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Interactive model trading for resilient systems decisions

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Abstract

The Interactive Model-Centric Systems Engineering research effort is interested in developing knowledge necessary to leverage the increasing involvement of computational models in system design. A key activity in such model-centric environments is the selection and usage of models to generate data for decision making. Extending work from prior demonstrations, this paper presents a case study where insights are gained via usage and comparison of multiple models. The results highlight the need to explore how model choice and tradeoff can impact the attractiveness of alternative systems. Sixteen tradespaces of cost-benefit data are generated via combined pair-wise usage of four alternative evaluative models (performance and cost calculations) and four alternative value models (calculating the "goodness" of different levels of performance and cost). These tradespaces are used to determine attractive Pareto efficient Space Tug vehicles, as well as insights that are less sensitive to model choice. No best model is shown, but rather different models provide insights into different aspects of the system evaluation and valuation activity. Two categories of insights are highlighted: patterns in the structure of the decision problem (i.e. how "value" is defined and what systems might be feasible), and artifacts of the models themselves (i.e. how to mitigate against misleading results due to model abstractions).

Keywords: models; modeling; evaluative models; value models; fidelity; robust solutions; tradespace exploration; resilience

1. Introduction

Data-driven decision making is in increasingly used phrase to describe a paradigm where evidence, often in the form of digital artifacts, is used to support a methodical approach to making decisions. Implied in this approach is a numerical basis, possibly supported by large databases of information, where the "data" is leveraged for compelling insights that would (presumably) result in better decisions (than a less data-driven approach). In the world of systems engineering, especially early in the lifecycle, where empirical data may be lacking, a model-based approach is increasingly being used. Such model-based approaches leverage computational techniques to generate *artificial* data about (potential) systems. The term *artificial* is not meant pejoratively, but rather to reflect the human-made abstraction that is used in order to generate the data [1]. Since models are abstractions, they are necessarily deficient to some degree in their predictive power to describe a system (form, function, behavior, operations, etc.) as it *actually will be experienced* later in the lifecycle. Various efforts have been made in many fields to address concepts such as fidelity, accuracy, precision, and so on, all in support of selecting appropriate models for a decision at hand.

1.1. Motivation

The Interactive Model-Centric Systems Engineering research program has proposed that systems engineers should not just try to select models to answer questions, but also to better reflect upon what can be learned using different models to answer the same question. Two previous papers published at CSER have addressed the two main types of models used in early lifecycle systems engineering: evaluative models and value models. The former tries to predict the performance and cost of potential alternative systems, while the latter tries to predict how much different levels of performance and cost *is worth* to different stakeholders. Both types of models require abstraction of reality, and both generate essential data needed for confident decision making. The prior papers have shown that using alternative model implementations simultaneously (i.e. not just picking one of them) in order to generate data, can provide insights that can make the ultimate decisions more resilient to uncertainties and deficiencies inherent in the act of modeling itself. Such resiliency can be manifested in decisions that are insensitive to uncertainties, or can be changed at low cost to account for new information as it unfolds.

This paper synthesizes the prior studies into a combine model choice and trading study in order to determine what kinds of additional insights could be had when taking this broader perspective. In this study, the researcher has interacted both with model choice and through active exploration of the resulting datasets. Interactivity has been found to be a useful mechanism for hypothesis generation and testing with dataset displaying emergent properties, and is a central topic of a current doctoral research effort [2].

2. Demonstration of combined value and evaluative model trading: Space Tug

In order to demonstrate the effects of trading both value and evaluative models, and the insights that can be gained by doing so, we will return to the Space Tug case used in the prior demonstration of separately considered value model trading and evaluative model trading [3]. The generic mission is therefore the same but the key questions have now combined:

> *A decision maker has a budget for an orbital transfer vehicle (a.k.a. "Space Tug") and thinks he knows what he wants (in terms of attributes of goodness of a system). But he is aware that he may not have formulated his value model correctly. Additionally, he is aware that Space Tugs are a developing technology, and the models used to evaluate them are not 100% validated. He wants to explore various uncertainties in his value model as well as a variety of evaluative model implementations in order to understand their impact on what makes a "good" system alternative and whether there are alternatives that are resilient to these uncertainties.*

For the combined demonstration, we used both sets of value models (four implementations) and evaluative models (also four implementations) described in our prior demonstrations. These resulted in 16 tradespaces worth of data generated via the pairwise combination of value and evaluative models listed in Table 1. Value models included multi-attribute utility (MAU), analytic hierarchy (AHP), cost-benefit analysis (CBA), and measure of effectiveness (MOE). Evaluative models included four implementations including the original (#1), new speed (#2), new material (#3), and combined new speed and material (#4). The details of these models can be found in their respective CSER papers [4,5]. For each of the 16 tradespaces we determined the Pareto set of alternatives (most efficient in benefit-cost tradeoff) and interactively determined appropriate fuzziness levels such that alternatives became insensitive in attractiveness (i.e. Pareto set membership) due to model choice. Additional emergent insights were captured are described below.

