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A UAV Case Study with Set-based Design

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Abstract. The DoD and Engineered Resilient Systems (ERS) community seek to leverage the capabilities of model-based engineering (MBE) early in the design process to improve decision making in AoAs. Traditional tradespace exploration with point-based design often converges quickly on a solution and engineering changes are required after this selection. Set-based design considers sets of all possible solutions and enables down-selecting possibilities to converge at a final solution. Using an Army case study and an open source excel add-in called SIPMath, this research develops an integrated MBE model and example that simultaneously generates numerous designs through physics models into the value and cost tradespace allowing exploration for set-based design analysis and producing a better efficient frontier than traditional point-based design AoAs. Grouping design decisions into sets based on their characteristic decision, and simultaneously evaluating the value and cost tradespace, allows for a set-based design approach that provides insight into the design decisions.

Introduction

Engineered Resilient Systems. The Department of Defense (DoD) and the Engineered Resilient Systems (ERS) program seek to leverage the capabilities of model-based engineering early in the design process to improve decision making in the analysis of alternatives (AoA). Analysis of

Alternatives is a DoD requirement of military acquisition policy to ensure that multiple design alternatives have been analysed prior to making costly investment decisions. (U.S. Office of Management and Budget, 2008) Advances in computing capabilities have increased the use of physics model-based systems engineering tools to simulate the performance of a large number of system design variants in a relatively short time. (Rinaudo, Buchanan, & Barnett, 2016) As the number of system design variants analysed continues to grow, the subsequent analysis of such large volumes of data can become time consuming. An enhanced tradespace is required and enabled by DoD high-performance computing (HPC) capabilities. Tradespace exploration (TSE) supports engineered resilient system design and development by providing analysts and decision makers with an understanding of capabilities, gaps, and potential compromises required to facilitate the realization of 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)

Tradespace exploration of traditional point-based design quickly converges on a solution that is a point in the solution space, thus necessitating modification of the chosen solution until it eventually meets the design objectives. While this may intuitively appear to be an effective approach, it has been shown to be a costly and time consuming process. When an inferior point-based design is chosen, the subsequent iterations to refine that solution can be time consuming and lead to a suboptimal design. (Iansiti, 1995) (Kalyanaram & Krishnan, 1997) Conversely, TSE of set-based design considers sets of all possible solutions and enables down-selecting possibilities to converge at a final solution. When a larger number of solutions are considered in the beginning, the likelihood of identifying the optimal solution increases. An investment to fully define and explore the tradespace in the beginning, provides for moving quickly towards convergence and the discovery of an ultimate solution that may have been missed in a traditional point-based design process. For DoD and ERS, set-based design is useful for projects with a large number of design variables, tight coupling among design variables, conflicting requirements, flexibility in requirements allowing for trades, or technologies and design problems that are not well understood. (GovEvents, 2017)

Case Study Motivation. Sponsored by ERS, a research team at the Army Armament Research, Engineering, and Development Center (ARDEC) has been developing a UAV case study using AoA best practices in order to provide a hypothetical, yet plausible example suitable for comparing systems engineering tradeoff analysis methods in the context of new product development efforts. (Cilli, 2017) To enhance realism, the case study contains a detailed narrative incorporating many viewpoints and presents initial information in an unstructured manner. To reflect reality, the case is written such that it involves a healthy dose of ambiguity and uncertainty. Characteristics of various product structure elements available to form system alternatives are described such that rough order of magnitude estimation methodologies suitable for conceptual design studies can be used to approximate cost, schedule, and performance consequences for a given concept. The case study then sorts through the glut of information to bring order out of chaos and ultimately identifies system level solutions that best balance competing objectives in the presence of uncertainty in order to inform initial conceptual requirements. Although this case study provides a solution, it is structured in a way that invites other researchers to explore the tradespace through other methods and compare and contrast the efficiency and effectiveness of different systems engineering and decision management techniques.

This case study is designed to be publicly releasable in order to encourage maximum participation throughout the research community. As such, Gundlach's textbook, "Designing Unmanned Aircraft Systems: A Comprehensive Approach" is used as the primary basis for all physical architecture descriptions of the notional Unmanned Aircraft Vehicles (UAVs) and the stakeholder requirements are developed, from which many mathematical relationships linking system characteristics to cost, schedule, and performance are derived. (Gundlach, 2012)

Overview. Using the ARDEC UAV case study described in the UAV Case Study section, this research develops an integrated MBE model and example that can simultaneously propagate design decisions through physics models into the value and cost tradespace In the UAV Tool section. The section on Set-Based Design describes using an open source Excel add-in called SIPMath by Probability Management for the near instantaneous identification and exploration of a large tradespace allowing for the set-based design analysis desired by the ERS program on a realistic pre-milestone A AoA example. (Probability Management, 2017) In addition, the availability of solutions to the AoA in the case study allows realistic comparison between the set-based design methodology and traditional point-based design AoA in the Set-Based Design section. Lastly this paper concludes with future research and conclusions.

UAV Case Study

In the case study, stakeholders require a small UAV to perform surveillance missions. There are four design decisions: engine type, operating altitude, wingspan, and two sensor packages that affect the value of the system. For the engine, there is a choice between an electric engine and a piston engine. The wingspan and altitude choices are continuous design variables. Each sensor package contains two different sensors an EO sensor and an IR sensor with different fields of view and resolutions. Propagating these design choices through the intermediary calculations, the system objectives and value measures can be calculated following the assessment flow diagram in Figure 1. 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) 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 1, each calculation diagram represents a different physics based models and other mathematical relationships such as those in Figures 4 and 8. Specifically, there are models to calculate the weight of the UAV, the weight of the sensors, the endurance, the cruising velocity, the probability of detecting objects, the cost, and the labor hours required to create the UAV.

