Interactive value model trading for resilient systems decisions

By
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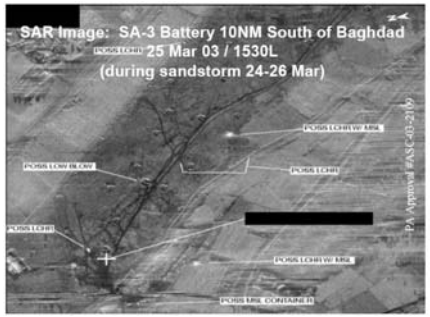
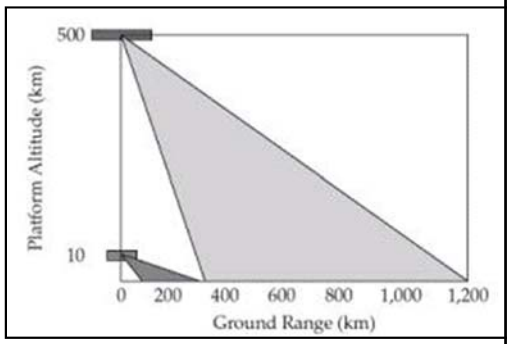
Stevens Institute of Technology
Hoboken, NJ

www.stevens.edu/sse/CSER2015org

Attempting to Meet a National Need

Enabling all-weather detection of forces, in the 1990's, the US Air Force began an effort to move radar to space





Discoverer II 1998

24 satellites,
IOC: ??
cost: $10B

Cancelled in 2000

- High costs, **lack of stated req'ts** or CONOPs, trade-off analyses
- Would overtax existing systems

Space-Based Radar (SBR) 2001

9 satellites,
IOC: 2008
cost: $34B

Effectively cancelled in 2005

- **Lack of agreement among stakeholders**, no approved CONOPs
- No plan for downstream acquisition issues

Space Radar (SR) 2005

? satellites,
IOC: 2015
cost: $??B

Cancelled in 2008

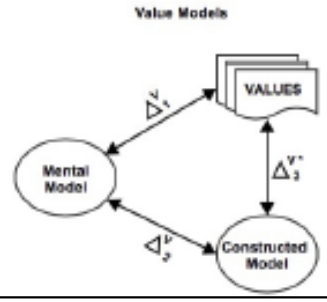
- **Failed to meet req'ts oversight**
- Lacked long-term funding plan

Key mission for the US government, but programs repeatedly cancelled, partly due to inability to effectively characterize cost and benefits of program under uncertainty

Model Choice and Tradeoffs for Resilient Decisions

- Models increasingly used to predict system performance, and costs and benefits
- Every model is an abstraction from reality; important to understand implications of embedded assumptions
- Sensitivity analyses essential, yet many studies resource constrained and neglect
- Since assumptions impact results of models, choices of model parameters important for "within" model sensitivity, AND most importantly, choices of models themselves
- Correctness of most appropriate model may be *uncertain*
- Resilient decisions are those that perform well in spite of such uncertainties and sensitivities (e.g. "correct" and appropriate model choice)

		Mental Model v. Values: Low Δ_1 (truthful)	Mental Model v. Values: High Δ_1
Constructed Model v. Mental Model	Low Δ_2 (trust)	**Correct Trust:** Trust present. Correct representation of values.	**Type I error:** Trust present. Incorrect representation of values.
	High Δ_2	**Type II error:** Trust not present. Correct representation of values.	**Justified Mistrust:** Trust not present. Incorrect representation of values.



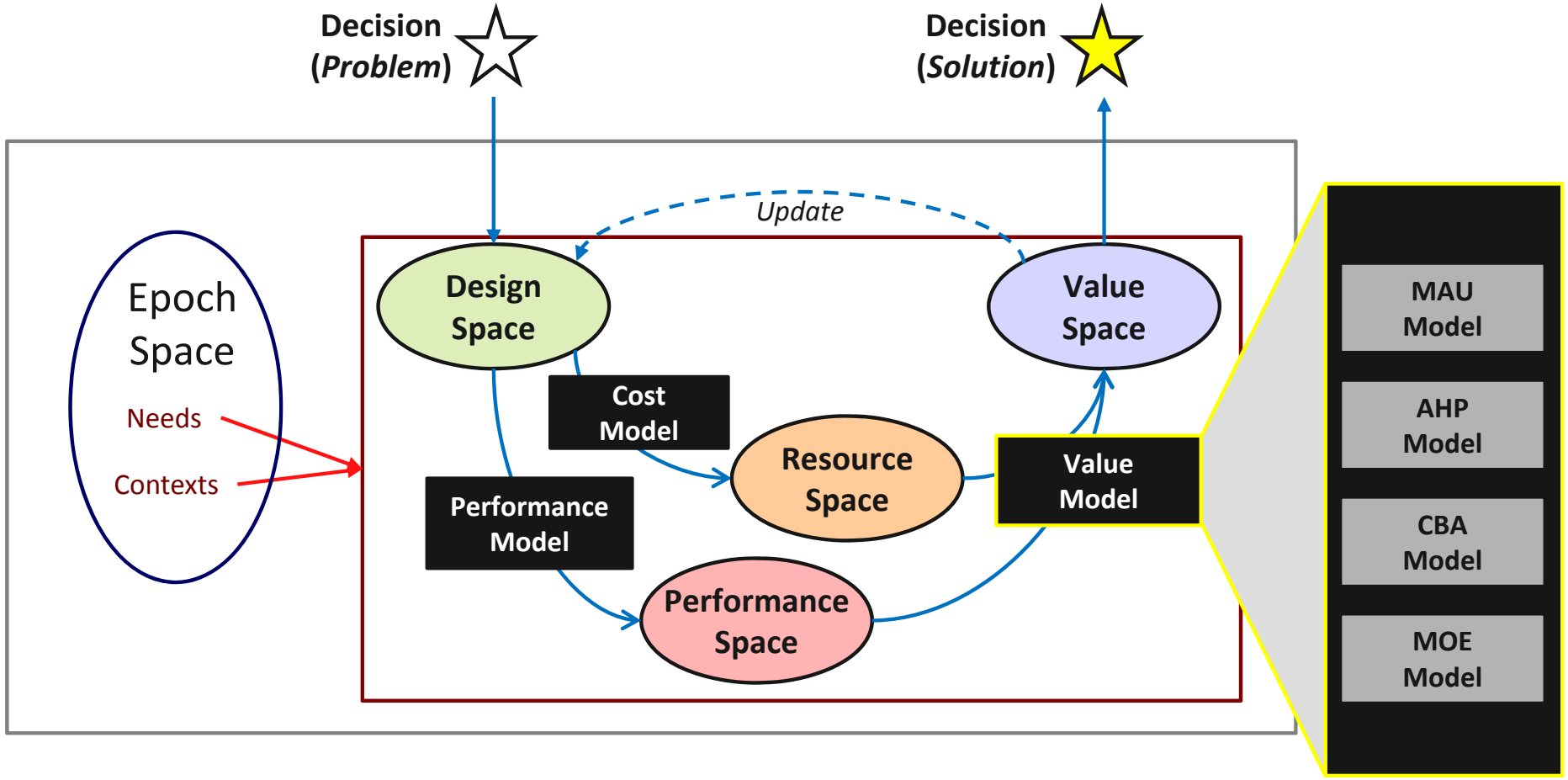
Preliminary research was done to trade "within model" sensitivities in value models, investigating the potential for interaction in refining value model parameter choices*

*Ricci, N., Schaffner, M.A., Ross, A.M., Rhodes, D.H., and Fitzgerald, M.E., "Exploring Stakeholder Value Models Via Interactive Visualization," 12th CSER, Redondo Beach, CA, March 2014.

How can we perform effective "sensitivity" analyses in terms of model choice so as to enable resilient decision outcomes?

Design-Value Loop Perspective

Selection of value model is just as important as performance model and cost model



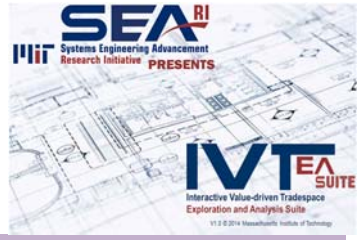
What if we had better understanding and trust in the implications of model choice?

Approach

- Demonstration case: Space Tug
  - 1 Decision Maker for the system
  - Has a budget and thinks he knows what he wants
  - Three types of value model uncertainties:
    - What value model best represents his preferences?
    - What parameters for a given value model best represent his preferences?
    - What if he really doesn't know what his true preferences are and instead wants a robust solution?

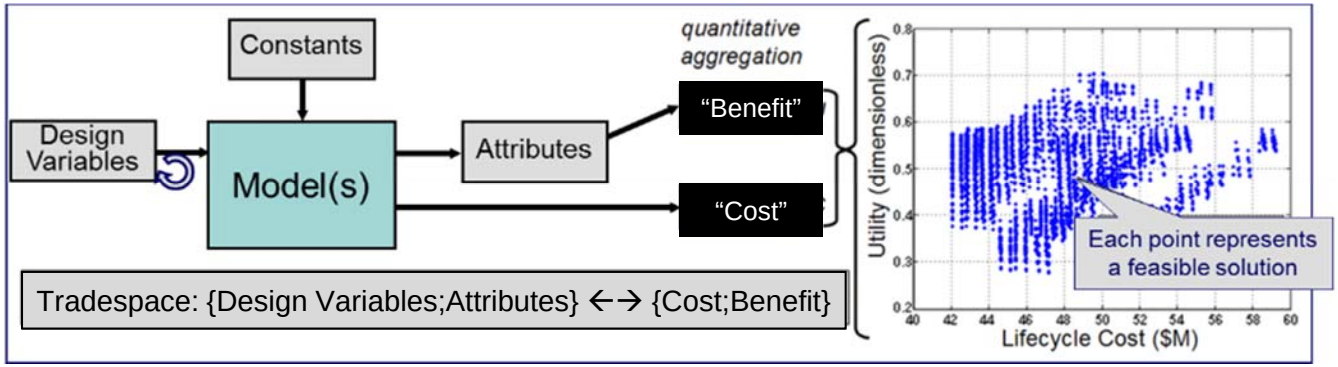
Investigated in CSER14 paper

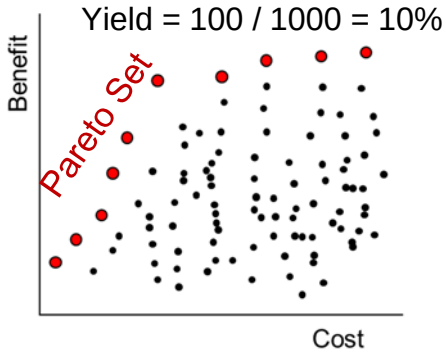
- Method:
  1. Use four different value models to represent benefit/cost tradeoffs
  2. Identify most efficient solutions for each value model (Pareto sets)
  3. Compare preferred alternatives across value models
  4. Identify cross-value model potential alternatives (Joint Pareto Analysis)
  5. Either converge on value model formulation (construct→mental) or seek solutions insensitive to model formulation

