



Using Set-Based Design to Inform System Requirements and Evaluate Design Decisions

Gregory Parnell, University of Arkansas

Eric Specking, University of Arkansas

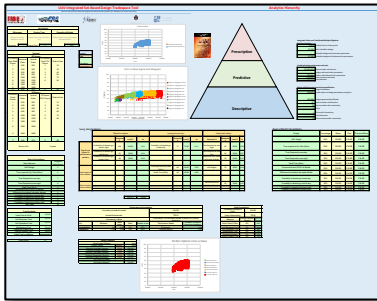
Simon, Goerger, US Army ERDC

Matthew Cilli, US Army CCDC Armaments Center

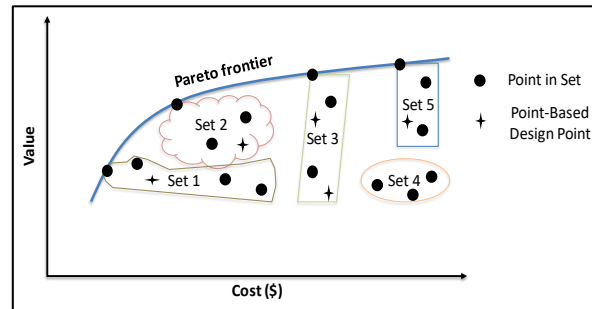
Edward Pohl, University of Arkansas

Bottom Line Up Front

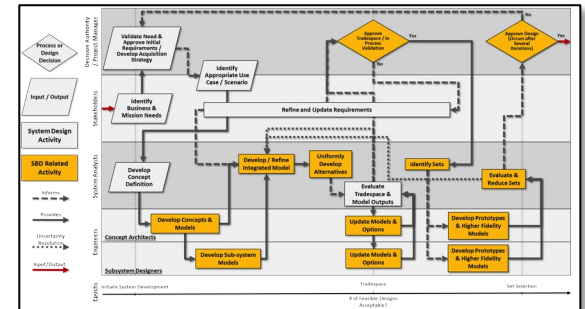
SBD UAV Demonstration Model



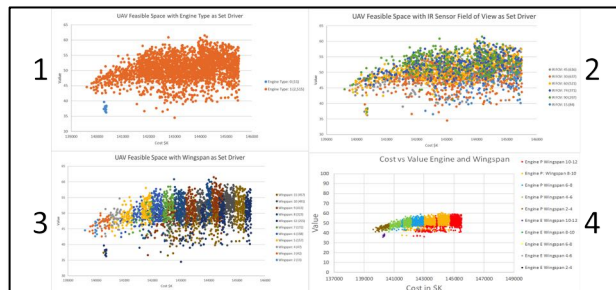
SBD vs. PBD



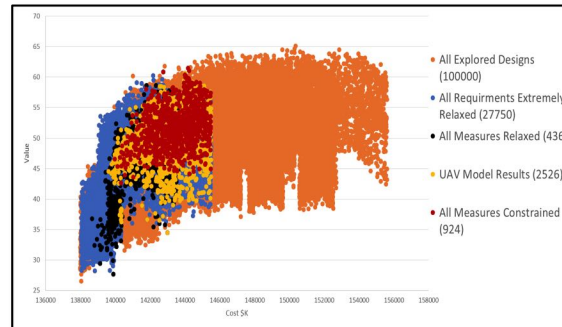
SBD Implementation



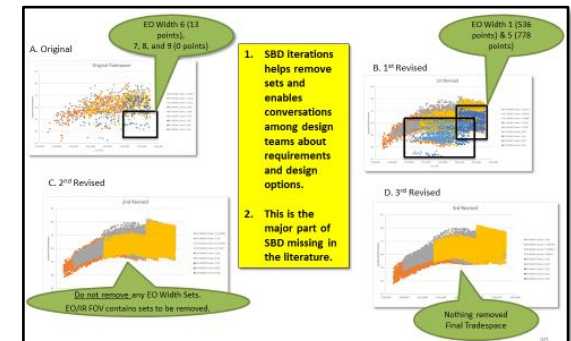
SBD Helps Assess Design Decisions



SBD Helps Assess the Impact of Requirements on the Feasible Tradespace



SBD Helps to Inform System Engineers and Stakeholders



Overview

- ☐ UAV Case Study
- ☐ Point-Based vs. Set-Based Design
- ☐ SBD Implementation
- ☐ Design Decision Evaluation
- ☐ Requirements Analyses
- ☐ System Engineers/Stakeholders Interactions
- ☐ SBD Challenges
- ☐ Future Research & Summary

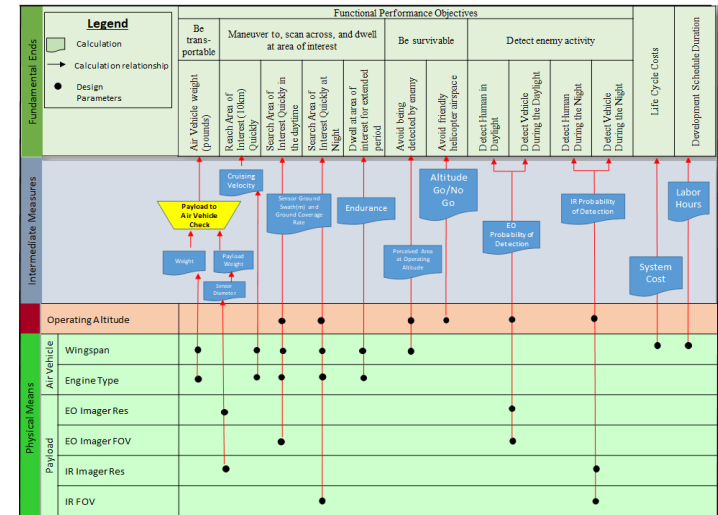
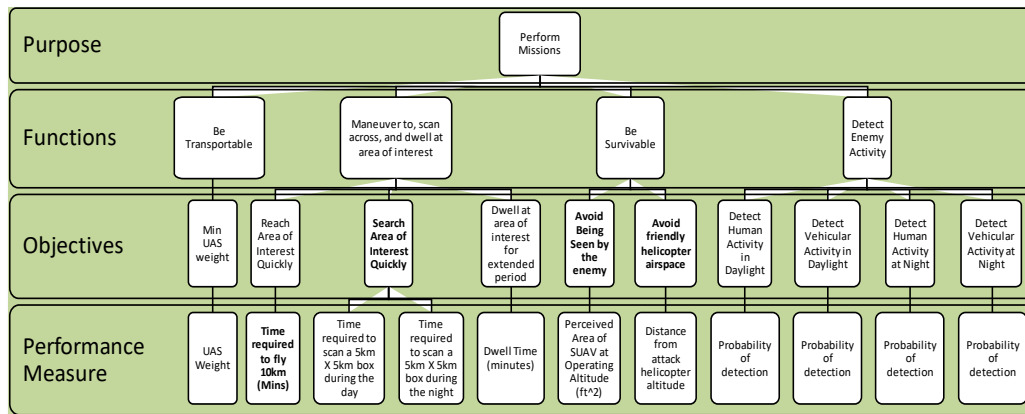
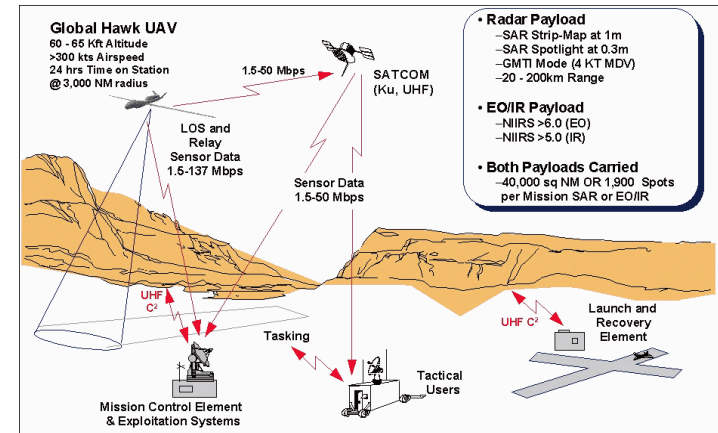
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UAV Demonstration Data

1. Using a notional UAV Case Study, this research applies the Trade-off Analytics Framework and SBD to the case study.
2. Seven design decisions were propagated through models to performance measures, value, and cost.



Synthesizing Results – Additive Value Model

1. The first step is to develop a value curve for each performance measure that scales from a required performance level to an ideal performance level.
2. Any alternative that does not meet a requirement for any performance measure is considered infeasible.
3. For all feasible alternatives, the additive value model calculates each alternative's value.

Note: There exist several utility and value models in addition to additive value model shown in this example.

$$v(x) = \sum_{i=1}^n w_i v_i(x_i)$$

where

$v(x)$ is the alternative's value,

$i = 1$ to n is the number of the measure,

x_i is the alternative's score on the i^{th} measure,

$v_i(x_i)$ is the single dimensional value of a score of x_i ,

w_i is the weight of the i^{th} measure,

$$\sum_{i=1}^n w_i = 1$$

and (all weights sum to one).

The additive model assumes preferential independence. See Keeney & Raiffa, 1976, and Kirkwood, 1997 for additional models.

Life Cycle Cost Model

Hardware Cost

$$\begin{aligned}
 \text{Air Vehicle Recurring Unit Cost (\$K 2013)} &= \text{FlyWeight} * 1.002 \\
 \text{Air Frame Unit Recurring Cost (\$K 2013)} &= \text{PayloadWeight} * 5.607 \\
 \text{Propulsion Unit Recurring Cost (\$K 2013)} &= (\text{FlyWeight} - \text{PayloadWeight}) * 1.808 \\
 \text{Payload Average Unit Cost (\$K 2013)} &= 0.5 * \text{AirFrameUnitCost} \\
 \text{Total Hardware Cost (\$K 2013)} &= \text{TotalGroundStation} + \text{AirVehicleUnitCost} + \\
 &\quad \text{PayloadAverageCost} + \text{PropulsionUnitCost} + \text{AirFrameUnitCost}
 \end{aligned}$$

Support Costs

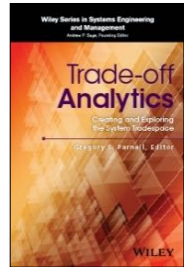
$$\begin{aligned}
 \text{Unit Level Manpower Cost (\$K 2013)} &= 250 * 0.5 * \text{NumberOfSystems} \\
 \text{Unit Operations Cost (\$K 2013)} &= (24676 + 0.8286 * 1156 * \text{TotalAirCraftInventory}) * 1/10 \\
 \text{Maintenance Cost (\$K 2013)} &= \left(41223 + 0.1261 * \text{AirElementsWeight} * \right) * \frac{1}{10} \\
 &\quad \text{AgeOfAircraft} * \text{TotalAircraftInventory} \\
 \text{Sustaining Support Cost (\$K 2013)} &= \text{TotalHours}^{0.7303} * \text{NumberOfSystems} \\
 \text{Indirect Support Cost (\$K 2013)} &= 2777 * e^{(0.01824 * \text{NumberOfSystems})}
 \end{aligned}$$