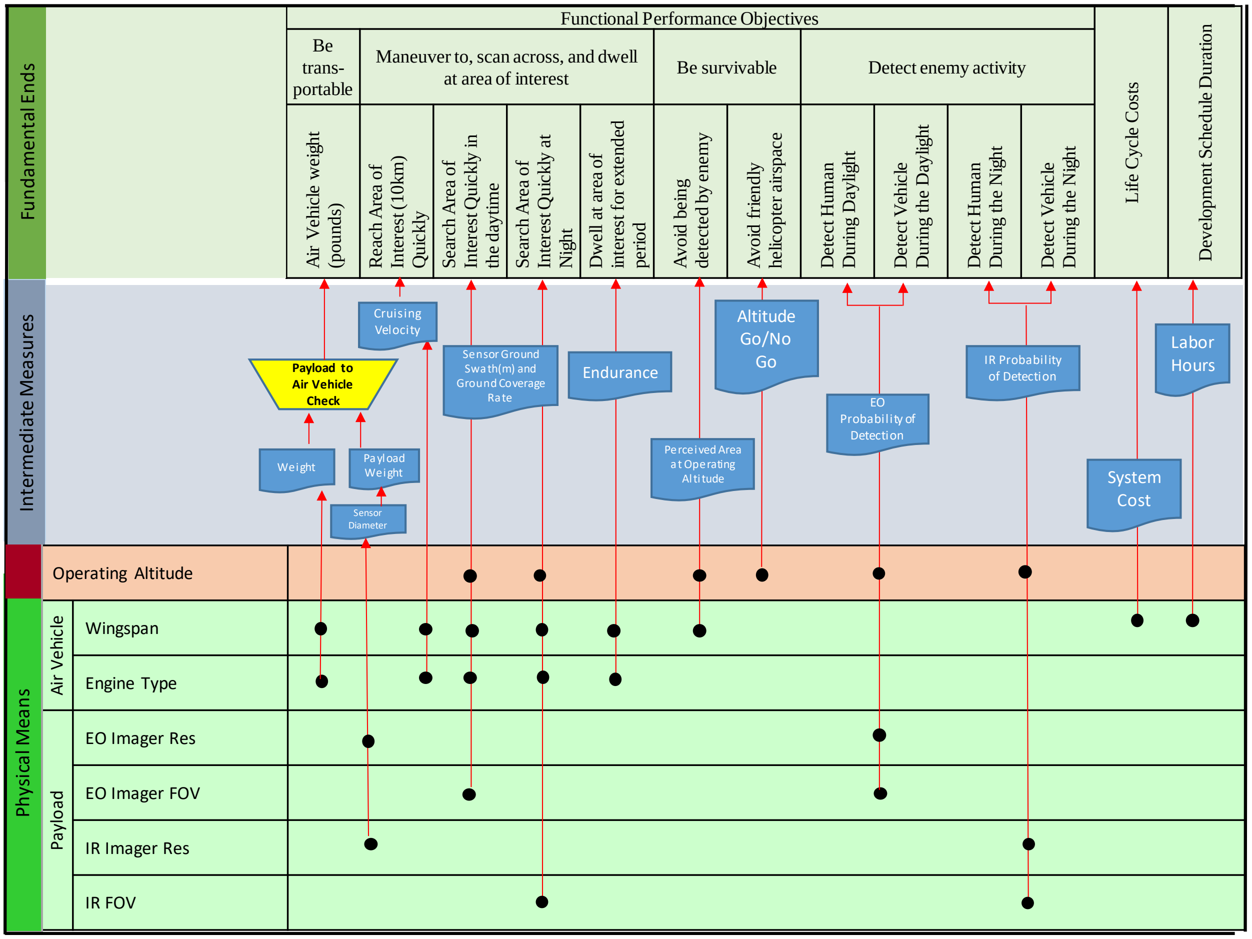


Figure 1. ARDEC UAV Case Study Assessment Flow Diagram (Cilli, 2017)

In the case study, the value of an objective is calculated using the multi-objective additive value model as described in Parnell 2017. (Parnell, 2017) This multi-objective value is calculated using the value curves and summarized value model in Figures 3 and 4. The value model contains 10 value measures to meet the objectives in Figure 1: UAV weight, time required to fly 10 km, time required for the EO sensor to scan, time required for the IR sensor to scan, dwell time, perceived area of UAV, and the probability of detecting humans and vehicles both during the day and at night. In the value curves in Figure 2, the relative value on the y-axis from zero (minimum acceptable) to 100 (ideal) is given for each measure on the x axis. Using these value curves, value scores for a particular system on each measure are calculated in Figure 3. These value scores are multiplied by the swing weights in Figure 3 to calculate the weighted value on each measure. Lastly, the weighted values on the measures are summed to calculate the total system value. Figure 3 shows the calculation of value for 1 alternative.

