Many-Objective Visual Analytics:

Rethinking the Design of Complex Engineered Systems

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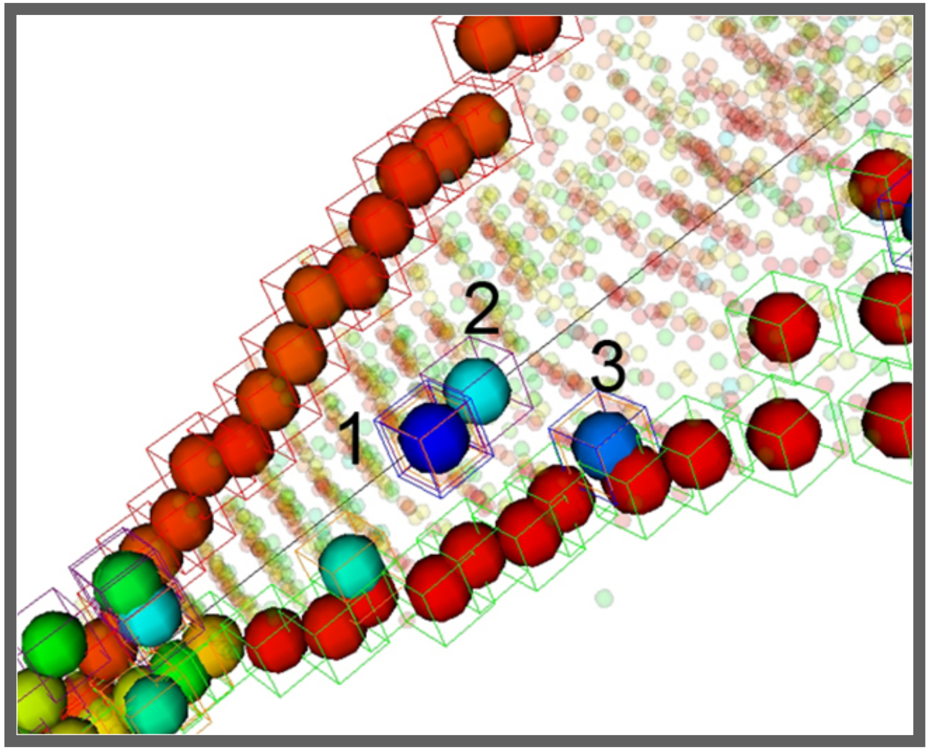

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XSEDE

Extreme Science and Engineering Discovery Environment

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WHERE DISCOVERIES BEGIN

PENNSTATE

Key Points

- (1) Proposing the "**Many-Objective Visual Analytics**" framework for complex engineered systems design.

- (2) Seeking to avoid **cognitive myopia** (*too limited a view of optimality*) and **cognitive hysteresis** (*preconceptions limit discoveries*)

- (3) **Arrow's Paradox**: optimizing aggregated performance measures does not optimize individual components in a predictable fashion

- (4) **Preferences develop and evolve opportunistically** in response to how changing formulations provide solutions with desirable characteristics (*what is the non-dominated problem?*)

- (5) Operational use of MOEAs requires efficiency, effectiveness, reliability, and controllability—proof must be based on **rigorous algorithm diagnostics**

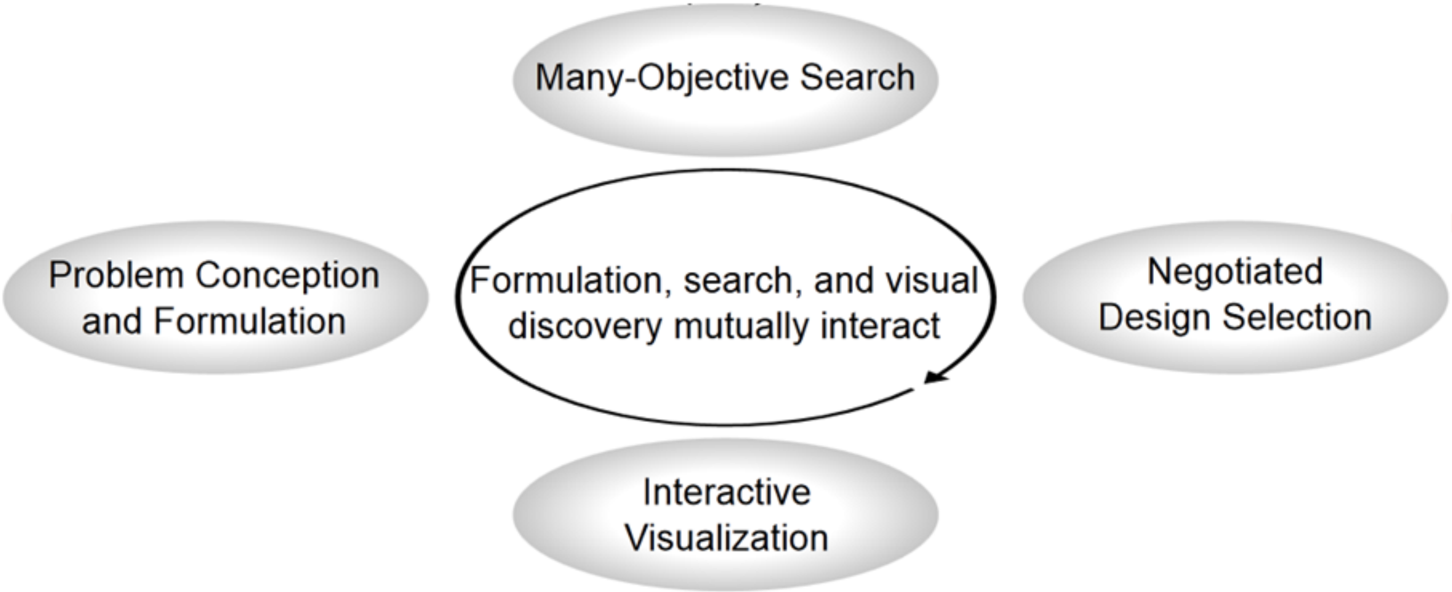
Defining the Problem is **THE PROBLEM**

- ***What are complex engineered systems?***

Systems where the "…tightly coupled interacting phenomena yield a collective behavior that cannot be derived by the simple summation of the behavior of the parts".

Bloebaum*, C. L. and McGowan, A.-M. R., 2010, "Design of Complex Engineered Systems," *ASME Journal of Mechanical Design, 132(12), 120301* *(*Bloebaum USNSF Program Manager for Engineering Design)*

Many-Objective Visual Analytics



- Complex engineered systems
  - Emergent behavior
  - Challenging design space: constraints, interactions, discontinuities, nonlinearities
  - Validity of a priori preferences? Goals?
- Many-Objective Visual Analytics (MOVA)[1]
  - Iterative, not linear
  - Mutual feedbacks, constructive learning[2]

[1] Woodruff et al, Structural and Multidisciplinary Optimization (In-Press)
[2] Tsoukias, European Journal of Operational Research (2008)

The Software Ecosystem

Stakeholder Interviews

- Identify Design Parameters
- Identify Key Objectives
- Identify Constraints

Variables
Assumptions
Constants
…

Requirements
Goals
…

Application Program Interfacing (API)

- Identify existing modeling tools
- Integrate with modeling tools through API
- Build new models if necessary
- Expose API to optimization tools

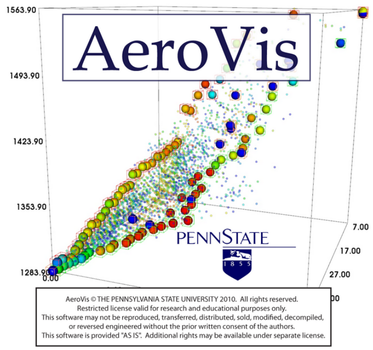
Design Parameters
Key Objectives
Constraints

Multi-Objective Optimization

- Massively parallel search using multi-objective evolutionary algorithms (MOEAs)
- **Borg MOEA** for many-objective optimization

Explore, Visualize, Communicate

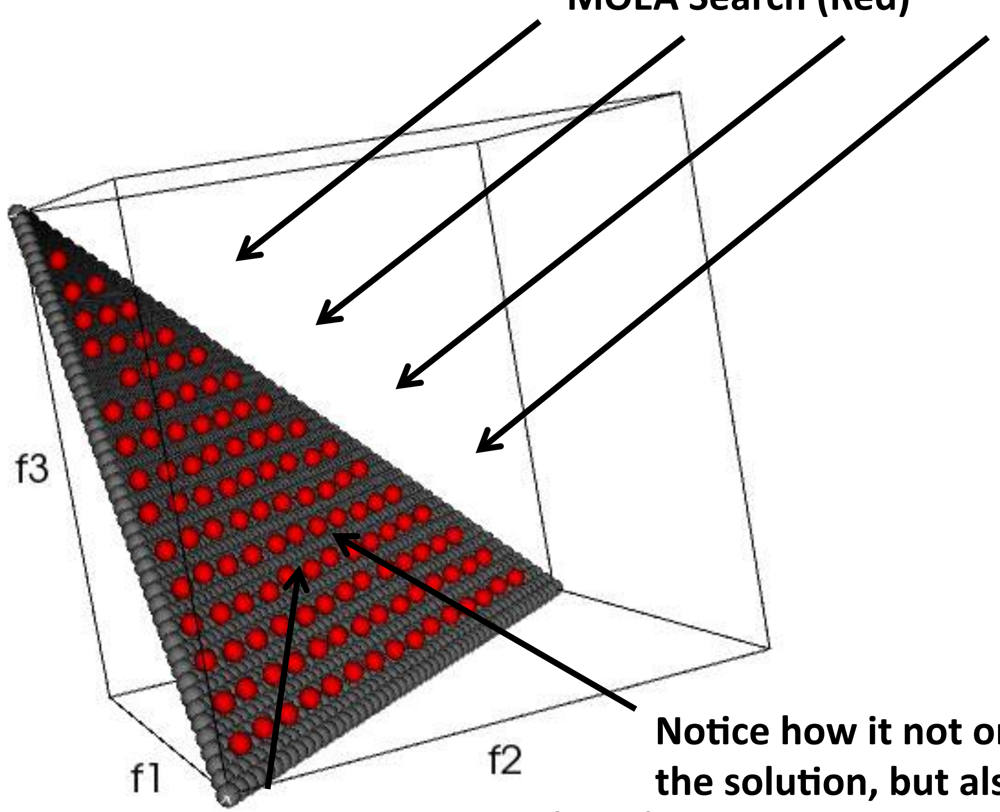
- Watch designs "evolve" and identify key interactions between design parameters, objectives, and constraints
- Provide an accessible visualization roadmap of key tradeoffs to Decision Maker



