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Demonstrating Set-Based Design Techniques- A UAV Case study

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Demonstrating Set-Based Design Techniques- A UAV Case study

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Abstract

The Department of Defense (DoD) and Engineered Resilient Systems (ERS) community seek to improve decision making in the Analysis of Alternatives (AoA) process by incorporating resilience and leveraging the capabilities of model-based engineering (MBE) early in the design process. Traditional tradespace exploration utilizing Point-Based Design (PBD) often converges quickly on a solution with subsequent engineering changes to modify the design. However, this process can lead to a suboptimal solution if an incorrect initial solution is chosen. Enabled by MBE, Set-Based Design (SBD) considers sets of all possible solutions and enables down-selecting possibilities to converge on a final solution. Using a US Army Armament Research, Development, and Engineering Center case study and an open source Excel® add-in called SIPmath, this research develops an integrated MBE case study demonstration that simultaneously generates numerous designs using physics models into the value and cost tradespace allowing for tradespace exploration and SBD. In addition, this research explores incorporating resilience quantification and uncertainty into SBD.

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1. Introduction

1.1. ERS Program

In recent years there has been an increased need for resilience in complex military and civilian systems due to evolving adversarial and environmental threats. As systems become increasingly interconnected and technology advances more quickly, it becomes harder for systems to resist threats. Often systems are used in unplanned missions or new scenarios with different threats. Therefore, systems need to be resilient not only to planned threats and functions, but they also need to be resilient to uncertain threats and be easily modified to add new functionality.

> *"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, et al., 2017)

As a response to the need for resilient systems, the Department of Defense (DoD) has created the Engineering Resilient Systems (ERS) program. ERS focuses on the effective and efficient design and development of complex resilient engineered systems throughout their lifecycle. Analysis of Alternatives (AoA) is a DoD requirement of military acquisition policy to ensure multiple design alternatives have been analyzed prior to making costly investment decisions. (U.S. Office of Management and Budget, 2008) In the military and defense industries, current AoAs using requirements analysis do not always plan for future threats, missions, or scenarios. Through ERS, the DoD seeks to improve its AoAs and get better buying power by: addressing resilience early in the design cycle, using tradespace and analytics tools and high-performance computing to explore the design space, and using Computational Research & Engineering Acquisition Tools and Environments (CREATE) shown in *Figure 1*. (Holland, 2015)

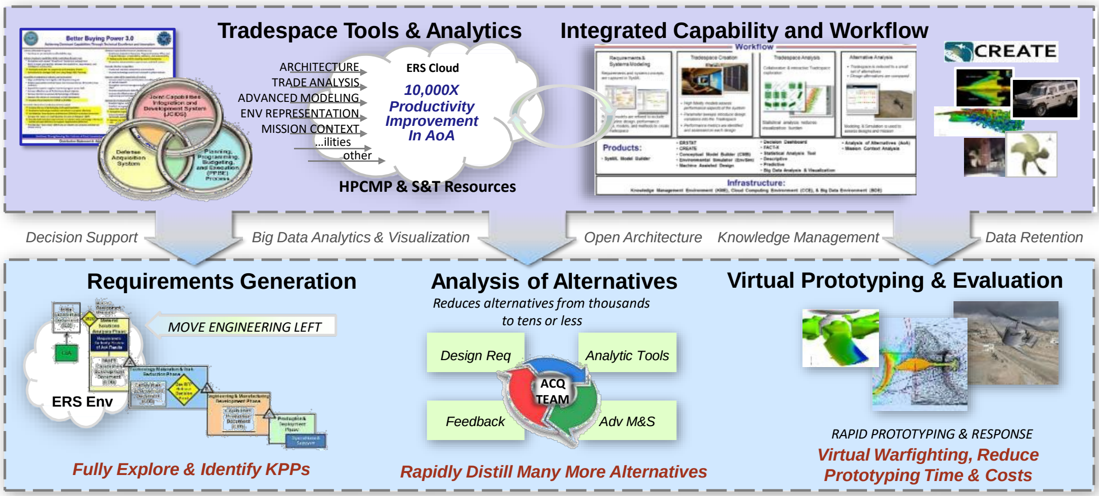


Figure 1- ERS Summary (Holland, 2015)

To engineer resilient systems, system designers and managers must contemplate design options considering various scenarios, missions, functions and their performance measures, threats including environmental conditions, adversary actions, detectable performance degradation, uncertain survivability, and measurable recovery over time. Resilient design options include means for flexible adaptability, which provide the ability to reconfigure and/or replace components during the system lifetime. The criteria to evaluate the design options must include the impact on performance, cost, and schedule. A trade-off analysis is critical to ensure senior decision makers can determine the affordability of systems and their design options allowing for improved resilience.

1.2. AoA Improvements

In current AoA best practices, analysts begin by identifying missions, scenarios, threats, and capability gaps. Based on these, possible system solutions are identified. However, these solutions have typically been Point-Based Design (PBD) solutions which do not fully explore the design space. Specifically, “at a minimum, the AoA must include the following alternatives: the baseline, alternatives based on potential, yet unfunded improvements to the baseline, [and] alternatives identified in the AoA study guidance (for example allied systems etc.)" (OAS, 2013) Then cost drivers, performance measures, and relevant "illities" need to be determined. To quantify the future capabilities of these alternatives, analysts perform modeling and simulation. Using these results, the value and the costs are determined for the alternatives considered. Lastly, the affordability of the systems is analyzed using trade-offs between both the value and cost estimates.

To incorporate ERS into AoAs, the three steps in red in *Figure 2* have been identified as new steps to be added to the current AoA process (Small C. , et al., 2017). Instead of considering a limited number of Point-Based Designs, the design space should be expanded and options to improve resilience should be added. Options to extend the service lifetime should also be evaluated. Lastly, analysis of resilience options and resilience tradeoffs need to be made. To improve the AoA process, the DoD (especially the Navy) is interested in using SBD to expand the design space considered and improve their buying power. (Specking, et al., 2017) (Singer, Doerry, & Buckley, 2009)

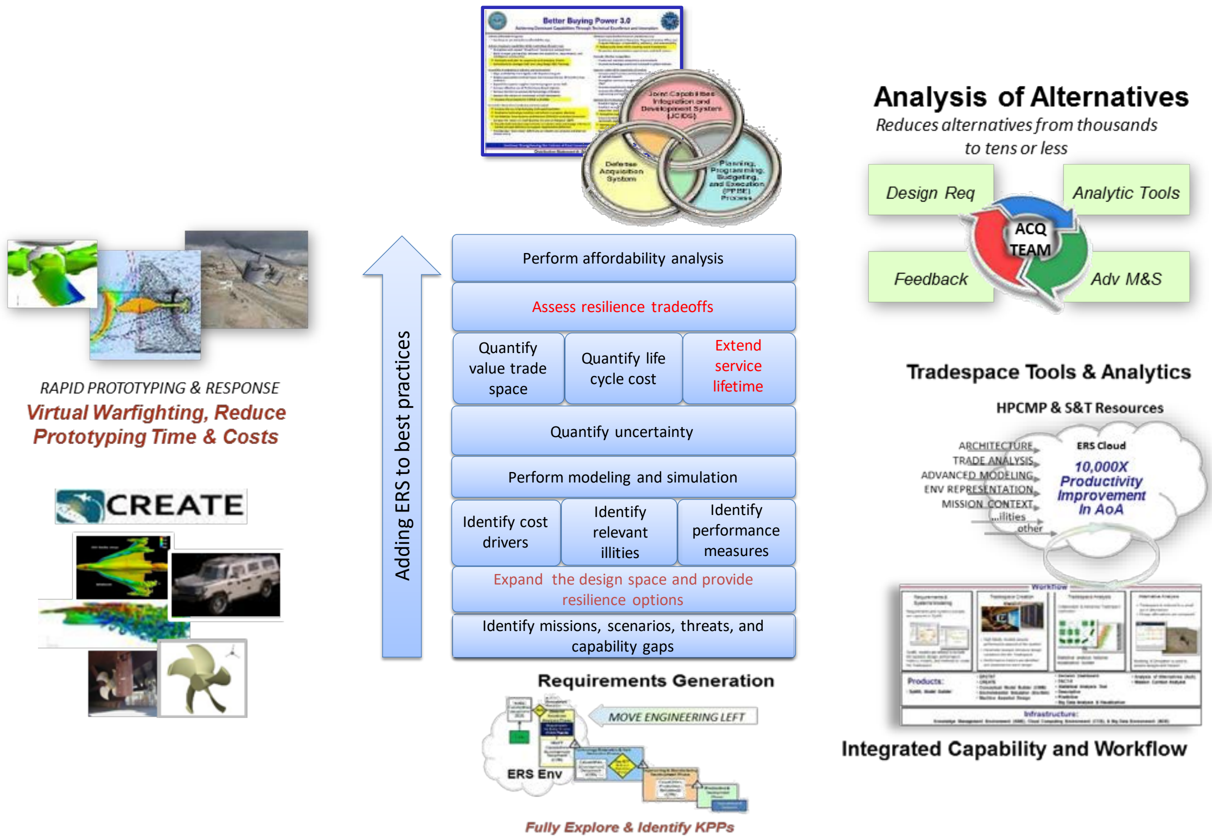


Figure 2- Incorporating ERS into AoAs (Small C. , et al., 2017)

1.3.MBE and Set-Based Design to Improve AoAs

The DoD and the ERS program seek to leverage the capabilities of model-based engineering early in the design process to improve decision making in the AoA. Advances in computing capabilities have increased the use of models (e.g., physics-based performance models) and simulations to explore the design space by simulating the performance of a large number of system design variants in a relatively short time. (Rinaudo, Buchanan, & Barnett, 2016) Tradespace exploration (TSE) supports engineered resilient system design and development by providing mission analysts, designers, systems analysts, and decision makers with an understanding of capabilities, gaps, and potential trade-offs required to achieve system objectives. Additionally, decisions can be made throughout a system's lifecycle that continuously redefine its capabilities, performance, cost, manufacturability, delivery, and sustainability. (Kelley, Goerger, & Buchanan, 2016) TSE provides decision makers with an understanding of candidate system component choices and the implications of decisions on multiple missions across joint war fighting environments. (Spero, Avera, Valdez, & Goerger, 2014)

TSE of traditional PBD quickly converges on a single design, resulting in the modification of the chosen solution until it meets the design objectives. While this may seem to be an effective approach, if an inferior Point-Based Design is chosen, the following refinements can be time consuming and end at a suboptimal design. (Iansiti, 1995) (Kalyanaram & Krishnan, 1997) However, using SBD for TSE considers sets of all possible solutions and enables eliminating possibilities to converge at a final solution. When many solutions are considered in the beginning, the likelihood identifying an optimal solution increases. While it is a large investment to fully define and explore the tradespace, SBD provides for the discovery of an optimal solution which may have been missed by a Point-Based Design process. For DoD and ERS, Set-Based Design is useful for projects with many design variables, tight coupling among design variables, conflicting requirements, flexibility in requirements allowing for trades, or technologies and design problems not well understood. (GovEvents, 2017)

1.4.Research Objective

Based on the desires and needs of ERS, this research seeks to develop and implement an integrated trade-off analytics framework (See Figure 3) for a hypothetical unmanned aerial vehicle (UAV) case study developed by the Army Armament Research Development and Engineering Center (ARDEC) to stimulate and focus academic discussion regarding systems engineering tradeoff analyses. (Cilli, Decision Framework Approach Using the Integrated Systems Engineering Decision Management (ISEDM) Process., 2017) Using this framework, this research seeks to develop, refine, and implement methods for performing SBD in the UAV case study. In addition, this research also seeks to develop methods to incorporate model-based engineering, resilience quantification, and uncertainty in physics, cost, and value models, into SBD.

In the remainder of the document, Section 2 describes the integrated trade-off analytics framework applied to the UAV case study. Section 3 defines SBD. Section 4 details the UAV case study used, much of which is included in Appendix 1. Section 5 demonstrates the implementation of the trade-off analytics framework and SBD for the model. Lastly, Section 6 describes the advantages and insights of this methodology, implementation challenges, and concludes the paper.

2. Integrated Trade-off Analytics Framework

To sufficiently explore the design space and analyze resilient systems, we have developed an integrated trade-off analytics framework for defining and evaluating complex engineered systems considering multiple missions, scenarios, uncertainties, functions, and measures. (Small C. , et al., 2017) Using Model-Based Engineering (MBE), this framework prescribes an integrated model which simultaneously propagates design decisions all the way to the affordability tradespace. This framework uses the three types of analytics: descriptive, predictive, and prescriptive. The descriptive section of the framework describes what the system is and how it will be used. The predictive section includes the models predicting performance, cost, etc. And the prescriptive section uses the requirements and values of decision makers to determine feasible solutions and evaluate trade-offs between feasible solutions. This framework can be applied to PBD or SBD. Visually this framework is shown as an influence diagram in Figure 3 with all nodes defined in Table 1. An influence diagram is a concise representation of a decision opportunity. (Parnell, Bresnick, Tani, & Johnson, 2013) Influence diagrams identity the variables and their relationships but suppress the details. Influence diagrams use four nodes: decision, uncertainty, constant, and value. A decision node represents the decision alternatives or options and is displayed by a rectangle. An uncertainty node represents the different outcomes of an uncertain event and is depicted as an oval. Constant nodes are not use in Figure 3. Lastly, an influence diagram has value nodes denoting the decision makers' preferences for potential system outcomes and is depicted as a hexagon. This influence diagram has three value nodes: value (based on performance versus objectives), life-cycle cost, and affordability (value versus cost for the service life). In the diagram, arrows are used to display influences. There are two types of influences: a probabilistic relationship and the availability of information. The time sequence of the events is from left to right. Conditional notation is used to reduce the number of arrows shown in the influence diagram. For example, the annotation, L|D, R means the service life is dependent on the design decisions, D, and the response decisions, R. Each of the nodes is described in Table 1.

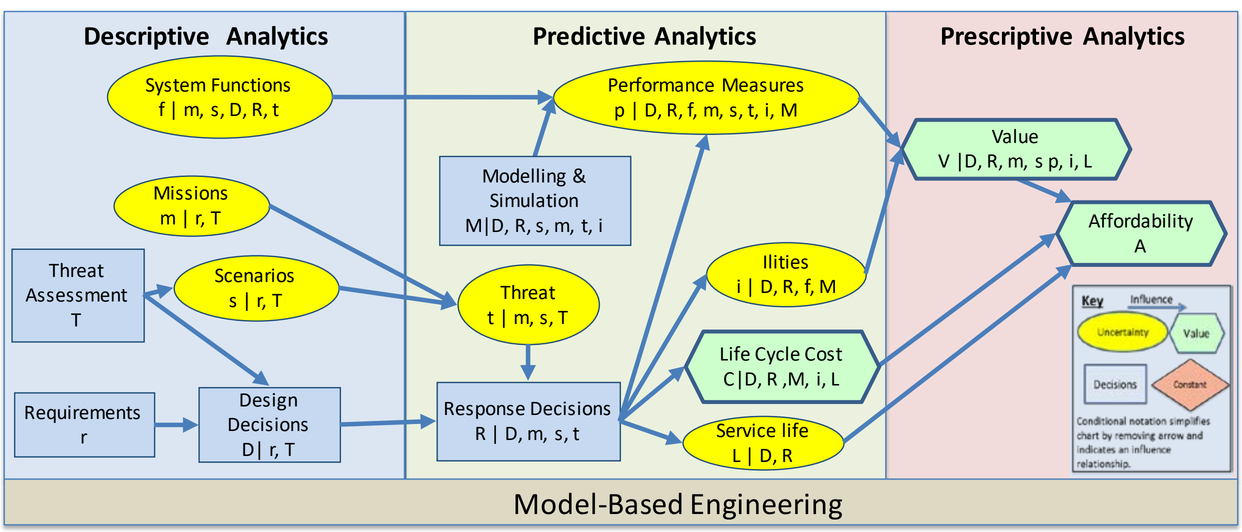


Figure 3- Framework for Integrated Analysis of Alternatives (Small C. , et al., 2017)

Table 1- Node Definitions for the Integrated Framework Influence Diagram

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.

This integrated framework is based on four important concepts. First, the framework makes use of models or simulations to explore the design space. Second, the framework uses Multiple Objective Decision Analysis (MODA) to convert performance measures to a multiple objective value model that prescriptively defines the value tradespace. (Parnell, Bresnick, Tani, & Johnson, 2013) Third, the integrated framework means the design decision are simultaneously propagated through all the intermediary calculations to the value and cost tradespace. This is a very critical component not used in most AoAs. Often there are four separate teams, designers, capability and value analysts, cost analysts, and risk analyst, performing the analysis in AoAs. It is challenging to coordinate the analysis of the four teams. Using separate teams to perform the analysis in different areas can result in inconsistent uncertainty analysis, changes not propagated through the entire analysis, and errors if the different teams do not communicate well. Using an integrated and simultaneous approach to modelling, this framework removes these risks and errors, in addition to speeding up the ability of the AoA to handle changes. Fourth, includes uncertainties in the framework allows for assessment of uncertainty in the performance and cost tradespace.

3. Set-Based Design

Set-Based Design (SBD) is an alternative to PBD on which there have been many publications since Ward et al. first described the process in 1995. (Ward, Liker, Cristiano, & Sobek, 1995) In these publications, SBD approaches typically breaks down the overall system design problem into multiple distinct disciplines each using sets of possibilities. This allows the disciplines to work independently defining and eliminating infeasible alternatives, whilst communicating information among the teams on the feasibility of the combinations of sets of alternatives. In this process, a leader is required to identify ranges of design variables for the disciplinary design teams and adjudicates the disciplinary design decisions when conflicts arise. Once enough information and data are available to eliminate alternatives from consideration as the process moves forward. In SBD, models and simulations can also be used to develop the tradespace to explore the value, cost, and risk for multiple concepts and multiple architectures for each concept.

In point-based design, several potential designs are generated and analyzed. From these the best is selected as a solutions and modified until a solutions is found. (Liker, Sobek, Ward, & Cristiano, 1996) PBD analyzes a finite number of points in the tradespace and is dependent of the expertise of the system design team to identify and develop the initial alternatives. Unlike PBD, SBD explicitly considers sets of design choices instead of discrete points. Exploring the ranges of design choices, SBD considers the entire design space, breaking the tradespace into sets. Each set may include thousands of points. Since SBD explores significantly more points than PBD, SBD can potentially identify points in sets on the Pareto frontier better than the original PBD points. These differences between PBD trade-off analytics and SBD trade-off analytics are shown in Figure 4.