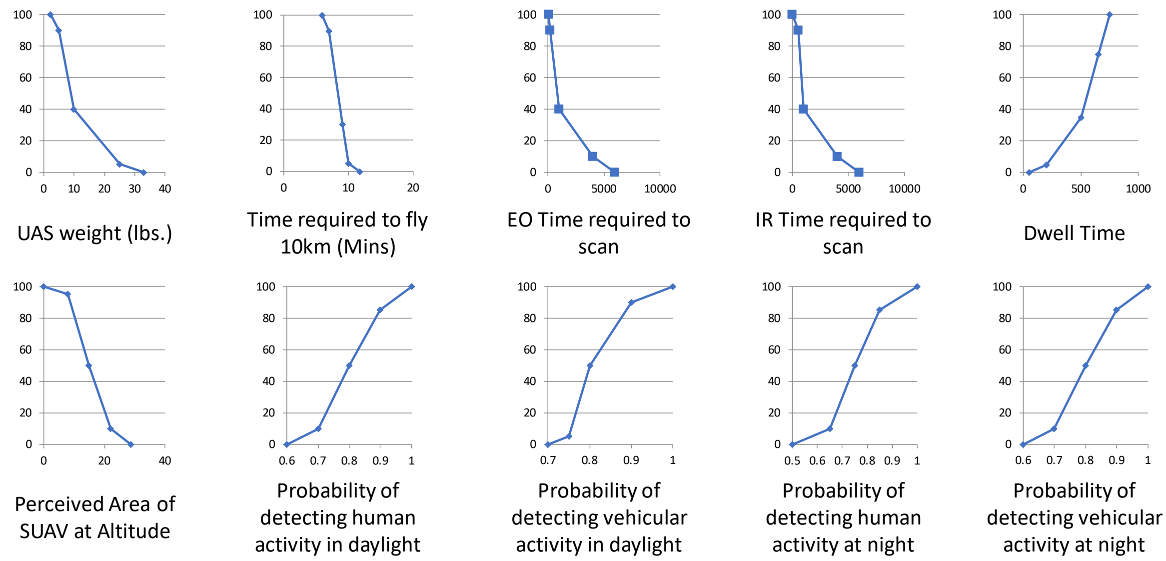


Figure 2. Value Curves (Performance vs Normalized Value)

Value Calculations				
Value Measure	Value Measure Data	Value Score	Swing Weight	Weighted Value
UAS Weight	3.0	97	0.10	10
Time required to fly 10km (Mins)	10.1	5	0.10	0
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)	1,045.59	40	0.10	4
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)	5,256.82	4	0.10	0
Dwell Time (Mins)	72.18	1	0.10	0
Percieved Area of SUAV at Altitude	5.03	97	0.10	10
Probability of detecting a human in daylight	0.83	60	0.09	6
Probability of detecting a vehicle in daylight	0.83	61	0.11	7
Probability of detecting a human at night	0.82	75	0.11	8
Probability of detecting a vehicle at night	0.82	58	0.11	6
Value	**52.3**		1.1	**52.3**

Figure 3. Value Calculations

The cost for each system is calculated using the cost model in Figure 4. This cost model is a simple early pre-milestone A cost model which calculates an estimated cost based on the wingspan of the UAV. (Gundlach, 2012)

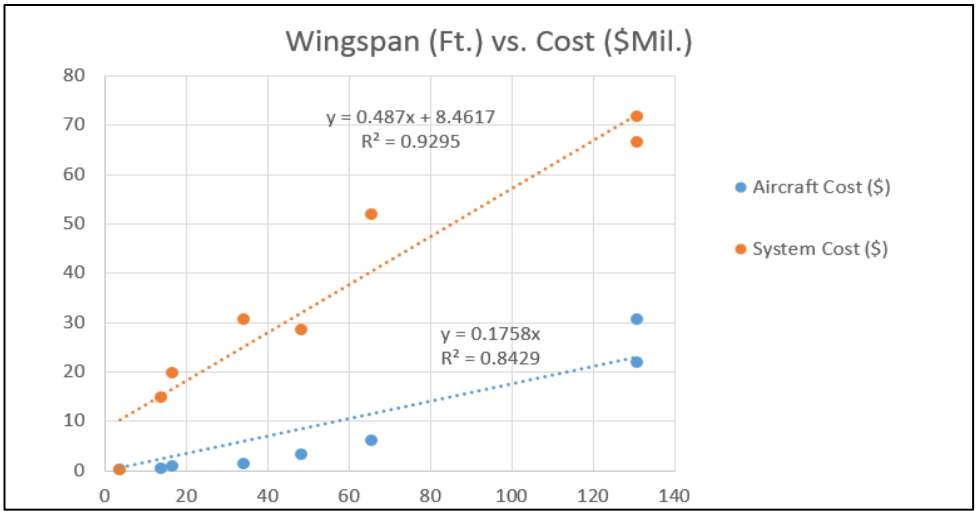


Figure 4. Case Study Cost Model

In the case study, 64 specific point solutions were generated for the problem. However, it is important to note when compared to common practices and the minimum required by AoAs, identifying 64 solutions is far superior. (Small, et al., 2017) Propagating each of these point solutions through all of the models, reveals that only 29 of the 64 initial point-based designs meet the minimum requirements of the value model. The value and costs for these 29 point-based designs are mapped in the value vs cost tradespace in Figure 5.