Table 1. Value and evaluative models used in demonstration

Evaluative Model: *Value Model*	*Implementation #1 (Original)*	*Implementation #2 (New Speed)*	*Implementation #3 (New Material)*	*Implementation #4 (New Speed and Material)*
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

3. Results

The results of this demonstration will be presented as a value model by evaluative model and evaluative model by value model comparison. That is, we repeated our value model tradeoff study [4] for *each* of the evaluative models (4 value models x 1 evaluative model) x 4 evaluative models. Then we repeated our evaluative model tradeoff study [5] for each of the value models (4 evaluative models x 1 value model) x 4 value models. We did this in order to demonstrate generalization of the approach we took within the prior studies, and to highlight the intent as one that aims to gain knowledge about the impact of model choice, rather than selection of the "best" alternative.

3.1. Value model trading for each evaluative model

As described in the earlier value model trading case, there are four pairs of objectives considered when determining Pareto efficient design sets [4]. These are (1) MAU-COST, (2) AHP-COST, (3) CBA-COST, and (4) MOE-COST, with each value model resulting in a metric quantifying the expected benefit and cost of an alternative. Each value model has intentionally kept the cost metric as a distinct objective in order to explicitly highlight the various cost versus benefit tradeoffs that determine value. This is reflected in the objective sets each having cost as well as the appropriate value model metric for benefit. Table 2 describes the size of the 0% fuzzy Pareto sets for each of the value models when using each of the evaluative model implementations (e.g. *Eval Model #1* is the original model). These sets represent the most efficient benefit-cost tradeoff alternatives for a given value model-evaluative model pair tradespace. The joint set contains those alternatives that appear in all of the Pareto sets across the value models for a given evaluative model. The compromise set contains those alternatives in the Pareto set defined by considering all of the objectives simultaneously for a given evaluative model. For this study, each objectives set was assigned to a notional decision maker (DM) to help conceptualize the study (i.e. what if four different DMs had four different value models, how do we find alternatives that will satisfy all (or most) of them?).

Table 2. Pareto sets sizes for value models using each evaluative model implementation

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

3.1.1. Evaluative model #1 (original model)

Evaluative model #1 has a potential tradespace size of 384 designs, enumerated across three design variables (payload size, propulsion type, and fuel tank size). Table 3 lists the designs that are almost joint Pareto efficient (a.k.a. "promising designs), appearing in 3 out of 4 Pareto sets.

Table 3. Promising designs that are joint Pareto efficient across 3 out of 4 value models in evaluative model #1

ID NUMBER	**PARETO EFFICIENT FOR**	**INVALID FOR**	**DETAILS**
1	2, 3, 4	1	small biprop min fuel
11	2, 3, 4	1	small cryo near min fuel
63	1, 2, 3		med nuke near max fuel
95	1, 2, 3		large nuke near max fuel
127	1, 2, 3		xl nuke near max fuel
128	1, 2, 3		xl nuke max fuel

As one increases the degree of acceptable fuzziness (i.e. distance from the Pareto front), the number of designs in a given fuzzy Pareto set increases. The first fully joint (across 4 out of 4 value models) Pareto efficient design, which appears at a fuzzy level of 7%, is design 52, a medium payload, electric propulsion, medium fuel tank design. Fig. 1 illustrates the relative sizes of the fuzzy joint Pareto sets at 0% and 7% fuzzy levels.

3.1.2. Evaluative model #2 (new speed model)

Evaluative model #2 has a potential tradespace size of 384 designs, enumerated across three design variables (payload size, propulsion type, and fuel tank size). This model implementation has a new (higher fidelity) speed model. Table 4 lists the designs that are almost joint Pareto efficient, appearing in 3 out of 4 Pareto sets.