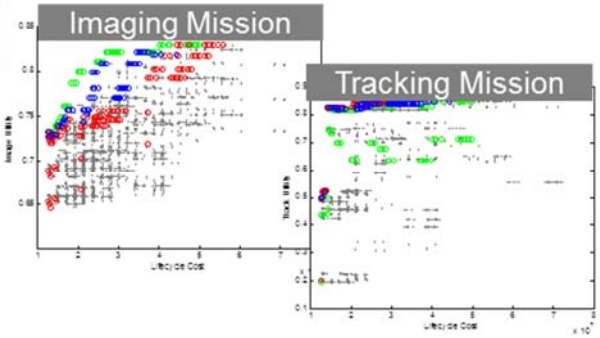


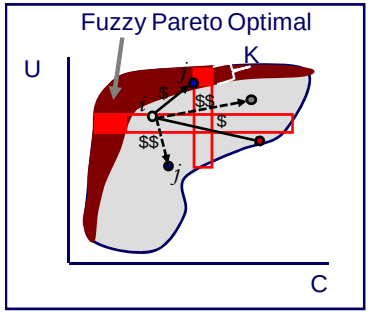
Used tradespace exploration to see consequences on potential solutions of model choices
Used IVTea Suite software (internal MIT) for visuals and analyses

Tradespace Concepts





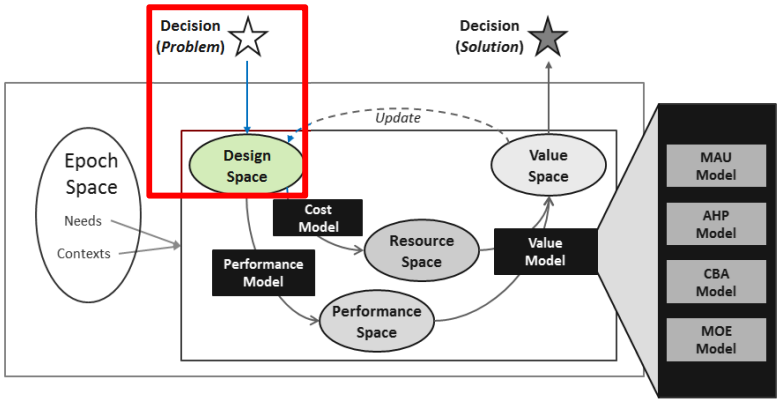




- **Scatterplot**: 2D plot where x,y position of point indicates scores in those dimensions (often benefit and cost)
- **Yield**: Fraction of design space considered valid
- **Pareto Set**: Non-dominated (most efficient) set of designs for given objectives (i.e. improvement in one objective results in degradation of other objective)
- **Joint/Compromise**: Joint designs are in multiple individual Pareto sets; compromise designs are in combined objective Pareto set but not individual Pareto sets
- **K% Fuzzy Pareto Set**: Designs that are included in Pareto set when allowing for within K% of Pareto frontier

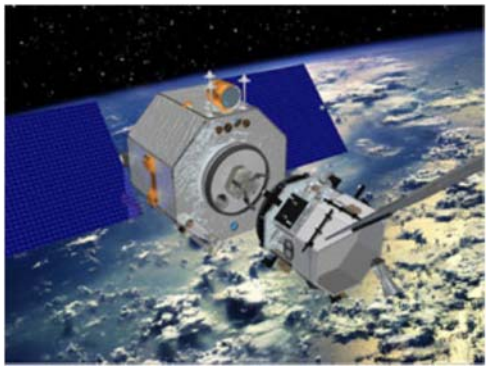
Space Tug
Design Space

- Define the problem to be solved
- Key decision makers define their decision criteria (attributes)



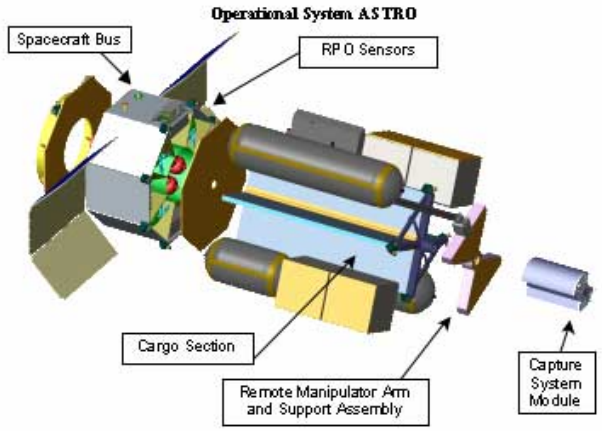
General purpose vehicle to intercept, interact with, and accelerate other vehicles

Decision problem: *what would be a valuable design for such a vehicle?*



Attributes
- ❑ Delta-V
- ❑ Capability
- ❑ Response time

Design Space (N=384)*
- ❑ Manipulator Mass
  - Low (300kg)
  - Medium (1000kg)
  - High (3000 kg)
  - Extreme (5000 kg)
- ❑ Propulsion Type
  - Storable bi-prop
  - Cryogenic bi-prop
  - Electric (NSTAR)
  - Nuclear Thermal
- ❑ Fuel Load - 8 levels
- ❑ Design for Change (DfC)
  - None, level-1, level-2

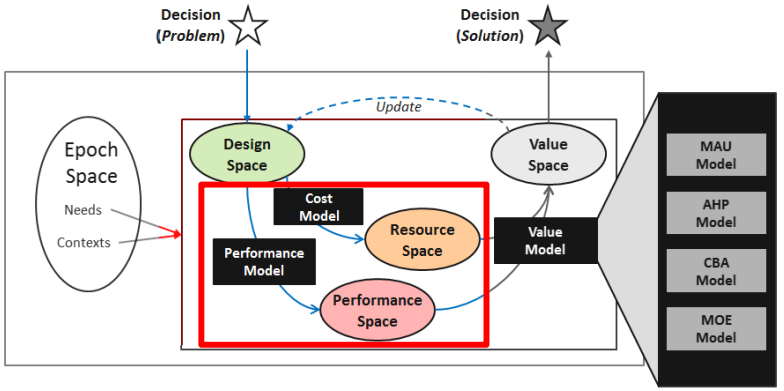


*Fitzgerald, M.E., Ross, A.M., and Rhodes, D.H., "Assessing Uncertain Benefits: a Valuation Approach for Strategic Changeability (VASC)," INCOSE International Symposium 2012, Rome, Italy, July 2012.

Space Tug

Performance and Resource Spaces

- Given the Design space, how can each alternative be evaluated?
- Performance space and Resource space generated by evaluating the Design space through models



Performance Model

Propulsion System	I_{sp} (sec)	Base Mass m_{p0} (kg)	Mass Fract. m_{pf}	High Impulse
Storable biprop	300	0	0.12	Y
Cryo	450	0	0.13	Y
Electric	3000	25	0.30	N
Nuclear	1500	1000	0.20	Y

Propulsion System Mass	$M_p = m_{p0} + m_{pf} M_f$
Bus Mass	$M_b = M_p + m_{bf} M_c$
Dry Mass	$M_d = M_b + M_c$
Wet Mass	$M_w = M_d + M_f$

Delta-V	$\Delta v = g\, I_{sp}\, \ln(M_w / M_d)$
Capability	*Table lookup*
Speed	*Table lookup*

Cost Model

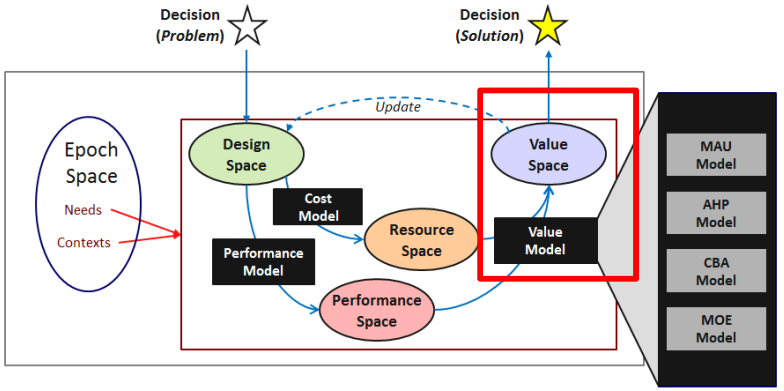
$$C = c_w\, M_w + c_d\, M_d$$

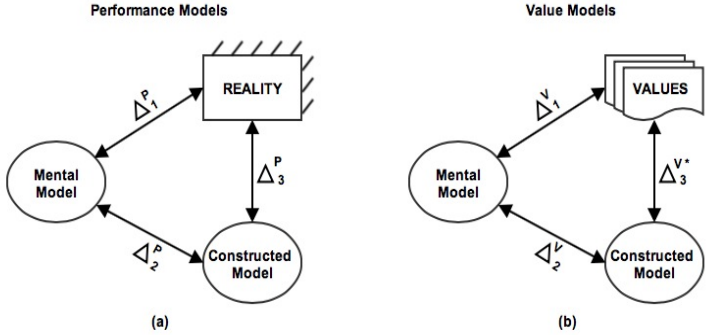
These types of models can be validated through empirical tests, among other techniques; for this study, low fidelity models were used*

*McManus, H., and Schuman, T., "Understanding the Orbital Transfer Vehicle Tradespace," AIAA-2003-6370, Sept. 2003

Space Tug
Value Space

- Once designs have been evaluated in terms of resources required for performance, each design must be *valuated* through judgment
- Judgment is determined by an individual's "value" model
- Many alternative constructed value models are possible
  - —MAU, AHP, CBA, MOE, TOPSIS, CPT, NPV, …
- **Value model choice matters**





- Value models are difficult to validate, as no clearly observable "ground truth" may exist
- Various techniques do exist to increase trust in a given value model**
- Unlike performance models, value models tend to not receive explicit attention during engineering design and evaluation

**Ricci, N., Schaffner, M.A., Ross, A.M., Rhodes, D.H., and Fitzgerald, M.E., "Exploring Stakeholder Value Models Via Interactive Visualization," 12th CSER, Redondo Beach, CA, March 2014