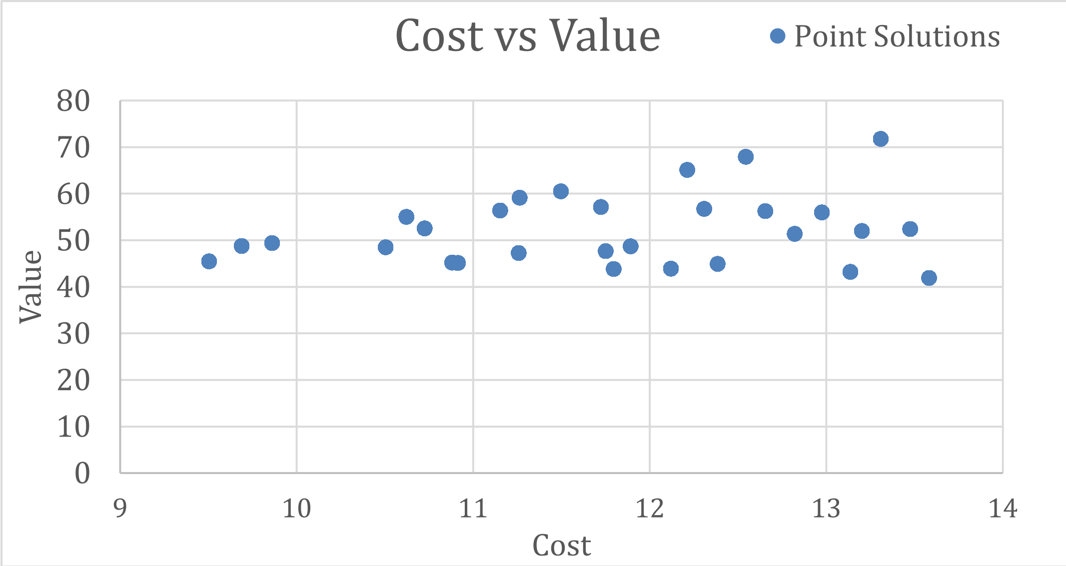


Figure 5. Value vs Cost for Point-Based Solutions

UAV Tool

Tradespace Analytics Tool Design. Using the ARDEC case study, our ERS research team has created an integrated model-based systems engineering tool that propagates design decisions made into physics-based models and regression models to eventually calculate value and cost of an alternative. For the continuous design decisions wingspan and flying altitude, the upper and lower levels were identified and placed as bounds for each decision. The sensor package design decision from the case study was split into two separate decisions, the IR sensor and the EO sensor to allow for more flexibility. Specifically, the sensors were treated as discrete choices between 14 IR sensors and 15 EO Sensors. The engine choice was simply treated as a discrete choice between the two engines.

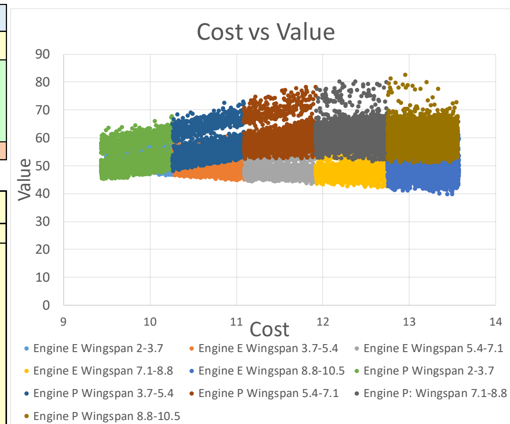
Control Panel. The five design choices were placed on the control panel in Figure 6 allowing for users to select design decisions. Within this control panel, a user can select a desired wingspan, engine type, operating altitude and sensor combination. Following the AoA best practices used in the ARDEC case study, the design choices are simultaneously propagated through the calculations in the AFD (Figure 1) to the value and cost tradespace. (Parnell, 2017)

UAV Integrated Set-Based Design Tradespace Tool

Research sponsored by ERDC ERS program and data provided by ARDEC (Dr. Matthew Cilli and his UAV team)

Air Vehicle					
Wingspan		Engine Type		Operating Altitude	
Wingspan must be between 2 and 10.5		*Engine Type must be either E or P*		*Flying altitude must be between 300 and 10,000 and either less than 500 or greater than 3000 m*	
Wingspan	5.2	Engine Type	E	Altitude	302

Legend
Data
Calculation
Notional Data



Payload							
EO Imager				IR Sensor			
EO Sensor:	Horizonal Pixels	Vertical Pixels	Field of View	IR Sensor:	Horizonal Pixels	Vertical Pixels	Field of View
1	100	100	3	1	100	100	3
2	120	100	3	2	120	120	3
3	120	120	3	3	240	240	3
4	240	240	4	4	240	240	4
5	360	360	5	5	360	240	4
6	400	300	5	6	300	300	4
7	480	360	5	7	160	120	3
8	320	240	3	8	240	180	4
9	540	360	4	9	320	240	5
10	780	600	6	10	320	240	6
11	960	840	7	11	480	320	7
12	960	720	8	12	320	240	9
13	1280	840	9	13	512	480	10
14	1080	720	10	14	512	360	15
15	1280	720	15				
15	1280	720	15	7	160	120	3

Value Calculations	
Value Measure	Weighted Value Score
UAS Weight	10
Time required to fly 10km (Mins)	0
EO Time required to scan (minutes)	4
IR Time required to scan (minutes)	0
Dwell Time (Mins)	0
Percieved Area of SUAV at Altitude	10
Probability of detecting a human in daylight	6
Probability of detecting a vehicle in daylight	7
Probability of detecting a human at night	8
Probability of detecting a vehicle at night	6
Total Value	52