Life Cycle Cost

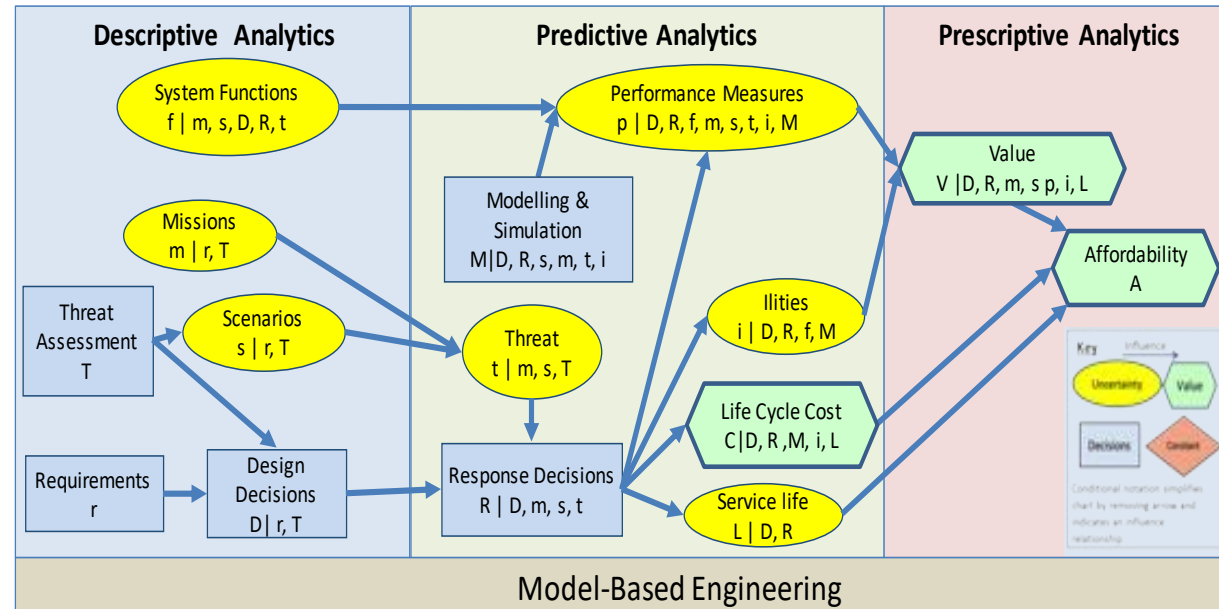
$$\begin{aligned}
 \text{Life Cycle Cost (\$K 2013)} &= \text{TotalHardwareCost} * \text{NumberOfSystems} \\
 &+ (\text{Unit Level Manpower Costs} + \text{Unit Operations Costs} + \text{Maintenance Cost} + \text{Sustaining Support Cost} + \text{Indirect Support Cost}) \\
 &* \text{Service Life}
 \end{aligned}$$

We use a lifecycle cost model to estimate cost throughout the UAV's lifecycle.

Developed Integrated Trade-Off Analytics Framework




1. Describe integrated framework with analytics terms
2. Retain the sound mathematical foundation
 - a. Multiple Objective Decision Analysis for value
 - b. Life Cycle Cost
 - c. Value and Cost Risk
3. Retain SIPmath for MC simulation
4. Identify sets to explore the tradespace



The integrated model uses MBE to simultaneously assess the value, cost, and risk of the tradespace to identify affordable, efficient decisions.

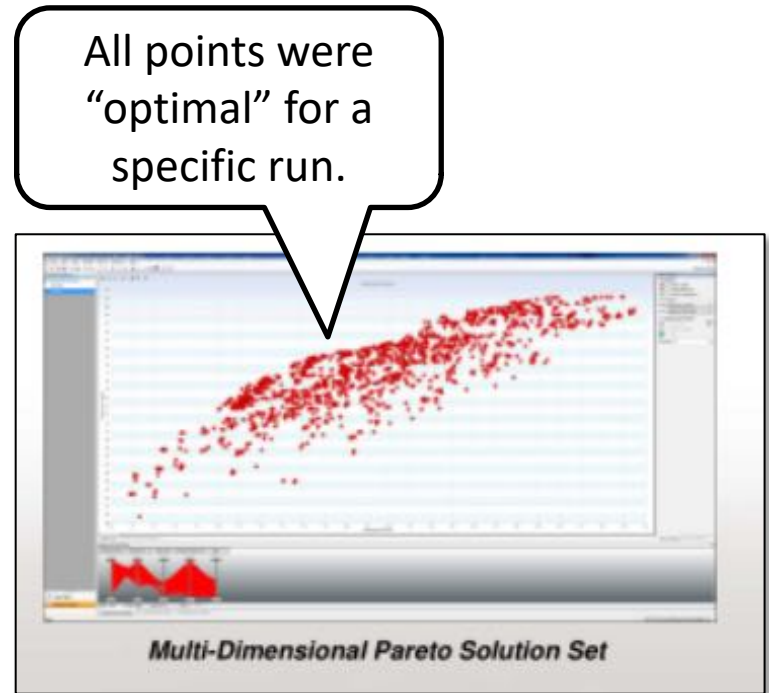
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Point-Based Design Best Practices

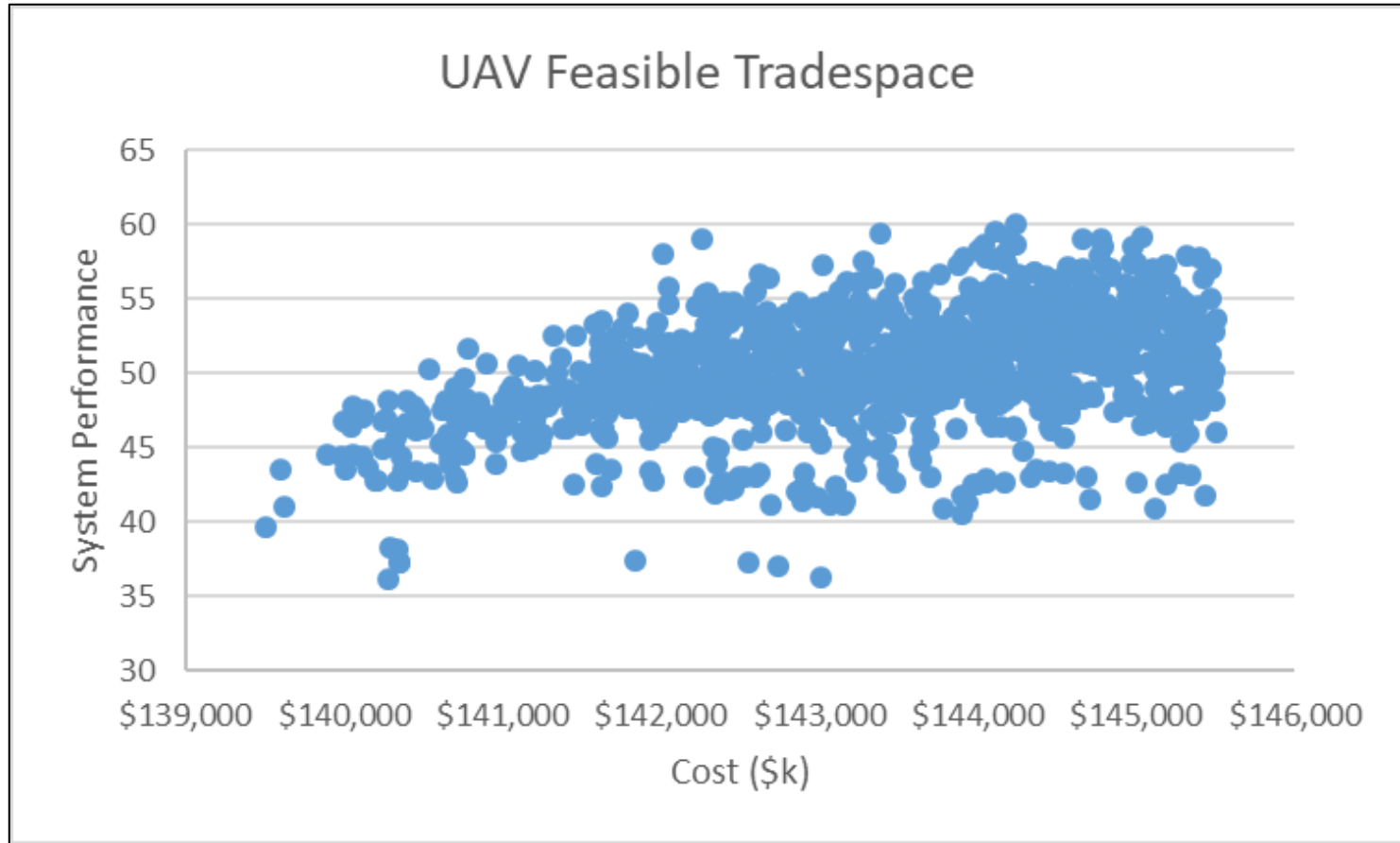
1. Develop integrated models to explore the tradespace
2. Use optimization to identify Pareto frontier in cost vs. value space, e.g.,
 - a. Whole System Trades Analysis Tool (WSTAT)
 - i. Sandia National Laboratory
 - ii. Genetic Algorithm
 - b. Advanced Collaborative Systems Optimization Modeler (ACSOM)
 - i. Wayne State
 - ii. IP with heuristic
3. Help identify promising point designs for next development phase



https://www.sandia.gov/CSR/_assets/documents/WSTAT.pdf

Heuristic optimization techniques are used to find Pareto solutions, but optimality is not guaranteed due to significant non-linearity in the tradespace.

Tradespace Representation



1. Monte-Carlo representation of the feasible tradespace helps to identify a Pareto Frontier.
2. Does not provide insights into how to assess design decisions or requirements.

Set-Based Design Distinctions

1. “Considers large number of designs”
2. “Allow specialist to consider a design from their own perspective and use the intersection between individual sets to optimize a design”
3. “Establish feasibility before commitment”
4. Set-Based Design is a concurrent engineering alternative that provides improved stakeholder value through extensive uncertainty resolution and improved alternative designs

D. J. Singer, N. Doerry, and M. E. Buckley, “What Is Set-Based Design?,” Naval Engineers Journal, vol. 121, no. 4, pp. 31–43, 2009.

The Second Toyota Paradox: How Delaying Decisions Can Make Better Cars Faster

Allen Ward • Jeffrey K. Liker • John J. Crittiano • Durward K. Sobek II

David J. Singer, PhD., Captain Norbert Doerry, PhD., and Michael E. Buckley

What is Set-Based Design?

ABSTRACT

On February 4, 2008 Admiral Paul Sullivan, Commander of the Naval Sea Systems Command, sent out a letter entitled: Ship Design and Analysis Tool Goals. The purpose of the widely distributed memorandum was to state the requirements and high-level capability goals for NAVSEA design systems and analysis tools. In this memo, Admiral Sullivan expressed the need for evolving models and analysis tools to be compatible with, among other things, Set-Based Design (SBD). Admiral Sullivan's memo was a major step towards improving ship design programs with new, more powerful analytical support tools but many have asked, “What is Set-Based Design and how does it relate to Naval Ship Design?”

SBD is a complex design method that requires a shift in how one thinks about and manages design. The set-based design paradigm can replace point based design construction with design discovery; it allows more of the design effort to proceed concurrently and defers detailed specifications until tradeoffs are more fully understood. This paper describes the principles of SBD, citing improvements in design practices that have set the stage for SBD, and relating these principles current Navy ship design issues.

INTRODUCTION

Traditional design process or methods have often failed due to the inherent complexity of large-scale product design. The push to exclude the human in design through automation has left a void. Many optimization codes, expert systems, and synthesis loops cannot capture the depth or intent of a human designer. Designing large complex systems, such as naval vessels, requires human involvement but the increased complexity of these vessels also requires a new approach to design.

