CSER 2017 15 YEARS
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Interactive model trading for resilient systems decisions

Adam M. Ross and Donna H. Rhodes
Massachusetts Institute of Technology

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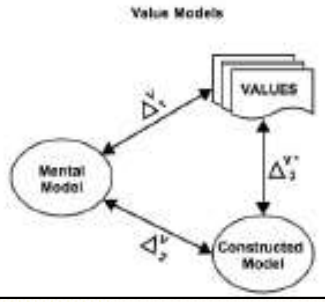
Model Choice and Tradeoffs

- 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

Constructed Model v. Mental Model		Low Δ_1 (truthful)	High Δ_1
	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.



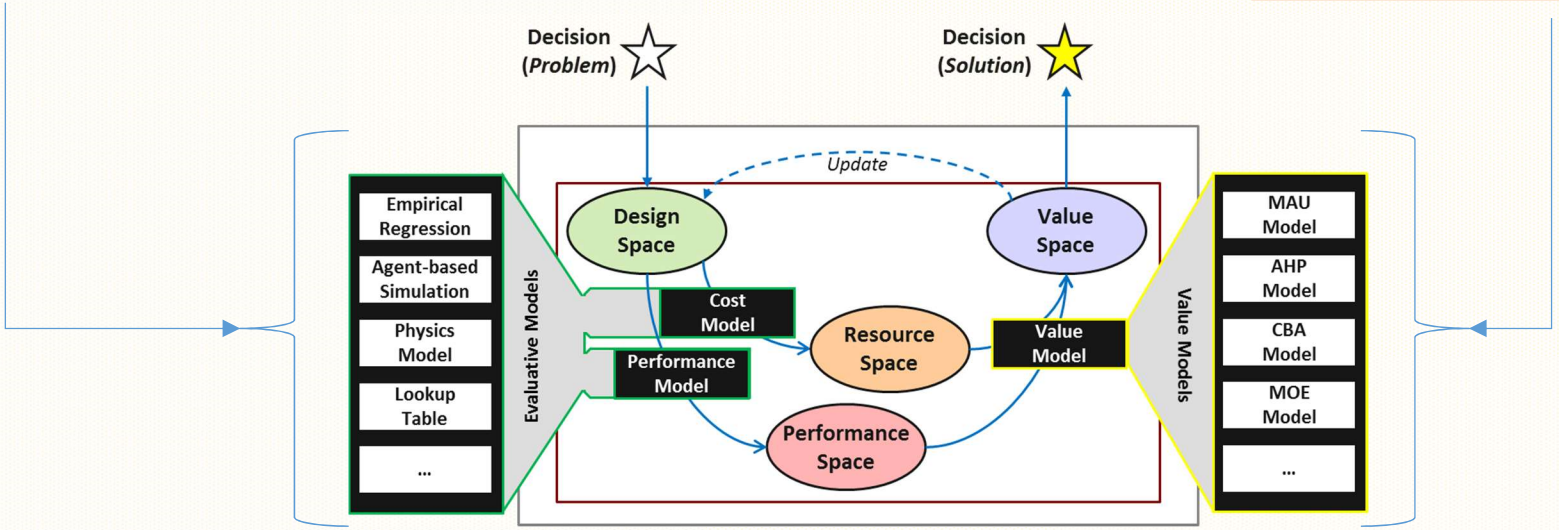
Preliminary research was done to trade "within model" sensitivities in value models, investigating the potential for interaction in refining value model parameter choices*

*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?

Model Choice and Trading

CSER 2016: **Evaluative Model Trading** CSER 2015: **Value Model Trading**



- Model choice occurs throughout the design-value loop
- Model choice impacts the relative attractiveness of different alternatives
- Comparing models develops further insight into case
  - Use to build confidence in knowledge / trust in model
  - Use to select a single model to move forward with (e.g. optimization), or groups for ensemble analyses
  - Use to identify alternatives robust to model choice