Value Model 1

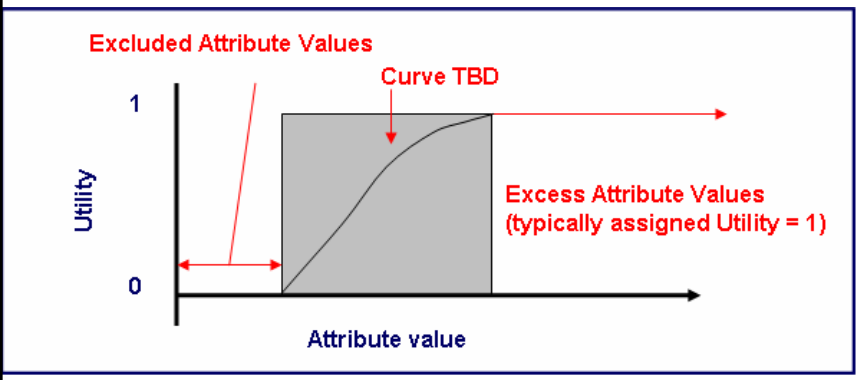
Multi-Attribute Utility (MAU)

MAU Model

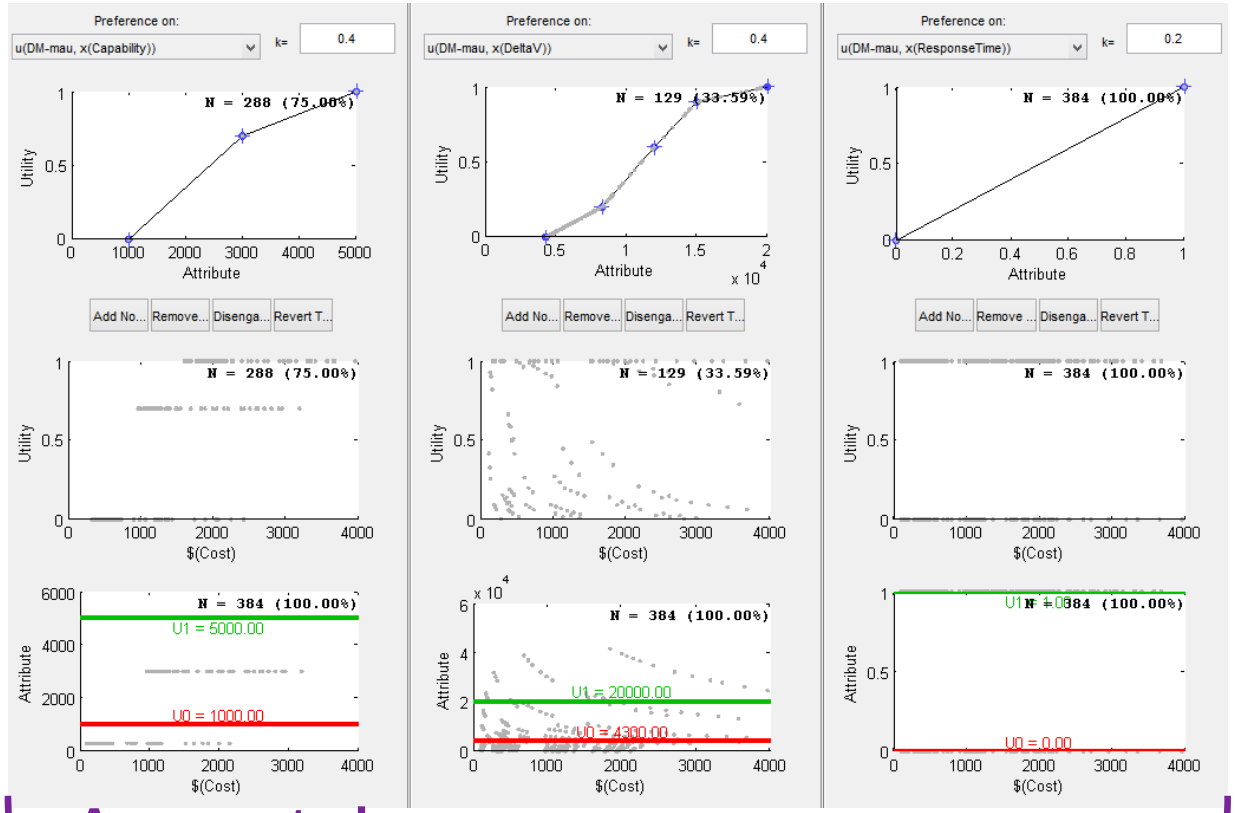
Attributes (X_i): Capability | Delta V | Response Time

Each attribute is normalized through a utility function

Single Attribute Utilities (U_iX_i)



SAU curves and k_i swing weights are elicited from the decision maker

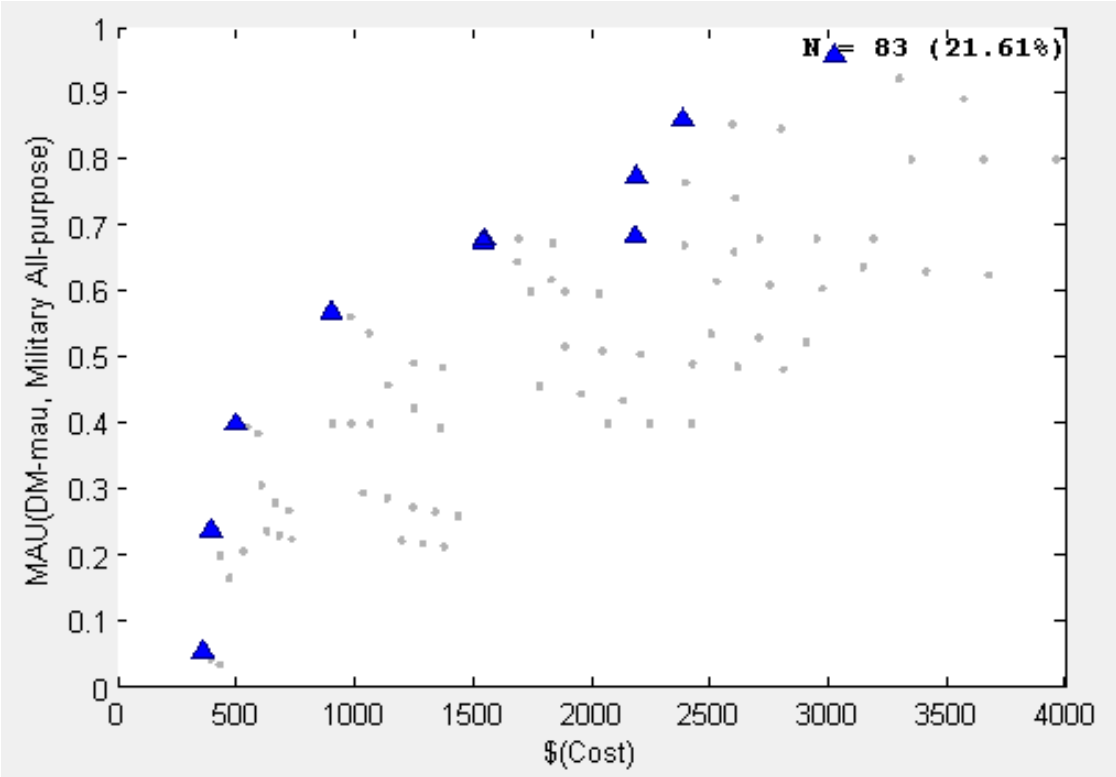


Aggregated

$$U(\hat{X}) = \frac{[\prod_{i=1}^{n}(K \cdot k_i \cdot U_i(X_i) + 1)] - 1}{K} \quad \text{where} \quad K = -1 + \prod_{i=1}^{n}(K \cdot k_i + 1)$$

Pro: Explicit value model provides transparency; Con: Unintuitive mathematical formulation

MAU Tradespace



- Alternatives that fail to meet minimum levels in one or more attributes are deemed “invalid”
- Tradespace Yield is 21.61%
- 10 designs are in Pareto Set

Value Model 2

Analytic Hierarchy Process (AHP)

AHP Model

Attributes (X_i): **Capability** **Delta V** **Response Time**

Higher is Better ⇨

Lower is Better ⇨

	x(Capability)	x(DeltaV)	x(ResponseTime)
x(Capability)	1	1	2
x(DeltaV)	1	1	2
x(Response Time)	1/2	1/2	1

Matrix scores are elicited via pairwise comparisons by the decision maker

Determine weights

$$k_i = \frac{\sum_{q=1}^{n} \frac{a_{i,q}}{\sum_{p=1}^{n} a_{p,q}}}{n}$$

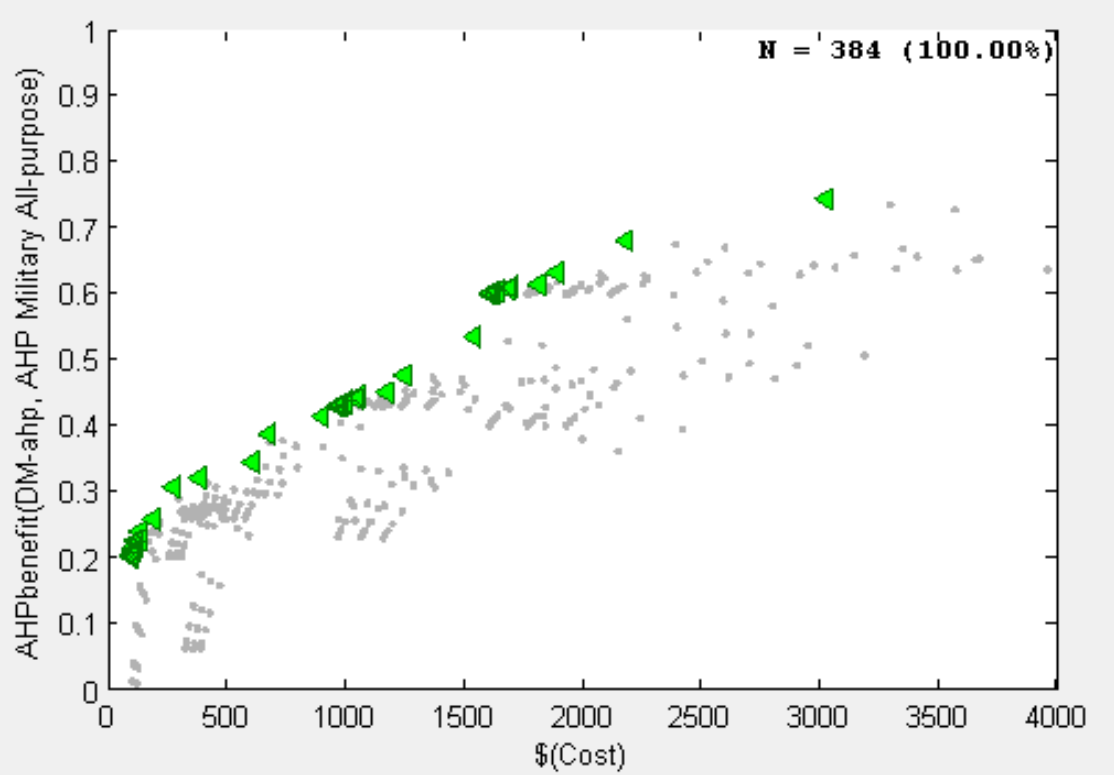
Each attribute is normalized against its possible range

$$AHP_i(X_i) = \frac{(X_i - X_{i,min})}{X_{i,max} - X_{i,min}}$$

$$AHP(\hat{X}) = \sum_{i=1}^{n} k_i \cdot AHP_i(X_i)$$

Pro: Straightforward elicitation; Con: Opaque value traceability, questionable basis

