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Convergent Set-Based Design in Integrated Analysis of Alternatives: Designing Engineered Resilient Systems

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Convergent Set-Based Design in Integrated Analysis of Alternatives: Designing Engineered Resilient Systems

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Abstract

This thesis presents a comprehensive package for understanding and expanding set-based design quantification through the definition and demonstration of Convergent set-based design (SBD). Convergent SBD is a technique developed for the Engineered Resilient Systems program sponsored by the Department of Defense. Convergent SBD contributes a repeatable methodology with the goal of mathematically eliminating inefficient sets. The study of Convergent SBD led to the development of dominance identification criteria equations using comparison of statistical means. The demonstration of Convergent SBD also illustrates the effect of mission resilience in the tradespace and the impact mission resilience has on preference. Finally, Convergent SBD contributes to mathematical identification of the previously heuristic based set drivers and set modifiers and discusses additional decision analyst uses for this information. Presented as a complete thesis, Convergent SBD provides a foundational mathematical technique for eliminating sets and a method for converging to an efficient, affordable solution or group of solutions.

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1. Introduction

The research detailed in this thesis describes the techniques developed and demonstrated for the research sponsor, the Engineering Research and Development Center. The thesis begins with an introduction chapter which introduces the Engineered Resilient Systems (ERS) program, a survey of literature in key areas of investigation, and the proposed research question for this thesis. This is followed by a discussion of the hypothesized solution to the thesis research question. Then the methodology for the demonstration is described. The results of the demonstration are detailed in Chapter 4 and discussed along with ideas for further research in Chapter 5. The final chapter summarizes the concluding thoughts of the research. An appendix containing additional data is also attached.

1.1. The Engineered Resilient Systems Program

The goal of the Department of Defense (DoD) sponsored ERS program is the effective and efficient design and development of affordable, resilient engineered complex systems throughout the system lifecycle. (Sitterle, et al. 2015) These engineered resilient systems are needed as DoD systems "have to cope with a wide range of missions with high degrees of uncertainty and risk." (Goerger, Madni and Eslinger 2014) To develop these resilient complex systems, technologies and techniques enabled by tradespace analysis, affordability analysis, modeling and simulation (M&S), and other techniques must be expanded to design a system in the face of changing requirements, to work in new environments, and to meet the challenges of adaptive adversaries. These techniques must also design a system which is useable, sustainable, modifiable, and cost-effective. Thus, the ERS program must develop a way to design a system or system of systems which are resilient and affordable from the outset. (Goerger, Madni and Eslinger 2014)

1.1.1. Model-Based Engineering

As a means to be “effective and efficient,” the ERS program “seeks to leverage the capabilities of a model-based engineering (MBE) integrated framework to look at cost, performance, and resilience early in the design process with the goal of improving acquisition decision making.” (Wade, Goerger, et al. In Review) MBE (and similarly model-based systems engineering (MBSE)) shifts from a sequential document-based paradigm to guiding the specification, design, integration, and validation of a system through modeling and simulation (M&S). (Estefan 2008) Recent improvements in computing capabilities have made MBE and MBSE realistic for complex systems. (Rinaudo, Buchanan and Barnett 2016) Through the ERS program use of many physics, capability, simulation, and value models, MBE and MBSE enables this research to help achieve the goals of the ERS program. The models, goals, and technology enablers of the ERS program are illustrated in Figure 1.

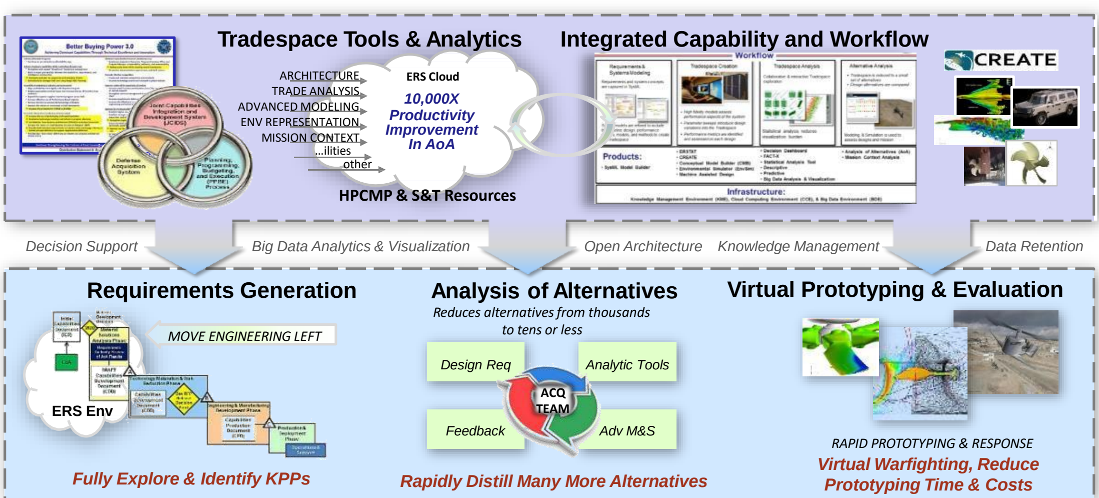

Figure 1: Overview of the ERS Program built upon MBE and MBSE. (Holland 2015)

1.1.2. Analysis of Alternatives

The “design and development” component of this research focuses the timeframe of investigation to “Pre-Milestone A.” (Cottam, Specking, et al. 2016) Milestone A is the first major approval gate for military acquisitions. (Defense Acquisition University 2017) To receive Milestone A approval, several requirements must be satisfied according to U.S. Code § 2366a. One critical requirement is “that an analysis of alternatives has been performed consistent with study guidance developed by the Director of Cost Assessment and Program Evaluation.” (U.S.C. § 2366a) This identifies analysis of alternatives (AoA) as an area of investigative focus for the ERS program.

An AoA is “an analytical comparison of the operational effectiveness, suitability, risk, and life cycle cost of alternatives.” (Office of Aerospace Studies 2013) As a military acquisition policy requirement, the DoD uses AoA to ensure multiple design alternatives have been analyzed prior to making acquisition investment decisions. (U.S. Office of Management and Budget 2008) The best practices for AoA are listed in Table 1 below, sequentially in the current document-based paradigm.

Table 1: Sequential Task of Document-Based AoA (Galorath Incorporated 2013)

Step	**Task**
1.	Procure key performance parameters.
2.	Identify affordability goals and weighted figures of merit.
3.	Gather requirements, features, and performance.
4.	Define technical baseline alternatives and assumptions.
5.	Perform technical design analysis for each alternative.
6.	Perform cost schedule analysis.
7.	Assess benefits based on figures of merit.

Table 1 (Cont.)

Step	Task
8.	Perform probabilistic risk analysis.
9.	Assess alternatives and select optimal alternative.
10.	Document analysis and lessons learned.

The steps listed in Table 1 are sound practices; however, there are two potential drawbacks to this sequential procedure. This first drawback is the well-documented difficulty responding to changes (requirements, goals, assumptions, etc.) in earlier steps at later steps in a sequential, waterfall procedure. (Estefan 2008) When executed properly, this document-based process often involves rework and redesign. Comparing the sequential process with MBE and MBSE, we find these activities are accomplished through models which grow in detail over time as a unit and eliminate this drawback. (Estefan 2008) This concept of model growth may be seen in Figure 2. In addition, the models driving the major development phases of the project are themselves developed by basic sub-processes. These sub-processes are repeated as many times as necessary, implying the potential for quick response to changes. (Estefan 2008)

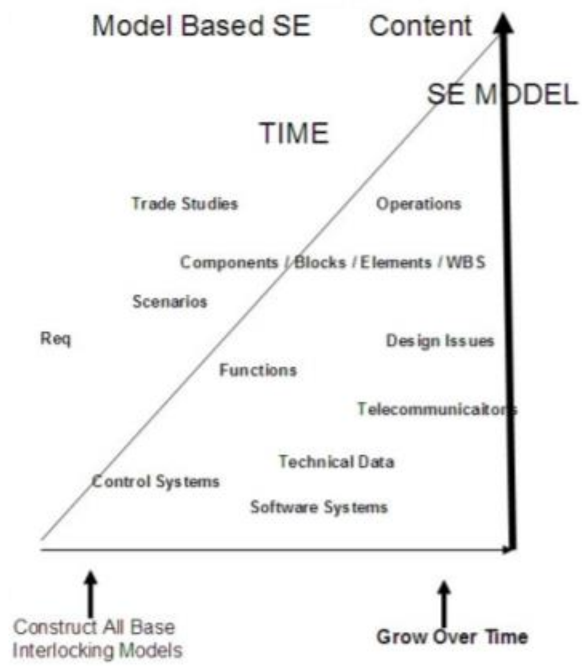

Figure 2: Generic SE Integrated Model Growth Over Time. (Estefan 2008)

The second drawback of current AoA best practices is the lack of processes and guidelines for designing for resilience. (Office of Aerospace Studies 2013) To satisfy the DoD demand for designed resilient systems, Figure 3 illustrates the incorporation of the ERS objectives into AoA best practices. It should be noted the practices in Figure 3 are not as rigidly defined as in Table 1. While the same tasks are mentioned, the arrangement is closer to an MBE or MBSE interpretation. The three practices added to AoA best practices when incorporating ERS are (1) expand the design space and provide resilience options, (2) extend service lifetime, and (3) assess resilience tradeoffs. (C. Small, G. Parnell and E. Pohl, et al. 2017) These new ERS tasks will be assessed through techniques enabled by exploration of tradespace analysis, affordability analysis, and M&S.

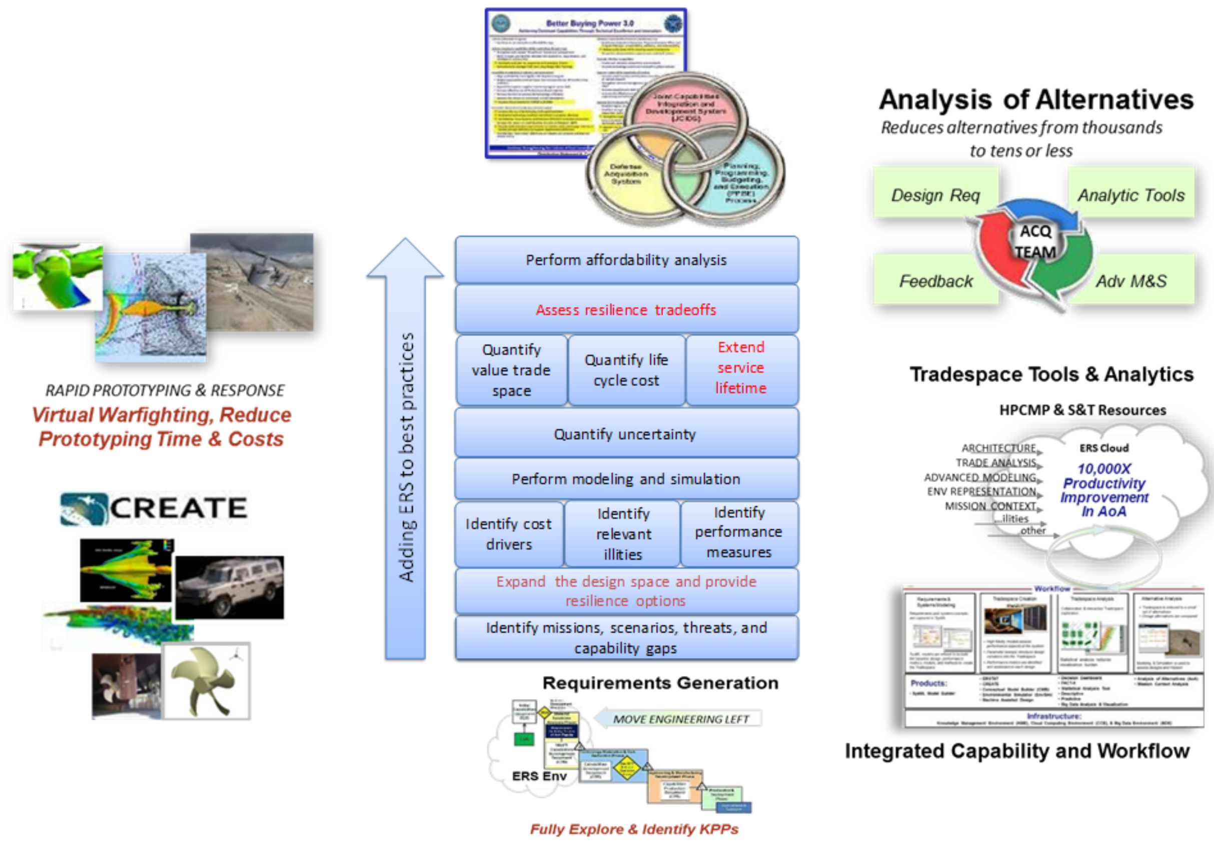

Figure 3: Incorporating ERS into AoA (ERS Practices in Red) (C. Small, G. Parnell and E. Pohl, et al. 2017)

Incorporating MBE and MBSE with the AoA best practices produces the integrated and simultaneous AoA. An integrated AoA requires interlocking decision analysis models to define performance parameters, goals, requirements, and benefits, physical constraint models to define alternatives and baseline performance, simulation models for alternative performance assessment and risk analysis, and cost models for life-cycle cost analysis. (Wade, Goerger, et al. In Review) The status quo on many defense programs involves "three separate groups performing performance, cost, and risk analyses. These efforts are rarely ever integrated. The systems tradespace is not explicitly identified and explored." (Parnell, Goerger and Pohl 2017) When implemented with MBE and MBSE, these models work together to assess problem definition changes, understand the effects of design changes, and explore the engineered resilient complex systems tradespace with responsive insights for decision makers. (Wade, Goerger, et al. In Review)

1.1.3. An Engineered Resilient Complex System

Resilience as a term does not have a consensus accepted definition among the design community. (Cottam, Engineering Resilience Systems Literature Survey 2018) The DoD perspective of resilience emphasizes two main areas: the success of the mission despite adversity and a wide array of system variants designed for use in a variety of unforeseen mission contexts. (Goerger, Madni and Eslinger 2014) The DoD perspective, coupled with further investigation of resilience led to the following definition of an engineered resilient system for the ERS program:

> A resilient engineered system is able to successfully complete its planned mission(s) in the face of a disruption (environmental or adversarial), and has capabilities allowing it to successfully complete future missions with evolving threats. (Specking, Cilli, et al. 2017)

This definition makes clear distinction between two types of resilience: a short-term resilience during the mission, and a long-term resilience in the future. These types are called short-term or "mission resilience" and long-term or "platform resilience." (Wade, Parnell, et al. 2018) The interaction between these types of resilience and the overall capability of the system may be seen in Figure 4. In Figure 4, note individual missions are represented by continuous green circles, these missions may be spaced differently, overlap, or require slightly different (within the scenario context) capabilities of the system, but the system will complete the mission as long as it retains minimum capability. Platform resilience represents the potential for enhancements of the system. The figure gives examples of when these enhancements may be implemented and it is often possible the missions that follow are beyond the original mission scope of the system. (Wade, Parnell, et al. 2018) In designing an engineered resilient complex system, it is important the short-term and long-term capabilities of the system are analyzed.