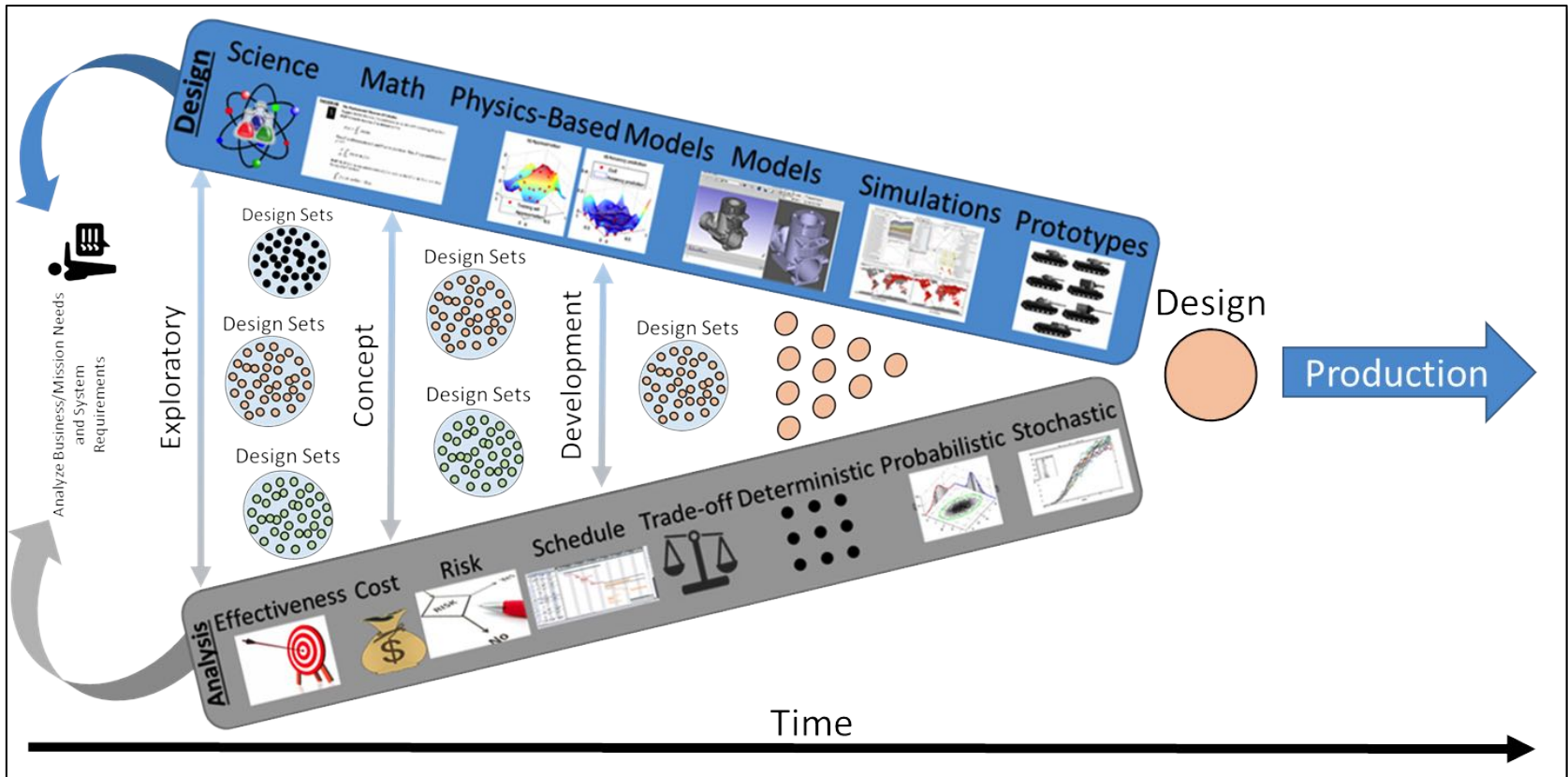
Advanced designs in the United States has begun to emphasize the use of a multidisciplinary team-based concurrent engineering approach, with notable successes in the automotive (Chrysler Viper, Ford Mustang) and aircraft industries (Boeing 777). Integrated Product Teams (IPT's) have also been advocated for future naval ship design (Kenne and Tibbitts 1994; Bennett and Lamb 1994; Frenn et al. 1998). During the LFD17 design core cross-functional design teams were co-located or labeled in a virtual environment to perform the overall design task. The designer members of a cross-functional team are able to comprehend, process, and negotiate the complex range of issues and constraints relevant to a particular design.

Kenne et al (2006) discuss the critical need for a collaborative product development environment to provide a solution to some of the Navy's critical cost and future design issues. Recently a Global Shipbuilding Industrial Base Benchmarking Study (May 2005) was completed. This is a comprehensive study that concluded that the major areas of research needed to make the construction of Naval vessels cost competitive are in the areas of design, engineering, and production engineering. Current analysis of the country's ability to design and build the next generation of vessels has also shown that there is a serious shortage of engineers and a loss of critical skills due to attrition in the experienced design community. The result is that younger, less experienced engineers have been given the role of ship design manager where in the past older, more practiced engineers had typically been used to fill this role. Because of this, new methods for design communication, negotiation, and information transfer are needed to augment the experience of the younger ship design managers. This transition to younger designers is an opportunity to change the way in which the

Commercial and government organizations have used Set-Based Design.

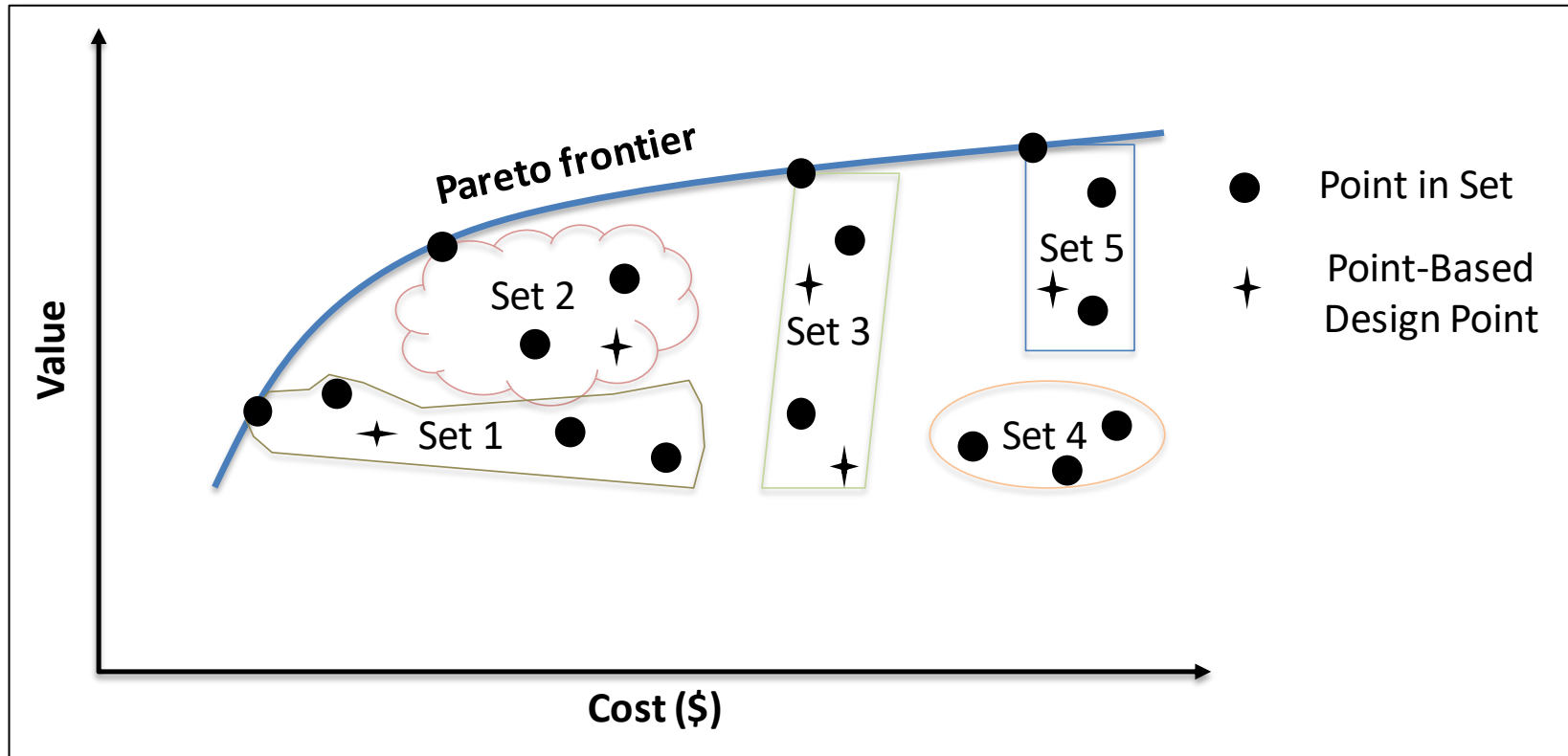
Literature lacks insights on how to implement SBD in a team-based environment.

SBD Visualization



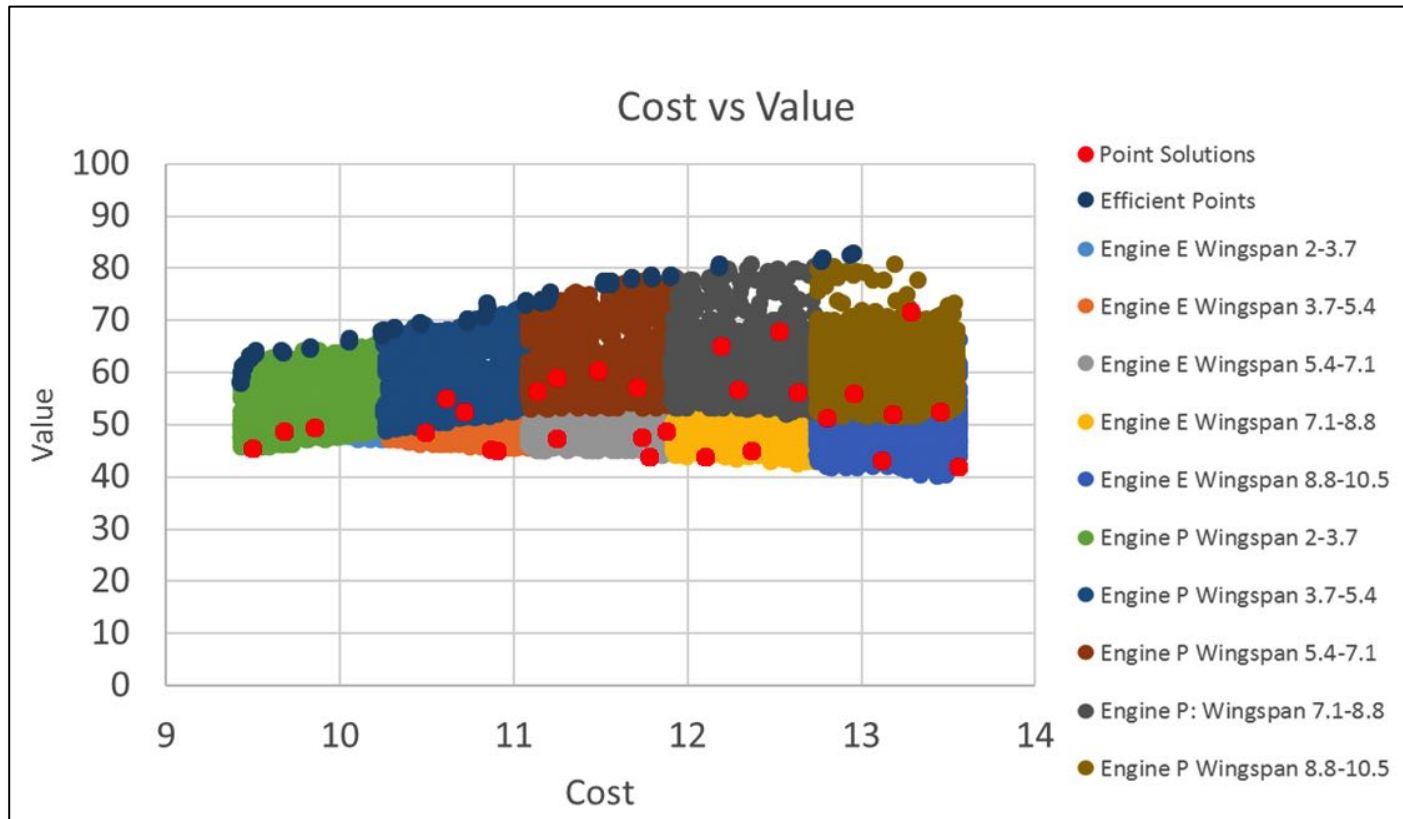
1. Singer et al. do not provide how to perform SBD. This figure provides a visual representation that encompasses Singer et al.'s SBD characteristics.
2. SBD requires design and analysis techniques to perform uncertainty resolution and assess design feasibility on the large number of alternatives.