LET'S MOTIVATE "MOVA" WITH A REAL WORLD ILLUSTRATION

Watching Convergence & Diversity

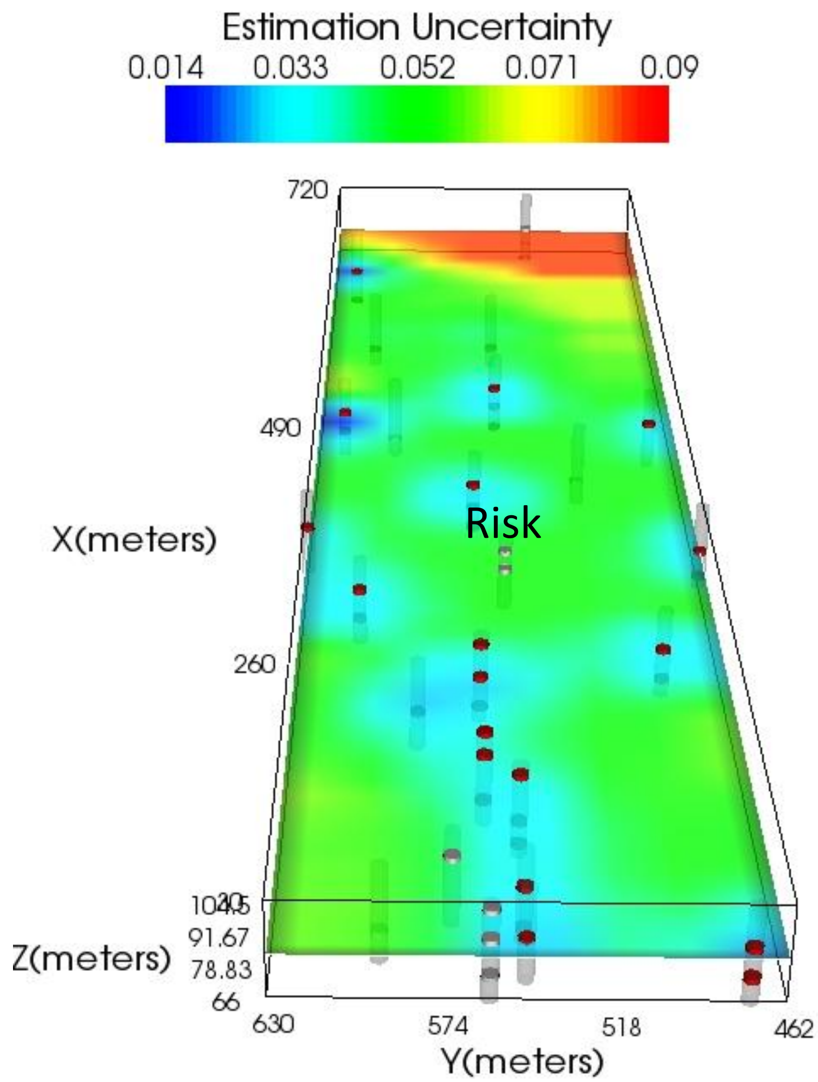
Three-objective Test Problem



- Visualize dynamics
  - To understand search
  - To avoid errors or wasted effort due to arbitrary termination choices
  - Can meaningfully compare formulations or algorithms
- Stakeholders see the full context of what was gained

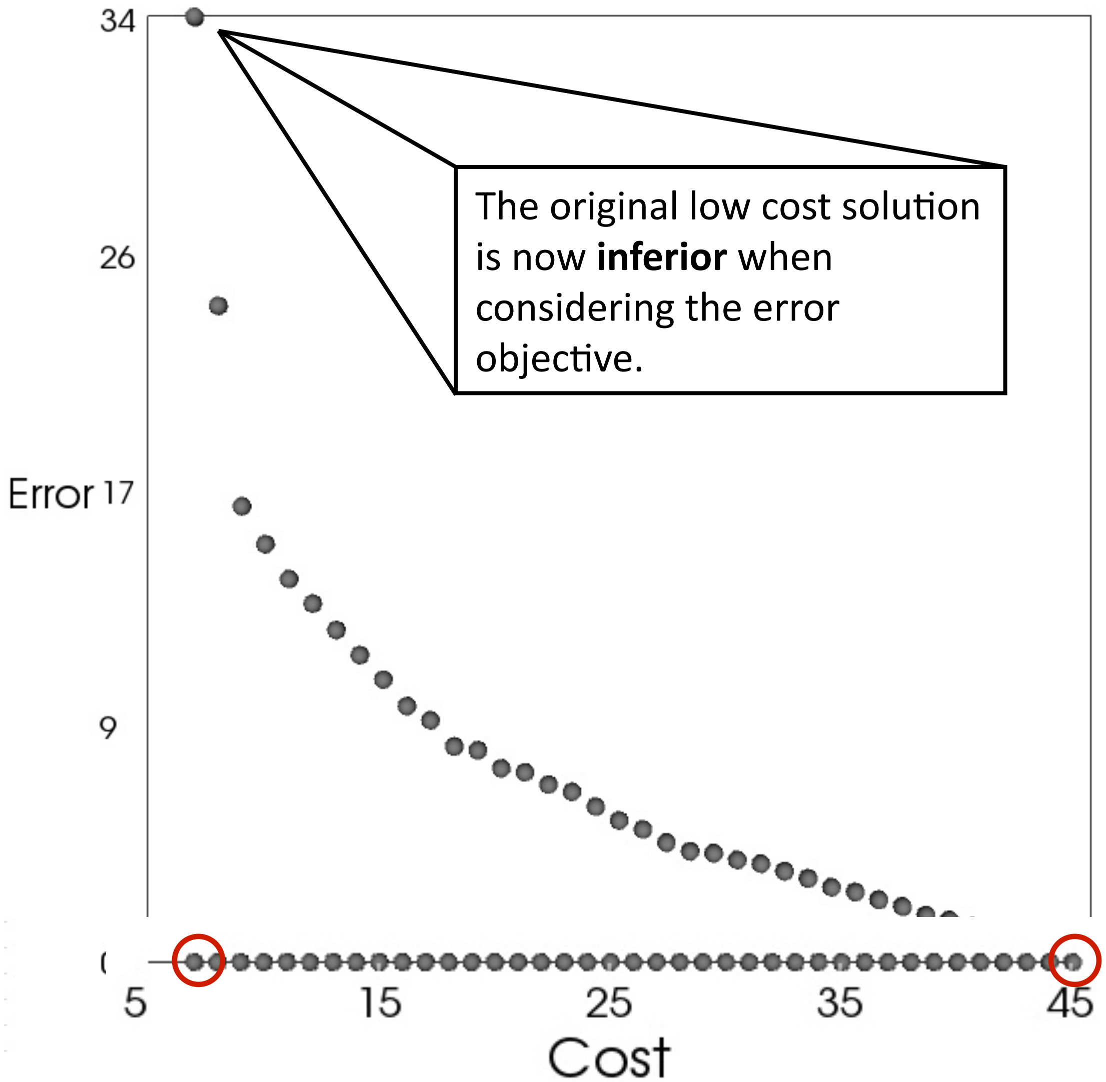
Long-Term Groundwater Monitoring Network Design

- How can we optimally sample a minimum subset of wells?
- Tools:
  - PCE contaminant plume
  - Evaluations based on Quantile Kriging
- Objectives:
  - Sampling Cost
  - Mapping Error
  - Risk (Uncertainty)
  - Mass Error



The Benefits of Many Objectives

- Single Objective Design Problem…
- Two Objective Design Problem…
- Many-Objective Design Problem…
  - More compromise solutions
  - Considers many subproblems
    - Two and three objective subsets
    - Difficult to specify manually



