

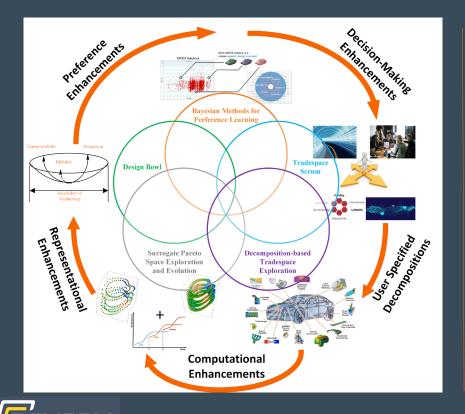
Simulating the Tradespace with Synthetic Data AI4SE/SE4AI Workshop

Dr. Cameron J. Turner

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Project Context



- Scope: Enhance the abilities of stakeholders to balance vehicle performance or capabilities versus project risk, budget, and schedule in a visual virtual environment
- Key Goal: Enhance rapid, effective trade space exploration and analysis to guide the development of vehicle-level requirements

• Efforts in:

- Decomposition-Based Tradespace Exploration
- Surrogate Pareto Space Exploration and Evolution
- Design "Bowl" Modeling
- Bayesian Methods for Preference Learning
- Best-Practices in Tradespace Scrums

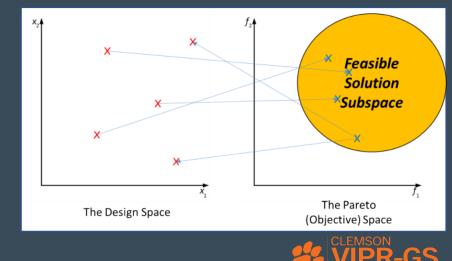


The Tradespace

Function	Soln 1	Soln 2	 Soln N
Convert	100 hp ICE	120 hp ICE	 50 hp Hub Motors
Store	10 gal JP7	15 gal JP7	 1kW-hr Battery
Convert	4-Wheels	6-Wheels	 Oval Tracks

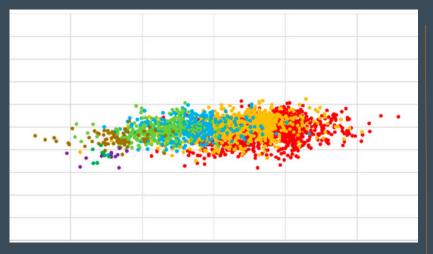
 The Tradespace is visualized in terms of an objective space

 Each point in the Tradespace represents a solution to a Morphological Matrix





Tradespace Modeling



• Generating a representation of the Tradespace has been a significant effort

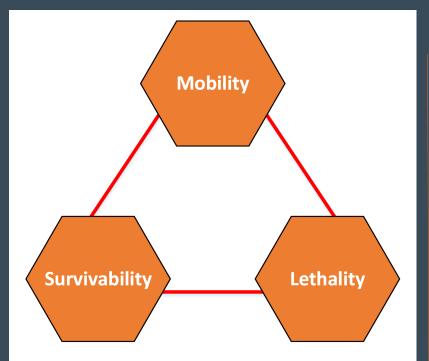
• Need to represent "-ilities"

- Functional Objectives (FO)
- Input Variables
- Derived Attributes
- Intermediate Calculated Parameters
- Defined Constants
- Other FO





"-ilities"

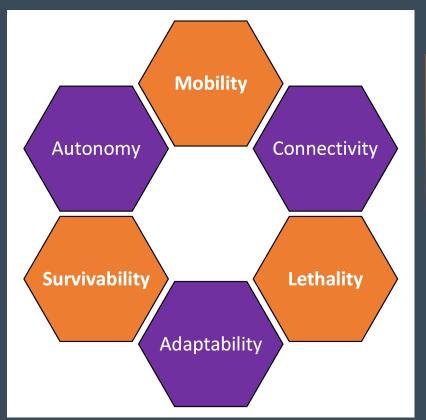


- Represent subsets of the considerations of the Steel Hexagon
 - Developed from the concept of the Steel Triangle
 - Mobility Survivability Lethality





"-ilities"



- Represent subsets of the considerations of the Steel Hexagon
 - Developed from the concept of the Steel Triangle
 - Mobility Survivability Lethality
 - Add Autonomy Connectivity - Adaptability