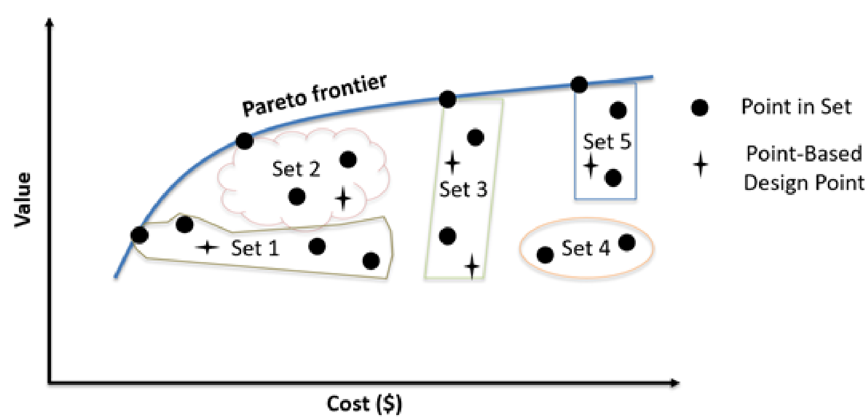


Figure 4- Value versus Cost Tradespace with PBD and SBD (Wade et al, 2018)

Future research is needed to develop mathematically sound SBD trade-off analysis techniques to be applied throughout the system design life cycle. SBD can change how engineers and design teams approach system designs. To fully take advantage of SBD, designers will need to further embrace Model-Based Engineering (MBE) approaches. Models and simulations provide the data necessary to ensure feasible alternatives and perform trade-off analytics. Because SBD considers the entire design space, the complexity of system design trade-off analytics is drastically increased, especially for more complex systems where performance estimates may require High Performance Computers (HPCs) to calculate. SBD trade-off analytics method(s) that are mathematically sound, tractable, and repeatable are needed to help identify the design choices, explore, and evaluate the potential design space.

4. ARDEC UAV Case Study

4.1. Introduction

Sponsored by ERS, a research team at ARDEC has been developing a UAV case study to provide a hypothetical, yet plausible example for comparing systems engineering trade-off analysis methods in the context of new product development efforts. (Cilli, Decision Framework Approach Using the Integrated Systems Engineering Decision Management (ISEDM) Process., 2017) Gundlach's textbook, "Designing Unmanned Aircraft Systems: A Comprehensive Approach" is used as the primary basis for all physical architecture descriptions of the notional UAVS and requirements as well as many of the mathematical relationships that propagate design decisions to value and cost. (Gundlach, 2012) (Small C. , et al., 2018) Many of the other mathematical relationships are based on observations from UAV descriptions from Compendium Drone 2013. (Armada International, 2013)

In the case study, stakeholders require a small UAV to perform surveillance missions. There are 7 design decisions fully broken down in Table 2: engine type, operating altitude, wingspan, and the field of view and resolution for two sensor packages that affect the value of the system. Overall the small system must be transportable. It must maneuver to, scan across, and dwell at an area of interest. It must be survivable. And lastly, it must detect adversary activity. The functions, objectives, and performance measures for the UAV case study are displayed in the value hierarchy in Figure 5. In an assessment flow diagram (AFD), the flow of calculations from physical choices through intermediate performance calculations to various value measures is graphically represented from the bottom of the diagram to the top. (Parnell, 2017) Following the UAV Case Study Assessment Flow Diagram in Figure 6, the design choices in Table 2 are propagated through intermediary equations to the value measures in Figure 5. The bottom rows are the design choices, the middle section is the intermediate performance calculations with each shape being a different calculation, and the top section shows the various value measures and objectives. The arrows represent calculation relationships. To move from the design decisions to the value measures in Figure 5, each calculation diagram represents a different physics based model or other mathematical relationship. These models and calculations are fully documented in Appendix 1.

Table 2- Design Choices

Design Choice	Options
Engine	Discrete Choice: • Electric • Piston
Wingspan	Continuous choice: • 2 ft. to 12 ft.
Operating Altitude	Continuous choice: • 300 m. to 1000 m.
Electro-Optical (EO) Sensor Resolution	Discrete Choice: • 200 Pixels X 200 Pixels • 400 Pixels X 400 Pixels • 600 Pixels X 600 Pixels • 800 Pixels X 800 Pixels • 1000 Pixels X 1000 Pixels • 1200 Pixels X 1200 Pixels • 1400 Pixels X 1400 Pixels • 1600 Pixels X 1600 Pixels • 1800 Pixels X 1800 Pixels
EO Sensor Field of View	Discrete Choice: • 15 Degrees • 30 Degrees • 45 Degrees • 60 Degrees • 75 Degrees • 90 Degrees
Infrared (IR) Sensor Resolution	Discrete Choice: • 200 Pixels X 200 Pixels • 400 Pixels X 400 Pixels • 600 Pixels X 600 Pixels • 800 Pixels X 800 Pixels • 1000 Pixels X 1000 Pixels • 1200 Pixels X 1200 Pixels • 1400 Pixels X 1400 Pixels • 1600 Pixels X 1600 Pixels • 1800 Pixels X 1800 Pixels
IR Sensor Field of View	Discrete Choice: • 15 Degrees • 30 Degrees • 45 Degrees • 60 Degrees • 75 Degrees • 90 Degrees

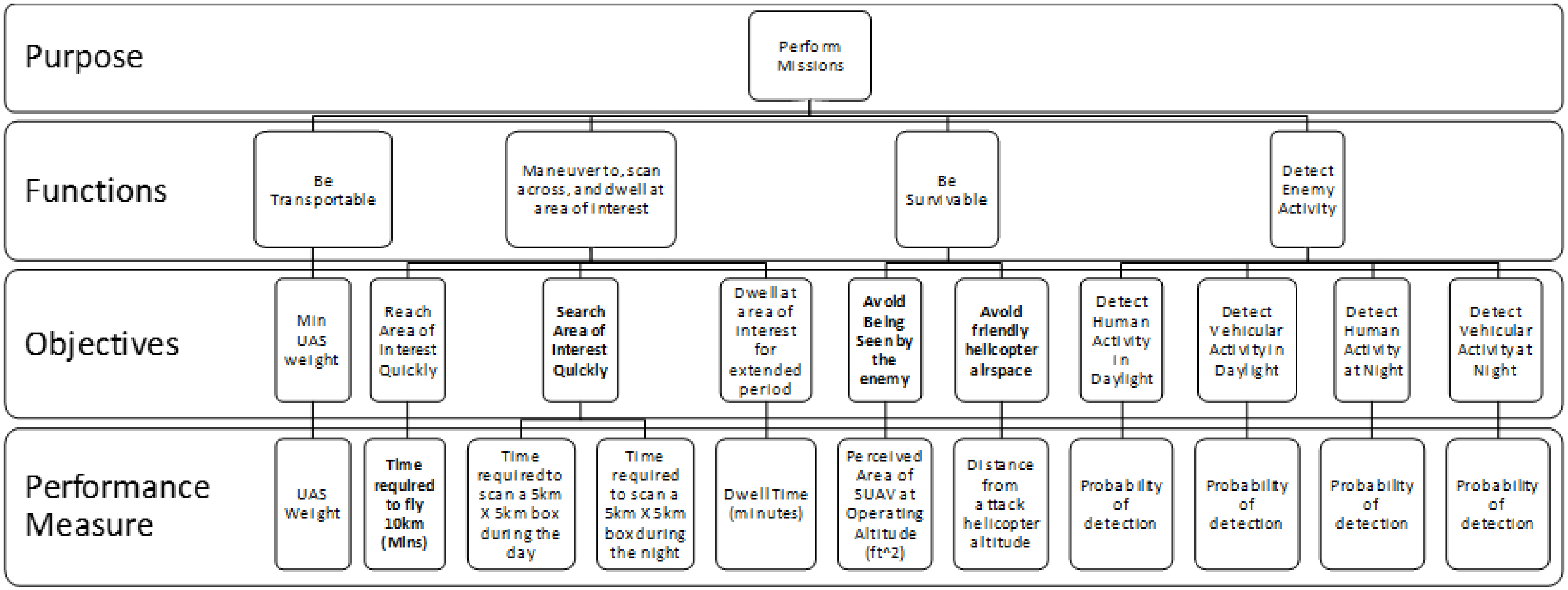


Figure 5- UAV Case Study Value Hierarchy

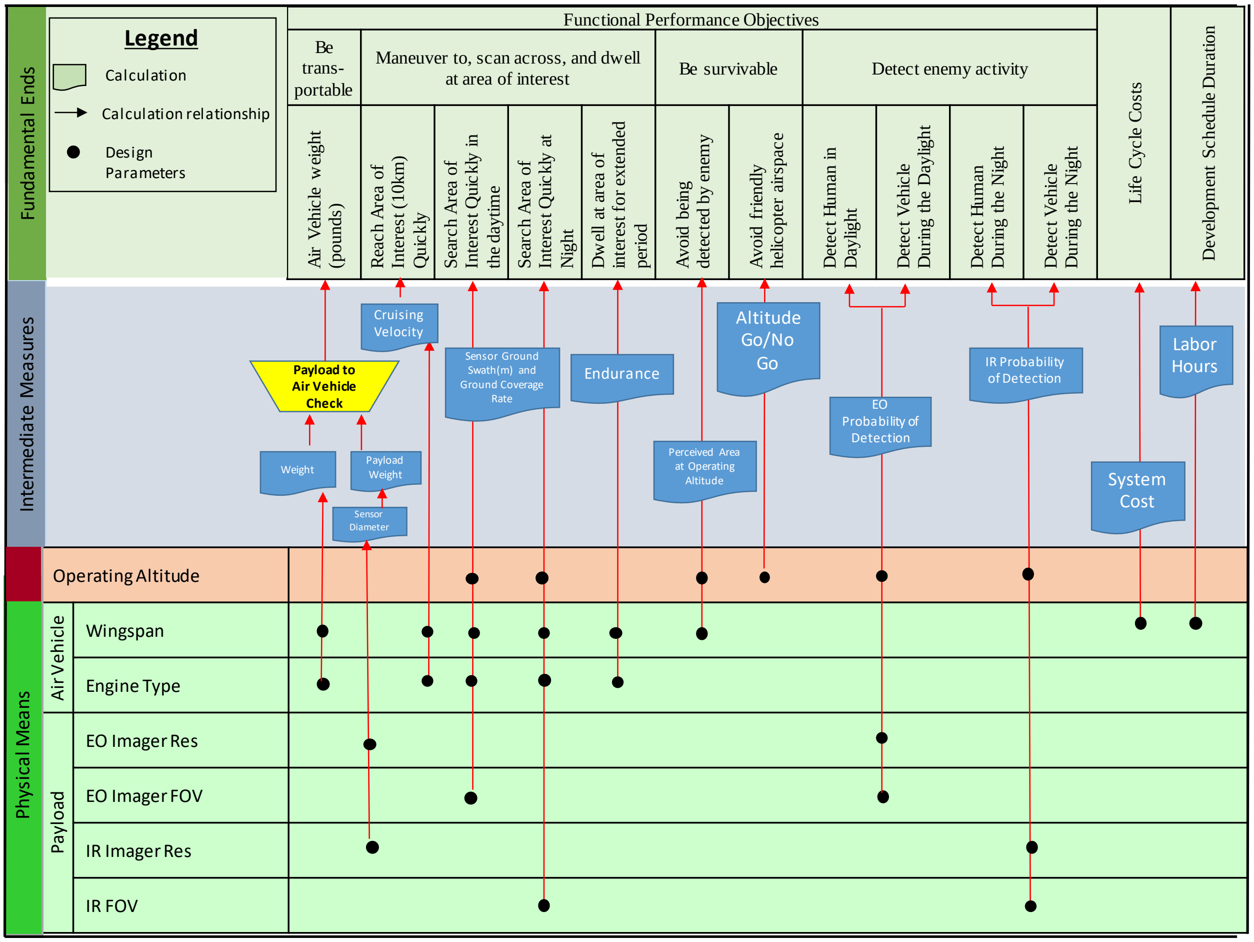


Figure 6- ARDEC UAV Case Study Assessment Flow Diagram (Cilli, 2017)

To calculate the value for any alternative this case study uses a multi-objective value approach as described in Parnell 2017. (Parnell, 2017) This value is calculated using the value curves, swing weights, and value calculations shown in Figures 7, 8, and 9 respectively. For each performance measure in the value hierarchy, there is a value curve that calculates the value between the minimum acceptable and the ideal for each measure. In the value curves in Figure 7, the relative value for a performance score is shown on the y-axis, from zero (minimum acceptable) to 100 (ideal) vs. the respective performance that earns that value, shown on the x axis. The weight for each performance measure is determined using the swing weight matrix method described in Parnell 2017. The swing weight matrix for the case study is shown in Figure 8. Using the value curves and an alternatives performance, the value for a particular system on each measure are calculated. These value scores are multiplied by the swing weights in Figure 8 to calculate the weighted value on each measure. Lastly, the weighted values on the measures are summed to calculate the total system value. An example of this value calculation is shown in Figure 9.

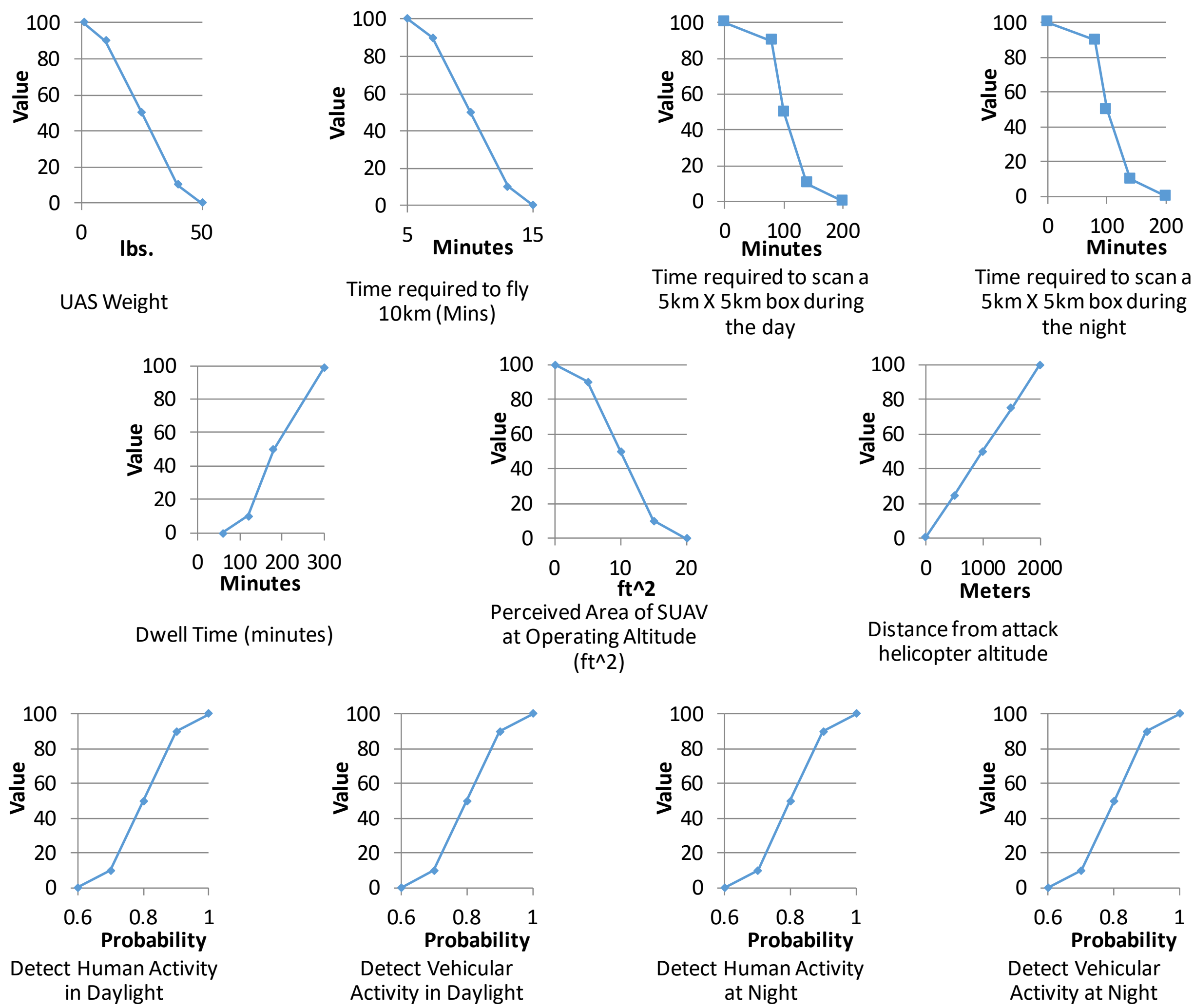


Figure 7- Case Study Value Curves

Swing Weight Matrix

	Critical to mission			Important to mission			Fixable with dollars		
		fi	wi		fi	wi	Assessed fi	fi	wi
Significant impact of performance variation	Probability of detecting a vehicle night	100	0.14	Probability of detecting a human day	75	0.10	Time Required to scan night	60	0.08
	Probability of detecting a vehicle day	99	0.14				Time Required to scan day	50	0.07
	Probability of detecting a human night	98	0.14				Difference from attack helicopter altitude	50	0.07
Some impact of site variation				Time required to fly 10km (Mins)	60	0.08	Percieved Area of SUAV at Altitude	20	0.03
				Dwell Time (Mins)	60	0.08			
				UAS Weight	50	0.07			
Minor impact of site variation									

sum of fi	722.00

Figure 8- Case Study Swing Weights

Value Calculations				
Value Measure	Performance	Value Score	Swing Weight	Weighted Value
UAS Weight	28	41	0.07	3
Time required to fly 10km (Mins)	7	92	0.08	8
Time Required to scan day	47	94	0.07	7
Time Required to scan night	47	94	0.08	8
Dwell Time (Mins)	691	100	0.08	8
Percieved Area of SUAV at Altitude	7	78	0.03	2
Difference from attack helicopter altitude	435	22	0.07	2
Probability of detecting a human day	0.74	25	0.10	3
Probability of detecting a vehicle day	0.80	51	0.14	7
Probability of detecting a human night	0.61	1	0.14	0
Probability of detecting a vehicle night	0.80	49	0.14	7
Value			1.0	**46.4**

Figure 9- Example Value Calculation

4.2. Case Study Changes

Similar to real world AoAs, the case study assumptions changed several times. Besides small changes throughout the process, there were 8 large changes detailed in Table 3 during this research affecting data used for the case study.