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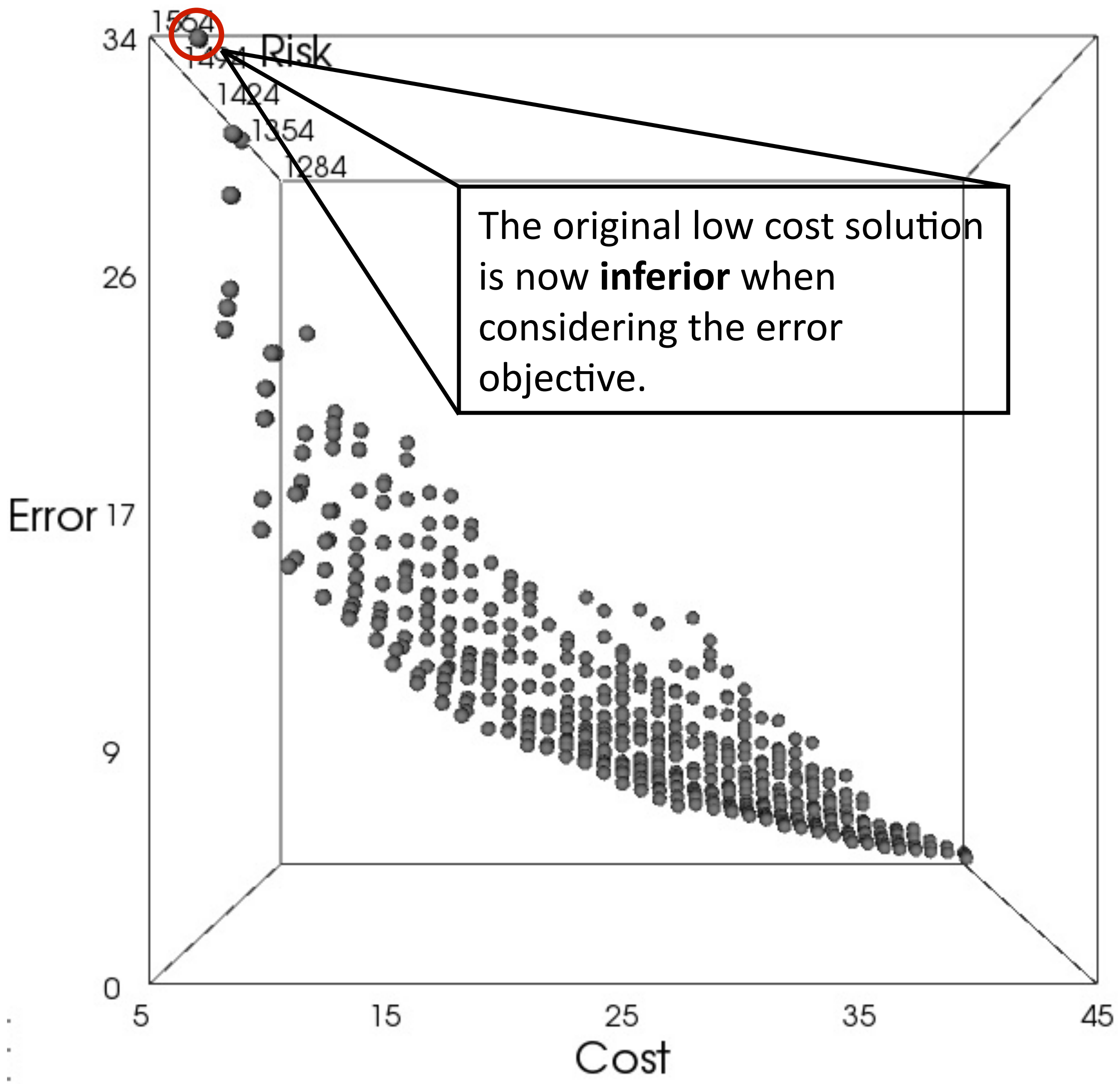

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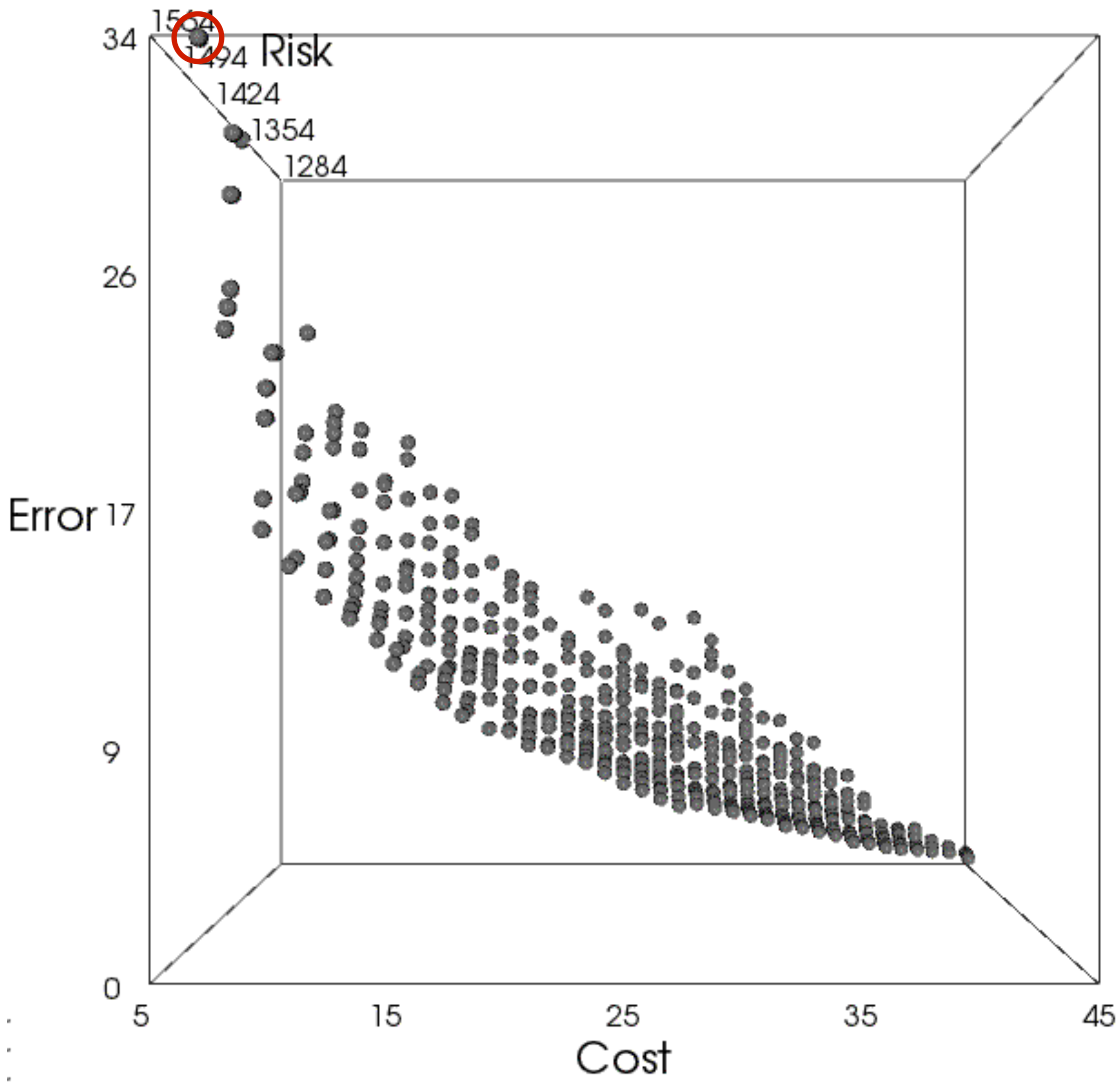

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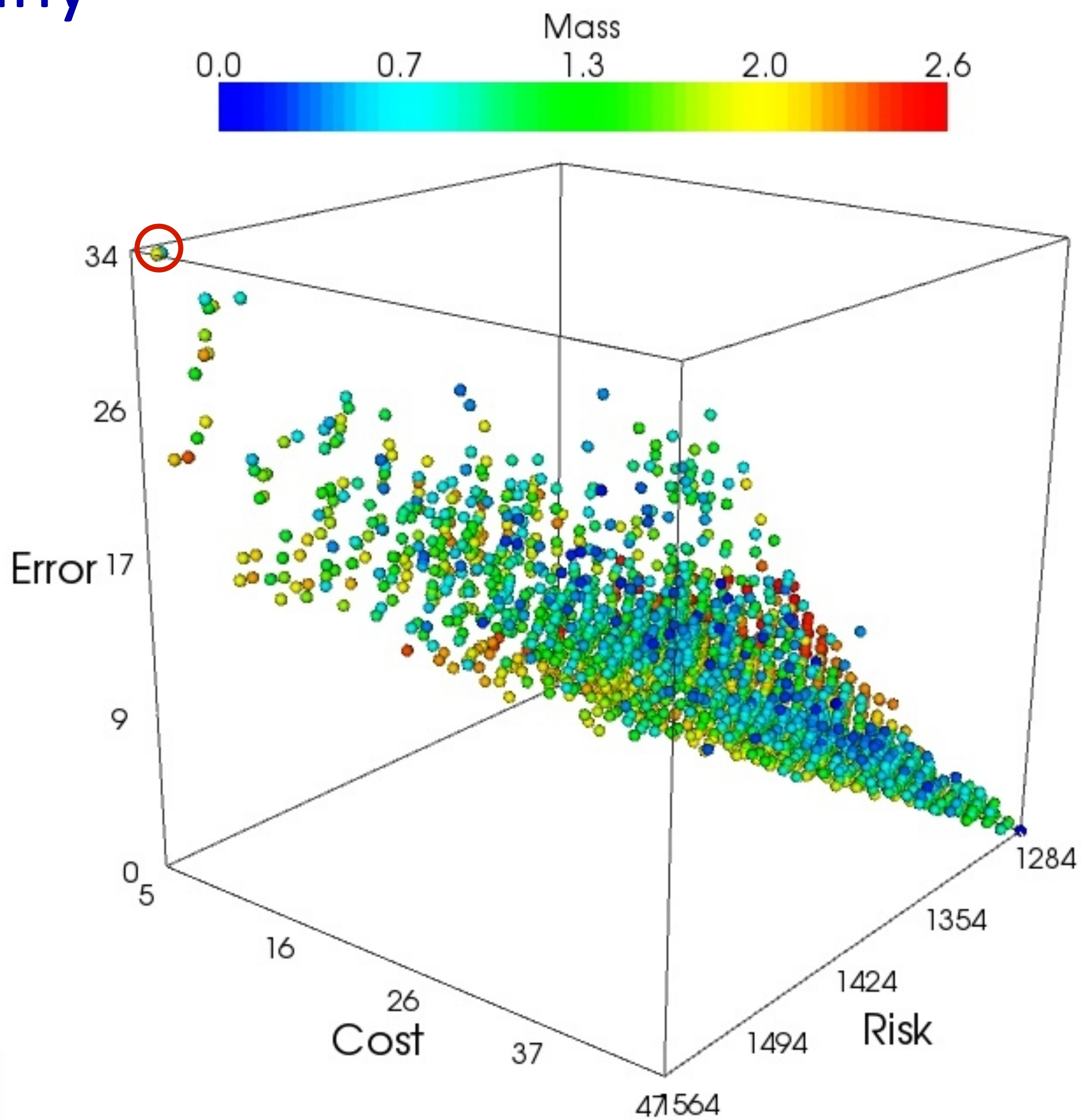

