain of the model and the original capabilities selections. If the system model does not provide performance values that align with the capability range or goals of the system, then the process needs to go back to step 6 to modify the component selection.
10. Assessing Termination Conditions. Once the steps highlighted above result in a component selection and an assessment of the system performance (steps 8 and 9), the performance metrics are then scored via the LPP methodology using the results from step 8 and the boundary values for those capability metrics developed in steps 2 and 3. A termination decision can then be made. If the R_V rules are violated, a new iteration needs to be done by going back to step 6. Otherwise, a decision can be made to terminate the process or iterate again.

There are several possibilities from literature on how to determine a stopping condition for this process. There is the approach of Genetic Algorithms (Holland 1975) where there is a preset number of generation set to iterate through. There is Simulated Annealing (Kirkpatrick 1983), where the latest LPP score can be compared to the best calculated before. Whether the latest score, and the component selection that led to that score, is accepted would be based on whether it is better the scores that came before, or on the "temperature" of the system and the Boltzman distribution check. The greater the number of iterations through the process, the less likely that a worse (larger) LPP score would be accepted.

The method chosen to determine the termination condition is the Tabu Search. The Tabu Search (Glover 1989) is explained in Section 2.4.2.3. The Tabu Search provides

the means to store the results from prior iterations, and maintains the best result that has been found in this process. If a component selection is repeated, the Tabu Search algorithm would identify that and cause a different component selection to occur, as mentioned in step 6. When a better LPP score is detected, it would hold the new, best LPP score through the iterations, along with the component selection associated with that score. Also, like Genetic Algorithms, Tabu Search can be set to terminate after a pre-defined number of iterations. The process will also terminate if there are no more unique component combinations to try. In this process, that would happen when all options in the sorted component lists have been tried.

Throughout the process, aggregate system attributes, such as total weight, cost, power consumption, along with estimated performance estimates, are calculated. Many of these steps, especially data collection, WBS development, and metric calculations, are similar to the life-cycle cost analysis (LCCA) process by Blanchard (2004). However, these rules bring the use of MOO down to the capabilities, pre-design level where material selection is an intermediate step between capability selection and performance calculations. The addition of rules also helps create SCs that are both technically viable and provide a basis for more detailed understanding of the requirements and the interdependencies of system components. These interdependencies can be assessed using feedback loops, as a complex system. With cost as one of many attributes, cost and technical performance measures can be simultaneously calculated.

4.3.3 Government Model Use.

This research uses a government model used by the SE OPT that the author helped develop. This model implements portions of the framework process in Section 4.3.2.

The components of the government model and the components that have been added are depicted in Figure 4-7.

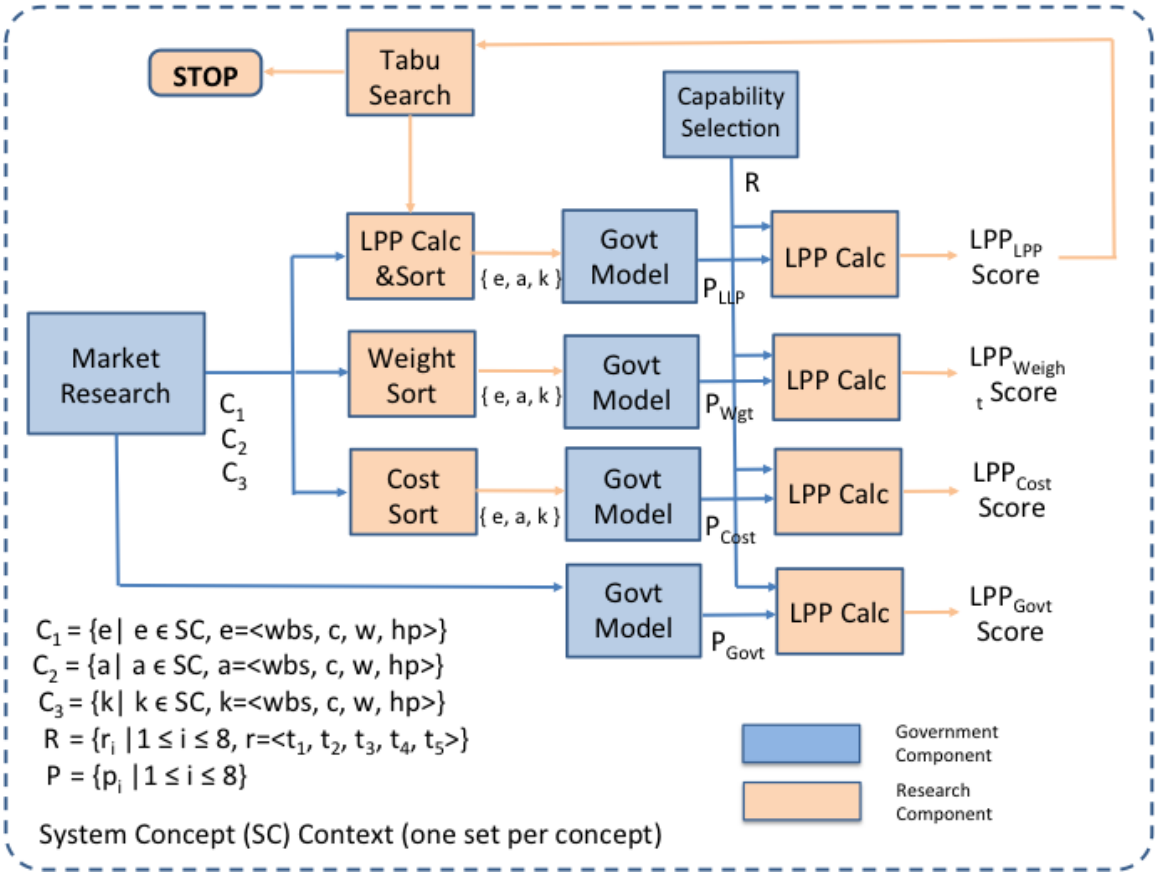

Figure 4-7. Hybrid Government and Research Model Using LPP.

The government model is comprised of three components that are implemented as Microsoft Excel files. The first component is the Market Research database. This component implements steps 1 and 4 of the framework process. It contains data on possible components for each WBS element representing portions of the Amphibious Combat Vehicle (ACV). Each component has a WBS value, and entries for procurement cost, weight, horse power, and electrical power production or consumption. The second component is the capability selection file. This file lists all the possible capabilities

available to the requirements organization, the spread of values possible for each capability, and the values chosen per capability for a specific System Concept (SC). This satisfies step 2 of our framework. The third component of the model is the combined cost and technical performance estimation spreadsheet. This spreadsheet has data organized by WBS element, and stores component data selected for the SC in the relevant base body worksheet. It calculates the estimated cost and the technical performance of the SC,

and provides the results in a summary worksheet. It fulfills step 8 and 9 of the framework as it implements the R_M and R_V rules. The spreadsheets were all reviewed, validated and verified by the SE OPT SMEs.

Each SC of the ACV vehicle has a set of these 3 files, resulting in 24 original files for the 8 SCs used in this research. Each SC Market Research file highlights components that were chosen by Subject Matter Experts (SMEs) in the SE OPT to fulfill the capabilities selected by the requirements organization for that SC, and what components or values were chosen for the cost and technical performance calculations. This satisfies step 5 of our framework, step 6 for the original government component selection for the SC, and the step 7 R_M rules for interoperability and incompatibility issues.

This research adds 5 main modules or activities to the government model. Three modules conduct step 6 in the framework to conduct our experiment. They take sets of possible components from the Market Research database that have already been selected by SMEs for a specific system concept, and generate a sorted list of components that can be used within the government cost and technical performance estimation spreadsheet. These three modules sort the components, per WBS element, using LPP, weight and

cost. The LPP sorting module must first generate the LPP score for individual components, per

WBS element. Once the LPP score is generated for each component within a WBS element, it can then be sorted. The weight and cost modules take the data from the Market Research database, and simply sort the components from the vector of data associated with each component.

The fourth module is the LPP calculator that takes the output from the government cost/technical performance spreadsheet and provides an LPP score for the entire system concept. The module takes as input the boundary ranges of the capabilities that are eligible for LPP optimization. This requires a review of the capabilities and their options from the government Capability Decomposition spreadsheet. This review is presented in Appendix D. The final result is a list of capabilities with LPP boundary values (t_1, …, t_5) that are then input into the LPP calculator. This satisfies step 3 of our framework.

The 5th module provides a review of the SC LPP scores using the Tabu Search methodology. If the LPP scores show that the SC technical or cost estimates are in an unacceptable range, then the components chosen are recorded so they can be avoided in the future, and the framework goes to step six for calculating a new set of components to evaluate. If the latest LPP score is better (i.e, smaller) than the current best score, then the new score and the selected component list is recorded. If the counter has not been exceeded within Tabu, and untried combinations are available, then another run is executed. Otherwise, the current best result with its selected components and its related cost and performance estimates are the answer.

4.3.3.1 Variables.

All variables in this research are used iteratively for each of the eight SCs we are reusing from the SE OPT case, which came from our case study. From the Market Research database, we have the following sets and variables.

$C_1 = \{e_i \mid e \in SC, e=<wbs, c, w, hp>\}$, where e is an engine, i is # of engine types (4.13)

$C_2 = \{a_j \mid a \in SC, a=<wbs, c, w, hp>\}$, where a is an armor/hull, j is # of armor types (4.14)

$C_3 = \{k_l \mid k \in SC, k=<wbs, c, w, hp>\}$, where k is a track, l is # of track types (4.15)

C_1, C_2, and C_3 are sets of possible engines, armor/hull, and track types, respectively. Each component variable (e, a, and k) is a vector that holds the following variables:

wbs: The wbs ID number of the specific component.

c: The cost of the specific component.

w: The weight of the specific component.

hp: The horse power provided by the specific component.

The three research modules accepting C_1, C_2, and C_3 from the Market Research database will each output a single instantiation of e, a, and k. The following is a list of the variables that are output.

LPP: e_{LPP}, a_{LPP}, and k_{LPP} that goes into a separate gov't cost/technical spreadsheet.

Weight: e_{wgt}, a_{wgt}, and k_{wgt} that goes into a separate gov't cost/technical spreadsheet.

Cost: e_{cost}, a_{cost}, and k_{cost} that goes into a separate gov't cost/technical spreadsheet.

With these three separate government spreasheets, the existing engine, armor, and track data is replaced within the correct worksheet using the wbs number in each vector.

When the government cost/technical spreadsheet computes the SC cost and performance, it outputs the set P, containing the following nine performance and cost variables we use in LPP processing as criteria or metrics:

SC_{WS}: Max water speed.

SC_{RB}: Reserve buoyancy

SC_{LS}: Max land speed

SC_{VCI}: Vehicle Cone Index

SC_{LR}: Land range

SC_{MR}: Max firepower range

SC_{crew}: Crew number needed

SC_{GP}: Ground pressure

SC_{cost}: Life Cycle Cost

$P = \{ SC_{WS}, SC_{RB}, SC_{LS}, SC_{VCI}, SC_{LR}, SC_{MR}, SC_{crew}, SC_{GP}, SC_{cost} \}$

We will collect the nine values here from each of the four government modules, forming four sets; LPP, Weight, Cost, and SEOPT. Before we compute the LPP score for an SC for each of these sets, we need the boundary values for each of the capabilities we are using as criteria into LPP. From the capability selection spreadsheet, we develop a set R which contains vectors, r_i, that hold the capability or criteria name, LPP class, and t_1 through t_5 needed for LPP S-1 and S-2 class criteria.

$$R = \{r_i \mid 1 \leq i \leq 9, r = <\text{name, LPP class, } t_1, t_2, t_3, t_4, t_5,>\} \quad (4.14)$$

This is used for to process the data within LPP, Weight, Cost, and SEOPT.

4.3.3.2 LPP Use.

The LPP mechanism is used two ways within this framework. First, it is used to select specific material components from the Market Research database. The output of the LPP, components with associated LPP values, provides the means to form a sorted list so specific material components can be entered into the government cost/technical performance spreadsheet. The way LPP is used is to judge the overall optimality of the system concept with the chosen components, using output from the government cost/technical performance spreadsheets.

The LPP mechanism does not need much in terms of the variables being independent, dependent, design variables or constraints (Messac 1996). We need to have at least two criteria for the LPP algorithm, and the number of criteria, the criterias used, and the boundary values used for the criteria need to all be the same when calculating LPP scores for the four different versions of the SC. The criteria values can be either discrete or continuous.

As for the boundary values R, this method expects that the capabilities being used as criteria have at least two values to mark the end points, t_1 and t_5. The middle points can then be calculated as needed. The PP and LPP method does not assume that the distribution of the boundary values is linear or equidistant from each other.

4.3.3.3 Termination.

As explained before, the termination of the framework will be based on the Tabu Search metaheuristic method. As this framework is mainly a manual process, the Tabu counter was set initially to one to see if the hypothesis testing would be successful by choosing LPP optimal components. This setting ended up being successful through a single run of the framework compared to the SME-generated results.

4.3.4 Framework Summary.

While the focus has been on pre-MS A activities, this model and framework can also evolve as the program matures through its acquisition phases. As components are selected by the prime during design, R_C and R_M rules can be modified to selected pre-chosen components within a design. Also, R_P rules can be refined as the design produces more realistic performance estimate models. Also, new components, possibly science and technology (S&T) systems, can be added to the database as components for

evaluation. Finally, the WBS of the model allows for easier identification of cost variances in the program as it matures.

Chapter 5: Model Evaluation Using the ACV Case

To evaluate the combined cost/technical performance framework using LPP, we chose the SE OPT case. This real-world case provides a wealth of data that can be used to test major elements of the model. This includes a long list of capabilities with a range of attributes that show the spread of user preference, a database of components with data concerning cost, weight, and power, a standard WBS for assigning components to the 18 vehicle subsystems, rules embedded within the SE OPT tools that show how components were selected (R_C, R_P, and R_V rules), and performance relationship studies that show, for instance, the horsepower, weight, and water speed relationships that can be expected with an ACV using the assumed EFV hull shape.

Additionally, an analysis of the SE OPT data showed that a bottoms-up approach taken by the model is more appropriate. First, there was a lack of data on the 1970s vintage Assault Amphibious Vehicle (AAV), based on the data available in the market research files. This makes analogous cost estimation very difficult. Secondly, a correlation analysis using Minitab was conducted of the eight EFV-like SCs. The SC cost-to-weight Pierson correlation was .515, but with a p-value of .192. Using $\alpha = .05$, this p-value indicates that there is not enough statistical proof that the correlation is not zero. Hence, we cannot prove a correlation between the weight and cost that could be used for a parametric CE. Conducting the same correlation analysis on the groups of engines and hull/armor choices gave conflicting results:

- Engine cost to weight correlation was -.491, p-value = .045

- Hull cost to weight correlation was +.628, p-value = .001
- Engine cost to HP correlation was .628, p-value = .028

Therefore, different major components will have different effects on the weight factor that affects many vehicle attributes, such as vehicle ground pressure and reserve buoyancy.

As a first step, we reviewed the ACV capabilities (Appendix D). Of the 152 capabilities, most would not apply to the LPP MOO techniques. For instance, 69 capabilities listed values that are directly related to design choices developed in later program phases. These include capabilities such as availability, maintainability, ability to scale obstacles of a certain height, etc. Twenty other capabilities had LCCE cost impacts and a place affecting specific WBS lines, such as training, but would not be an impact on component selection or vehicle performance. Finally, there were 74 capabilities that could be used to determine component selection. These included capabilities such as having a target laser rangefinder capability. Of the 152 capabilities, 11 capabilities had a numerical range of capabilities choices, with eight not dependent on future design or non-vehicle factors, such as maintainability.