Table 3- UAV Case Study Changes

Iteration	Model	Descriptive	Predictive	Prescriptive
1	Initial Case Study			
2	Multiple Changes	The case study was redeveloped from the ground up and given new design choices.	And entirely new set of physics models was used. The only remaining model was the probability of detection.	A completely new value model and new cost model.
3	Design Choices	The set of design choices was expanded as new combinations of sensors were added.	None	None
4	Value Model	None	None	Preferences on value curves were changed. Changing preferences for alternatives.
5	Value Model	None	None	The value curves were changed once more to allow more feasible solutions.
6	Value Model	None	New calculation for distance to attack helicopter added or all alternatives.	A new value measure (distance from attack helicopter) was added.
7	Design Choices	New alternatives for sensor FOV were added and altitude options were reduced after a discussion with Dr. Ham.	None	None
8	Swing Weights	None	None	Swing weights were changed after a discussion with Dr. Ham.
9	Cost Model	None	Cost model was changed to a lifecycle cost model.	None

With each change typical AoAs without integrated and simultaneous MBE techniques face difficulties such as recalculating consistent performance, costs, and risk for the systems. In many traditional AoAs, different groups such as cost analysts, capability analysts, risk analysts, or other groups perform the analysis on different areas of the AoA. Accordingly, if changes are not continually communicated between teams, this can lead to inconsistencies in analysis. However, the integrated and simultaneous MBE methodology described in this paper is resilient to changes. During the analysis the model was able to easily respond to each of the changes described. Due to the integrated and simultaneous calculation of value and cost, each change in the case study was simultaneously propagated through both the value and cost models removing issues with communication, and minimizing effort required to update the AoA.

Moreover, another advantage of the integrated framework was the ability to propagate these changes quickly and to identify the increase in infeasible solutions based on the new data. For instance, in the 4^{th} iterations of the case study, the value curves and minimum requirements were very aggressive, and no solutions were feasible. However, this was not realized until these changes were propagated into the SBD model which showed no feasible solutions in the design space. This insight provided by the model and the use of the trade-off analytics framework and SBD led to changes in the value curves to allow more feasible solutions resulting in the 5^{th} iteration of the model.

5. Trade-off Analytics for UAV Case Study

5.1. Overview

Using the ARDEC UAV Case study, this research has created a tradespace tool and model for use in generating, developing, and exploring Set-Based Design techniques. Following the trade-off analytics hierarchy, this methodology uses an integrated and simultaneous approach using cell referencing directly propagating the design decisions (from Table 2) made on the control panel in Figure 10 through the intermediary calculations in the AFD in Figure 11, adapted from the case study, through a value model, and through a cost model. In addition to the case study, this tradespace tool has fully implemented the trade-off analytics framework and incorporates uncertainty in performance, cost, and value; investigates resilience and perfect options allowing the case study to explore the resilience options, expands the cost model to a lifecycle cost model and explores the entire design space.

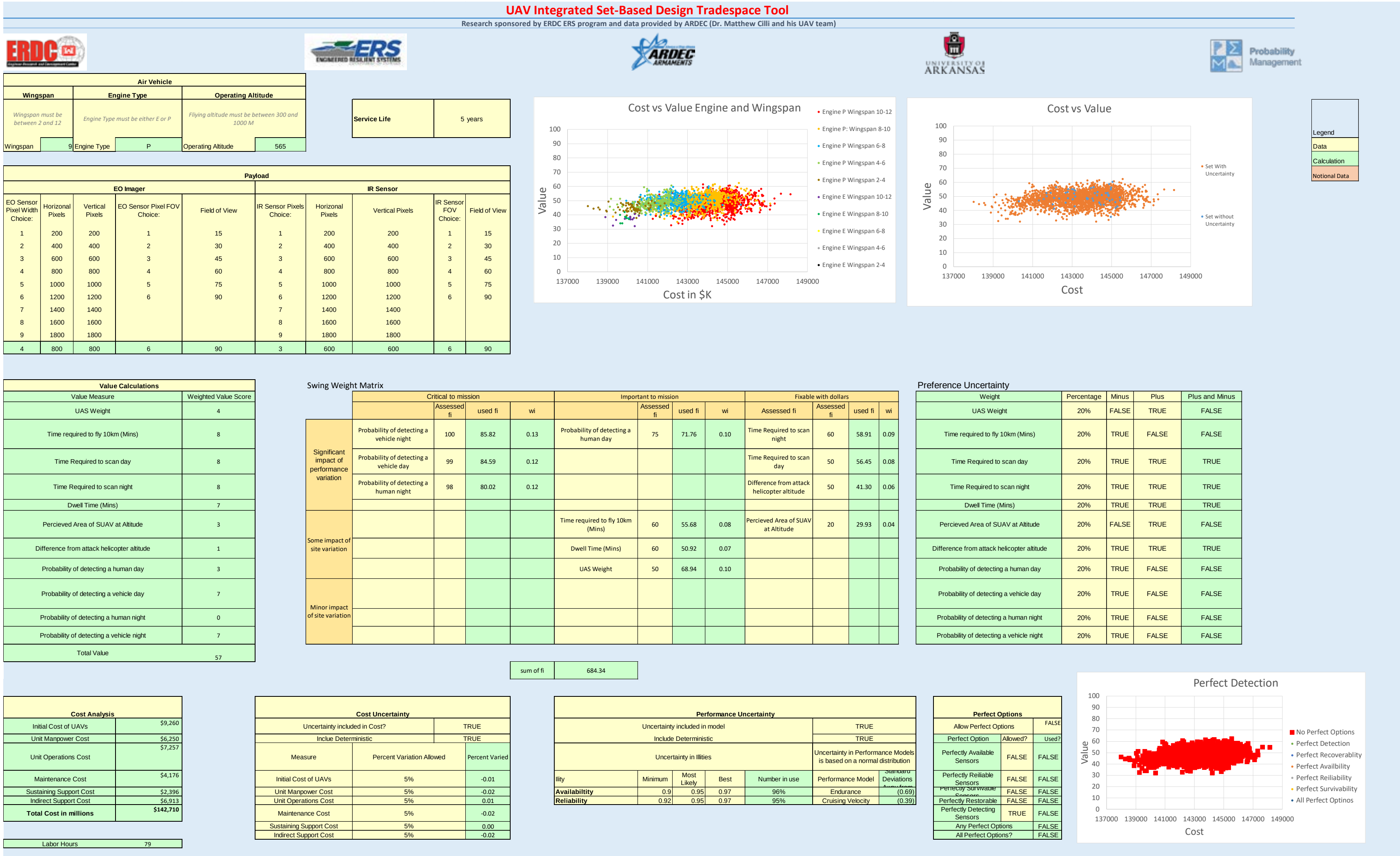


Figure 10- UAV Tradespace Tool Control Panel

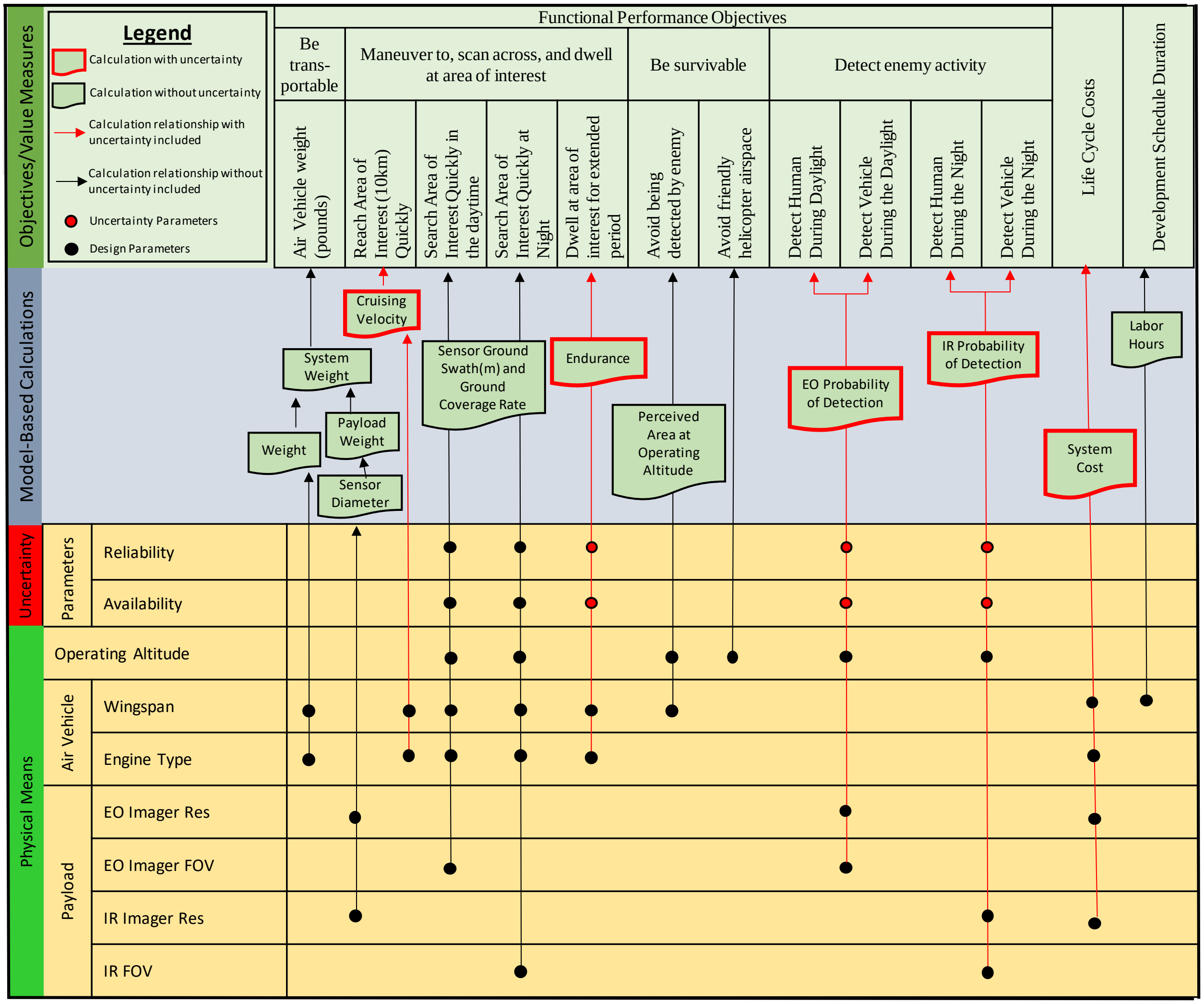
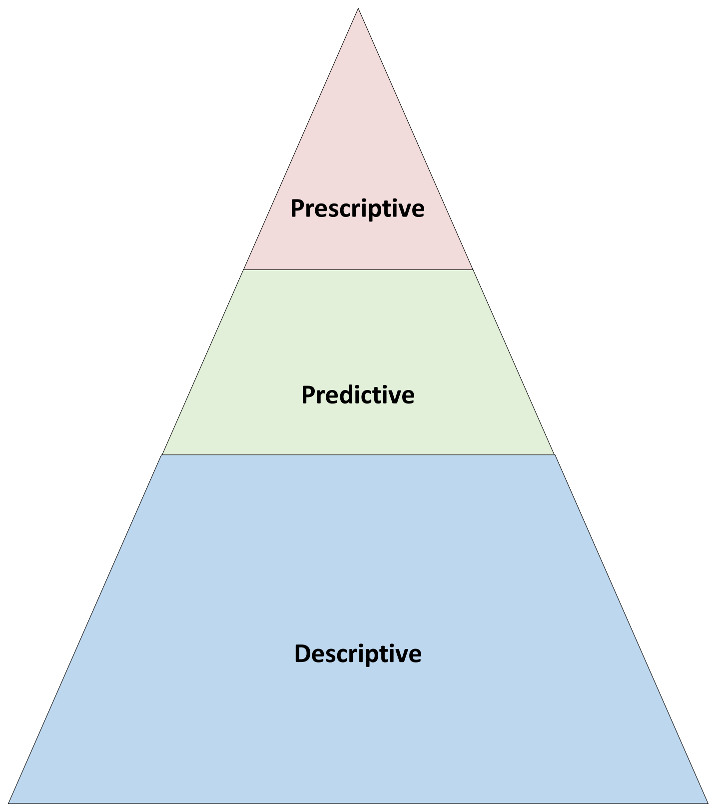


Figure 11- UAV Tradespace Tool Assessment Flow Diagram

5.1.1. SBD with SIPmath®

To perform Set-Based Design, this research uses an Excel® add-in called SIPmath® from Probability Management to generate thousands of design alternatives to enable tradespace exploration and analysis. (Probability Management, 2017) By using native Excel with random numbers and data tables, SIPmath allows for Monte Carlo simulation within Excel. Using Monte Carlo simulations, design choices in the control panel in Figure 10 can be based on random numbers for each choice as shown in Figure 12. Each of these is a unique random number which is varied as SIPmath changes the seed that is used to generate each instance of the random numbers and outputs the value and cost for a unique system for each seed. Figure 12 shows one instance of the random numbers based on a single seed. For each iteration of a Monte Carlo simulation, SIPmath® varies a seed which changes each of the random numbers. Specifically, each of the continuous decisions (wingspan and altitude) are made by using a continuous distribution to distribute the choices throughout the entire range. Each of the discrete design choices are made by sectioning the range of 0-1 into equal partitions based on the number of options in that design parameter. For instance, if there are 5 discrete options, 0-0.2 represents the first option, 0.2-0.4 represents the second option, 0.4-0.6 represents the third, etc. Using a uniform random variable for each discrete design choice, the choice for each instance of the Monte Carlo simulation is chosen based on where the random variable falls within the partitions. Since each of the design choices are uniform, the distribution of solutions will uniformly explore the entire design space.

Using this methodology, we generated 100,000 alternatives for use in exploring and analyzing the tradespace using SBD techniques. Although there were 100,000 alternatives identified in this tool, any number of solutions can be generated using SIPmath. Summarized in the Analytics Hierarchy in Figure 12, this model simultaneously propagates each of the 100,000 alternatives through 47 physics models and formulas into 11 performance measures and a life cycle cost model. This results nearly 22 million intermediary physics model calculations. Propagating these solutions into the value and cost tradespace, we discovered 2,576 feasible solutions meeting the minimum requirements in the value model and all feasibility requirements.



Integrated Value and Cost Model
Multiple Objective Decision Analysis

2,576	Feasible Cost vs Value points
97,424	Total infeasible designs
95,549	Infeasible designs with stocastic parameters
1,874	Infeasible designs with deterministic parameters

Predicted design performace and costs

21,900,000	Physics model calculations
98,070	Designs with stochastic parameters
1,930	Designs with deterministic parameters
1,100,000	Value measure estimates
100,000	Cost estimates

Design definition and uncertainty specification

7	Design Parameters
145,800	Combinations of design parameters using bins
100,000	Designs generated by SIPmath
47	Physics models and formulas
19	Physics models with uncertainty
4	Illities
2	Illities with Uncertainty
11	Value Measures
8	Value measures with uncertainty

Figure 12- Trade-off Analytics Hierarchy

Using the large number of solutions, designers can gain insights into the decisions through SBD. Graphing the sets into cost vs. value space can show which design decisions drive the value and cost. These decisions are called design set drivers. All other design decisions are called design set modifiers which modify the solutions and change the value and cost but are not the main source of variation within the value and cost tradespace. Using this heuristic method, the tradespace tool showed that the design drivers for the case study were the wingspan and the engine type. To perform the Set-Based Design discussed in Section 2, sets are determined by combinations of design set drivers. For instance, after binning the design space of the wingspan into 5 partitions, the case study included 10 design sets:

1. Wingspan 2-4 ft. with Engine E

2. Wingspan 4-6 ft. with Engine E
3. Wingspan 6-8 ft. with Engine E-
4. Wingspan 8-10 ft. with Engine E
5. Wingspan 10-12 ft. with Engine E
6. Wingspan 2-4 ft. with Engine P
7. Wingspan 4-6 ft. with Engine P
8. Wingspan 6-8 ft. with Engine P
9. Wingspan 8-10 ft. with Engine P
10. Wingspan 10-12 ft. with Engine P

Using these partitions of the design space as the sets, this methodology graphs the solutions into the value vs. cost tradespace. Without the uncertainty analysis, the basic value and cost tradespace is shown in Figure 13.