"-ilities"

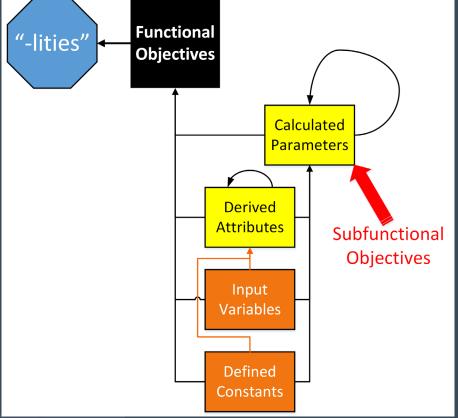


- Represent subsets of the considerations of the Steel Hexagon
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Functional Objectives



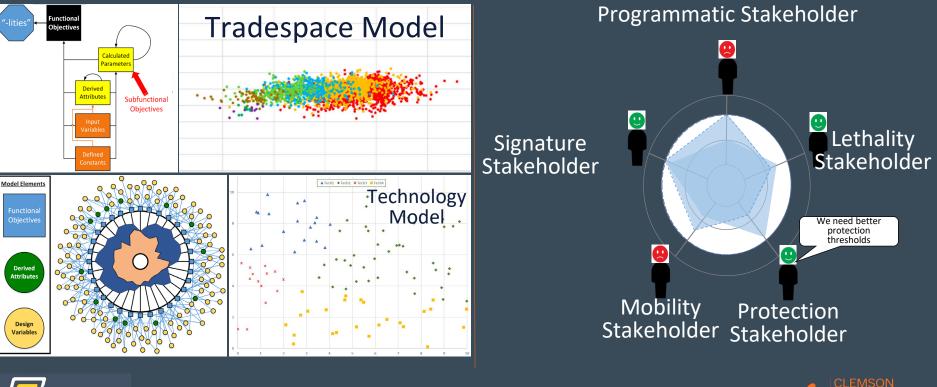
 Functional Objectives provide metrics to evaluate the "-ilities"

- Functional Objectives are built from
 - Calculated Parameters
 - Derived Attributes
 - Input Variables
 - Defined Constants





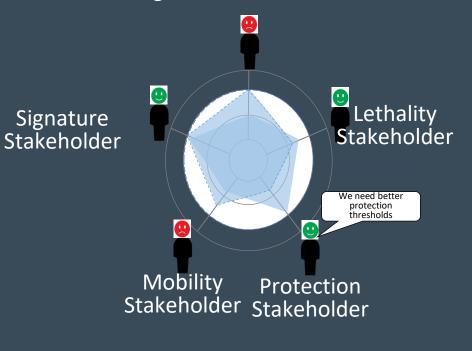
Tradespace Decision-Making





Tradespace Decision-Making





Programmatic Stakeholder



Al Agents to the Rescue

- Can we use AI Agents to simulate real decisionmakers
 - With Human DMs in the Loop
 - Or, as pure simulations
- Allowing:



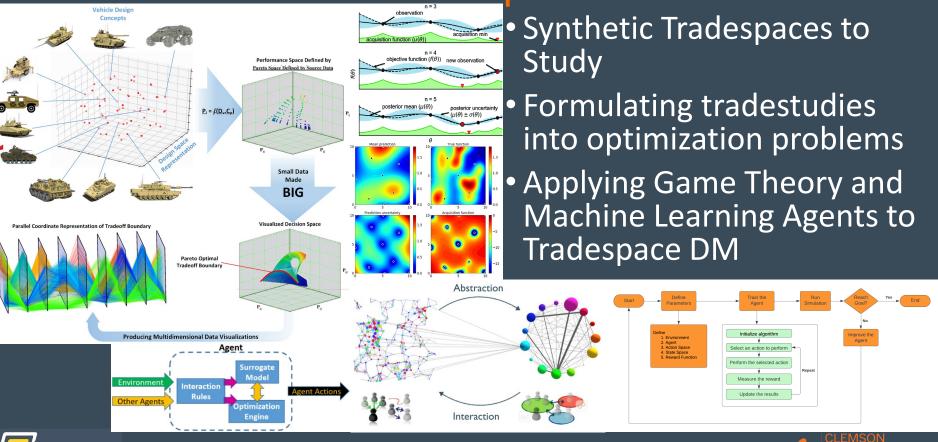
Adapted from https://clearcode.cc/blog/game-theory-attribution/

- To Identify conflicts of importance in advance
- Study the efficacy of the tradespace problem
- Explore the downstream impacts of trades





How to Accomplish This...