We assigned most factors as soft class-2 (S-2), which means bigger is better. Some may question why not use the S-4 class—range is better—to promote threshold and objective capability targets. Our rationale was that the OVO rule in PP/LPP would allow other capability parameters to come into play and hence not let one parameter become optimal while having other parameters reach undesirable values.

We added the parameter of cost because the SCs were partially judged by their ultimate cost. Through various SE OPT discussions, the target of $10–12 million APUC per vehicle was mentioned as tolerable, while the APUC of $16.5 million for the EFV was not tolerable, based on the original decision to terminate the EFV Program. The capability range values have been normalized, with the highest value within a capability having a 1.

Each SC has specific targets for each capability (Table 5-1). The target is used to define the t_1 through t_5 boundary values of the five regions of the S-1 and S-2 LPP parameters. The SC's target in each parameter becomes the t_3 value of the LPP range for that parameter, defining the boundary between the tolerable and undesirable regions.

Table 5-1. Capability Targets for LPP Parameters for ACV SCs

Criteria	Fast	Lethal	Tough	Lethal 2	Tough 2	PSC1	PSC2	ASC
SC_{WS}: Max water speed.	10	8	8	8	8	8	8	8
SC_{RB}: Reserve buoyancy	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
SC_{LS}: Max land speed	45	45	45	45	45	45	45	45
SC_{VCI}: Vehicle Cone Index	300	300	300	300	300	300	300	300
SC_{LR}: Land range	4	4	4	4	4	4	4	4
SC_{MR}: Max firepower range	2000	2500	2000	2500	2000	2500	2500	1800
SC_{crew}: Crew number needed	17	17	17	17	17	17	17	17
SC_{GP}: Ground pressure	15	15	15	15	15	15	15	15

We next define the R_C rules for selecting components to assign to the proper WBS line. Looking at the market research files for the SCs, a large majority of WBS components do not have any options for material selection. The components with multiple options are hull/armor, engine, and tracks. For example, the R_C rules for the engine component are:

1. For max water speed of 6 knots (kt), engine horsepower >= 600.
2. For max water speed of 8 kt, engine horsepower >= 1150.

3. For max water speed of 10 kt, engine horsepower >= 1500.

These were developed from the water speed, engine horsepower, and vehicle weight charts developed for the SE OPT study by Naval Sea Systems Warfare Center (NSWC) Carderock (SE OPT 2012a).

Once a subset of components is selected for a WBS element, then a specific component is selected using three different methods. The primary method used LPP to define the optimal component choice, creating the t_1 through t_5 values using the mean and standard deviations of component attribute values across the component population (Figure 5-1).

Engines >= 8 knots Water Speed											Sum(Z)	Z (Weight)	Z (Cost)	Z (HP)
2.01.04.01	Vehicle	Subsystem	Engine System	Primary Engine System (1.1.3)	L-3 AVDS-1790-9A	Primary Engine System (1.1.3)	5088.6	$416,744	1197.96		2.78074	0.22167	0.301444	2.257625
2.01.04.01	Vehicle	Subsystem	Engine System	Primary Engine System (1.1.3)	L-3 AVDS-1790	Primary Engine System (1.1.3)	4994	$509,353	1498.12		1.80569	0.21624	0.4496115	1.13984
2.01.04.01	Vehicle	Subsystem	Engine System	Primary Engine System (1.1.3)	MTU 883 CRI	Primary Engine System (1.1.3)	3960	$926,097	1499		6.85573	0.15698	5.561844	1.13691
2.01.04.01	Vehicle	Subsystem	Engine System	Primary Engine System (1.1.3)	MTU 10V2000M93	Primary Engine System (1.1.3)	4928	$238,933	1500.8	Cost LPP	1.42262	0.21246	0.0792406	1.130915
2.01.04.01	Vehicle	Subsystem	Engine System	Primary Engine System (1.1.3)	Cummins QSK45	Primary Engine System (1.1.3)	12980	$297,277	1598.62		2.31138	1.39591	0.1103079	0.805164
2.01.04.01	Vehicle	Subsystem	Engine System	Primary Engine System (1.1.3)	Cummins KTTA50	Primary Engine System (1.1.3)	10890	$309,779	1799.62		1.456	0.91674	0.1303105	0.408953
2.01.04.01	Vehicle	Subsystem	Engine System	Primary Engine System (1.1.3)	MTU 16V2000M84	Primary Engine System (1.1.3)	7436	$600,111	2184.2		1.48888	0.51242	0.8792626	0.097195
2.01.04.01	Vehicle	Subsystem	Engine System	Primary Engine System (1.1.3)	MTU MT 883 Ka-524 (sea mode)	Primary Engine System (1.1.3)	5995	$851,611	2701		NA	0.27362	3.651117	Out of Bounds
2.01.04.01	Vehicle	Subsystem	Engine System	Primary Engine System (1.1.3)	MTU 10V 890	Primary Engine System (1.1.3)	1826	$717,725	1233	Weight	3.722	0.06733	1.6319535	2.022719
						Avg	6455.29	540847.84	1690.26					
	t1	t2	t3	t4	t5	Min	1826.00	238933.01	1197.96					
Weight	-523.421	2965.934	6455.289	9944.644	13433.998	Max	12980.00	926096.94	2701.00					
Cost	$40,821	$290,834	$540,848	$790,861	$1,040,875	Std Dev	3489.35	250013.51	480.46					
HP	729.329	1209.793	1690.258	2170.722	2651.187									

Figure 5-1. Example of LPP Calculations for Automated Component Selection using MS Excel.

In this case, each component had two or three parameters that could be consistently used: cost, weight, and horsepower. The other methods selected the component using the least cost or weight. This provided a comparison against the LPP method of component selection. Tables 5-2, 5-3, 5-4, 5-5, and 5-6 provide the results of processing the engine

and armor/hull components for LPP values, and ranking them by LPP, weight, and cost values.

Table 5-2. Engine Components, >8 Kts, LPP Assessment and Ranking.

Engines, >8 Kts	WBS	Weight	Cost	Hp	LPP Value	LPP Rank	Weight Rank	Cost Rank
L-3 AVDS-1790-9A	2.01.04.01	5088.6	$416,744	1197.96	2.780739	6	5	4
L-3 AVDS-1790	2.01.04.01	4994	$509,353	1498.12	1.805692	4	4	5
MTU 883 CRI	2.01.04.01	3960	$926,097	1499	6.855734	8	2	9
MTU 10V2000M93	2.01.04.01	4928	$238,933	1500.8	1.422616	2	3	1
Cummins QSK45	2.01.04.01	12980	$297,277	1598.62	2.311382	5	9	2
Cummins KTTA50	2.01.04.01	10890	$309,779	1799.62	1.456004	3	8	3
MTU 16V2000M84	2.01.04.01	7436	$600,111	2184.2	1.388878	1	7	6
MTU MT 883 Ka-524 (sea mode)	2.01.04.01	5995	$851,611	2701	NA	9	6	8
MTU 10V 890	2.01.04.01	1826	$717,725	1233	3.722003	7	1	7

Table 5-3. Engine Components, >10 Kts, LPP Assessment and Ranking

Engines, >10 Kts	WBS	Cost	Weight	Hp	LPP Value	LPP Rank	Weight Rank	Cost Rank
L-3 AVDS-1790	2.01.04.01	4994	$509,353	1498.12	2.333186	3	3	4
MTU 883 CRI	2.01.04.01	3960	$926,097	1499	6.592135	6	1	7
MTU 10V2000M93	2.01.04.01	4928	$238,933	1500.8	1.943809	2	2	1
Cummins QSK45	2.01.04.01	12980	$297,277	1598.62	7.847435	7	7	2
Cummins KTTA50	2.01.04.01	10890	$309,779	1799.62	2.688051	4	6	3
MTU 16V2000M84	2.01.04.01	7436	$600,111	2184.2	1.635645	1	5	5
MTU MT 883 Ka-524 (sea mode)	2.01.04.01	5995	$851,611	2701	3.46832	5	4	6

Table 5-4. Armor/Hull: 7.62 mm Protection, LPP Assessment and Ranking

Armor/Hull: 7.62 mm Protection	WBS	Weight	Cost	Hp	LPP Value	LPP Rank	Weight Rank	Cost Rank
7.62 AAV monolithic	2.01.01.01	14460	$754,692	N/A	0.157755	1	2	1
7.62 2519 monolithic	2.01.01.01	18310.99	$863,815	N/A	0.712692	5	5	2
7.62 5059 monolithic	2.01.01.01	20163	$1,020,127	N/A	1.711126	6	6	6
7.62 RHA monolithic	2.01.01.01	20163	$1,020,127	N/A	1.711126	7	7	7
7.62 2519 EFV space frame	2.01.01.01	16125	$880,963	N/A	0.482928	3	4	3
7.62 2139 spaceframe	2.01.01.01	13312	$919,280	N/A	0.406754	2	1	5
7.62 2139 monolithic	2.01.01.01	15335	$918,677	N/A	0.523095	4	3	4

Table 5-5. Armor/Hull: 12.5 mm Protection Assessment and Ranking.

Armor/Hull: 12.5 mm Protection.	WBS	Weight	Cost	Hp	LPP Value	LPP Rank	Weight Rank	Cost Rank
12.7 2519 SiN Space Frame	2.01.01.01	20368	$1,468,149	N/A	0.624377	3	2	6
12.7 2519 SiC Space Frame	2.01.01.01	20368	$1,444,689	N/A	0.503849	2	3	5
12.7 2519 AlO Space Frame	2.01.01.01	20932	$1,422,328	N/A	0.494622	1	4	3
12.7 5059 SiN Space Frame	2.01.01.01	21168	$1,567,483	N/A	1.451755	8	5	9
12.7 RHA SiN Space Frame	2.01.01.01	21202	$1,489,074	N/A	0.806661	6	6	7
12.7 2519 Monolithic	2.01.01.01	26021	$1,299,106	N/A	1.507364	9	9	1
12.7 2519 with 7.62 Monolithic	2.01.01.01	22513	$1,425,176	N/A	0.733493	7	7	4
12.7 2139 spaceframe	2.01.01.01	17555	$1,506,464	N/A	0.648946	4	1	8
12.7 2139 monolithic	2.01.01.01	22869	$1,387,249	N/A	0.69648	5	8	2

Table 5-6. Armor/Hull: 14.5 mm Protection Assessment and Ranking.

Armor/Hull: 14.5 mm Protection	WBS	Weight	Cost	Hp	LPP Value	LPP Rank	Weight Rank	Cost Rank
14.5 AAV with EAAK	2.01.01.01	18860	$875,856	N/A	0.052162	1	1	1
14.5 2519 SiN Space Frame	2.01.01.01	22387	$1,595,822	N/A	0.743069	7	3	7
14.5 2519 SiC Space Frame	2.01.01.01	22387	$1,560,632	N/A	0.683031	3	4	6
14.5 2519 AlO Space Frame	2.01.01.01	23232	$1,527,062	N/A	0.6872	4	8	5
14.5 2519 Monolithic	2.01.01.01	29213	$1,347,688	N/A	N/A	10	7	2
14.5 2519 with 7.62 Monolithic	2.01.01.01	23914	$1,499,480	N/A	0.733513	5	9	4
14.5 5059 SiN Space Frame	2.01.01.01	23187	$1,695,158	N/A	0.967829	9	5	10
14.5 RHA SiN Space Frame	2.01.01.01	23221	$1,616,749	N/A	0.83871	6	6	8
14.5 2139 spaceframe	2.01.01.01	19574	$1,634,139	N/A	0.639284	2	2	9
14.5 2139 monolithic	2.01.01.01	25819	$1,449,132	N/A	0.934898	8	10	3

Once the components are selected, the component values for cost, weight, and horse power (if applicable) are entered into the government cost/technical performance estimation spreadsheet. The total weight, cost, and performance values can now be generated. The R_M rules are used to ensure that the components selected can interact. In this case, there was one rule for selecting an enhanced suspension when vehicle weight was greater than 85,000 pounds (lbs). Microsoft Excel was then used to automatically compare the performance results within the capability ranges. The results of the SCs stayed within the ranges, not requiring another pass.

The previously detailed steps were used three times, using LPP, minimum cost, and minimum weight to select components. The SE OPT figures were the control. The output of the 32 cost/technical performance spreadsheets are provided below in eight tables (Tables 5-7 to 5-14), one for each system concept. The tables also contain the LPP boundary values for each criteria in each system concept. These values are needed in LPP calculations to determine the LPP score.

Table 5-7. Government Model Output of LPP Criteria for the FAST SC.

SC	Criteria Name	LPP Class	t1	t2	t3	t4	t5	Govt Model Output LPP	Govt Model Output Weight	Govt Output Model Cost	Govt Output Model SEOPT
Fast	SC_{WS}: Max water speed.	S-2	6	7	10	11	12	10	8.8	8.8	10
	SC_{RB}: Reserve buoyancy	S-2	0.1	0.2	0.30	0.35	0.4	0.23	0.30	0.20	0.23
	SC_{LS}: Max land speed	S-2	40	42.5	45	50	60	60	60	60	60
	SC_{VCI}: Vehicle Cone Index	S-2	200	250	300	350	400	309	309	309	309
	SC_{LR}: Land range	S-2	2	3	4	6	8	4	4	4	4
	SC_{MR}: Max firepower range	S-2	0	1500	2000	2250	2500	2000	2000	2000	2000
	SC_{crew}: Crew number needed	S-2	10	13	17	17.5	18	17	17	17	17
	SC_{GP}: Ground pressure	S-1	8	11	15	20	25	9.38	8.58	9.68	9.4
	SC_{cost}: Life Cycle Cost	S-1	8	10	12	14	16.5	11.13	11.68	10.49	11.40

Table 5-8. Government Model Output of LPP Criteria for the LETHAL SC.

SC	Criteria Name	LPP Class	t1	t2	t3	t4	t5	Govt Model Output LPP	Govt Model Output Weight	Govt Output Model Cost	Govt Output Model SEOPT
Lethal	SC_{WS}: Max water speed.	S-2	6	7	8	10	12	8.6	7.7	8.6	8.1
	SC_{RB}: Reserve buoyancy	S-2	0.1	0.2	0.30	0.35	0.4	0.26	0.28	0.16	0.21
	SC_{LS}: Max land speed	S-2	40	42.5	45	50	60	60	60	60	60
	SC_{VCI}: Vehicle Cone Index	S-2	200	250	300	350	400	300	300	300	300.2
	SC_{LR}: Land range	S-2	2	3	4	6	8	4	4	4	4
	SC_{MR}: Max firepower range	S-2	0	1500	2500	3000	3500	2500	2500	2500	2500
	SC_{crew}: Crew number needed	S-2	10	13	17	17.5	18	17	17	17	17
	SC_{GP}: Ground pressure	S-1	8	11	15	20	25	10.48	10.12	11.6	11.02
	SC_{cost}: Life Cycle Cost	S-1	8	10	12	14	16.5	12.55	13.18	12.17	12.70

Table 5-9. Government Model Output of LPP Criteria for the TOUGH SC.

