Interactive value model trading for resilient systems decisions

By

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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)

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

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

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:
    o What value model best represents his preferences?
    o What parameters for a given value model best represent his preferences?
    o What if he really doesn’t know what his true preferences are and instead wants a robust solution?

• 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

Investigated in CSER14 paper

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
• 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?

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

Attributes

- Delta-V
- Capability
- Response time

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

<table>
<thead>
<tr>
<th>Propulsion System</th>
<th>$I_{sp}$ (sec)</th>
<th>Base Mass $m_{p0}$ (kg)</th>
<th>Mass Fract. $m_{pf}$</th>
<th>High Impulse</th>
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</table>

### 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*

• 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

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Value Model 1
Multi-Attribute Utility (MAU)

Attributes ($X_i$):

Each attribute is normalized through a utility function

Single Attribute Utilities ($U_i X_i$)

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

where \(K = -1 + \prod_{i=1}^{n} (K \cdot k_i + 1)\)

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

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

Capable Delta V Response Time

Single Attribute Utilities (UiXi)
Attributes (Xi):
Aggregated

Excluded Attribute Values

Curve TBD

Excess Attribute Values (typically assigned Utility = 1)
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)

**Attributes (X<sub>i</sub>):**

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<thead>
<tr>
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<th>Capability</th>
<th>Delta V</th>
<th>Response Time</th>
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<td>x(DeltaV)</td>
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<tr>
<td>x(Response Time)</td>
<td>1/2</td>
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<td>1</td>
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</table>

Matrix scores are elicited via pairwise comparisons by the decision maker.

Determine weights

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

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
• No alternatives are deemed “invalid”
• Tradespace Yield is 100%
• 43 designs are in Pareto Set
Value Model 3
Cost-Benefit Analysis (CBA)

Monetization functions are elicited from the decision maker

\[
CBA_i(X_i) = \begin{cases} 
\frac{m_i}{r_i}(1 - e^{-r_iX_i}) & \text{if } X_i \geq X_{i,min} \\
0 & \text{if } X_i < X_{i,min}
\end{cases}
\]

Each attribute is normalized through a monetization function

Pro: Evaluation on an intuitive scale; Con: Noncommercial systems, monetization questionable
No alternatives are deemed “invalid”
Tradespace Yield is 100%
17 designs are in Pareto Set
Value Model 4
Measure of Effectiveness (MOE)

MOEs are elicited from the decision maker

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

In this case, used \( \text{Delta}V \) as single dimension of value

MOE Model

\[ \text{MOE}(X_i) = X_i \]
No alternatives are deemed “invalid”
Trade space Yield is 100%
13 designs are in Pareto Set
Alternative Tradespaces

MAU (Mau, Military Al-purpose)

AHP (Mau, AHP Military Al-purpose)

CBA (Mau, CBA, Military Al-purpose)

MOE (Mau, MOE, Military Al-purpose)

MAU-Cost Pareto Set ▲ AHP-Cost Pareto Set ▲ CBA-Cost Pareto Set ▲ MOE-Cost Pareto Set ▼
Cross Plotted Tradespaces

Some common designs

Clearly dominated designs
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**

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

### Table: Compromise Designs (0% fuzzy)

<table>
<thead>
<tr>
<th>Design</th>
<th>Cost</th>
<th>PropMass</th>
<th>Capability</th>
<th>DeltaV</th>
<th>ResponseTime</th>
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<th>MassFrac</th>
<th>Mass</th>
<th>DeltaMass</th>
<th>MAU</th>
<th>DM-mau, x(Capability)</th>
<th>DM-mau, x(ResponseTime)</th>
<th>AHPBenefits(DM-ahp, AHP Military All-purpose)</th>
<th>CBABenefits(DM-cta, CBA Military All-purpose)</th>
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## Promising Designs

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<td>MAU, CBA, MOE</td>
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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

Joint Pareto Designs

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<tr>
<th>Design#</th>
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Compromise Pareto Designs

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Fuzzy Joint Pareto Designs

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<th>Threshold Fuzzy Level</th>
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</tbody>
</table>

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

- Having DFC1 or DFC2 increases its changeability*.

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52 + DFC1 = 180
52 + DFC2 = 308
53 + DFC1 = 181
53 + DFC2 = 309

*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

Model comparisons and tradeoffs

MAU Model

AHP Model

CBA Model

MOE Model

“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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