AHP Tradespace



- No alternatives are deemed “invalid”
- Tradespace Yield is 100%
- 43 designs are in Pareto Set

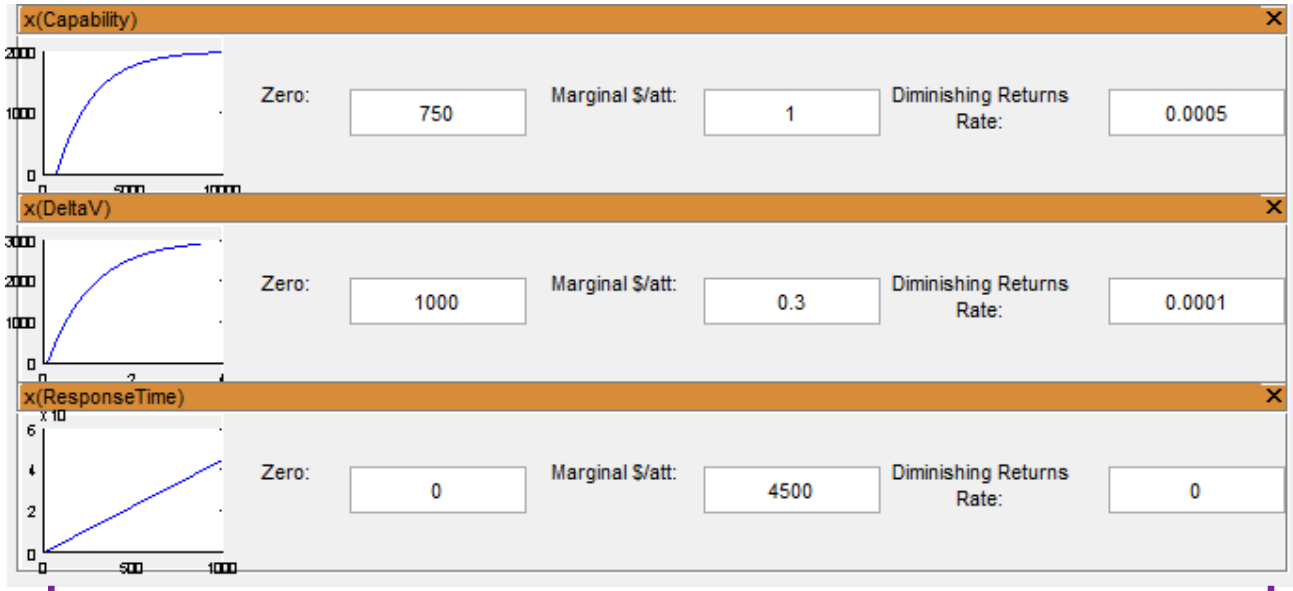
Value Model 3

Cost-Benefit Analysis (CBA)

CBA Model

Higher is Better ⇨

Lower is Better ⇨



Monetization functions are elicited from the decision maker

Aggregated

$$CBA_i(X_i) = \frac{m_i}{r_i}(1 - e^{-r_i \cdot X_i})$$

$$CBA_i(X_i) = 0$$

$$X_i \geq X_{i,min}$$

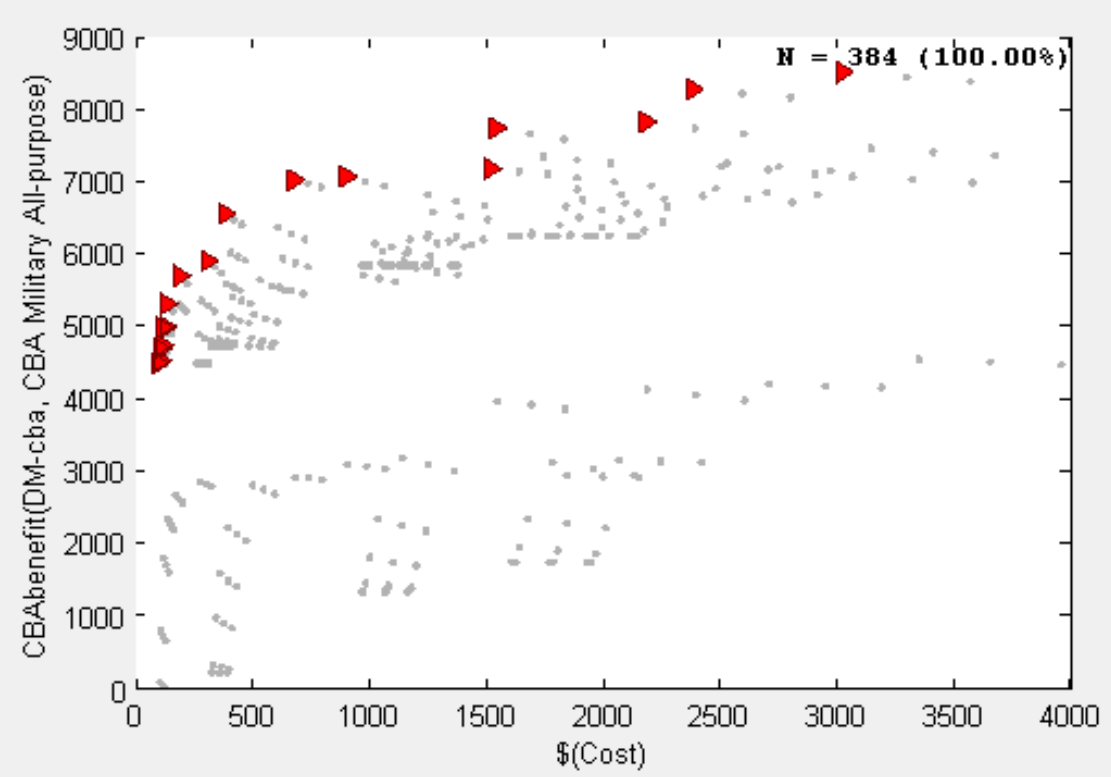
$$X_i < X_{i,min}$$

$$CBA(\hat{X}) = \sum_{i=1}^{n} CBA_i(X_i)$$

Each attribute is normalized through a monetization function

Pro: Evaluation on an intuitive scale; Con: Noncommercial systems, monetization questionable

CBA Tradespace



- No alternatives are deemed “invalid”
- Tradespace Yield is 100%
- 17 designs are in Pareto Set

Value Model 4

Measure of Effectiveness (MOE)

MOE Model

Performance Model

Evaluated

MOEs are elicited from the decision maker

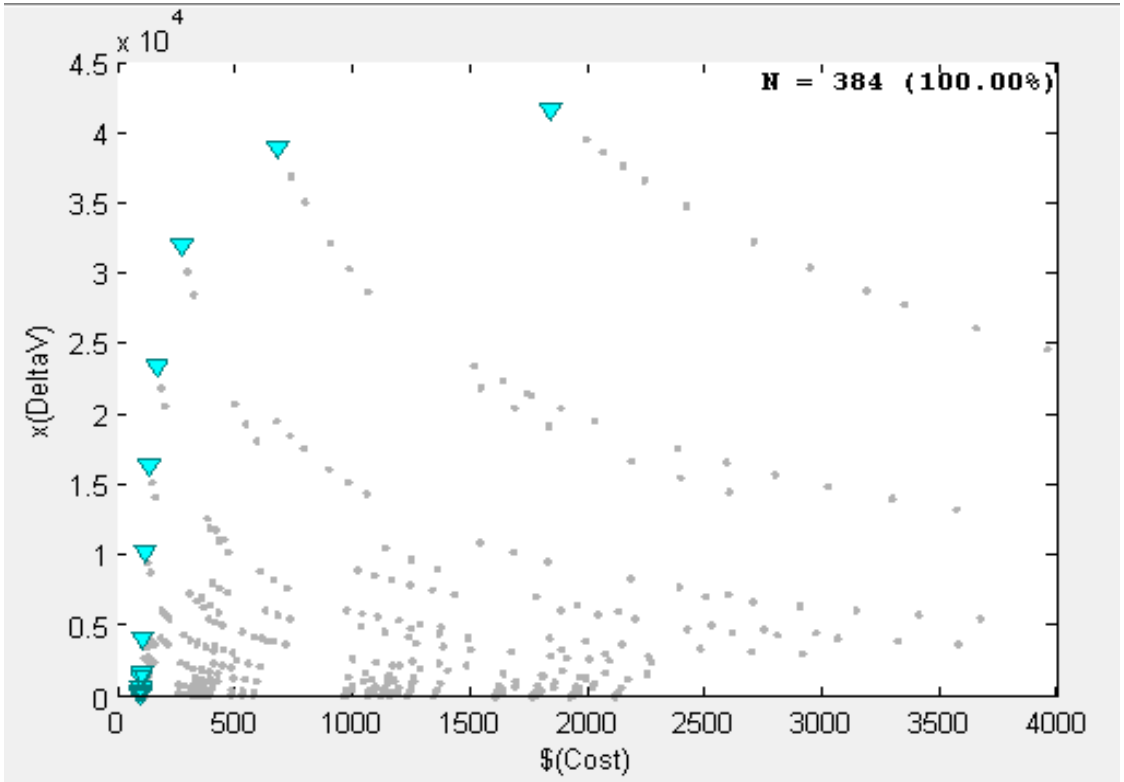
$$MOE(X_i) = X_i$$

In this case, used *DeltaV* as single dimension of value

Each attribute can be normalized, or treated independently in natural units

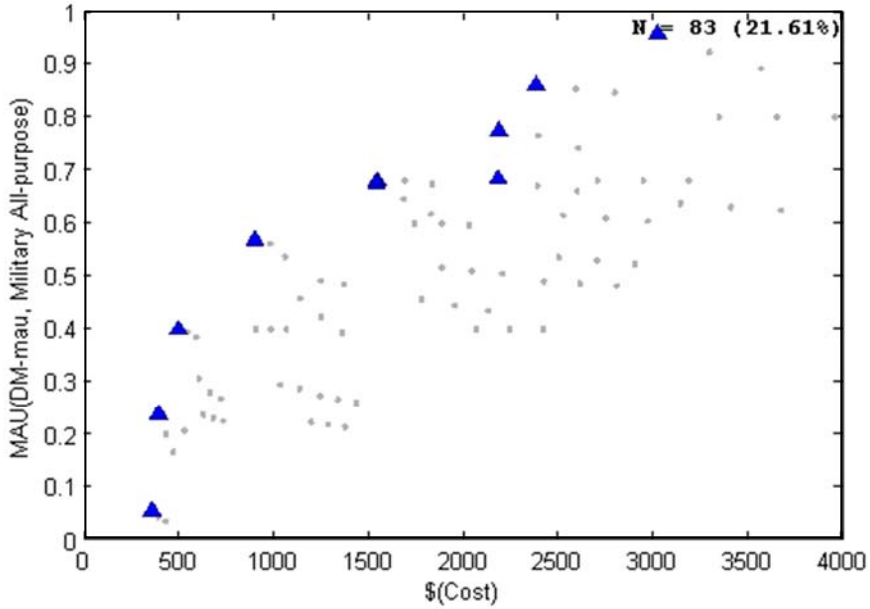
Pro: Evaluation on intuitive scale; Con: Potentially myopic, lack of effective aggregation