SC	Criteria Name	LPP Class	t1	t2	t3	t4	t5	Govt Model Output LPP	Govt Model Output Weight	Govt Output Model Cost	Govt Output Model SEOPT
Tough	SC_{WS}: Max water speed.	S-2	6	7	8	10	12	8.6	7.7	8.6	8
	SC_{RB}: Reserve buoyancy	S-2	0.1	0.2	0.30	0.35	0.4	0.22	0.28	0.17	0.21
	SC_{LS}: Max land speed	S-2	40	42.5	45	50	60	60	60	60	60
	SC_{VCI}: Vehicle Cone Index	S-2	200	250	300	350	400	300.2	300	300	300.2
	SC_{LR}: Land range	S-2	2	3	4	6	8	4	4	4	4
	SC_{MR}: Max firepower range	S-2	0	1500	2000	2250	2500	2000	2000	2000	2000
	SC_{crew}: Crew number needed	S-2	10	13	17	17.5	18	17	17	17	17
	SC_{GP}: Ground pressure	S-1	8	11	15	20	25	10.92	10.16	11.51	11.03
	SC_{cost}: Life Cycle Cost	S-1	8	10	12	14	16.5	12.33	12.30	11.30	11.80

Table 5-10. Government Model Output of LPP Criteria for the LETHAL2 SC.

SC	Criteria Name	LPP Class	t1	t2	t3	t4	t5	Govt Model Output LPP	Govt Model Output Weight	Govt Output Model Cost	Govt Output Model SEOPT
Lethal2	SC_{WS}: Max water speed.	S-2	6	7	8	10	12	8.1	7.7	8.6	8
	SC_{RB}: Reserve buoyancy	S-2	0.1	0.2	0.30	0.35	0.4	0.23	0.17	0.14	0.19
	SC_{LS}: Max land speed	S-2	40	42.5	45	50	60	60	60	60	60
	SC_{VCI}: Vehicle Cone Index	S-2	200	250	300	350	400	300	300	300	300
	SC_{LR}: Land range	S-2	2	3	4	6	8	4	4	4	4
	SC_{MR}: Max firepower range	S-2	0	1500	2500	3000	3500	2500	2500	2500	2500
	SC_{crew}: Crew number needed	S-2	10	13	17	17.5	18	17	17	17	17
	SC_{GP}: Ground pressure	S-1	8	11	15	20	25	10.79	11.55	11.92	11.33
	SC_{cost}: Life Cycle Cost	S-1	8	10	12	14	16.5	12.91	13.16	12.53	13.06

Table 5-1. Government Model Output of LPP Criteria for the TOUGH2 SC.

SC	Criteria Name	LPP Class	t1	t2	t3	t4	t5	Govt Model Output LPP	Govt Model Output Weight	Govt Output Model Cost	Govt Output Model SEOPT
Tough2	SC_{WS}: Max water speed.	S-2	6	7	8	10	12	8.6	7.7	8.6	8.1
	SC_{RB}: Reserve buoyancy	S-2	0.1	0.2	0.30	0.35	0.4	0.22	0.25	0.13	0.18
	SC_{LS}: Max land speed	S-2	40	42.5	45	50	60	60	60	60	60
	SC_{VCI}: Vehicle Cone Index	S-2	200	250	300	350	400	300	300	300	300
	SC_{LR}: Land range	S-2	2	3	4	6	8	4	4	4	4
	SC_{MR}: Max firepower range	S-2	0	1500	2000	2250	2500	2000	2000	2000	2000
	SC_{crew}: Crew number needed	S-2	10	13	17	17.5	18	17	17	17	17
	SC_{GP}: Ground pressure	S-1	8	11	15	20	25	10.91	10.55	12.7	11.45
	SC_{cost}: Life Cycle Cost	S-1	8	10	12	14	16.5	13.93	14.63	13.52	14.10

Table 5-2. Government Model Output of LPP Criteria for the PSC1 SC.

SC	Criteria Name	LPP Class	t1	t2	t3	t4	t5	Govt Model Output LPP	Govt Model Output Weight	Govt Output Model Cost	Govt Output Model SEOPT
PSC1	SC_{WS}: Max water speed.	S-2	6	7	8	10	12	8.5	7.5	8.5	8
	SC_{RB}: Reserve buoyancy	S-2	0.1	0.2	0.30	0.35	0.4	0.21	0.24	0.12	0.18
	SC_{LS}: Max land speed	S-2	40	42.5	45	50	60	60	60	60	60
	SC_{VCI}: Vehicle Cone Index	S-2	200	250	300	350	400	300	300	300	300
	SC_{LR}: Land range	S-2	2	3	4	6	8	4	4	4	4
	SC_{MR}: Max firepower range	S-2	0	1500	2000	2250	2500	2000	2000	2000	2000
	SC_{crew}: Crew number needed	S-2	10	13	17	17.5	18	17	17	17	17
	SC_{GP}: Ground pressure	S-1	8	11	15	20	25	11	10.64	12.13	11.85
	SC_{cost}: Life Cycle Cost	S-1	8	10	12	14	16.5	12.64	13.30	13.19	13.10

Table 5-3. Government Model Output of LPP Criteria for the PSC1 SC.

SC	Criteria Name	LPP Class	t1	t2	t3	t4	t5	Govt Model Output LPP	Govt Model Output Weight	Govt Output Model Cost	Govt Output Model SEOPT
PSC2	SC_{WS}: Max water speed.	S-2	6	7	8	10	12	8.6	7.6	8.6	7.6
	SC_{RB}: Reserve buoyancy	S-2	0.1	0.2	0.30	0.35	0.4	0.22	0.28	0.17	0.21
	SC_{LS}: Max land speed	S-2	40	42.5	45	50	60	60	60	60	60
	SC_{VCI}: Vehicle Cone Index	S-2	200	250	300	350	400	300	300	300	300
	SC_{LR}: Land range	S-2	2	3	4	6	8	4	4	4	4
	SC_{MR}: Max firepower range	S-2	0	1500	2000	2250	2500	2000	2000	2000	2000
	SC_{crew}: Crew number needed	S-2	10	13	17	17.5	18	17	17	17	17
	SC_{GP}: Ground pressure	S-1	8	11	15	20	25	10.95	10.19	11.54	11.06
	SC_{cost}: Life Cycle Cost	S-1	8	10	12	14	16.5	12.42	13.15	12.26	12.70

Table 5-4. Government Model Output of LPP Criteria for the ASC SC.

SC	Criteria Name	LPP Class	t1	t2	t3	t4	t5	Govt Model Output LPP	Govt Model Output Weight	Govt Output Model Cost	Govt Output Model SEOPT
ASC	SC_{WS}: Max water speed.	S-2	6	7	8	10	12	8.6	7.8	8.6	8
	SC_{RB}: Reserve buoyancy	S-2	0.1	0.2	0.3	0.35	0.4	0.24	0.27	0.14	0.21
	SC_{LS}: Max land speed	S-2	40	42.5	45	50	60	60	60	60	60
	SC_{VCI}: Vehicle Cone Index	S-2	200	250	300	350	400	300	300	300	300
	SC_{LR}: Land range	S-2	2	3	4	6	8	4	4	4	4
	SC_{MR}: Max firepower range	S-2	0	1500	2000	2250	2500	2000	2000	2000	2000
	SC_{crew}: Crew number needed	S-2	10	13	17	17.5	18	17	17	17	17
	SC_{GP}: Ground pressure	S-1	8	11	15	20	25	10.72	10.36	11.84	11.07
	SC_{cost}: Life Cycle Cost	S-1	8	10	12	14	16.5	10.88	11.50	10.51	10.90

Using the nine criteria values for each SC for each of the four component selection methods, overall LPP scores were calculated (Table 5-15) using easily constructed Excel spreadsheets. We ensured that the $n_{sc} = 9$, $\beta = 2$, and that concavity stayed positive for all LPP calculations.

The data from the four methods was checked for normality, and each one was found to be normal, using $\alpha = .05$. The normal probability plots (Figure 5-2) and the Anderson-Darling tests were conducted using Minitab.

To check that our model provides a more optimal solution using the defined capability ranges for the nine parameters from the SE OPT study, we conducted hypothesis testing. As LPP seeks a minimum value, we expect the mean of the LPP scores using the LPP component selection method to be less than the mean of the SE OPT data and the selection methods using strictly cost or weight values. Because our sample size is less than 30, we used a paired t-test.

Table 5-15. LPP Scores for All SCs for All Component Selection Methods

System Concept	SEOPT	LPP	Cost	Weight
FAST	0.184398344	0.183061939	0.206980629	0.169968371
LETHAL	0.205334769	0.184799646	0.286319765	0.198746305
TOUGH	0.193227691	0.195262409	0.275394891	0.181629609
LETHAL2	0.256485094	0.202548502	0.310060658	0.287530293
TOUGH2	0.282387232	0.219492166	0.318965641	0.276090109
PSC1	0.273587944	0.203340718	0.323127389	0.218999872
PSC2	0.217576912	0.197984745	0.280625852	0.203589231
ASC	0.193336337	0.179425853	0.303866747	0.176150381
Avg	0.22579179	0.195739497	0.288167697	0.214088021
Std Dev	0.039174999	0.013202462	0.037246734	0.044796527
Sample size	8	8	8	8

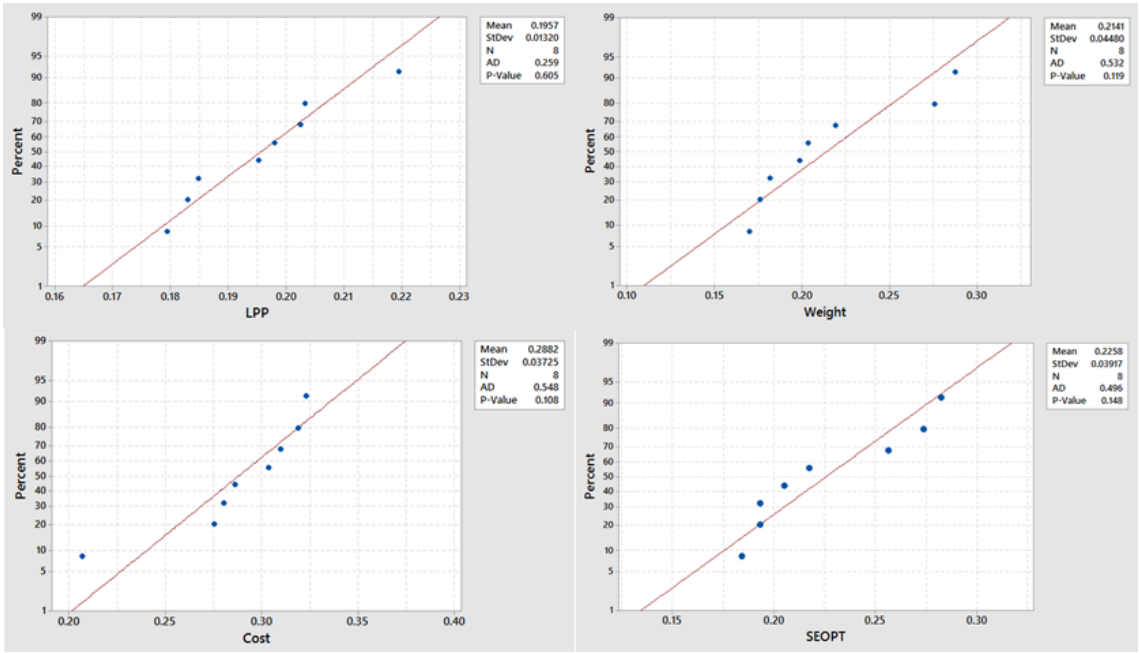

Figure 5-2. Normal Probability Plots for the Four Sets of LPP Values

Our hypothesis against the SE OPT values are as follows, using α = .05:

1. H_0: $\mu_{SE\ OPT} \leq \mu_{LPP}$ (5.1)

   H_A: $\mu_{SE\ OPT} > \mu_{LPP}$ (5.2)

2. H_0: $\mu_{SE\ OPT} \leq \mu_{Cost}$ (5.3)

H_A: $\mu_{SE\ OPT} > \mu_{Cost}$ (5.4)

3. H_0: $\mu_{SE\ OPT} \leq \mu_{Weight}$ (5.5)

   H_A: $\mu_{SE\ OPT} > \mu_{Weight}$ (5.6)

The first hypothesis test, represented by equations (5.1 and 5.2), is a one-tailed test. The alternate hypothesis is that the SE OPT mean of the LPP scores for the 8 system concepts is greater than the mean using our LPP model to choose components to satisfy the capability requirements. As LPP is a minimization algorithm, a greater mean indicates a worse result. For the second (5.3 and 5.4) and third (5.5 and 5.6) hypothesis tests, we want to see if the results of using simple attributes of cost and weight provide results which are also better than the SE OPT results, so these tests are one-tailed also.

We also have the following tests to compare our LPP component selection method within our model with simple methods of trying to minimize cost or weight. Just like hypothesis test # 1, hypothesis test #4 conducts a one-tailed test (formulas 5.7 and 5.8). The alternate hypothesis checks to see if the mean of the scores for the eight system concepts using cost as a component selection factor is greater than the mean of the system concept LPP scores using LPP as the component selection method. If we cannot reject the null hypothesis, then our LPP method did not perform statistically better than using cost. Hypothesis test #5 (5.9 and 5.10) is set the same way, except it examine the use of weight rather than cost.

4. H_0: $\mu_{Cost} \leq \mu_{LPP}$ (5.7)

   H_A: $\mu_{Cost} > \mu_{LPP}$ (5.8)

5. H_0: $\mu_{Weight} \leq \mu_{LPP}$ (5.9)

$$H_A: \mu_{Weight} > \mu_{LPP} \quad (5.10)$$

The results of the hypothesis testing are displayed in Figure 5-3.

Hypothesis test #1 shows that there is statistically significant evidence that the mean of the SEOPT scores for the eight SCs is greater than the mean of the SE OPT LPP scores. We can see that our methodology of picking components using an automated LPP process to fulfill targeted capability values at given cost ranges worked better than the human estimate of most likely values. Hypothesis Test #2 failed to show that the SEOPT mean was greater than the means based on using cost to choose components. The p-value is so high, it indicates that the mean using cost is greater than the mean using the SEOPT SMEs. Hypothesis test #3 failed to disprove the null hypothesis. Therefore, we could not show that using the SEOPT method performed worse than the weight method. Hence, the LPP method was the only method that performed better than the SE OPT method. However, when checking cost and weight methods against the LPP component selection method itself, only test #4 showed that there is significant statistical evidence that the LPP method provided more optimal results. Test #5, LPP versus weight, could not show statistically significant evidence that the mean for the weight method was greater than the mean using LPP.

Part of the explanation of why the weight method seemed to do as well as the SE OPT results is that the weight attributes used to select components was an attributes that had direct impact on the capability parameters used to assess the LPP scores for the SCs. Capabilities such as reserve buoyancy and ground pressure are proportional to weight. The lower the vehicle weight, the higher the reserve buoyancy, assuming no change to vehicle shape, which is better

(class S-2). Ground pressure, which affects the type of terrain the vehicle can move within, decreases, which again results in a better score (class S-1).