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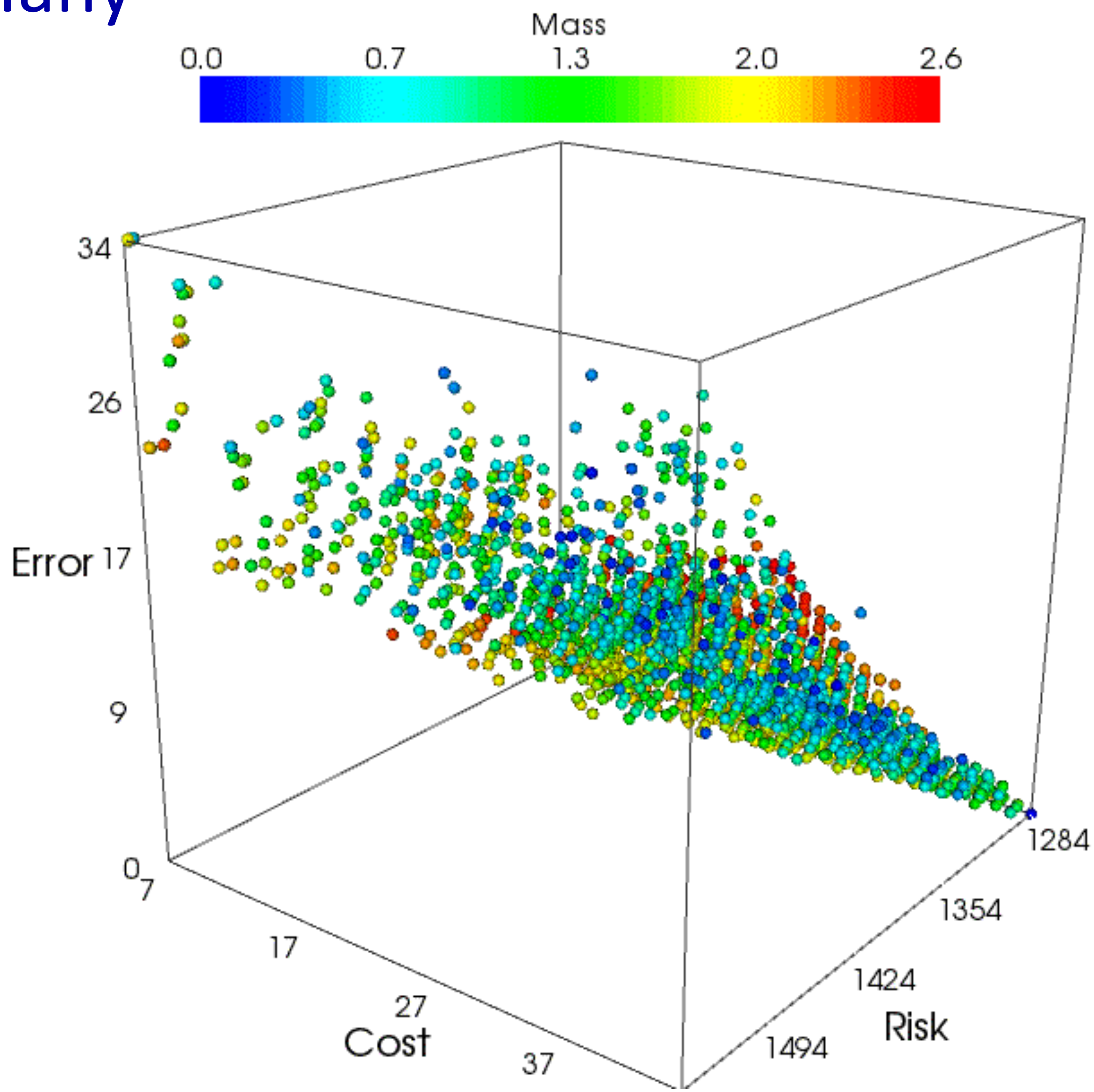
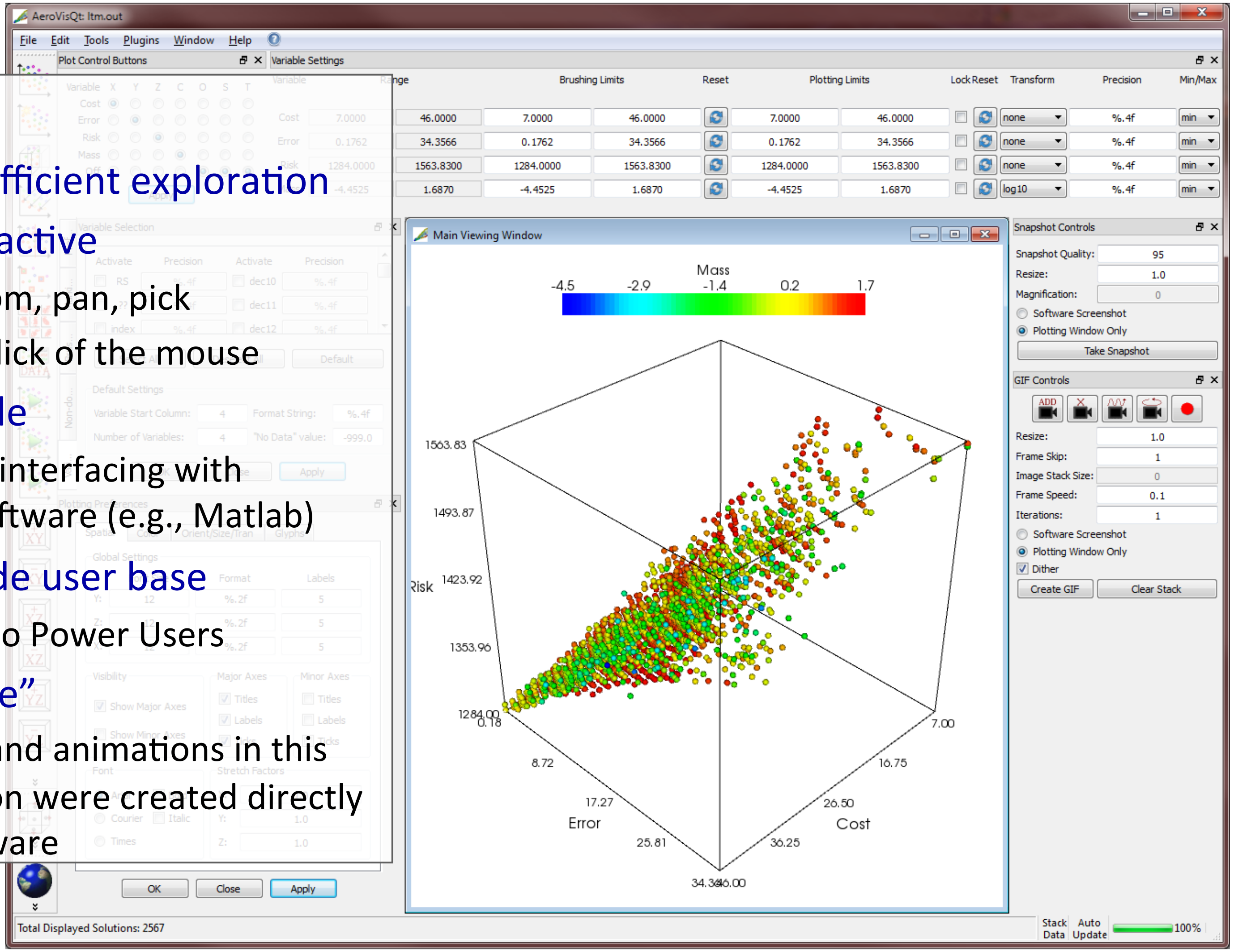