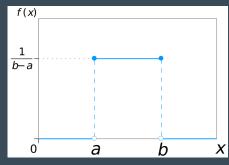


Synthetic Tradespace: Defining Variables

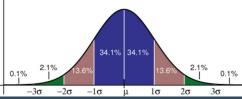
- Variables are defined using several methods
- Constant Variables
 Have 1 known value
- Binary Variables
 - 1 if on, 0 if off
- Discrete Valued
 - Result of a selection of Binary Variables

Continuous Variables

• Defined by a range (uniform)



Defined by a distribution (gaussian)







Initial Synthetic Tradespace

4 Subfunctional Objectives

- Back Deck Overhang
- Running Gear Contact Patch Area
- (SMET FCC) Length
- (SMET FCC) Curb-to-Curb Turning Diameter

Requires 54 Input Variables

- 13 are continuous
- 6 are discrete valued
- 27 binary variables
- 6 constant variables
- 2 functional variables
- 12 Derived Attributes
- 9 Constants





Formulating Optimization: All-in-One (AiO) MOP

$$\begin{array}{ll} \text{minimize} & \mathbf{f}(\mathbf{x}_{g},\,\mathbf{x}_{\text{loc}}) = [\mathbf{f}_{1}(\mathbf{x}_{g}),\,\mathbf{f}_{2}(\mathbf{x}_{g},\,\mathbf{x}_{\text{loc}})] \\ \text{s.t.} & \mathbf{x}_{g} \in \mathsf{X}_{g},\,\mathbf{x}_{\text{loc}} \in \mathsf{X}_{\text{loc}} \end{array}$$

Goal:

- 1. Compute Pareto points to AiO MOP
- 2. Perform tradespace analysis to choose a preferred efficient design

Strategy:

- 1. Decompose AiO MOP into two subproblems (SP1 & SP2)
- 2. Find a preferred efficient design to AiO MOP by computing efficient designs and Pareto points to SP1 & SP2

SP1:
min
$$\mathbf{f}_1(\mathbf{x}_g)$$

s.t. $\mathbf{x}_g \in X_g$

SP2:

$$\begin{array}{l} {\rm nin} \; \mathbf{f}_2(\mathbf{x}_{\rm g}, \, \mathbf{x}_{\rm loc}) \\ {\rm s.t.} \; \; \mathbf{x}_{\rm g} \in {\rm X}_{\rm g} \, , \mathbf{x}_{\rm loc} \in {\rm X}_{\rm loc} \end{array}$$





Formulating Optimization: Coordination Problem (COP)

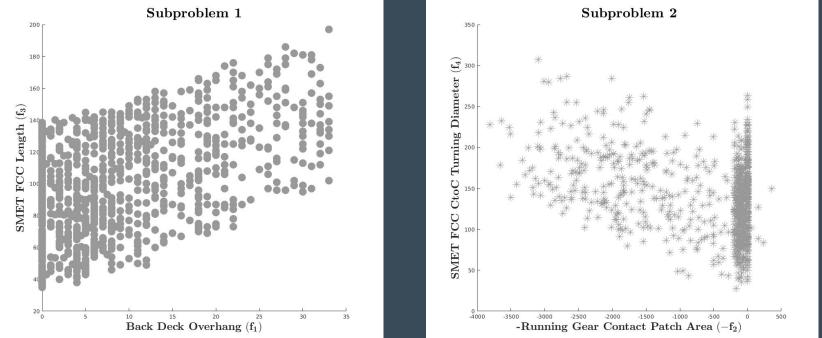
SP 1:SP 2:min $f_1(\mathbf{x}_g)$ min $f_2(\mathbf{x}_g, \mathbf{x}_{loc})$ s.t. $\mathbf{x}_g \in X_g$ s.t. $\mathbf{x}_g \in X_g, \mathbf{x}_{loc} \in X_{loc}$