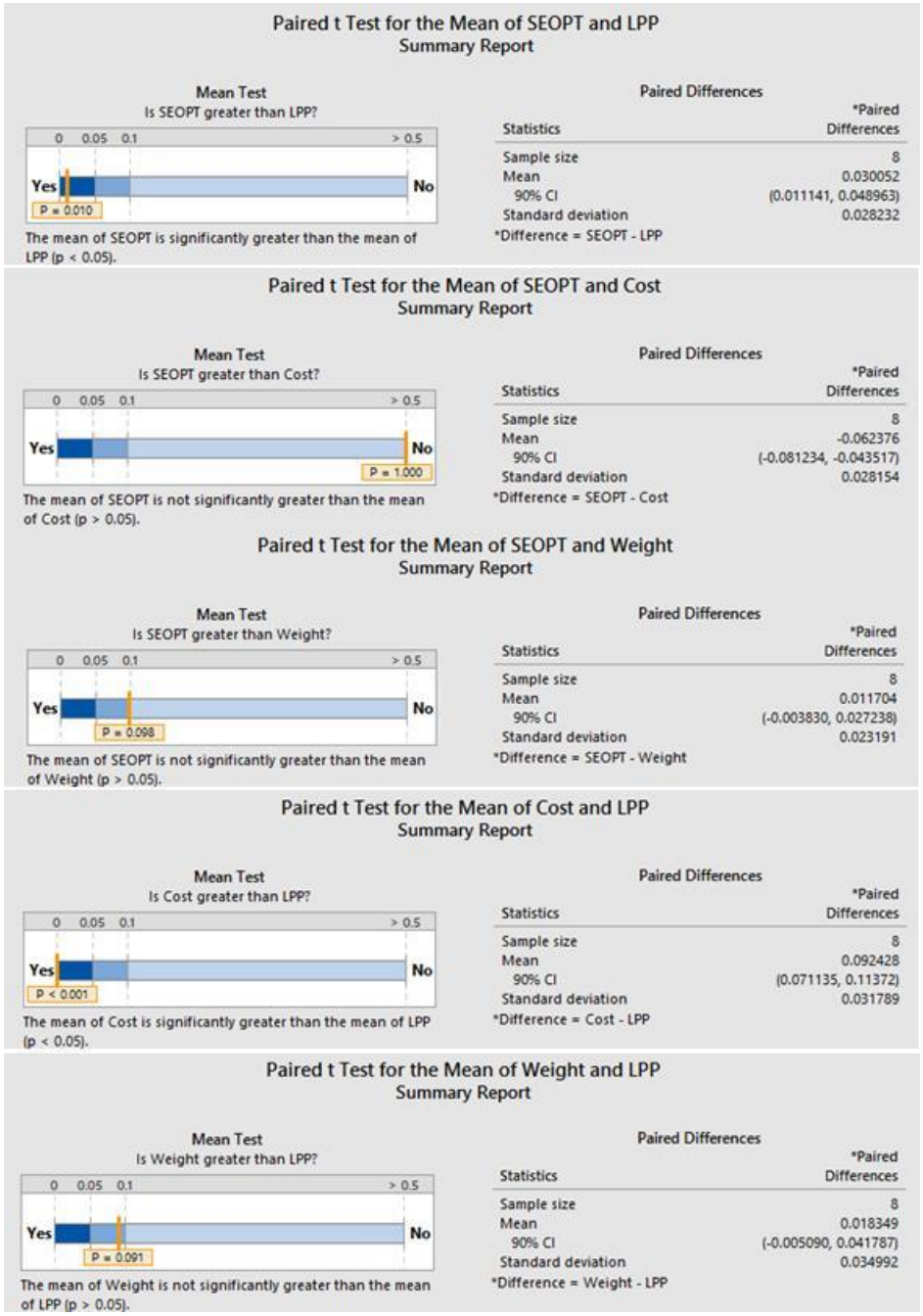

Figure 5-3. Hypothesis Test Results Using Minitab

To be fair, the SE OPT did not try to find an optimal mix of known components. It provided triangular cost and weight estimates of expected low, most likely, and high values and then used those values to provide expected low, most likely, and high performance values. It is hard to predict how an individual developer shall pick components to satisfy capability targets. However, the SC results varied when using different optimization strategies. Optimizing for cost could easily affect negatively capabilities dependent on weight. Hence, it is not realistic that combinations could be found that would provide capabilities all along the low or high estimate range. Picking components using the LPP method with attributes that align to vehicle capability attributes could provide a better idea of the "should cost" estimate of chosen capabilities. The LPP estimate provides a more optimal combination of components and their related cost and performance impacts, rather than simply trying to reduce cost.

Chapter 6: Conclusion

In this study, we addressed the area of pre-MS A, early-phase SE that required a combined cost and performance estimation of different SCs. The goal was to address the goals of picking preferred capability targets to define a system's requirements and have requirements decision makers informed of their estimated costs and performance.

The problem space is ill-defined. We took a mixed-methods approach to define the area. This included revisiting pre- and post-WSARA root cause analysis for cost growth to understand what causes are the most important to address during the development phase. By putting programs into group memberships of relevant cost growth causes, calculating conditional probability measures, and conducting clustering analysis, we saw that cost estimation and requirements understanding and selection are the predominant causes. This was the case for three of the four Services (Army, Air Force, and Joint programs), and for all types of systems except for embedded The data also showed that cost and schedule estimate errors should not be grouped together, as done in the WSARA model.

We further defined the area through creating new cases of programs conducting integrated cost and performance modeling while trying to determine their requirements. Cases in the open literature do not exist. This research conducted a multiple-case study, using exploratory cases for a conducting both comparative analysis using a replication logic approach and conducting pattern patching against a framework using the Friedman and Sage Systems framework for Systems Engineering case studies. These cases, the SE OPT analysis of the ACV, the AAS Program, and Army Force Basing, provide key ideas

concerning the need for data collection, feedback and iterative processes, and the methods of cost estimation in those efforts.

The case study had issues in terms of reliability, as each was dependent on the openness and policies of the program offices involved. Hence, there was a wide disparity of data and data sources used amongst the three cases, and no one protocol could be used to gather the information. The case with the greatest amount of information was the SE OPT case, in which the author had direct participation for over a year. The author attempted to prevent bias by focusing on key units of analysis within each case, although Yin (2009) contends that the internal validity issue caused by bias is not an issue with exploratory cases. The author attempted to get the cases reviewed by the sources. The ACV program responded with a review of the entire work, while the Army Force Basing and AAS programs provided approval without comment.

The comparative case analysis informed the creation of an integrated cost and technical performance model that uses system-dynamic-like feedback loops and an LPP MOO method for decision-making. The model mapped capability targets to total cost and technical performance estimates, with the selection of components as a necessary intermediate step. The selection of component uses both heuristics and LPP to balance against conflicting attributes and uses LPP in an undefined preferences environment.

We assessed this framework using data from the SE OPT ACV case. We conducted statistical analysis of the eight system concepts of the SE OPT effort and the component database. Initial correlation analysis of the cost and weight of the original SE OPT system concepts showed that there was not significant statistical evidence to show non-zero correlation between cost and weight. Hence, parametric cost estimation would not be a

good choice. This reinforced the predominantly engineering bottoms-up cost estimation approach of the model.

The model was partially automated and built reusing MS Excel calculation spreadsheets originally developed by the author for the SE OPT. We ran the process and calculated LPP values against the SE OPT data, as well as data obtained using the LPP component selection. We also used minimum cost and weight methods of component selection. Hypothesis testing showed that the LPP component selection provided more optimal results, and the model in general showed how to provide an optimality measure versus the range of capabilities being used to define system requirement.

A key development within this model were the techniques to use LPP in pre-design or conceptual-stage development to better select required capabilities of a system. PP and LPP are normally assigned range values via user judgment. In this study, as we did not have users available, we automated the assignment process via two methods. First, we used the idea of capability ranges which are easily understood from a requirements perspective and mapped them to the five boundary values needed for LPP processing. Second, we used simple means and standard deviations calculations of component attributes. We calculated the mean and standard deviation of simple characteristics, such as weight or horsepower in engine component entries in the market research database, to be able to calculate LPP scores from that data. Overall, the analysis can be done with tools as simple as MS Excel to produce results.

There are three major limitations of the current framework. First, the framework and model instantiations are domain dependent. The model was developed for a combat vehicle, so it is a well-defined system with a standardized WBS structure and vehicle

architecture. The focus on the interplay of weight, performance, and cost is more focused on hardware-centric systems. Second, the current model needs further automation. Going through the rule sets outlined in the framework was partially a manual process to understand the performance impact of component selection via LPP, and selecting other components as necessary. Third, the effort could only be tested on one system type. Additionally, the variety of available components to be selected via LPP was limited with the SE OPT market research database. While there were several entries for major components, such as engines and armor, it was limited in many others, such as transmissions, tracks, road wheels, etc.

Our model and framework can be used not only for pre-MS A activities but conceptually can be reused through the life cycle of a system to provide more refined cost and performance estimates. For future work, this methodology needs to be tested against other programs and use a more extensive database of possible components. Also, the methodology needs to be further automated.

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Appendix A. AST Program Response

Advanced Sensor Technologies (AST) Input to Ed DeVilliers' PhD Research Project

February 2013

1 of 6

AST Responses to Ed DeVilliers' Specific Questions Regarding his Research Project:

APMSE Background 1. "What is your background with the program?"
AST Response: I am the Advanced Airborne Sensor (AAS) Deputy Assistant Program Manager System Engineering (DAPMSE) overseeing the AAS Systems Engineering development effort.

APMSE Background 2. "What are your areas of expertise and amount of experience in these areas?"
AST Response: I am Defense Acquisition Workforce Improvement Act (DAWIA) Level III certified in Program Management and Systems Engineering with 27 years of acquisition experience. I have a Bachelor of Science degree in Physics, Master of Science degree in Electrical Engineering, and a Master of Arts degree in Business Administration.

APMSE Background 3. "What other programs have you been involved in?"
AST Response: I have worked on acquisition programs at the Naval Sea Systems Command (NAVSEA), Naval Air Systems Command (NAVAIR) and Space and Naval Warfare Systems Command (SPAWAR).

Program Background 4. "Please describe the program—elements such as its ACAT level, size of the government and developers teams, general timeline, purpose, and its products."
AST Response: The Advanced Sensor Technologies (AST) is the program office responsible for the development of the Littoral Surveillance Radar System and the Advanced Airborne System under Program Executive Office Aircraft (PEO(A)).

The Littoral Surveillance Radar System (LSRS), is an Active Electronically Scanned Array (AESA) radar system hosted on a modified U.S. Navy P-3C Block Mod Upgrade Program (BMUP) aircraft. The LSRS aircraft provide Component Commanders with highly accurate battle space situational awareness as an integrated Intelligence, Surveillance, Reconnaissance and Targeting (ISR&T) asset.

The Navy has programmed the development of the follow-on system, the Advanced Airborne Sensor (AAS), which is an evolutionary spiral to the currently deployed LSRS and will be hosted on the P-8A, the Navy's Multi-Mission Maritime Aircraft (MMA). Like LSRS, AAS will provide an airborne high resolution near real-time radar surveillance system. Employment will also increase the Component Commanders' war fighting effectiveness by ensuring a situational awareness advantage, achieving information dominance throughout all campaign phases, and providing on-demand, actionable sensor data to support precision targeting against threats at sea and on land. By maximizing the incorporation of Commercial Off-The-Shelf (COTS) technologies, AAS will be highly supportable, maintainable, scalable, and upgradeable, with the goal of reduced unit production and life cycle costs. AAS is an Acquisition Category (ACAT) 1D program.

Program Background 5. "Is the program producing a new type of system, or is it replacing an existing system with similar requirements?"
AST Response: See response to Question 4.

Program Background 6. "Who were the major stakeholders in the program (requirements agency, operational advocates, test organizations, etc.)?"
AST Response:
- Acquisition Office for P-8A and AAS: Navy Program Executive Office, Air ASW, Assault and Special Mission Programs, (PEO (A))
- Requirements (CDD, CPD) and Resource Sponsor: Deputy Chief of Naval Operations for Integration of Capabilities and Resources (N8)
- Flight Clearance: Naval Air Systems Command (NAVAIR)
- Operations and Logistics: Commander Patrol and Reconnaissance Group
- Operational Testing: Commander Operational Test and Evaluation Force (COMOPTEVFOR)
- P-8A Program Office: PMA-290
- AAS Prime Contractors: Dual-Prime Team of Raytheon and Boeing
- P-8A Prime Contractor: Boeing

Cost 7. "How did cost play a factor in determining what operational requirements or KPPs were finally chosen for the system?"
AST Response:
The AAS Requirements and Resource Sponsor (N8) leveraged Integrated Capabilities Documents (ICDs), LSRS Operational Requirements Document (ORD), and Fleet input to develop the AAS Key Performance Parameters (KPPs) and Attributes captured in the AAS Capabilities Development Document (CDD). In the development of the AAS CDD, N8 solicited inputs from the AST Program Office and AAS IPT to understand the industry technology base and actual LSRS operational capabilities demonstrated in the Fleet. Early in the AAS Technology Development Phase, the AAS IPT generated a Cost Analysis Requirements Document (CARD) that included a AAS "Government Candidate Design" that scoped a notional design for the AAS system that the AAS Cost Team utilized to develop an associated notional Cost Estimate for the development and procurement of the AAS system. The AAS CDD development process utilized the draft CDD and associated CARD and Cost Estimate in a feedback loop to ensure the approved CDD operational requirements drove an technologically achievable and cost effective AAS program.

Cost 8. "What types of cost were estimated to determine the impact of including certain requirements?"
AST Response:
The AAS CARD and associated Cost Estimate included the entire Total Ownership Cost (TOC) for the AAS system. All phases of the program (Technology Development, Engineering and Manufacturing Development, Procurement, Operations and Support (O&S) and Disposal) were included in the AAS Cost Estimate that supported the CDD development process.

Cost 9. "Did you have a requirements agency in charge of the requirements generation, and if so, how were they involved in the process of estimating cost and technical performance based on their requirements choices?"
AST Response:
As indicated in the response to Cost 7 and 8, the requirements agency (N8) utilized the AAS IPT generated CARD and Cost Estimate in a feedback loop in support of the CDD development

process. Draft changes to the AAS CDD became draft changes to the AAS CARD, Government Candidate Design, and associated Cost Estimate, and then the updated Cost Estimate was fed back to the requirements agency in a feedback loop to inform the CDD development process.

Cost 10. "Did program operational requirements or KPPs change throughout program execution based on actual or estimated costs?"
AST Response:
Once the AAS CDD development process outlined in Cost 7, 8, and 9 was completed, the CDD was approved and AAS operational requirements and KPPs have remained stable throughout program execution.

Cost 11. "What was the typical length of time needed to officially change or remove operational requirements or KPPs if the program felt the need to do so?"
AST Response:
As indicated in Cost 10, the AAS operational requirements and KPPS have remained stable throughout program execution.

Team 12. "Was there a specific team set up to estimate cost in coordination with generating operational requirements or KPPs, or was it conducted by the normal organizational structure of the program? If a specific team was formed, can you describe this team (size, areas of expertise)?"
AST Response:
At the commencement of the AAS Technology Development (TD) Phase a strong Government Team, was established to generate the AAS CARD, Government Candidate Design, and Cost Estimate. The Government Team consisted of Government personnel and Contractor System Matter Experts (SMEs) in all required disciplines, including technical design, supportability, and cost. The Government Team was maintained throughout the CDD development process and program execution. The Government Team has provided ongoing feedback to the requirement agency (N8) regarding Capabilities Production Document (CPD) development, design to cost, and should cost initiatives.

Team 13. "Describe the process the program/team used to analyze costs and requirements."
AST Response:
See responses to Cost 7, 8, and 9.

Team 14. "Did the program / team meet consistently? If so, describe the typical schedule".
AST Response:
As a AAS Government Team was stood up at the commencement of the AAS TD Phase and remained stable throughout program execution, the AAS Requirements/Cost Government Team was ingrained in the day to day program operations.

Team 15. "Was the program / team composed of people very proficient with the program's domain?"
AST Response:
See responses to Team 12 and 14.