Software for Visual Analytics



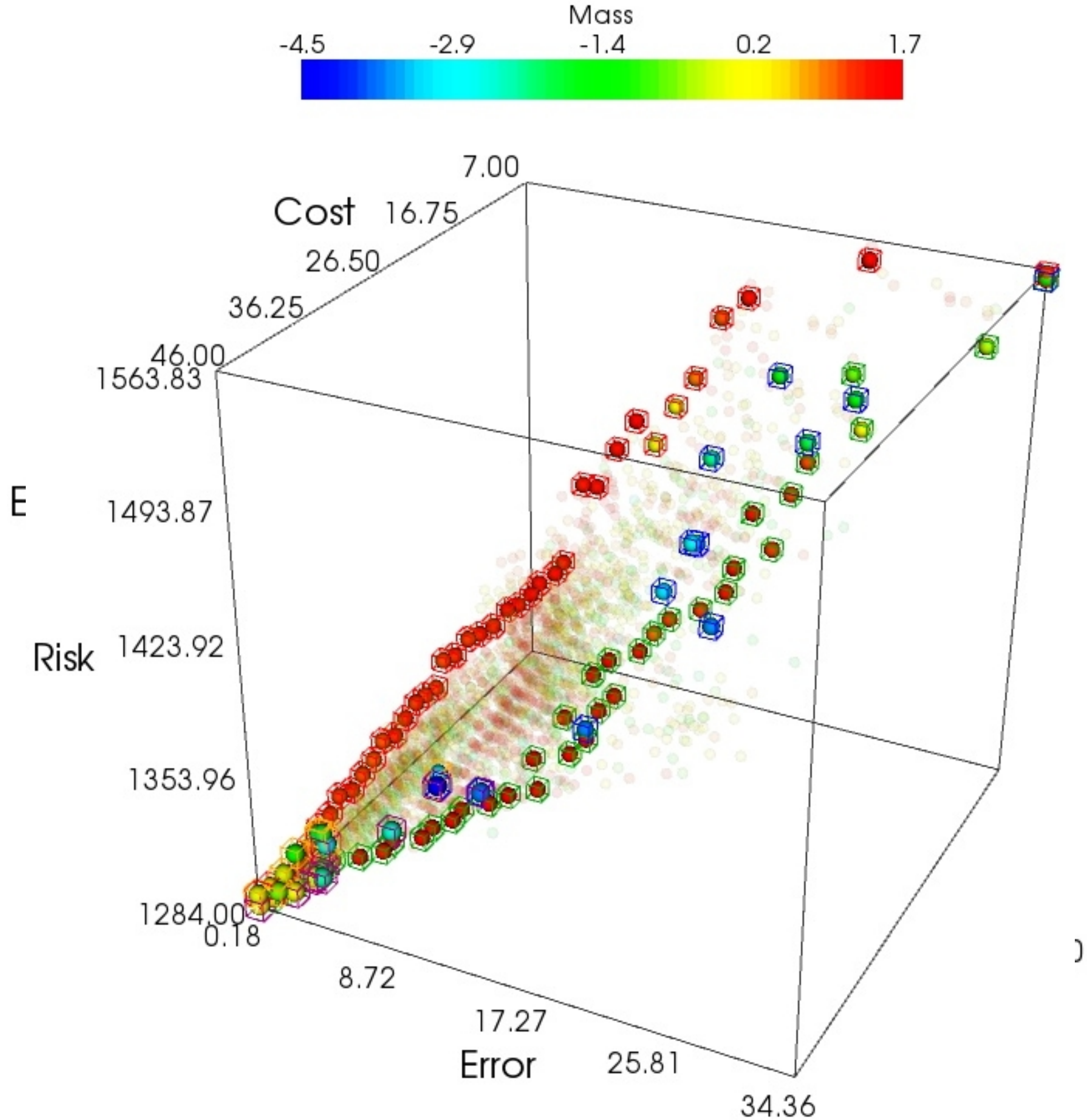
- AeroVis
  - Facilitates efficient exploration
  - Highly interactive
    - Rotate, zoom, pan, pick
    - All with a click of the mouse
  - Customizable
    - Plugins for interfacing with external software (e.g., Matlab)
  - Serves a wide user base
    - Beginners to Power Users
  - “Presentable”
    - All visuals and animations in this presentation were created directly in the software

Long-Term Groundwater Monitoring Network Design

Four Objectives and 33-Million Possibilities

2570 Optimal Alternatives

3 Compromises



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Four Design Objectives and 33-Million Possibilities

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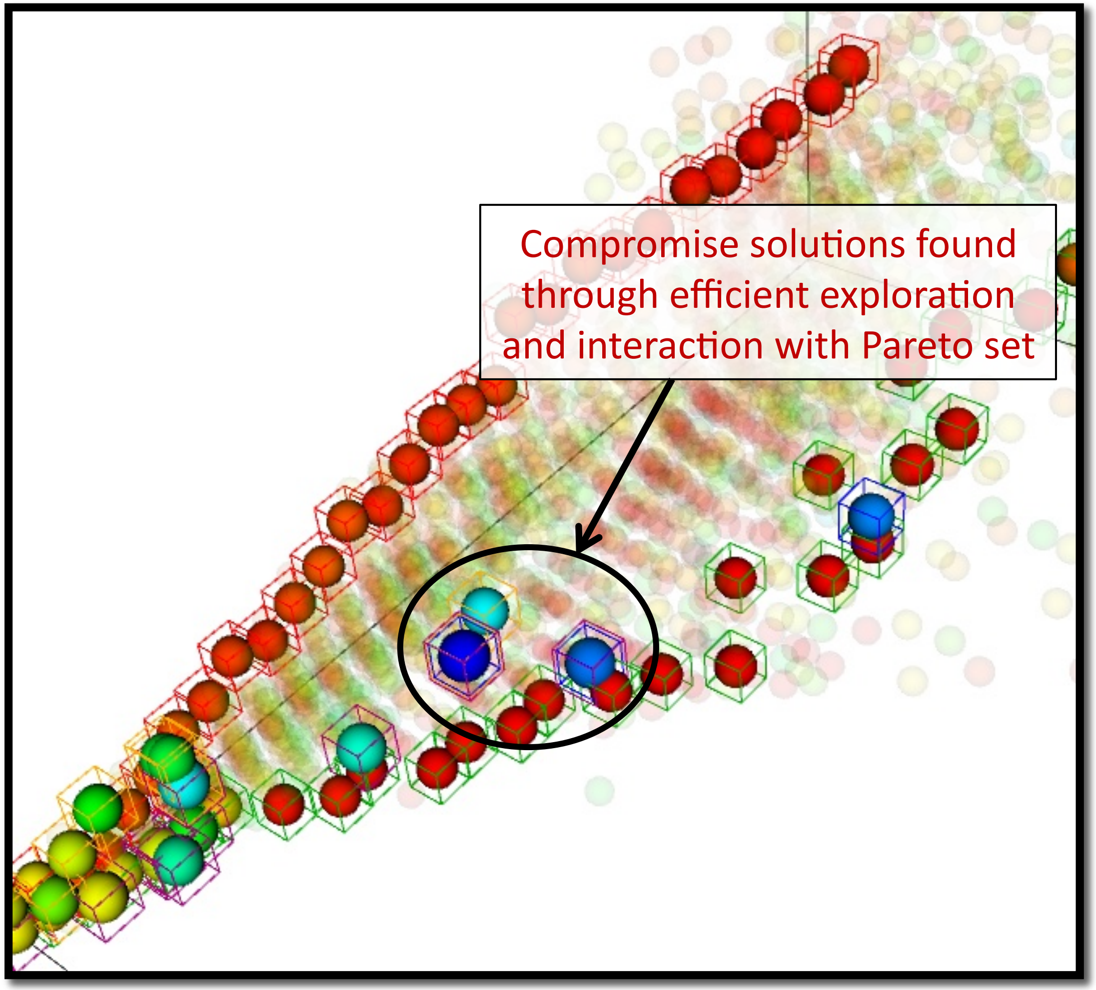
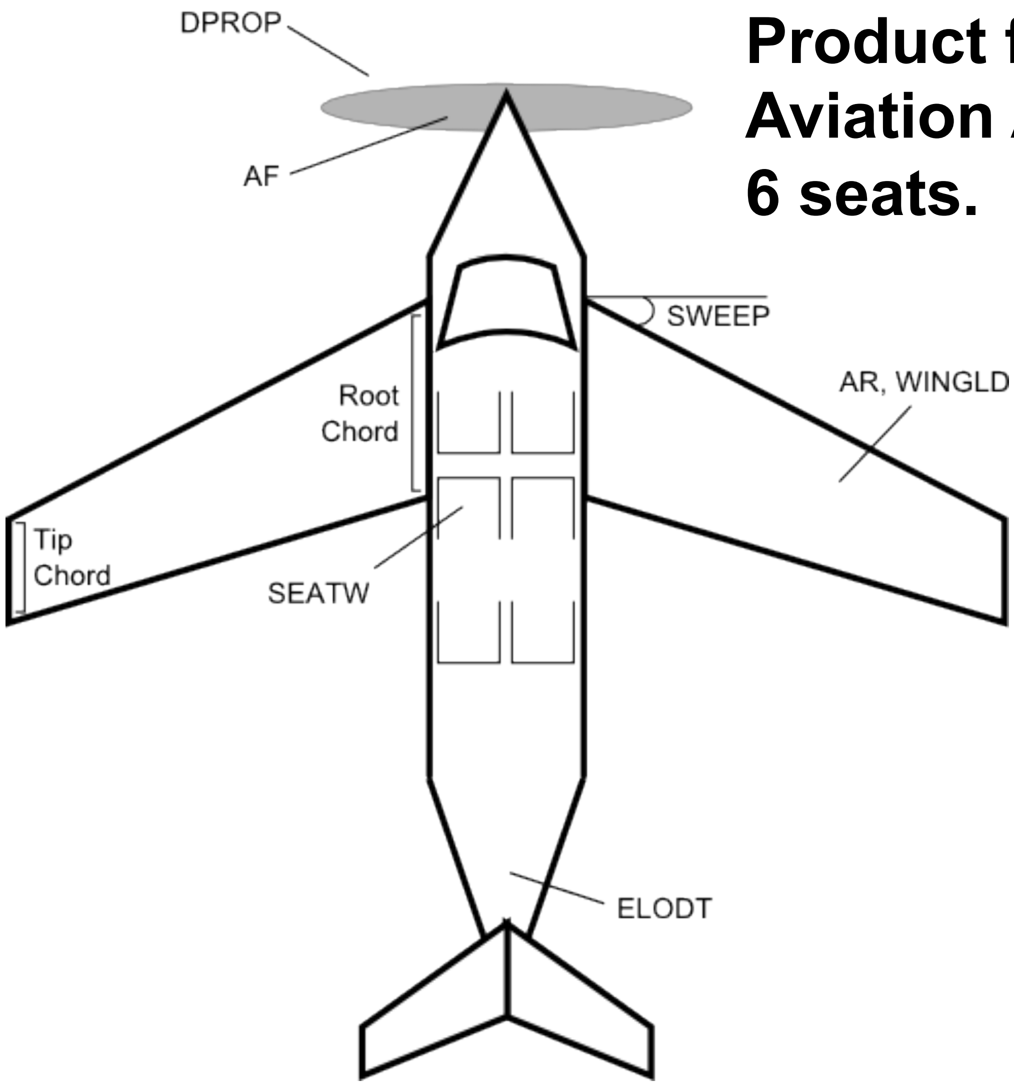


ARROW'S PARADOX: THE HIDDEN COSTS OF AGGREGATION

Problem Statement



Product family for three General Aviation Aircraft (GAA): 2, 4, and 6 seats.