Explicitly considering choice of models supports resilient decisions

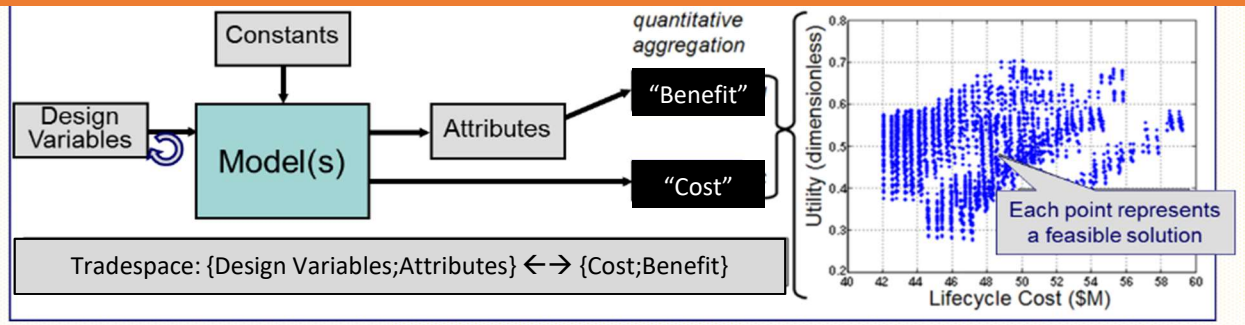
Approach

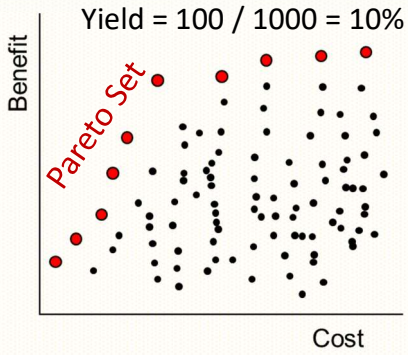
- In this paper we combine the value model and evaluative model choices to look for emergent patterns and insights
- 16 tradespaces of data in the 4 x 4 model combinations
- For each tradespace, determined benefit-cost Pareto Sets
- Interactively determined fuzziness levels such that at least one alternative became insensitive to model choice

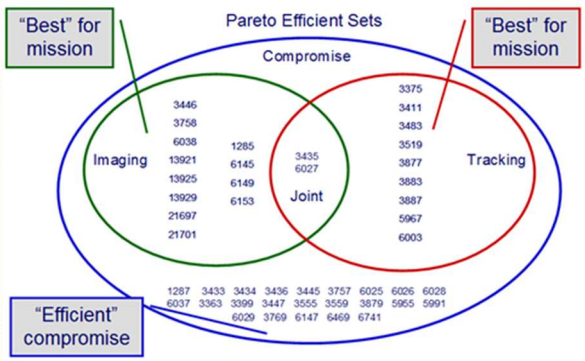
Evaluative Model: Value Model	Implementation #1 (Original) *Baseline (low) fidelity*	Implementation #2 (New Speed) *Improved evaluative fidelity*	Implementation #3 (New Material) *Improved representation fidelity*	Implementation #4 (New Speed and Material) *Both improvements*
MAU	1-MAU	2-MAU	3-MAU	4-MAU
AHP	1-AHP	2-AHP	3-AHP	4-AHP
CBA	1-CBA	2-CBA	3-CBA	4-CBA
MOE	1-MOE	2-MOE	3-MOE	4-MOE

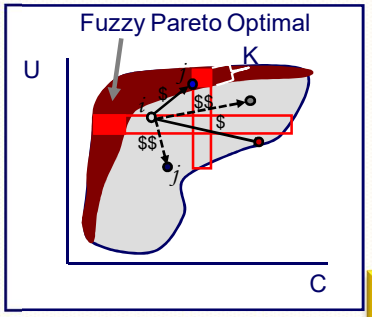
Tradespace Concepts

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









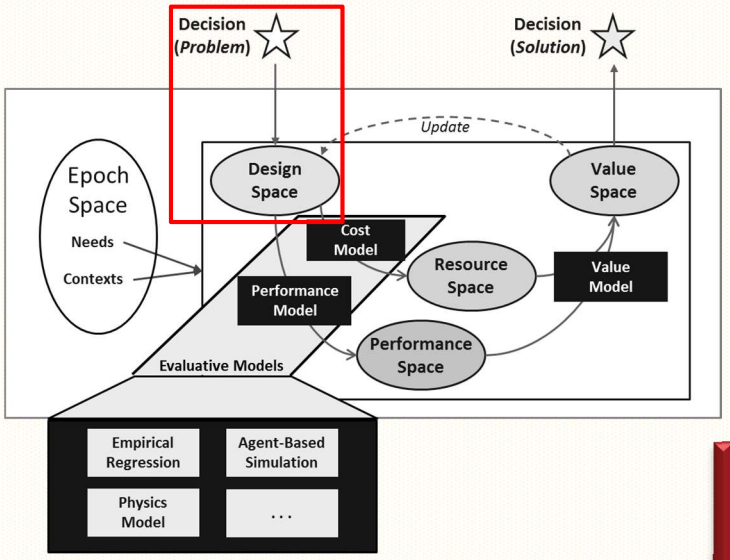
- **Scatterplot**: 2D plot where x,y position of point indicates scores in those dimensions (often benefit and cost)
- **Yield**: Fraction of design space considered valid
- **Pareto Set**: Non-dominated (most efficient) set of designs for given objectives (i.e. improvement in one objective results in 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