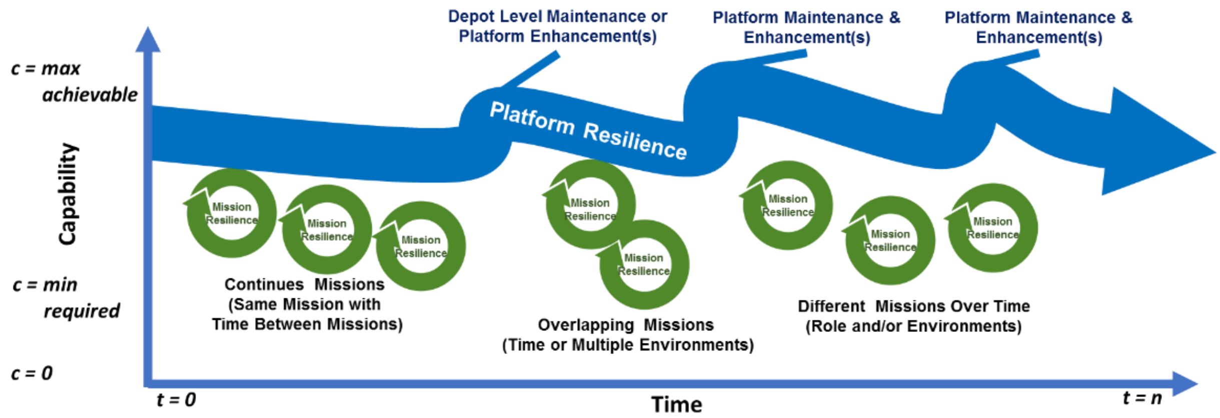

Figure 4: Mission and Platform Resilience Interacting with System Capability Over Time (Wade, Parnell, et al. 2018)

To enable the design of resilient complex systems, resiliency must be measurable in terms of capability. In a complex system, the overall capability of the system must satisfy the multiple competing objectives required of the system. (C. Small, G. Parnell and E. Pohl, et al. 2017) In terms of the decision analysis models previously discussed, capability is disaggregated into individual performance measures and can be interpreted through the lens of weighted value to the design goal. There is currently a gap in literature for a mathematical paradigm to express long-term platform resilience in terms of capability, performance, or value for engineered resilient systems. (Wade, Parnell, et al. 2018) For mission resilience, the literature does propose a method for measurement. This method views mission resilience as an ility which influences all other performance measures in the presence of a disruption. (Wade, Goerger, et al. In Review) A visual modeling of one performance measure experiencing a disruption over time may be seen in Figure 5. The performance of the system must be in one of four states: full performance, no performance, reduced performance without recovery, or reduced performance with recovery. (Specking, Parnell, et al. 2017)

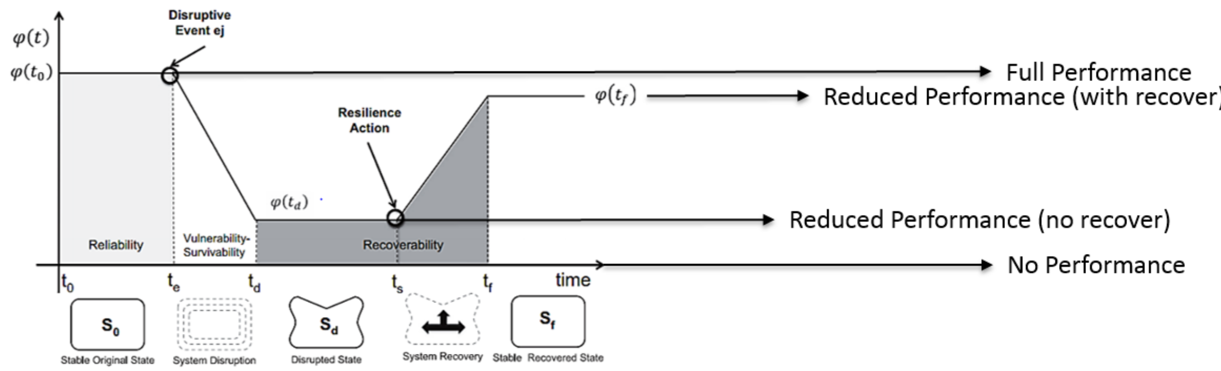

Figure 5: System Performance States With Resilience Over Time. (Henry and Ramirez-Marquez 2012)

Under this interpretation, resilience may be measured as the performance recovered above what is expected in the recovery action. (Wade, Goerger, et al. In Review) Given a disruption has only a chance of occurring, for calculation within a value model the expected performance must be considered. The equation for expected performance may be seen as the calculation of a mission chain in Equation 1. In Equation 1, p_i represents performance level at each *i* performance state. From left to right, expected value is the product of the probability of system availability, A_a, the probability of mission occurrence across all missions, m_{am}, the probability of a scenario given a mission, s_{ams}, the probability of mission reliability, Rm_{amsx}, the probability of threat actualization, Th_{amsxt}, the probability of each survival state (full, reduced, reduced with recovery, or no survival), Su_{amsxty}, and the probability of restoration, $r_{amsxtyz}$. (Specking, Parnell, et al. 2017)

$$\sum_{a=1}^{2} P(A_a) \sum_{m=1}^{M} P(m_{am}) \sum_{s=1}^{S} P(s_{ams}) \sum_{x=1}^{2} P(Rm_{amsx}) \sum_{t=1}^{T} P(Th_{amsxt}) \sum_{y=1}^{3} P(Su_{amsxty}) \sum_{z=1}^{2} P(r_{amsxtyz})\, p_i$$

Equation 1: Expected Performance with Mission Resilience (Specking, Parnell, et al. 2017)

When considering Equation 1, it is important to note most parameters (availability, mission, scenario, reliability, threat likelihood, and full survivability) are currently calculated in DoD mission chains. (Specking, Parnell, et al. 2017) The addition of the resilience measurement requires only three additional estimations: partial survivability or likelihood of survival with diminished capacity (currently estimated but lumped into full survival or no survival at some cutoff percentage), likelihood of mid-mission restoration, and recoverability; the latter two may be estimated with simulation. (Specking, Parnell, et al. 2017) The ability to measure resilience requires all ilities that effect all the performance measures for resilience of complex systems in the ERS program.

1.1.4. Trade-off Analytics Framework for Affordability

The final and binding aspect of the ERS program purpose is the descriptor “affordable.” The ERS program supports the Better Buying Power (BBP) directives of the DoD. (C. Small, G. Parnell and E. Pohl, et al. 2017) Among the broad scope of the BBP implementation, BBP “seeks to achieve dominant capabilities while controlling lifecycle costs.” (US Under Secretary of Defense for Acquisition, Tech. and Logistics 2015) In terms directly relevant to the ERS program, the BBP directives seek to “achieve affordable programs,” “anticipate and plan for responsive and emerging threats,” and “provide clear and objective ‘best value’ definitions.” (US Under Secretary of Defense for Acquisition, Tech. and Logistics 2015) To achieve better buying power, the ERS program seeks is to understand the tradespace of complex system designs and identify the designs which provide the most overall weighted capability per dollar. (Parnell, Goerger and Pohl 2017)

To assist in understanding the decisions and uncertainties which affect the complex system tradespace, the ERS program has established an integrated trade-off analytics framework. (Small, Parnell and Pohl 2016) The ERS program uses trade-off analytics to create a structure to achieve the most desirable balance among trade-offs in the complex system tradespace. (G. S. Parnell

2017) The latest version of this framework may be seen in Figure 6. The framework itself is developed using an MBE and MBSE implementation. Figure 6 is an influence diagram which includes "conditional notation." (Small, Pohl, et al. 2017) Conditional notation within the nodes simplifies the visual complexity of the figure and is used in place of arrows when applicable. In addition, the framework classifies the analytics relevant to each node as descriptive, predictive, or prescriptive. These analytics give a decision analyst insight into "what has happened," "what is going to happen," and "what should be done" respectively. (Gartner 2018)

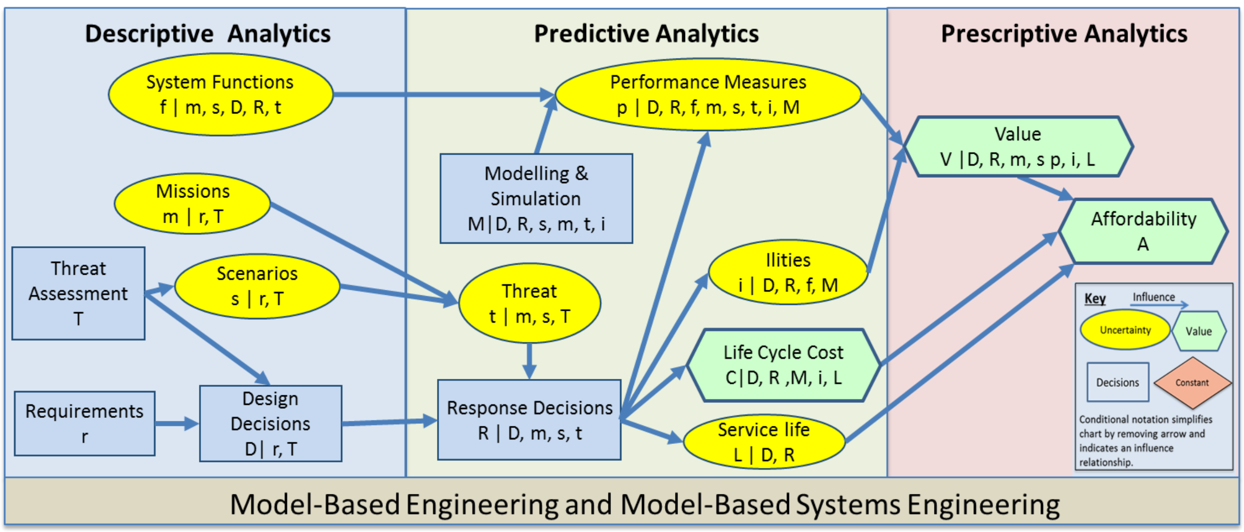

Figure 6: MBE and MBSE Framework for Integrated Analysis of Alternatives (Wade, Parnell, et al. 2018)

A detailed description of every node and interaction in Figure 6 may be found in the appendix. Of key importance is the ERS program framework interpretation of affordability as influenced by value and cost over service life. Value is the measure of overall weighted capability of a system design across multiple competing objectives. (Parnell, Bresnick, et al. 2013) Within the integrated framework, the ERS program uses Multiple Objective Decision Analysis (MODA) to assess value-based trade-offs. (Parnell, Goerger and Pohl 2017) MODA integrates the first three steps of the AoA task list in Table 1 including: identify key performance parameters, identify affordability goals and weighted figures of merit, and gather requirements, features, and performance. MODA suits the integrated framework as the model is intended to allow updates to as the environment or decision makers change. (G. Parnell 2007) The MODA value model coupled with a life-cycle cost model provides a mechanism for assessing benefits based on figures of merit and assessing alternatives for affordability in resilient complex system design.

1.2.Set-Based Design

Perhaps most vital to a successful AoA is generating quality alternatives to analyze that span the decision space. In decision analysis there is a quote, "If you want better solutions, you need better alternatives." (Parnell, Bresnick, et al. 2013) Status quo AoA falls back on traditional alternative generation techniques and supplies a low bar for alternatives including a minimum of just three: "the baseline," "modified baseline," and "alternatives identified in the AoA study guidance (for example allied systems, etc.)" (Office of Aerospace Studies 2013) No matter if there are three or dozen of alternatives crafted in this manner, each of these is considered to be a "point design" and an AoA which considers only these is called "Point-Based Design" (PBD). (Parnell, Goerger and Pohl 2017)

For complex system design, an AoA using PBD may experience two disadvantages. The first disadvantage to PBD is rework and reanalysis. Once the alternatives are analyzed and a base case is accepted, changes may be made as new constraints or requirements are added or relaxed. Incremental changes are made which force the design to be assessed against the updated design and requirements changes, leading to the first disadvantage of PBD. (Liker, et al. 1996) The second disadvantage to PBD is even a thorough study of a complex system design with dozens of unique crafted alternatives are insufficient to define the tradespace for decision makers. (Parnell, Goerger and Pohl 2017)

In contrast to PBD is a technique called Set-Based Design (SBD), which many engineers and engineering managers are beginning to adopt. (Parnell, Goerger and Pohl 2017) In contrast to finding an initial solution to iterate, SBD defines sets of design values as variables. (Parnell, Goerger and Pohl 2017) Set are defined as a labeled section of the design space which shares at least one, but not all, design characteristics. (Wade, Parnell, et al. 2018) The SBD process tends to start with the entire design space and sets are gradually filtered as requirement are refined. Since sets are being filtered, new designs are rarely added to the design space. (Ward, et al. 1995) Because of this high-level elimination of design space, “the initial AoA performed on the larger set remains viable for the reduced set. This limits the probability of rework while adding fidelity to the remaining designs accounts for design modifications.” (Parnell, Goerger and Pohl 2017) A visual comparison of PBD iterating towards a final solution and SBD converging towards a final solution in the design space may be seen in Figure 7.

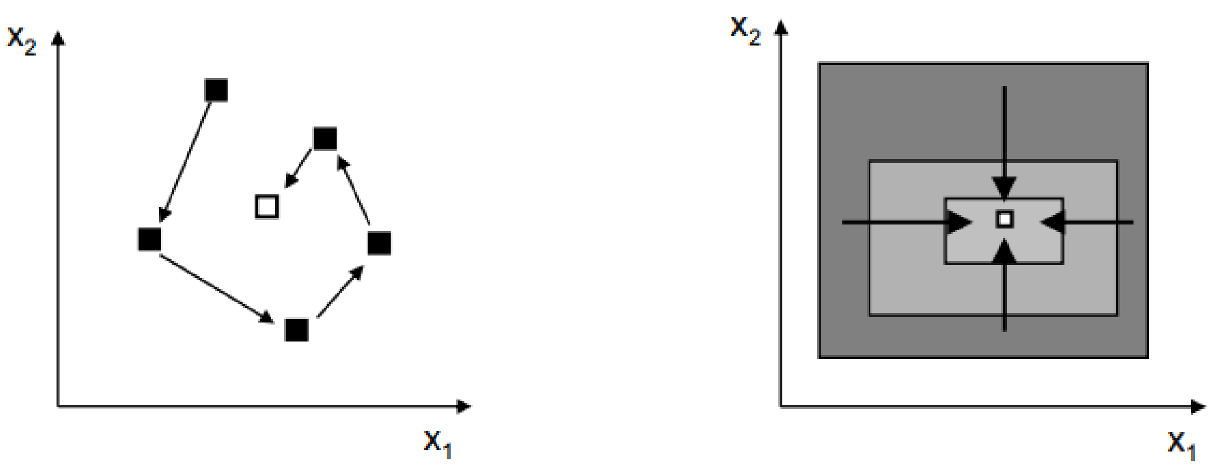

Figure 7: PBD with Rework Towards Final Solution in the Design Space (Left). SBD Converging Towards Final Solution in the Design Space (Right). (Paredis, et al. 2006)

SBD is currently being implemented within the ERS program and aligns with the ERS goals listed in the previous section, particularly with MBE and MBSE. (C. Small, G. S. Parnell, et al. 2018) When used with M&S, SBD Pareto frontiers are found by analyzing sets' response surfaces. (Whitcomb and Berry 2017) In addition, Small et al. uses heuristics with SBD to identify "set drivers" which are "a fundamental design decision that defines the system platform," and "set modifiers" which are "a component that can be modified to perform future missions without redesigning the platform." (C. Small, G. S. Parnell, et al. 2018) In the status quo, identification of the set drivers provides analyst insight into design decisions that allow for trimming of sets. (C. Small, G. S. Parnell, et al. 2018)

The methodology for SBD in the ERS program involves the use and integration of performance and cost models with a Monte Carlo simulation software. (Parnell, Goerger and Pohl 2017) The Monte Carlo software generates a uniform random sample from each a set of each design variable and each alternative generated is propagated through the performance and cost models. The Monte Carlo software currently used by SBD in the ERS program is called SIPmath from Probability Management. (Savage 2017) A MODA model then calculates the performances for each capability using a value model to obtain the value of the alternative. (Parnell, Goerger and Pohl 2017) When plotted against the cost of each alternative, the tradespace is defined and visualized as an example of SBD in the ERS program may be seen in Figure 8. Figure 8 also illustrates the heuristic method of identifying set-drivers in a system of limited design choices and has identified engine type and wingspan as the set drivers in this UAV analysis. (C. Small, G. S. Parnell, et al. 2018) This implementation of SBD, hereto referred to as "heuristic SBD" provides insights to decision makers into the trade-offs in a design space.

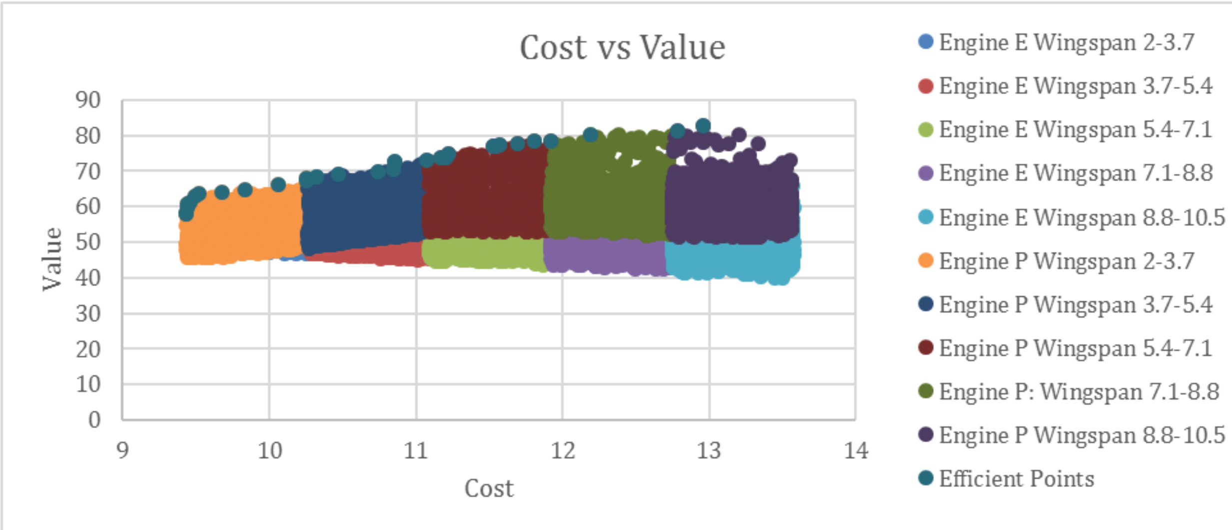

Figure 8: Value Versus Cost Plot of a UAV ERS System Design Study Using SBD. (C. Small, G. S. Parnell, et al. 2018)

1.3. Research Question

Based on analysis of the research above, this thesis has identified two areas of opportunity in applying SBD to the ERS program for viability and applicability in complex DoD system applications. The first opportunity is to perform AoA on sets in more detail and to gather greater insight into set trade-offs. Heuristic SBD neatly aligns with the AoA process listed in Table 1 and the MBE/MBSE integration of AoA can flexibly respond to requirements change. (C. Small, G. S. Parnell, et al. 2018) However, heuristic SBD does not leverage AoA on sets, outside of the heuristic identification of set-drivers and set-modifiers. While the current SBD heuristic is useful and the significantly expanded exploration of the design-space is shown to yield better solutions than status quo PBD, opportunity exists to exploit the ability of SBD to perform AoA on the larger set and have it hold for the reduced set; thus, decreasing rework and reanalysis in the design of resilient complex systems.