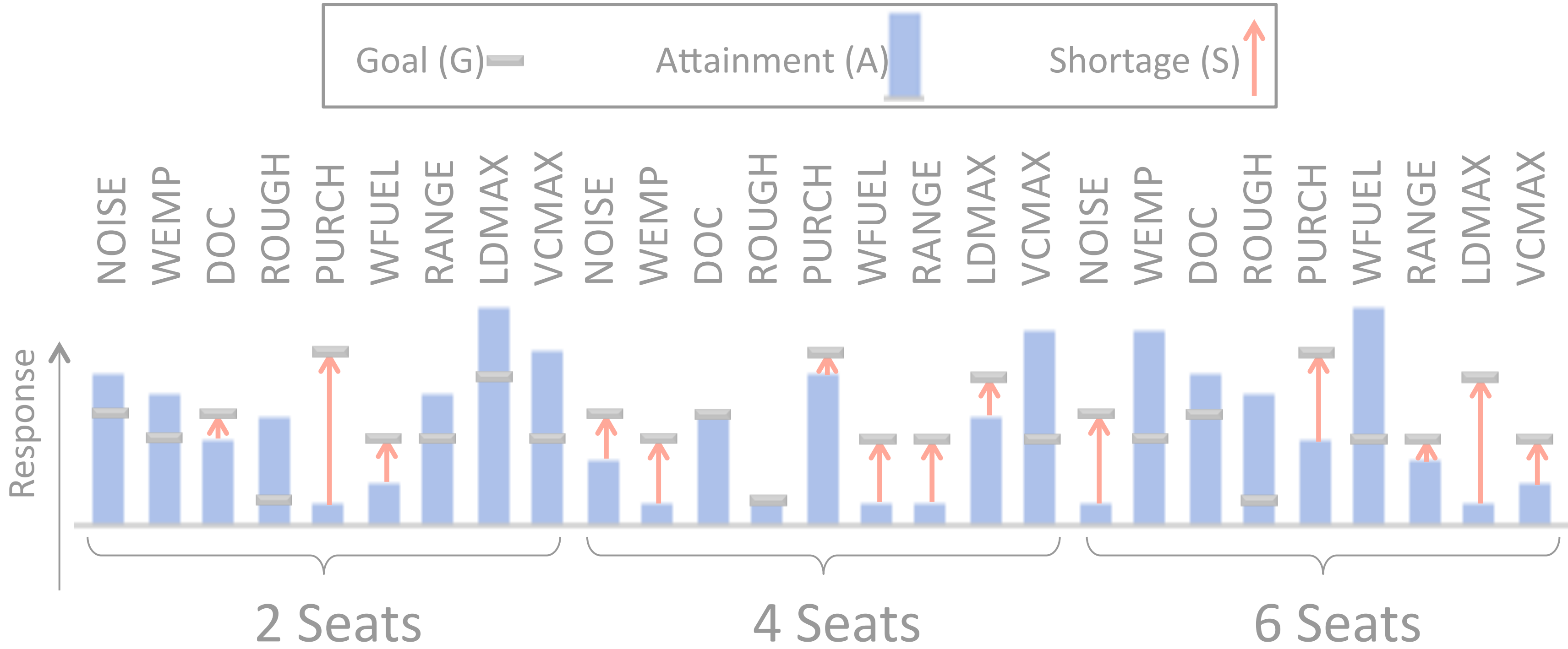
Balancing _Commonality_ vs _Performance_

9 decision variables per aircraft

9 performance criteria per aircraft

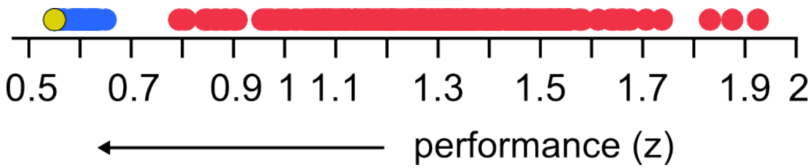
3 different formulations:
-1 objective (yellow)
-2 objectives (blue)
-10 objectives (red)

Single Objective Problem Formulation



Non-preemptive goal program[1]: minimize $z = \sum \frac{S}{G}$

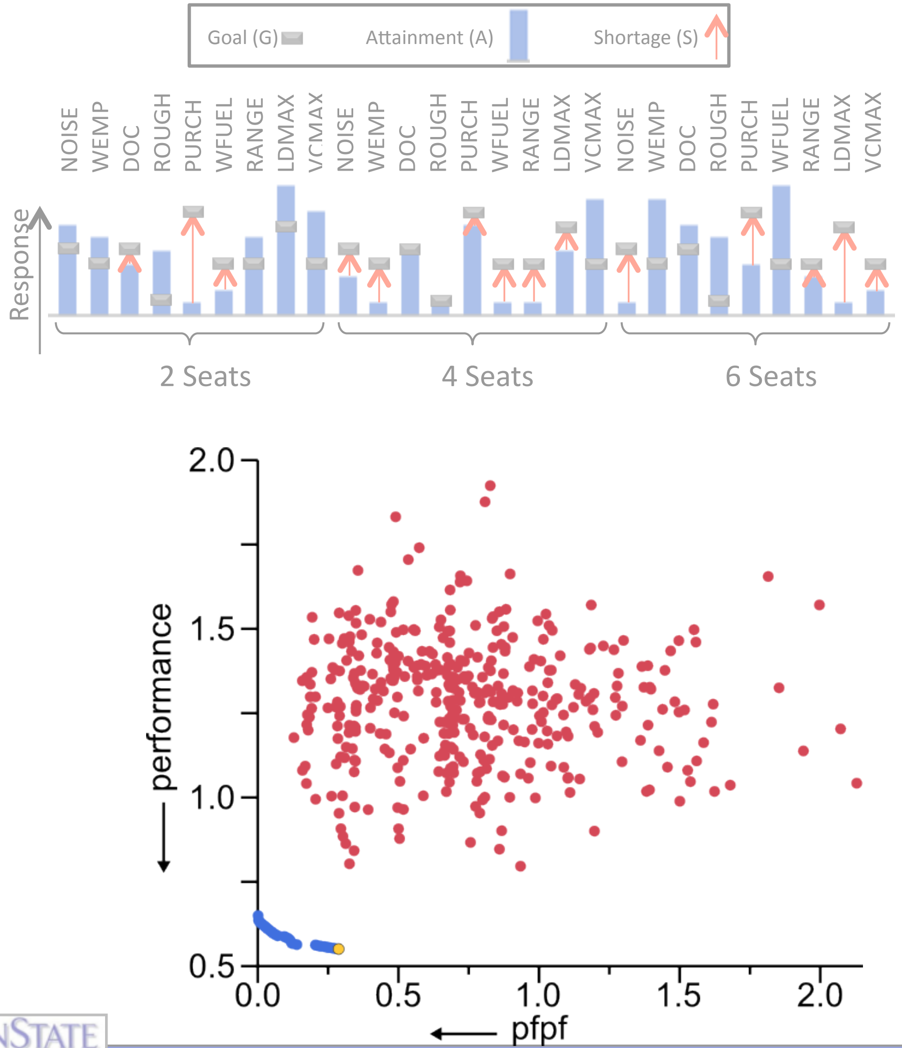
- Responses normalized to goal level
- Single aggregate “compromise” objective



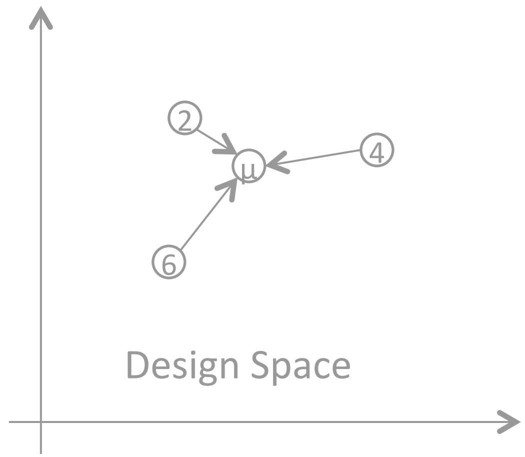
[1] Simpson et al, Proc. AIAA/ISSMO SMO Conference (1996)

Two Objective Problem Formulation

First objective: minimize $z = \sum \frac{S}{G}$



Second objective: minimize PFPF



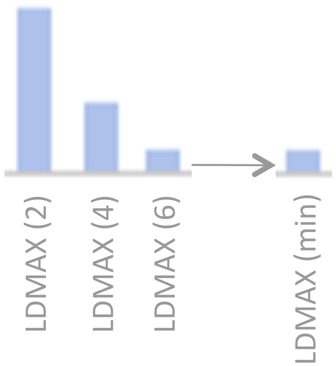
Product Family Penalty Function (PFPF[1]):

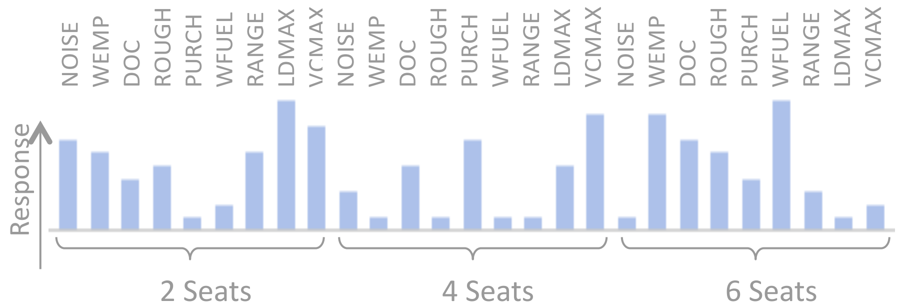
- Total distance in design space from all three aircraft designs (2, 4, 6) to the mean design (μ).
- Explore tradeoff between performance and commonality.