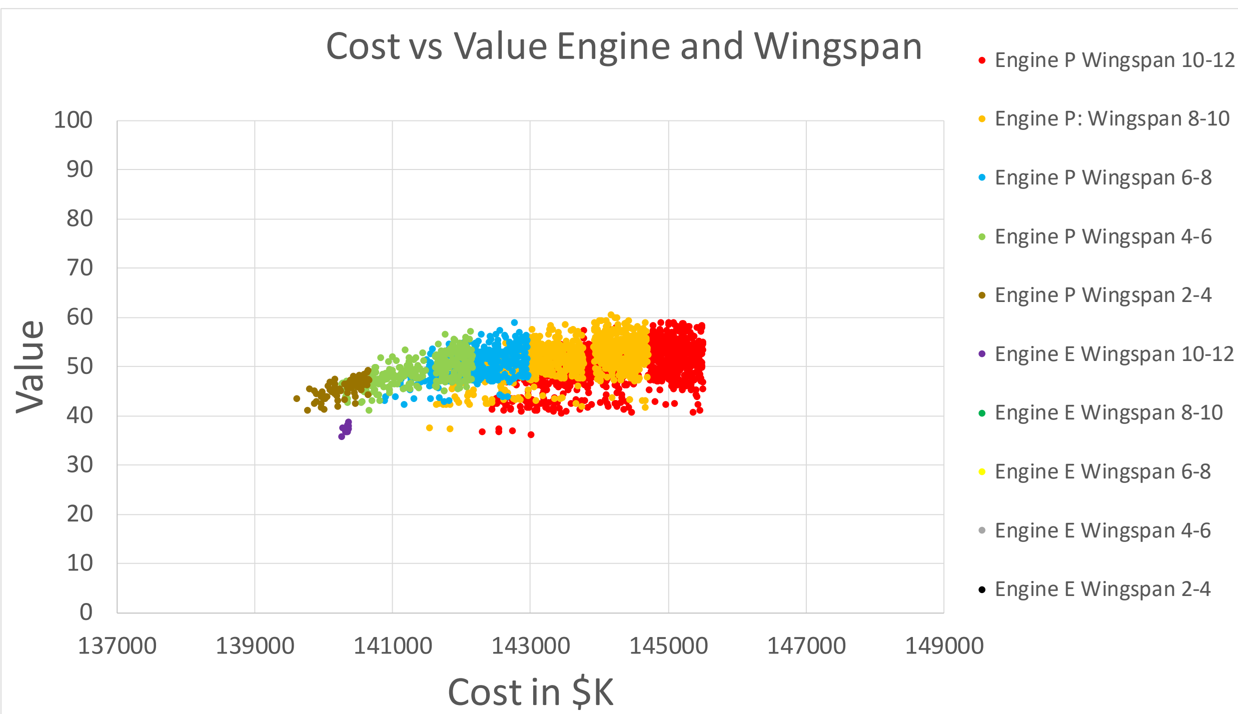


Figure 13- Cost vs Value without uncertainty

From this graph, decision makers gain greater insight into the design space than traditional Point-Based Design. Since the entire design space is fully mapped with thousands of possible solutions, decision makers can see that only a few solutions with a wingspan of 10-12 feet were met the minimum requirements. Based on this, the sets containing no feasible solutions can be eliminated. In addition, the solutions for the piston engines dominate the electric engine and have higher value for the same cost. Accordingly, designers might eliminate the electric engines from consideration. Moreover, designers can see that as the wingspan increases the cost and value also incrementally increase. However, the value begins to decrease as the ability of the soldier to carry the system and the probability of enemy detecting the larger aircraft begins to increase at wingspans greater than 10. However, although Point-Based Design may provide a point in a one of the sets, they do not map the entire design space, nor does Point-Based Design explore what decisions drive cost and value and are thus not able to provide these types of insights.

Lastly, this methodology identifies a better efficient frontier than Point-Based Design. Using an earlier version of the tool and the original 32 Point-Based Designs provided by the initial case study, SBD was able to dominate all solutions of the case study in Figure 14 providing better value for lower cost.

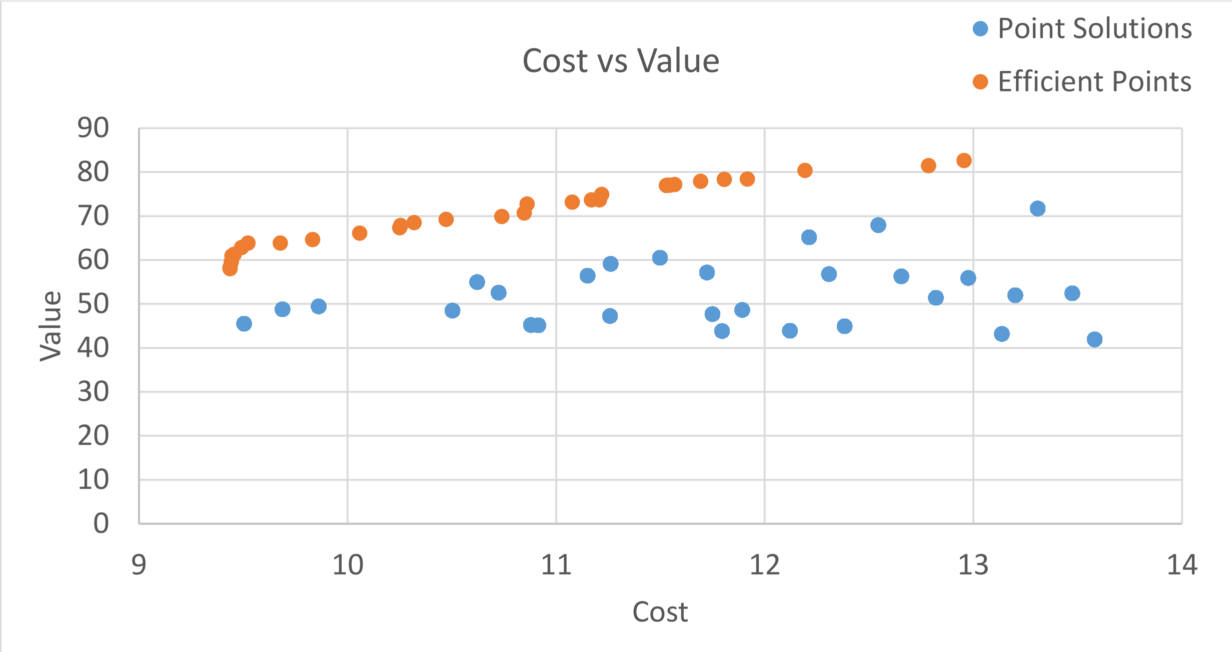


Figure 14- Cost vs Value SBD Efficient Points and UAV Case Study Point Solutions (Small C. , et al., 2018) (Small, et al., 2017)

5.2. SBD and Trade-off Analysis

In addition to the UAV case study cost vs value analysis, this tool also incorporates the entire trade-off analytics framework and allows designers to see the effects of perfect resilience options and uncertainty in cost, performance, and value in the tradespace using Set-Based Design.

5.2.1. Life Cycle Cost Model

In the original case study, the cost model was simplistic, only incorporating wingspan into the calculation. However, real world costs are much more complex. To better understand the true system costs, the costs of the entire life cycle must be assessed. Based on understanding from experts at the Army Corps of Engineers Engineering Research and Development Center (ERDC), this analysis incorporates the cost model below. This cost model incorporates both the hardware costs and the support costs into the total costs of a system. (Richards, 2018)

Hardware Cost

$$Air\ Vehicle\ Recurring\ Unit\ Cost\ (\$K\ 2013) = FlyWeight * 1.002$$

$$Air\ Frame\ Unit\ Recurring\ Cost\ (\$K\ 2013) = PayloadWeight * 5.607$$

$$Propulstion\ Unit\ Recurring\ Cost\ (\$K\ 2013) = (FlyWeight - PayloadWeight) * 1.808$$

$$Payload\ Average\ Unit\ Cost\ (\$K\ 2013) = 0.5 * AirFrameUnitCost$$

$$\begin{aligned} Total\ Hardware\ Cost(\$K\ 2013) = {} & TotalGroundStation + AirVehicleUnitCost \\ & + PayloadAverageCost + PropulsionUnitCost + AirFrameUnitCost \end{aligned}$$

Support Costs

$$Unit\ Level\ Manpower\ Cost\ (\$K\ 2013) = 250 * 0.5 * NumberOfSystems$$

$$\begin{aligned} & Unit\ Operations\ Cost\ (\$K\ 2013) \\ & \qquad = (24676 + 0.8286 * 1156 * TotalAirCraftInventory) * 1/10 \end{aligned}$$

$$Maintenance\ Cost\ (\$K\ 2013) = \begin{pmatrix} 41223 + 0.1261 * AirElementsWeight * \\ AgeOfAircraft * TotalAircraftInventory \end{pmatrix} * \frac{1}{10}$$

$$Sustaining\ Support\ Cost\ (\$K\ 2013) = TotalHours\hat{}0.7303 * NumberOfSystems$$

$$Indirect\ Support\ Cost\ (\$K\ 2013) = 2777 * e^{(0.01824 * NumberOfSystems)}$$

Life Cycle Cost

$$Life\ Cycle\ Cost\ (\ \$K\ 2013) = TotalHardwareCost * NumberOfSystems +$$

$$\begin{aligned} & (Unit\ Level\ Manpower\ Costs + Unit\ Operations\ Costs + Maintenance\ Cost \\ & \qquad + Sustaining\ Support\ Cost + Indirect\ Support\ Cost) * Service\ Life \end{aligned}$$

In the tool, the number of systems operated, the total aircraft inventory, and the service life are choices that can be varied. In the instance used in this research, the service life is 5 years and the number of systems operated and total aircraft inventory are 50 UAVS.

5.2.2. Using Mission Chain Analysis to Incorporate Resilience

The resilience options in the trade-off analytics framework are 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. This methodology seeks to investigate these resilience options through the ilities (availability, reliability, survivability, and recoverability). While many AoAs include the ilities as value measures, this methodology has incorporated the use of mission chain analysis using the ilities to analyze the effect of resilience on various performance measures. (Wade et al. 2018)

In typical mission chain analysis, analysts multiply the performance of a system by the probability of a system being available to perform a mission, the reliability percentage, and the probability the system with survive a threat as a simple decision tree. To further aid in the ability to analyze resilience, this methodology adds the possibility that the system survives but has degraded performance. If the system has a degraded performance, the system also has a chance of recovering performance. This calculation methodology is shown as decision tree in Figure 15.

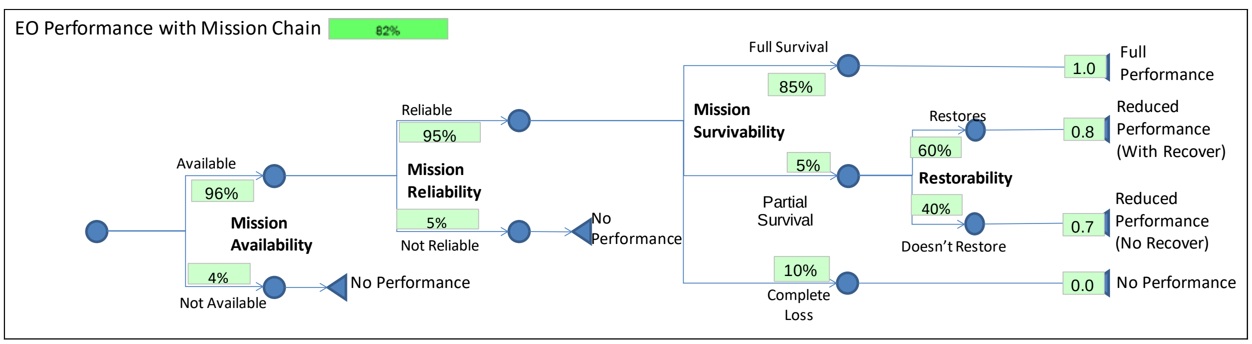


Figure 15- Mission Chain with Resilience

5.2.3. Using Perfect Options to Explore the Value of Resilience Options

To incorporate the value of mission resilience response decisions to threats, this methodology uses perfect options. Instead of attempting to determine a list of possible actions or methods, the value of perfect options explores the sensitivity of the model to various parameters informing decision makers of their relative importance. This type of analysis exploring the design space to determine which parameters are the most important has previously been performed on Air Force systems. (Stafira Jr., Parnell, & Moore, 1997) In this model, we explore five different perfect options (perfect availability, perfect reliability, perfect survivability, perfect restorability, and perfect detection) in the mission chain. These measures directly influence and determine the mission chain and are related to various resilience response decisions and depending on their importance, decisions makers can pursue different resilience response strategies to make the system perform better. For instance, if the availability of the system is the most important ility, purchasing more systems or including duplicate sensors or components on the ground can improve the performance. However, if the reliability is the most important ility, a decision maker may wish to add a duplicate sensor to the UAV so if a sensor fails during mission, the backup sensor will still work. If the survivability is the most important ility, the decision maker may wish to incorporate hardening to increase performance. If the restorability is the most important, the decision maker may wish to pursue strategies to improve the restorability. Lastly, if perfect detection is more important than the ilities, the decision maker may wish to pursue research better sensors and include the option to include new sensors developed in the future. Overall, exploring perfect options can provide decision makers with insight into which resilience response options can have the greatest impact on performance.

In this model we explicitly allow the user to choose which perfect options are considered using the control panel section in Figure 16.

Perfect Options		
Allow Perfect Options		TRUE
Perfect Option	Allowed?	Used?
Perfectly Available Sensors	TRUE	FALSE
Perfectly Reiliable Sensors	TRUE	TRUE
Perfectly Survivable Sensors	TRUE	FALSE
Perfectly Restorable Sensors	TRUE	FALSE
Perfectly Detecting Sensors	TRUE	FALSE
Any Perfect Options		TRUE
All Perfect Options?		FALSE

Figure 16- Perfect Options Control Panel

Depending on the whether the user allows each of the types of perfect options, the model uses the random numbers to determine which perfect options are used in a specific instance of the system. Each of the random numbers is a uniform distribution between 0 and 1. If the perfect option is allowed, the option is used if the random number for that option is above 0.5. This allows for instances of alternatives with and without perfect options allowing for direct comparison.

Running each perfect option through the tradespace tool provides insight into which perfect options provide the most relative. The tradespace for the perfect options in graphed in Figure 17.

Figure 17- Cost vs Value for Perfect Options

According to these results, in this case study, improving survivability would provide the most value to the system. Beyond survivability, both perfect availability and perfect reliability provide value to the system. Alternatively, adding more restorability to the system would not add much value. Therefore, analysts should investigate resilience response decisions that increase survivability, such as system hardening, to increase the value of the system. However, this analysis only explores the value of perfect options and does not address the costs. Instead it provides areas that designers may wish to research how to improve.

Lastly, through exploring perfect options this research discovered that not only can improving the ilities increase value, but if the option is cheap enough, it can reduce the costs. This is because as performance increases with perfect options, some of the cheaper sets that did not meet the minimum requirements now meet the requirements. If the cost to increase the ility in turn making the set feasible is less than the difference in the cost, investigating perfect options may reveal cheaper sets.

5.2.4. Uncertainty

In AoAs there are large amounts of uncertainty. To better explore the effects of uncertainty on the tradespace using SBD, this methodology incorporates uncertainty in all the performance measures, cost, and decision maker preferences for the system.

Uncertainty in performance was incorporated using two different approaches. The first approach is to incorporate the uncertainty in the physics-based calculations. The calculations used in the case study are derived from actual points and have different variance associated with each model. For instance, in Figure 18, the equations for the piston engine and electric engine to calculate endurance based on weight each have a variance around the prediction line. This is because the models are based on simple linear regression. In the model, this type of uncertainty was included in both the endurance and cruising velocity calculations.

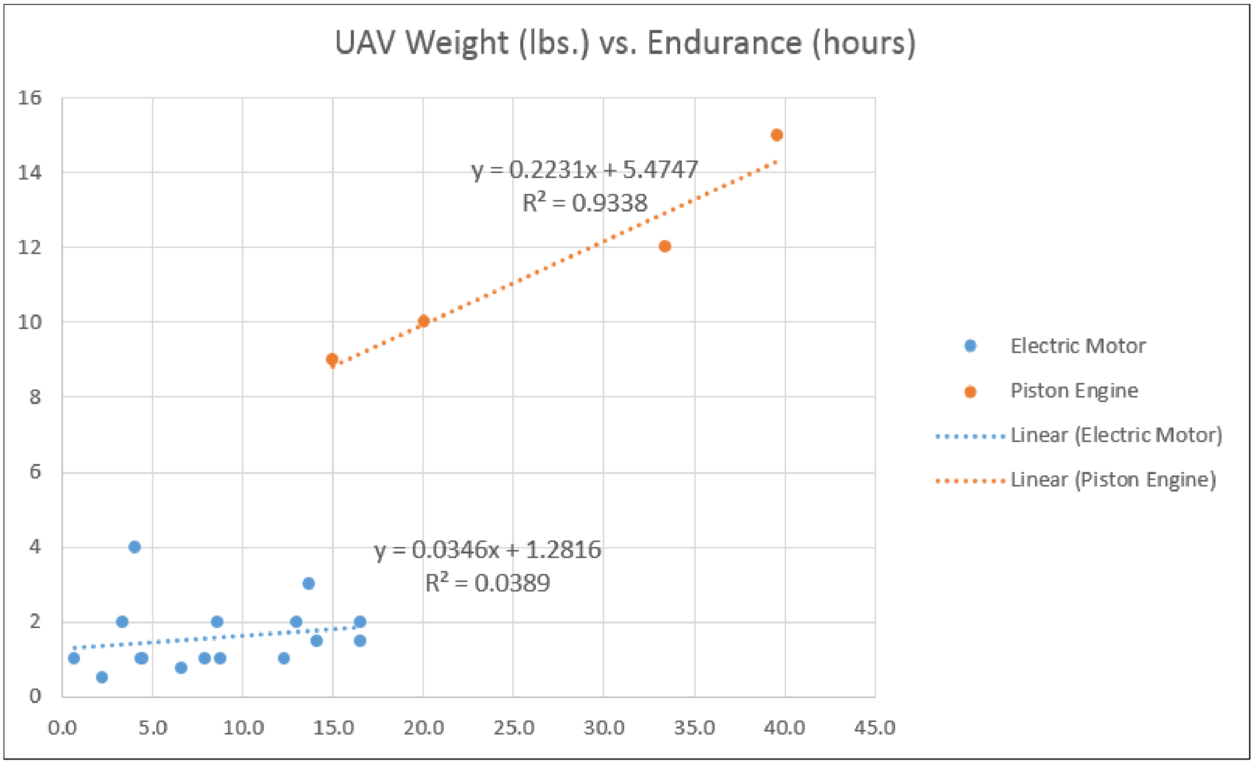


Figure 18- UAV Endurance Physics model.

The second approach is to include uncertainty in the ilities used in calculating the performance. In this analysis, uncertainty was included in availability and reliability. However, uncertainty could be included in all ilities.

To incorporate uncertainty in these two sections the tradespace tool allows the user to select parameters to increase or decrease the uncertainty in the model using the section on the control panel shown in Figure 19. Using a triangular distribution selected by the user on the control panel and the corresponding SIPmath random numbers, each instance of the Monte Carlo simulation assesses a different value for the ilities. Since there is a variance that can be calculated around the physics models, using random numbers the performance is modified by a standard normal distribution based on the variance.

Performance Uncertainty						
Uncertainty included in model					FALSE	
Include Deterministic					TRUE	
Uncertainty in Illities					Uncertainty in Performance Models is based on a normal distribution	
Ility	Minimum	Most Likely	Best	Number in use	Performance Model	Standard Deviations Away from predicted
Availabiltity	0.9	0.95	0.97	95%	Endurance	-0.69
Reliability	0.92	0.95	0.97	95%	Cruising Velocity	-0.39

Figure 19- Performance Uncertainty Control Panel Section

These two types of uncertainties are propagated through the model as shown in red in the AFD in Figure 11 eventually impacting 8 out of the 11 value measures.