The second opportunity is to identify mathematical techniques to eliminate inferior design areas. The heuristic of the ERS program implementation of SBD identifies set-drivers and set-modifiers for further exploration but does not provide any guidance for reducing the design area. The classical interpretation of SBD, listed above and visualized in Figure 7, converges through elimination of the design area either by constraints or analysis. The structured ability to eliminate sets and converge towards a solution by a sound mathematical foundation is key “For SBD to enter the mainstream as a viable alternative to PBD.” (Specking, et al. 2017)

The identified opportunities led to the following research question: How can quantitative SBD be leveraged to eliminate sets by mathematical set analysis and converge towards a solution or group of affordable solutions using the integrated trade-off analytics framework? Any solution to this research question requires implementation ability within the ERS program. Finally, the solution will be required to show viability for a complex system and the system’s complex design space as will often be found in DoD projects.

2. Convergent Set-Based Design

The following chapter will describe and propose a solution to the research question termed “Convergent set-based design,” or Convergent SBD. Convergent SBD is a mathematical technique for set elimination and design space refinement used with MBE/MBSE. The goal of Convergent SBD is to establish a repeatable process for set analysis which results in converging towards a group of affordable solutions.

2.1. Definition

Convergent SBD is defined as the technique of repeatedly analyzing sets and statistically determining tradespace dominance to eliminate dominated design area towards efficient solutions. Convergent SBD is an iterative process whereby eliminating design area increases the fidelity and sample sizes of the remaining sets allowing for tighter statistical comparisons to better identify dominated design areas. The sets analyzed maintain their definition throughout the iteration process. Convergent SBD may not iterate infinitely as it must terminate when no more eliminations are possible. A visual icon diagram of the Convergent SBD process may be seen in Figure 9. The first 5 sequential icons in the diagram represent the steps in traditional SBD. Any preference, parameter, or performance modeling changes require the Convergent SBD process to be reinitialized and repeated.

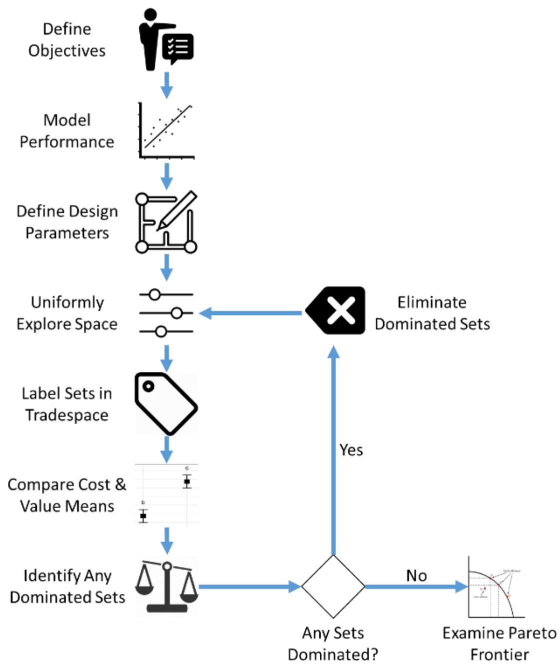

Figure 9: Iconographic Flow Chart for the Convergent SBD Iterative Process.

Cost and value mean comparisons are only performed on a collection of mutually exclusive and collectively exhaustive sets. An example of a collection of mutually exclusive and collectively exhaustive sets is the collection of sets seen in Figure 8 above where all alternatives identified in the tradespace are classified into exactly one set. Noting that Figure 8 classifies sets based on two fixed design characteristics, the number of sets required to create a mutually exclusive and collectively exhaustive collection are the number of options/intervals in a design characteristic multiplied by the number of options/intervals in all design characteristics (if any) cross-applied. In Figure 8, the number of options of design characteristic 1 (engine type) is two; the number of intervals of design characteristic 2 (wingspan) is five; thus, the number of sets which form a mutually exclusive and collectively exhaustive collection is ten. The number of collections which are mutually exclusive and collectively exhaustive are the sum of all combinations of 1 to n-1 design characteristics $\left[\binom{n}{n-1} + \binom{n}{n-2} + \cdots + \binom{n}{1}\right]$. If we suppose the system design in Figure 8 has three design characteristics (Note: Figure 8 must have at least three design characteristics as the definition of a set requires at least one characteristic to be unconstrained), then we see each characteristic may be a collection $\binom{3}{1} = 3$ and each pair of characteristics may be a collection $\binom{3}{2} = 3$ which identifies six possible collections of mutually exclusive and collectively exhaustive sets. The ability to define and examine all possible mutually exclusive and collectively exhaustive set collections provides a significant amount of control and detail for decision analysts.

The "Compare Cost & Value Means" step in Convergent SBD step makes cost and value mean comparisons using Tukey's method and the Studentized Range Distribution. (Engineering Statistics Handbook 2018) In Convergent SBD, Tukey's method of analysis is performed directly on the sets. As comparisons are made on a collection of mutually exclusive and collectively exhaustive sets, value and cost domination directly identifies inefficient sets of the design space for elimination. Before domination can be identified, Tukey comparison assigns at least one number, starting at 0, to groups which sets fail to reject the null hypothesis of no statistical difference. Sets may have multiple numbers assigned, this implies the set is not statistically different from a set with a slightly lesser mean or a set with a slightly greater mean, but the greater mean set is statistically different than the lower mean set at some confidence level. Because of this, sets have a lower bound grouping and an upper bound grouping. Sets are dominated when one of the following two criteria are true:

a. A set provides less value than another at the same level of cost.

b. A set provides the same level of value as another at higher cost.

These criteria correspond with the (a) and (b) forms of Equation 2 which require the upper bound and lower bound groupings and restate (a) and (b) above in a more technical manner. (a) For sets which share a given cost lower bound, a set is dominated if the maximum value lower bound of all qualified sets is greater than the value upper bound of any single set. (b) For sets which share a given value upper bound, a set is dominated if the minimum cost upper bound of all qualified sets is less than the cost lower bound of any single set.

a. $Max\{LV_{LC}\} > UV_k \quad \forall\ k \in LC$

b. $Min\{UC_{UV}\} < LC_k \quad \forall\ k \in UV$

Equation 2(a) and 2(b): Criteria for Identification of Dominance in Set Analysis.

As mentioned, the iterative process of Convergent SBD terminates when no new sets are identified as dominated in some iteration. This must be due to one of three reasons:

1. Only one set of each design characteristic remains.
2. The remaining collection of sets are clearly distinct from each other at the chosen statistical confidence.
3. The remaining collection of sets are completely indistinct from each other at the chosen statistical confidence.

It is here the Convergent SBD process mathematically defines a set driver as a design parameter which demonstrates its fundamental nature to the platform by providing clear distinctions in the tradspace in terms of cost and value (reason 2). Reason 3 mathematically defines a set modifier as a component which may be modified at will for future missions as the design does not provide a distinct impact on cost or value when selected at any remaining level. Using these criteria and the statistical methods detailed, Convergent SBD builds upon the advantages of current SBD heuristics and provide a repeatable and defendable mathematical process of elimination and refinement for decision analysts and stakeholders.

2.2. Assumptions of Convergent SBD

Convergent SBD shares the assumptions of current ERS SBD and Tukey's method. The assumptions and modeling requirements of current ERS SBD are discussed in section 1.2. The assumptions of Tukey's method include: (Engineering Statistics Handbook 2018)

1. The observations being tested are independent within and among the groups.
2. The groups associated with each mean in the test are normally distributed.
3. There is equal within-group variance across the groups associated with each mean in the test.

As justification for these assumptions, it is clear the current ERS SBD alternative generation process produces independent observations. In the instances where some second design characteristic may not be chosen unless another first characteristic is chosen, the collection of mutually exclusive and collectively exhaustive sets will always account for these by only considering second sets which hold to the choices of the first characteristic. The second assumption is theorized to hold by the central limit theorem enabled by the significantly large sample sizes generated when using ERS SBD. The final assumption is theorized to hold by the uniform generation method of ERS SBD across all unconstrained design characteristics. These assumptions and the ability of Convergent SBD to hold to these assumptions provides the mathematical foundation for the elimination of sets in the Convergent SBD technique.

3. Squad Enhancement Demonstration Methodology

This chapter will describe a demonstration to test and evaluate the Convergent SBD technique within the ERS program. The demonstration to be described is an extension of a previous ERS program study. The use of the Convergent SBD technique will be shown in its ability to integrate with the current methods and techniques to achieve the goals of the ERS program. Special attention will be paid to any additional accommodations Convergent SBD requires.

3.1. Squad Enhancement Background

The original squad enhancement study from MacCalman et al. used several squad enhancement options to "propose an experimental design MBSE methodology that illuminates system design trade decisions." (MacCalman, et al. 2015) Squad enhancement options included technologies which could be added to a military squad such as robots and UAVs or technologies which could increase capabilities of the squad such as rifle enhancements and helmet sensors. The squad enhancements were chosen as the initial study for the many variable relations and trade-offs necessary because of the mostly fixed capacity of a military squad. It is important to note this study was performed notionally and not directly aligned with any DoD enhancement programs and the content is public. It is also relevant to note this study did not explicitly consider resilient system performance in the evaluation and generation of alternatives.

The data driven approach for trade-off analysis in the original study used design of experiments with M&S to create robust regression equations. This application of MBSE produced an understanding of performance trade-offs in the design space, even going so far as to allow for Monte Carlo alternative generation as seen in Figure 10. Each box in Figure 10 defines the trade-off relationship between two *design* variables. This is like defining the larger area in the design space for SBD as shown in Figure 7 (right). However, the original study did not classify the design alternatives into sets. In addition, while the original study provided an arbitrary way to filter alternatives based on requirements, the original study did not propose a method for filtering solutions based on capability, performance, or value.

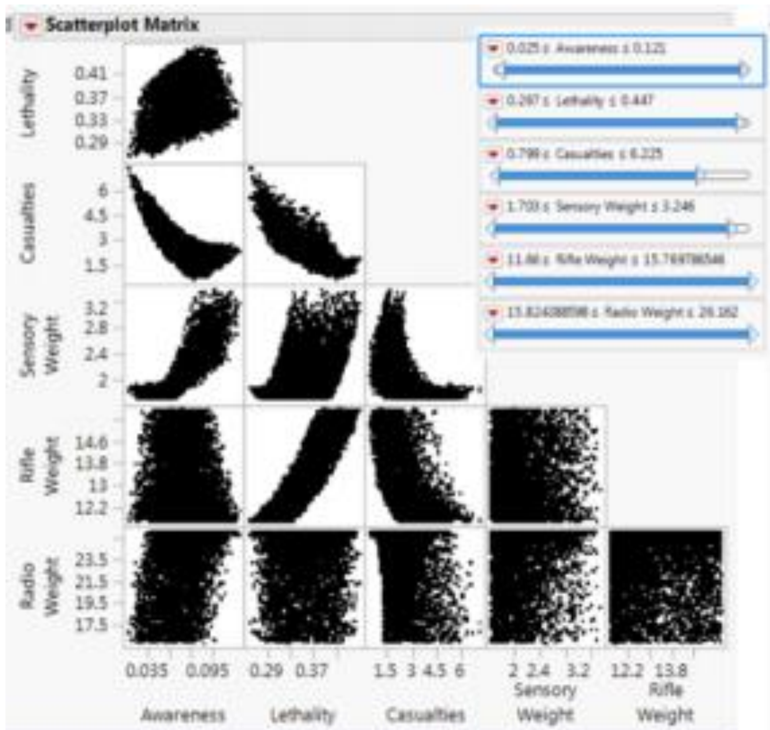

Figure 10: Monte Carlo Alternative Generation and Filtering Mechanism in Original Squad Enhancement Study. (MacCalman, et al. 2015)

As heuristics SBD as well as Convergent SBD requires a definition of the tradespace to evaluate sets, the original study does define the value and cost space for a handful of point-based alternatives. The alternatives compared in the original MODA study are completely notional and not correlated to the MBSE alternatives previously mentioned. In addition, the objectives in the value model and subsequent performance measures of the original study are also unconnected with the performance measures in the MBSE data above. Because of this data disconnect, some notional relations from the design space to the tradespace needed to be created in this thesis. The notional relations will be detailed in the following section.

3.2.Adaptations from MacCalman Study

Several adaptations from the original study for the demonstration of Convergent SBD. The purpose of all adaptations being to tie the MBSE performance regression equations to the value model, facilitate mission resilience quantification, limit the scope of notional equations unique to this thesis, or perform SBD. The overall goal of the original study adaptations is to preserve and leverage as much of the trade-off analysis as possible within the study's notional value and cost model.

The first original study adaptations are to tie the MBSE performance regression equations to the value model. The first change is to choose the enhancements to evaluate. Based on the data provided in the original study, the enhancements selected are the addition of one or multiple UAV(s), rifle enhancements, body armor enhancements, and the addition of one or multiple robots. These are modeled as independent systems, each with a "status quo" option or allowing for no enhancement to any or all systems. To accommodate these systems in the tradespace, the value model was redefined primarily around the elimination of the communication objective which did not correlate with the data. The revised value model may be seen in Figure 11. The full value model and swing weight matrix may be seen in the appendix. For comparison, MacCalman's original value model may also be found in the appendix.

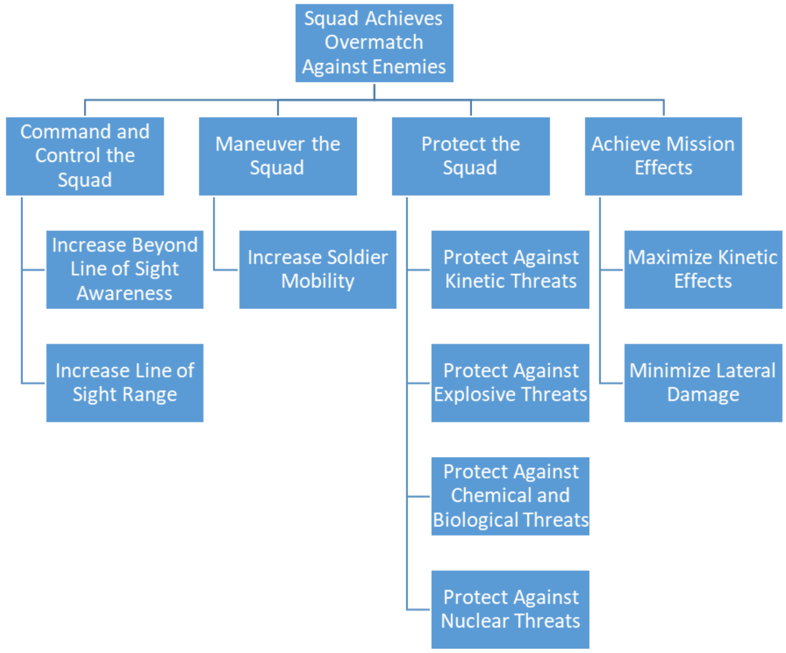

Figure 11: Thesis Research Squad Enhancement Value Model.

The next original study adaptations are to facilitate mission resilience quantification. Mission resilience quantification, as calculated in Equation 1, requires ility estimations including availability, reliability, survivability, and recoverability. Also required for mission resilience calculation are system performance in a reduced state and a reduced state with recovery. All of these probabilities and performances were notionally estimated for all natural performance measures within the thesis research value model.

The third original study adaptation is to limit the scope of notional equations unique to this thesis. Because the inputs of the regression equations in the original are ratio from min to max, to use these equations, this research had to redefine the design parameters as ratio outputs as well. The research inputs may be seen below in Table 2 and the original study model inputs may be seen in the appendix. Again, the original study model inputs do not correlate with the original study MODA model. In addition, for the performances measured on discrete constructed scales found in the original study MODA model, the design parameters of this research became the discrete choice of constructed rating.

Table 2: Research Design Parameters

Parameter	Continuous/Discrete	Range/Options
Number of UAVs	Discrete	{0, 1, 2}
UAV 1 Speed	Continuous	[50-200]
UAV 1 Detection Range	Continuous	[1.5-2.5]
UAV 1 Number of Missiles	Discrete	{0, 1, 2}
UAV 2 Speed	Continuous	[50-200]
UAV 2 Detection Range	Continuous	[1.5-2.5]
UAV 2 Number of Missiles	Discrete	{0, 1, 2}
Rifle Enhancement	Discrete	{No, Yes} ~ {0, 1}
Rifle Enhanced Range	Continuous	[1-2]
Rifle Enhanced Fire Rate	Continuous	[1-3]
Rifle Enhanced Hit Prob	Continuous	[1-2]
Rifle Enhanced Lat Leth Mitigate	Discrete	{1, 2, 3, 4, 5}
Body Armor Enhancement	Discrete	{No, Yes} ~ {0, 1}
BA Enhanced Kinetic Prot	Discrete	{1, 2, 3, 4, 5, 6, 7, 8, 9}
BA Enhanced Chem-Bio Prot	Discrete	{1, 2, 3, 4, 5, 6, 7, 8, 9}
BA Enhanced IED Prot	Discrete	{1, 2, 3, 4, 5, 6, 7, 8}
BA Enhanced Nuc Radiation Prot	Discrete	{1, 2, 3, 4, 5, 6, 7}
Number of Robots	Discrete	{0, 1, 2}
Robot 1 Speed	Continuous	[3-10]
Robot 1 IED Sensor Prob Detect	Continuous	[1-2]
Robot 1 Classification Range	Continuous	[1-2]
Robot 2 Speed	Continuous	[3-10]
Robot 2 IED Sensor Prob Detect	Continuous	[1-2]
Robot 2 Classification Range	Continuous	[1-2]

The fourth original study adaptations were to enable the use of SBD. Heuristic SBD requires the tradespace to be defined with MBE/MBSE. The previous adaptations and the original study had already defined the value-space. The last adaptation created an MBE cost model based on the original studies notional MODA analysis. The cost model equations were developed by fitting equations to the min/max costs provided by the original study. In addition, the costs were disaggregated into lifecycle components of research and development, unit cost, training cost, maintenance costs, and disposal costs.