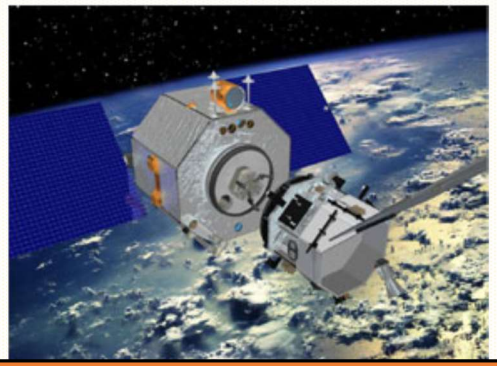
Reintroducing Space Tug

Same case as prior papers

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

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





Attributes

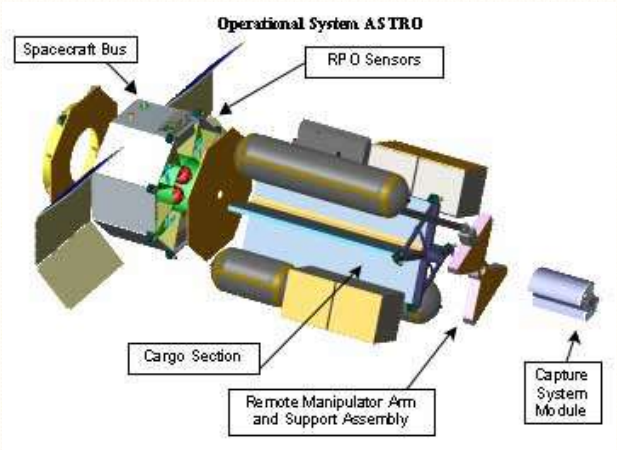
- Delta-V
- Capability
- Response time
- Lifecycle Cost

Performance

Cost

Design Space (N=384)*

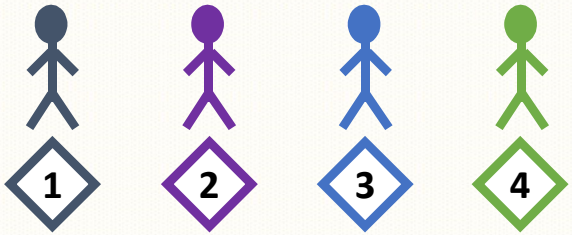
- Manipulator Mass
  - Low (300kg)
  - Medium (1000kg)
  - High (3000 kg)
  - Extreme (5000 kg)
- Propulsion Type
  - Storable bi-prop
  - Cryogenic bi-prop
  - Electric (NSTAR)
  - Nuclear Thermal
- Fuel Load - 8 levels
- Design for Change (DfC)
  - None, level-1, level-2

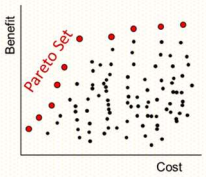


*Fitzgerald, M.E., Ross, A.M., and Rhodes, D.H., "Assessing Uncertain Benefits: a Valuation Approach for Strategic Changeability (VASC)," INCOSE International Symposium 2012, Rome, Italy, July 2012.

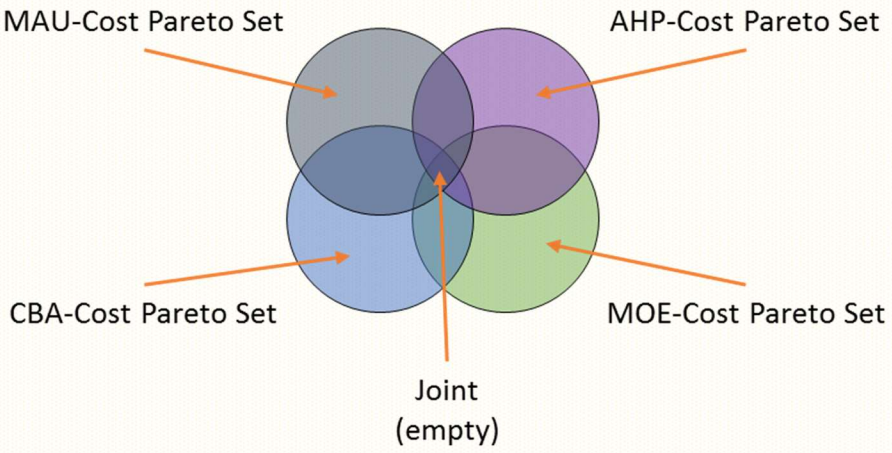
Baseline Results

Hypothetical 4 decision makers (DMs)