To incorporate uncertainty in the cost, a selectable variation was used to create uncertainty in each of the cost types. The user can select a certain percentage of variation around the predicted value in the control panel section in Figure 20. Using unique uniform distribution random numbers based on the choices in the control panel, uncertainty can be propagated through the lifecycle cost model. For instance, if the user selects 5% variation, the cost will vary uniformly from 97.5% of the calculated cost to 102.5% of the calculated costs.

Cost Uncertainty		
Uncertainty included in Cost?	TRUE	
Inclue Deterministic	FALSE	
Measure	Percent Variation Allowed	Percent Varied
Initial Cost of UAVs	5%	-0.01
Unit Manpower Cost	5%	-0.02
Unit Operations Cost	5%	0.01
Maintenance Cost	5%	-0.02
Sustaining Support	5%	0.00
Indirect Support Cost	5%	-0.02

Figure 20- Cost Uncertainty Control panel Section

One of the most unique types of uncertainty is the uncertainty in preferences. Although preferences are elicited using the swing weight matrix methodology, preferences are still not completely static or deterministic. Often different decision makers have different preferences and different desires. This leads to compromises in the swing weight matrix. However, by incorporating uncertainty in the preferences, the effects of different preferences can be analyzed.

The section on the control panel in Figure 21 allows users to select the variation amount and whether the variation is above, below, or around the elicited value. Specifically, that means that based on the instance of uniformly distributed random numbers, the unnormalized weight used in the model can be varied around the unnormalized elicited weight. For instance, if 20% variation above and below is selected the unnormalized weight can range from 90-110% of the elicited number. If only below is selected, the unnormalized weight can vary from 80-100% of the elicited number. And if only above is selected, the weight used can vary from 100-120% of the elicited weight.

Preference Uncertainty

Weight	Percentage	Minus	Plus	Plus and Minus
UAS Weight	20%	FALSE	TRUE	FALSE
Time required to fly 10km (Mins)	20%	TRUE	FALSE	FALSE
Time Required to scan day	20%	TRUE	TRUE	TRUE
Time Required to scan night	20%	TRUE	TRUE	TRUE
Dwell Time (Mins)	20%	TRUE	TRUE	TRUE
Percieved Area of SUAV at Altitude	20%	FALSE	TRUE	FALSE
Difference from attack helicopter altitude	20%	TRUE	TRUE	TRUE
Probability of detecting a human day	20%	TRUE	FALSE	FALSE
Probability of detecting a vehicle day	20%	TRUE	FALSE	FALSE
Probability of detecting a human night	20%	TRUE	FALSE	FALSE
Probability of detecting a vehicle night	20%	TRUE	FALSE	FALSE

Figure 21 -Preference Uncertainty Control Panel Section

By using the random numbers and SIPmath in the uncertainties, designers can gain insight into exactly how uncertainty affects the tradespace. Based on the different types of uncertainty, the tradespace will vary in different ways. In general, the uncertainty makes the design space more fluid and continuous and increases the overlap of sets. However, one of the intriguing features of incorporating uncertainty is how performance and value can increase. Although generally not expected, incorporating variation in performance expands the range of different sets. In some situations, sets can have reduced number of feasible solutions within them if the set has a value measure near the minimum requirement and it drops below the minimum requirement. However, some sets can also have new feasible solutions, which were not feasible due to performance lower than the minimum requirement, performing better than the minimum requirements. This reflects real world analysis as systems often are better or worse than expected.

As performance was varied, the range of value achieved by each set in Figure 22 expanded, however, the costs remained the same. Depending on each set, the expansion in the range is different however. As seen in Figure 22, the piston engine with a wingspan range of 4-6 ft. had a larger increase in range than the wingspan of 6-8 ft. This is because depending on where the system performs on the value curves, changes in performance in different systems can provide different value. For instance, if we have s-shaped value curves such as probability of detection in Figure 7, meaning value doesn't increase very much until a certain level where value increases large amounts for small levels of changes but after a certain point there are diminishing gains, depending on where a system lies on each of the value curves the variation may drastically change performance. Specifically, if one set is near the upper end of one value curve, and the bottom end of the other value curve and another set that lies near the middle of both value curves. Without uncertainty the sets may have similar value. However, variations in performance in the set near the ends of the value curves might not drastically change the value of the system, but the system with performances near the middle of the value curves may have a much larger range in possible value.

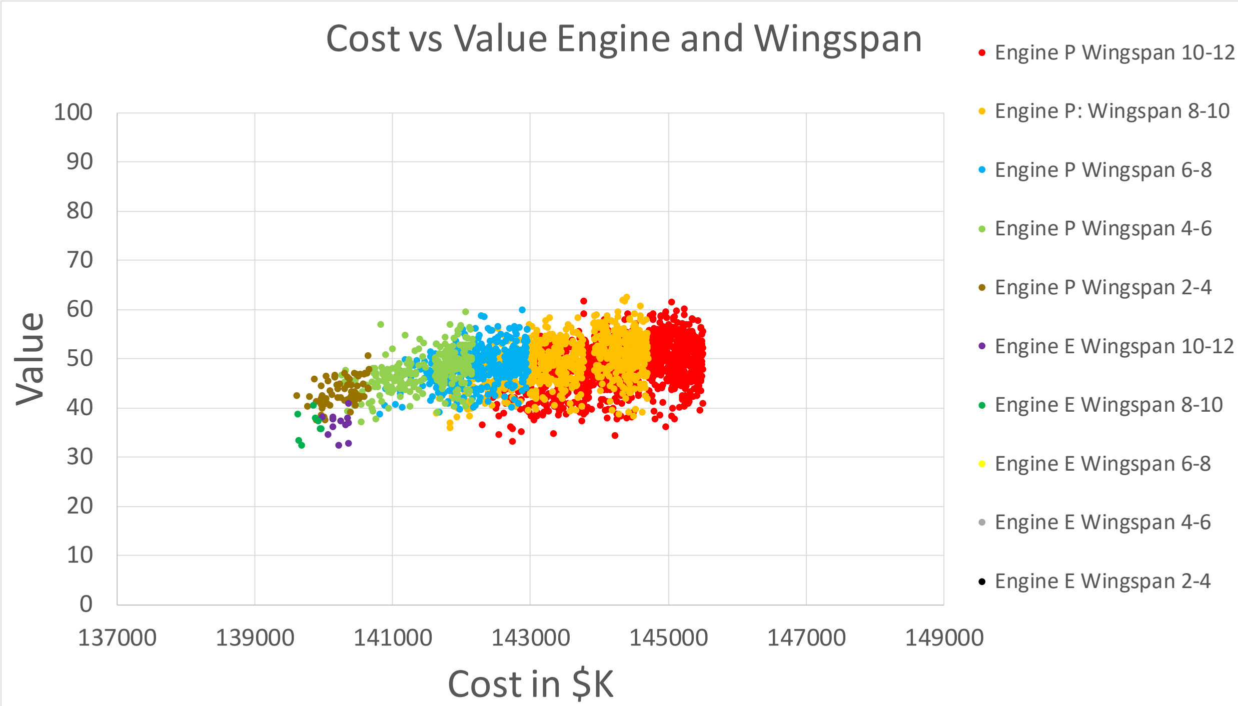


Figure 22- Cost vs Value with performance uncertainty

Adding uncertainty in the costs blended the boundaries between sets and overlaps more in the value and cost tradespace as shown in Figure 23. In particular, the piston engine UAVs with a wingspan of 8-10 and 10-12 overlap in the tradespace, making them more difficult to distinguish. However, this demonstrates how uncertainty can allow the performance and costs of sets to overlap in the tradespace in the real world.

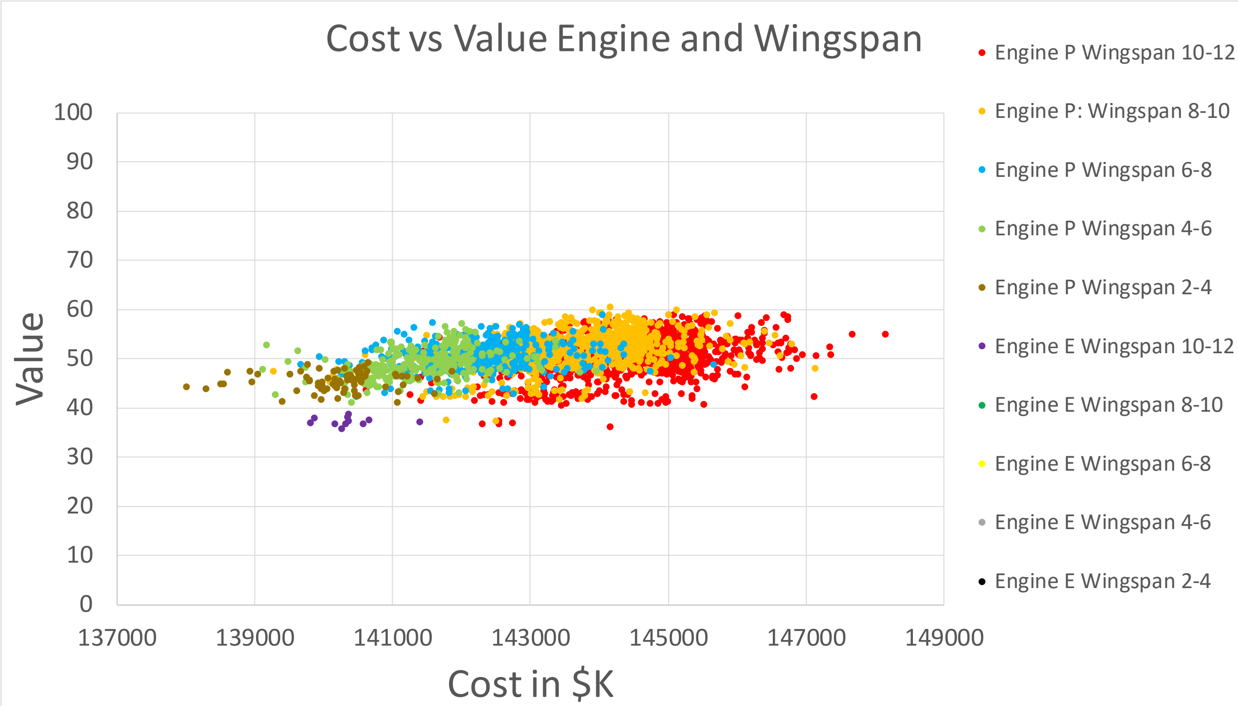


Figure 23- Cost vs Value with Cost Uncertainty

Lastly, incorporating the preference uncertainty into the model shows how much the tradespace and sets are sensitive to the weighting elicitation. In Figure 24, this case study and model is not extremely sensitive to swing weight preferences, this will not always be the case. In many situations depending on the performance of sets, the preference of decision makers for different sets may switch with uncertainty in preferences. For instance, although it did not occur in this case study, one set deterministically dominated in the value and cost tradespace by another set might not be dominated if the preferences for different value measures change.

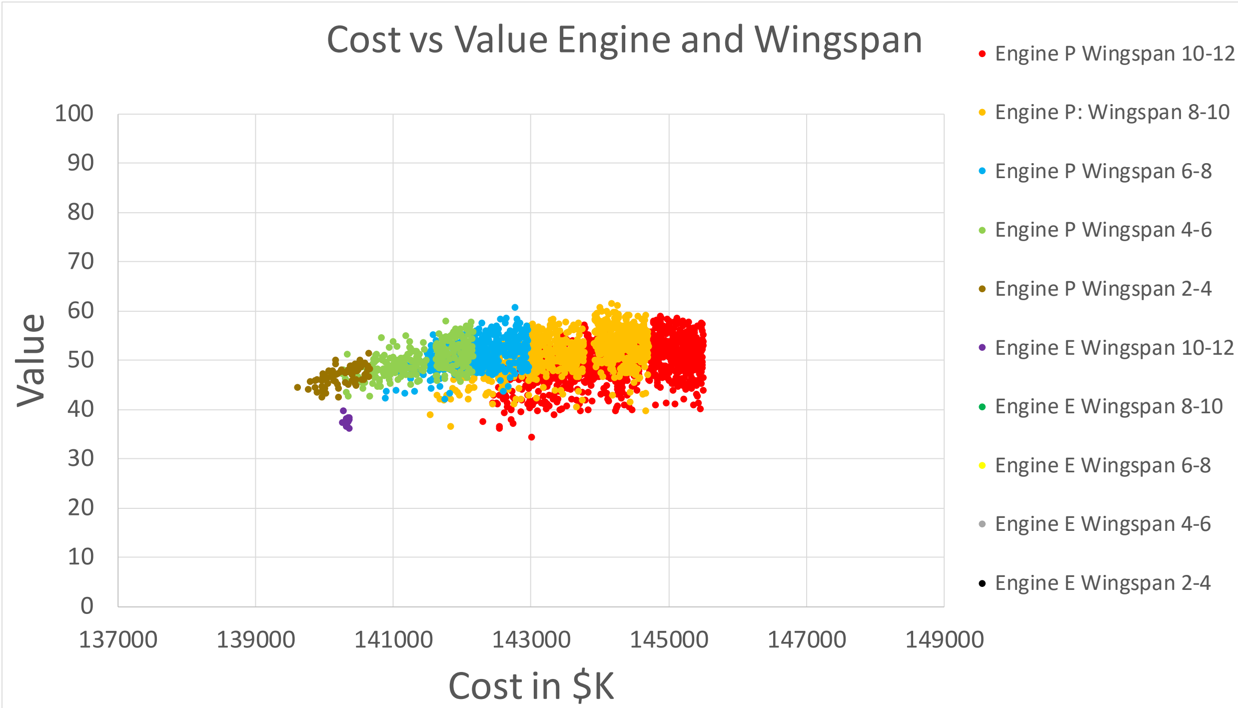


Figure 24- Cost vs Value with preference uncertainty

Incorporating all types of uncertainties in the model provides the tradespace in Figure 25. In this model the boundaries beyond the sets are blurred and the sets overlap. Showing how in the real world, many systems that deterministically appear to be different may in fact have similar performance. In addition, analyzing the tradespace in this manner provides the decision makers with insights into which sets are susceptible to large variation due to uncertainty and which have more predictable performance. This alone based on the risk preferences of a decision maker can be key in an analysis. For if the decision maker is very risk averse, they may wish to choose a system that determistically performs worse than others but has far less uncertainty or less probability of performing very poorly.

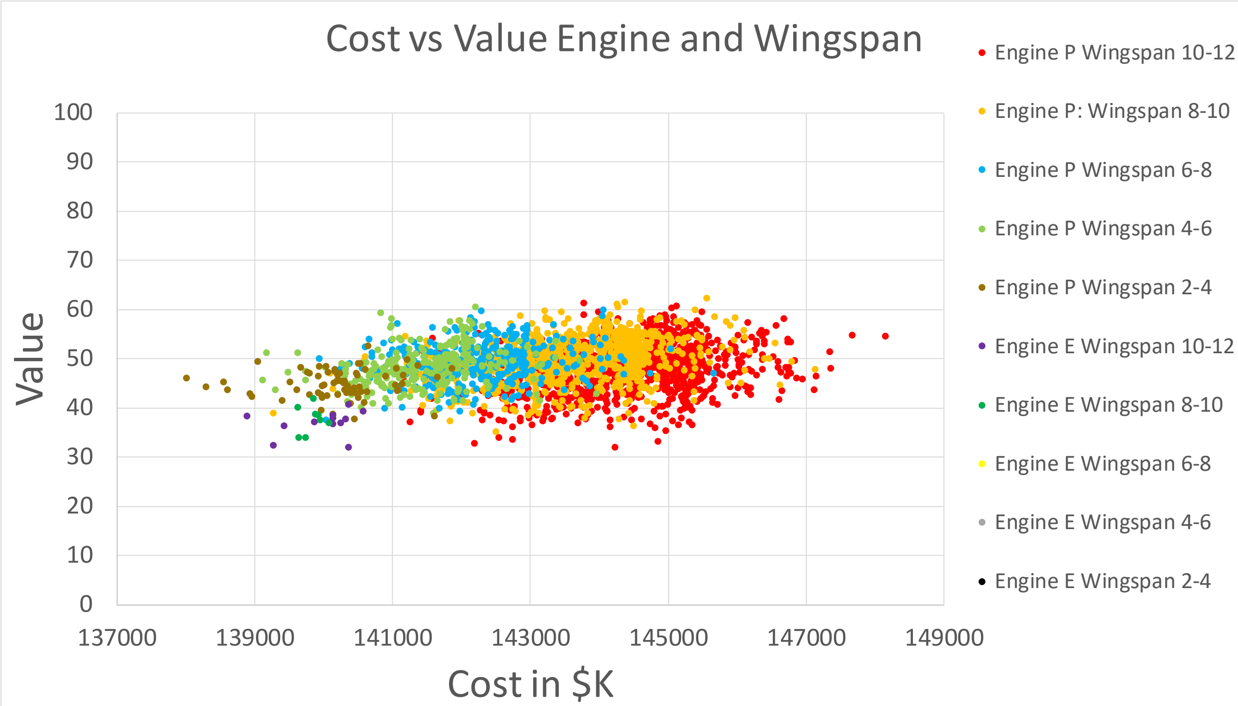


Figure 25- Cost vs Value with All Uncertainties Included

6. Conclusions

This thesis research has developed an integrated framework for trade-off analytics as well as a detailed repeatable model. Using an Excel add-in SIPmath, this research develops a realistic method to perform Set-Based Design. Using Set-Based Design combined with the trade-off analytics framework provides a methodology that is robust to changes.

Overall this research demonstrated the ability of SBD to discover insights including: 1) identifying design set drivers and design set modifiers, 2) identifying a better efficient frontier than standard Point-Based Design, 3) identifying the value that can be provided by resilience options and the ilities, revealing the importance of including ilities in the calculation of performance, and 4) identifying how various sets and different sections of the tradespace can be affected by various uncertainties. In addition, this research shows the ability of SBD to quickly analyze the design space, revealing infeasible requirements and solutions throughout the design process even as the AoA continually adapts.