Team 16. "What resources were at the program's / teams disposal to conduct its analysis?"
AST Response:
See responses to Team 12 and 14.

Team 17. " Any existing data from prior programs available?"
AST Response:
The LSRS program provided significant input into the AAS CDD development process, CARD, and program execution. LSRS actual operational capabilities demonstrated in the Fleet and historical development and O&S cost data was utilized to inform the CDD development process, CARD and AAS TOC Estimate. The historical O&S cost data included the depot level maintenance, repair, sparing, and software maintenance.

Team 18. "Did the team experience any turnover? If so, can you describe the nature of the turnover—number of people, possible reasons, etc."
AST Response:
The AAS Government Team was stood up at the commencement of the AAS TD Phase and remained stable throughout program execution. There was minimal turnover in team membership.

Team 19. "What was the program's / teams tools and products?"
AST Response:
The AAS Government Team utilized industry standard management, engineering, and cost estimating tools such as Microsoft Project ©, MATLAB ©, and COBRA ©.

Cost 20. "What cost estimation techniques were used, and how was that work linked to the technical performance estimate? CERS can easily come up with a cost figure for requirements that are not really executable".
AST Response:
See responses to Cost 7, 8, and 9.

Cost 21. "How did programmatic considerations, such as schedule and cost elements usually found in an Acquisition Strategy, feed into both the cost and technical modeling?"
AST Response:
See responses to Cost 7, 8, 9, & 10 and Team 12.

Cost 22. "What was the team composition used in the process? I found that for Amphibious Combat Vehicle, having a full mix of SMEs, SEs, Acquisition Professionals, Log, etc. who really knew the domain were all necessary and needed to be involved continually from the beginning."
AST Response:
See response to Team 12.

Cost 23. "How much were the initial operational requirements affected through this iterative process? I am not interested in specific requirements, per se, but more the amount of change experienced and how Acquisition and Requirements personnel interacted in the process."
AST Response:

See responses to Cost 7, 8, & 9 and Team 12.

Cost 24. "As the process used provided a baseline cost / performance model and acquisition assumptions / decisions, was this baseline used and updated during program execution, and was the cost / technical estimation process used beyond the initial analysis stage?"
AST Response:
See responses to Cost 7, 8, & 9 and Team 12.

Summary AST Response.
The Government Team continues to provide feedback to the requirements agency (N8) regarding Capabilities Production Document (CPD) development, design to cost, and should cost initiatives. AAS trade studies were performed with cost considerations and within and across requirements and functions to support the functional analyses and allocation of performance requirements. The AAS program design to cost initiatives commenced during the Technology Development (TD) Phase and continued into the Engineering and Development (EMD) Phase. The AAS design incorporated successful TD Phase risk reduction efforts that yielded a mature system definition with design margin. An evolutionary approach to system development is being used to meet AAS performance requirements through the use of upgradeable COTS components and an open architecture approach to support future growth. The focus on design-to-cost resulted in achieving a goal of a low cost, evolutionary system design. The resulting system design was the lowest risk entry point for EMD while providing flexibility to upgrade and grow system performance as market-driven changes improve access to higher performance elements.

Appendix B. Force Basing Interview Notes

The following are notes taken during a phone interview with the Force Basing Branch staff on Mar 5, 2013 and reviewed for accuracy by the participants.

Participants:

1. Karen Short.
2. Victor Robertson.
3. Jeff Jones.

Interviewer: Ed DeVilliers

1. What are the current roles of the interviewees?
    a. Karen Short. She is the Branch Chief, Force Basing, Formations Architecture, in System of Systems Engineering (SoSE), organization under the Assistant Secretary of the Army (Acquisition, Logistics, and Technology) (ASA(ALT)). Her branch conducts for Reference Architecture development for Force Basing, which includes the three areas of Integrated Base Defense (IBD), Communications/Computing Infrastructure (CCI), and Base Infrastructure (BI). She has been in the branch for about 1 year, with the first 2-3 months as the deputy, and the remainder of the time as the branch lead.
    b. Vic Robertson. He came into the branch in the summer of 2010, and transitioned into the contractor role in July of 2012. He is now a support contractor working for Karen Short as the Lead Integrator for Force Basing.
    c. Jeff Jones. He is a support contractor working for Karen Short who has helped lead the development of the first reference architecture for IBD.
2. What are the educational and professional backgrounds of the interviewees?
    a. Karen Short: Ms. Short has a BS in Engineering and an MBA from the University of Tennessee. She has 12 years experience in government acquisition in the Systems Planning, Research, Development and Engineering (SPRD&E) area (level 3), with a former position as a lead systems engineer developing missile systems.
    b. Vic Robertson. Mr. Robertson is a graduate of the U.S. Military Academy (’79) with a MS in War Planning from Ft. Leavensworth. He has 21 years experience as an Army officer, and 10 years experience within the acquisition community as a systems integrator.
    c. Jeff Jones. Mr. Jones is a graduate of the U.S. Military Academy (’76) with a MS in Electrical Engineering (1989). He served in the Corps of Engineers and gained a Professional Engineer (PE) designation in 1980. After serving in the

commercial world in the trucking and shipping arena for 3 years, Mr. Jones started supporting the Future Combat System (FCS) program as a systems engineer and also worked within PEO Integration.

3. What were the most rewarding and frustrating aspects of the Reference Architecture effort?

    a. Jeff Jones: The most rewarding aspect was the people, and the teams that were formed. Other rewarding aspects were being able to work to short timelines while being able to produce good and new products. The most frustrating aspect of the job in Force Basing was getting the needed people to participate in the effort.

    b. Vic Robertson: Vic did not find the job frustrating. He saw this as a result of his role. First, he was not responsible for the effort. Second, his role was more external audience focused. His role was in explaining the products of the group. IN this role, he was assisted by Jeff Jones, and he helped Jeff get more external stakeholder involvement. In this role with Jeff, he did share Jeff's frustrations in trying to explain to external stakeholders why they should care about the Reference Architecture effort, and explaining repeatedly the process, and distinguishing their role with the roles played by the stakeholders.

    c. Karen Short: Ms. Short found the quality of the people as the most rewarding aspect, along with the high quality of the products and processes that resulted from their work. This was especially true since she did not have to pick these people herself. They were already part of the branch when she arrived. She shares the frustration of Jeff and Vic of the repeated need to convince others that their process can benefit them. It is a very political situation where many first think that the Reference Architecture effort is moving into their own area of responsibility.

4. In conducting their work in Reference Architectures, how did they relate to the three mission areas of IBD, CCI and BI?

    They did work in all 3 areas as they have worked Force Basing implementations. These architectures have been use by the three trail bosses (one for each mission area) – current PMs who have been given authority through the Force Basing governance structure to lead and coordinate the efforts of various PMs managing individual Force Basing programs with their own established requirements. The Trail Bosses, with their own staffs from their own PM Offices, review the reference architectures and determine what systems/programs can use the architecture, what part of the architecture is relevant and for what periods of time those architectures should be used. As the use of the architectures is determined, the programs undergo a review process by a FB Council of Colonels (FB CoC).

5. How specifically were the architectures used?

    Jeff: The Trail Boss, in coordination with the PMs of the component systems, could use the architecture to jump start the acquisition and design effort by finding parts of

the architecture that could be used. The Reference Architecture branch reviews requirements across programs. This leads to a reference architecture that determines recommended architectures and implementations for various requirement areas, and this leads to a larger SoS architecture. This goes to the Trail Boss who then analyzes the individual programs against the Reference Architecture. This leads to the Trail Boss implementing an Acquisition Strategy across programs. The Trail Boss is empowered to enforce this Acquisition Strategy on the individual programs by the Army Acquisition Executive (AAE).

6. How is cost integrated into the development of the architecture?

   Jeff: Focus first is not on cost but on the approved requirements and capabilities needed for the Program of Record (PoR). Cost data is collected, and the reference architecture effort has collected a lot of cost data from various efforts. Cost is then used to form Candidate Capability Packages. These are possible implementation choices for the reference architecture where cost is used to make choices when decisions are needed between possible choices.

7. Does the trail boss use cost to determine the Acquisition Strategy concerning what parts of the reference architecture to use among the PoRs?

   Karen: Yes. Chart #22-23 of the Force Basing Overview presentation are examples of the use of the architectures and the analysis of cost that goes into deciding what of the architecture gets implemented.

   The Trail Boss will look at the current situation of a program, and assess what is not integrated but needs to be integrated.

VCSA approves IBD Trail Boss kitting plan

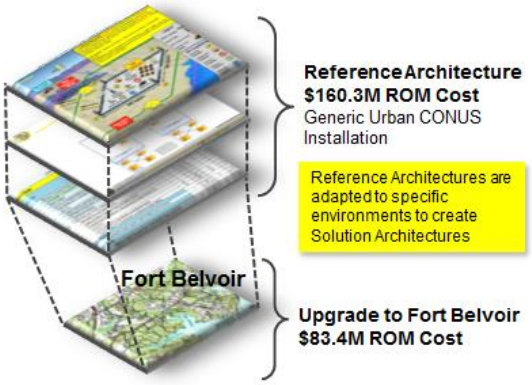
- VCSA approved the proposed IBD kitting methodology of retaining systems for Basic Kits, Expansion Reserves and Training Kits
- VCSA Taskings:
  - TRADOC provides requirements and testing criteria plan
  - ASA ALT develops plan to develop and implement kit integration
  - ASA ALT provides necessary mitigation cost estimates that address the kitting and preposition of IBD
  - G-3/5/7 to issue an EXORD / Directed Requirement to justify costs in Army FY15-19 Program Objective Memorandum (POM) submission

Force Basing reference architectures support Trail Boss acquisition approach

NSE: Non-Standard Equipment
TB: Trail Boss
IBD: Integrated Base Defense

IBD Architecture: Urban Solution for Fort Belvoir

Reference Architecture	$160.3M	Cost for Generic Urban CONUS Installation
Subtract	$44M	Costs not applicable to the Fort Belvoir site
Specific **Solution Architecture** for Fort Belvoir	= $116.3M	Cost for complete architecture at Fort Belvoir
Subtract	$32.9M	Savings from using existing installed systems: InterGraph system, PTZ cameras, Desktop Alert Enterprise, CoBRA Command Kit, and AIE systems.
Total Upgrade Cost	= $83.4M	Cost to upgrade



Fort Belvoir Analysis based on IUBIP JCD critical functions of Detect, Assess, Warn, Defend and Recover

Investment required to upgrade Fort Belvoir (IBD scope) to the Solutions Architecture capabilities - $83.4M

8. How is cost estimated – team formation, methods, etc.?
   Jeff: The reference architecture effort has cost analysts who got cost data on systems, working with the Army Center for Cost Analysis. The ACCA certified the data.

Vic: Getting a good cost estimate requires socialization among customers to get support for what they want to field, i.e., what parts of the reference architecture should be implemented.

For example, the kitting plan received TRADOC input on requirements and test criteria that would impact cost, and G-3 provided support in issuing requirements in line with the reference architecture and getting needed funding. In the Ft. Belvoir example, working with Ft Belvoir identified existing capabilities/materials available that could be reused. This resulted in a $32.9M saving. Additionally, working with Ft. Belvoir identified $44M in reference architecture capabilities not applicable to Ft. Belvoir. Overall, this resulted in the IBD effort going down from a $160.3M effort based on the reference architecture to $83.4M.

Vic: Another key point is that once the reference architecture is established, do the analysis for a particular PoR is relatively quick. For example, the Ft. Belvoir analysis took only 3 days.

9. Is the lesson learned that the reference architecture and cost data collection eases analysis and answering questions?

   Vic: Yes.

10. What are the main take-aways you would want to see in the paper?

    Jeff:

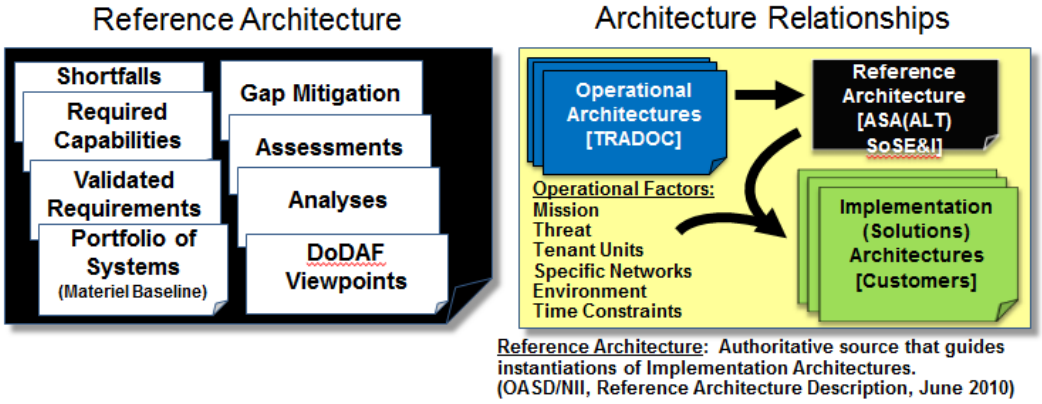
    a. The reference architecture effort brings people together to get a common understanding of the needs of PoRs.
    b. Keep customers in the process, and this helps in understanding the problem up front very well.
    c. The main point is to help the Trail Boss to form an effective Acquisition Strategy.
    d. The team needed to do this was generally 5 core members with 3-8 more people consistently involved, and 20+ people that could be called upon as needed.

    Vic: Have people understand what a reference architecture is and how it helps program managers. Look at slides 5-7 of the FB Overview presentation. Overall, the reference architecture provides a template and an initial start of an implementation architecture/design to jump start analysis for a specific PoR, and it provides a broader context that includes different perspectives.

    Jeff: Reference architectures whittled down the number of material solutions to make better SoS solutions. It makes the problem easier to manage, although it does reduce choice.

The problem:
How to effectively and efficiently design & equip tactical formations, base camps, and installations using a system of systems approach?