[1] Simpson et al, Concurrent Engineering (2001)

Ten Objective Problem Formulation

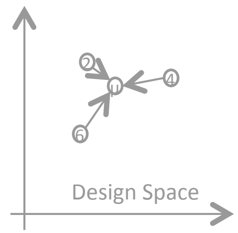
First nine objectives: min-max / max-min

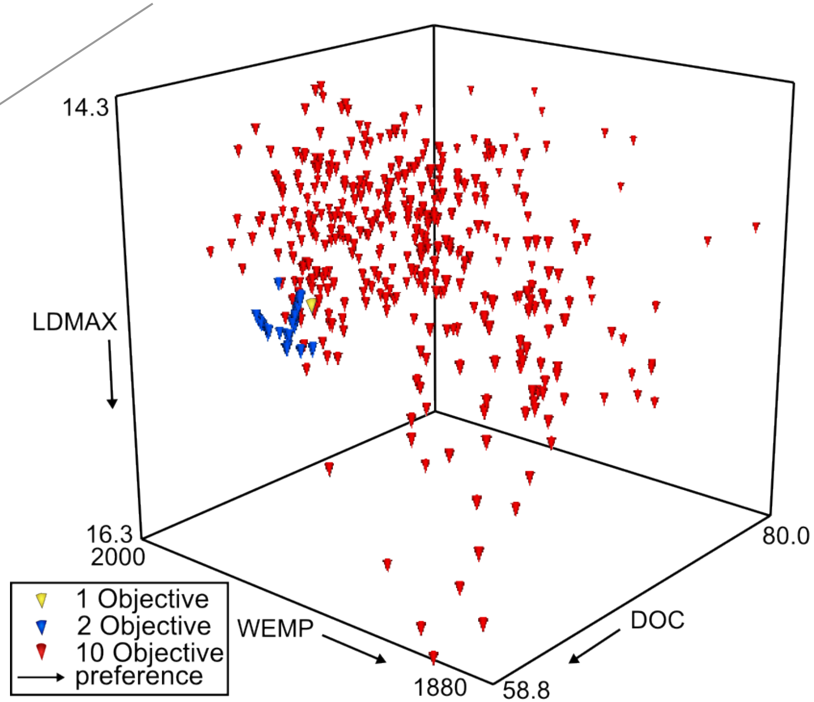




For example, maximize minimum LDMAX.

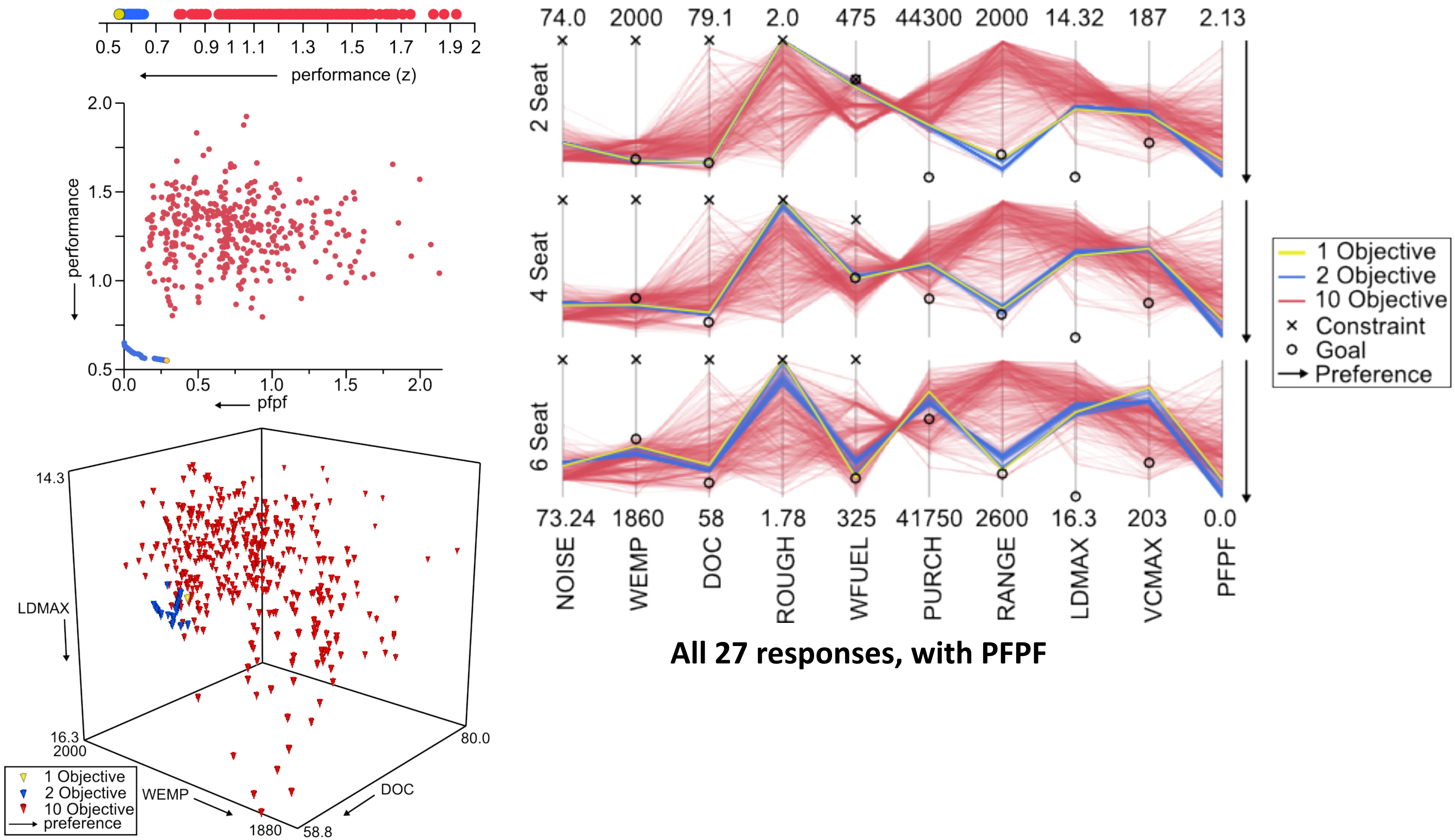
Tenth Objective: minimize PFPF





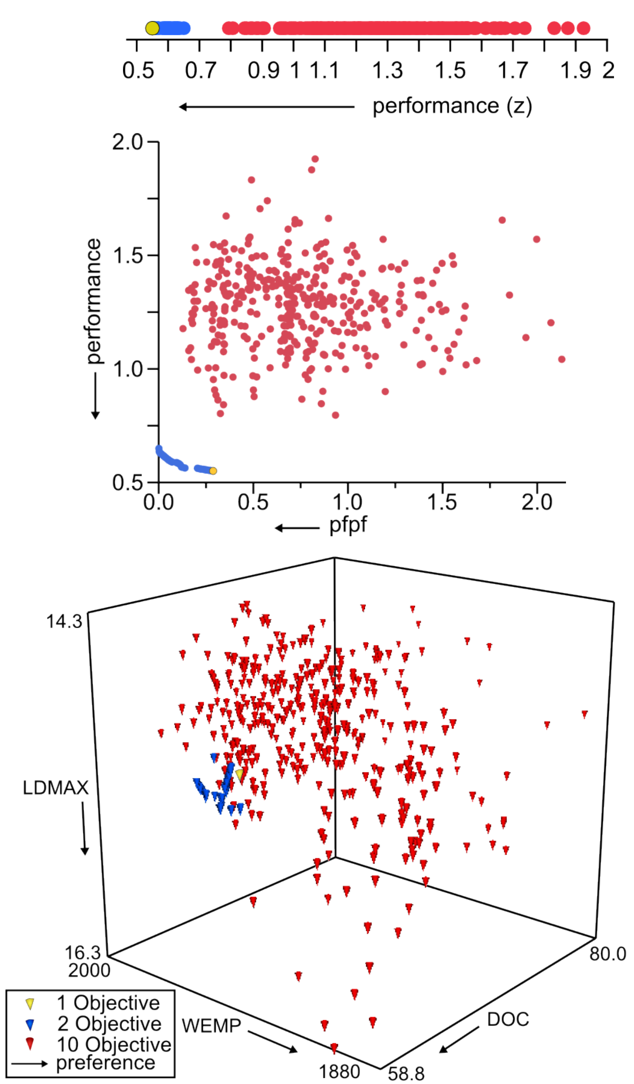
[1] Shah et al, Multi-objective Evolutionary Optimisation for Product Design and Manufacturing (2011)

Fewer Objectives Yield Fewer Alternatives

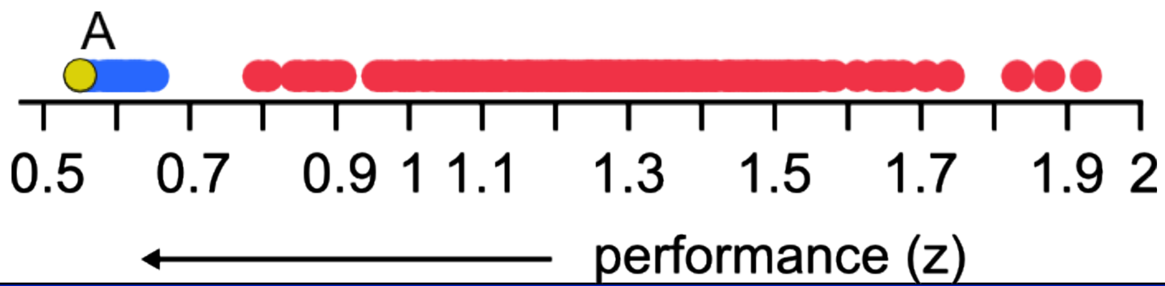


All 27 responses, with PFPF

Formulation Drives Design Selection



- Single-objective
  - One optimal solution (A) w.r.t. one objective



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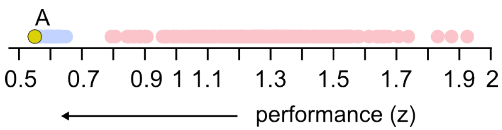