Lastly this research shows the ability of MBE and the trade-off analytics framework developed to quickly adapt to changes and to efficiently explore the design space throughout an AoA process quickly providing insights to designers that can lead to changes in the AoA process. Due in large part to this research, the creator of the UAV case study has begun to incorporate major portions of this methodology and Set-Based Design within his systems engineering trade-off analysis for the ARDEC. (Cilli, 2018)

7. Future Research

There are four major areas for future research: 1) an online trade-off analytics tool, 2) set-based design methodology, 3) resilience options, and 4) UAV case study improvements. First, in support of the ERS research effort at ERDC this tradespace tool will be implemented in an online trade-off analytics tool (TradeBuilder). Second, in this study the sets drivers were determined by using a heuristic method by looking at the impact of design decisions on the cost and value tradespace. To increase the feasibility of set-based design methodology, a repeatable, mathematical method of defining set-drivers needs to be developed. Third, the resilience options research needs to be expanded to include explicit resilience options as well as the cost of resilience options. Lastly, to improve the realism of the model the cost model could be expanded to include a learning curve for large procurements and the time-value of money.

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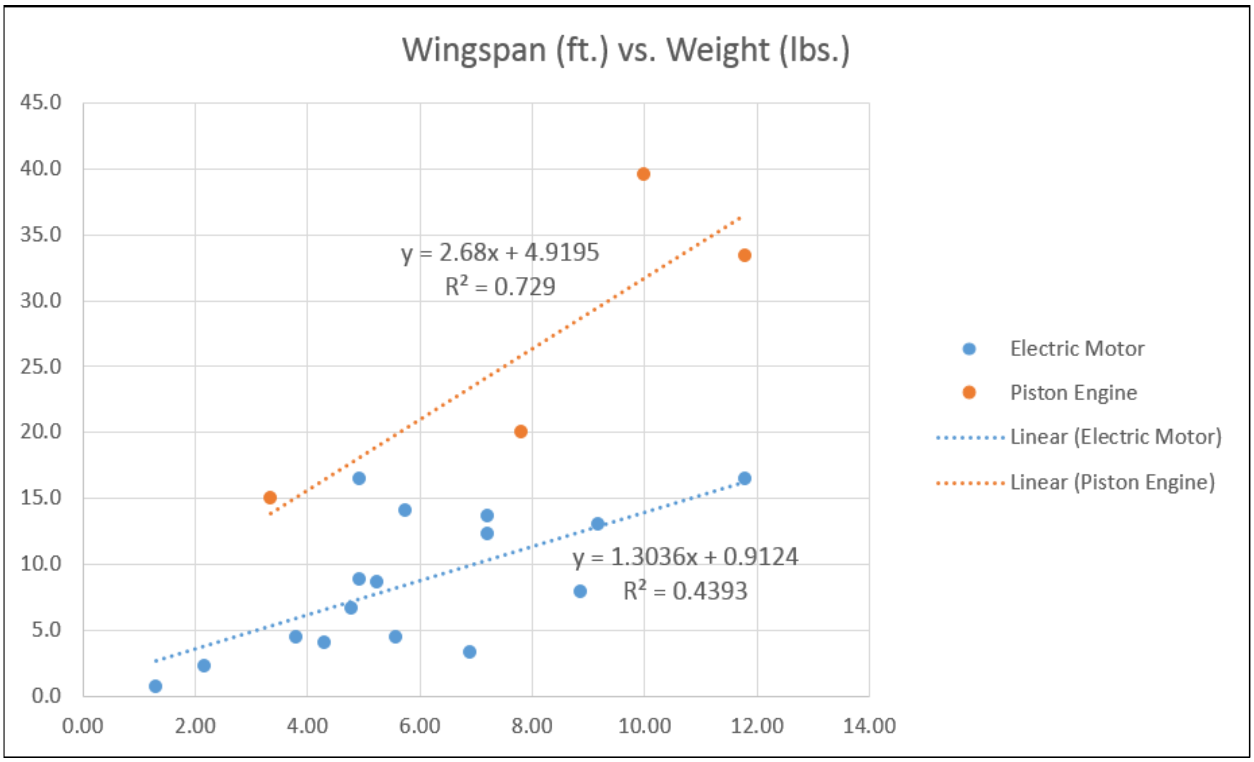
9. Appendix I. Case Study Calculations

This appendix includes the physics model calculations that lead from the design decisions to the value measures. Specifically, it includes: UAV Weight Calculations, Operating Altitude Distance to Attack Helicopter Altitude and Perceived Area at Operating Altitude, Endurance, Cruising Velocity, and Sensor Calculations.

9.1. UAV Weight Calculations



$$Fly\ Weight$$

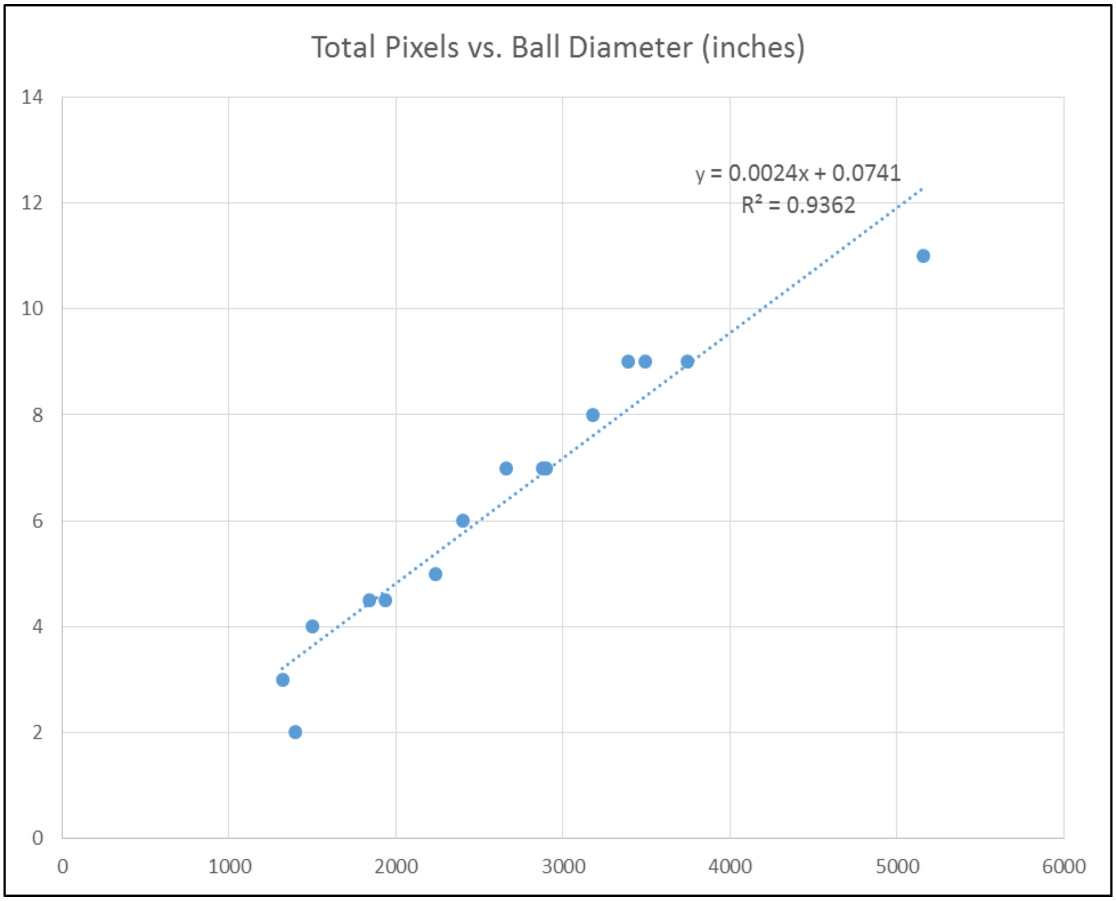
$$If\ Electric\ Engine{:}\ Fly\ Weight\ (lbs.) = Wingspan * 1.3 + 0.91$$

$$if\ Piston\ Engine{:}\ Fly\ Weight\ (lbs.) = Wingspan * 2.68 + 4.92$$

$$Max\ Payload$$

$$If\ Electric\ Engine{:}\ Max\ Payload\ (lbs.) = FlyWeight * 0.18$$

$$If\ Piston\ Engine{:}\ Max\ Payload\ (lbs.) = FlyWeight * 0.31$$



$$Ball\ Sensor\ Diameter\ (inches) = (EO\ Horizontal\ Pixels + EO\ Vertical\ Pixels + IR\ Horizontal\ Pixel + IP\ Vertical\ Pixels) * 0.0024 + 0.0741$$

$$Sensor\ Weight\ (lbs.) = \ 0.0164 * 1.5 * SensorDiameter^3$$

$$Total\ Payload\ Weight = Sensor\ Weight + Communications\ Weight$$

$$Communications\ Weight = notionally\ assumed\ 0.5\ lbs.$$

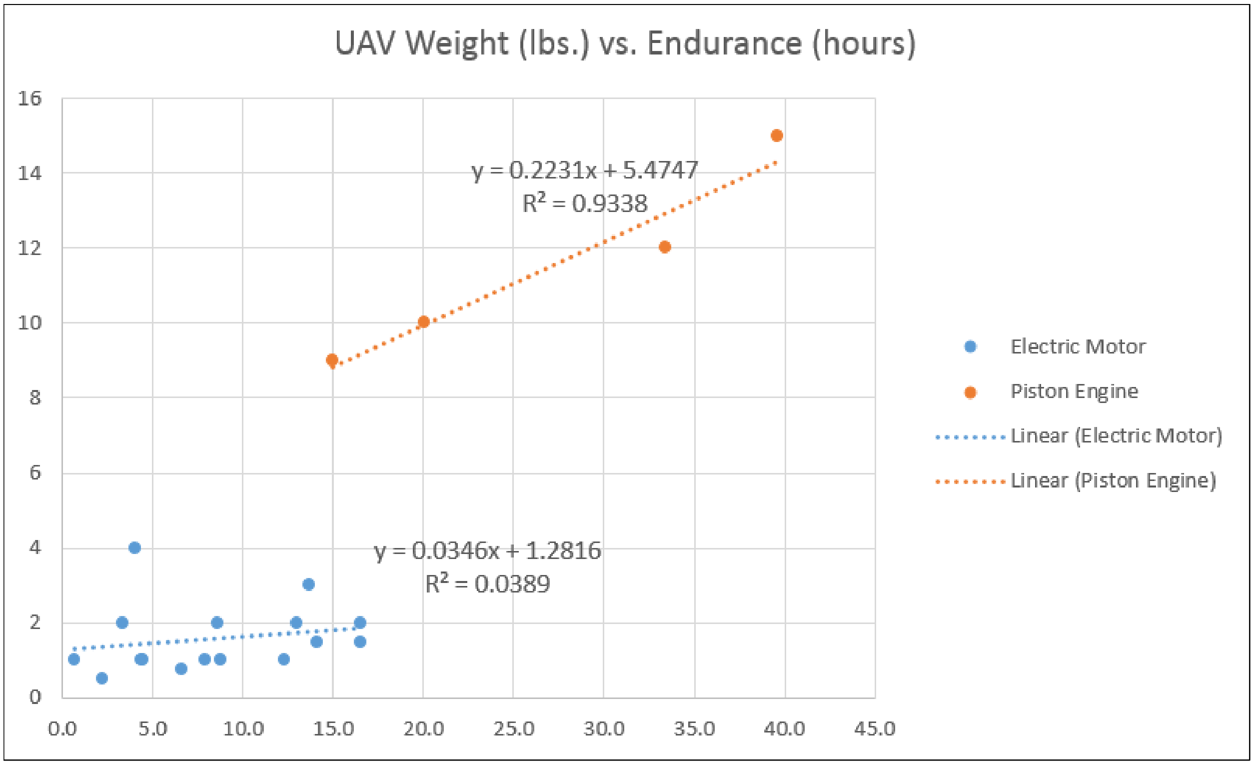
9.2. Operating Altitude Distance to Attack Helicopter Altitude and Perceived Area at Operating Altitude

$$If\ Electric\ Engine: Length\ (ft.) = \frac{Wignspan}{1.92}$$

$$If\ Piston\ Engine: Length\ (ft.) = \frac{Wignspan}{1.62}$$

$$Percieved\ Area\ at\ Operating\ Altitude\ = \frac{Length^2}{4} * \frac{500}{OperatingAltitude}$$

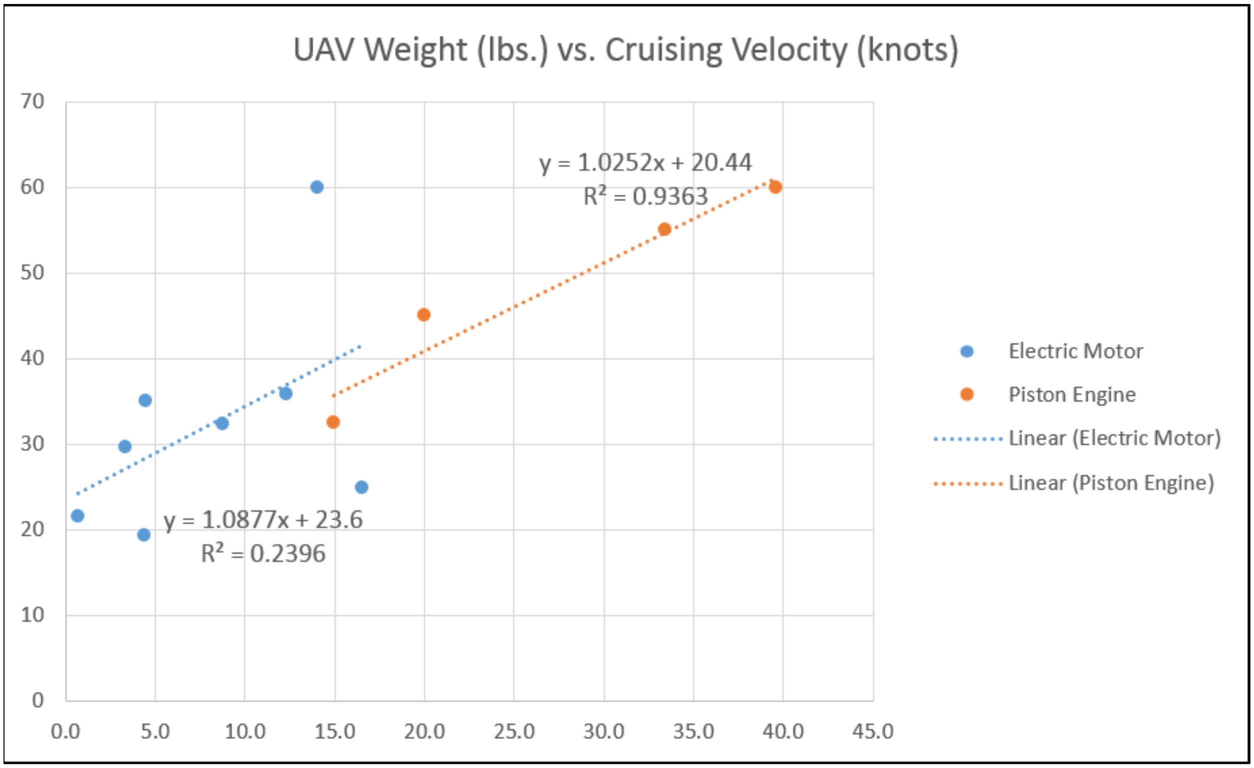
9.3. Endurance



$$If\ Electric\ Engine: Endurance\ (hours) = 0.0346 * FlyWeight + 1.2816$$

$$If\ Piston\ Engine: Endurance\ (hours) = 0.2231 * FlyWeight + 5.4747$$

9.4.Cruising Velocity



$$If\ Electric\ Engine: Cruising\ Velocity\ (knots) = 1.0877 * FlyWeight + 23.6$$

$$If\ Piston\ Engine: Cruising\ Velocity\ (knots) = 1.0252 * FlyWeight + 20.44$$

$$Time\ Required\ to\ fly\ 10km\ (mins) = \frac{10}{CruisingVelocity * 1.852} * 60$$

$$Dwell\ Time(mins) = Endurance * 60 - 2 * TimeToReach10KM$$

9.5. Sensor Calculations

Use Johnson criteria method as presented in Chapter 14 of Jay Gundland's *Designing Unmanned Aircraft Systems: A Comprehensive Approach* for estimating probability of detection given range to target, horizontal pixels, vertical pixels, and field of view.

For these estimates, assume an operating altitude of 3,000 meters and a slant angle from normal to be 0. For target characteristic dimensions, assume human target to be 0.5m width and 1.75m length. Assume a military vehicle to be 3.66m width and 7.93m length.

$$d_c = \sqrt{W_{target} * L_{target}}$$

The normal Ground Sample Distance (GSD) is given by

$$GSD_H = 2 \cdot \tan\left(\frac{FOV_H}{2 \cdot H_{Pix}}\right) \cdot R$$

$$GSD_V = 2 \cdot \tan\left(\frac{FOV_V}{2} \cdot V_{Pix}\right) \cdot R$$

The number of cycles across the target is

$$N = \frac{d_c}{2 \cdot GSD_{Avg}}$$

The probability of detection is

$$P(N) = \frac{(N/N_{50})^{2.7+0.7(N/N_{50})}}{1+(N/N_{50})^{2.7+0.7(N/N_{50})}}$$

For detection, assume N_{50} value is 0.75.