Solution Process:
Develop reference architecture for tactical formations, base camps, and installations



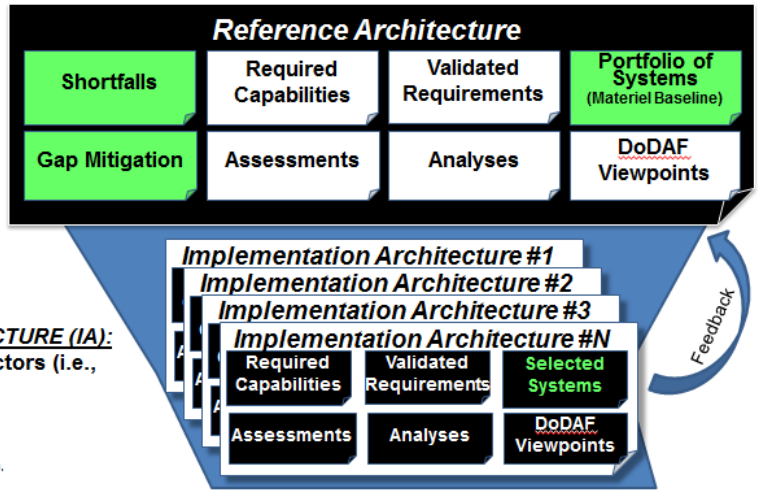
Reference Architecture: Authoritative source that guides instantiations of Implementation Architectures.
(OASD/NII, Reference Architecture Description, June 2010)

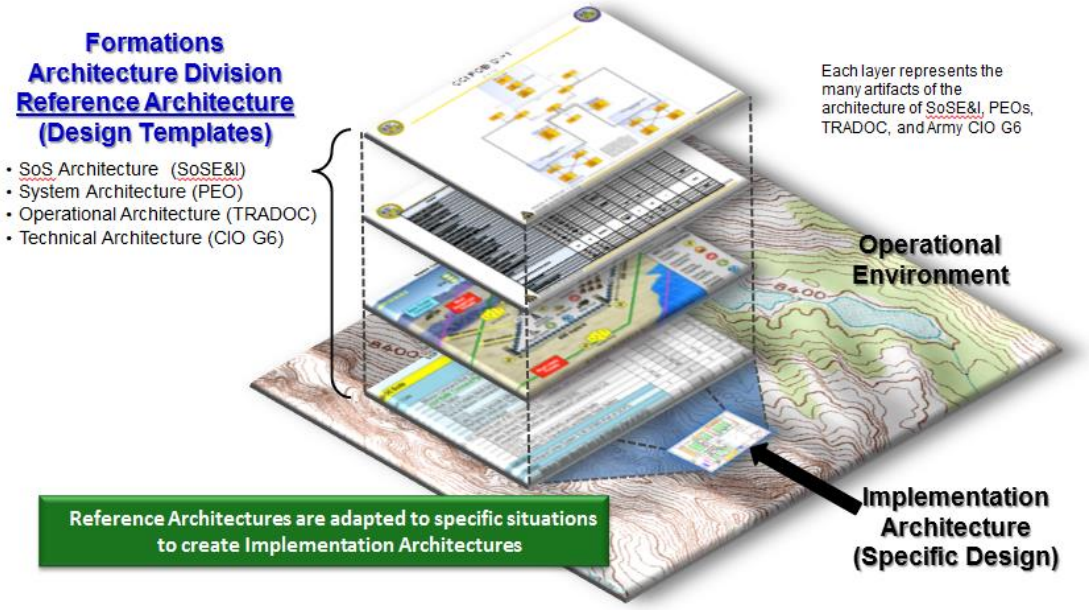
REFERENCE ARCHITECTURE (RA):
- ***General Scope***
- ***Optimized Requirements-based design***
- ***Capability-based system portfolio***
- ***All PEO systems considered, RDECOM & COTS***
- ***Learns from Implementation Arch's***
- ***Provides guidance & templates for Implementation***

IMPLEMENTATION ARCHITECTURE (IA):
- **Optimized for situational factors (i.e., cost, program, METT-TC)**
- **Subset of the RA systems**

METT-TC: factors of the military situation = Mission, Enemy, Troops, Terrain, Time, Civil Considerations

Reference Architecture:	***Implementation Architecture:***
Authoritative source that guides instantiations of Implementation Architectures. (OASD/NII, Reference Architecture Description, June 2010)	*a framework or structure that portrays the relationships among all the elements of something that answers a problem. Abstract elements are replaced by real world, physical elements. [also called "Solution Architecture". (OASD/NII, Reference Architecture Description, June 2010)*





Vic: Reference architectures need to be maintained, because of changes to needs and technology. As seen in the slides below (and reinforced by Jeff), the reference architecture effort supports the POM. Also, reference architectures are designed to support executable implementation architectures in the near term. That is what allows the Trail Boss to use the reference architecture to establish an executable Acquisition Strategy across multiple PoRs.

INITIAL Design: establishes reference architecture and first SoS design
ANNUAL Design: subsequent SoS Design for next POM cycle
Update Design: modifies a design to make it consistent with recent changes

Force Basing Capability Set Years	Work Year					
	FY 11	FY12	FY13	FY14	FY15	FY16
FB CS15	Initial Design	Update Design	Update Design	Update Design	Field	Archive
FB CS16	Delivered in 2011	Annual Design	Update Design	Update Design	Update Design	Field
FB CS17		Delivered in 2012	Annual Design	Update Design	Update Design	Update Design
FB CS18				Annual Design	Update Design	Update Design
FB CS19					Annual Design	Update Design
FB CS20						Annual Design

(FB: Force Basing) (CS: Capability Set) (RA: Reference Architecture)

Initial Design: a Reference Architecture (RA) that is created from scratch. Includes scope of the RA, portfolio of systems (materiel baseline"), requirements analysis, operational analysis, required capabilities and finally down-selection of systems with architecture and analysis that is recommended to a Trail Boss or other customer for acquisition strategy development and execution. Requires more effort than Updated and Annual Designs.

Updated Design: modifies an initial or annual design to make it consistent with changes such as Trail Boss guidance, and funding decisions. The design supports that year's IWSR / WSR and acquisition strategy.

Annual Design: Annual Design supports a fielding year in a POM cycle subsequent to the fielding years in Initial or Updated Designs.

Force Basing Capability Set Years	Work Year					
	FY 11	FY12	FY13	FY14	FY15	FY16
FB CS15	Initial Design	Update Design	Update Design	Update Design	Field	Archive
FB CS16		Annual Design	Update Design	Update Design	Update Design	Field
FB CS17			Annual Design	Update Design	Update Design	Update Design
FB CS18				Annual Design	Update Design	Update Design
FB CS19					Annual Design	Update Design
FB CS20						Annual Design

FB: Force Basing

Effort used for different types of Force Basing reference architectures is carefully metered to create and keep the architectures current

Appendix C. Force Basing Reference Architecture Development Process

The Reference Architecture (RA) Development Process is a system of systems (SoS) engineering approach employing Development Planning (DP) principles and Model Based System Engineering (MBSE) techniques to reliably produce a RA that is well supported by analysis and ready for use by various customers. See Figure 1, RA Development Process. This document discusses only the RA Design process which is comprised of: RA Definition, Systems Data, Use Case Development, and RA Analysis and Design.

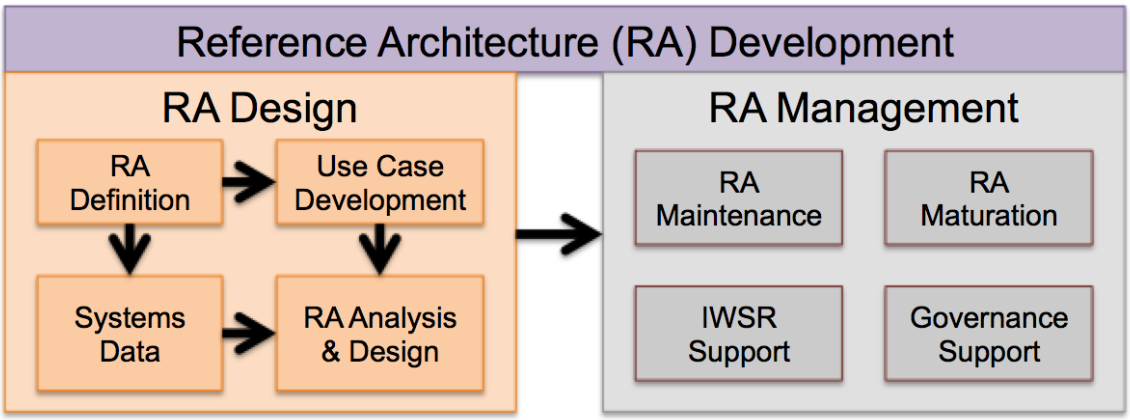


Figure 1. RA Development Process

A. **RA Definition:** Given the requirement for a RA, the RA Definition Process clearly defines the scope and the deliverables, builds the RA Development Team (RDT), identifies stakeholders, identifies authorative references, establishes Team schedule and battle rhythm, and produces several artifacts which the Team agrees represent the RA. The process begins with a period of Mission Analysis and culminates in a formal Face-to-Face Kick-off week during which all RA Definition deliverables are vetted by the Team to include stakeholders. See Figure 2, RA Definition Flow Chart.

   1. **Build RA Development Team (RDT):** Assemble the core professionals who develop the RA to include a Team Lead, Lead System Engineer, Architect, System Data Manager, and Operational Subject Matter Expert(s) (SME(s)) plus operations analysts and a cost analyst matrixed to the Team. This core Team is rounded out by the addition of various stakeholders.

   2. **Define Deliverables:** Leadership clearly defines the content of the RA and RA delivery date as the RDT is being assembled. In the charts that follow, deliverables that are outputs of processes are indicated by "D#".

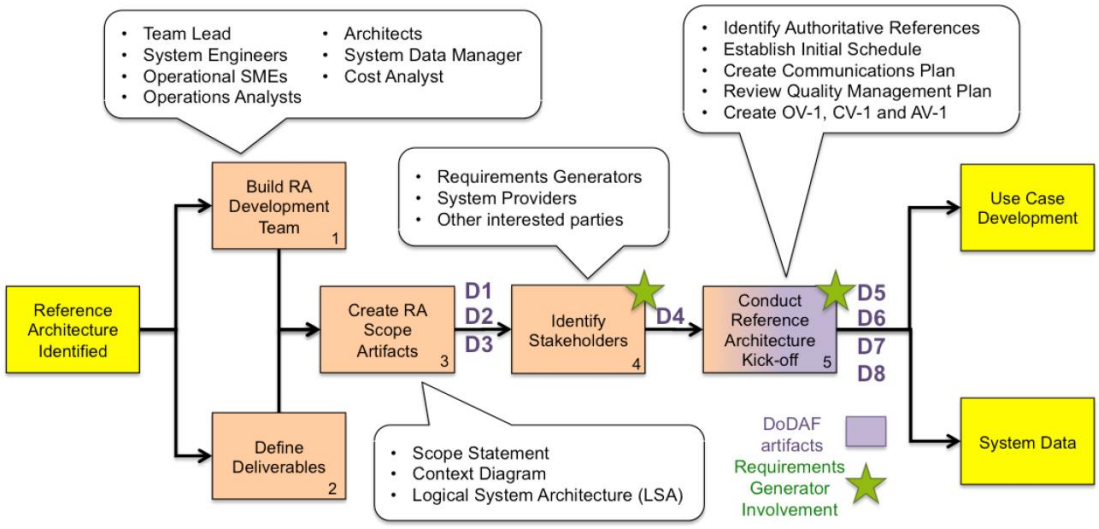


Figure 2. RA Definition Flow Chart

3. **Create RA Scope Artifacts:** The RDT drafts the RA scope statement, logical system architecture (LSA) (the categories of systems in the RA), and context diagram (defines interactions between the RA and entities outside the RA).

   Output: D1 = Scope Statement, D2 = Logical System Architecture (LSA), and D3 = Context Diagram

4. **Identify Stakeholders:** Given the scope and LSA, identify organizations that produce requirements (Requirements Generators), provide systems (System Providers) or are parties interested in the RA scope (Interested Parties) and request their participation in the RA effort. These are the stakeholders whose participation is essential for effective Development Planning.

   Output: D4 = Team List (RDT core personnel plus stakeholder representatives)

5. **Conduct RA Kick-off:** The RA Kick-off is a leadership event that brings the RDT together for Team building, vetting of artifacts, solidification around the RA scope and familiarization with the RA development process. Coming out of the Kick-off, all RA Definition deliverables are drafted and vetted with stakeholders resulting in agreement across the Team on terms, definitions and path forward.

   Output: D5 = List of Authoritative References, D6 = High Level Operational Graphic (OV-1), D7 = Overview and Summary Information (AV-1) and D8 = Vision (CV-1) artifacts.

B. **System Data:** Given the scope and LSA, the RDT must catalogue all possible systems available to satisfy required capabilities within the system categories of the LSA. The process starts with a blank spreadsheet or database and ends with the

largest set of possible systems and related data the Team can generate. In the end, the system data includes disposition of every system and other notes pertinent to the system selection process and acquisition strategy. See Figure 3, System Data Flow Chart.

1. **Construct System Functional Decomposition (SV-4) (High Level):** A high level set of system functions pertinent to the scope is created to map to systems and to operational activities to serve as the link between system functionality and operational activities (see SV-5a (Operational Activities to Systems Functions Matrix) in Use Case Development Process and Create Materiel Baseline in RA Analysis and Design). The Joint Common System Function List (JCSFL) Level 2 Function Groups are preferred for the high level SV-4 functions, but RDTs are not limited to that list. Additional functions may be added, but must be at the appropriate high level. The JCSFL is used to ensure maximum alignment with Joint personnel and systems.

   Output: D9 = System Function Decomposition (SV-4) (High Level)

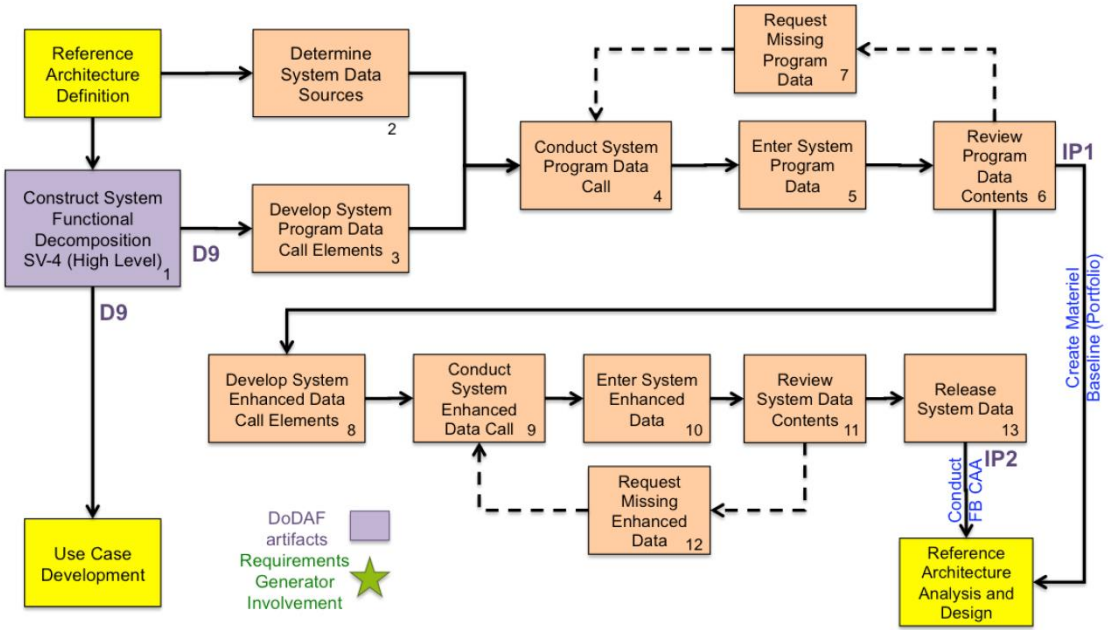


Figure 3. System Data Flow Chart

2. **Determine System Data Sources:** Leveraging SMEs and stakeholders, likely systems and system data sources are identified in preparation for the data call.
3. **Develop System Program Data Call Elements:** In preparation for the data call, specific system program data are identified such as system name, functional description, owning Program Executive Office (PEO), technical readiness level

(TRL), fielding date, Point of Contact (POC) contact data, and cost POC contact data.

4. **Conduct System Program Data Call:** Formal tasking channels are utilized to secure system program data from government system owners. Should commercial system data be required, the RDT System Data Manager personally reaches out to appropriate companies for system data.
5. **Enter System Program Data:** Data sources provide data that is collated into a combined spreadsheet or database. The data sources also identify the functions (from the SV-4) that are performed by the system.
6. **Review Program Data Contents:** Once received and collated, the data is checked for completeness.