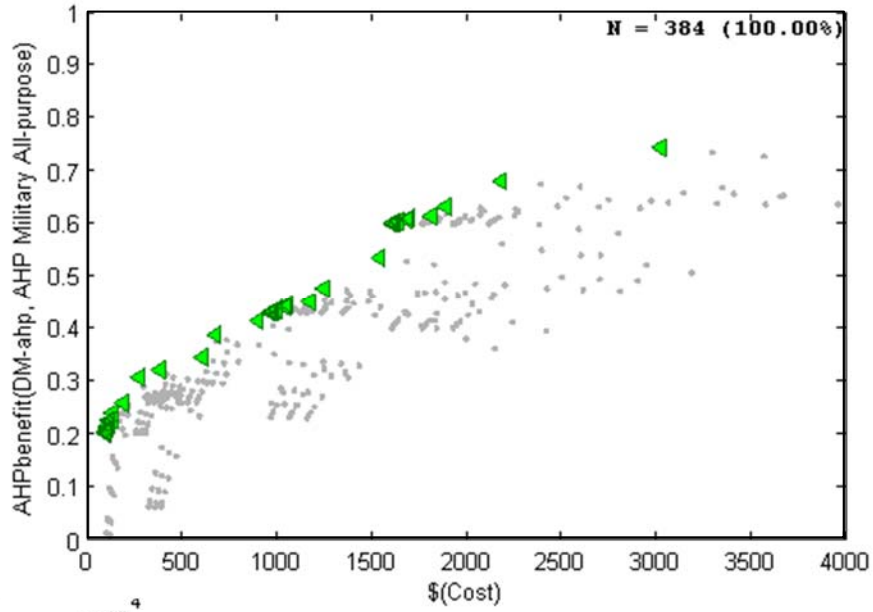
MOE Tradespace

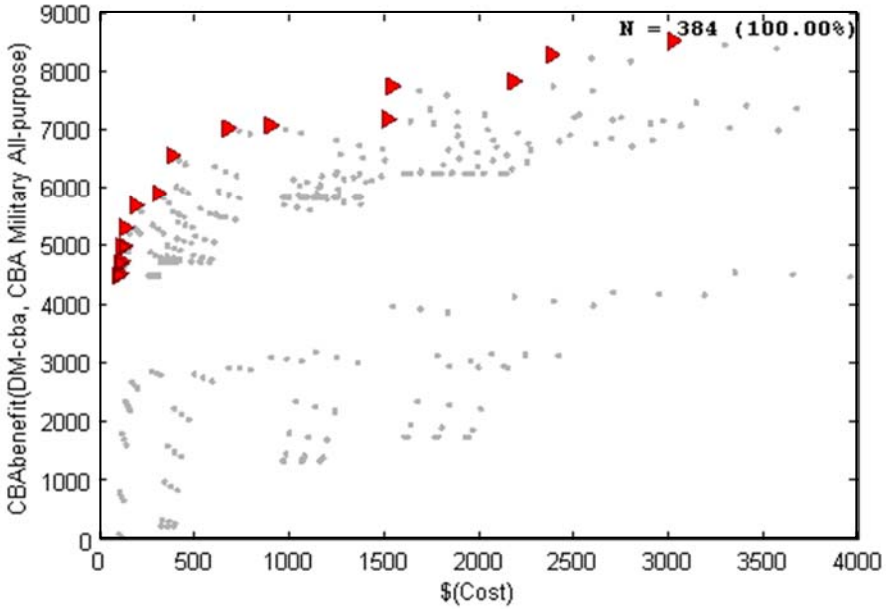


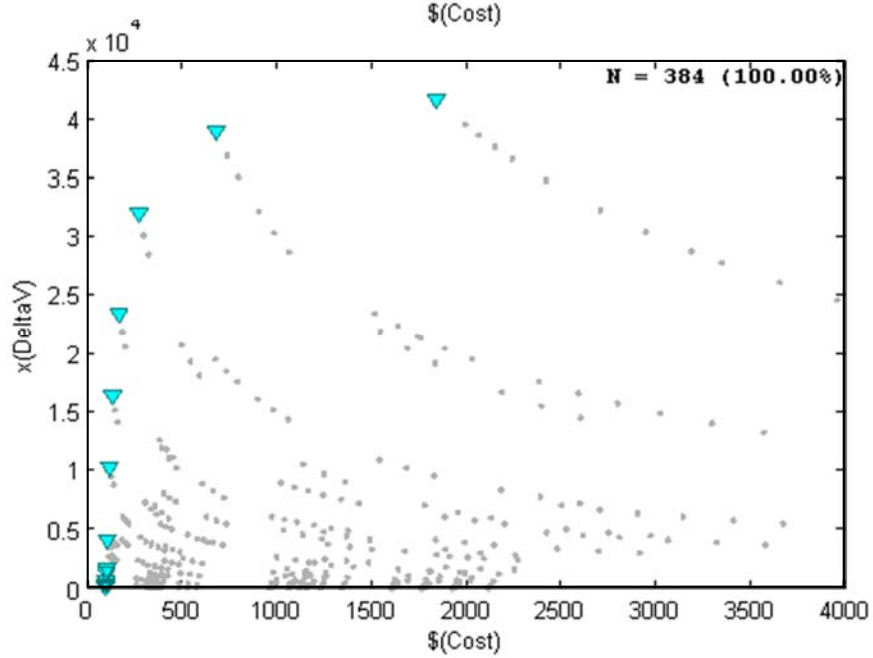
- No alternatives are deemed “invalid”
- Tradespace Yield is 100%
- 13 designs are in Pareto Set