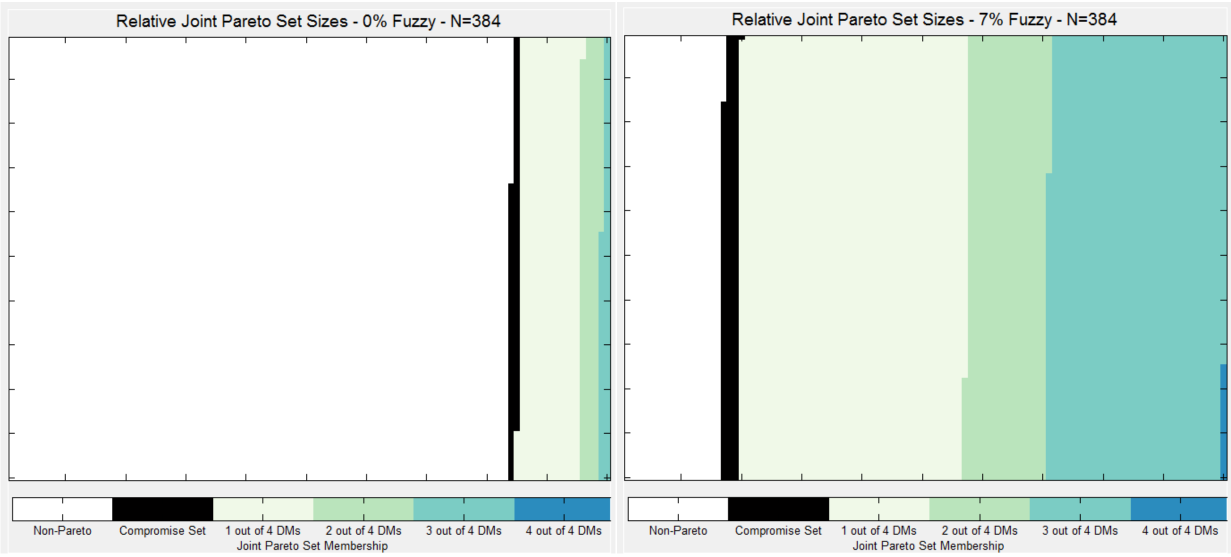

Fig. 1. Gridmap showing relative sizes of 0% (left) and 7% (right) fuzzy joint Pareto sets in evaluative model #1

Table 4. Promising designs that are joint Pareto efficient across 3 out of 4 value models in evaluative model #2

ID NUMBER	PARETO EFFICIENT FOR	INVALID FOR	DETAILS
1	2, 3, 4	1	small biprop min fuel
9	2, 3, 4	1	small cryo min fuel
87	1, 2, 3		large elec near max fuel
119	1, 2, 3		xl elec near max fuel
120	1, 2, 3		xl elec max fuel

The same design 52 appears as the first fully joint Pareto efficient at a 7% fuzzy level. For this evaluative model, it looks like the electric propulsion type passes the nuclear type in terms of "promising" for the new speed model. The first joint Pareto design appears at the same fuzzy level as the original evaluative model.

3.1.3. Evaluative model #3 (new material model)

Evaluative model #3 has a potential tradespace size of 768 designs, enumerated across four design variables (payload size, propulsion type, fuel tank size, and material type). This model implementation added "fidelity" to the design space description, allowing for variation in the material type between aluminum and carbon. Table 5 lists the designs that are almost joint Pareto efficient, appearing in 3 out of 4 Pareto sets.

Table 5. Promising designs that are joint Pareto efficient across 3 out of 4 value models in evaluative model #3

ID NUMBER	PARETO EFFICIENT FOR	INVALID FOR	DETAILS
1	2, 3, 4	1	small biprop min fuel
11	2, 3, 4	1	small cryo near min fuel
63	1, 2, 3		med nuke near max fuel
95	1, 2, 3		large nuke near max fuel
128	1, 2, 3		xl nuke max fuel
512	1, 2, 3		xl nuke max fuel CARBON

Two fully joint (across 4 out of 4 value models) Pareto efficient designs appears at a fuzzy level of 6%: design 52 (medium payload, electric propulsion, medium fuel tank, aluminum design), and design 435 (like 52, but with carbon and one size smaller fuel tank).

3.1.4. Evaluative model #4 (new speed and material model)

Evaluative model #4 has a potential tradespace size of 768 designs, enumerated across four design variables (payload size, propulsion type, fuel tank size, and material type). This model implementation incorporates both the (higher performance fidelity) new speed model as well as the (higher design fidelity) new material model. Table 6 lists the designs that are almost joint Pareto efficient, appearing in 3 out of 4 Pareto sets.

Table 6. Promising designs that are joint Pareto efficient across 3 out of 4 value models in evaluative model #4

ID NUMBER	PARETO EFFICIENT FOR	INVALID FOR	DETAILS
1	2, 3, 4	1	small biprop min fuel
9	2, 3, 4	1	small cryo min fuel
120	1, 2, 3		xl elec max fuel
504	1, 2, 3		xl elec max fuel CARBON

The same two fully joint Pareto efficient designs appear at fuzzy level 6% as in evaluative model #3: designs 52 and 435. Fig. 2 illustrates the relative sizes of the fuzzy joint Pareto sets at 0% and 6% fuzzy levels.