Trade-off Analytics with Point-Based vs. Set-Based Design



1. Design points can be grouped in sets.
2. SBD seeks to identify the most promising sets.

PBD vs. SBD In Practice

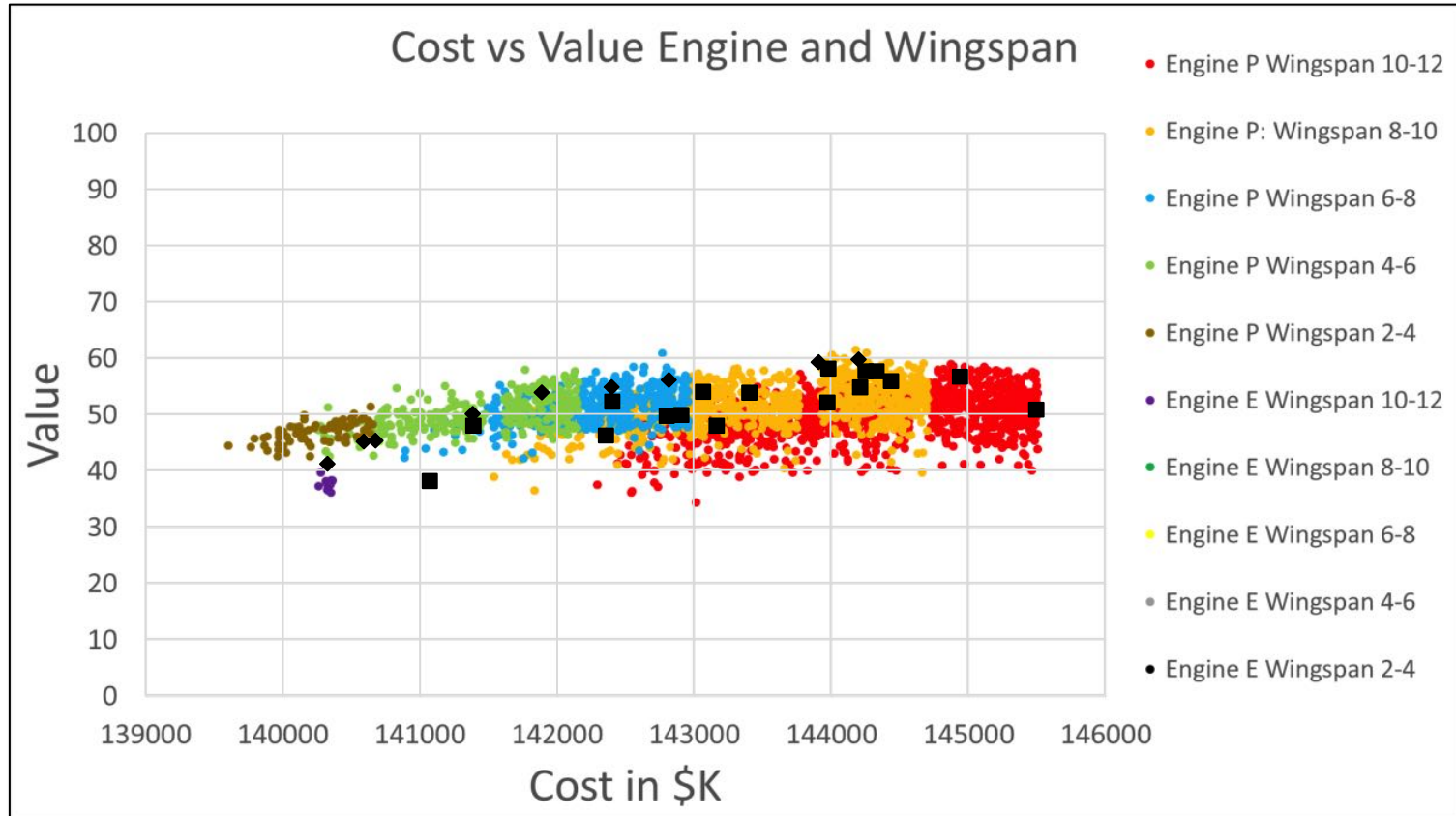


1. Sets are determined by engine type and wingspan. Deterministic analysis shows the value vs cost for the 10 sets.
2. In iteration 2 of the notional case study, SBD identified improved solutions compared to the original 32 point solutions.



SBD TSE Validation Process


100,000 SBD Points with Genetic Algorithm Points



1. Initial Goal: Use optimization to validate SBD.
2. Heuristic algorithms are commonly used to find efficient design points.
3. Validation process using Excel's genetic algorithm in Solver (evolutionary) coded into a custom macro to vary cost and find maximum value.

TSE with SBD found 189 design points that dominated the genetic algorithm points!

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Design Sets

- 1. Design decisions can be discrete or continuous**
- 2. Performance calculated based on design decisions and scenarios**
- 3. Types (mutually exclusive and collectively exhaustive)**
 - a. Design set drivers: fundamental design decisions that define platform characteristics for future missions**
 - b. Design set modifiers: design decisions that are “added on” to the platform and can be modified to adapt to new missions and/or scenarios**

SBD requires a methodology to identify the set drivers.

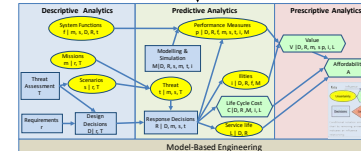
Early Design SBD Process

1. 7 step process to use SBD with the Integrated Trade-off Analysis Framework in early system design.
2. Informs requirements and converges to a set of sets to carry to next design phase.

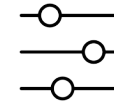
Analyze Business/Mission
Needs and System
Requirements



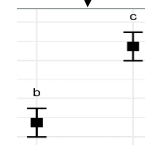
Develop
Integrated
Model



Uniformly
Develop
Alternatives



Evaluate
Tradespace



No

of Feasible
Designs
Acceptable?

Yes

Feasible Designs

Identify Sets




Evaluate Sets



Select Set(s)



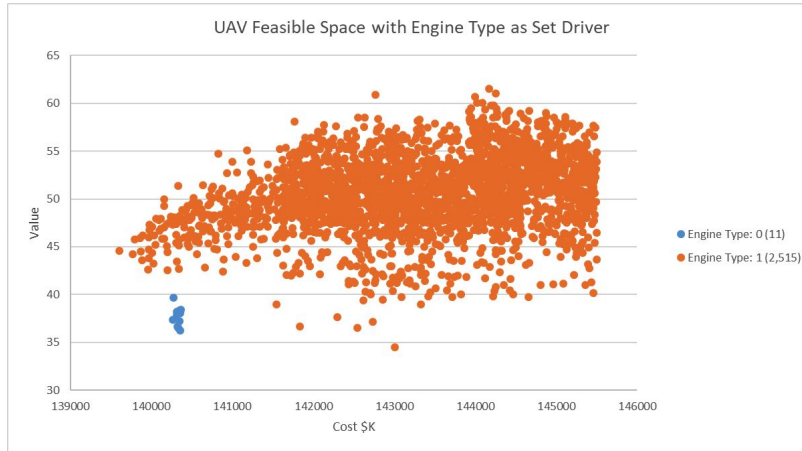
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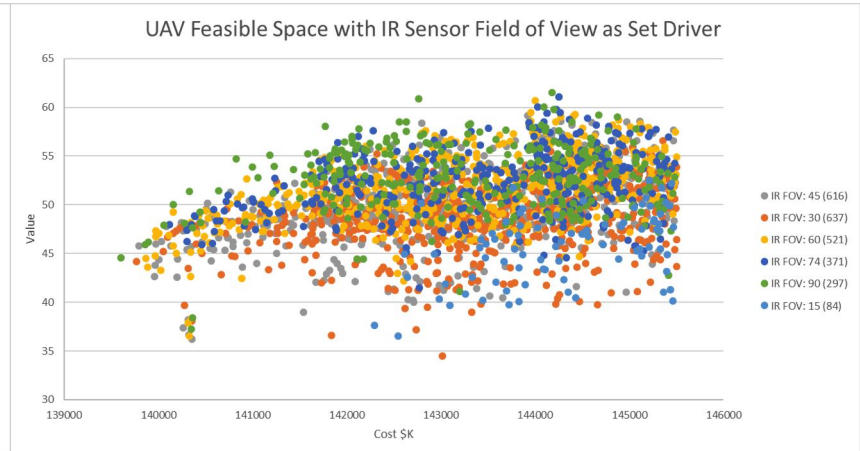