Cost in millions	$11
Labor Hours	36

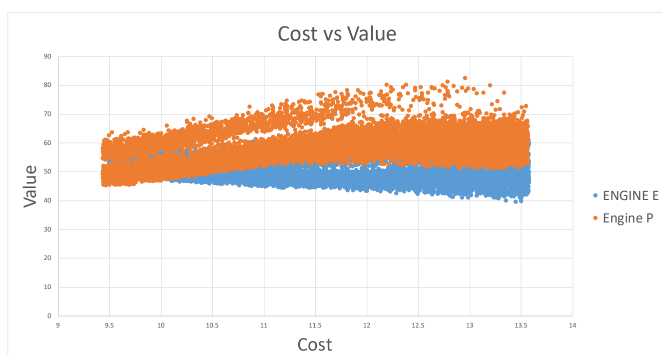


Figure 6. UAV Tradespace Tool Control Page

Models and Worksheets. To propagate the design decisions to performance measures, the UAV tool uses the physics based models and the mathematical relationships from the case study. Each model or mathematical relationship was given its own excel sheet such as the weight calculation page in Figure 7. Moreover, all physics equations and mathematical relationships are dynamically-linked through cell referencing allowing for simultaneous calculations meaning any update in design decisions immediately propagates throughout the model.

Wingspan	5.2
Engine Type	E
Fly Weight	7.7

Sensor Weight	4.2
Communications Link Weight	0.5
Total Payload Weight	4.7

Max Payload	1.38
Appropriate Payload?	FALSE

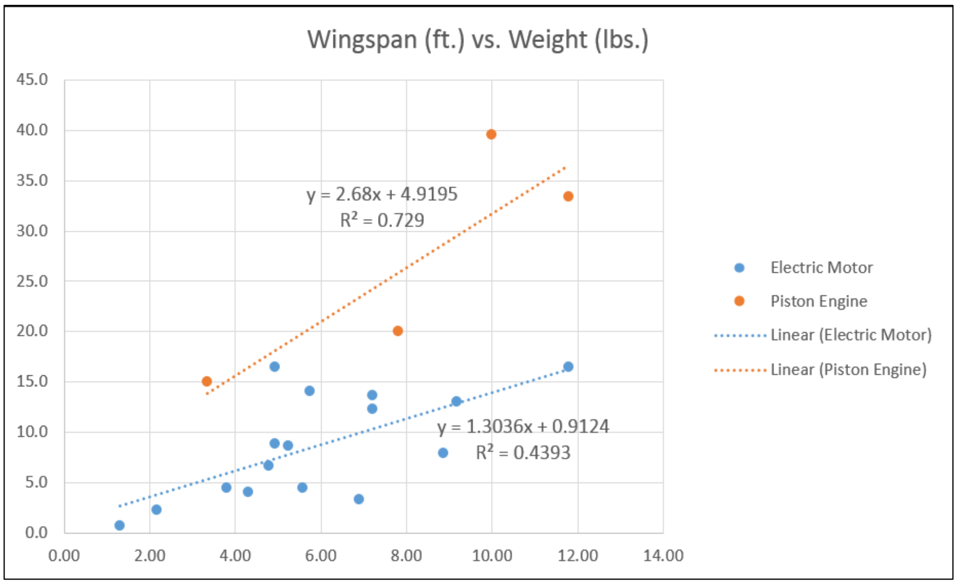


Figure 7. UAV Weight Calculations

Just as in the case study, these performance measures are propagated into the same multi-objective decision analysis model summarized in Figures 2 and 3. In addition, the cost is calculated using the same cost model in Figure 4. Once again, because this is an integrated model with cell referencing throughout, these calculations are simultaneous meaning that changes to the design decisions are immediately propagated to both value and cost and displayed on the control panel in Figure 6.

Set-Based Design

Defining the Sets. In the set-based design perspective, design decisions are composed two types of decisions. (Specking, et al., 2017) A design set driver is a fundamental design decision that defines the system platform. While a design set modifier is a component that can be modified to perform future missions without redesigning the platform. Accordingly, the sets in set-based design can be defined as the collection of design points of one instantiation of design set drivers. Moreover, some sets can be eliminated using stochastic and deterministic dominance in the value-cost tradespace.

In the case study, the design set drivers are the wingspan and the engine type. The operating altitude and sensor combinations are design set modifiers. Therefore, the sets for the case study are the combinations of wingspan and engine type.

Propagation of design decisions with Probability Management. In order to explore the design space and perform set-based design, an open source Excel add-in called SIPMath from Probability Management is used to vary the design choices (Probability Management, 2017). The design decisions are varied by performing Monte Carlo simulations for the continuous and discrete design decisions.

To explore the designs space, the simulation is run 30,000 times creating 30,000 possible solutions, some of which are eliminated using feasibility checks. Through these 30,000 possible solutions, the design space is explored and mapped in cost and value space. However, because some of the variables are continuous and therefore have infinite possibilities, the design space can never be exhaustively explored.

The resulting model is summarized in the Analytics Hierarchy displayed in Figure 8. Overall, for each of the 29,750 feasible system designs, there are 10 value measures and a cost model. There is a total of 1,380,000 calculations that are used to predict 100,000 value measures estimates and 10,000 cost estimates. Using the value model summarized in Figures 2 and 3, these value measure and cost estimates result in 29,750 sets of value and cost that map and explore the tradespace and allow for tradeoffs between value and cost as insights into how to perform set-based design.