3.3.Convergent Set-Based Design Implementation

As mentioned in the previous section, the performance models of the original study were leveraged to explore the value-space and cost models were created to explore the cost-space. Quantitative SBD was implemented in the same method described in section 1.2 which involves the use and integration of performance and cost models with a Monte Carlo simulation software, SIPmath.

Using SIPmath in Excel, a uniform random variable is assigned for each design parameter (see Table 2) so that the maximum amount of the design space is explored. The number of random numbers generated per run was set to 10,000. This is translated to 10,000 unique alternatives. The control panel reads each random number and interprets it as a design choice which is propagated through the performance and cost models. One additional requirement for Convergent SBD is the labeling of sets. To do this for a mutually exclusive and collectively exhaustive collection of each design parameter in Excel, a second “iteration control panel” was created consisting of two parts. The first part of the iteration control panel interprets the random numbers and labels them as the discrete option or specific interval (also called “bin”) accordingly. An image of the iteration control panel with specific labels for some alternative is provided in Figure 12.

UAV			
Number	Speed	Detection Range	Number of Missiles
{0, 1, 2}	[50-200]	[1.5-2.5]	{0,1,2}
1UAV	1SBin:1	1DetDistBin:1	UAV1Miss2
(IF Num = 2)			

Rifle				
Enhanced	Range	Fire Rate	Probability of Hit	Lateral Lethal Mitigation
{0, 1}	[1-2]	[1-3]	[1-2]	{1, 2, 3, 4, 5}
EnhRif	1RngBin:10	1FRBin:4	1HPrbBin:2	LethMit_4

Body Armor				
Enhanced	Kinetic Protection	Chem-Bio Protection	IED Protect	Nuclear Radiation Protection
{0, 1}	{1, 2, …, 9}	{1, 2, …, 9}	{1, 2, …, 8}	{1, 2, …, 7}
EnhBA	KinProt_9	ChemProt_1	IEDProt_1	NucProt_1

Robot			
Number	Speed	IED Sensor Probability	Classification Range
{0, 1, 2}	[3, 10]	[1, 2]	[1, 2]
2Rob	1RSBin:2	1IEDBin:3	1CRBin:7
(IF Num = 2)	2RSBin:3	2IEDBin:5	2CRBin:10

Figure 12: Iteration Control Panel Interpreting and Labeling Random Numbers Generated by SIPmath.

The second part of the iteration control panel defines the design space. As Convergent SBD seeks to eliminate sets and design area in each iteration, the iteration control panel is updated with each elimination. Both the control panel, which generates the alternatives based on the SIPmath random number and the labels created in Figure 12 rely on this second part of the iteration control panel. The iteration control panel possesses information of the number of intervals/options remaining, the width of the interval, the starting interval, the minimum interval value, and then a list of the intervals or discrete options. A sample of the second part of the iteration control panel may be seen in Figure 13. This second part of the iteration control panel allows for dynamic updating and accurate identification for the creation of alternatives and labeling of sets.

	Range (# of Bins)	Interval Width	Starting (Cont)	Min (Cont)	Intervals or List (If Discrete)		
Num UAV	3	NA	Discrete	NA	0UAV	1UAV	2UAV
UAV 1: Speed	10	15	1	50	1SBin:1	1SBin:2	1SBin:3
UAV 1: Detection Range	10	0.1	1	1.5	1DetDistBin:1	1DetDistBin:2	1DetDistBin:3

Figure 13: Design Area Controlled in Second Part of the Iteration Control Panel.

To view the resulting value and cost of the 10,000 alternatives, SIPmath outputs were defined for total cost and total weighted value. These outputs are displayed in the SIPmath generated “PMTable” sheet in the Excel implementation, where each row of the table represents one unique alternative. To enable set analysis, an output was defined for each of the labels shown above in Figure 12. These outputs also are displayed in the PMTable for each of the 10,000 alternative generated. The labels allow for each of the 10,000 alternatives to be correctly identified in sets by any of the 24 design parameters. A small excerpt of the PMTable may be seen in Figure 14.

Index	Value	Cost	NumUAVO	UAV1SO	UAV1DetRngO	UAV1NumMissO
Values	75	68.46782	1UAV	1SBin:1	1DetDistBin:1	UAV1Miss2
1	29.35162	37.58079	1UAV	1SBin:1	1DetDistBin:1	UAV1Miss1
2	31.65611	39.6251	2UAV	1SBin:2	1DetDistBin:1	UAV1Miss0
3	43.17437	46.45773	1UAV	1SBin:2	1DetDistBin:1	UAV1Miss1
4	58.0977	65.47613	2UAV	1SBin:1	1DetDistBin:1	UAV1Miss2
5	23.3692	23.87885	0UAV			
6	77.08025	77.55606	2UAV	1SBin:2	1DetDistBin:1	UAV1Miss2
7	69.5673	77.76082	2UAV	1SBin:2	1DetDistBin:2	UAV1Miss0
8	62.69677	69.13984	2UAV	1SBin:1	1DetDistBin:1	UAV1Miss2
9	29.10645	32.8403	0UAV			
10	74.92815	68.46782	1UAV	1SBin:1	1DetDistBin:1	UAV1Miss2

Figure 14: PMTable Outputs Excerpt with Value, Cost, and Set Labels.

The final necessity for Convergent SBD implementation is the computerized execution of the elimination logic found throughout Chapter 2 and specifically in Equation 2(a) and 2(b). This was accomplished through the use of an Excel macro and may be viewed in the appendix. The macro for Convergent SBD consists of three functions. The first function uses Tukey's method to make comparisons and label the lower and upper similarity bounds. The second function implements Equation 2(a) and 2(b) and determines which sets are to be eliminated. The final function outputs the all comparisons and names all eliminate sets and then updates the second part of the iteration control panel to define the new design space. All three functions carry out their tasks in concert at the click of a button, ensure that the implementation of Convergent SBD is usable, responsive, and can get results in a timely manner.

3.4. Application within ERS Program

As previously mentioned, to successfully address the research question Convergent SBD requires implementation ability within the quantitate SBD. Convergent SBD must leverage MBE/MBSE, integrated with the expanded AoA, evaluate engineered resilient systems, and adhere to the trade-off analytics framework. The following subsections will briefly discuss the applicability of Convergent SBD in each of these key areas.

3.4.1. Use of MBE/MBSE through Convergent SBD

The implementation of Convergent SBD does leverage MBE/MBSE through the use of the M&S regression equations performed in the original study. The natural performance measures translatable from the original research are manipulated into this research including beyond line of sight capability, line of sight capability, and lethality. Physics models relate the performance tradeoffs for the remaining natural measure including, IED protection, maneuverability, and soldier speed. These physics and performance simulation models are integrated with the value and cost models mentioned previously for a complete MBE integrated package.

3.4.2. Integrated AoA with Convergent SBD

As found in Chapter 1, integrated AoA requires interlocking decision analysis models to define performance parameters, goals, requirements, and benefits, physical constraint models to define alternatives and baseline performance, simulation models for alternative performance assessment and risk analysis, and cost models for life-cycle cost analysis. The Convergent SBD implementation interlocks all of these models within its Excel implementation with the notable exception of simulation models for risk analysis. The squad enhancement demonstration of Convergent SBD does all calculations deterministically. This should not imply Convergent SBD cannot incorporate uncertainty, but it is not implemented within this research. The lack of uncertainty analysis will be revisited in the discussion of Chapter 5.

3.4.3. Engineering Resilient Systems in Convergent SBD

The ability to design with consideration of mission resilience is incorporated into the squad enhancement demonstration in the natural measures which the estimation of the "ilities" were possible. These measures include beyond line of sight, line of sight, and maneuverability. Mission resilience was calculated in accordance with Equation 1. An example of the probability tree created by Equation 1 may be seen in Figure 15. Note the equations relating ility probabilities and performance capabilities at the various system states are notional. The bright green box in the top left of the below figure is the expected performance with resilience.

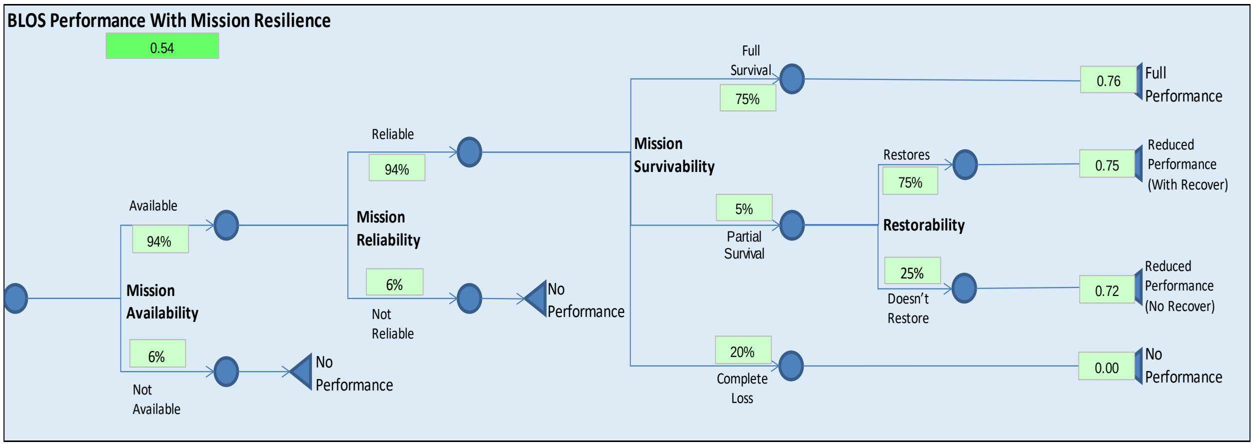

Figure 15: Expected Performance with Mission Resilience Calculation for the Beyond Light of Sight Measure.

3.4.4. Trade-off Analytics of Convergent SBD

The extent to the squad enhancement demonstration of Convergent SBD aligns with the trade-off analytics framework in Chapter 1 may be seen below in Figure 16. Figure 16 presents the trade-off analytics framework with color coding on the outline of the nodes. Nodes outlined in green are fully/dynamically implemented within the demonstration and nodes with orange outlines are partially implemented within the demonstration.

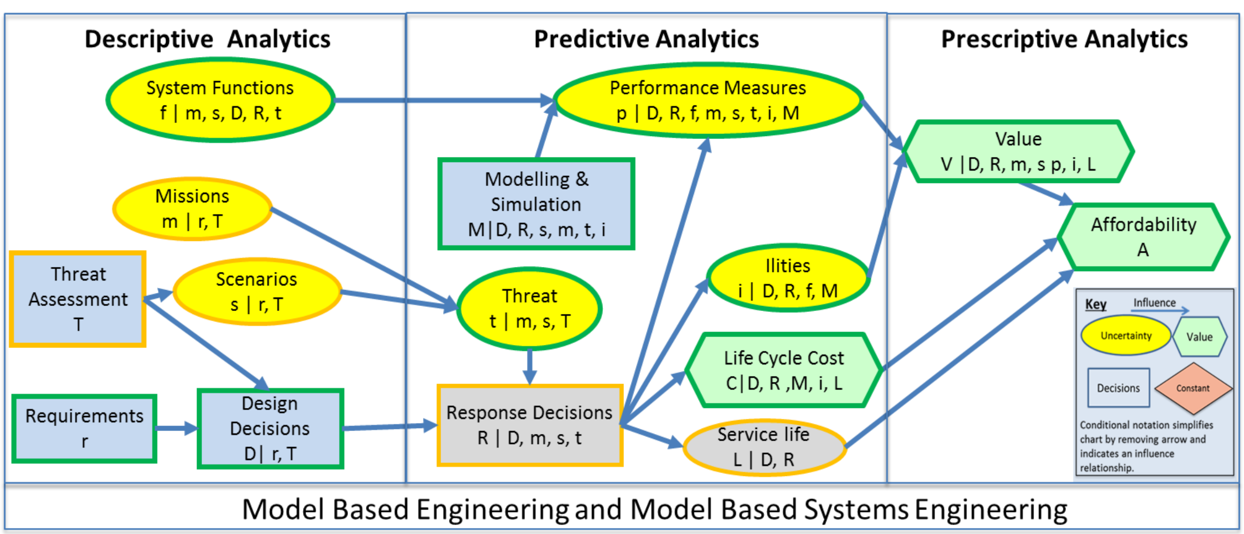

Figure 16: Trade-off Analytics in the Squad Enhancement Demonstration.

The non-fully implemented nodes include threat assessment, missions, scenarios, response decisions, and service life. In each case, the nodes are not fully implemented due to a simplifying assumption. The squad enhancement demonstration assumes the threat assessment was completed and the threat actualized and implemented for mission resilience is the expected threat. The demonstration provides analysis given a single mission and scenario. The demonstration does not specify the nature of the response decisions but does calculate a response within the mission resilience calculations. Finally, service life is deterministically fixed and options/methods for expanding the service life of a given alternative are not explored within the squad enhancement demonstration. Despite these assumptions, the squad enhancement demonstration of Convergent SBD does use the ERS integrated trade-off analytics framework. These assumptions and potential relaxations of the assumptions will be revisited in the discussion of Chapter 5.

4. Squad Enhancement Results

The following chapter details the results of the squad enhancement demonstration of Convergent SBD. The chapter begins with the effect of the mission resilience calculations. The chapter then lists the impacts of Convergent SBD in set analysis and elimination of parts of the design area. For further investigation, the resulting Convergent SBD eliminations and final design space will be disclosed at two levels of statistical confidence in the set analysis; where alpha equals 0.95 and alpha equals 0.99 respectively. These results will be discussed in the subsequent chapter.

4.1. Impact of Mission Resilience on the Design Space

The initial tradespace without mission resilience calculated may be thought of as the most aligned results to the original study which also did not calculate resilience. The visual effect mission resilience has on the tradespace may be seen in Figure 17. Figure 17 illustrates the tradespace without resilience, the efficient points of this tradespace (in green), and the efficient frontier of the tradespace with resilience (in orange). As seen in Figure 17, all of the green efficient points of the tradespace without resilience are dominated by the efficient frontier of the tradespace with resilience.

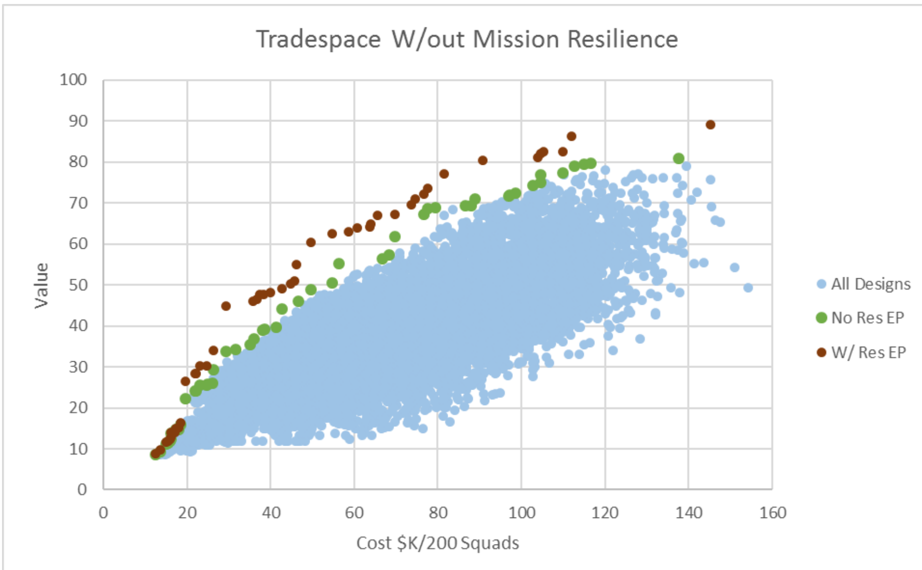

Figure 17: The Tradespace without Mission Resilience

The inclusion of mission resilience did not have an impact in any costs of the alternatives. The inclusion of mission resilience strictly raised the expected value of every alternative; by an average of 7.4 out of 100 points of value (119% of the average value). The 7.5 points of value average was not uniform among the alternatives. The alternatives gained a minimum of 0.3, maximum of 13.8, and had a standard deviation of 4.3 points gained. The variance in value increases led to re-ordering of the alternatives by rank of value. Of the 10,000 identical alternatives ranked from highest value to lowest across the two analyses, the average displacement was 510 ranks.

4.2. Impact of Convergent Set-Based Design

The first step in Convergent SBD requires an initial run (iteration 0) of SBD. The initial run of SBD using MBE with 10,000 feasible alternatives generated is illustrated in Figure 18. Figure 18 identifies 47 efficient points out of 184 sets composing 24 mutually exclusive and collectively exhaustive collections. All of the collections are created from each single design characteristic. The average value and cost of an alternative is 45.6 value score and $69.7K/200 squads. The design area from midpoint of value of the efficient frontier to midpoint of cost on the opposite end is approximately 44 value-cost units wide.