Assess Design Decisions with Sets

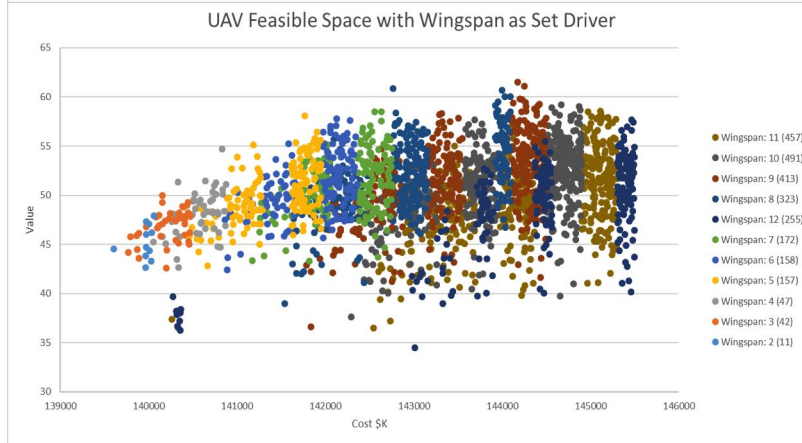
1



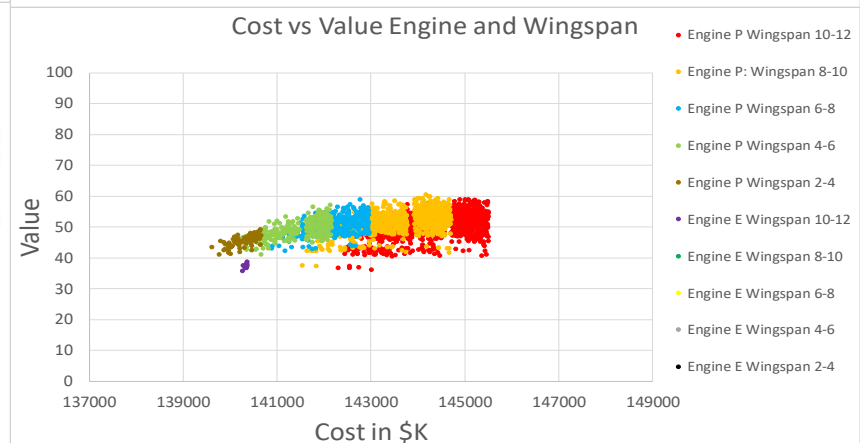
2



3




4



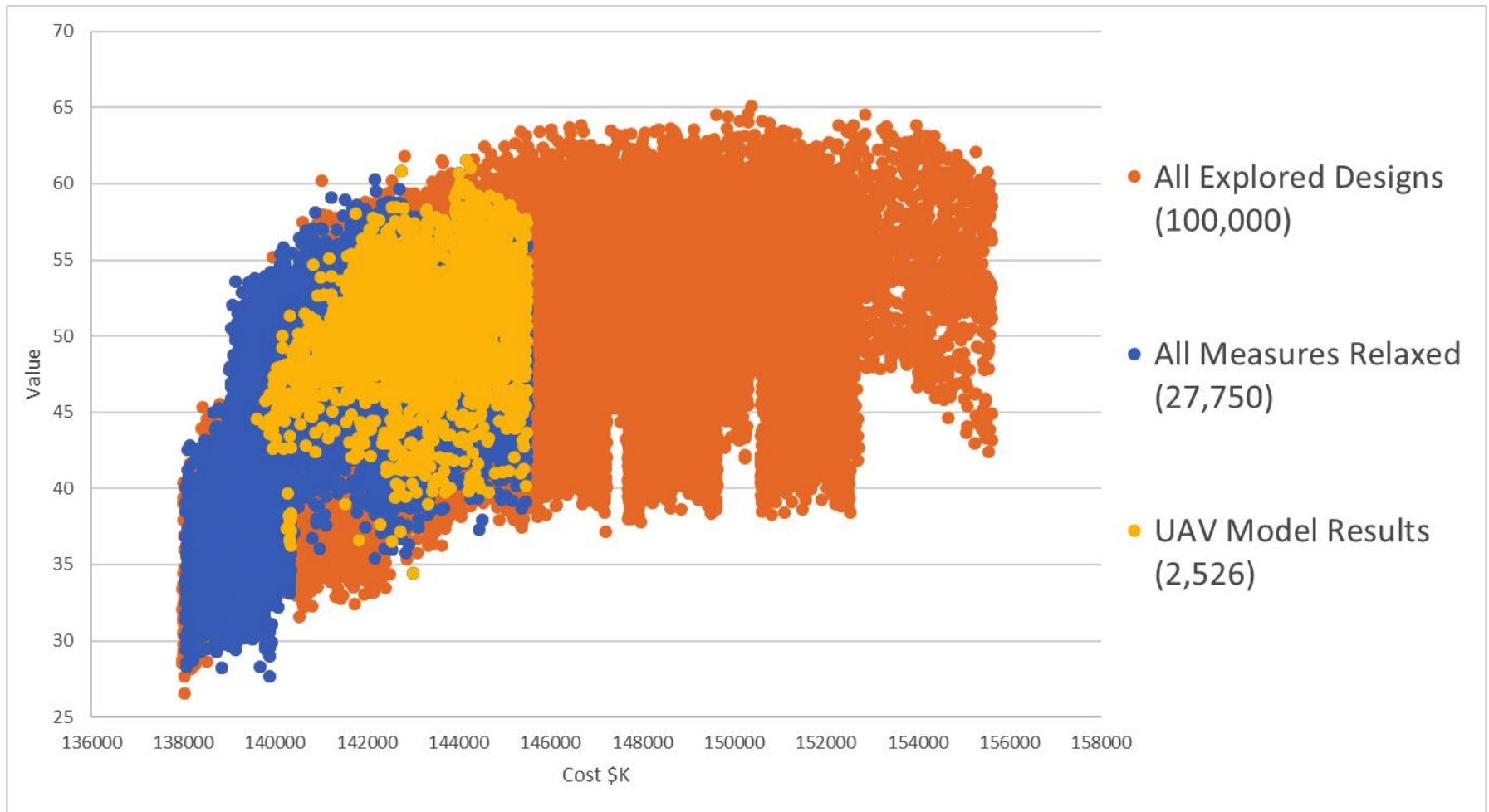
Sets provide insights about design decisions not obvious using points alone.

- 1. Less than 1% of blue engines are feasible (11 out of 500,000)**
- 2. IR Sensor Field of View not a useful set driver (requires more analysis)**
- 3. Wingspan may be a useful set driver**
- 4. Combination of engine and wingspan provides additional information**

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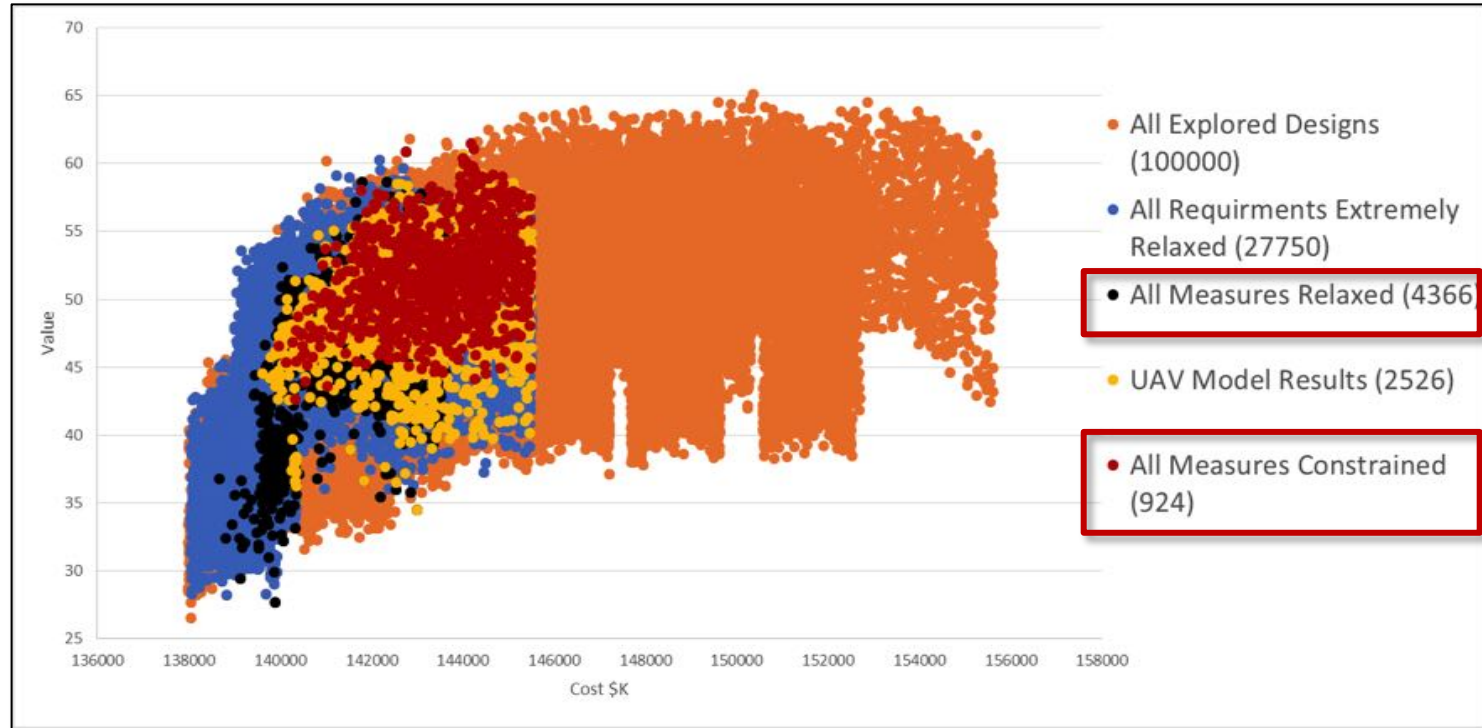
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Requirements Analysis with SBD



Physics-based parametric models removed 72% of the tradespace (orange to blue). The remaining 28% is determined by requirements.

Effects of Changes in All Requirements

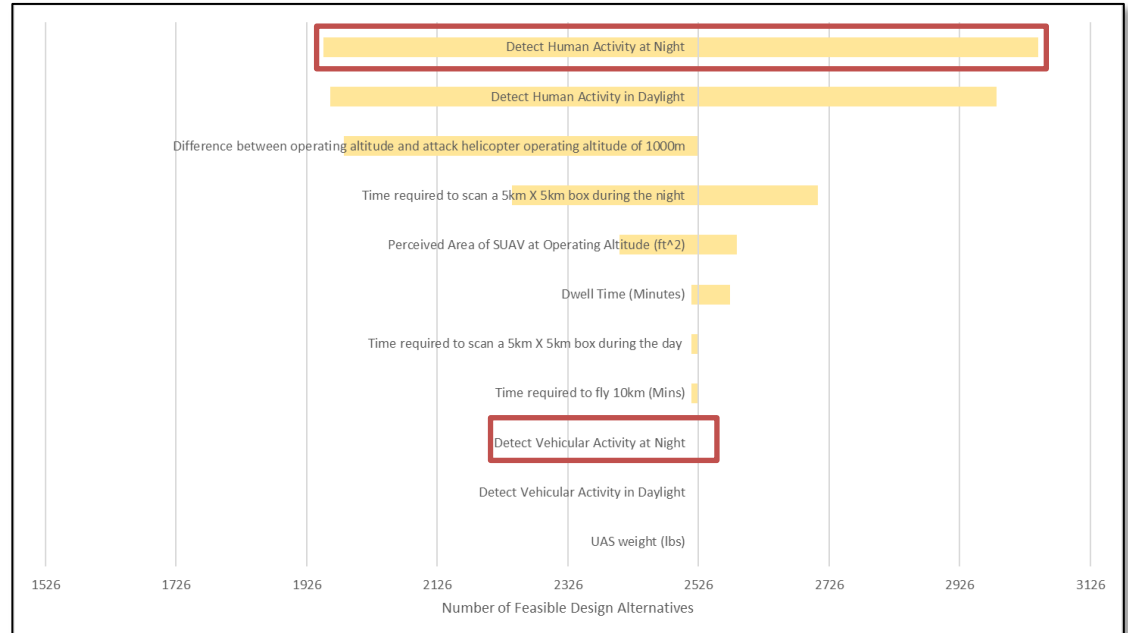


Varying all requirements dramatically changes the number of feasible designs (79% change – 924 to 4366).

- 1. Relaxation: 4,366 feasible designs**
- 2. Constrained: 924 feasible designs**

Effects of individual requirement changes

Performance Measure	Relaxed	UAV Case Study	Constrained
UAS weight (lbs)	60	50	40
Time required to fly 10km (minutes)	20	15	10
Time required to scan a 5km X 5km box during the day (minutes)	220	200	180
Time required to scan a 5km X 5km box during the night (minutes)	220	200	180
Dwell Time (minutes)	30	60	90
Perceived Area of SUAV at Operating Altitude (ft ²)	18	16	14
Difference between operating altitude and attack helicopter operating altitude of 1000 m	0	0	250
Detect Human Activity in Daylight	0.5	0.6	0.7
Detect Vehicular Activity in Daylight	0.5	0.6	0.7
Detect Human Activity at Night	0.5	0.6	0.7
Detect Vehicular Activity at Night	0.5	0.6	0.7