(Cilli, 2017) (Gundlach, 2012)

$$FeetToMeters = \frac{1}{3.281}$$

$$N_{50} = 0.75$$

9.5.1. EO Calculations

$$EO\ GSD_h = 2 * TAN\left(\frac{EOFOV * \frac{\pi}{180}}{2 * EOHorizontal}\right) * OperatingAltitude * FeetToMeters$$

$$EO\ GSD_v = 2 * TAN\left(\frac{EOFOV * \frac{\pi}{180}}{2 * EOVertical}\right) * OperatingAltitude * FeetToMeters$$

$$Dc_{Human} = \sqrt{0.5 * 1.75}$$

$$Dc_{Vehicle} = \sqrt{3.66 * 7.93}$$

$$EO\ N_{human} = \frac{Dc_{Human}}{EO_{GSD_h} + EO_{GSD_V}}$$

$$EO\ N_{Vehicle} = \frac{Dc_{Vehicle}}{EO_{GSD_h} + EO_{GSD_V}}$$

$$EO_{GroundSwath}\ (m) = \left(TAN\left(0.5 * EOFOV * \frac{\pi}{180}\right) - TAN\left(-0.5 * EOFOV * \frac{\pi}{180}\right)\right) * \frac{OperatingAltitude}{3.281}$$

$$EO\ Ground\ Coverage\ Rate\ \left(\frac{m^2}{s^2}\right) = EO_{GroundSwath} * CruisingVelocity * 1.852/3.6$$

$$Probaiblity\ of\ Detecting\ a\ Human\ in\ the\ Day = \frac{\left(\frac{EO\ N_{Human}}{0.75}\right)^{2.7+0.7*\left(\frac{EO\ N_{Human}}{N_{50}}\right)}}{1 + \left(\frac{EO\ N_{Human}}{0.75}\right)^{2.7+0.7*\left(\frac{EO\ N_{Human}}{N_{50}}\right)}}$$

$$Probability\ of\ Detecting\ a\ Vehicle\ in\ the\ day = \frac{\left(\frac{EO\ N_{Vehicle}}{0.75}\right)^{2.7+0.7*\left(\frac{EO\ N_{Vehicle}}{N_{50}}\right)}}{1 + \left(\frac{EO\ N_{Vehicle}}{0.75}\right)^{2.7+0.7*\left(\frac{EO\ N_{Vehicle}}{N_{50}}\right)}}$$

$$Timerequired\ to\ scan\ a\ 5km\ box\ by\ 5km\ box\ during\ the\ Day = \frac{25000000 * 60}{EOGroundCoverageRate}$$

9.5.2. IR Calculations

$$IR\ GSD_h = 2 * TAN\left(\frac{IRFOV * \frac{\pi}{180}}{2 * IRHorizontal}\right) * OperatingAltitude * FeetToMeters$$

$$IR\ GSD_v = 2 * TAN\left(\frac{IRFOV * \frac{\pi}{180}}{2 * IRVertical}\right) * OperatingAltitude * FeetToMeters$$

$$Dc_{Human} = \sqrt{0.5 * 1.75}$$

$$Dc_{Vehicle} = \sqrt{3.66 * 7.93}$$

$$IR\ N_{human} = \frac{Dc_{Human}}{IR_{GSD_h} + IR_{GSD_V}}$$

$$IR\ N_{Vehicle} = \frac{Dc_{Vehicle}}{IR_{GSD_h} + IR_{GSD_V}}$$

$$IR_{GroundSwath}\ (m) = \left(TAN\left(0.5 * IRFOV * \frac{\pi}{180}\right) - TAN\left(-0.5 * IRFOV * \frac{\pi}{180}\right)\right) * \frac{OperatingAltitude}{3.281}$$

$$IR\ Ground\ Coverage\ Rate\ \left(\frac{m^2}{s^2}\right) = IR_{GroundSwath} * CruisingVelocity * 1.852/3.6$$

$$Probaiblity\ of\ Detecting\ a\ Human\ at\ Night = \frac{\left(\frac{IR\ N_{Human}}{0.75}\right)^{2.7+0.7*\left(\frac{IR\ N_{Human}}{N_{50}}\right)}}{1 + \left(\frac{IR\ N_{Human}}{0.75}\right)^{2.7+0.7*\left(\frac{IR\ N_{Human}}{N_{50}}\right)}}$$

$$Probability\ of\ Detecting\ a\ Vehicle\ at\ Night = \frac{\left(\frac{IR\ N_{Vehicle}}{0.75}\right)^{2.7+0.7*\left(\frac{IR\ N_{Vehicle}}{N_{50}}\right)}}{1 + \left(\frac{IR\ N_{Vehicle}}{0.75}\right)^{2.7+0.7*\left(\frac{IR\ N_{Vehicle}}{N_{50}}\right)}}$$

$$Timerequired\ to\ scan\ a\ 5km\ box\ by\ 5km\ box\ at\ night = \frac{25000000 * 60}{IRGroundCoverageRate}$$

10. Appendix 2- Case Study UAV Tradespace Tool

Appendix 2 provides the components of the Case Study UAV Tradespace Tool. The control panel of the tool contains all choices made by either the SIPMath random numbers or the user. In the intermediary calculations, the design choices are propagated through the physics-based models described in Appendix 1 and in the paper to the value measures. These value for each instance is calculated using the additive value model panel. And the cost for each instance is calculated in the cost model panel.

All Appendix 2 Figures follow the legend below

Legend
Data
Calculation
Notional Data

10.1. Control Panel Components

Air Vehicle					
Wingspan		**Engine Type**		**Operating Altitude**	
Wingspan must be between 2 and 12		*Engine Type must be either E or P*		*Fliying altitude must be between 300 and 1000 M*	
Wingspan	9	Engine Type	P	Operating Altitude	565

Payload									
EO Imager					IR Sensor				
EO Sensor Pixel Width Choice:	Horizonal Pixels	Vertical Pixels	EO Sensor Pixel FOV Choice:	Field of View	IR Sensor Pixels Choice:	Horizonal Pixels	Vertical Pixels	IR Sensor FOV Choice:	Field of View
1	200	200	1	15	1	200	200	1	15
2	400	400	2	30	2	400	400	2	30
3	600	600	3	45	3	600	600	3	45
4	800	800	4	60	4	800	800	4	60
5	1000	1000	5	75	5	1000	1000	5	75
6	1200	1200	6	90	6	1200	1200	6	90
7	1400	1400			7	1400	1400		
8	1600	1600			8	1600	1600		
9	1800	1800			9	1800	1800		
4	800	800	6	90	3	600	600	6	90

Service Life	5 years

Swing Weight Matrix

	Critical to mission				Important to mission				Fixable with dollars			
		Assessed fi	used fi	wi		Assessed fi	used fi	wi	Assessed fi	Assessed fi	used fi	wi
Significant impact of performance variation	Probability of detecting a vehicle night	100	85.82	0.13	Probability of detecting a human day	75	71.76	0.10	Time Required to scan night	60	58.91	0.09
	Probability of detecting a vehicle day	99	84.59	0.12					Time Required to scan day	50	56.45	0.08
	Probability of detecting a human night	98	80.02	0.12					Difference from attack helicopter altitude	50	41.30	0.06
Some impact of site variation					Time required to fly 10km (Mins)	60	55.68	0.08	Percieved Area of SUAV at Altitude	20	29.93	0.04
					Dwell Time (Mins)	60	50.92	0.07				
					UAS Weight	50	68.94	0.10				
Minor impact of site variation												

sum of fi	684.34

Preference Uncertainty

Weight	Percentage	Minus	Plus	Plus and Minus
UAS Weight	20%	FALSE	TRUE	FALSE
Time required to fly 10km (Mins)	20%	TRUE	FALSE	FALSE
Time Required to scan day	20%	TRUE	TRUE	TRUE
Time Required to scan night	20%	TRUE	TRUE	TRUE
Dwell Time (Mins)	20%	TRUE	TRUE	TRUE
Percieved Area of SUAV at Altitude	20%	FALSE	TRUE	FALSE
Difference from attack helicopter altitude	20%	TRUE	TRUE	TRUE
Probability of detecting a human day	20%	TRUE	FALSE	FALSE
Probability of detecting a vehicle day	20%	TRUE	FALSE	FALSE
Probability of detecting a human night	20%	TRUE	FALSE	FALSE
Probability of detecting a vehicle night	20%	TRUE	FALSE	FALSE

Cost Uncertainty		
Uncertainty included in Cost?		TRUE
Inclue Deterministic		TRUE
Measure	Percent Variation Allowed	Percent Varied
Initial Cost of UAVs	5%	-0.01
Unit Manpower Cost	5%	-0.02
Unit Operations Cost	5%	0.01
Maintenance Cost	5%	-0.02
Sustaining Support Cost	5%	0.00
Indirect Support Cost	5%	-0.02

Performance Uncertainty						
Uncertainty included in model					TRUE	
Include Deterministic					TRUE	
Uncertainty in Illities					Uncertainty in Performance Models is based on a normal distribution	
Ility	Minimum	Most Likely	Best	Number in use	Performance Model	Standard Deviations Away from predicted
Availabiltity	0.9	0.95	0.97	96%	Endurance	(0.69)
Reliability	0.92	0.95	0.97	95%	Cruising Velocity	(0.39)

Perfect Options		
Allow Perfect Options		FALSE
Perfect Option	Allowed?	Used?
Perfectly Available Sensors	FALSE	FALSE
Perfectly Reiliable Sensors	FALSE	FALSE
Perfectly Survivable Sensors	FALSE	FALSE
Perfectly Restorable Sensors	FALSE	FALSE
Perfectly Detecting Sensors	TRUE	FALSE
Any Perfect Options		FALSE
All Perfect Options?		FALSE

Value Calculations	
Value Measure	Weighted Value Score
UAS Weight	4
Time required to fly 10km (Mins)	8
Time Required to scan day	8
Time Required to scan night	8
Dwell Time (Mins)	7
Percieved Area of SUAV at Altitude	3
Difference from attack helicopter altitude	1
Probability of detecting a human day	3
Probability of detecting a vehicle day	7
Probability of detecting a human night	0
Probability of detecting a vehicle night	7
Total Value	57

Cost Analysis	
Initial Cost of UAVs	$9,260
Unit Manpower Cost	$6,250
Unit Operations Cost	$7,257
Maintenance Cost	$4,176
Sustaining Support Cost	$2,396
Indirect Support Cost	$6,913
Total Cost in millions	**$142,710**

10.2. SIPMath Random Variables (1 Instance)

Design Choice Random Numbers		
Measure	Random Number	Distribution
Wingspan	0.68	Uniform
Engine Type	0.88	Uniform
Altitude	0.38	Uniform
EO Sensor Pixels	0.64	Uniform
IR Sensor Pixels	0.34	Uniform
EO Sensor FOV	0.96	Uniform
IR Sensor FOV	0.88	Uniform

Preference Uncertainty Choice Random Numbers		
Measure	Random Number	Distribution
UAS Weight	0.95	Uniform
Time required to fly 10km (Mins)	0.22	Uniform
Time Required to scan day	0.18	Uniform
Time Required to scan night	0.55	Uniform
Dwell Time (Mins)	0.95	Uniform
Percieved Area of SUAV at Altitude	0.50	Uniform
Difference from attack helicopter altitude	0.93	Uniform
Probability of detecting a human day	0.16	Uniform
Probability of detecting a vehicle day	0.72	Uniform
Probability of detecting a human night	0.90	Uniform
Probability of detecting a vehicle night	0.71	Uniform

Performance Uncertainty Choice Random Numbers			
Measure	Random Number	Distribution	Uncertainty Included in Meaure
Uncertainty Included in Endurance	0.11	Uniform	FALSE
Uncertainty Included in Cruising Velocity	0.07	Uniform	FALSE
Endurance Standard Deviations Away	-0.69	Standard Normal	
Cruising Velocity Standard Deviations Away	-0.39	Standard Normal	
Day or Night	0.60	Uniform	
Availability	0.98	Triangular	
Reliability	0.75	Triangular	
Is Uncertainty Included in the Model	TRUE		

Cost Uncertainty Random Numbers			
Measure	Random Number	Distribution	Uncertiainty Included in Meaure
Is Uncertainty Included in Cost	0.73	Uniform	TRUE
Initial Cost of UAVs	0.65	Uniform	
Unit Manpower Cost	0.91	Uniform	
Unit Operations Cost	0.38	Uniform	
Maintenance Cost	0.95	Uniform	
Sustaining Support Cost	0.44	Uniform	
Indirect Support Cost	0.84	Uniform	

Perfect Options Random Numbers		
Measure	Random Number	Distribution
Reliability	0.63	Uniform
Availability	0.08	Uniform
Survivability	0.06	Uniform
Recoverability	0.14	Uniform
Detection	0.46	Uniform

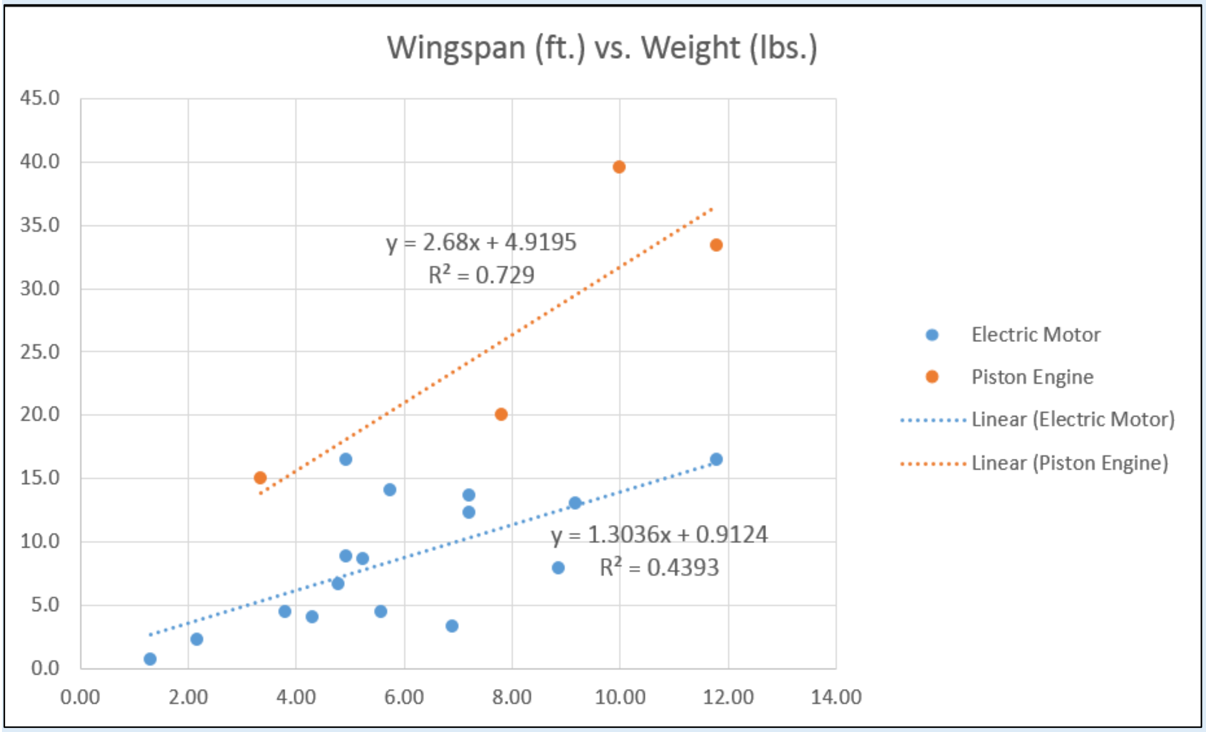
10.3. Intermediary Calculation Pages

10.3.1. Weight

Wingspan	8.8
Engine Type	P
Fly Weight	28.5

Sensor Weight	7.7
Communications Link Weight	0.5
Total Payload Weight	8.2

Max Payload	8.83
Appropriate Payload?	TRUE



10.3.2. Length

Engine Type	P
Wingspan	8.8
Vehicle Length	5.4

Legend
Data
Calculation
Notional Data

Number of Calculations	3

Number of Physics Calculations	1
Number of Physics Calculations/ Models w/ uncertainty	0

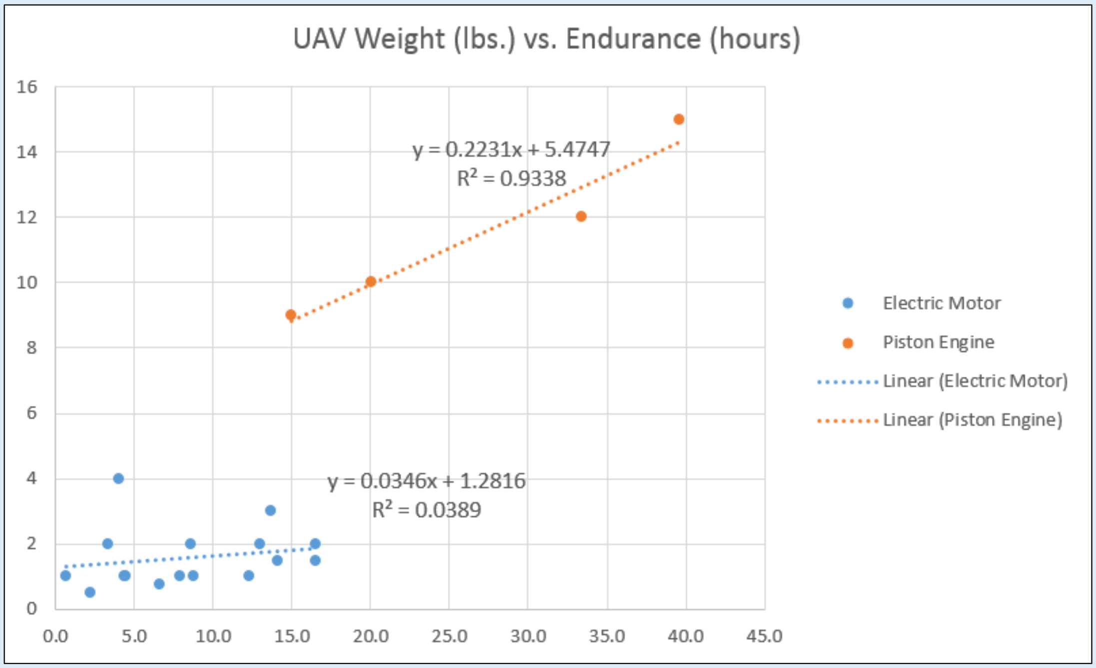
10.3.3. Endurance

Endurance in hours	11.73827
Endurance with Uncertainty (True or False)	FALSE

Number of Physics Calculations/ Models	1
Number of Physics Calculations/ Models w/ uncertainty	1

Number of Calculations	22

Standard Deviation	
Piston Engine	0.557830721
Electic Engine	0.930603926

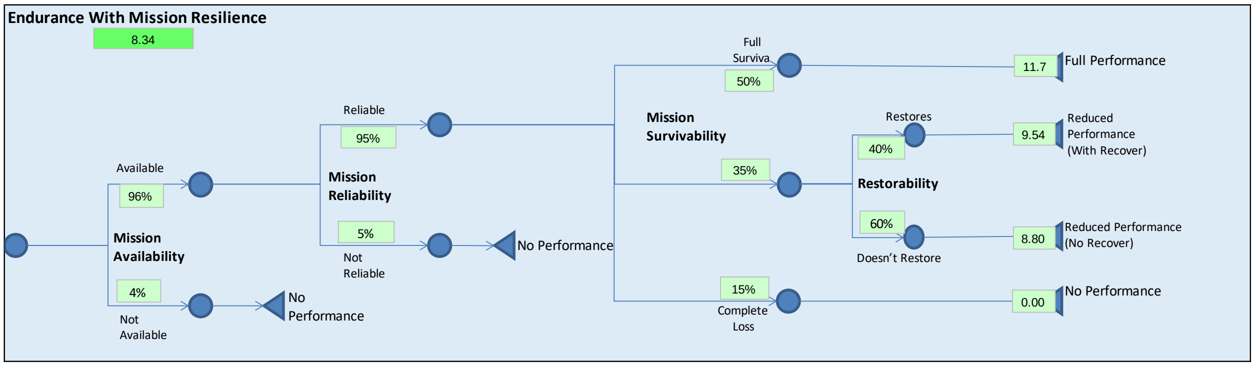


Probability of	%
Availability	96%
Reliability	95%
Full Survival	50%
Partial Survival	35%
Complete Loss	15%
Restorability	40%