Let $\mathbf{x}_{g}^{*} \in X_{g}$ be preferred design for SP1 $\epsilon = (\epsilon_{1}, \epsilon_{2}) \ge 0$ be relaxation for two objectives in SP1

- Let $\mathbf{x}_{g}^{*} \in X_{g}$ be weakly efficient to SP1. If there exists $\mathbf{x}_{loc}^{*} \in X_{loc}$ such that $(\mathbf{x}_{g}^{*}, \mathbf{x}_{loc}^{*})$ is weakly efficient for SP2, then $(\mathbf{x}_{g}^{*}, \mathbf{x}_{loc}^{*})$ is weakly efficient for AiO MOP.
- If $(\mathbf{x}_{g}, \mathbf{x}_{loc})$ is weakly efficient to COP then it is weakly efficient to AiO MOP.



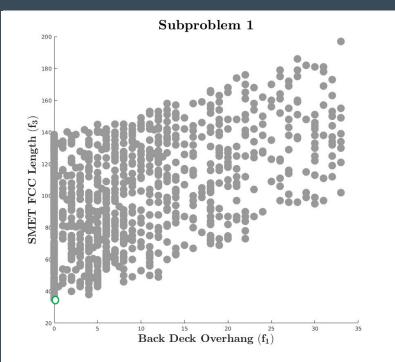
Example: Outcome sets in Tradespaces

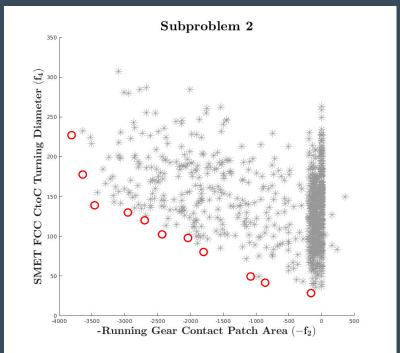






Pareto sets in Tradespaces





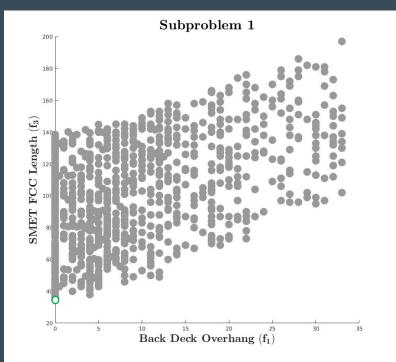


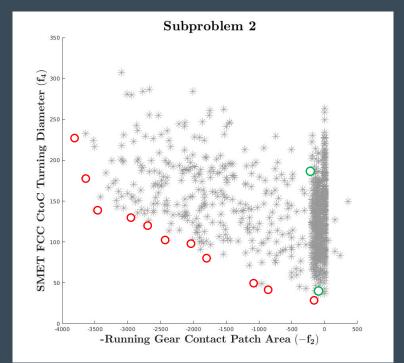
Pareto set • (singleton)

Pareto set $\,\cdot\,$



Pareto sets in Tradespaces





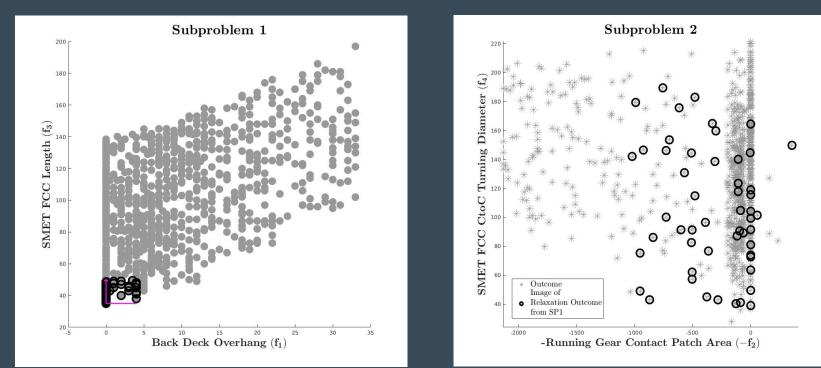


Pareto set • (singleton)