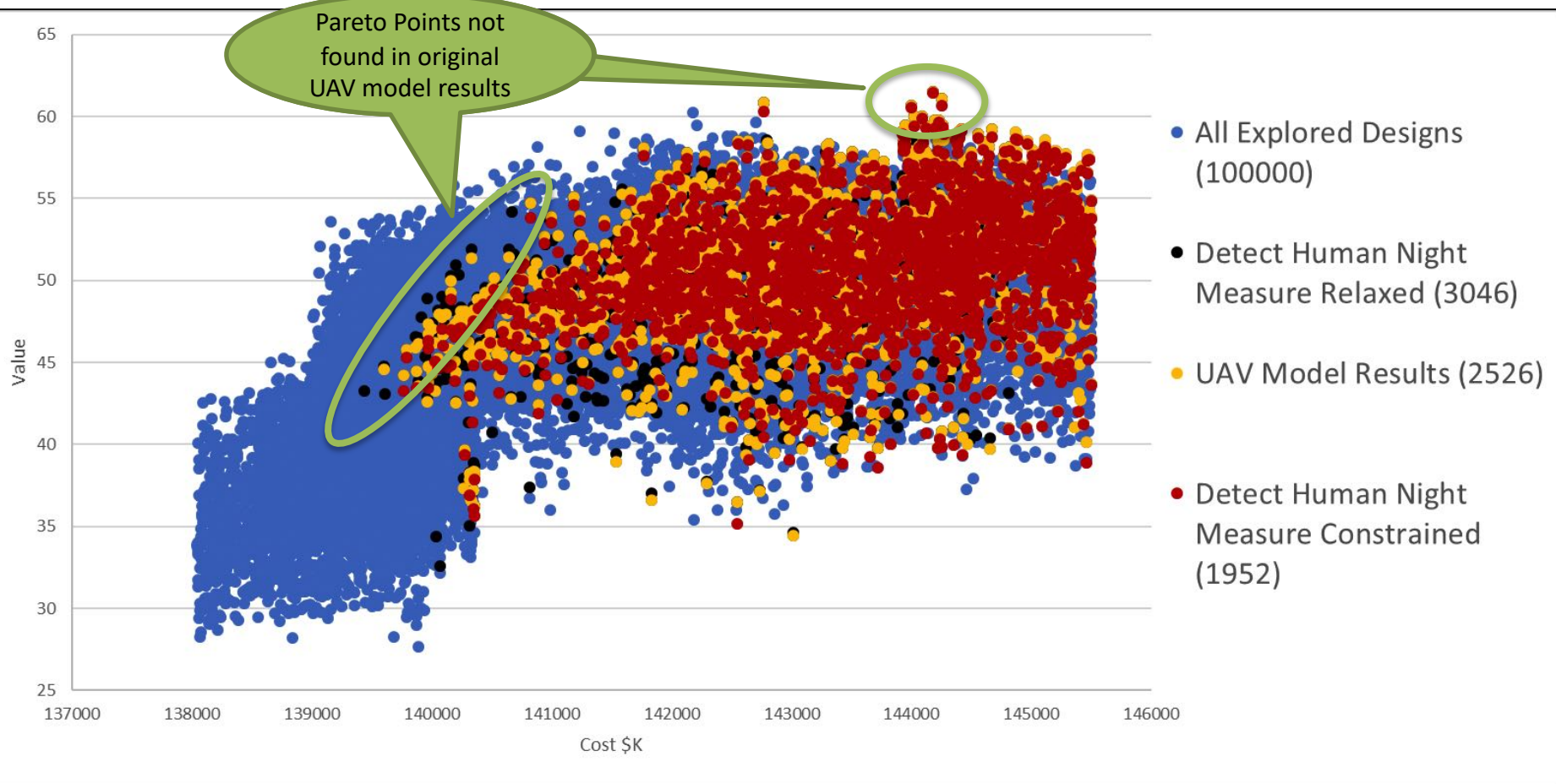


Not all requirements have a significant impact on the feasible tradespace.

- Detect Human Activity at Night: Impacts the number of feasible designs**
- Detect Vehicular Activity at Night: No impact on the number of feasible designs**


Evaluating the Design Space

Detect Human Activity at Night



Changing the tradespace has the potential to generate Pareto solutions not found in the original analysis.

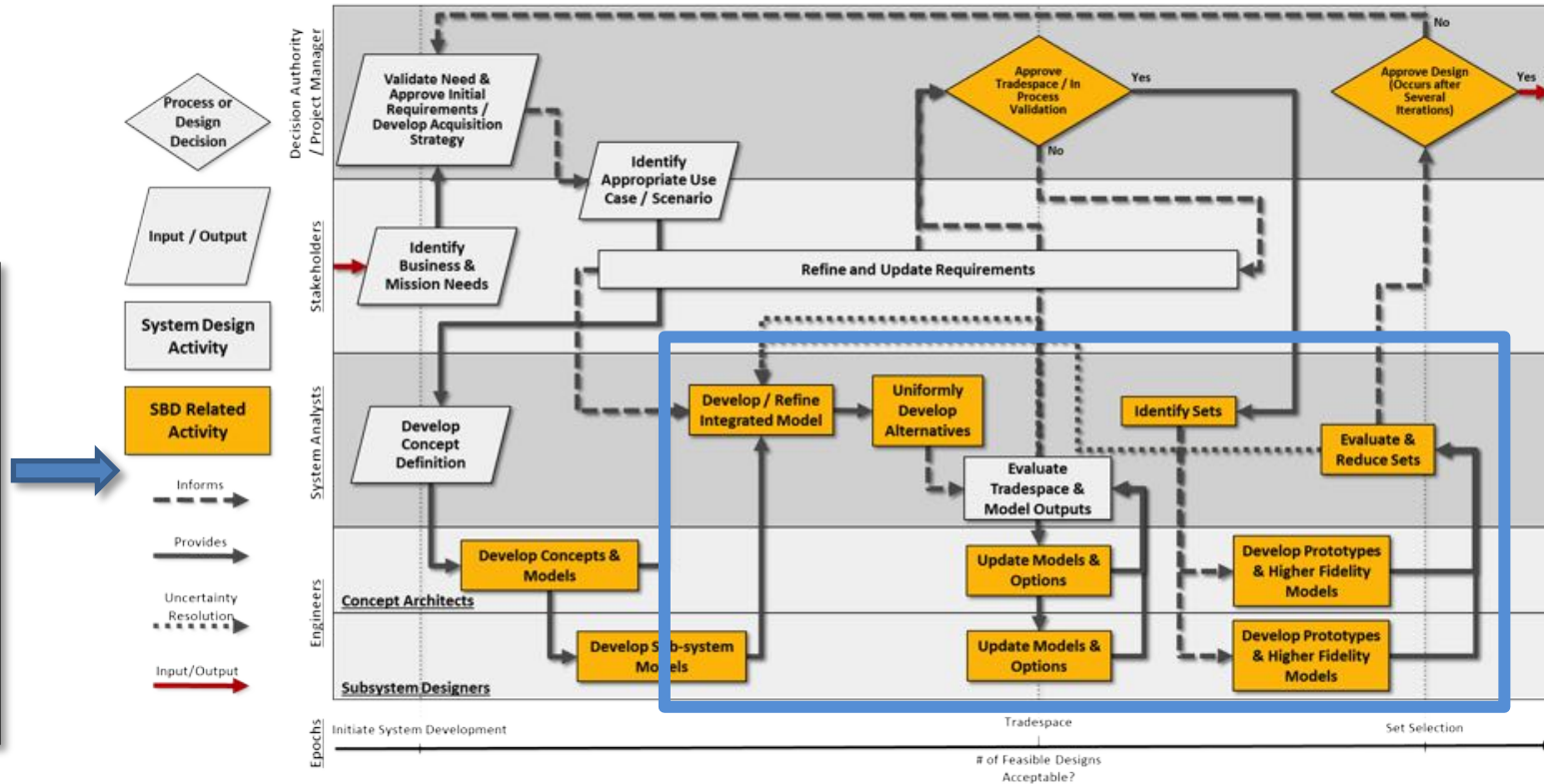
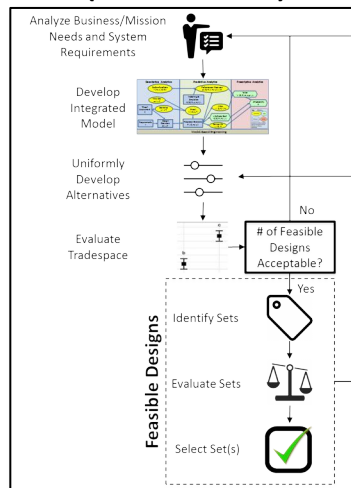
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Early Design SBD Process

System Engineering View (Socio-technical)

System Analysis View (Technical)



SBD requires greater analytical effort than traditional PBD methods. The added cost is justified by the potential for increased program resilience under uncertainty and greater potential to develop better system designs.

This process captures the right information from the right people at the right time and executes the analytics in near real-time.

Example of removing dominated design decision options with EO sensor design teams interaction.

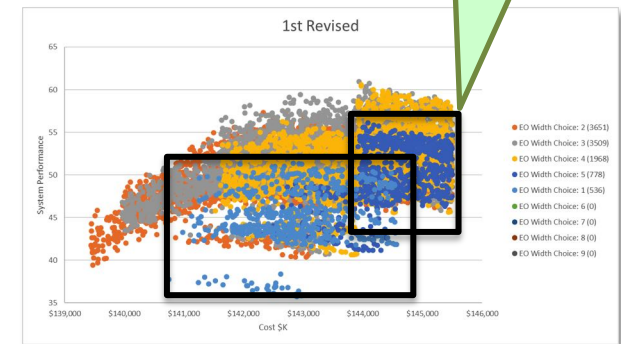
1. SBD iterations helps remove sets and enables conversations among design teams about requirements and design options.

2. This is the major part of SBD missing in the literature.

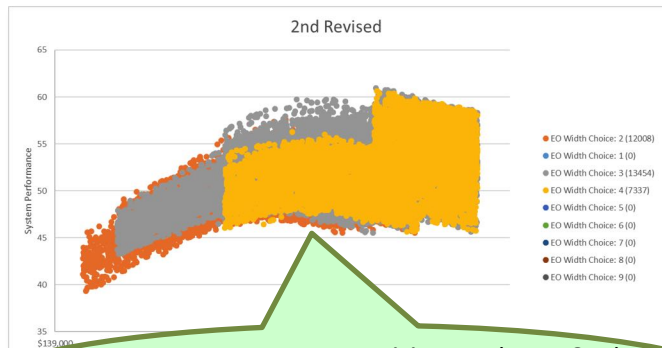
A. Original



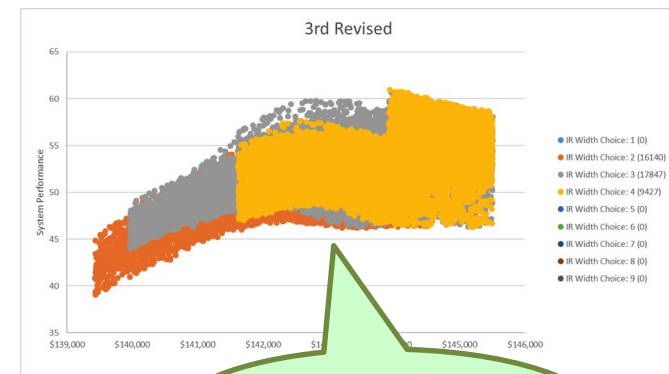
B. 1st Revised



C. 2nd Revised



D. 3rd Revised



Summary of Tradespace Refinement Results for All Design Teams

Decision Options Removed

Tradespace			
Design Decision	Initial	1 st Revised	2 nd Revised
Wingspan			
Engine Type	E		
Operating Altitude	600 – 1000		
EO Sensor Width	6 – 9	1, 5	
EO Sensor Field of View		15	30
IR Sensor Width	6 – 9	1, 5	
IR Sensor Field of View		15	30