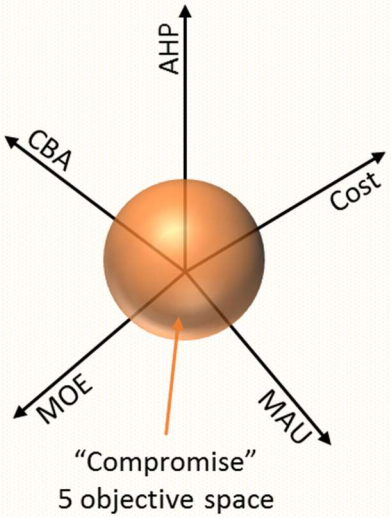




Each has their own value model to interpret goodness on the SAME attributes

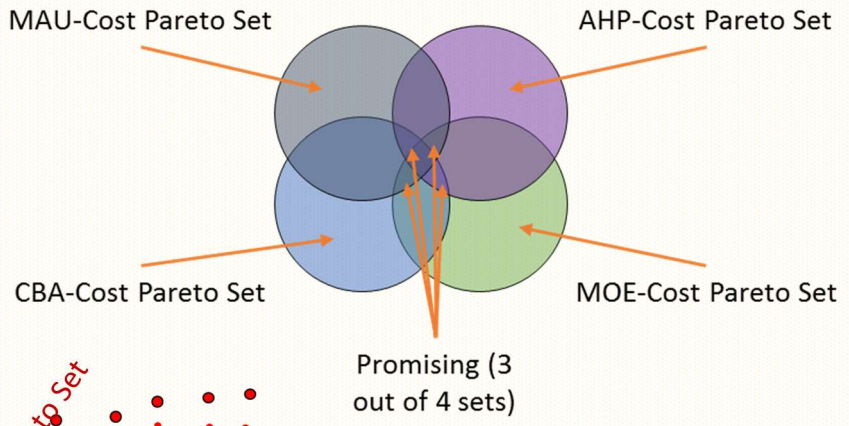


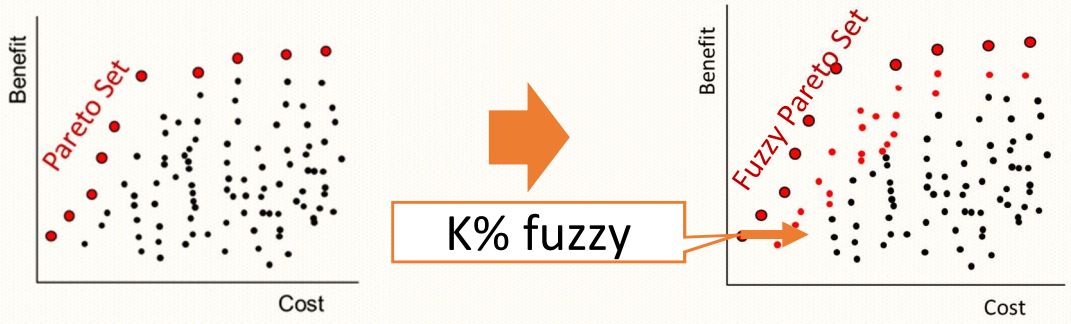
OBJECTIVES SET	# DESIGNS IN 0% PARETO SET			
	Eval Model #1	*Eval Model #2*	*Eval Model #3*	*Eval Model #4*
1: MAU-COST	10	9	15	16
2: AHP-COST	43	10	54	19
3: CBA-COST	17	6	25	5
4: MOE-COST	13	13	20	20
JOINT	0	0	0	0
COMPROMISE	6	2	15	5