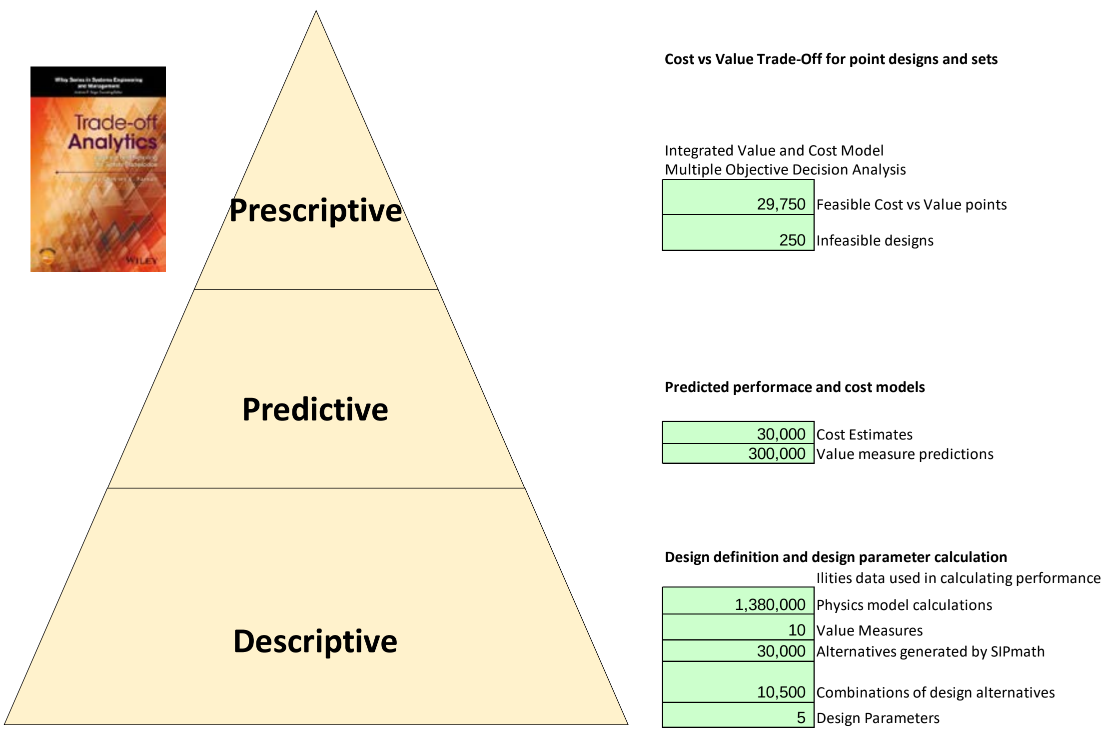


Figure 8. UAV Tradespace Tool Analytics Hierarchy

The value and costs for the solutions developed by the model are graphed in Figure 9. Directly comparing the value and cost identified by the 64 point solutions by mapping the efficient frontier of solutions of the model to the 64 points in Figure 10. This shows that none of the 64 initial points reside on the efficient frontier. Therefore, strictly considering exploring the design space, set-based design is an improvement over point-based design. In addition, set-based design offers much more insight into the design process than simply identifying better point-based solutions.