Alternative Tradespaces



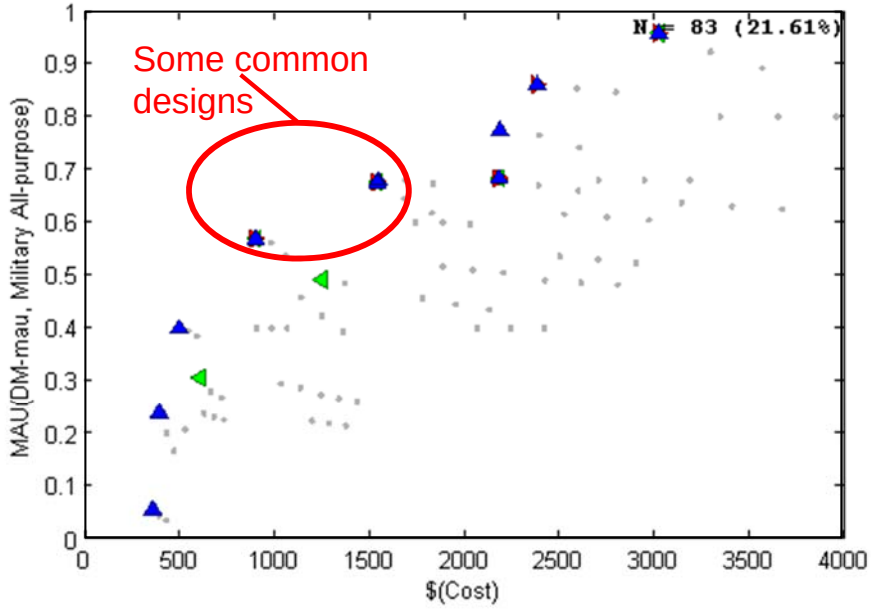


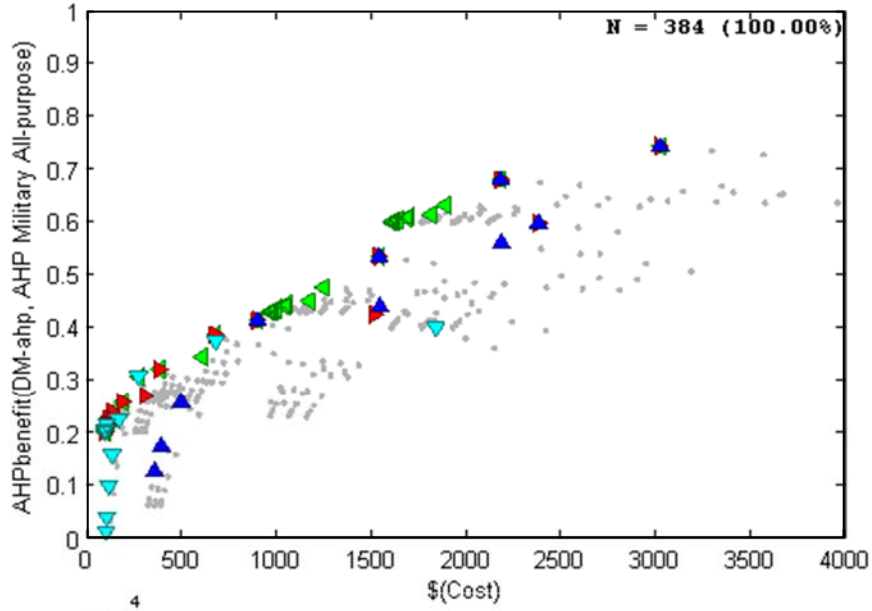


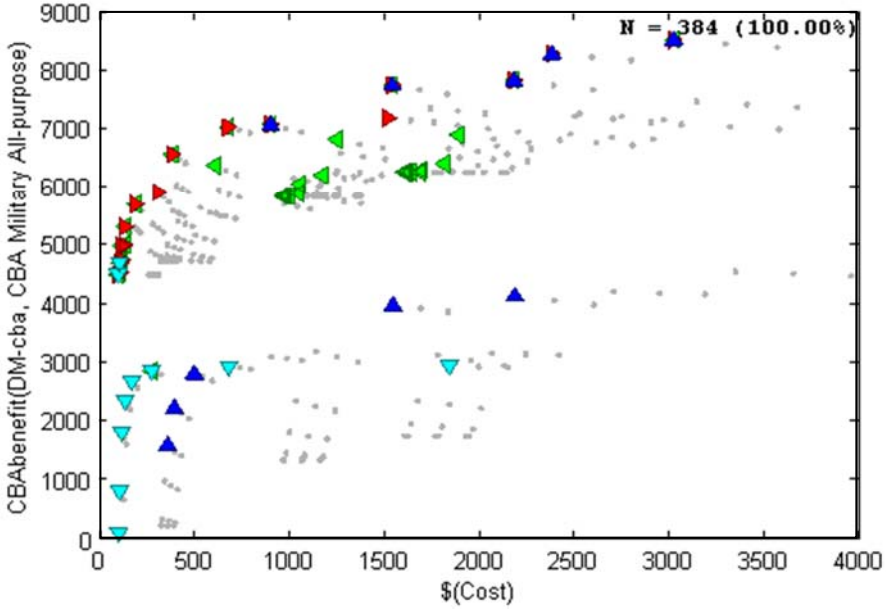


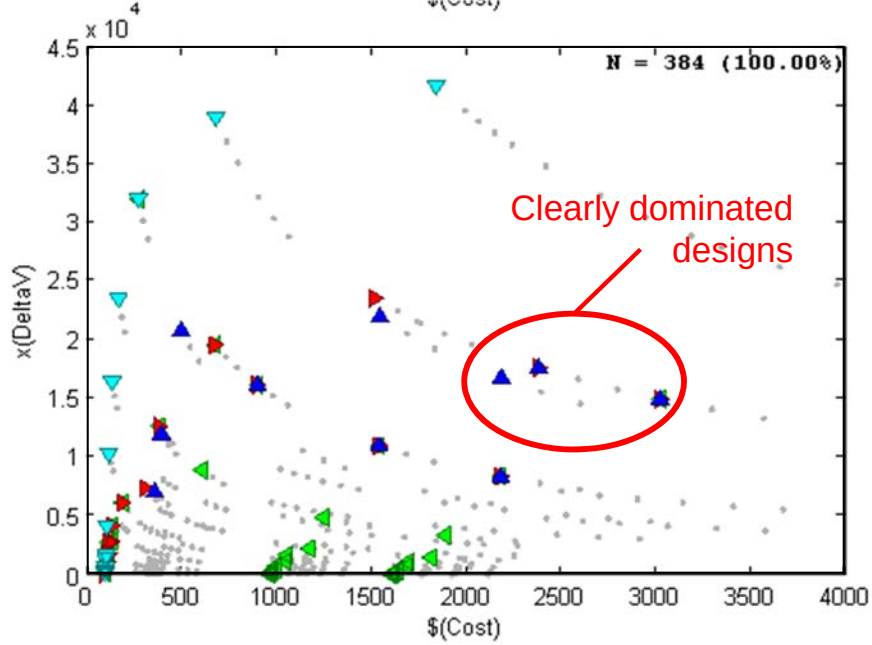
MAU-Cost Pareto Set ▲ AHP-Cost Pareto Set ◀ CBA-Cost Pareto Set ▶ MOE-Cost Pareto Set ▼

Cross Plotted Tradespaces









MAU-Cost Pareto Set ▲ AHP-Cost Pareto Set ◀ CBA-Cost Pareto Set ▶ MOE-Cost Pareto Set ▼

Joint Pareto Analysis

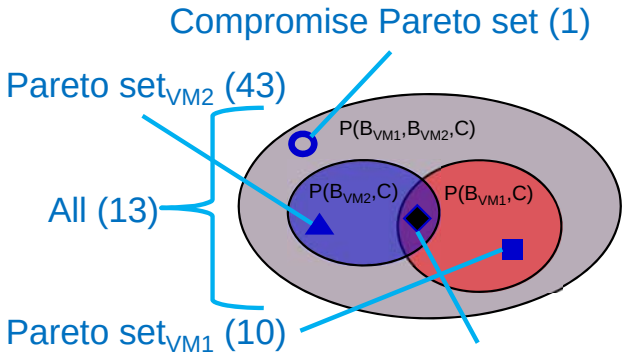
Objective Sets:

$(Cost) MAU(DM-mau, Military	1
$(Cost) AHPbenefit(DM-ahp, AHP	2
$(Cost) CBAbenefit(DM-cba, CBA	3
$(Cost) x(DeltaV)	4

Summary:

	# designs	
TOTAL	384	
VALID		
Set 1	83	
Set 2	384	
Set 3	384	
Set 4	384	
All	83	
0% PARETO		
Set 1	10	**MAU**
Set 2	43	**AHP**
Set 3	17	**CBA**
Set 4	13	**MOE**
All	18	**MAU-AHP-CBA-MOE (no invalid)**
Joint	0	**In every Individual Pareto**
Compromise	6	**In All, not Individual Pareto**

64 designs
(in "All" set, including partial "invalid")



ID Number	Pareto Efficient For	Invalid For
1	2, 3, 4	1
2	2, 4	1
3	2, 3	1
4	2, 3	1
5	2, 3	1
9	2, 4	1
10	2, 4	1
11	2, 3, 4	1
12	2, 3	1
13	2, 3	1
14	2, 3	1
17	4	1
18	4	1
19	4	1
20	4	1
21	4	1
22	2, 4	1
23	4	1
24	4	1
29	3	1
30	2, 3	1
31	2, 3	1
32	3	1
52	1	
53	1	
54	1	
55		
56		
61		
62	2	
63	1, 2, 3	
64		
65	2	1
66	2	1
67	2	1
68	2	1
69	2	1
73	2	1
74	2	1
75	2	1
76	2	1
77	2	1
87	1	
88		
93	2	1
94	2	
95	1, 2, 3	
96	1, 3	
97	2	1
98	2	1
99	2	1
100	2	1
101	2	1
105	2	1
106	2	1
107	2	1
108	2	1
109	2	1
119	1	
120		
125	2	1
126	2	1
127	1, 2, 3	
128	1, 2, 3	

What can we learn through this type of analysis?

- Joint designs are "best" (efficient for all)
- Compromise designs are most efficient tradeoffs
- Close to joint designs can be considered "promising"

Compromise Designs

	55	56	61	64	88	120
$(Cost)	904	2064	530.4	1740	2704	3344
$(Cost)	904	2064	530.4	1740	2704	3344
$(Cost)	904	2064	530.4	1740	2704	3344
$(Cost)	904	2064	530.4	1740	2704	3344
$(Cost)	904	2064	530.4	1740	2704	3344
dv(DesignforChange)	0	0	0	0	0	0
dv(DesignID)	55	56	61	64	88	120
dv(PayloadMass)	1000	1000	1000	1000	3000	5000
dv(PropMass)	10000	30000	1200	30000	30000	30000
dv(PropType)	3	3	4	4	3	3
x(Capability)	1000	1000	1000	1000	3000	5000
x(DeltaV)	32201.5	38632.1	4631.69	21555.2	32266.6	27829.3
x(ResponseTime)	0	0	1	1	0	0
x(DeltaV)	32201.5	38632.1	4631.69	21555.2	32266.6	27829.3
iv(BaseMass)	25	25	1000	1000	25	25
iv(DryMass)	5025	11025	3240	9000	15025	19025
iv(SpecificImpulse)	3000	3000	1500	1500	3000	3000
iv(MassFrac)	0.3	0.3	0.2	0.2	0.3	0.3
iv(WetMass)	15025	41025	4440	39000	45025	49025
MAU(DM-mau, Military All-purpose)	0.4	0.4	0.20663	0.6	0.68	0.8
u(DM-mau, x(Capability))	0	0	0	0	0.7	1
u(DM-mau, x(DeltaV))	1	1	0.016584	1	1	1
u(DM-mau, x(ResponseTime))	0	0	1	1	0	0
AHPbenefit(DM-ahp, AHP Military All-purpose)	0.36912	0.43099	0.3039	0.4667	0.53996	0.66749
CBAbenefit(DM-cba, CBA Military All-purpose)	3102.5546	3165.3788	5648.5995	7350.9275	4219.1029	4556.0464

Compromise Designs (0% fuzzy)
55
56
61
64
88
120

These are the “new” designs considered when identifying efficient designs across ALL value models

Promising Designs

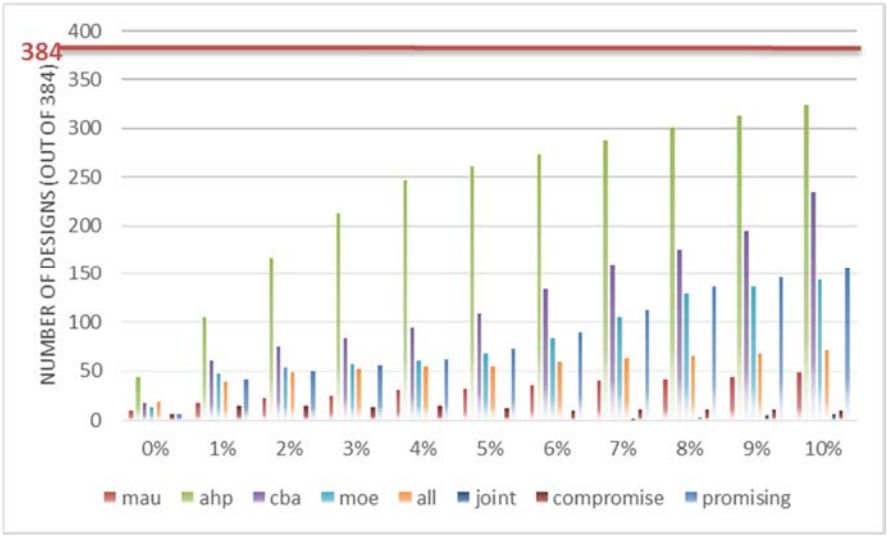
	1	11	63	95	127	128
$(Cost)	96.876	105.24	900	1540	2180	3020
$(Cost)	96.876	105.24	900	1540	2180	3020
$(Cost)	96.876	105.24	900	1540	2180	3020
$(Cost)	96.876	105.24	900	1540	2180	3020
$(Cost)	96.876	105.24	900	1540	2180	3020
dv(DesignforChange)	0	0	0	0	0	0
dv(DesignID)	1	11	63	95	127	128
dv(PayloadMass)	300	300	1000	3000	5000	5000
dv(PropMass)	30	300	10000	10000	10000	30000
dv(PropType)	1	2	4	4	4	4
x(Capability)	300	300	1000	3000	5000	5000
x(DeltaV)	142.608	1697.46	16149.6	10984.1	8387.01	14948.9
x(ResponseTime)	1	1	1	1	1	1
x(DeltaV)	142.608	1697.46	16149.6	10984.1	8387.01	14948.9
iv(BaseMass)	0	0	1000	1000	1000	1000
iv(DryMass)	603.6	639	5000	9000	13000	17000
iv(SpecificImpulse)	300	450	1500	1500	1500	1500
iv(MassFrac)	0.12	0.13	0.2	0.2	0.2	0.2
iv(WetMass)	633.6	939	15000	19000	23000	47000
MAU(DM-mau, Military All-purpose)	NaN	NaN	0.5692	0.67607	0.68376	0.95796
u(DM-mau, x(Capability))	NaN	NaN	0	0.7	1	1
u(DM-mau, x(DeltaV))	NaN	NaN	0.92299	0.49017	0.20941	0.89489
u(DM-mau, x(ResponseTime))	1	1	1	1	1	1
AHPbenefit(DM-ahp, AHP Military All-purpose)	0.20114	0.2161	0.4147	0.53522	0.68045	0.74358
CBAbenefit(DM-cba, CBA Military All-purpose)	4500	4702.108	7075.5553	7745.3006	7827.9318	8517.5532