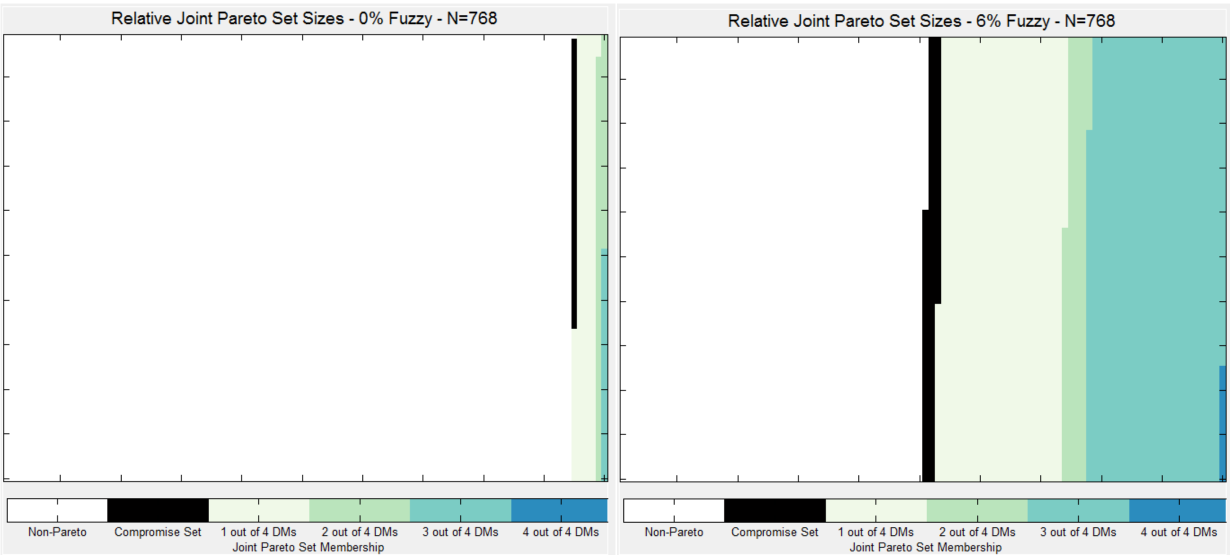

Fig. 2. Gridmap showing relative sizes of 0% (left) and 7% (right) fuzzy joint Pareto sets in evaluative model #4

The addition of having carbon as a material type affects the first joint Pareto design, as this matches model #3. But in that case the change from 7% to 6% is likely an artifact of the increased cost range due to the addition of very expensive carbon designs to the tradespace (i.e. fuzzy level is calculated as a fraction of the tradespace cost range, so the addition of more expensive designs will make a given design appear relatively closer to the Pareto front). The new speed model makes electric more promising than nuclear type propulsion, as both model #2 and model #4 drop all promising nuclear designs and add promising electric designs.

3.1.5. Summary across the evaluative models

All four evaluative model implementations corroborate a tension between the MAU and MOE value models. That is, MOE value model prefers inexpensive, small designs in order to maximize delta-V, but none of those designs meet minimum acceptable performance levels for MAU, so they are considered invalid for the MAU value model. The MAU and MOE value models are in tension, as the MOE value model prefers low mass designs (strongly driven by small payloads). This can be seen in Fig. 3, which illustrates the single attribute utility score as a function of payload capability across the four evaluative models. As payload capability goes up, so too does the mass of the alternatives. The red triangles indicate the designs that MOE views as Pareto efficient, while the blue triangles are the designs in the MAU Pareto set. Many red triangles are below the U0 (red) line in the figure, which correspond to the minimum acceptable level of capability for the utility model. The MAU model (which includes the illustrated single attribute utility curves, as well as utility curves for other attributes), requires that payload capability be greater than the minimum possible size. This clearly shows that MOE and MAU value is in tension. This insight applies across all of the evaluative models and is an *insight about the nature of the value models*.

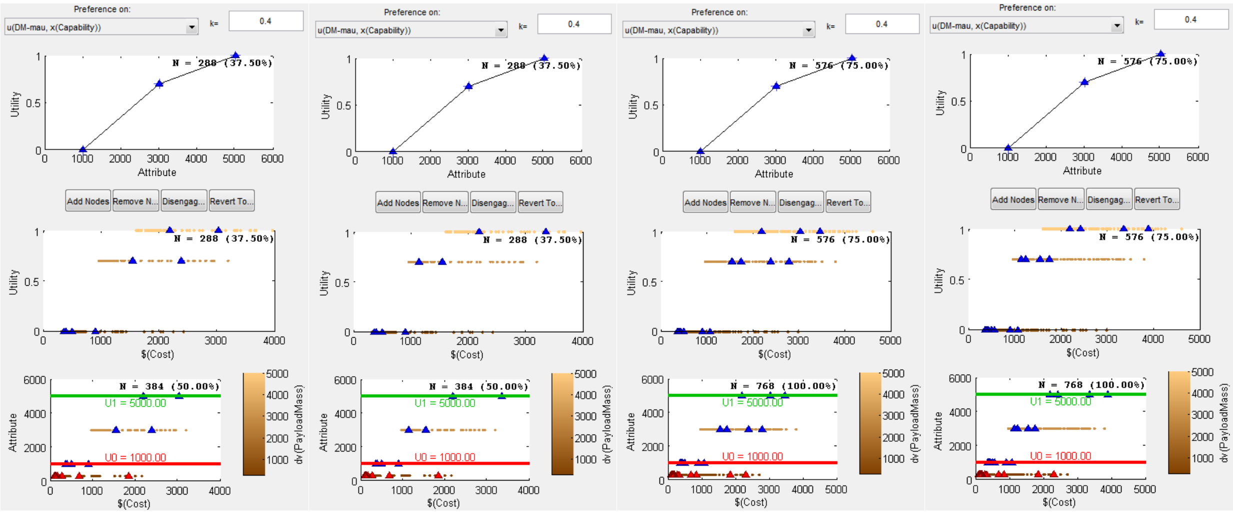

Fig. 3. Comparison of the payload capability single attribute utility function impact across the four evaluative models with MAU (blue triangle) and MOE (red triangle) Pareto sets indicated