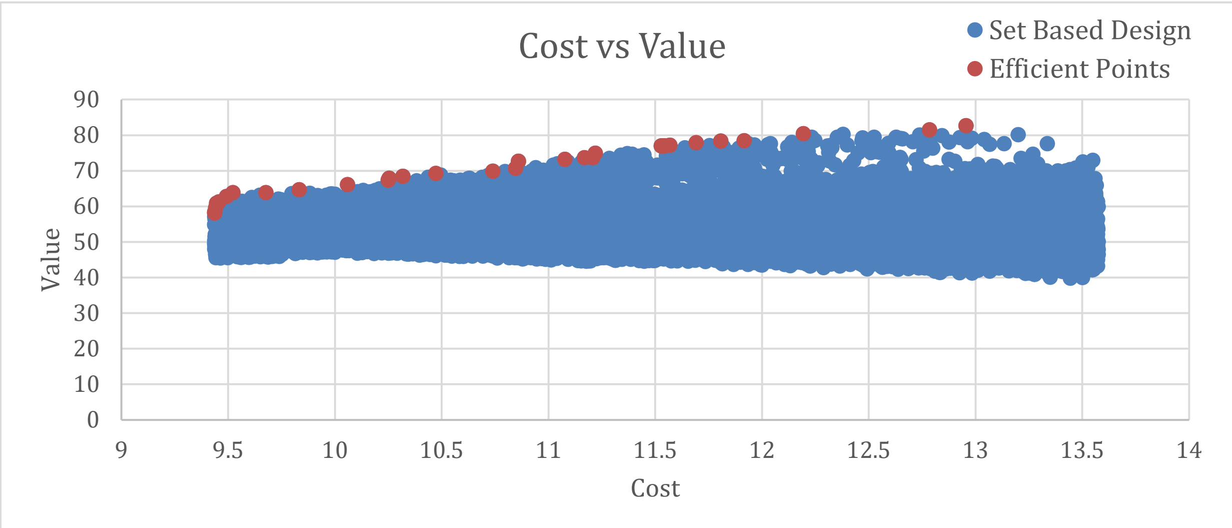


Figure 9. SBD Solutions

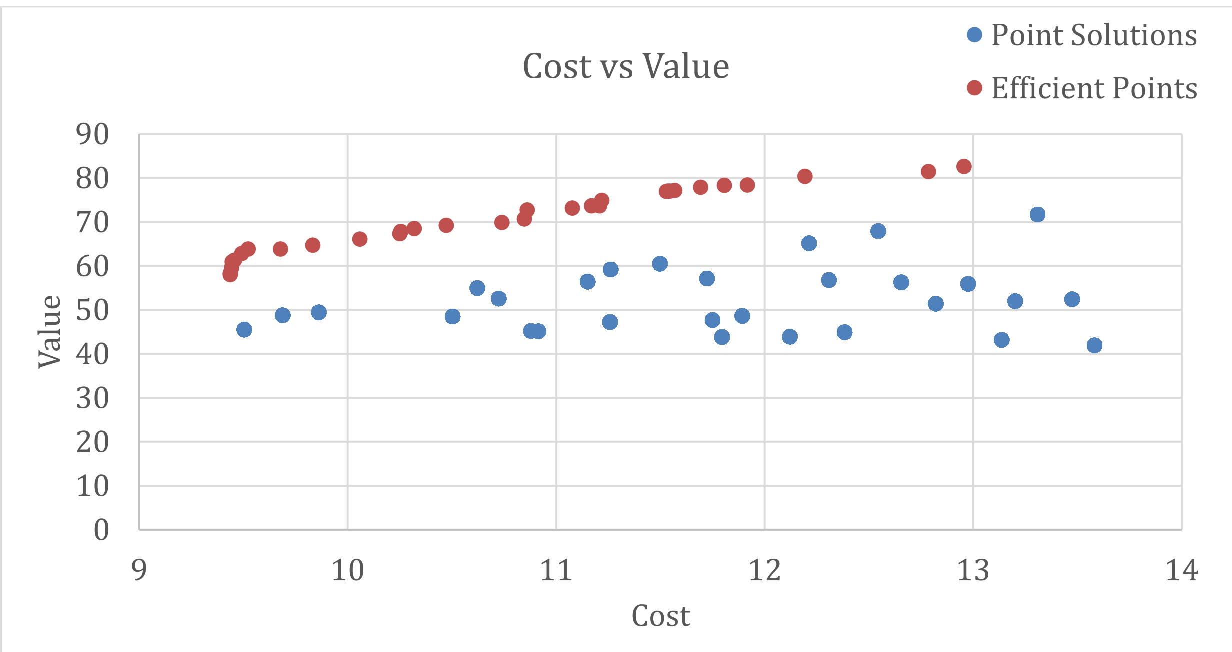


Figure 10. SBD Efficient Frontier vs Point Solutions

Beyond expanding the design space to fully explore the tradespace, set-based design seeks to delay design decision until more information is known. To do this, some sets need to be reduced or trimmed to help designers focus on the best sets. In order to gain insight into this process, sets can be graphically displayed in terms of the design set drivers. For instance, in Figure 11, the solutions are graphed according to the wingspan and engine-type sets. Each set contains the feasible solutions that exist when choosing the specific wingspan and engine type listed and varying all other decisions. In this case study, the engine type E set has lower value but similar costs compared to engine type P. Also, the various wingspans increase the value slightly but also increase the cost. In other words, there is no clear best wingspan since there is a slight increase in value. Accordingly, since engine p has similar cost but higher value, the design set driver engine type can be trimmed by removing Engine E. This allows the analyst to increase the model details to only include piston engines and delay the decision on which wingspan to use until more is known.

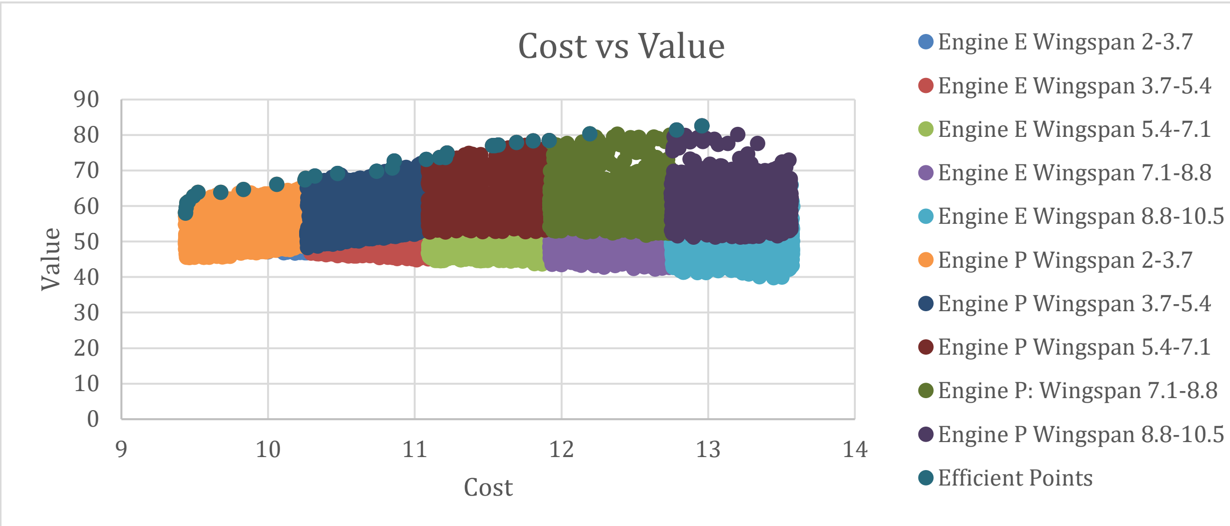


Figure 11.Sets by Design Drivers

Overall, separating the solutions into their sets can provide insight allowing for trimming of sets as well as insight into which decisions should be delayed until more knowledge is gained. These insights can also give analysts into the cost and value drivers. Consequently, analysts gain insight into what sets they might wish to expand or investigate even further in order to increase value and costs.