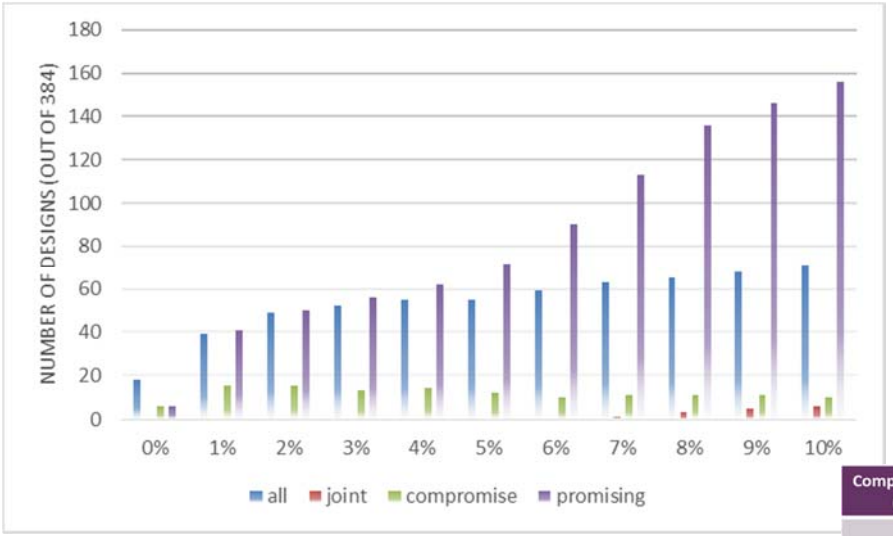
Promising Designs (3 out of 4 Pareto)	Pareto for	Invalid for
1	AHP, CBA, MOE	MAU
11	AHP, CBA, MOE	MAU
63	MAU, CBA, MOE	
95	MAU, CBA, MOE	
127	MAU, CBA, MOE	
128	MAU, CBA, MOE	

These designs are “almost” joint Pareto; if we focus on 3 out of the 4 value models

What about “fuzzy” Pareto alternatives?

Fuzzy Pareto Designs





As fuzziness increases, number of "interesting" designs increases

6 designs

Joint Pareto Designs

Design#	0%	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%
52								Joint Pareto -->			
53									Joint Pareto -->		
180									Joint Pareto -->		
181										Joint Pareto -->	
308										Joint Pareto -->	
309											Joint P

23 designs

Compromise Pareto Designs

Design#	0%	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%
40										Compromise	
55	Compr	Pareto Efficient -->									
56	Compr	omise					Pareto Efficient -->				
61	Compr	omise		Pareto Efficient -->							
64	Compr	omise				Pareto Efficient -->					
72											Compr
80							Compromise		Pareto Efficient -->		
85					Compromise						Pareto
88	Compr	omise									
120	Compr	omise								Pareto Efficier	
183		Compromise		Pareto Efficient -->							
184		Compromise									
192		Compromise					Pareto Efficient -->				
207									Compr	Pareto Efficier	
213								Compromise			
216		Compromise									
248		Compromise									
311		Compromise				Pareto Efficient -->					
312		Compromise									
320		Compromise					Pareto Efficient -->				
335										Compr	Pareto
344		Compromise									
376		Compromise									

Compromise Designs (0% fuzzy)
55
56
61
64
88
120

Fuzzy Joint Pareto Designs

	52	53	180	181	308	309
$(Cost)	358.8	393.6	394.08	431.76	429.36	469.92
$(Cost)	358.8	393.6	394.08	431.76	429.36	469.92
$(Cost)	358.8	393.6	394.08	431.76	429.36	469.92
$(Cost)	358.8	393.6	394.08	431.76	429.36	469.92
$(Cost)	358.8	393.6	394.08	431.76	429.36	469.92
dv(DesignforChange)	0	0	1	1	2	2
dv(DesignID)	52	53	180	181	308	309
dv(PayloadMass)	1000	1000	1000	1000	1000	1000
dv(PropMass)	600	1200	600	1200	600	1200
dv(PropType)	3	3	3	3	3	3
x(Capability)	1000	1000	1000	1000	1000	1000
x(DeltaV)	7075.88	11982.2	6498.54	11073.7	6008.61	10294.6
x(ResponseTime)	0	0	0	0	0	0
x(DeltaV)	7075.88	11982.2	6498.54	11073.7	6008.61	10294.6
iv(BaseMass)	25	25	25	25	25	25
iv(DryMass)	2205	2385	2425.5	2623.5	2646	2862
iv(SpecificImpulse)	3000	3000	3000	3000	3000	3000
iv(MassFrac)	0.3	0.3	0.3	0.3	0.3	0.3
iv(WetMass)	2805	3585	3025.5	3823.5	3246	4062
MAU(DM-mau, Military All-purpose)	0.055518	0.23923	0.043971	0.19994	0.034172	0.16625
u(DM-mau, x(Capability))	0	0	0	0	0	0
u(DM-mau, x(DeltaV))	0.13879	0.59808	0.10993	0.49986	0.08543	0.41563
u(DM-mau, x(ResponseTime))	0	0	0	0	0	0
AHPbenefit(DM-ahp, AHP Military All-purpose)	0.12741	0.17461	0.12186	0.16587	0.11714	0.15838
CBAbenefit(DM-cba, CBA Military All-purpose)	1601.0172	2234.6138	1503.904	2139.4718	1416.9802	2050.7057

Fuzzy Joint Designs	Threshold Fuzzy Level
52	7%
53	8%
180	8%
181	9%
308	9%
309	10%

These designs are not "optimal" but they are "good" w.r.t. to all four value models

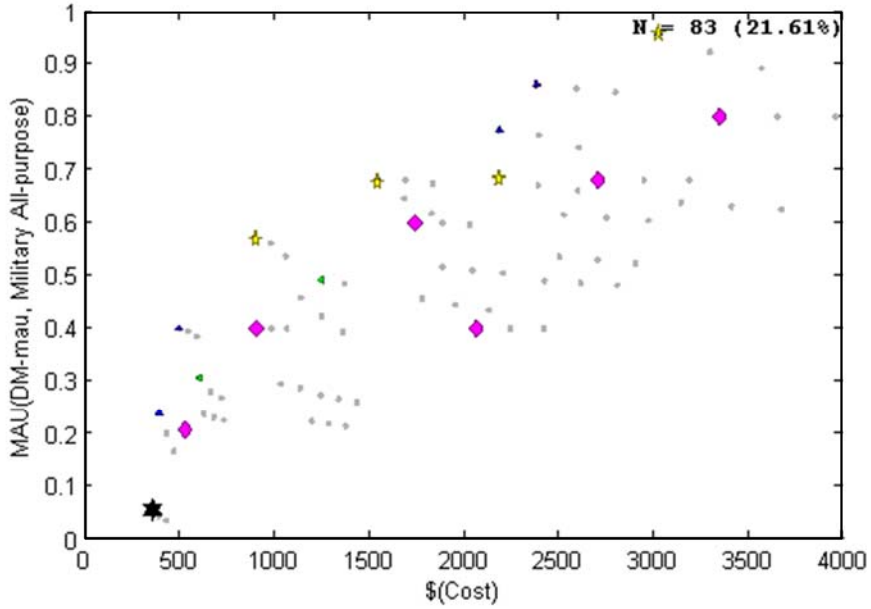
52 + DFC1 = 180
52 + DFC2 = 308

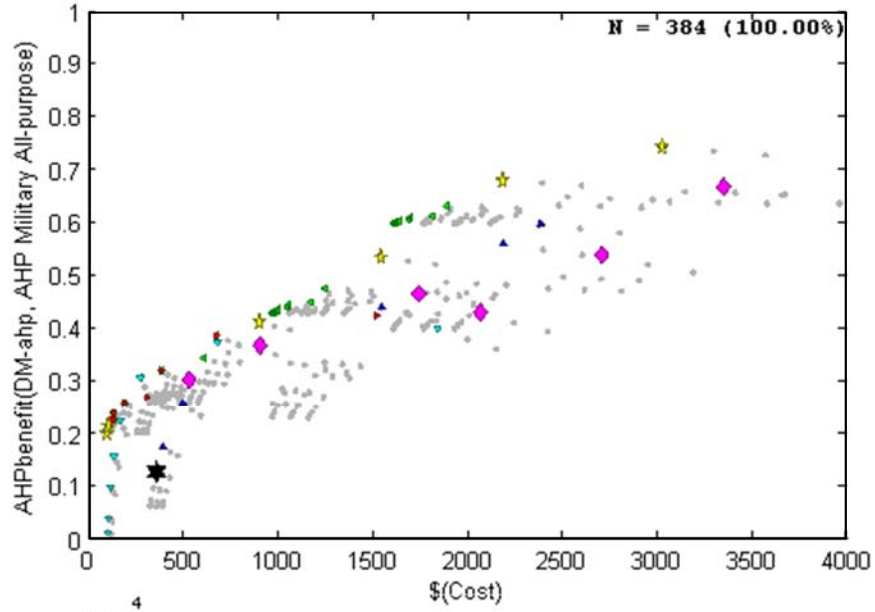
53 + DFC1 = 181
53 + DFC2 = 309

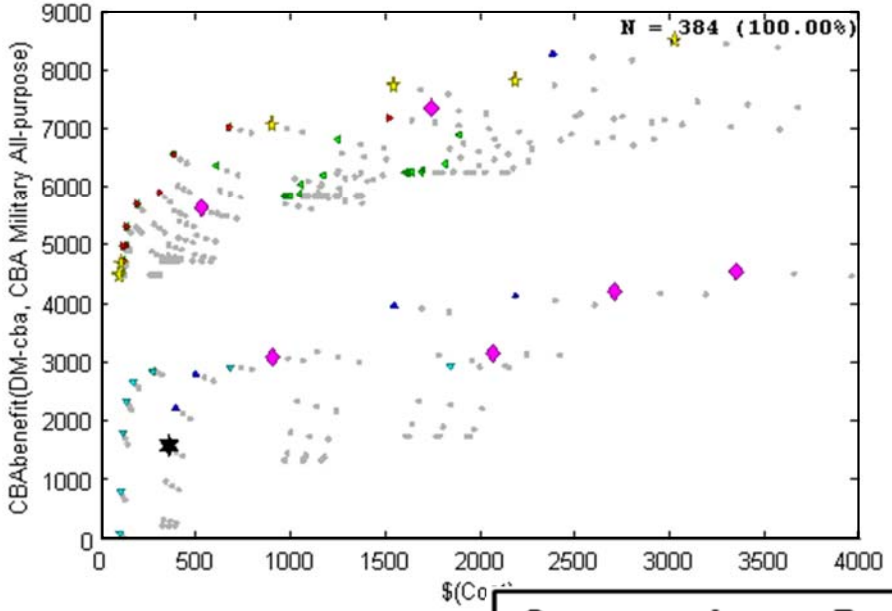
Having DFC1 or DFC2 increases its changeability*