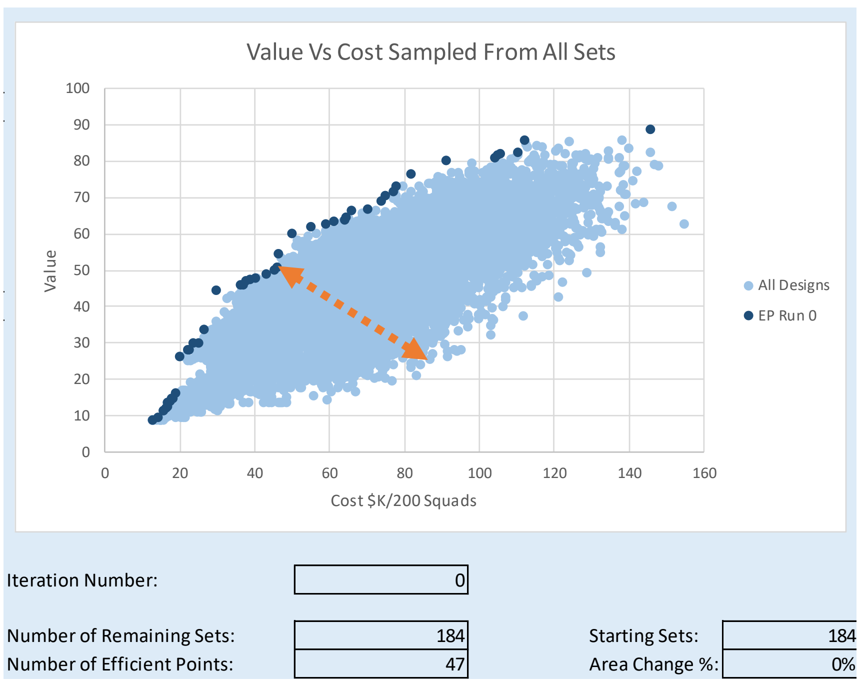

Figure 18: Initial Run of Set-Based Design with All Sets. Orange Arrow Represents Tradespace Width

The next iterations of Convergent SBD were performed assuming an alpha value of 0.95 in the Tukey's method comparisons. The results design area statistics at each iteration are summarized in Table 3.

Table 3: Design Area Summary Statistics: Alpha = 0.95

Iter.	Feasible Alternatives	# Sets	# Sets Eliminated	Coll-ections	Area Width	Val Avg.	Cost Avg.	New EPs
0	10,000	184	--	24	44	45.6	69.7	--
1	10,000	149	35	24	39	50.4	62	52
2	10,000	121	28	24	25	52.2	56.2	55
3	10,000	111	10	24	23	52.7	53.9	54
4	10,000	111	0	24	23	52.7	53.9	0

The 4th iteration does not eliminate any sets, satisfying the requirement for iteration termination. The full final comparison matrices of the 111 remaining sets in 24 collections may be found in the appendix. Figure 19 is an excerpt of the comparison matrices which illustrates two collections at final convergence for reasons 2 and 3 listed in Section 2.1. The top comparisons between the "number of robots" design parameter shows clear statistical distinction in terms of cost and value and thus sets may not be eliminated. The bottom comparisons between the "robot 1 speed" design parameter shows perfect statistical indistinction among the sets and thus sets may not be eliminated. By the definition in Section 2.1, of the 24 design parameters, at final convergence; 14 are identified as set drivers, 9 as set modifiers, and 1 singleton collection. The classification of set drivers, set modifiers, and singleton collections may be found in Table 5, with the classifications from alpha equals 0.99 iterations.

Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
0Rob	0	0		0Rob	0	0
1Rob	1	1		1Rob	1	1
2Rob	2	2		2Rob	2	2
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1RSBin:1	0	0		1RSBin:1	0	0
1RSBin:2	0	0		1RSBin:2	0	0
1RSBin:3	0	0		1RSBin:3	0	0
1RSBin:4	0	0		1RSBin:4	0	0
1RSBin:5	0	0		1RSBin:5	0	0
1RSBin:6	0	0		1RSBin:6	0	0

Figure 19: Comparison Matrices for Number of Robot and Robot 1 Speed.

Figure 20 illustrates the tradespace after the 4th and terminating iteration. All the efficient points after each iteration are also shown to highlight the Pareto frontier continuing to increase in quality. Figure 20 also plots 10,000 generated alternatives and is composed of the same sets as in Figure 18, but the remaining sets are refined with more alternatives within them.

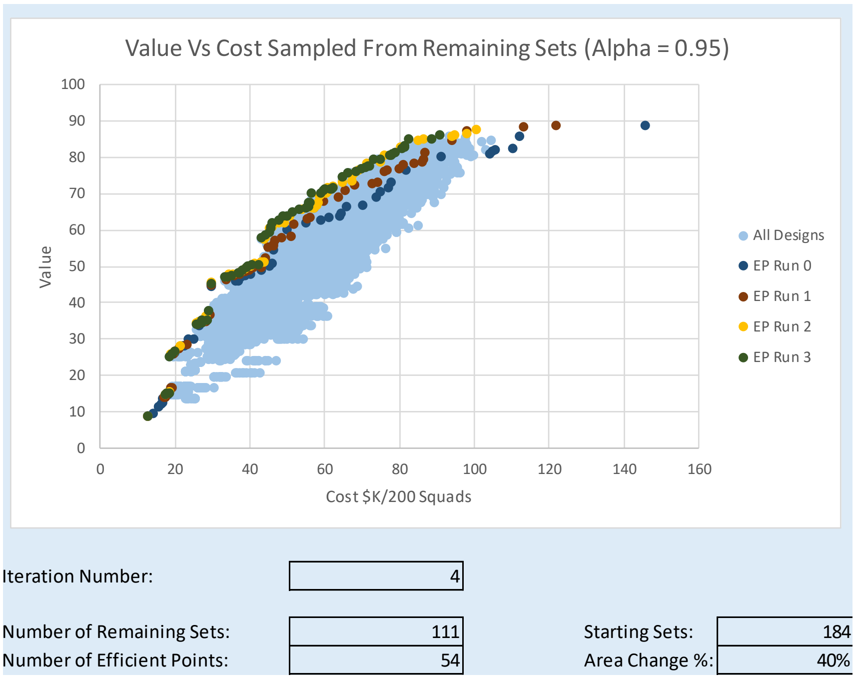

Figure 20: Tradespace at Final Convergence with 10,000 Alternatives, Alpha = 0.95.

The next iterations of Convergent SBD were performed assuming an alpha value of 0.99 in the Tukey's method comparisons. The results design area statistics at each iteration are summarized in Table 4.

Table 4: Design Area Summary Statistics: Alpha = 0.99

Iter.	Feasible Alternatives	# Sets	# Sets Eliminated	Coll-ections	Area Width	Val Avg.	Cost Avg.	New EPs
0	10,000	184	--	24	44	45.6	69.7	--
1	10,000	153	31	24	37	51.1	63.5	55
2	10,000	133	20	24	28	51.5	58.6	63
3	10,000	123	10	24	25	52.0	56.3	54
4	10,000	120	3	24	22	51.9	55.5	42
5	10,000	119	1	24	21	51.7	55.2	40
6	10,000	119	0	24	21	51.7	55.2	0

With alpha equal to 0.99, the 6th iteration does not eliminate any sets, satisfying the requirement for iteration termination. The full final comparison matrices of the 119 remaining sets in 24 collections may be found in the appendix. Of the 24 design parameters, at final convergence; 14 are identified as set drivers, 10 as set modifiers, and 0 singleton collections. The list of these may be seen in Table 5.

Table 5: Classification of Set Types at Final Convergence

Parameter	Type at α = 0.95	Type at α = 0.99
Number of UAVs	Driver	Driver
UAV 1 Speed	Driver	Driver
UAV 1 Detection Range	Driver	Driver
UAV 1 Num Missiles	Driver	Driver
UAV 2 Speed	Modifier	Modifier
UAV 2 Detection Range	Modifier	Modifier
UAV 2 Num Missiles	Driver	Driver
Rifle Enhancement	Driver	Driver
Rifle Enhanced Range	Driver	Modifier
Rifle Enhanced Fire Rate	Modifier	Modifier
Rifle Enhanced Hit Prob	Modifier	Modifier
Rifle Enhanced Lat Leth Mitigate	Driver	Driver
Body Armor Enhancement	Driver	Driver
BA Enhanced Kinetic Prot	Driver	Driver
BA Enhanced Chem-Bio Prot	Driver	Driver
BA Enhanced IED Prot	Singleton	Driver
BA Enhanced Nuc Radiation Prot	Driver	Driver
Number of Robots	Driver	Driver
Robot 1 Speed	Modifier	Modifier
Robot 1 IED Sensor Prob Detect	Driver	Driver
Robot 1 Classification Range	Modifier	Modifier

Table 5 (Cont.)

Parameter	Type at α = 0.95	Type at α = 0.99
Robot 2 Speed	Modifier	Modifier
Robot 2 IED Sensor Prob Detect	Modifier	Modifier
Robot 2 Classification Range	Modifier	Modifier

Figure 21 illustrates the tradespace after the 6th and terminating iteration. Only the efficient points after the original run 0 and iteration 5 are shown for simplicity in showing the increase in quality of solutions. Figure 21 plots 10,000 generated alternatives and should be compared to the tradespace illustrated in Figure 18 and Figure 20. Following Figure 21, the next chapter will discuss the results.

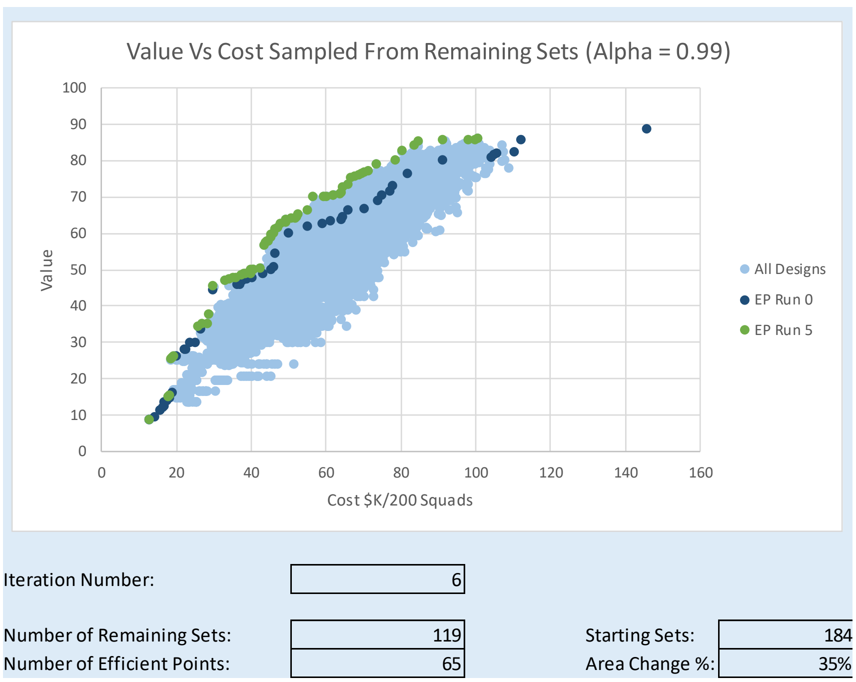

Figure 21: Tradespace at Final Convergence with 10,000 Alternatives, Alpha = 0.99.

5. Squad Enhancement Discussion

The following chapter discusses the results of SBD for insights into the research question. The first section discusses the demonstration using the integrated trade-off framework. The second section discusses the insights and effectiveness of Convergent SBD in identifying useful information for stakeholders and decision makers. The third section discusses opportunities for future research.

5.1.Discussion of Demonstration in ERS

As implied by Figure 15, the squad enhancement demonstration was fully enabled by the integrated trade-off analytics framework, but with a few limiting assumptions. All of the limiting assumptions affected the ability of the demonstration to calculate and evaluate system resilience. From the data found in section 4.1, it is clear mission resilience had a demonstrable impact on the tradespace even with the limiting assumptions. Additionally, the incorporation of mission resilience produced important results in two key areas. This first is incorporating mission resilience strictly raised the expected value of the alternatives and by an average of 7.5 value points. This result is consistent with the conception of mission resilience as "recovery above expectation." The second key finding is the significant change in alternative value rank-order. This implies that resilience must be a consideration in system design as it will likely change the preference of decision makers.

The incorporation of mission resilience requires the successful integration of MBE/MBSE. With the significant adaptations of the original study, the tradespace, sets, and efficient solutions are able to be identified using SBD. The study modifications provide additional insights to the decision makers when using SBD. Through these modifications, we find this research may also adapt to requirements as demonstrated explicitly by the incorporation of mission resilience and through the use of the trade-off analytics framework. In addition, through the value and cost model, this research also contains the ability to adapt to preference and information changes which was not as easy in the original study.

The final discussion topic in this subsection is system complexity. While complexity is a subjective term, this research demonstrates the ability of the integrated trade-off analytics framework (and Convergent SBD) to analyze complex system designs. In particular, this research was able to design four independent systems working concurrently. A statistical summary of the complexity of this demonstration may be seen in Figure 26. In Figure 26 is the number of possible combinations (or alternatives) as 7.35E+19. This is an impossibly high number of alternatives to evaluate with PBD. The number of alternatives also implies a significantly complex design space. The complexity of the tradespace is determined in part by the number of possible alternatives, but also by the number of competing objectives. While nine objectives are not high for a DoD system, it creates a tradespace of non-obvious solutions and requires modeling, as was demonstrated, to evaluate the large numbers of alternatives.

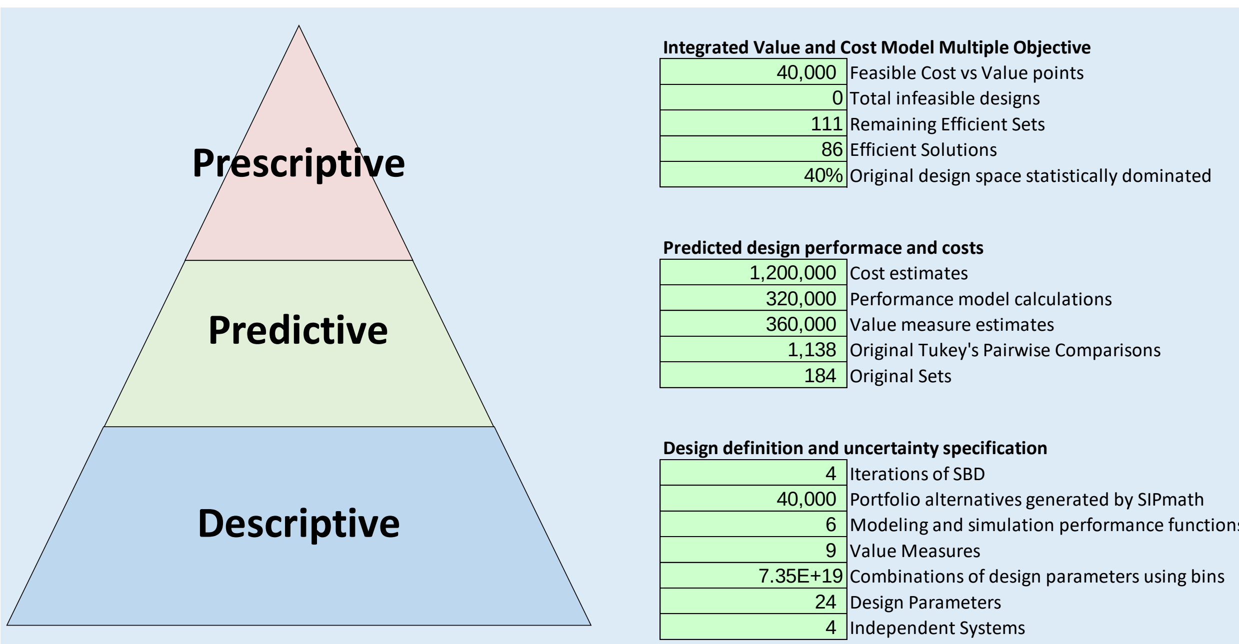

Figure 22: Trade-off Analytics Hierarchy for the Squad Enhancement Demonstration (Alpha = 0.95 when referring to number of iterations).

5.2. Discussion of Convergent Set-Based Design

The following subsections will discuss the results of the Convergent SBD methodology. This discussion includes set analysis, set quality, set driver/modifier, and the effect of the alpha value.

5.2.1. Set Analysis

To begin, it is clear the Convergent SBD methodology was able to perform analysis on sets rather than points. It is also clear that sets and design area were eliminated. This had the expected effect of reducing the design space by eliminated dominated sets. The width of the design area in SBD, as illustrated in Figure 18, provides a comparative measure for the density of solutions away from the efficient frontier. At both levels of alpha, the width of the design area was monotonically shrinking in each set-eliminating iteration, implying the eliminations were justifiable by the dominance criteria in Equation 2. Additionally, at both alpha levels, each set-eliminating iteration resulted in newly identified efficient points. This is the result of refinement and increased investigation into the efficient sets as expected with Convergent SBD. Perhaps most notable is iteration 5 of the alpha equal 0.99 investigation which eliminated a single set and still identified 40 efficient points previously undiscovered. This phenomenon should not be surprising in such a complex design space as even the elimination of a single set reallocates hundreds to thousands of generated alternatives to investigate efficient sets.