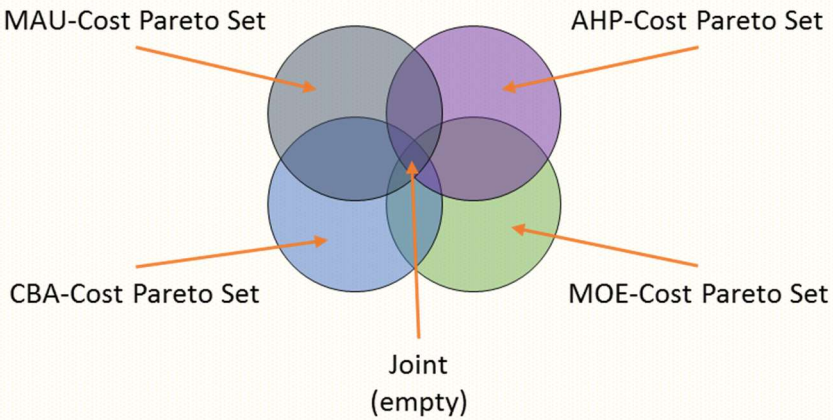


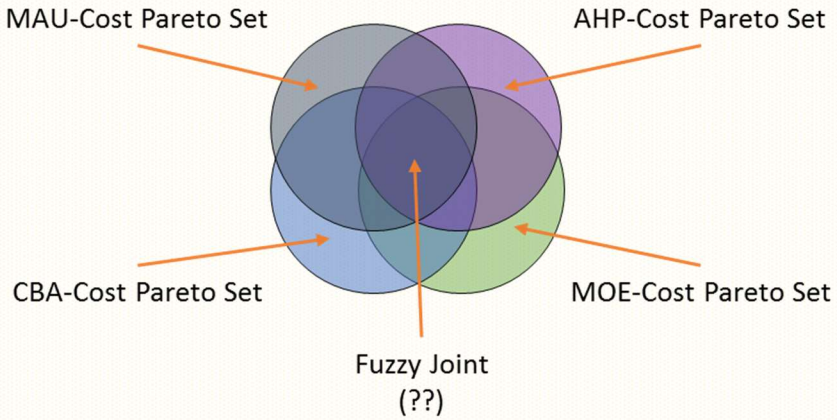
Beyond Simple Set Overlap

- Promising are "best" for 3 out of 4 DMs
- Fuzzy joint are "best" allowing for K% uncertainty









Results Across Evaluative Models

For each of 4 evaluative models, identified promising and fuzzy joint designs across value models

ID NUMBER	Evaluative Model #1	#2	#3	#4	Value Model 1	2	3	4	DETAILS
1	✓	✓	✓	✓	X	✓	✓	✓	small biprop min fuel
9		✓		✓	X	✓	✓	✓	small cryo min fuel
11	✓		✓		X	✓	✓	✓	small cryo near min fuel
52	7%	7%	6%	6%	~	~	~	~	med elec med fuel
63	✓		✓		✓	✓	✓		med nuke near max fuel
87		✓			✓	✓	✓		large elec near max fuel
95	✓		✓		✓	✓	✓		large nuke near max fuel
119		✓			✓	✓	✓		xl elec near max fuel
120		✓		✓	✓	✓	✓		xl elec max fuel
127	✓				✓	✓	✓		xl nuke near max fuel
128	✓		✓		✓	✓	✓		xl nuke max fuel
435			6%	6%	~	~	~	~	med elec near min fuel carbon
504				✓	✓	✓	✓		xl elec max fuel carbon
512			✓		✓	✓	✓		xl nuke max fuel carbon

Legend

✓ : in Pareto Set

~ : in Fuzzy Pareto Set

K%: in K-Fuzzy Joint Pareto Set

X : is invalid

E Models: (1) baseline, (2) new speed, (3) new material, (4) combined

V Models: (1) MAU, (2) AHP, (3) CBA, (4) MOE

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9		✓		✓	X	✓	✓	✓	small cryo min fuel
11	✓		✓		X	✓	✓	✓	small cryo near min fuel
52	7%	7%	6%	6%	~	~	~	~	med elec med fuel
63	✓	✓	✓	✓	✓	✓	✓		med **nuke** near max fuel
87		✓			✓	✓	✓		large elec near max fuel
95	✓	✓	✓	✓	✓	✓	✓		large **nuke** near max fuel
119		✓			✓	✓	✓		x elec near max fuel
120		✓		✓	✓	✓	✓		x elec max fuel
127	✓	✓		✓	✓	✓	✓		xl **nuke** near max fuel
128	✓	✓	✓	✓	✓	✓	✓		xl **nuke** max fuel
435			6%	6%	~	~	~	~	med elec near min fuel carbon
504				✓	✓	✓	✓		xl elec max fuel carbon
512			✓	✓	✓	✓	✓		xl **nuke** max fuel carbon