   Output: IP1 = System data list or database suitable for determining Materiel Baseline (Portfolio)

7. **Request Missing Program Data:** If received data is incomplete, the sending agency is contacted for correction. When appropriate, POCs are contacted directly.
8. **Develop System Enhanced Data Call Elements:** Enhanced data call elements includes performance specifics, Space, Weight, Power and Cooling (SWAP-C), official graphics, official picture, and cost data (that is collected separately by cost analysts).
9. **Conduct System Enhanced Data Call:** Formal tasking channels are utilized to secure system enhanced data from government system owners. Should commercial system data be required, the RDT System Data Manager personally reaches out to appropriate companies for system data.
10. **Enter System Enhanced Data:** Data sources provide data that is collated into a combined spreadsheet or database. Cost data is collected separate from other data and protected.
11. **Review System Data Contents:** Once received and collated, the data is checked for completeness.
12. **Request Missing Enhanced Data:** If received data is incomplete, the sending agency is contacted for correction. When appropriate, POCs are contacted directly.
13. **Release System Data:** When completed, the system data is provided by the System Data Manager to the RDT Lead for use in RA Analysis and Design.

    Output: IP2 = System data list or database suitable for RA Analysis and Design

C. **Use Case Development.** The Use Case Development process includes Requirements Analysis, Operational Analysis and Use Case Preparation. Use Cases are system agnostic vignettes selected in concert with Requirements Generators to expose required capabilities in an operational context. When completed, the Requirements

Generators and the RDT core Team understand the restated required capabilities (RCs) and their prioritization; understand how the RCs manifest in operational context; and are all using the same language. See Figure 4, Use Case Development Flow Chart.

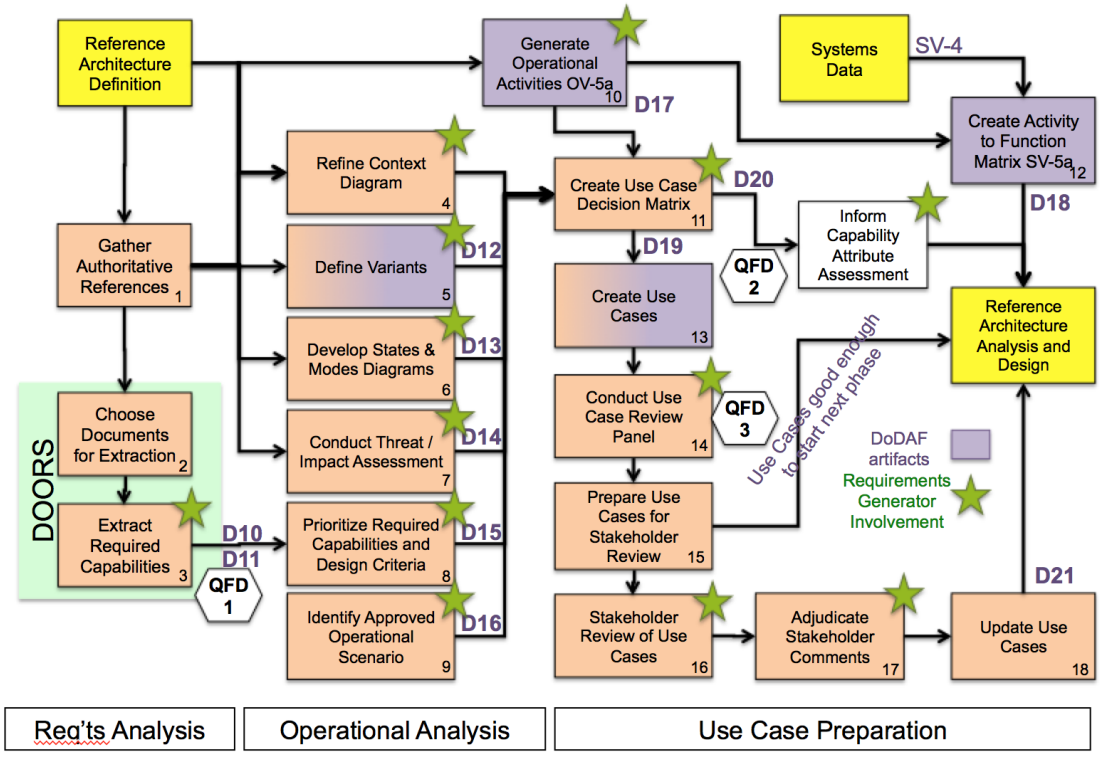


Figure 4. Use Case Development Flow Chart

1. **Gather Authoritative References:** Using the list of authoritative references, the RDT gathers those references from various authoritative sources. These authoritative references are pertinent to both doctrine / Concept of Operations (CONOPS) and requirements.
2. **Choose Documents for Extraction:** The authoritative references are screened for applicability to determine which are the ones containing required capabilities. These documents are placed into Dynamic Object-Oriented Requirements System (DOORS).
3. **Extract Required Capabilities:** Using the DOORS tool, the required capabilities (RCs) are extracted, restated in canonical form and vetted with stakeholders. When necessary, conflicting or similar RCs are normalized through negotiation with the Requirements Generators.

   Output: D10 = DOORS report of extracted RCs and D11 = RC traceability report

4. **Refine Context Diagram:** Given the authoritative references regarding CONOPS and doctrine, the context diagram is revisited to add new external influences and exchanges.

   Output: Refined Context Diagram

5. **Define Variants:** When in an ill-defined or infinite problem space, create variants that represent specific problems within the problem space to which the RA applies. Make each variant unique and create the number of variants needed to represent a significant amount of the problem space. Minimize the number of variants used.

   Output: Variants used in RA design

6. **Develop States and Modes Diagrams:** Deepen Team understanding of the variant bound problem space by developing States (Condition at a particular time), Transition (Criteria to change from one State to another), and Modes (Activity / Activities that applies to State) of the RA. This step puts the operational space in engineering context, ensuring the discussion from operator to engineer remains consistent. States and Modes drive some Use Case options.

   Output: D13 = RA States and Modes Diagrams with Transitions

7. **Conduct Threat / Impact Assessment:** Identify and assess priority of perturbations to the RA. These drive some Use Case(s) options.

   Output: D14 = RA Threat / Impact Assessment

8. **Prioritize Required Capabilities and Design Criteria:** Once the RCs are extracted, restated and normalized, the Requirements Generators must prioritize them. This is the first of six Quality Function Deployment (QFD) exercises pertinent to Capability Attribute Assessment (CAA) that drive the RDT toward design decisions in RA Analysis and Design (RAD). Additionally, those RCs that cannot be rewritten as testable statements, may become design criteria.

   Output: D15 = Stakeholder Prioritized RCs and identified design criteria

9. **Identify Approved Operational Scenario:** When constructing Use Cases, a high level operational scenario approved by the Requirements Generators should be used. The RDT choses an approved scenario that fits the intent of the design space.

   Output: D16 = Approved Operational Scenario identified by Stakeholder

10. **Generate Operational Activities OV-5a:** Operational activities are used in the Use Case process to express capabilities. The operational activities can be gathered from doctrinal references, activities lists or even as the Use Cases are being constructed. The OV-5a (Operational Activity Decomposition Tree) becomes a record of operational activities pertinent to the RA.

    Output: D17 = OV-5a (Operational Activities Tree)

11. **Create Use Case Decision Matrix:** The Use Case Decision Matrix maps RCs to candidate Use Cases. Since Use Cases are resource consuming, the minimum number required to expose all the RCs in an operational context must be identified. This is a creative step, but subject to negotiation with Requirements Generators as their priorities must be considered. It is desired that all RCs be exposed in at least two Use Cases.

    Outputs: D19 = Use Case Decision Matrix with D20 = Prioritized Use Cases and QFD 2

12. **Create Activity to Function Matrix (SV-5a):** The SV-5a (Operational Activity to Systems Function Traceability Matrix) maps the functions in the SV-4 to the operational activities in the OV-5a. During RA Analysis and Design, this mapping assists the Team in identifying functions pertinent to each Use Case activity and making it easier to search for systems with those functions.

    Output: D18 = SV-5a (Operational Activity to Systems Function Traceability Matrix)

13. **Create Use Cases:** Use cases are a hybrid of text and model. The Use Case format includes no specific systems (system agnostic) but instead emphasizes the activities required to complete a Use Case. Models common to Use Cases are the OV-2 (Operational Resource Flow Description), OV-5b (Operational Activity Model) and the OV-3 (Operational Resource Flow Matrix) as pertinent to a problem.

14. **Conduct Use Case Review Panel:** With Use Cases drafted, Requirements Generators return and review the RDT work.

    Output: Use Case corrections and QFD 3

15. **Prepare Use Cases for Stakeholder Review:** Use Cases are corrected and sent to a wider set of stakeholders to review. These corrected Use Cases are sufficient to begin RA Analysis and Design.

    Output: Use Cases for wider review and initial use in RA Analysis and Design

16. **Stakeholder Review of Use Cases:** Stakeholders review the Use Cases and provide comments on a comment matrix.

17. **Adjudicate Stakeholder Comments:** Upon receipt, the RDT assesses stakeholder comments for validity.

18. **Update Use Cases:** Once all stakeholder comments are adjudicated, the necessary changes are made to the Use Cases and they are finalized.

    Output: D21 = Final version of Use Cases (with OV-2 & OV-5b)

D. **RA Analysis and Design (RAD).** RAD is the final step in the RA Design process. Here the System Data and the Use Cases come together with rigorous analysis to

determine the combination of systems that best satisfies the RCs. See Figure 5, RAD Flow Chart.

1. **Plan RAD Activity:** RAD is an intense period of analysis and design requiring detailed planning for all products to be delivered on time in quality condition. Also, System Providers play a large role in RAD, so their participation must be planned well. If time is short, Face-to-Face meetings are required, necessitating increased planning and activity to prepare locations.

2. **Create Materiel Baseline (Portfolio):** The Use Case activities are mapped to systems. The systems are then assessed by System Providers for their appropriateness. Those that are deemed inappropriate are moved and the remaining systems become the Materiel Baseline (MB) – all those systems that are appropriate for the scope of the RA. This is also known as the Portfolio.

   Output: D23 = Materiel Baseline (Portfolio)

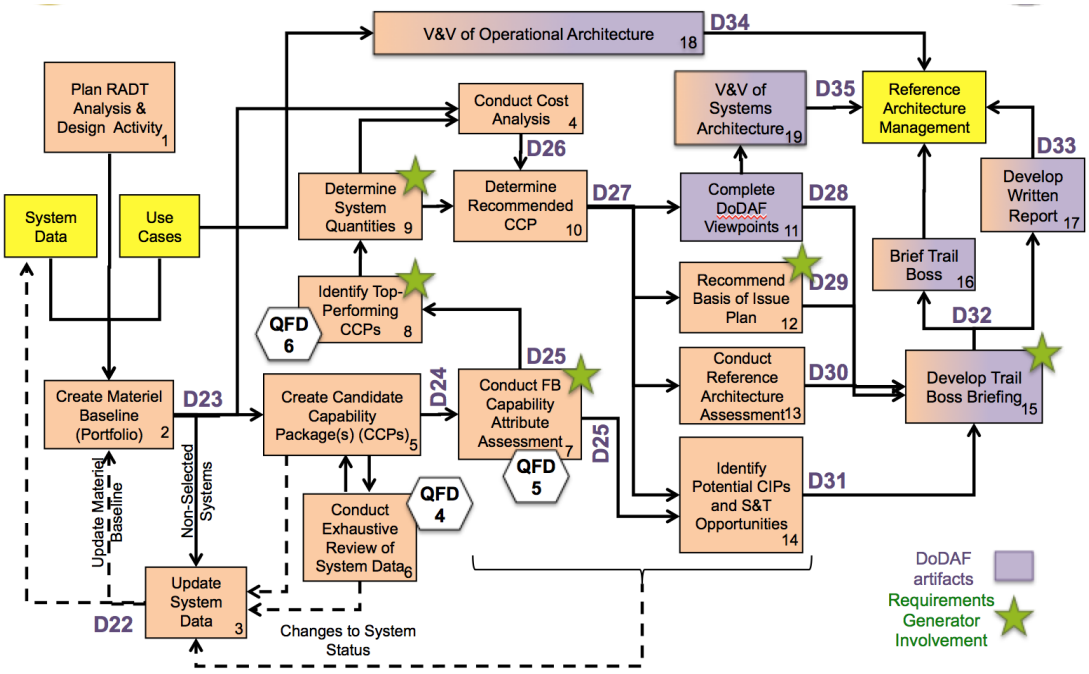


Figure 5. RAD Flow Chart

3. **Update System Data:** As the RAD process progresses, all information on systems is added to the system data list or database as a record of disposition for each system. This update process is continuous and the updated system data with annotations is a deliverable.

   Output: D22 = Updated System Data

4. **Conduct Cost Analysis:** Once the Materiel Baseline is established, the cost analysts focus cost data gathering on this smaller group of systems. As RAD progresses, the cost analysts track changes (additions and subtractions) to the Materiel Baseline. Eventually, their analysis is available to assist in decision making and is incorporated in the report.

   Output: D26 = Cost Data and Analysis

5. **Create Candidate Capability Packages (CCPs):** With the Materiel Baseline determined, the RDT then starts the process of selecting the subset of systems that best fulfills the RCs without "gold plating". These subsets – each of which must satisfy all the Use Cases – are called Candidate Capability Packages (CCPs). Each CCP is time stamped, i.e., the CCP and its reference architecture are prepared for a particular implementation or fielding date such as FY16. The next objective of RAD is to select the best / recommended CCP.

   Output: D24 = List of CCPs

6. **Conduct Exhaustive Review of System Data:** The system data is then evaluated to ensure each system has been considered and either added to the Materiel Baseline or rejected. As systems are added, they are incorporated into a CCP. These systems are often not required by a Use Case but are non-the-less necessary for the problem space to be considered adequate. At this point, QFD 4 is completed in preparation for the next step.

7. **Conduct Capability Attribute Assessment (CAA):** CAA provides a qualitative measure of each CCP's capability against the RCs. Though some quantitative data may exist to aid in scoring the CCPs, most data is qualitative. This analysis completes QFD 5 and results in a hierarchy of CCPs based upon their degree of satisfying RCs in the context of the Use Cases. In addition, the scoring also identifies those capabilities that are not addressed completely by a CCP. The inadequacy is called a "shortfall".

   Output: D25 = Scored CCPs with Identified Shortfalls

8. **Identify Top-Performing CCPs:** This step is reasonably straight forward - the RDT lead must choose the CCPs that performed the best in the CAA scoring. These CCPs are then subjected to sensitivity analysis to ensure the rank order is not spurious. Though at least three CCPs should be selected, more may be selected with justification. During this step, QFD 6 is completed.

9. **Determine System Quantities:** The top-performing CCPs are then assessed to determine the quantities of each system for each of the variants identified during operational analysis. Quantities may vary between CCPs and that could have an impact on cost analysis. In addition, scaling between variants minimizes the number of systems to manage for all variants, but some systems may not scale or be appropriate for certain variants, so some substitution from the Materiel Baseline may be required to meet RCs for those variants.

10. **Determine Recommended CCP:** Given the scoring of the CCPs, the sensitivity analysis and the cost analysis based upon the system quantities, the RDT lead decides which CCP is the best choice to recommend for the RA. This decision is based on best performance against the RCs with cost data provided for information. If a cost ceiling is established, that ceiling influences this decision. The recommended CCP is known as FYXXCP where the XX is the year of fielding.

    Output: D27 = Recommended CCP with system quantities for all variants and cost data / analysis (FYXXCP)

11. **Complete DoDAF Viewpoints:** Given the CCP decision, system viewpoints (SV-1, Systems Interface Description, and / or SV-2, Systems Resource Flow Descriptions) and standard viewpoint StdV-1 (Standards Profile) are completed and added to the package of system architecture viewpoints.