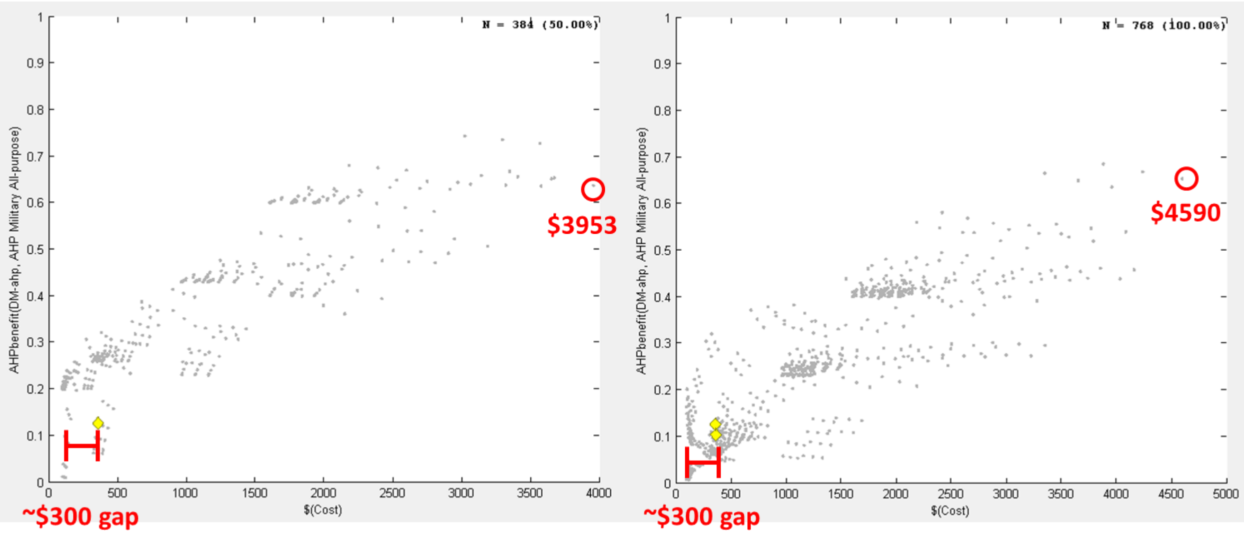

Fig. 4. Comparing evaluative model #1 first joint Pareto design at fuzzy level 7%(left) and evaluative model #4 first joint Pareto at fuzzy level 6% (right) illustrates how increase in maximum cost design impacts fuzzy metric

Another insight is that the minimum fuzzy level for the appearance of joint Pareto designs decreased from 7% to 6% when adding the new material model (in evaluative models #3 and #4). Design 52 is the key design in both cases (with design 435 also in model #3 and #4), and according to the analysis, these designs do not move much across the evaluative models. Instead, the change in fuzzy level required appears to be an artifact of both how the fuzzy Pareto number is calculated and having more expensive designs appearing in the tradespace. Fig. 4 shows the increased cost range in the tradespace due to the addition of higher cost designs (the new more expensive carbon version designs in models #3 and #4). This is an example of a *modeling artifact* and not an insight about the designs themselves.

3.2. Evaluative model trading for each value model

For this part of the case, we look at the tradespaces for a given value model across the four different evaluative models [5] (essentially repeating the early evaluative model trade case for each of the four value models). For the Pareto set category tables, the categories are different than in the corresponding Pareto sets described in the earlier evaluative model trading case paper. The categories are consistent across the examples below, however. These categories range from A to K, with each corresponding to different patterns of Pareto set membership across models.

3.2.1. Multi-attribute Utility (MAU) model

Looking across the evaluative models within the MAU value model is what was done in the 2016 CSER paper (evaluative model trading). Table 7 below summarizes the results of which designs are Pareto efficient for a given evaluative model. Six categories of designs are apparent in this table.

Table 7. Designs, marked in gray with check, for model implementations in which they are efficient for the MAU value model

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	✓	

- **A.** Designs 52, 53, and 63 (and their carbon counterparts) are always efficient across the model implementations.
- **B.** Designs54, 87, and 119 are efficient across the model implementations, and their carbon counterparts are only efficient under the new speed model (model #4).
- **D.** Designs 86 and 120 are efficient only under the new speed model (models #2 and #4), as are their carbon counterparts (in model #4).
- **E.** Designs 96 and 128 are efficient only under the old speed model (models #1 and #3), as are their carbon counterparts (in model #3).
- **F.** Design 127 is efficient only under the original model (model #1).
- **K.** Design 95 (and its carbon counterpart) is efficient under each of the models except the combined model (model #4).

3.2.2. Analytic Hierarchy Process (AHP) model

The next value model, AHP, was then compared across the evaluative models. First we identified designs that are in the Pareto set within each model. These designs are described in Table 8. Ten categories of designs are apparent in this table.