E Models: (1) baseline, (2) new speed, (3) new material, (4) combined

V Models: (1) MAU, (2) AHP, (3) CBA, (4) MOE

Legend

✓ : in Pareto Set

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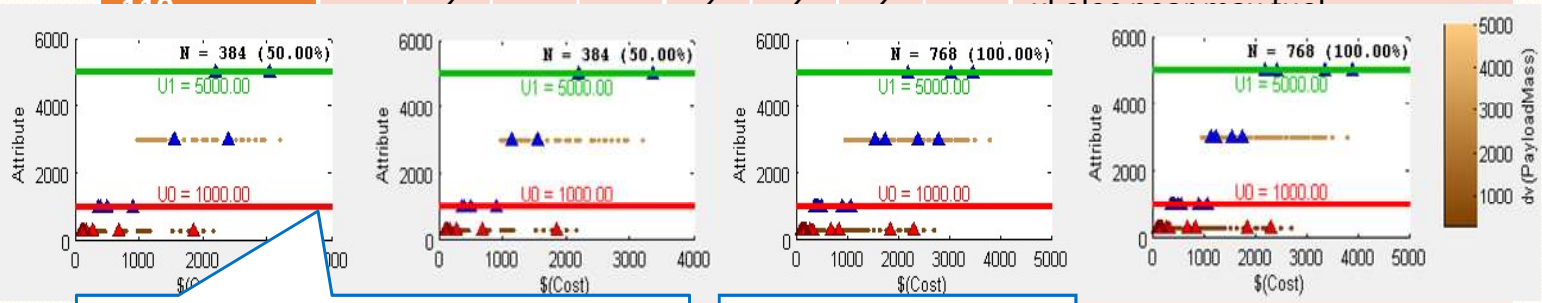
1. **New speed model (2&4) rec's elec over nuke**

This is an insight about the sensitivity of rec to fidelity

Results Across Evaluative Models

For each of 4 evaluative models, identified promising and fuzzy joint designs across value models

ID NUMBER	Evaluative Model #1	#2	#3	#4	Value Model 1	2	3	4	DETAILS
1	✓	✓	✓	✓	X	✓	✓	✓	**small** biprop **min fuel**
9		✓		✓	X	✓	✓	✓	**small** cryo **min fuel**
11	✓		✓		X	✓	✓	✓	**small** cryo **near min fuel**
52	7%	7%	6%	6%	~	~	~	~	med elec med fuel
63	✓		✓		✓	✓	✓		med nuke near max fuel
87		✓			✓	✓	✓		large elec near max fuel
95	✓		✓		✓	✓	✓		large nuke near max fuel
									...lec max fuel carbon
512			✓		✓				...uke max fuel carbon



Min acceptable level for MAU

▲ MAU Pareto Design
▲ MOE Pareto Design

E Models: (1) baseline, (2) new speed, (3) new material, (4) combined
V Models: (1) MAU, (2) AHP, (3) CBA, (4) MOE

Legend
✓ : in Pareto Set
~ : in Fuzzy Pareto Set
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X : is invalid

1. **New speed model rec's elec over nuke**
2. **MOE and MAU are in tension (MOE rec's small mass, MAU finds unacceptable)**

This is an insight about the nature of the value models

Results Across Evaluative Models

For each of 4 evaluative models, identified promising and fuzzy joint designs across value models

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11	✓		✓		X	✓	✓	✓	small cryo near min fuel
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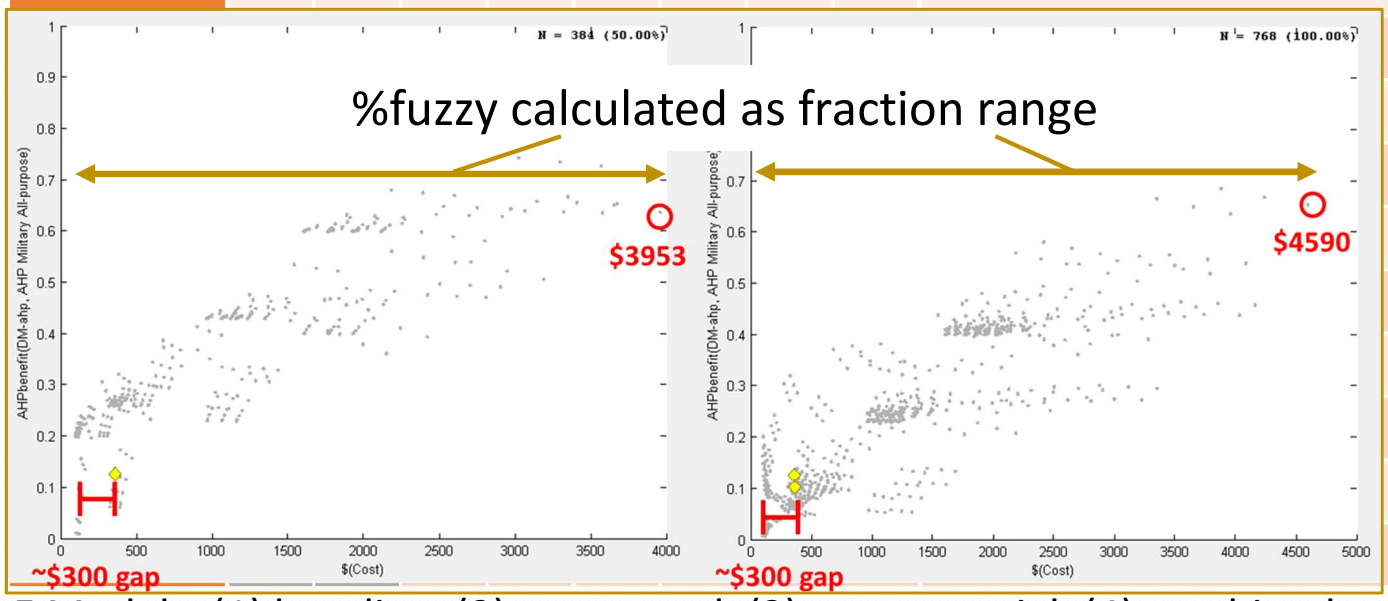