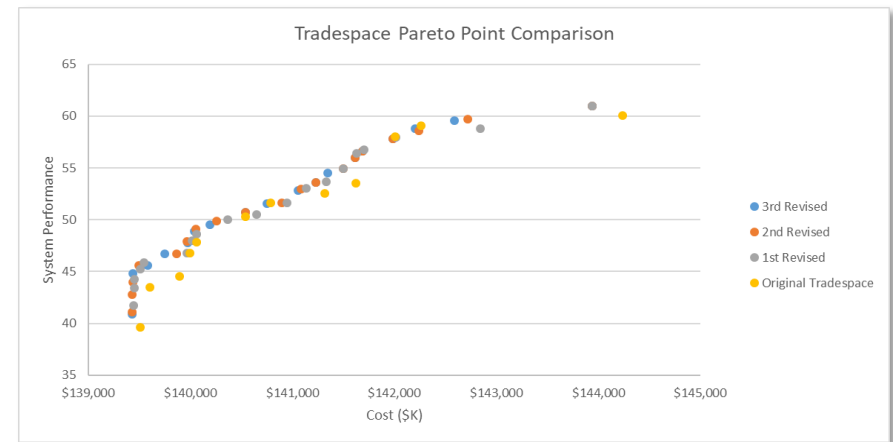
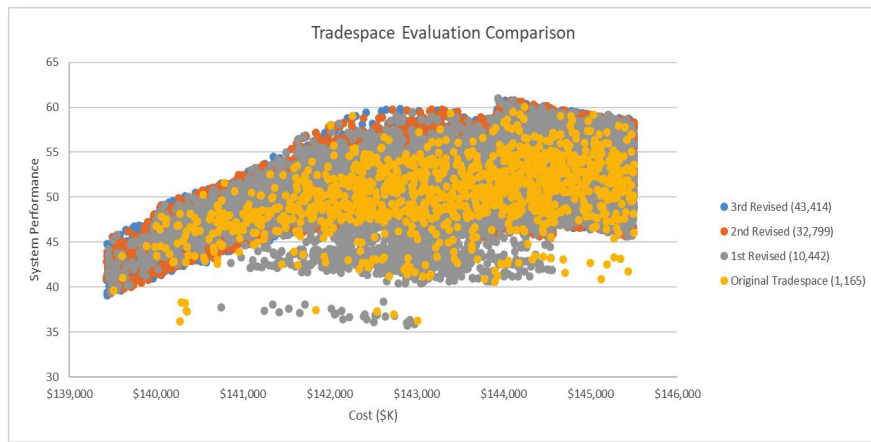
Final Tradespace

Design Decision	Final Decision Options
Wingspan	2 – 12
Engine Type	P
Operating Altitude	300 – 599
EO Sensor Width	2, 3, 4
EO Sensor Field of View	45, 60, 75, 90
IR Sensor Width	2, 3, 4
IR Sensor Field of View	45, 60, 75, 90

- Conversations with design teams about requirements and design options should be held with each team of subject matter experts.**
- SBD Iteration is repeated until a final tradespace selected dependent upon the project schedule.**

Impact of Tradespace Refinement

Tradespace	Counts			Percentages	
	Sampled	Feasible	Pareto Points	Feasible (of Sampled)	Pareto Points (of feasible)
Initial	100000	1165	12	1.2%	1.03%
1st Revised	100000	10442	19	10.4%	0.18%
2nd Revised	100000	32799	19	33%	0.06%
3rd Revised	100000	43414	18	43%	0.04%



Pareto frontier is not dramatically effected by tradespace refinement process. This demonstrates that SBD finds good design alternatives no matter the feasible space.

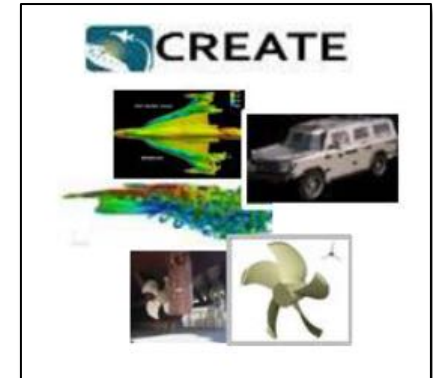
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Challenges using SBD

1. PBD to SBD culture change
2. Rapid assessment of complex design solutions for viability
3. Mission effects generation and assessment on larger sets of alternatives using M&S
4. Storage, sustainment, and access to large data sets (e.g., tera, peta, exa, etc.) for extended periods of time (decades)
5. Data set linkage across domains and specialties
6. Mathematically sound and repeatable processes for down selecting and grouping viable systems into representative bins for presentation to decision makers



Future Research

Development of a Model-Based System Engineering Framework suitable for SBD that includes:

1. Integrated modeling of value, cost, and risk
2. Multi-resolution M&S
3. Uncertainty resolution
4. High fidelity supportability models
5. High fidelity cost models

Look for strategic partners to help integrate SBD into your system engineering processes.

For example, SBIR research.

Proceedings of the American Society for Engineering Management 2019 International Annual Conference
E. Schott, E.-H. Ng, H. Keathley, and C. Kregici ed.

INTEGRATING SET-BASED DESIGN INTO THE DEPARTMENT OF DEFENSE ACQUISITIONS SYSTEM TO INFORM PROGRAMMATIC DECISIONS

Major Nicholas J. Shallcross
University of Arkansas
nshallc@uark.edu

Gregory S. Parnell, Ph.D.
University of Arkansas
gparnell@uark.edu

Edward A. Pohl, Ph.D.
University of Arkansas
epohl@uark.edu

Dennis M. Buede, Ph.D.
Innovative Decisions, Inc.
dmbuede@innovativedecisions.com

Abstract
Over the years, the Department of Defense (DoD) has implemented several significant modifications to its acquisition process with the goal of producing timely and cost-effective systems. These changes, however, have done little to curb major design problems, delays and cost overruns to programs. Many DoD acquisition programs use Point-Based Design (PBD) approaches, frequently resulting in premature design decisions resulting in subsequent schedule delays, and cost overruns. Delays and increased costs are a result of the time-consuming activities undertaken to fix the selected PBD solution prior to the resolution of key technology and budget uncertainties. Set-Based Design (SBD) is a concurrent system design and analysis alternative to PBD, which systematically resolves program uncertainties early in the design phase, potentially reducing the need for costly and inefficient redesign activities. In application, SBD evaluates multiple design concepts for a longer period of time into the design process, while simultaneously resolving requirements and design uncertainties. Commercial manufacturing and defense related industries have successfully employed SBD in product development (PD). This success suggests that a DoD feasibility and integration assessment of an SBD process for PD of a large-scale DoD acquisition programs is required. This research reviews current DoD acquisition processes, provides a strategic framework for SBD integration into these processes, and identifies critical integration challenges for future research. This paper concludes that integration of SBD into major DoD acquisition processes is both feasible and economical, as well as a credible and defensible methodology for making complex design decisions under uncertainty.

Keywords
Set-Based Design, Defense Acquisition, Decision Analysis, Model-Based Systems Engineering, Uncertainty Resolution, Tradespace Exploration

Introduction
The United States Department of Defense (DoD) currently invests trillions of dollars into weapon system research, development, and acquisition (United States Government Accountability Office, 2017). Responsibility for this significant investment lies with an equally large and complex defense acquisition system; a system that has periodically implemented significant changes to address the root causes of costly systemic problems and risks. Since the 1990s, the Government Accountability Office (GAO) has identified DoD weapon system acquisitions as a high-risk area. The reason for this perpetual designation lies within a history of significant and unanticipated cost and schedule growth, resulting in numerous Num-McCurdy cost breaches (United States Government Accountability Office, 2013). To address these concerning issues, the DoD published Department of Defense Instruction (DoDI) 5000.02 for the Operation of the Defense Acquisition System. This document significantly increased emphasis on

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ADVANCING ARCHITECTURE TO SUPPORT NATIONAL SECURITY

Demonstrating Set-Based Design Concepts in Support of U.S. Army Acquisition Decisions

MAJ Nicholas J. Shallcross, MS
Ph.D. Student
Industrial Engineering Dept
University of Arkansas
nshallc@uark.edu
&
United States Army
nicholas.j.shallcross.mil@mail.mil

Gregory S. Parnell, Ph.D.
Director, M.S. in Operations Management
Industrial Engineering Dept
University of Arkansas
gparnell@uark.edu
&
Innovative Decisions, Inc.
gparnell@innovativedecisions.com

Edward A. Pohl, Ph.D.
Department Head
21st Century Professor of Industrial Engineering
Industrial Engineering Dept
University of Arkansas
epohl@uark.edu

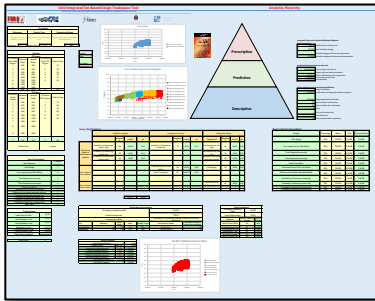
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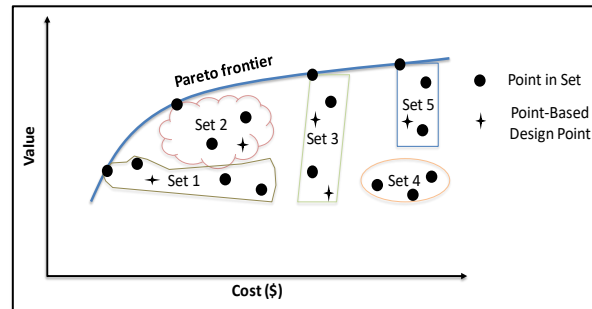
Summary