Table 8. Designs, marked in gray with check, for model implementations in which they are efficient for the AHP value model

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	22	✓	✓	✓	✓	406	✓	✓
B	9	✓	✓	✓	✓	393		✓
C	127	✓	✓	✓	✓	511	✓	
D	21, 23, 87, 118, 119, 120		✓		✓	405, 407, 471, 502, 503, 504		✓
E	10, 11, 12, 13, 14, 31, 77, 94, 109, 126, 128	✓		✓		394, 395, 396, 397, 398, 415, 461, 478, 493, 510, 512	✓	
F	4, 5	✓				388, 389		
G	55					439		✓
H	1	✓	✓	✓	✓	385		
I	30	✓				414	✓	
J	2, 3, 62, 63, 65, 66, 67, 68, 69, 73, 74, 75, 76, 93, 95, 97, 98, 99, 100, 101, 105, 106, 107, 108, 125	✓		✓		386, 387, 446, 447, 449, 450, 451, 452, 453, 457, 458, 459, 460, 477, 479, 481, 482, 483, 484, 485, 489, 490, 491, 492, 509		

- **A.** Design 22 (and its carbon counterpart) is always efficient across the model implementations.
- **B.** Design 9 is efficient across the model implementations, and its carbon counterpart (design 393) is only efficient under the new speed model (model #4).
- **C.** Design 127 is efficient across the model implementations, and its carbon counterpart (design 511) is only efficient under the old speed model (model #3).
- **D.** Designs 21, 23, 87, 118, 119, and 120 are efficient only under the new speed model (models #2 and #4), as are their carbon counterparts (in model #4).
- **E.** Designs 10, 11, 12, 13, 14, 31, 77, 94, 109, 126, and 128 are efficient only under the old speed model (models #1 and #3), as are their carbon counterparts (in model #3).
- **F.** Designs 4 and 5 are efficient only under the original model (model #1).

- **G.** Design 439 is the carbon version of design 55, but is only efficient in the carbon variant under the new speed model (model #4).
- **H.** Design 1 is efficient across all of the model implementations, but its carbon variant is never efficient.
- **I.** Design 30 is only efficient in the original model (model #1) and its carbon counterpart replaces it as efficient under the old speed model (model #3).
- **J.** These designs are only efficient in the old speed model (model #1 and model #3), but their carbon variants are never efficient.

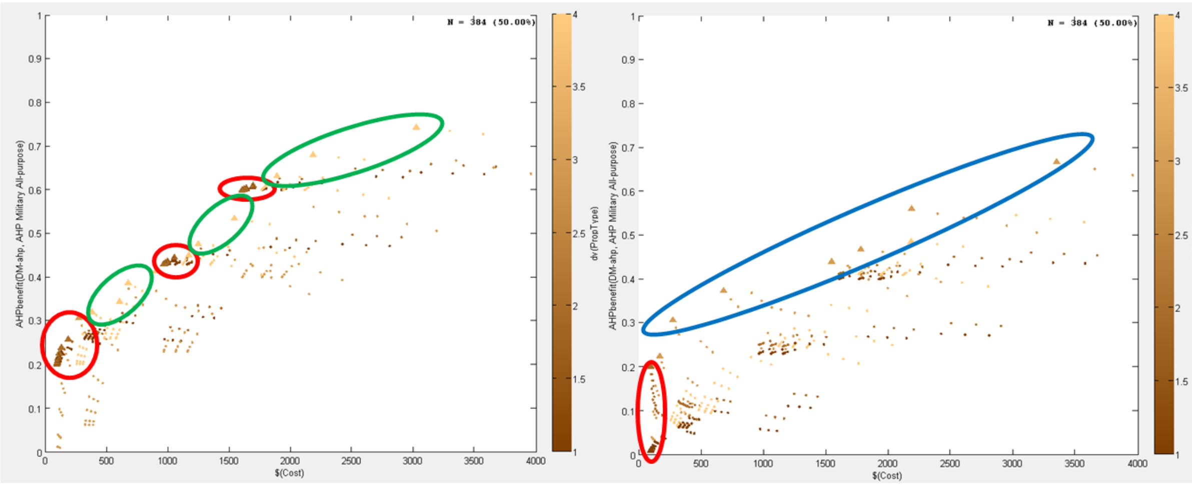

Fig. 5. AHP tradespace scatterplot under the old speed models (#1 and #3, left) and new speed models (#2 and #4, right), with families of designs indicated by propulsion type (red=biprop/cryo, green=nuclear, blue=electric)

As can be seen in Fig. 5, electric vehicles (blue) replace nuclear vehicles (green) on the Pareto front under the new speed model (old speed models #1 and #3 on left, and new speed models #2 and #4 on right).

3.2.3. Cost-Benefit Analysis model

The next value model, CBA, was then compared across the evaluative models. First we identified designs that are in the Pareto set within each model. These designs are described in Table 9. Six categories of designs are apparent in this table.