Future Research

There are three major areas for future research: research on set-based design and tradespace exploration, improvements to the case study and the design model, and research on applying set-based design to complex systems. Currently this demonstration model is focused on the early stages of set-based design. However, for these methods to be useful for the DoD, the set-based methodology must be able to move forward in the design stages. To do this, methods of trimming or reducing the number of sets must be developed.

To improve the realism of the model and the case study to allow for better analysis of techniques, the model will be expanded to continue research into improving the AoA process for ERS. Specifically, there are seven areas of expansion that will be included in the UAV model.

1. Resilience Options and Measures. As ERS is looking for more resilient solutions, resilience options as well as methods to measure and incorporate resilience, specifically resilience to threats during missions and platform resilience to adapt to new threats as a platform, into the value model will be included as the model.
2. Resilience, Value, and Cost Trade-offs. As resilience is included, methods to perform

trade-offs between all three areas of interest must be developed.

3. Life Cycle Cost Model. Currently, the cost model for the case study is a function of wingspan, however to increase the realism of the case study, a new cost model must be developed that not only incorporates system costs, but operating, maintenance, and disposal costs.
4. Illities. As the model increases in detail, all relevant illities will be included to follow the framework to incorporate ERS into AoA best practices.
5. Uncertainty. Currently uncertainty is not included in the case study, but it will be included in the future.
6. Simulations. As the sets mature, simulation will be used to predict value measures and incorporate uncertainty rather than regression equations.
7. Scenario Analysis. Various scenarios with different adversarial and environmental threats will eventually be included in the analysis.

The third research area is using set-based design for complex systems, including systems of systems, which will significantly increase the modeling and simulation complexity. Further research is needed to determine set-based design can scale to meet these challenges.

Summary

The ERS program seeks to leverage the capabilities of model-based systems engineering early in the design process to improve decision making in AoAs and select better system designs. With advances in computing allowing for increased use of physics driven model based engineering tools, we can identify and explore a larger tradespace. Traditional tradespace exploration with point-based design often converges quickly on a solution, leading to modification of the chosen solution until it eventually meets the design objectives. However, this is only effective when the optimal solution is chosen. For complex systems, this prospect is very unlikely. When an inferior point-based design is chosen, the subsequent iterations to refine that solution can be time consuming and lead to a suboptimal design. (Iansiti, 1995) (Kalyanaram & Krishnan, 1997) Conversely, TSE of set-based design considers sets of all possible solutions and enables down-selecting possibilities to converge at a final solution.

Using the ARDEC case study, this research developed an integrated MBE model and example that can simultaneously propagate design decisions through physics models into the value and cost tradespace. Using an open source Excel add-in called SIPMath by Probability Management allows for the near instantaneous exploration of a large tradespace allowing for the set-based design analysis desired by the ERS program on a realistic pre-milestone A AoA example. Exploring the tradespace in this manner, analysts can identify far more solutions and a better efficient frontier that what traditional point-based design can identify. By determining sets by the design drivers analysts can perform set-based design on systems. This method can provide insight into the design decisions that allow for trimming of sets and delaying of some design decisions until information is available to confirm the best design solution by looking at the sets in the value and cost tradespace.

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Biography

Colin Small is a research assistant at the University of Arkansas. He is currently working on the Engineered Resilient Systems research program. He graduated with a Bachelor's of Science in Industrial Engineering from the University of Arkansas in May 2016, and is intending to graduate with his Masters of Science in Industrial Engineering in May 2018 and pursue a Ph.D. in Operations Research and Industrial Engineering at the University of Texas at Austin in the Fall of 2018.

Dr. Gregory Parnell is a Research Professor in the Department of Industrial Engineering at the University of Arkansas and Director of the M.S. in Operations Management program. He was lead editor of *Decision Making for Systems Engineering and Management*, (2nd Ed, 2011), lead author of the *Handbook of Decision Analysis, Wiley Operations Research/ Management Science Series* (2013), and editor of *Trade-off Analytics: Creating and Exploring the System Tradespace,* (2017). He previously taught at the West Point, the U.S. Air Force Academy, the Virginia Commonwealth University, and the Air Force Institute of Technology. He has a Ph.D. from Stanford University.

Dr. Randy Buchanan is a Senior Research Analyst at the Institute for Systems Engineering Research (ISER) for the U.S. Army Engineer Research and Development Center (ERDC). He earned his Ph.D. in Engineering from Leeds Metropolitan University, England, an M.S in Physics and B.S. in Electronics from Pittsburg State. He worked as an electrical and biomedical engineer, and served in professorial and administrative roles at Pittsburg State, Kansas State, and Southern Mississippi Universities. Areas of research include systems engineering, aerospace instrumentation, transducer/sensor development, acoustics, coatings/materials/thin films characterization, spectroscopy, cryogenics, and automated planetary & space simulation environmental systems.

Dr. Matthew Cilli serves as a systems engineering manager and data scientist for a research and development organization of the U.S. Army where he is responsible for leading multi-organizational teams through trade-space exploration exercises to help teams find system level solutions that balance competing trades of cost, schedule, and performance in the presence of uncertainty. He earned his Ph.D. in Systems Engineering from Stevens Institute of Technology. He also holds a Masters of Technology Management from the University of Pennsylvania's Wharton Business School and a Bachelor's and a Master's degree in Electrical Engineering from Villanova University and NYU Polytechnic respectively.

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