E Models: (1) baseline, (2) new speed, (3) new material, (4) combined

V Models: (1) MAU, (2) AHP, (3) CBA, (4) MOE

Legend

✓ : in Pareto Set

~ : in Fuzzy Pareto Set

K%: in K-Fuzzy Joint Pareto Set

X : is invalid

1. **New speed model rec's elec over nuke**
2. **MOE and MAU are in tension**
3. **The %fuzzy at first joint decreases with new material model**

This is a modeling artifact

Results Across Value Models

For each of 4 value models, identified promising and fuzzy joint designs across evaluative models

Concept of category: a design can fall into one or more Pareto sets generated by the different evaluative models

The number of possible categories is $\sum_{k=0}^{N} \frac{N!}{k!\,(N-k)!}$

N is number of models

So for N=4 models, the number of possible categories is 16.

- Designs that fall into particular categories may have differential appeal, especially if particular models are deemed less trustworthy
- Those designs that fall into categories with higher rank (e.g. 4 out of 4 or 3 out of 4) are likely to be more appealing (i.e. robust to model variation)

For MAU

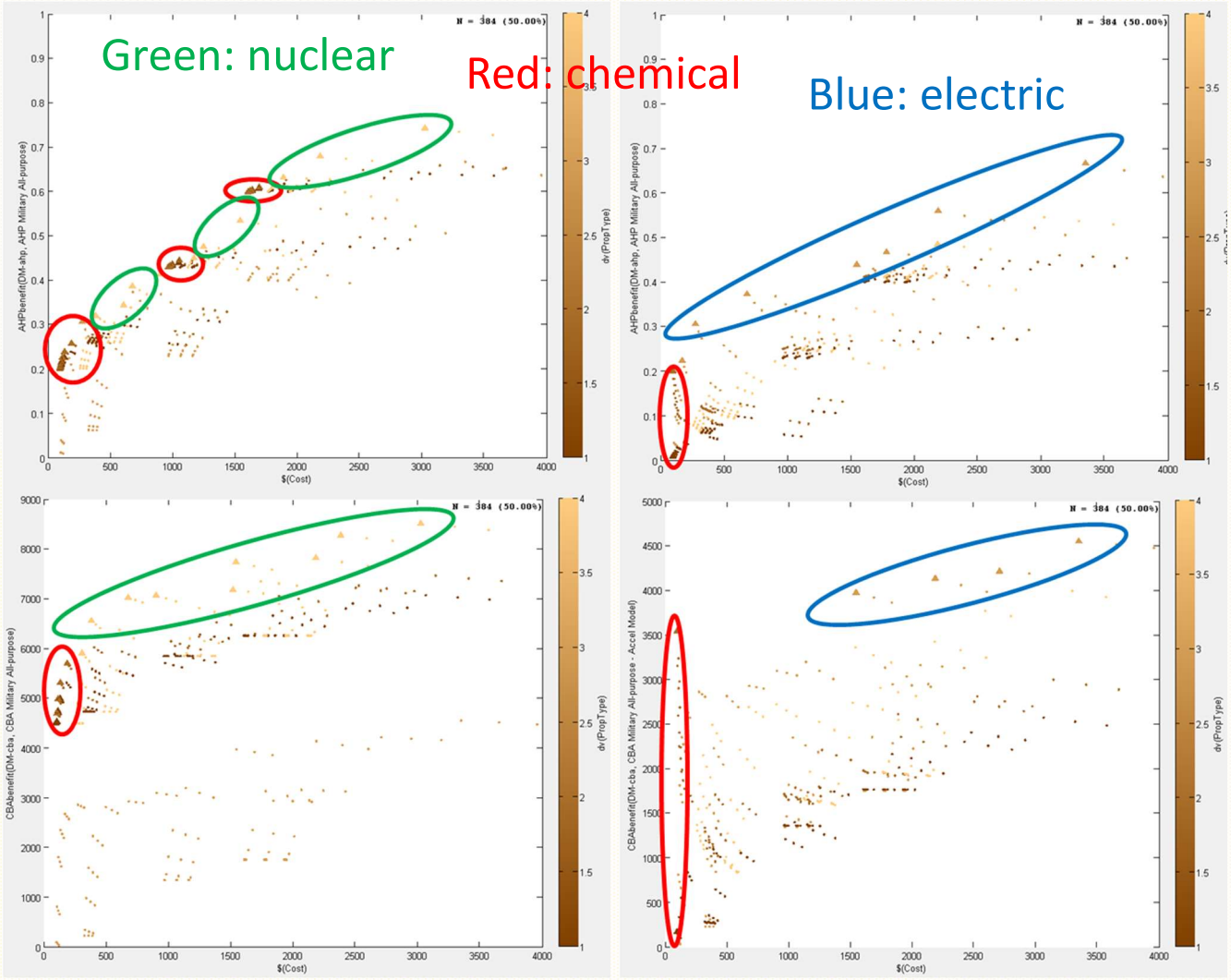
Category	Design ID (Aluminum)	*Eval Model #1*	*Eval Model #2*	*Eval Model #3*	*Eval Model #4*	Design ID (Carbon)	*Eval Model #3*	*Eval Model #4*
A	52, 53, 63	✓	✓	✓	✓	436, 437, 447	✓	✓
B	54, 87, 119	✓	✓	✓	✓	438, 471, 503		✓
D	86, 120		✓		✓	470, 504		✓
E	96, 128	✓		✓		480, 512	✓	
F	127	✓				511		
K	95	✓	✓	✓		479	✓	