Table 9. Designs, marked in gray with check, for model implementations in which they are efficient for the CBA value model

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*
D	9, 120		✓		✓	393, 504		✓
E	11, 12, 13, 14, 29, 30, 31, 63, 95, 96, 128	✓		✓		395, 396, 397, 398, 413, 414, 415, 447, 479, 480, 512	✓	
F	4, 5, 127	✓				388, 389, 511		
H	1	✓	✓	✓	✓	385		
J	3, 32	✓		✓		387, 416		
L	87, 88, 119		✓			471, 472, 503		

- **D.** Designs 9 and 120 are efficient only under the new speed model (models #2 and #4), as are their carbon counterparts (in model #4).
- **E.** Designs 11, 12, 13, 14, 29, 30, 31, 63, 95, 96, and 128 are efficient only under the old speed model (models #1 and #3), as are their carbon counterparts (in model #3).

- **F.** Designs 4, 5, and 127 are efficient only under the original model (model #1).
- **H.** Design 1 is efficient across all of the model implementations, but its carbon variant is never efficient.
- **J.** These designs are only efficient in the old speed model (model #1 and model #3), but their carbon variants are never efficient.
- **L.** Designs 87, 88, and 119 are only efficient in the new speed model (model #2) without carbon as an option (model #3)

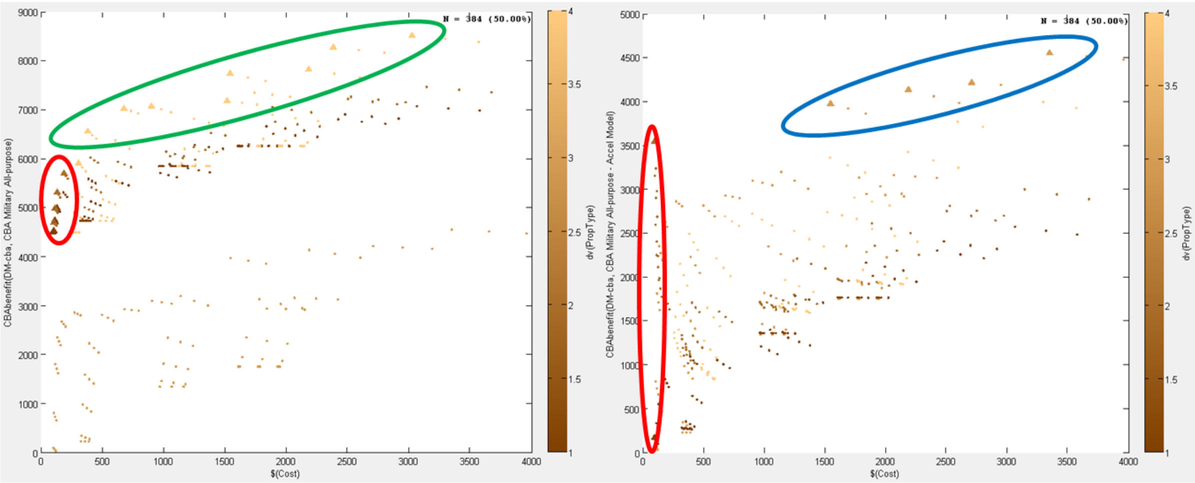

Fig. 6. CBA tradespace scatterplot under the old speed models (#1 and #3, left) and new speed models (#2 and #4, right), with families of designs indicated by propulsion type (red=biprop/cryo, green=nuclear, blue=electric)

Similar to the pattern for the AHP value model, Fig. 6 shows that electric vehicles replace nuclear vehicles on the Pareto front under the new speed model.

3.2.4. Measure of Effectiveness model

The next value model, MOE, was then compared across the evaluative models. First we identified designs that are in the Pareto set within each model. These designs are described in Table 10. Two categories of designs are apparent in this table.

Table 10. Designs, marked in gray with check, for model implementations in which they are efficient for the MOE value model

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	18, 19, 20, 21, 22, 23, 24	✓	✓	✓	✓	402, 403, 404, 405, 406, 407, 408	✓	✓
H	1, 2, 9, 10, 11, 17	✓	✓	✓	✓	385, 386, 393, 394, 395, 401		

- **A.** Designs 18, 19, 20, 21, 22, 23, and 24 (and their carbon counterparts) are always efficient across the model implementations.
- **H.** Designs 1, 2, 9, 10, 11, and 17 are efficient across all of the model implementations, but their carbon variants are never efficient.