The literature concerning qualitative SBD wrote of a process which converged to a final solution. While Convergent SBD clearly converged to better solutions than heuristic SBD and PBD, the number of possible alternatives and sets are still quite large. The most likely opportunities to converge even further lie in the fixing of set modifiers (discussed in detail below) and by applying the method on higher level collections of mutually exclusive and collectively exhaustive sets. The results above define 24 collections, each defined by a single design parameter. As mentioned in Section 2.1, collections may be defined by up to n-1 design parameters. This was not demonstrated due to the constraints of the elimination program in its Excel implementation. However, as in qualitative SBD, specific interactions of multiple design parameters are able to be excluded in the theory of Convergent SBD, leading to an even smaller and more refined design space and tradespace. It is likely, though not demonstrated, these higher order interaction comparisons lead to even better solutions and a tight set of solutions along the Pareto Frontier.

5.2.2. Set Quality

The next part of the Convergent SBD discussion focuses on the quality of the remaining sets and alternatives after iterations. With all of the iterations at alpha = 0.95 and most of the iterations at alpha = 0.99, the average value and cost of the 10,000 generated alternatives were improving. However, this average value does improve in iterations 4 and 5 of the alpha = 0.99 analysis. Because the area width of the design space continues to shrink in the identified iterations, the only reason the average value will not improve in an iteration is if some high-value sets are eliminated. While it is difficult to identify the set responsible for this, an illustration of this scenario may be found in Figure 23. In Figure 23, the increased variance of set B in terms of value may lead to some high-value alternatives, but the average value of set B is little different from the average value of set A. Because of the clear increase in cost of set B over set A, set B meets the elimination criterion.

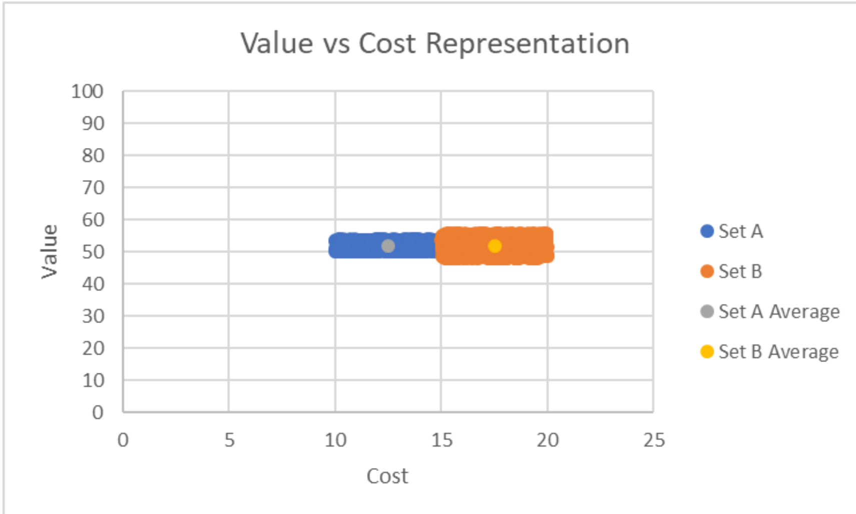

Figure 23: Illustration of Set B Elimination Scenario.

Figure 23 presents a clear picture of a set justified for elimination, but the elimination of the set removes an efficient point(s). This is likely the cause of the non-improving average alternative found in iterations 4 and 5 of the alpha equals 0.99 analysis. This presents a challenge to the effectiveness of Convergent SBD as there exists a scenario in which Convergent SBD eliminates an efficient solution. The response to this scenario is two-part: first, the purpose of SBD is to perform analysis on the set level and eliminate inefficient sets, not perform analysis on specific points as in PBD. The second response must be to define the elimination criteria by the discretion of the decision maker. A decision maker may choose to accept the potential for loss of efficient solutions in the 95^{th}-99^{th} percentile extremes in favor of the clearly demonstrated improvements in the 95-99% design space. Or, a decision maker may choose to redefine the elimination criteria to protect any identified inefficient set(s) that contain efficient points. The latter is theoretically implementable within the demonstration by the ability of the integrated model to identify efficient points, correctly label them into their respective sets, and make these exceptions by the elimination program, though this requires future work to demonstrate the theory. A decision maker preferring the latter definition for elimination criteria would still work with Convergent SBD but may slow iterations and result in a larger design space at final convergence.

5.2.3. Set Drivers and Modifiers

The next part of the general Convergent SBD discussion is the classification of set drivers, modifiers, and singleton collections. As can be seen in Table 5, both analyses were mostly consistent in their identifications. Both analyses identified 14 of the 24 design parameters as set drivers. While this may seem high, the number of set drivers identified is possibly higher due to the unique construction of this demonstration. Each of the four enhancements are independent systems, and each of the four design parameters controlling the major architectures of the complex overall system were identified as drivers. The remaining design parameters may be thought of as set drivers or set modifiers for each of their respective systems. As an example, “number of robots,” an independent system, is identified as a set driver. Within the robots system enhancement “robot 1 IED probability of detection” is identified a set driver. This implies “robot 1 IED probability of detection” is key to understanding the value and cost of enhancing the squad with robots.

As previous literature and this research confirm, identifying set drivers provides decision analysts with strong insights into the focus of further investigation. The usefulness of identifying set modifiers is not as apparent. In Convergent SBD, the identification of set modifiers could be a useful tool for furthering Convergent SBD analysis into efficient, driving sets. This could be accomplished by arbitrarily eliminating all but one design characteristics of each set modifier to a single set. The theory of Convergent SBD supports this arbitrary elimination of design area as statistically the set modifiers are indistinct and will have no statistical impact on the area, but greatly reduce noise variance for better comparisons of set drivers. A visual example of the squad enhancement design area which adopts this idea may be seen in Figure 24. In Figure 24, the newly generated alternatives are plotted with the best efficient points from the final iteration at alpha equals 0.95 and it is clear that improvements have been found.

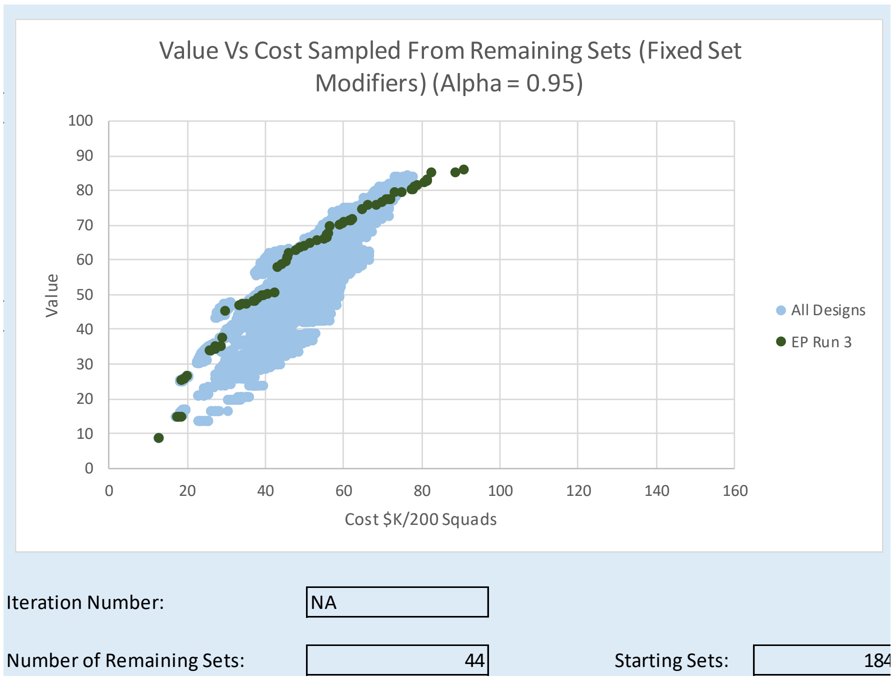

Figure 24: Fixed Set Modifiers Example Plotted with Efficient Points at Final Convergence.

There is a caution to be addressed before Convergent SBD may recommend using set modifiers in this fashion. First, at what iteration stage does an analyst eliminate set modifiers to a single set must be addressed. It would be most effective to perform this elimination of multiple sets in set modifiers immediately following the iteration they are identified. However, it is theoretically possible that the elimination of other sets and the increased sample sizes in the set modifiers would allow small distinctions to be identified. A possible example is the contrasting identifications of "rifle enhanced range" in Table 5 as a set driver and set modifier when alpha equals 0.95 and 0.99 respectively. It is possible due to the less remaining sets in the alpha equals 0.95 analysis, more samples in the "rifle enhanced range" led to a detectable difference in terms of value and cost. Thus, it would seem set modifiers must be eliminated to a single set after final convergence. In that case, the question of eliminating down to one set for all set modifiers at once or one at a time to attempt to detect differences should be addressed. This appears to be a rich research question as deeper investigation could reveal if set modifiers are eliminated down to a single set one at a time, other set modifiers could be identified as set drivers and thus each set modifier should be eliminated down and reset in turn, leading to a second iterative process built upon Convergent SBD.

5.2.4. Effect of Alpha Value

The comparison of alpha values set at 0.95 and 0.99 raised some questions mentioned early but also performed in the expected manner. Alpha set to 0.99 was more conservative than alpha set to 0.95, eliminating fewer sets over more iterations as expected. The final design spaces were comparable for both alpha values. Perhaps the most significant differences are found in the average alternative value and cost. Unexpected, alpha set to 0.99 was outperformed by alpha set to 0.95. What contributed to this is unknown without further investigation. From these analyses, no recommendation may be made as to the preference of the alpha value.

5.3.Future Work

This research has identified several areas for further investigation. The first involves the calculation for platform resilience. It is likely this calculation will be able to be incorporated with Convergent SBD. The second area is the relaxation of the assumptions made in the integrated trade-off analytics framework for this squad enhancement demonstration. How Convergent SBD and the MBE/MBSE paradigm handles multiple threats, missions, scenarios, and response decisions should be of great interest to the DoD. The third area adds uncertainty to the analysis. The Convergent SBD process inherently relies on set averages and at surface level it seems uncertainty may only effect set analysis to the extent the mean and standard deviation of the set changes. Despite this, uncertainty analysis should provide additional insights for decision makers. The fourth investigative focus should be on multi-level collection comparisons to eliminate sets based on combined interactions. The fifth area involves the proper process to leverage set modifiers as discussed above. And the final area for future work is specific recommendation testing on alpha values to find if an alpha value performs better than another and in what circumstances. It is clear from these areas for future work Convergent SBD will continue to have areas for improvement and discovery.

6. Conclusion

In conclusion, this thesis has presented the background, definition, demonstration, results, and future research for Convergent SBD integrated in AoA. These have been presented to provide proper context and answers for the research question: How can quantitative SBD be leveraged to eliminate sets by mathematical set analysis and converge towards a solution, or group of affordable solutions, using the integrated trade-off analytics framework? Through the theory and demonstration, it is clear Convergent SBD addresses this question, provides new insights for decision makers, and provides opportunities for further research.

In this thesis, Convergent SBD has been established as a mathematical technique of statistical set analysis and dominance identification. Convergent SBD built off the quantitative SBD research for the ERS program and provided a method for eliminating sets by equations proposed in this research. This thesis discussed the criteria for terminating the iterative process of Convergent SBD and mathematically defined and proposed an identification method for set drivers and set modifiers which had previously been determined heuristically. Finally, the assumptions and justifications of Convergent SBD were defined to ensure proper mathematical accountability.

To demonstrate Convergent SBD, a previous ERS MBSE study on squad enhancement technologies was leveraged. This original study was heavily adapted to work within the integrated trade-off analytics framework and these adaptations were specified. Specific steps for the implementation of Convergent SBD within the modified study were also listed. The demonstration used MBE/MBSE, performed AoA, quantified and measured mission resilience, and adhered to the integrated trade-off analytics framework. While the integrated trade-off analytics framework was implemented, several simplifying assumptions were detailed, all relating to resilience and not explicitly impacting the use of Convergent SBD.

The Convergent SBD demonstration was able to be incorporated into the integrated trade-off analytics framework indicating that the quantification of mission resilience had a measurable impact on the tradespace and could change the preferences of decision makers. The demonstration illustrated trade-off analysis could be performed directly on the sets. Set quality was discussed with additional areas Convergent SBD may address in the future, including decision maker preference on the potential to eliminate efficient points. Set drivers and set modifiers were mathematically identified and this research discussed potential uses in Convergent SBD for the unused set modifiers. The changing alpha value had the expected effects of more conservative eliminations at higher alpha values but were inconclusive in recommendation. Finally, several areas were identified for future work including platform resilience, uncertainty analysis, and procedures for leveraging set modifiers among others.

Overall, this thesis presented a comprehensive package for understanding and expanding set-based design quantification. The research has contributed a qualitative and quantitative definition of Convergent SBD with the goal of mathematically eliminating inefficient sets. The research contributed a demonstrably repeatable methodology to identify dominance according to developed elimination criteria equations. The demonstration also illustrated the effect of mission resilience in the tradespace and impact mission resilience has on preference. Finally, this research contributes a method of mathematical identification of the previously heuristic set drivers and set modifiers and discussed additional decision analyst uses for this information. Together, the research in this thesis provides a foundational mathematical technique for eliminating sets as qualitative SBD recommends and converging to an efficient, affordable solution or group of solutions.

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8. Appendix I: Trade-off Analytics Node Description: Source (Specking, et al. 2017)

Analytics Type	Node	Definition
Descriptive	Design Decisions, D	System design decisions (including set drivers and set modifiers) made with knowledge of the requirements and threat assessment.
	Missions, m	Chance node representing the missions the system is actually used on, this may or may not be included in the initial threat assessment or requirements analysis.
	Requirements, r	Decisions stating the required minimum performance in the planned system environments and threats.
	Scenarios, s	Chance node representing an uncertain scenario, which may or may not be in the original threat assessment or requirements analysis.
	System Functions, f	Chance node determining how the system is used, it is influenced by the missions and scenarios the future system is used in.
	Threat Assessment, T	Decision identifying the anticipated adversary or environmental threats the system could face in the planned missions and scenarios.
Predictive	Iities, i	Chance nodes such as reliability, survivability, availability, and other ilities affecting the performance and cost of the system.
	Life Cycle Cost, C	Value node depending on the design, the produceability, the supportability, and the response decisions.
	Modelling and Simulation (M&S), M	Decisions made about which methods and techniques are used to model and simulate the missions and scenarios used to predict system performance measures, ilities, and costs.
	Performance Measures, p	Chance node representing the performance measure predictions from modelling and simulation depending on the function, the ilities, and resilience response decisions.
	Response Decisions, R	Decision node representing short-term and long-term response decisions informed by threats during system operation. For example, selecting the most appropriate sensor for a new threat or environment.
	Service Life, L	Chance node affected by the performance of the system, the ilities, and the resilience response decisions.
	Threat, t	Chance node representing the uncertain threat depending on the mission. There can be different threats to different system functions. In this diagram, threat is the term used for any adverse event (environmental or adversary) which could degrade any capability of the system. This may or may not be in the original T.
Prescriptive	Value, V	Value node depending on the performance on all functions and the ilities.
	Affordability, A	Value node comparing value versus life cycle cost.