Results Across Value Models

For each of 4 value models, identified promising and fuzzy joint designs across evaluative models

AHP value model

CBA value model



Old speed model

New speed model

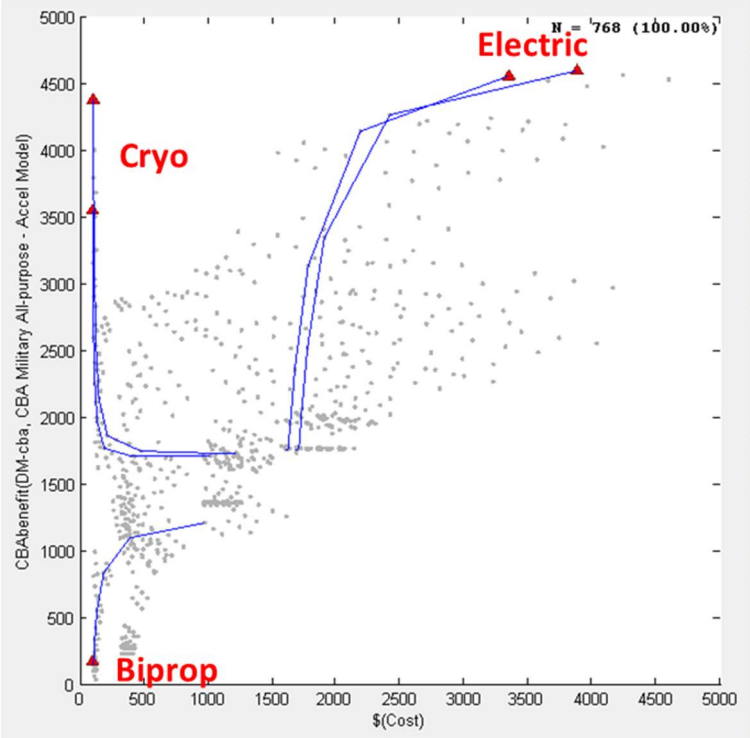
Similar patterns show up across evaluative and value models:

New speed model rec's electric over nuke

Please see paper for more details…

Discussion

- Two classes of insights
  1. Structural patterns for the decision problem
  2. Modeling artifacts
- As confidence and trust in models changes, the sensitivity of insights can be tracked
- Can quantitatively find solutions insensitive to particular subsets of model choice
- Can identify emergent insights due to interaction of factors (including physics and perception)
- Mental models are very unlikely to catch emergent behavior due to bounded rationality
- More rigorous consideration of model choice and tradeoffs can overcome these limitations



Emergent different trades of fuel for cost/benefit

Evaluative models predict how a system "might perform"
Value models predict how a system "might be valued"

Emergence exists at the intersection and across these models

Especially in early phase design, one must seek insights that are less sensitive to assumptions, as well as uncover tradeoffs revealed by the intersection of possible evaluative and value models

Thank you for your attention!

Questions?

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