Eric Specking
especki@uark.edu
479-575-7032

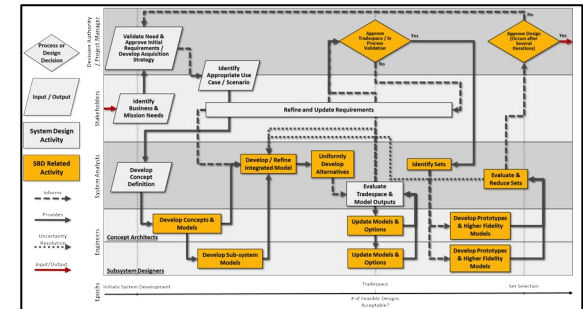
SBD UAV Demonstration Model



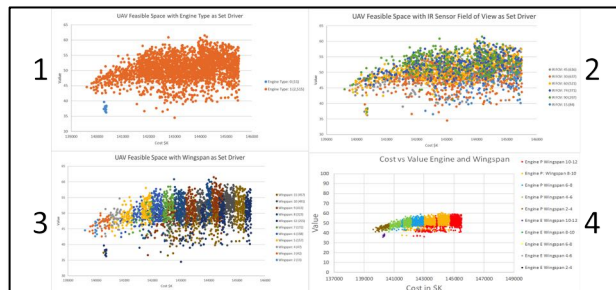
SBD vs. PBD



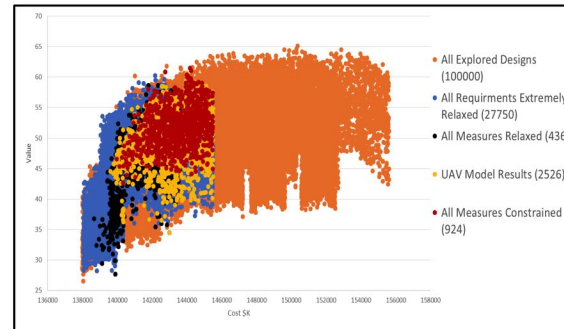
SBD Implementation



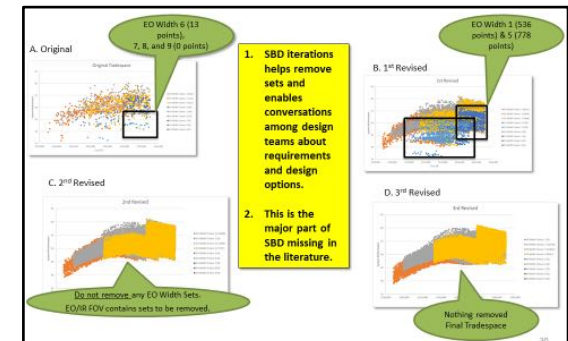
SBD Helps Assess Design Decisions



SBD Helps Assess the Impact of Requirements on the Feasible Tradespace



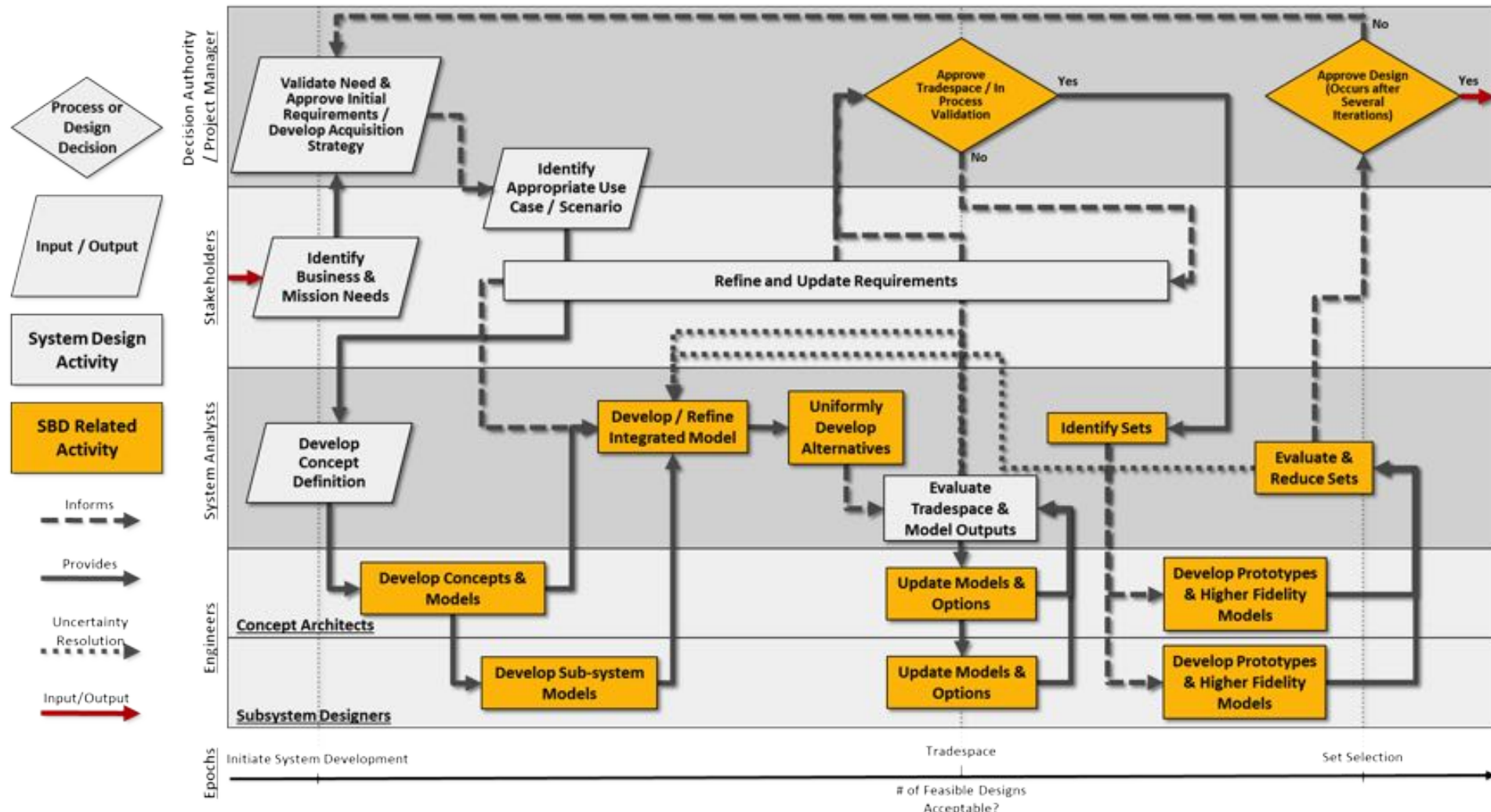
SBD Helps to Inform System Engineers and Stakeholders





SBD Process for Early Design

Eric Specking
especki@uark.edu
479-575-7032



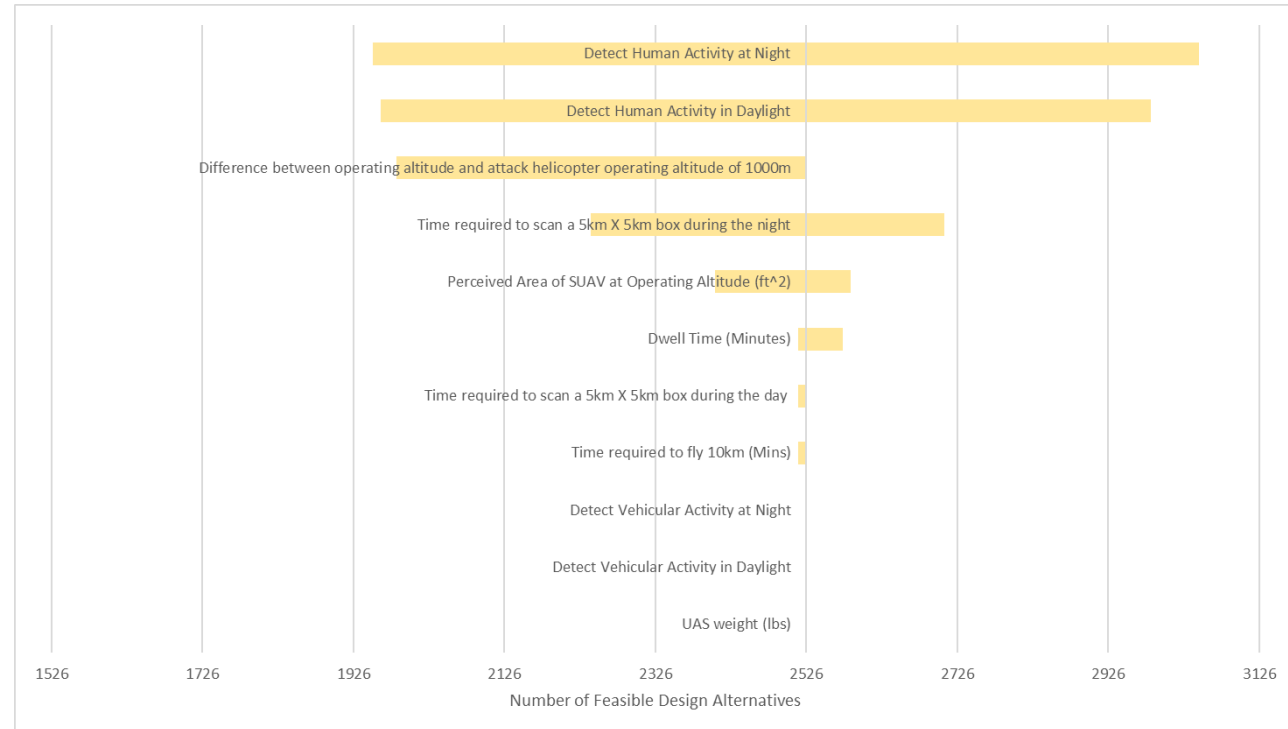
Requirement Change Overview

<u>Scenario</u>	<u>Feasible Designs</u>
All Explored Designs	100000
All Requirements Extremely Relaxed	27750
All Measures Relaxed	4366
UAV Model Results	2526
All Measures Constrained	924

<u>Measure</u>	<u>Relaxed</u>	<u>Constrained</u>	<u>Difference</u>
UAS weight (lbs)	2526	2526	0
Time required to fly 10km (Mins)	2526	2515	11
Time required to scan a 5km X 5km box during the day	2526	2515	11
Time required to scan a 5km X 5km box during the night	2709	2241	468
Dwell Time (Minutes)	2574	2515	59
Perceived Area of SUAV at Operating Altitude (ft^2)	2585	2405	180
Difference between operating altitude and attack helicopter operating altitude of 1000m	2526	1983	543
Detect Human Activity in Daylight	2983	1962	1021
Detect Vehicular Activity in Daylight	2526	2526	0
Detect Human Activity at Night	3046	1952	1094
Detect Vehicular Activity at Night	2526	2526	0

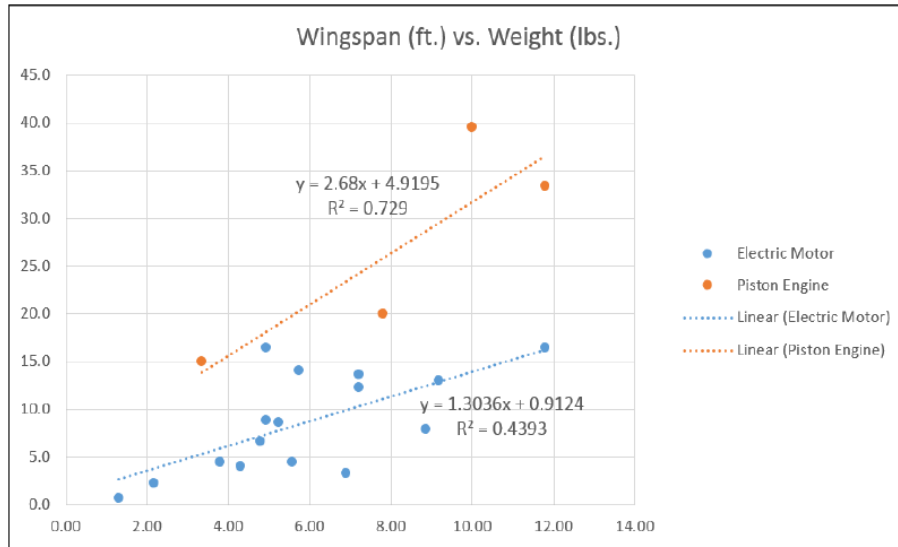
Infeasibility

- Physics
 - Appropriate payload (Max payload \geq total payload weight)
- Requirements (minimum acceptable)
 - UAV Weight (total payload weight)
 - Probability of detecting human day
 - Probability of detecting human night
 - Time required to scan box during day
 - Time required to scan box during night
- All others produce all feasible solutions no matter decision variables combination



1. Both analyses are consistent.
2. The payload weight effects requirements, but the total UAV weight does not effect feasibility

Infeasibility Based upon Physics



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*

Total Payload Weight = Sensor Weight + Communications Weight

Communications Weight = notionally assumed 0.5 lbs.

Small, C., Demonstrating Set-Based Design Techniques: A UAV Case study, Master's Thesis, Industrial Engineering, University of Arkansas, 2018

- 1. EO Sensor selection effects the UAV payload weight.**
- 2. Appropriate Payload = total payload weight < Max payload**

Engine Type P; Wingspan 12		Appropriate Payload (part of value cal)								
IRWidth		EOWidth								
FALSE		1	2	3	4	5	6	7	8	9
1	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE
2	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE
3	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
4	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
5	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
6	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
7	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
8	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
9	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE



Infeasibility Based upon Requirements

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

Total Payload Weight = Sensor Weight + Communications Weight

Communications Weight = notionally assumed 0.5 lbs.

Key

Top 50 percentile of value function **3.348514**

Minimum requirement \leq 50th
Percentile of value function **49.17342**

\leq Minimum requirement **129.0705**

1. If an UAV is feasible based upon physics, minimum requirements can still make a physics based feasibility, infeasible.

2. EO Sensor selection effects models provided by sensor design team.

IRWidth	Total payload weight								
	EOWidth								
	1	2	3	4	5	6	7	8	9
1	1	1	2	3	5	8	12	17	23
2	1	2	3	5	8	12	17	23	30
3	2	3	5	8	12	17	23	30	39
4	3	5	8	12	17	23	30	39	49
5	5	8	12	17	23	30	39	49	61
6	8	12	17	23	30	39	49	61	75
7	12	17	23	30	39	49	61	75	91
8	17	23	30	39	49	61	75	91	109
9	23	30	39	49	61	75	91	109	129