9. Appendix II: Excel Elimination Macro

Main Comparison Macro

```
Sub TukeyCompare()
Dim Ob As Integer, y As Integer, CountObs As Integer
Dim Col As Integer, z As Integer, Cnt As Integer, x As Integer
Dim CountV As Integer, CountC As Integer, UpBnd As Integer
Dim MasCount As Integer, VGroups As Integer, CGroups As Integer
Dim SetCount As Integer

Dim GrandSumV As Double, GrandSumC As Double
Dim SSUnCV As Double, SSUnCC As Double
Dim SSTV As Double, SSTC As Double
Dim SSTrV As Double, SSTrC As Double
Dim SSEV As Double, SSEC As Double
Dim MSEV As Double, MSEC As Double
Dim TukV As Double, TukC As Double

Dim Value(9999) As Double
Dim Cost(9999) As Double

Dim CompMat() As Variant
Dim OutMatV() As Variant, OutMatC() As Variant
Dim StuRng(20) As Double

#Copy Value and Cost for All Alternatives
For Ob = 0 To 9999

   Value(Ob) = Worksheets("PMTable").Range("C4").Offset(Ob, 0).Value
   Cost(Ob) = Worksheets("PMTable").Range("D4").Offset(Ob, 0).Value

Next
#Initialize Studentized Range at Alpha Value
For y = 2 To 20

   StuRng(y) = Worksheets("Comparisons").Range("D1").Offset(0, y).Value

Next
MasCount = 0
SetCount = 0
#Initialize Tukey Comparison Sub-Summations
For Col = 0 To 23
   GrandSumV = 0
```

```
   GrandSumC = 0
   SSUnCV = 0
   SSUnCC = 0
   SSTrV = 0
   SSTrC = 0
   CountObs = 0

#Make Master Comparison Matrix of Dynamic Size based on number of Sets
ReDim CompMat(Worksheets("Iteration CP").Range(Worksheets("Iteration
CP").Range("M2").Offset(Col, 0), Worksheets("Iteration CP").Range("M2").Offset(Col,
0).End(xlToRight)).count, 8)

#Single Set Error Check
   If UBound(CompMat()) > 1000 Then ReDim CompMat(1, 8)

   For y = 0 To UBound(CompMat())

      CompMat(y, 0) = Worksheets("Iteration CP").Range("M2").Offset(Col, y).Value
      CompMat(y, 1) = 0
      CompMat(y, 2) = 0#
      CompMat(y, 3) = 0#
      CompMat(y, 4) = 0#
      CompMat(y, 5) = 0#
      CompMat(y, 6) = 0
      CompMat(y, 7) = 0
      CompMat(y, 8) = ""

   Next

#Get Data for each alternative in the set
   For Ob = 0 To 9999

      For y = 0 To UBound(CompMat())

         If Worksheets("PMTable").Range("F4").Offset(Ob, Col) = CompMat(y, 0) Then

            CountObs = CountObs + 1
            GrandSumV = Value(Ob) + GrandSumV
            GrandSumC = Cost(Ob) + GrandSumC
            CompMat(y, 1) = 1 + CompMat(y, 1)
            CompMat(y, 2) = Value(Ob) + CompMat(y, 2)
            CompMat(y, 3) = Cost(Ob) + CompMat(y, 3)
```

```
            SSUnCV = Value(Ob) ^ 2 + SSUnCV
            SSUnCC = Cost(Ob) ^ 2 + SSUnCC
            Exit For
          End If

        Next

    Next

#Error Checking Legacy Code
    If CompMat(UBound(CompMat()), 3) = 0 Then UpBnd = UBound(CompMat()) - 1 Else
UpBnd = UBound(CompMat()) - 1

#Calculate SSTr
    For y = 0 To UpBnd
        CountV = 0
        CountC = 0

        SSTrV = CompMat(y, 2) ^ 2 / CompMat(y, 1) + SSTrV

        For z = 0 To UpBnd

          If CompMat(y, 2) / CompMat(y, 1) > CompMat(z, 2) / CompMat(z, 1) Then

            CountV = CountV + 1

          End If
          CompMat(y, 6) = CountV

        Next

        SSTrC = CompMat(y, 3) ^ 2 / CompMat(y, 1) + SSTrC

        For z = 0 To UpBnd

            If CompMat(y, 3) / CompMat(y, 1) > CompMat(z, 3) / CompMat(z, 1) Then

              CountC = CountC + 1

            End If

            CompMat(y, 7) = CountC
```

```
        Next

    Next

    #Correct Means
    SSTrV = SSTrV - GrandSumV ^ 2 / CountObs
    SSTrC = SSTrC - GrandSumC ^ 2 / CountObs

    SSTV = SSUnCV - GrandSumV ^ 2 / CountObs
    SSTC = SSUnCC - GrandSumC ^ 2 / CountObs

    #Calculate SSE
    SSEV = SSTV - SSTrV
    SSEC = SSTC - SSTrC

    #Calculate MSE
    MSEV = SSEV / (CountObs - UpBnd)
    MSEC = SSEC / (CountObs - UpBnd)

    #Calculate Tukey Comparison Value
    ReDim OutMatV(UpBnd, 1)
    ReDim OutMatC(UpBnd, 1)
    For y = 0 To UpBnd

#Group Lower and Upper Bounds
        For x = 0 To UpBnd
            If CompMat(x, 6) = y Then
                Cnt = 0
                For z = 0 To UpBnd

                    Select Case CompMat(z, 6)

                    Case Is > y

                        If Abs(CompMat(x, 2) / CompMat(x, 1) - CompMat(z, 2) / CompMat(z, 1)) <
StuRng(UpBnd) / 2 ^ (1 / 2) * (MSEV * (1 / CompMat(x, 1) + 1 / CompMat(z, 1))) ^ (1 / 2)
Then

                            If OutMatV(z, 0) = "" Then OutMatV(z, 0) = y Else OutMatV(z, 1) = y
                            OutMatV(z, 1) = y
                            Cnt = Cnt + 1

                        End If
```

```
                Case Is = y

                    If OutMatV(z, 0) = "" Then OutMatV(z, 0) = y Else OutMatV(z, 1) = y
                    If OutMatV(z, 1) = "" Then OutMatV(z, 1) = y

                Case Else

                End Select

            Next
            Exit For
        End If
    Next
    VGroups = y
    If Cnt = UpBnd - y Then Exit For
Next

For y = 0 To UpBnd
    For x = 0 To UpBnd
        If CompMat(x, 7) = y Then
            Cnt = 0
            For z = 0 To UpBnd

                Select Case CompMat(z, 7)

                Case Is > y
                    If Abs(CompMat(x, 3) / CompMat(x, 1) - CompMat(z, 3) / CompMat(z, 1)) <
StuRng(UpBnd) / 2 ^ (1 / 2) * (MSEC * (1 / CompMat(x, 1) + 1 / CompMat(z, 1))) ^ (1 / 2)
Then

                        If OutMatC(z, 0) = "" Then OutMatC(z, 0) = y Else OutMatC(z, 1) = y
                        OutMatC(z, 1) = y
                        Cnt = Cnt + 1

                    End If

                Case Is = y

                    If OutMatC(z, 0) = "" Then OutMatC(z, 0) = y Else OutMatC(z, 1) = y
                    If OutMatC(z, 1) = "" Then OutMatC(z, 1) = y

                Case Else
```

```
                    End Select

                Next
                Exit For
            End If
        Next
        CGroups = y
        If Cnt = UpBnd - y Then Exit For
    Next
    If CompMat(UpBnd, 0) = "" Then CompMat(UpBnd, 0) = "Other"

#Call Elimination Function to Implement Elimination Equations
    Call Eliminations(CompMat(), OutMatV(), OutMatC(), Col, UpBnd, VGroups, CGroups)
#Call RemoveFromCP Function to Update Iteration CP and Eliminate Design Area
    Call RemoveFromCP(CompMat(), Col, UpBnd)
    #Output Comparisons

    Worksheets("Comparisons").Range("A3").Offset(MasCount, 0).Value =
"Characteristic/Interval"
    Worksheets("Comparisons").Range("B3").Offset(MasCount, 0).Value = "Value Min Group"
    Worksheets("Comparisons").Range("C3").Offset(MasCount, 0).Value = "Value Max Group"
    Worksheets("Comparisons").Range("E3").Offset(MasCount, 0).Value =
"Characteristic/Interval"
    Worksheets("Comparisons").Range("F3").Offset(MasCount, 0).Value = "Cost Min Group"
    Worksheets("Comparisons").Range("G3").Offset(MasCount, 0).Value = "Cost Max Group"

    For y = 0 To UpBnd

        Worksheets("Comparisons").Range("A4").Offset(y + MasCount, 0).Value = CompMat(y,
0)
        Worksheets("Comparisons").Range("D4").Offset(y + MasCount, 0).Value = CompMat(y,
8)
        Worksheets("Comparisons").Range("E4").Offset(y + MasCount, 0).Value = CompMat(y, 0)

        For z = 0 To 1

            Worksheets("Comparisons").Range("B4").Offset(y + MasCount, z).Value = OutMatV(y,
z)
            Worksheets("Comparisons").Range("F4").Offset(y + MasCount, z).Value = OutMatC(y,
z)

        Next
```

```
    Next

    MasCount = MasCount + UpBnd + 4
    SetCount = UpBnd + SetCount
Next


Range("ItCount").Value = Range("ItCount").Value + 1

Application.Calculate
End Sub

#Elimination Logic
Sub Eliminations(ByRef CompMat() As Variant, OutMatV() As Variant, OutMatC() As Variant,
Col As Integer, UpBnd As Integer, VGroups As Integer, CGroups As Integer)

Dim i As Integer, j As Integer, k As Integer

Dim MaxValMin As Integer, MinCostMax As Integer
Dim First As Boolean, Multiple As Boolean, Cont As Boolean

#Implement Equation 2(a)
For k = 0 To CGroups

    First = True
    Multiple = False
    For i = 0 To UpBnd

        If OutMatC(i, 0) = k Then

            Select Case First

            Case True

                First = False
                MaxValMin = OutMatV(i, 0)

            Case Else

                Multiple = True
                If MaxValMin < OutMatV(i, 0) Then MaxValMin = OutMatV(i, 0)

            End Select
```

```
        End If
    Next

    If Multiple Then

        For i = 0 To UpBnd

            If OutMatC(i, 0) = k Then

                If MaxValMin - OutMatV(i, 1) > 0 Then

                    CompMat(i, 8) = "E"

                End If

            End If
        Next

    End If

Next

#Implement Equation 2(b)
For k = 0 To VGroups

    First = True
    Multiple = False
    For i = 0 To UpBnd

        If OutMatV(i, 1) = k Then

            Select Case First

            Case True

                First = False
                MinCostMax = OutMatC(i, 1)

            Case Else

                Multiple = True
                If MinCostMax > OutMatC(i, 1) Then MinCostMax = OutMatC(i, 1)
```

```
            End Select

        End If
    Next

    If Multiple Then

        For i = 0 To UpBnd

            If OutMatV(i, 1) = k Then

                If MinCostMax - OutMatC(i, 0) < 0 Then

                    CompMat(i, 8) = "E"

                End If

            End If
        Next

    End If

Next

End Sub

#Update And Eliminate Design Area in Iteration Control Panel
Sub RemoveFromCP(ByRef CompMat() As Variant, Col As Integer, UpBnd As Integer)

Dim y As Integer, x As Integer, count As Integer, min As Integer

'If Worksheets("Iteration CP").Range("K2").Offset(Col, 0).Value = "Discrete" Then
    count = 0
    min = UpBnd
    For y = 0 To UpBnd

        Worksheets("Iteration CP").Range("ActCorner").Offset(Col, 5 + y).Value = ""
        If CompMat(y, 8) <> "E" Then
            Worksheets("Iteration CP").Range("ActCorner").Offset(Col, 5 + count).Value =
CompMat(y, 0)
            count = count + 1
            If y < min Then min = y
```

```
        End If

    Next
    Worksheets("Iteration CP").Range("ActCorner").Offset(Col, 1).Value = count
    If Worksheets("Iteration CP").Range("ActCorner").Offset(Col, 3).Value <> "Discrete" Then

        If min > 0 Then Worksheets("Iteration CP").Range("ActCorner").Offset(Col, 3).Value =
min + Worksheets("Iteration CP").Range("ActCorner").Offset(Col, 3).Value
        Worksheets("Iteration CP").Range("ActCorner").Offset(Col, 4).Value =
Worksheets("Iteration CP").Range("ActCorner").Offset(Col, 4).Value + min *
Worksheets("Iteration CP").Range("ActCorner").Offset(Col, 2).Value

    End If

End Sub
```

Appendix III: Revised Value Model and Swing Weights

Value Model

Fundemental OBJ	Squad achieves overmatch against enemies in complex environments								
Function	Command and control the Squad		Maneuver the Squad	Protect the Squad				Achieve Mission Effects	
Sub-function	Maintain situational awareness								
Objectives	Incr. beyond line of sight awareness	Incr. line of sight range	Incr.soldier mobility	Protect against kinetic and explosive threats		Protect against chemical, biological and nuclear threats		Maximize kinetic effects	Min. lateral damage
Value Measures	Beyond LOS	Line of Sight	Weighted Mobility	Kinetic Protection	Protect from IEDs	Chem Bio Protection	Nuclear Radiation Protection	Lethality	Lethal Mitigation

x	BLOS capability	x	Detection Distance (meters)	x	Weighted Mobility	x	Protect capability	x	IED detect and protect	x	Chem Bio protection	x	Nuclear Radio protection	x	Lethal capability	x	Lethal mitigation capability
0	0	300	0	1	0	1	0	1	0	1	0	1	0	0	0	1	1
0.25	10	500	30	2	30	2	10	2	10	2	10	2	25	0.3	10	2	25
0.5	70	800	60	3	60	3	20	3	20	3	20	3	40	0.6	40	3	50
0.7	100	1000	85	4	80	4	40	4	40	4	35	4	50	0.8	80	4	70
1.001	100	1500.001	100	5	95	5	50	5	50	5	50	5	60	1.001	100	5	100
				6	100	6	60	6	60	6	60	6	80				
						7	70	7	70	7	70	7	100				
						8	85	8	85	8	80						
						9	100	9	100	9	100						

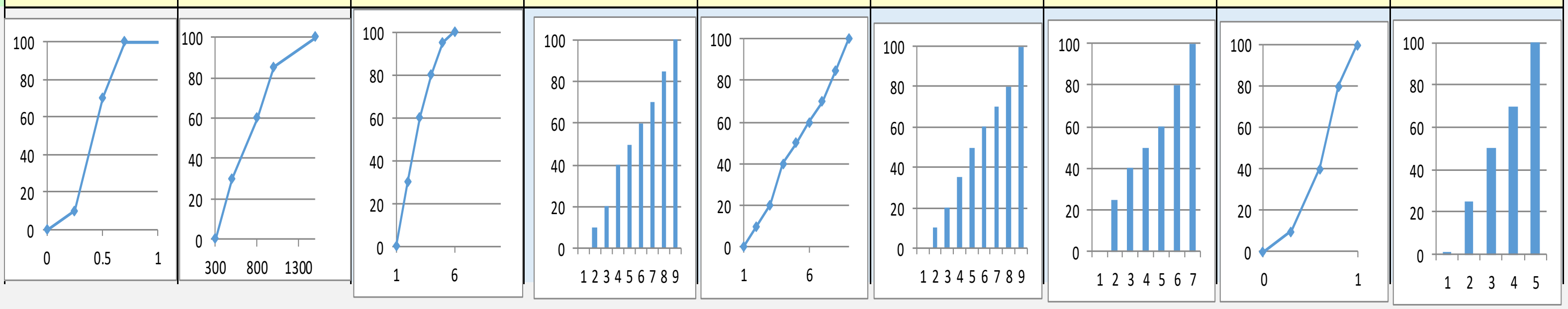
Note: x must be increasing. For natural scales add 0.0001 to the highest x value.

Legend

Data

Calculation

Graph of Value Curve



Swing Weight Matrix

Swing Weight Matrix

Capability Impact	Mission Critical	fi	wi	Enhables Capability	fi	wi	Enhance Capability	fi	wi
Significant impact	Lethality	100	0.21	Weighted Mobility	70	0.15			
				IED Protection	65	0.14			
	Beyond LOS	90	0.19						
	Kinetic Protection	70	0.15						
Medium Impact							Chem Bio Protection	15	0.03
				Detection Distance	40	0.08			
Minimal Impact	Lethal Mitigation	25	0.05				Nuclear Protection	5	0.01
		sum of fi		480					

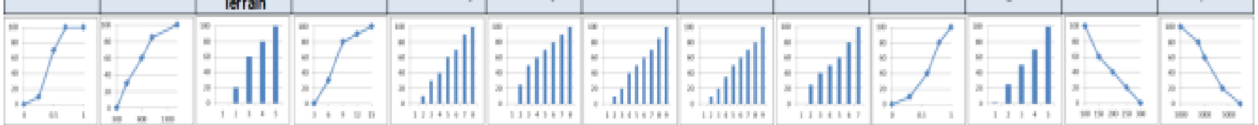
f_i = swing weight

w_i = normalized swing weight

9.1. MacCalman Value Model

Value Hierarchy Legend: Function Objective Value Measure

Squad achieves overmatch against enemies in complex environments												
Command and control the Squad					Maneuver the Squad	Protect the Squad			Achieve Mission Effects		Sustain the Squad	
Maintain situational		Maintain networked communications										
Incr. beyond line of sight awareness	Incr. line of sight range	Max. range	Max. bandwidth	Provide secured connectivity	Incr. soldier mobility	Protect against kinetic threats	Protect against chemical, biological, radiological, nuclear threats		Maximize kinetic effects	Min. lateral damage	Max. power efficiency	Min. logistical footprint
Beyond LOS	Detection Distance	Commo Range Various Terrain	Bandwidth	Secured Connectivity	Weighted Mobility	Kinetic Protection	Chem Bio Protection	Nuclear Radio Protection	Lethality	Lethal Mitigation	Power	Logistical Impact