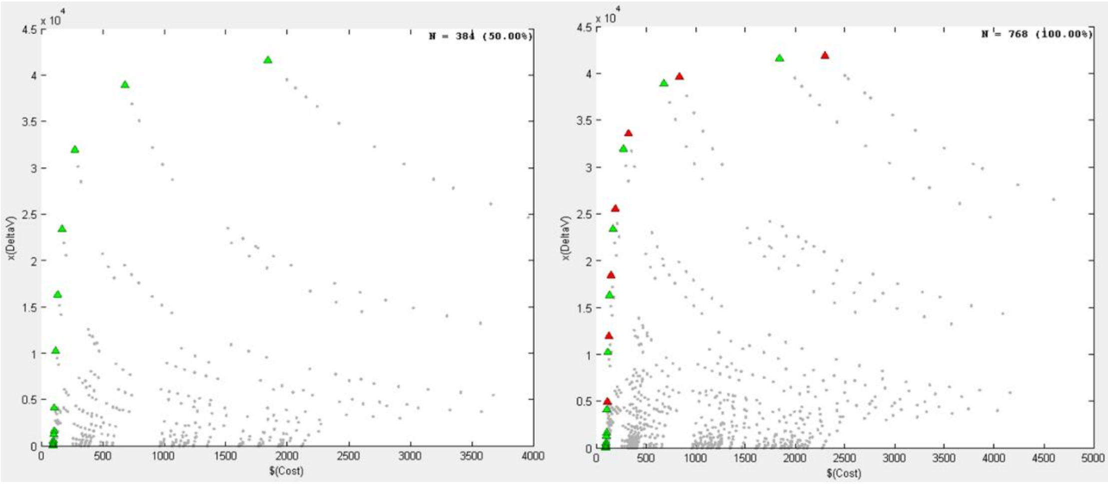

Fig. 7. Comparison of MOE value model across evaluative models #1 and #2 (left) and models #3 and #4 (right)

Fig. 7 shows the Pareto set in evaluative models #1 and #2 (left) in green triangles, and in models #3 and #4 (right) with the red triangles corresponding to the new carbon-version designs added in models #3 and #4. Notice how the sets do not change much, as the red points are just minor cost-increased version of their aluminum counterparts in green. This is due to the fact that this MOE (delta-V) is unaffected by the change in the model implementations relative to the original model. Carbon becomes Pareto efficient when cost gets high enough (i.e. not for the first couple of small designs. Small payloads dominate delta-V.

4. Discussion of combined value and evaluative model trading

The key take away from the combined value and evaluative model case is that doing this kind of activity can reveal two classes of insights:

1. insights into fundamental relationship between perspectives of value and what is possible (*structural patterns for the decision problem*), and
2. insights into modeling artifacts, both in how value is captured and how evaluation is performed (*modeling artifacts*).

The first class of insights sometimes appear to emerge through the course of analysis. This may be due to the fact that the relationships are buried in the interactions between factors of the problem and are not readily apparent in our mental models. For example, Fig. 8 shows the CBA value model scatterplot in the evaluative model #4 (combined new material and new speed model). Lines show Pareto efficient points connected to similar designs with different levels of fuel. For both the electric and biprop propulsion types there is a positive tradeoff of more fuel (= more cost) for more benefit. But counterintuitively the small cryo propulsion designs actually get less benefit for more fuel. This is because the added fuel actually decreases the speed of those small designs in spite of increasing the on-board delta-V. This is a consequence of the confluence of physics (i.e. the rocket equation and inertia) and expectations on what is considered beneficial. The very fact that the relationship between fuel mass and benefit plays out differently in different regions of the tradespace means that the complexity (in terms of number of factors to consider) likely would overwhelm an unaided human mind due to bounded rationality.

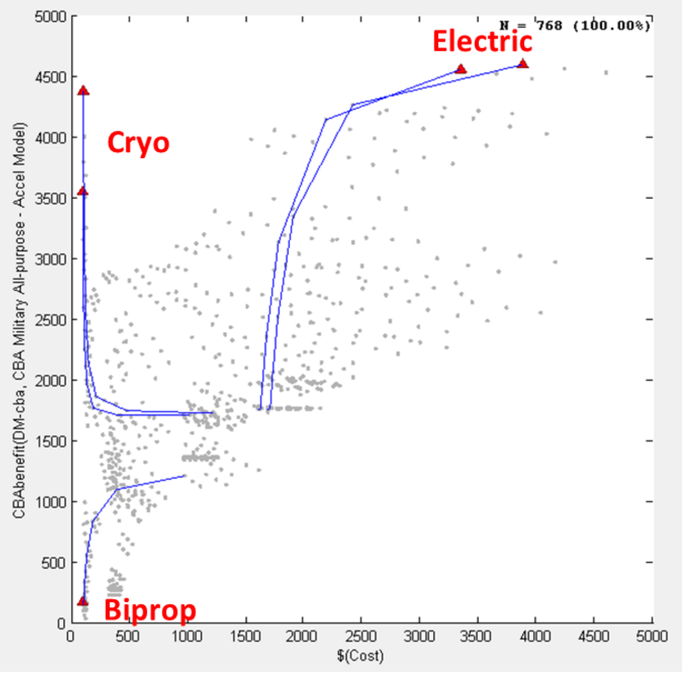

Fig. 8. CBA value model scatterplot for evaluative model #4 (combined new material and new speed)

Each evaluative model is one representation of how a system might "perform", while each value model is one representation of how a system might "be valued." The emergence described above would occur at the intersection of each possible evaluative and value model, as well as across them, as shown in this simple Space Tug demonstration. Systems engineers and analysts may benefit strongly by considering not only their choice of evaluative and value model, but also how their insights might vary if they were to include more than one of each type of model.

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