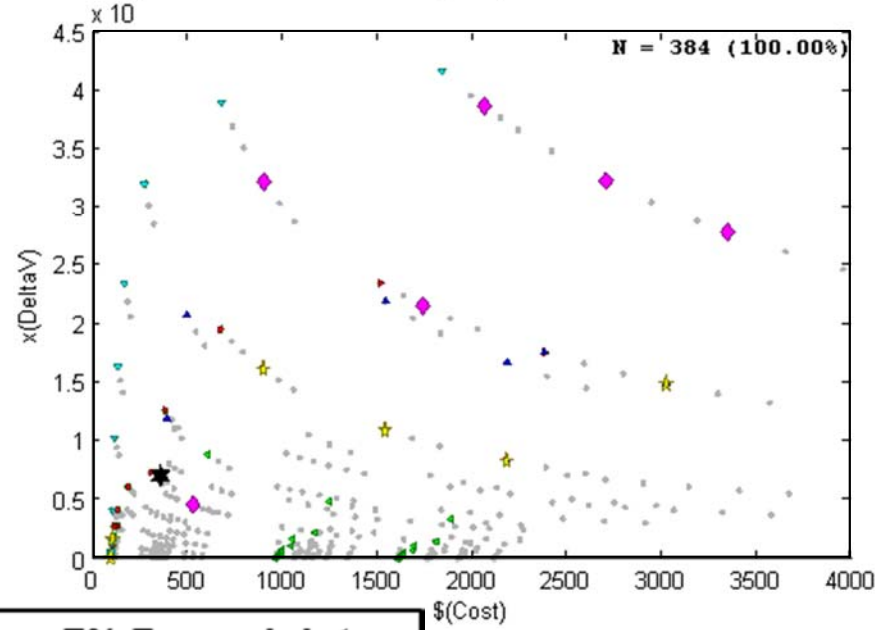
*value of changeability is not addressed in this study… see research on VASC (Fitzgerald et al. 2012)

Cross-Plotted Tradespaces with "New" Alternatives









Compromise ◆ Promising ★ 7% Fuzzy Joint ✱

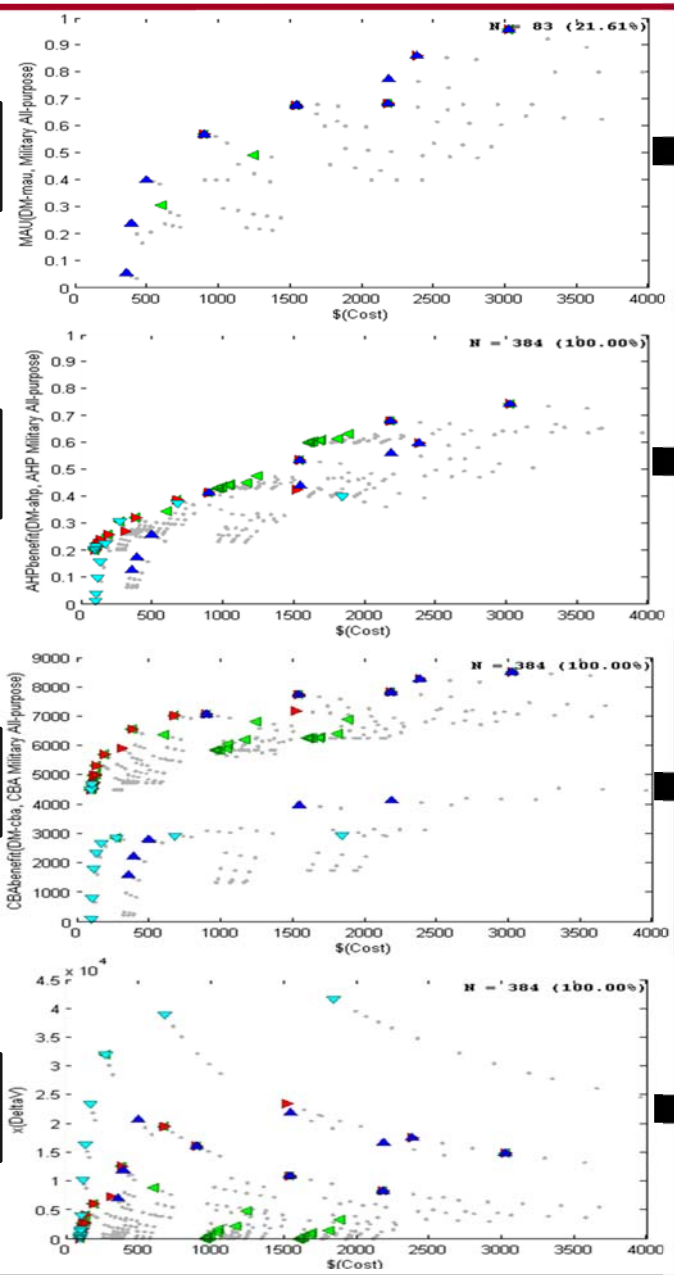
Value Model Tradeoffs

MAU Model

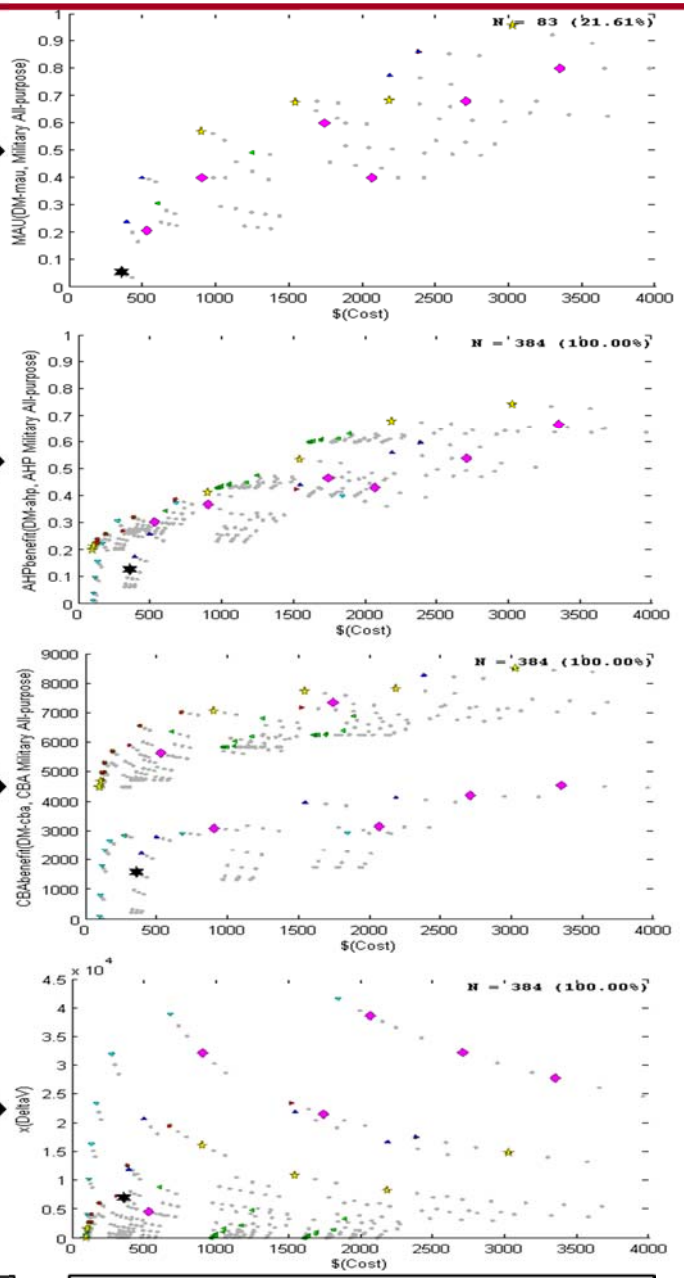
AHP Model

CBA Model

MOE Model



Model comparisons and tradeoffs



"Best" design(s)

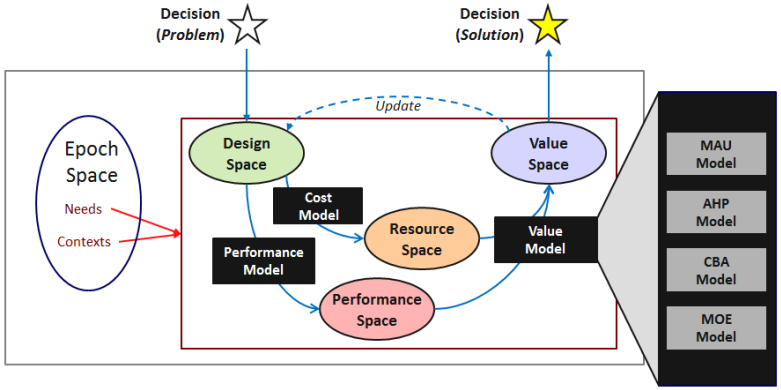
Design selection

Discussion

Using same performance and cost models, different "best" solutions arise as a consequence of value model choice

- Choice of value model determines the attractiveness of each solution
  - Distinct Pareto sets for each value model choice
- Each value model will likely highlight different systems
  - There were no joint Pareto solutions
- Can identify systems that do well across multiple value models
  - Compromise Pareto solutions were efficient tradeoffs between value models
  - Promising solutions were "almost" joint; may become so if dropping a value model
- Analysis useful if value model choice is uncertain or likely to change
  - Using these techniques, one can explore sensitivities to variation in not only value model parameters, but also the value models themselves
  - Structured approach for moving beyond "optimal" designs to include larger possibility space of good and robust solutions

Implications



- Demonstrated impact of value model choice on outcomes
- Analysts need to make explicit considerations on model choice
- Optimization is complementary approach, but model choice constrains potential quality of solution
- Human-in-loop can enhance model trust and truthfulness considerations, improving confidence in proposed solutions
- Cross-model sensitivity and Pareto analyses can be used to find resilient solutions
- Resilient decisions are enabled by resilient approaches

Explicit consideration of value model choice and tradeoffs, including identification of solutions robust to variation in value model can result in more resilient decisions in the long run

Thank you for your attention!

Questions?

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