System Properties	%
Degradibility	75%
Recoverability	25%

Performance Category	Score
Full Performance	11.74
Reduced (With Recover)	9.54
Reduced (No Recover)	8.80
No Performance	0.00

Adjusted Endurance	8.34



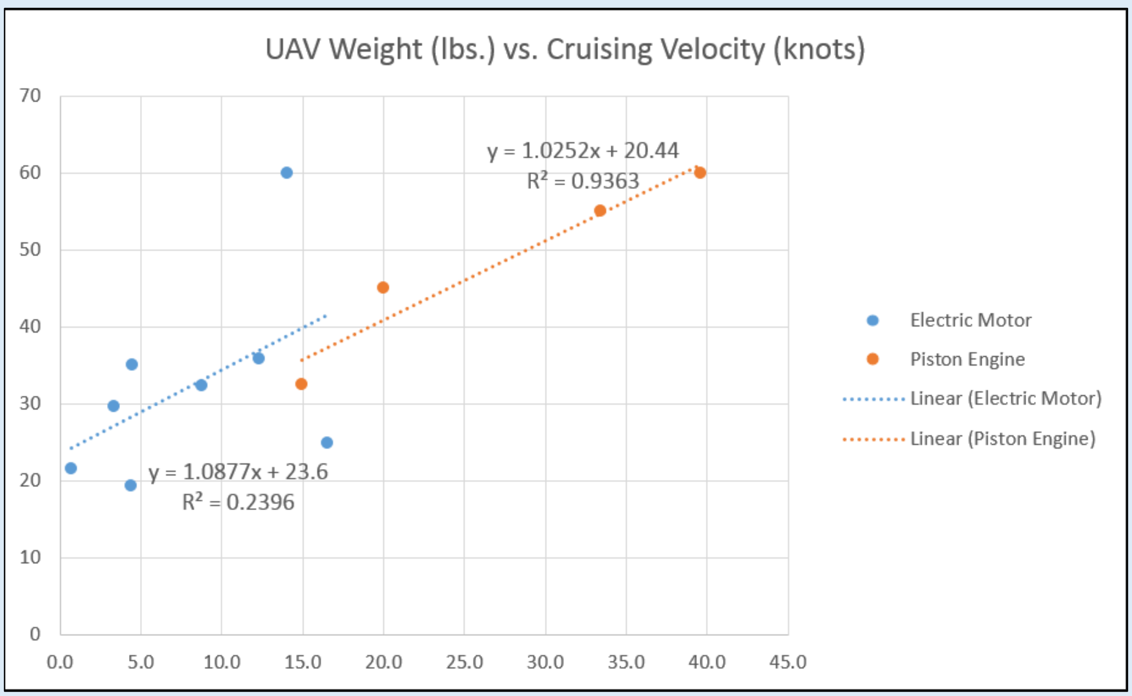
10.3.4. Cruising Velocity

UAV Weight	28
Airspeed	49.79
Standard Deviations Away	0.00
Airspeed with Uncertainty	49.79

Standard Deviation	
Piston Engine	3.2
Electric Engine	10.5

Dwell Time (Mins)	487
Time required to fly 10km (Mins)	6.5

Legend
Data
Calculation
Notional Data



10.3.5. Sensor Calculations

Dc_human, m	1
Dc_vehicle, m	5
N_50	1

Operating Altitude	565
Sensor Ball Diameter	7
Sensor Weight	8

EO Imager Pixels Horizontal	800
EO Imager Pixels Vertical	800
EO FOV	90
EO GSD_h	0.338
EO GSD_v	0.338
EO N_human	1.38
EO N_vehicle	7.96
EO Ground Swath (m)	345
EO Ground Coverage Rate (m^2/s^2)	8824
Probability of detecting a human during the day	92%
Probability of detecting vehicular activity during the day	100%

IR Pixels Horizontal	600
IR Pixels Vertical	600
IR FOV	90
IR GSD_h	0.45
IR GSD_v	0.45
IR N_human	1
IR N_vehicle	6
IR Ground Swath (m)	345
IR Ground Coverage Rate (m^2/s^2)	8824
Probability of detecting a human during the night	77%
Probability of detecting vehicular activity during the night	100%

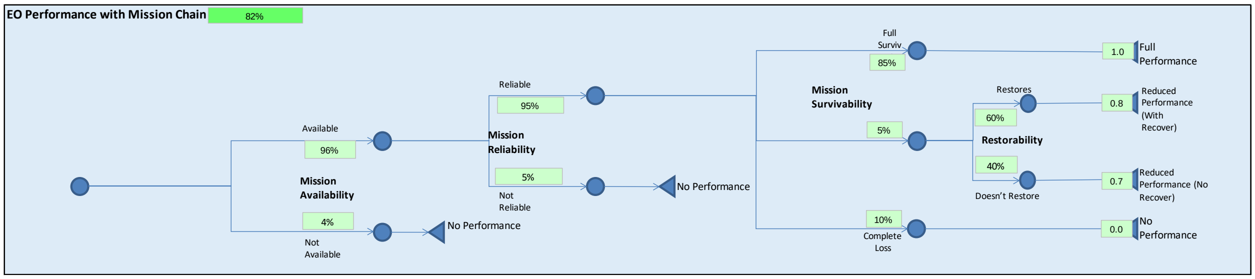
EO Time required to scan 5km x 5km Search Box Using Raster Scan Flight Pattern at proposed operating altitude and a slant angle from normal of zero. (minutes)	47
IR Time required to scan 5km x 5km Search Box Using Raster Scan Flight Pattern at proposed operating altitude and a slant angle from normal of zero. (minutes)	47

Probability of	%
Availability	96%
Reliability	95%
Full Survival	85%
Partial Survival	5%
Complete Loss	10%
Restorability	60%

System Properties	%
Degradibility	75%
Recoverability	25%

Performance Category	Score
Full Performance	1.00
Reduced (With Recover)	0.81
Reduced (No Recover)	0.75
No Performance	0.00

Adjusted EO sensor	82%
Adjusted probability detecting human activity during the day	75%
Adjusted probability detecting vehicular activity during the day	82%

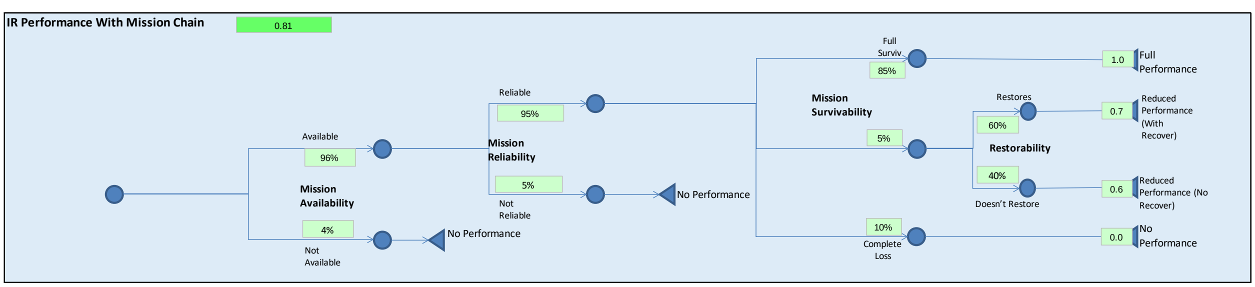


Probability of	%
Availability	96%
Reliability	95%
Full Survival	85%
Partial Survival	5%
Complete Loss	10%
Restorability	60%

System Properties	%
Degradibility	60%
Recoverability	25%

Performance Category	Score
Full Performance	1.00
Reduced (With Recover)	0.70
Reduced (No Recover)	0.60
No Performance	0.00

Adjusted IR sensor	0.81
Adjusted probability detecting human activity during at night	0.62
Adjusted probability detecting vehicular activity during at night	0.81



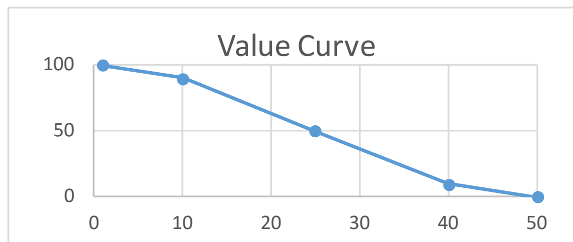
10.3.6. Altitude Based Calculations

Length	5.4
Operating Altitude	565.2
Percieved area at operating altitude	6.5
Absolute value of difference to 1000M operating altitude of attack helicoper	434.8

10.4. Value Model

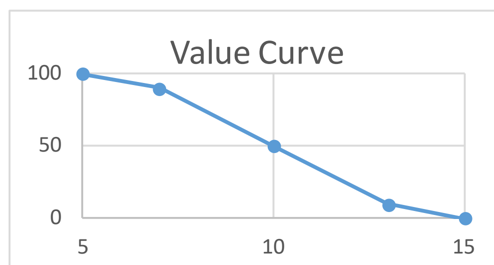
Function	Be transportable
Value Measure	UAS Weight

Score	Value of Score
x= Weight in lbs.	v(x)
1	100
10	90
25	50
40	10
50	0



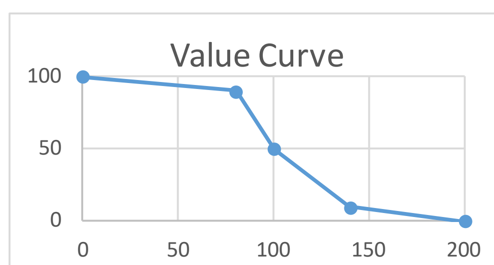
Function	Maneuver to, scan across, and dwell at area of interest
Value Measure	Time required to fly 10km (Mins)

Score	Value of Score
x= Time (Mins)	v(x)
5	100
7	90
10	50
13	10
15	0



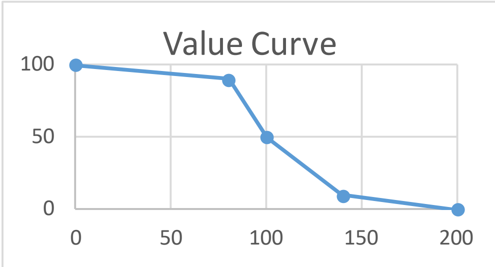
Function	Maneuver to, scan across, and dwell at area of interest
Value Measure	Time required to scan a 5km X 5km box during the day

Score	Value of Score
x= Time (Mins)	v(x)
0	100
80	90
100	50
140	10
200	0



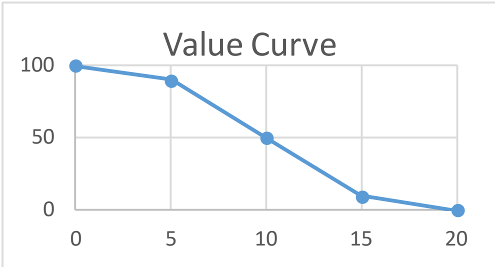
Function	Maneuver to, scan across, and dwell at area of interest
Value Measure	Time required to scan a 5km X 5km box during the day

Score	Value of Score
x= Time (Mins)	v(x)
0	100
80	90
100	50
140	10
200	0



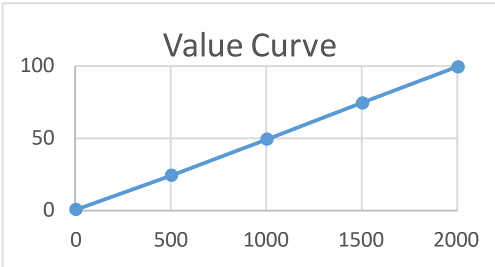
Function	Be Survivable
Value Measure	Percieved Area of SUAV at Operating Altitude (ft^2)

Score	Value of Score
x= Area in ft^2	v(x)
0	100
5	90
10	50
15	10
20	0



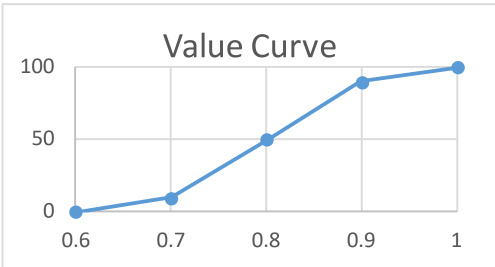
Function	Avoid friendly helicopter airspace
Value Measure	Difference between operating altitude and attack helicopter operating altitude of 1000m

Score	Value of Score
x= Distance (m)	v(x)
0	1
500	25
1000	50
1500	75
2000	100



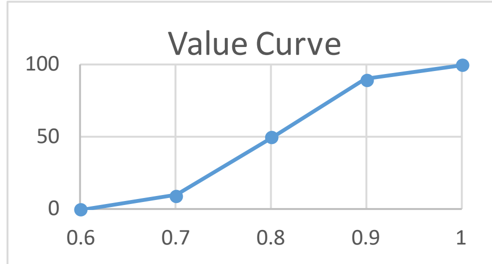
Function	Detect Enemy Activity
Value Measure	Probability of detection-Detect Human Activity in Daylignt

Score	Value of Score
x= %Probability	v(x)
0.6	0
0.7	10
0.8	50
0.9	90
1	100



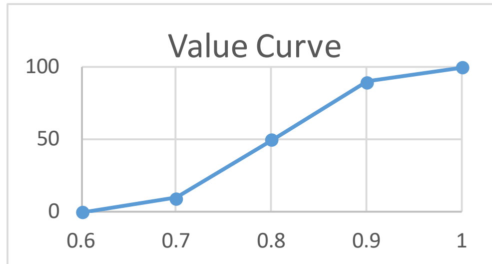
Function	Detect Enemy Activity
Value Measure	Probability of detection-Detect Vehicular Activity in Daylight

Score	Value of Score
x= %Probability	v(x)
0.6	0
0.7	10
0.8	50
0.9	90
1	100



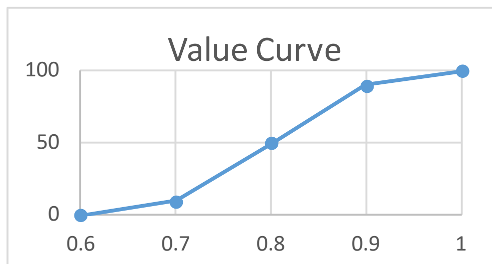
Function	Detect Enemy Activity
Value Measure	Probability of detection-Detect Human Activity at Night

Score	Value of Score
x= %Probability	v(x)
0.6	0
0.7	10
0.8	50
0.9	90
1	100



Function	Detect Enemy Activity
Value Measure	Probability of detection-Detect Vehicular Activity at Night

Score	Value of Score
x= %Probability	v(x)
0.6	0
0.7	10
0.8	50
0.9	90
1	100



Value Calculations

Value Measure	Performance Score	Value Score	Swing Weight	Weighted Value
UAS Weight	28	41	0.10	4
Time required to fly 10km (Mins)	7	92	0.08	8
Time Required to scan day	47	94	0.08	8
Time Required to scan night	47	94	0.09	8
Dwell Time (Mins)	487	99	0.07	7
Percieved Area of SUAV at Altitude	7	78	0.04	3
Difference from attack helicopter altitude	435	22	0.06	1
Probability of detecting a human day	0.75	31	0.10	3
Probability of detecting a vehicle day	0.82	58	0.12	7
Probability of detecting a human night	0.62	2	0.12	0
Probability of detecting a vehicle night	0.81	55	0.13	7
Value			1.0	**50.0**

10.5. Cost Model

Cost Parameters		
Total Aircraft Inventory		50
Number of Systems		50
Total Ground Station	$	50
Age of Aircraft		3
Total Hours		200

Hardware Costs		
Air Vehicle Unit Recurring Cost	$	29
Air Frame Unit Recurring Cost	$	46
Propulsion Unit Recurring Cost	$	38
Payload Average Unit Cost	$	23
Total Hardware Cost	$	185

Hardware Cost Breakdown		
Total SEPM Cost Development	$	41
Total SEPM Cost Production	$	28
System Test and Evaluation Development	$	17
System Test and Evaluation Production	$	8
Development Training Mean Cost	$	8
Development Training Median Cost	$	7
Development Training Standard Deviation	$	6
Data Development	$	5
Data Production	$	0.19
Tooling Development Mean	$	2.22
Tooling Development Standard Deviation	$	3.70
Tooling Production Mean Cost	$	11
Tooling Production Median	$	4.26
Tooling Produciton Standard Deviation	$	12
Common Support Equipment Mean	$	0.74
Common Support Equipment Median	$	0.19
Common Support Equipment Standard Deviation	$	1.67
Operational Site Activation Mean	$	32
Operational Site Activation Median	$	11
Operational Site Activation Standard Deviation	$	49
Initial Spare and Repair Parts Mean	$	34
Initial Spare and Repair Parts Median	$	22
Initial Spare and Repair Parts Standard Deviation	$	27

Support Costs		
Unit Level Manpower Cost	$	6,250
Unit Operations Cost	$	7,257
Maintenance Cost	$	4,176
Sustaining Support Cost	$	2,396
Indirect Support Cost	$	6,913

Cost Uncertainty		
Uncertainty included in Cost?	TRUE	
Measure	Percent Variation Allowed	Percent Varied
Initial Cost of UAVs	5%	-0.007272
Unit Manpower Cost	5%	-0.020317
Unit Operations Cost	5%	0.005930
Maintenance Cost	5%	-0.022430
Sustaining Support	5%	0.002771
Indirect Support Cost	5%	-0.016920

	Cost of UAVs	Unit Manpower Cost	Unit Operations Cost	Maintenance Cost	Sustaining Support Cost	Indirect Support Cost
UAV	$ 9,193	$ 30,615	$ 36,500	$ 20,413	$ 12,011	$ 33,979

System Cost	$ 142,710.44