    Output: D28 = Completed System Architecture viewpoints pertinent to the Selected / Recommended CCP

12. **Recommend Basis of Issue Plan:** The RDT discusses the CCP and, with all stakeholders, renders a recommended Basis of Issue Plan (BOIP) for the CCP. The allocation of the CCP (with quantities) to Modification Table of Organization and Equipment (MTOE), Theater Provided Equipment (TPE), training centers, etc., is recommended.

    Output: D29 = BOIP

13. **Conduct RA Assessment:** The Team discusses and captures facts about systems in terms of schedule, cost, technical and program data that the Team considers important for the Trail Boss to know. This assessment is just on the CCP systems and comes mainly from notes in the System Data list or database kept throughout the process.

    Output: D30 = RA Assessment (Recommended CCP)

14. **Identify Potential Capability Improvement Proposals (CIPs) and Science and Technology (S&T) Opportunities:** The shortfalls that are pertinent to the recommended CCP are reviewed for the Team to identify and recommend potential short term mitigating ideas or recommendations that could, given funding, improve CCP CAA score. Since improving the score means increased performance against the RCs, funding for these ideas may be supported. S&T opportunities are assessed and inform the S&T Program Objective Memorandum (POM). System improvements that increase capability (CIPs) are recommended to the Trail Boss.

    Output: D31 = Recommended S&T and CIP Opportunities Associated with Identified Shortfalls

15. **Develop Trail Boss Briefing:** All deliverables are assembled into a single briefing for the Trail Boss. This briefing is reviewed by the RDT higher headquarters elements prior to release.

    Output: D32 = Trail Boss briefing

16. **Brief Trail Boss:** The Trail Boss is briefed.

17. **Develop Written Report:** The RDT RA Design effort is reported in writing and signed by the Executive for System of Systems Engineering and Integration (SOSE&I).

    Output: D33 = Signed written report

18. **Verification and Validation (V&V) of Operational Architecture:** The RDT initiates V&V of its Operational Architecture by the appropriate authority.

    Output: D34 = V&V report(s) for Operational Architecture and Analysis

19. **Verification and Validation (V&V) of System Architecture:** The RDT initiates V&V of its System Architecture by the appropriate authority.

    Output: D35 = V&V report(s) for System Architecture and Analysis

Appendix D. ACV Capability List

MEF	Sub-Cat	Attribute	Components (Y/N)	Design Dep. Only	material WBS items	Class LPP
Move	Water Mobility	Maximum water speed (Calm/following seas)	Y	N	N	S-2
Move	Maneuver-ability	Forward/Reverse/Steering - Maintain Heading (Significant Wave Height)	N	Y	N	N/A
Move	Maneuver-ability	Pivot Steer	Y	N	N	N/A
Move	Maneuver-ability	Stopping Distance (From maximum speed)	N	Y	N	N/A
Move	Maneuver-ability	Controls	Y	N	N	N/A
Move	Maneuver-ability	Launch from L Class Shipping (Ship's speed)	N	Y	N	N/A
Move	Maneuver-ability	Operate / Survive in rough seas (Sea State)	N	Y	N	N/A
Move	Maneuver-ability	Plunging Surf Wave Height (Feet)	N	Y	N	N/A
Move	Maneuver-ability	Self Righting	N	Y	N	N/A
Move	Maneuver-ability	Reserve buoyancy	N	N	N	S-2
Move	Land Mobility	Maximum land speed - Road	Y	N	N	S-2
Move	Land Mobility	Maximum land speed - Cross Country	N	Y	N	N/A
Move	Land Mobility	Maximum land speed - Reverse	N	Y	N	N/A
Move	Land Mobility	Cross Country % / Road %	N	Y	N	N/A
Move	Agility	Negotiate X % forward & reverse slope	N	Y	N	N/A
Move	Agility	Forward & reverse movement and steering on X % side	N	Y	N	N/A
Move	Agility	Accelerate from 0 to 20 mph	N	Y	N	N/A
Move	Agility	Minimum ground clearance	Y	Y	N	N/A
Move	Agility	Turning Radius	N	Y	N	N/A
Move	Agility	Gap or trench crossing	N	Y	N	N/A
Move	Agility	Vertical wall climb	N	Y	N	N/A
Move	Agility	Negotiate obstacles with approach angles of no less	N	Y	N	N/A
Move	Agility	Negotiate departure angles of no less than	N	Y	N	N/A
Move	Agility	From maximum speed, stop in no greater than	N	Y	N	N/A
Move	Agility	Brakes hold at maximum weight on (X) % slope	N	Y	N	N/A
Move	Agility	Vehicle Cone Index (VCI)1	N	N	N	S-2
Move	Agility	Sustain lateral acceleration within turn radius	N	Y	N	N/A
Move	Range	Land Range (Miles)	Y	N	N	S-2
Move	Ops Environ	Maximum ambient temperature	N	Y	N	N/A
Move	Ops Environ	Minimum ambient temperature	N	Y	N	N/A
Move	Other Attributes	Towing (Land & Water)	Y	Y	N	N/A

MEF	Sub-Cat	Attribute	Components (Y/N)	Design Dep. Only	material WBS items	Class LPP
Move	Other Attributes	Navigation Means	Y	N	N	N/A
Move	Other Attributes	Situational Awareness Displays	Y	N	N	N/A
Move	Other Attributes	Thermal vision (other than gun sight)	Y	N	N	N/A
Move	Other Attributes	Thermal vision (area of coverage)	N	Y	N	N/A
Move	Other Attributes	Silent Watch (functions)	Y	N	N	N/A
Move	Other Attributes	Silent Watch (duration)	Y	Y	N	S-2
Move	Other Attributes	Vehicle Weight growth Allowance	N	N	N	N/A
Shoot	Firepower	Maximum effective range	Y	N	N	S-2
Shoot	Firepower	Lethality (target set up to)	Y	N	N	N/A
Shoot	Firepower	Stabilization (up to) (S - Stationary / M - Moving)	Y	N	N	N/A
Shoot	Degraded Mode	Traverse & elevate	Y	N	N	N/A
Shoot	Degraded Mode	Sighting	Y	N	N	N/A
Shoot	Engagement Envelope	Max azimuth	N	Y	N	N/A
Shoot	Engagement Envelope	Max elevation	N	Y	N	N/A
Shoot	Engagement Envelope	Max depression	N	Y	N	N/A
Shoot	Target Acquisition	Visibility	Y	N	N	N/A
Shoot	Target Acquisition	# of simultaneous targets	Y	N	N	N/A
Shoot	Reloading Capability	Ammo: Min Ready Ammo	Y	N	N	N/A
Shoot	Reloading Capability	Ammo: (Vehicle kills/Personnel kills)	N	Y	N	N/A
Shoot	Reloading Capability	Ammo: Stowed Ammunition	Y	N	N	N/A
Shoot	Reloading Capability	Reloading	Y	N	N	N/A
Shoot	Reloading Capability	Immediate Action	Y	N	N	N/A
Shoot	Other	Mixed Fleet Weapon Systems	N	Y	N	N/A
Communicate	Voice Communication	VHF Transmit & Receive	Y	N	N	N/A
Communicate	Voice Communication	UHF - LOS	Y	N	N	N/A

MEF	Sub-Cat	Attribute	Components (Y/N)	Design Dep. Only	material WBS items	Class LPP
Communicate	Voice Communication	UHF - SATCOM	Y	N	N	N/A
Communicate	Voice Communication	Remote Control from Crew Station	Y	N	N	N/A
Communicate	Data	VHF LOS (# of channels)	Y	N	N	N/A
Communicate	Data	UHF LOS (EPLRS) (# of channels)	Y	N	N	N/A
Communicate	Data	SATCOM (# of channels)	Y	N	N	N/A
Communicate	Data	Blue PLI distribution	Y	N	N	N/A
Communicate	Internal Communications (# of	Crew	Y	N	N	N/A
Communicate	Internal Communications (# of	Wireless	Y	N	N	N/A
Communicate	FIST Team Support	Mounting/Power/Antennas (Interface)	Y	N	N	N/A
Communicate	FIST Team Support	Additional VHF LOS	Y	N	N	N/A
Communicate	FIST Team Support	Additional UHF LOS	Y	N	N	N/A
Communicate	FIST Team Support	Additional SATCOM	Y	N	N	N/A
Communicate	FIST Team Support	Additional HF	Y	N	N	N/A
Communicate	FIST Team Support	AAO (FIST Specific Variant)	Y	N	N	N/A
Protect	Survivability (Vehicle)	DF Survive: Integrated Hull Design	Y	N	N	N/A
Protect	Survivability (Vehicle)	DF Survive: Appliqué Kit	Y	N	N	N/A
Protect	Survivability (Vehicle)	Ind. Fire Surv: Integrated Hull Design	Y	N	N	N/A
Protect	Survivability (Vehicle)	Ind. Fire Surv: Appliqué Kit	Y	N	N	N/A
Protect	Survivability (Vehicle)	Mine survivability	Y	N	N	N/A
Protect	Force protection (Personnel)	IED Protect: Integrated Hull Design	Y	N	N	N/A
Protect	Force protection (Personnel)	IED Protect: Appliqué Kit	Y	N	N	N/A
Protect	Force protection	Directed energy	Y	N	N	N/A
Protect	Force protection (Personnel)	Signature requirements (Visual, Acoustic, Thermal, Radar Cross Section)	N	Y	N	N/A
Protect	Force protection (Personnel)	Automatic Fire Sensing & Suppression System (AFSSS)	Y	N	N	N/A

MEF	Sub-Cat	Attribute	Components (Y/N)	Design Dep. Only	material WBS items	Class LPP
Protect	Force protection	Rocket Propelled Grenades (RPG)	Y	N	N	N/A
Protect	Force protection	Rapid Obscuration (By grenades)	Y	N	N	N/A
Protect	Force protection	Smoke Generation (By fuel injection)	Y	N	N	N/A
Protect	Force protection	Combat Identification	Y	N	N	N/A
Protect	NBC Protection	Prevention	Y	N	N	N/A
Protect	NBC Protection	Detection	Y	N	N	N/A
Protect	NBC Protection	(If Integrated) Warning	Y	N	N	N/A
Carry	Crew	Troop carrying capacity	Y	N	N	S-2
Carry	Crew	Troop Loads	N	Y	N	N/A
Carry	Crew	On-Board Equipment Material (OEM) Storage (Internal/External)	N	Y	N	N/A
Carry	Crew	Water Survival Equipment (PFDs)	Y	N	N	N/A
Carry	Environmental Controls	Heating	Y	N	N	N/A
Carry	Environmental Controls	Cooling	Y	N	N	N/A
Carry	Environmental Controls	Control	Y	N	N	N/A
Carry	Additional Days of Supply (per # of Troops &	Additional Days of Supply (per # of Troops & Crew)	Y	Y	N	N/A
Carry	Other Mission Essential Equipment	Other Mission Essential Equipment (lbs)	Y	N	N	N/A
Carry	Cargo (without troops)	Cargo (without troops)	N	Y	N	N/A
Carry	Litter Kit	Litter Kit	Y	N	N	N/A
Carry	MK154 Line Charge Kit	MK154 Line Charge Kit	Y	N	N	N/A
Carry	Lighting	Emergency Egress	Y	N	N	N/A
Carry	Lighting	Spot Light	Y	N	N	N/A
Carry	Lighting	Task Lighting	Y	N	N	N/A
Carry	Lighting	Navigation Lights	Y	N	N	N/A
Carry	Cammic Nets	Camic Nets (ULCANS)	Y	N	N	N/A
Mission Performance	Operational Availability A_o = MTBM/MTB	Operational Availability A_o = MTBM/MTBM+MDT	N	Y	N	S-2
Mission Performance	System Reliability	System Reliability	N	Y	N	S-2

MEF	Sub-Cat	Attribute	Components (Y/N)	Design Dep. Only	material WBS items	Class LPP
Transportability	Amphibious Shipping	Amphibious Shipping	N	Y	N	N/A
Transportability	Amphibious Shipping	Load/Off Load Method	N	Y	N	N/A
Transportability	Amphibious Shipping	Stowage areas	N	Y	N	N/A
Transportability	Amphibious Shipping	Landing Craft	N	Y	N	N/A
Transportability	MPS	Maritime Prepositioning Shipping	N	Y	N	N/A
Transportability	MPS	Load/Off Load Method	N	Y	N	N/A
Transportability	Rail	Rail	N	Y	N	N/A
Transportability	Truck (lowboy)	Truck (lowboy)	N	Y	N	N/A
Transportability	Air	Air	N	Y	N	N/A
Transportability	Crane Lift (structure/appurtenances)	Crane Lift (structure/appurtenances)	Y	N	N	N/A
Transportability	DOT Compatible	DOT Compatible (Width)	Y	N	N	N/A
Transportability	Ground	Ground pressure	Y	N	N	S-1
Sustainment	Attribute	Materiel Availability (JCIDS KPP) M_A = Number of End Items Operational/Total Population	N	Y	N	N/A
Sustainment	Attribute	Design For Reliability (JCIDS KSA)	N	Y	N	N/A
Sustainment	Attribute	MTBRR (Mean Time Between	N	Y	N	N/A
Sustainment	Attribute	Remove & Replace in hours)	N	Y	N	N/A
Sustainment	Maintainability	MR (On-Board Intermediate) = Maintenance Manhours/Op hour	N	Y	N	N/A
Sustainment	Maintainability	MCMT (On-Board Intermediate) = Corrective Maint Time/Total Number of Maint Actions	N	Y	N	N/A
Sustainment	Maintainability	Diagnostic: BIT/BITE	N	Y	N	N/A
Sustainment	Maintainability	Diagnostic: Prognostics	N	Y	N	N/A
Sustainment	Logistics support system	Depot maintenance support	N	Y	Y	N/A
Sustainment	Logistics support system	Intermediate maintenance	N	Y	Y	N/A
Sustainment	Logistics support system	Operator maintenance	N	Y	Y	N/A
Sustainment	Logistics support system	Supply Chain/PHS&T	N	Y	Y	N/A
Sustainment	Logistics support system	Technical Pubs	Y	N	Y	N/A

MEF	Sub-Cat	Attribute	Components (Y/N)	Design Dep. Only	material WBS items	Class LPP
Sustainment	Logistics support system	Support Data	Y	N	Y	N/A
Sustainment	Logistics support system	Computer Resources	N	Y	Y	N/A
Sustainment	Logistics support system	Software Support	N	Y	Y	N/A
Sustainment	Logistics support system	Support & Test Equipment	N	Y	Y	N/A
NET Ready	Attribute	Information Transport	N	Y	N	N/A
NET Ready	Attribute	Enterprise Services	N	Y	N	N/A
NET Ready	Attribute	Net Management	N	Y	N	N/A
NET Ready	Attribute	Information Assurance	N	Y	Y	N/A
System Training	Resource	Transition	N	N	Y	N/A
System Training	Resource	Initial	N	N	Y	N/A
System Training	Resource	Refresher	N	N	Y	N/A
System Training	Resource	Concurrency	N	N	Y	N/A
System Training	Resource	Unit	N	N	Y	N/A
System Training	Location	Transition	N	N	Y	N/A
System Training	Location	Initial	N	N	Y	N/A
System Training	Location	Refresher	N	N	Y	N/A
System Training	Location	Concurrency	N	N	Y	N/A
System Training	Location	Unit	N	N	Y	N/A