Pareto set $\,\cdot\,$



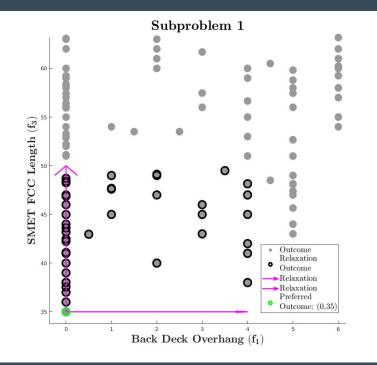
Relaxation in Subproblem 1

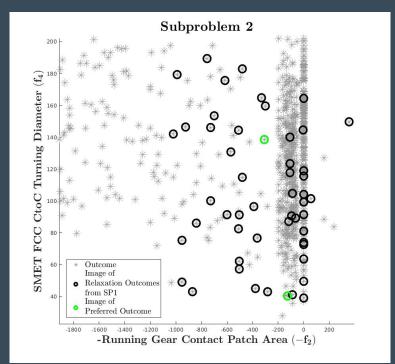






Relaxation in Subproblem 1

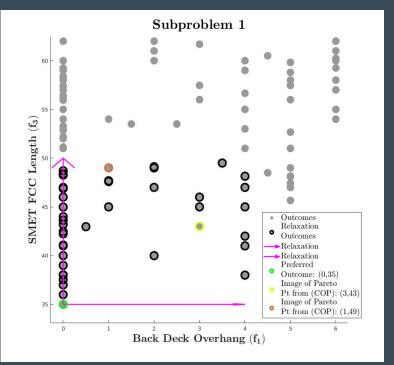


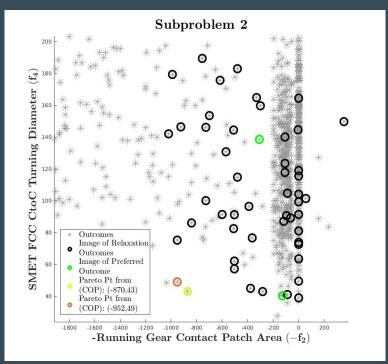






Pareto points to Coordination

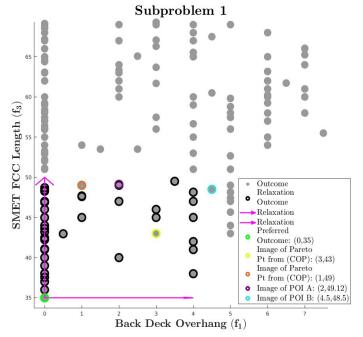


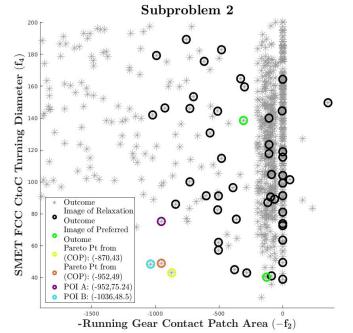






Choosing preferred Pareto point for AiO MOP





POI B = AiO preferred Pareto point •





Analysis in the design space

Preimage (design)	Pareto point for SP1 o	POI A	POI B o			
Drive configuration	identical					
Total volume	similar					
Length, width, heights	different					
Includes	-	winch <mark>or</mark> offload generator	winch <mark>and</mark> offload generator			





Now comes the AI Agents

• Current Work

• Defining and Training the Agents

Challenge – Acquiring sufficient data from Decision-Makers

• Future Work

- Once we have trained agents
- 1. Can we run Human-Inthe-Loop Simulations?
- 2. Can we run simulated DM sessions and identify key points of contention
- 3. Can we evaluate the Tradespace





The Research Team

Clemson University

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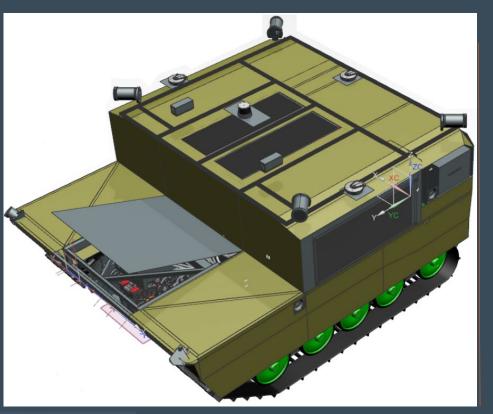
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Questions?

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