9.2. MacCalman Model Inputs

Decision Factors	Stakeholder Needs (Local Properties)	Simulation Input Model Description (MANA)	Low	High
SDR Detection Range	Increase the soldier's detection range.	Distance a solider can detect a target.	1.5	2.5
SDR AVG Time Between Det	Reduce the time needed for the soldier to detect a target.	For a discrete set of distances, the time it takes for the soldier to detect a target.	2	2
SDR Classification Range	Increase the range that a soldier can classify a target as a threat, friendly, or neutral	Distance a soldier can classify something as a threat, friendly, or neutral.	1	2
SDR Classification Prob	Improve on the soldier's ability to classify a target as a threat, friendly, or neutral.	The probability a soldier can classify a target correctly.	1	2
SDR FOV	Increase the soldier's field of view.	The soldier field of view.	50	180
SDR Speed	Increase the soldier's mobility with an increased load carrying capacity.	Soldier speed.	3	7
SDR No. Hits to Kill	Increase the body armor protection of the soldier.	The number of hits to kill a soldier agent.	3	5
SDR M4 Range	Increase the range of the soldier's Rifle	Range of the soldier's Rifle	1	2
SDR M4 Rate of fire	Increase the rate of fire of the soldier's Rifle	The soldier's Rifle shots per second	1	3
SDR M4 Hit rate	Increase the soldier's Rifle accuracy.	For a discrete set of distances, the probability of hitting a target.	1	2
SDR M249 Range	Increase the range of the soldier's Automatic Weapon	Range of the soldier's Automatic Weapon	1	2
SDR M249 Rate of fire	Increase the rate of fire of the soldier's Automatic Weapon	The soldier's Automatic Weapon shots per second	3	8
SDR M249 Hit rate	Increase the soldier's Automatic Weapon accuracy.	For a discrete set of distances, the probability of hitting a target.	1	2
SDR 40mm Range	Increase the range of the Grenadier Weapons' range	Grenadier Weapon's range.	1	2
SDR 40mm Hit Rate	Increase the Grenadier Weapon accuracy.	The Grenadier Weapon's accuracy.	1	2
SDR 40mm shot radius	Increase the shot radius of the Grenadier Weapon round.	The Grenadier Weapon's shot radius on impact.	5	20
Comms Delay	Decrease the time it takes for a solider to interpret incoming information from squad members.	The number of seconds between internal squad radio transmissions.	0	15
Inorganic SA - Latency	Decrease the time it takes to call for indirect fire and interpret information from UAV and Robots.	The number of seconds between external radio transmissions.	0	15
Inorganic SA - Reliability	Improve the soldier's ability to send, receive, and interpret information to external assets.	The probability of the sending and receiving an external radio transmission.	0.7	1
No. UAVs	Provide an organic UAV to the squad.	Number of squad organic UAVs	0	2
UAV Speed	Ensure the UAV has enough speed to maintain flight stability.	The speed of the UAV.	50	100
UAV Detection Range	Increase the detection range of the UAV.	Distance the UAV can detect a target.	1.5	2.5
UAV AVG Time Between Det	Reduce the time needed for the UAV to detect a target.	For a discrete set of distances, the time it takes for the UAV to detect a target.	1	2
UAV Classification Range	Increase the range that a soldier can classify a target as a threat, friendly, or neutral with a UAV.	Distance the UAV can classify something as a threat, friendly, or neutral.	1	2
UAV Classification Prob	Improve on the soldier's ability to classify a target as a threat, friendly, or neutral with a UAV.	The probability the UAV can classify a target correctly.	1	2
No. UAV Missiles	Provide a kinetic munitions to destroy threats.	Number of missiles on one UAV.	0	2
UAV Missile Shot Radius	Increase the shot radius of the UAV munitions without increasing collateral damage.	The UAV missile shot radius on impact.	10	50
UAV Missile Hit rate (Prob of Hit)	Increase the accuracy of the UAV munitions.	The probability of the UAV missile hitting a target.	0.3	1
No. Robots	Provide an organic Robot to the squad.	Number of squad organic Robots.	0	2
Robot Speed	Ensure Robot can traverse in a variety of terrain types.	The speed of the Robot.	3	10
Robot Detection Range	Increase the detection range of the Robot.	Distance the Robot can detect a target.	1.5	2.5
Robot Classification Range	Reduce the time needed for the Robot to detect a target.	Distance the Robot can classify something as a threat, friendly, or neutral.	1	2
Robot AVG Time Between Det	Increase the range that a soldier can classify a target as a threat, friendly, or neutral with a Robot.	For a discrete set of distances, the time it takes for the Robot to detect a target.	1	2
Robot Classification Prob	Improve on the soldier's ability to classify a target as a threat, friendly, or neutral with a Robot.	The probability the Robot can classify a target correctly.	1	2
Robot IED Sensor Class Prob	Increase the ability for a robot to detect and classify an IED.	The probability a Robot can detect and IED.	1	2
Robot No. Hits to Kill	Increase the Robot protection from kinetic fire.	The number of hits to kill a Robot agent.	4	6
Robot FOV	Increase the Robots field of view.	The Robot's field of view.	50	180
Robot Stealth	Reduce the size of the Robot in order to decrease the ability to detect the Robot.	The enemy's probability of detecting the Robot.	0.3	1

10. Appendix III: Final Convergence Comparison Output

10.1. Alpha = 0.95

Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
0UAV	0	0		0UAV	0	0
1UAV	1	1		1UAV	1	1
2UAV	2	2		2UAV	2	2
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1SBin:1	1	1		1SBin:1	0	0
1SBin:2	0	0		1SBin:2	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1DetDistBin:1	0	0		1DetDistBin:1	0	0
1DetDistBin:2	1	1		1DetDistBin:2	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
UAV1Miss0	0	0		UAV1Miss0	0	0
UAV1Miss1	1	1		UAV1Miss1	1	1
UAV1Miss2	2	2		UAV1Miss2	2	2
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
2SBin:1	0	0		2SBin:1	0	0
2SBin:2	0	0		2SBin:2	0	0
2SBin:3	0	0		2SBin:3	0	0
2SBin:4	0	0		2SBin:4	0	0

Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
2DetDistBin:1	0	0		2DetDistBin:1	0	0
2DetDistBin:2	0	0		2DetDistBin:2	0	0
2DetDistBin:3	0	0		2DetDistBin:3	0	0
2DetDistBin:4	0	0		2DetDistBin:4	0	0
2DetDistBin:5	0	0		2DetDistBin:5	0	0
2DetDistBin:6	0	0		2DetDistBin:6	0	0
2DetDistBin:7	0	0		2DetDistBin:7	0	0
2DetDistBin:8	0	0		2DetDistBin:8	0	0
2DetDistBin:9	0	0		2DetDistBin:9	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
UAV2Miss1	1	1		UAV2Miss1	1	1
UAV2Miss2	0	0		UAV2Miss2	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
NoEnhRif	0	0		NoEnhRif	0	0
EnhRif	1	1		EnhRif	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1RngBin:7	0	0		1RngBin:7	0	0
1RngBin:8	0	1		1RngBin:8	0	1
1RngBin:9	0	1		1RngBin:9	0	1
1RngBin:10	1	1		1RngBin:10	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1FRBin:1	0	0		1FRBin:1	0	0
1FRBin:2	0	0		1FRBin:2	0	0
1FRBin:3	0	0		1FRBin:3	0	0

1FRBin:4	0	0		1FRBin:4	0	0
1FRBin:5	0	0		1FRBin:5	0	0
1FRBin:6	0	0		1FRBin:6	0	0
1FRBin:7	0	0		1FRBin:7	0	0
1FRBin:8	0	0		1FRBin:8	0	0
1FRBin:9	0	0		1FRBin:9	0	0
1FRBin:10	0	0		1FRBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1HPrbBin:1	0	0		1HPrbBin:1	0	0
1HPrbBin:2	0	0		1HPrbBin:2	0	0
1HPrbBin:3	0	0		1HPrbBin:3	0	0
1HPrbBin:4	0	0		1HPrbBin:4	0	0
1HPrbBin:5	0	0		1HPrbBin:5	0	0
1HPrbBin:6	0	0		1HPrbBin:6	0	0
1HPrbBin:7	0	0		1HPrbBin:7	0	0
1HPrbBin:8	0	0		1HPrbBin:8	0	0
1HPrbBin:9	0	0		1HPrbBin:9	0	0
1HPrbBin:10	0	0		1HPrbBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
LethMit_4	0	0		LethMit_4	0	0
LethMit_5	1	1		LethMit_5	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
NoEnhBA	0	0		NoEnhBA	0	0
EnhBA	1	1		EnhBA	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
KinProt_8	0	0		KinProt_8	0	0

KinProt_9	1	1		KinProt_9	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
ChemProt_1	0	0		ChemProt_1	0	0
ChemProt_2	1	1		ChemProt_2	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
IEDProt_1	0	0		IEDProt_1	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
NucProt_1	1	1		NucProt_1	0	0
NucProt_2	0	0		NucProt_2	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
0Rob	0	0		0Rob	0	0
1Rob	1	1		1Rob	1	1
2Rob	2	2		2Rob	2	2
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1RSBin:1	0	0		1RSBin:1	0	0
1RSBin:2	0	0		1RSBin:2	0	0
1RSBin:3	0	0		1RSBin:3	0	0
1RSBin:4	0	0		1RSBin:4	0	0
1RSBin:5	0	0		1RSBin:5	0	0
1RSBin:6	0	0		1RSBin:6	0	0

Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1IEDBin:1	0	0		1IEDBin:1	0	0
1IEDBin:2	0	1		1IEDBin:2	1	1
1IEDBin:3	1	1		1IEDBin:3	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1CRBin:1	0	0		1CRBin:1	0	0
1CRBin:2	0	0		1CRBin:2	0	0
1CRBin:3	0	0		1CRBin:3	0	0
1CRBin:4	0	0		1CRBin:4	0	0
1CRBin:5	0	0		1CRBin:5	0	0
1CRBin:6	0	0		1CRBin:6	0	0
1CRBin:7	0	0		1CRBin:7	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
2RSBin:1	0	0		2RSBin:1	0	0
2RSBin:2	0	0		2RSBin:2	0	0
2RSBin:3	0	0		2RSBin:3	0	0
2RSBin:4	0	0		2RSBin:4	0	0
2RSBin:5	0	0		2RSBin:5	0	0
2RSBin:6	0	0		2RSBin:6	0	0
2RSBin:7	0	0		2RSBin:7	0	0
2RSBin:8	0	0		2RSBin:8	0	0
2RSBin:9	0	0		2RSBin:9	0	0
2RSBin:10	0	0		2RSBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
2IEDBin:1	0	0		2IEDBin:1	0	0
2IEDBin:2	0	0		2IEDBin:2	0	0
2IEDBin:3	0	0		2IEDBin:3	0	0
2IEDBin:4	0	0		2IEDBin:4	0	0

2IEDBin:5	0	0		2IEDBin:5	0	0
2IEDBin:6	0	0		2IEDBin:6	0	0
2IEDBin:7	0	0		2IEDBin:7	0	0
2IEDBin:8	0	0		2IEDBin:8	0	0
2IEDBin:9	0	0		2IEDBin:9	0	0
2IEDBin:10	0	0		2IEDBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
2CRBin:1	0	0		2CRBin:1	0	0
2CRBin:2	0	0		2CRBin:2	0	0
2CRBin:3	0	0		2CRBin:3	0	0
2CRBin:4	0	0		2CRBin:4	0	0
2CRBin:5	0	0		2CRBin:5	0	0
2CRBin:6	0	0		2CRBin:6	0	0
2CRBin:7	0	0		2CRBin:7	0	0
2CRBin:8	0	0		2CRBin:8	0	0
2CRBin:9	0	0		2CRBin:9	0	0
2CRBin:10	0	0		2CRBin:10	0	0

10.2. Alpha = 0.99

Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
0UAV	0	0		0UAV	0	0
1UAV	1	1		1UAV	1	1
2UAV	2	2		2UAV	2	2
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1SBin:1	1	1		1SBin:1	0	0
1SBin:2	0	0		1SBin:2	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1DetDistBin:1	0	0		1DetDistBin:1	0	0

1DetDistBin:2	1	1		1DetDistBin:2	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
UAV1Miss0	0	0		UAV1Miss0	0	0
UAV1Miss1	1	1		UAV1Miss1	1	1
UAV1Miss2	2	2		UAV1Miss2	2	2
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
2SBin:1	0	0		2SBin:1	0	0
2SBin:2	0	0		2SBin:2	0	0
2SBin:3	0	0		2SBin:3	0	0
2SBin:4	0	0		2SBin:4	0	0
2SBin:5	0	0		2SBin:5	0	0
2SBin:6	0	0		2SBin:6	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
2DetDistBin:1	0	0		2DetDistBin:1	0	0
2DetDistBin:2	0	0		2DetDistBin:2	0	0
2DetDistBin:3	0	0		2DetDistBin:3	0	0
2DetDistBin:4	0	0		2DetDistBin:4	0	0
2DetDistBin:5	0	0		2DetDistBin:5	0	0
2DetDistBin:6	0	0		2DetDistBin:6	0	0
2DetDistBin:7	0	0		2DetDistBin:7	0	0
2DetDistBin:8	0	0		2DetDistBin:8	0	0
2DetDistBin:9	0	0		2DetDistBin:9	0	0
2DetDistBin:10	0	0		2DetDistBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
UAV2Miss1	1	1		UAV2Miss1	1	1
UAV2Miss2	0	0		UAV2Miss2	0	0

Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
NoEnhRif	0	0		NoEnhRif	0	0
EnhRif	1	1		EnhRif	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1RngBin:8	0	0		1RngBin:8	0	0
1RngBin:9	0	0		1RngBin:9	0	0
1RngBin:10	0	0		1RngBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1FRBin:1	0	0		1FRBin:1	0	0
1FRBin:2	0	0		1FRBin:2	0	0
1FRBin:3	0	0		1FRBin:3	0	0
1FRBin:4	0	0		1FRBin:4	0	0
1FRBin:5	0	0		1FRBin:5	0	0
1FRBin:6	0	0		1FRBin:6	0	0
1FRBin:7	0	0		1FRBin:7	0	0
1FRBin:8	0	0		1FRBin:8	0	0
1FRBin:9	0	0		1FRBin:9	0	0
1FRBin:10	0	0		1FRBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1HPrbBin:1	0	0		1HPrbBin:1	0	0
1HPrbBin:2	0	0		1HPrbBin:2	0	0
1HPrbBin:3	0	0		1HPrbBin:3	0	0
1HPrbBin:4	0	0		1HPrbBin:4	0	0
1HPrbBin:5	0	0		1HPrbBin:5	0	0
1HPrbBin:6	0	0		1HPrbBin:6	0	0
1HPrbBin:7	0	0		1HPrbBin:7	0	0

1HPrbBin:8	0	0		1HPrbBin:8	0	0
1HPrbBin:9	0	0		1HPrbBin:9	0	0
1HPrbBin:10	0	0		1HPrbBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
LethMit_4	0	0		LethMit_4	0	0
LethMit_5	1	1		LethMit_5	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
NoEnhBA	0	0		NoEnhBA	0	0
EnhBA	1	1		EnhBA	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
KinProt_7	0	0		KinProt_7	0	0
KinProt_8	0	1		KinProt_8	0	1
KinProt_9	2	2		KinProt_9	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
ChemProt_1	0	0		ChemProt_1	0	0
ChemProt_2	1	1		ChemProt_2	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
IEDProt_1	0	0		IEDProt_1	0	0
IEDProt_2	1	1		IEDProt_2	1	1

Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
NucProt_1	1	1		NucProt_1	0	0
NucProt_2	0	0		NucProt_2	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
0Rob	0	0		0Rob	0	0
1Rob	1	1		1Rob	1	1
2Rob	2	2		2Rob	2	2
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1RSBin:1	0	0		1RSBin:1	0	0
1RSBin:2	0	0		1RSBin:2	0	0
1RSBin:3	0	0		1RSBin:3	0	0
1RSBin:4	0	0		1RSBin:4	0	0
1RSBin:5	0	0		1RSBin:5	0	0
1RSBin:6	0	0		1RSBin:6	0	0
1RSBin:7	0	0		1RSBin:7	0	0
1RSBin:8	0	0		1RSBin:8	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1IEDBin:1	0	0		1IEDBin:1	0	0
1IEDBin:2	1	1		1IEDBin:2	1	1
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
1CRBin:1	0	0		1CRBin:1	0	0
1CRBin:2	0	0		1CRBin:2	0	0
1CRBin:3	0	0		1CRBin:3	0	0
1CRBin:4	0	0		1CRBin:4	0	0
1CRBin:5	0	0		1CRBin:5	0	0

1CRBin:6	0	0		1CRBin:6	0	0
1CRBin:7	0	0		1CRBin:7	0	0
1CRBin:8	0	0		1CRBin:8	0	0
1CRBin:9	0	0		1CRBin:9	0	0
1CRBin:10	0	0		1CRBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
2RSBin:1	0	0		2RSBin:1	0	0
2RSBin:2	0	0		2RSBin:2	0	0
2RSBin:3	0	0		2RSBin:3	0	0
2RSBin:4	0	0		2RSBin:4	0	0
2RSBin:5	0	0		2RSBin:5	0	0
2RSBin:6	0	0		2RSBin:6	0	0
2RSBin:7	0	0		2RSBin:7	0	0
2RSBin:8	0	0		2RSBin:8	0	0
2RSBin:9	0	0		2RSBin:9	0	0
2RSBin:10	0	0		2RSBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
2IEDBin:1	0	0		2IEDBin:1	0	0
2IEDBin:2	0	0		2IEDBin:2	0	0
2IEDBin:3	0	0		2IEDBin:3	0	0
2IEDBin:4	0	0		2IEDBin:4	0	0
2IEDBin:5	0	0		2IEDBin:5	0	0
2IEDBin:6	0	0		2IEDBin:6	0	0
2IEDBin:7	0	0		2IEDBin:7	0	0
2IEDBin:8	0	0		2IEDBin:8	0	0
2IEDBin:9	0	0		2IEDBin:9	0	0
2IEDBin:10	0	0		2IEDBin:10	0	0
Characteristic/Interval	Value Min Group	Value Max Group		Characteristic/Interval	Cost Min Group	Cost Max Group
2CRBin:1	0	0		2CRBin:1	0	0
2CRBin:2	0	0		2CRBin:2	0	0

2CRBin:3	0	0		2CRBin:3	0	0
2CRBin:4	0	0		2CRBin:4	0	0
2CRBin:5	0	0		2CRBin:5	0	0
2CRBin:6	0	0		2CRBin:6	0	0
2CRBin:7	0	0		2CRBin:7	0	0
2CRBin:8	0	0		2CRBin:8	0	0
2CRBin:9	0	0		2CRBin:9	0	0
2CRBin:10	0	0		2CRBin:10	0	0