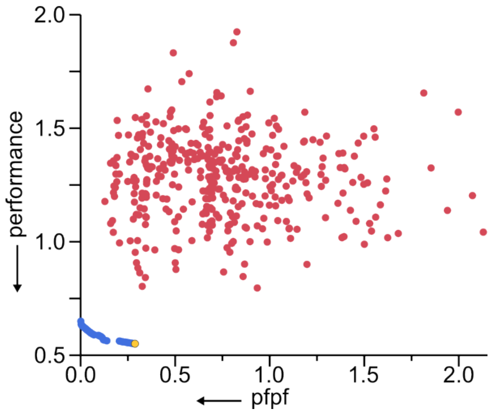

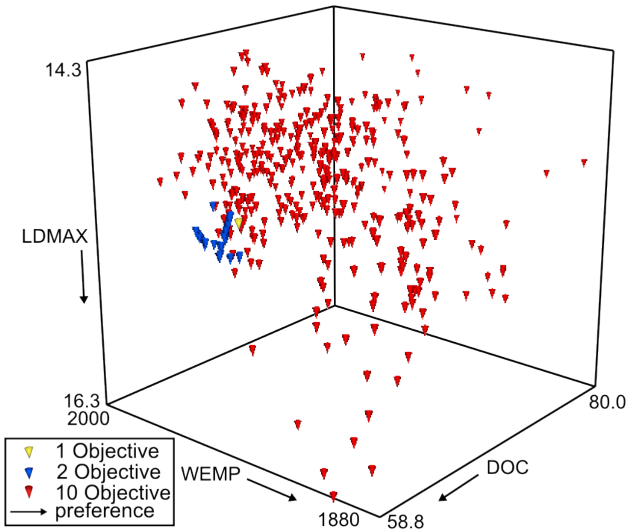

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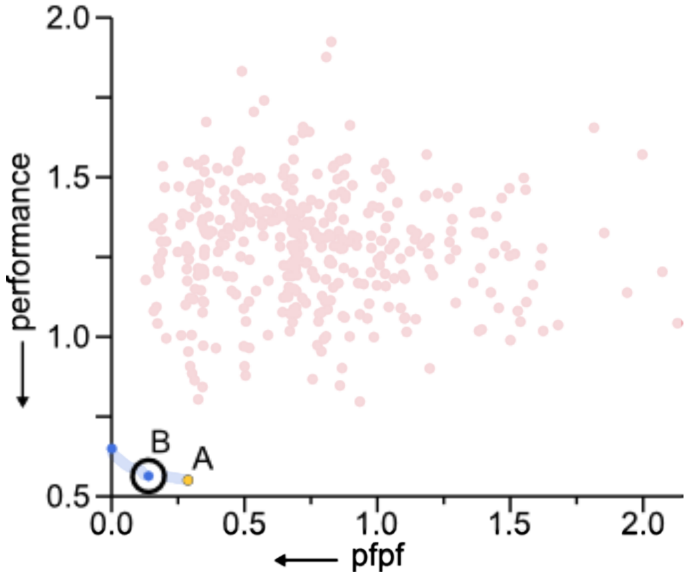
- Two-objective
  - One-dimensional Pareto front
  - Choose a compromise solution (B)



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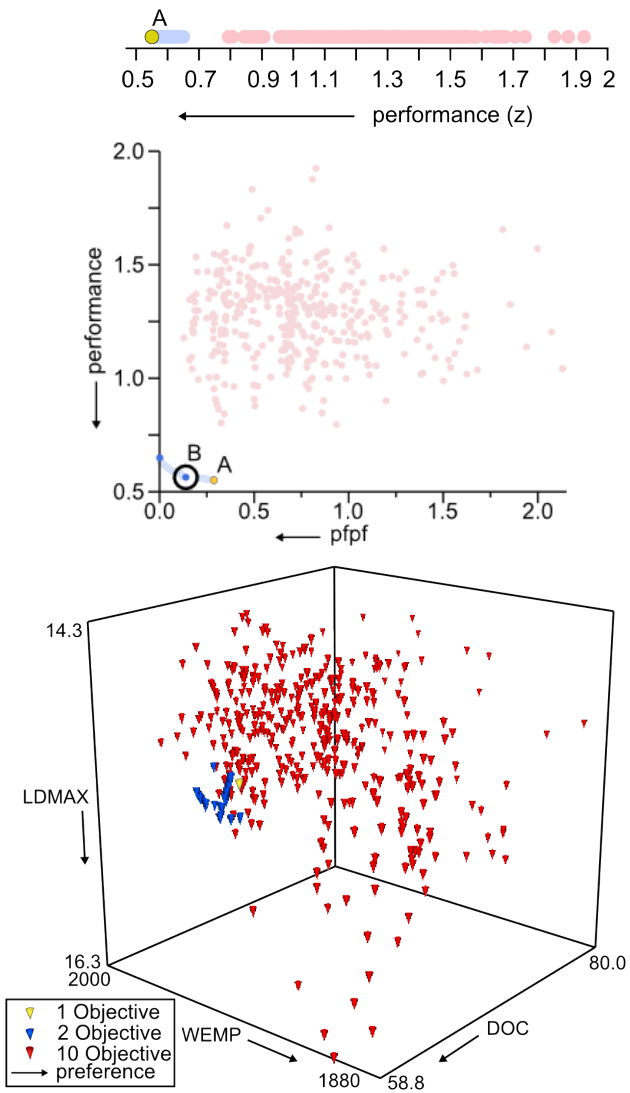

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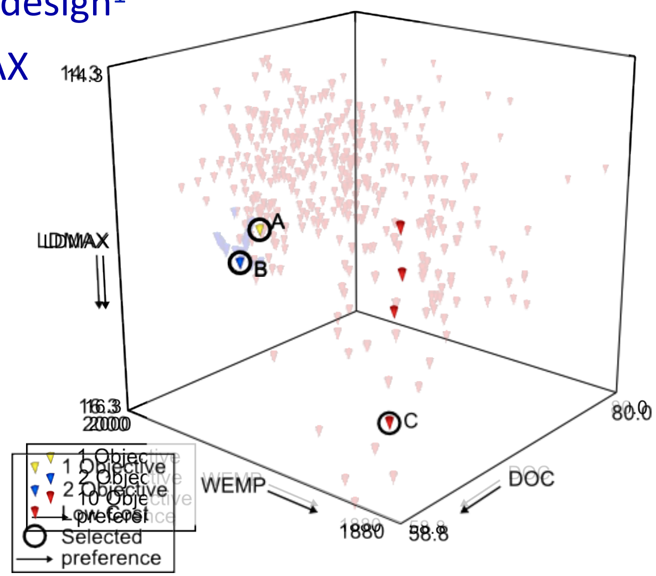
  - Many-dimensional Pareto front
  - Brush for low DOC and PURCH (highlighted glyphs)
  - Shop for compelling design[1]
  - Select for high LDMAX and VCMAX (C)
  - Inexpensive, high-performance aircraft
  - One of many design possibilities



[1] Balling, Proc. Third WCSMO (1999)

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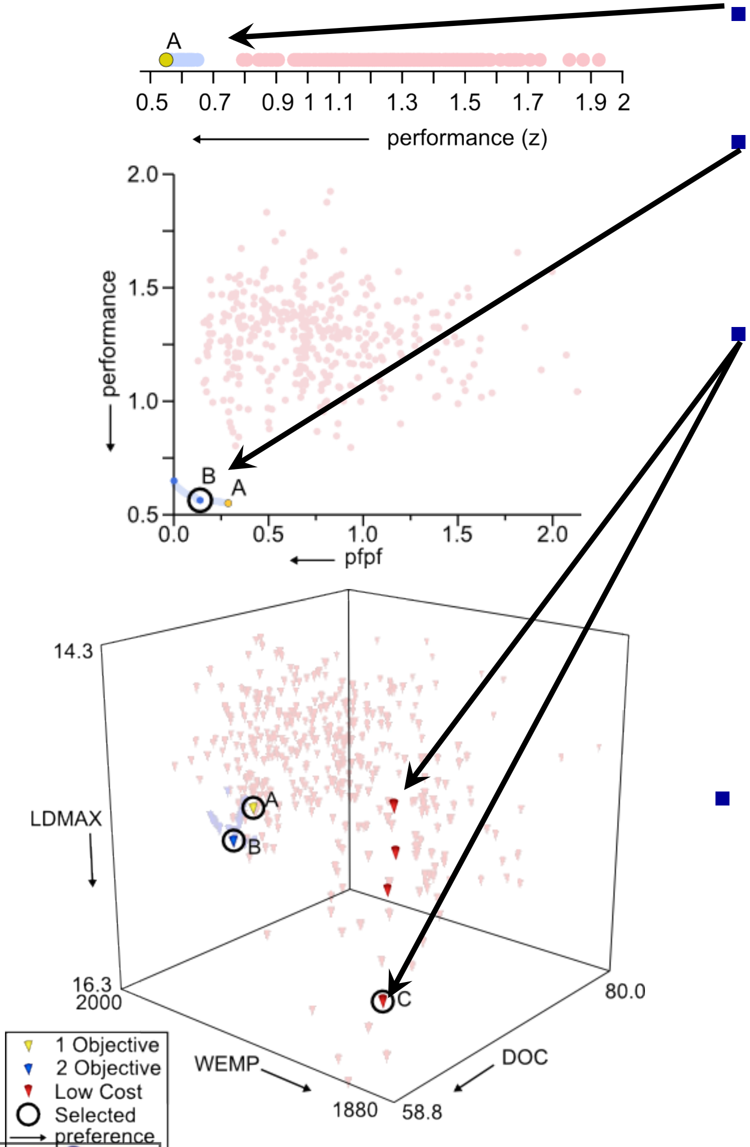

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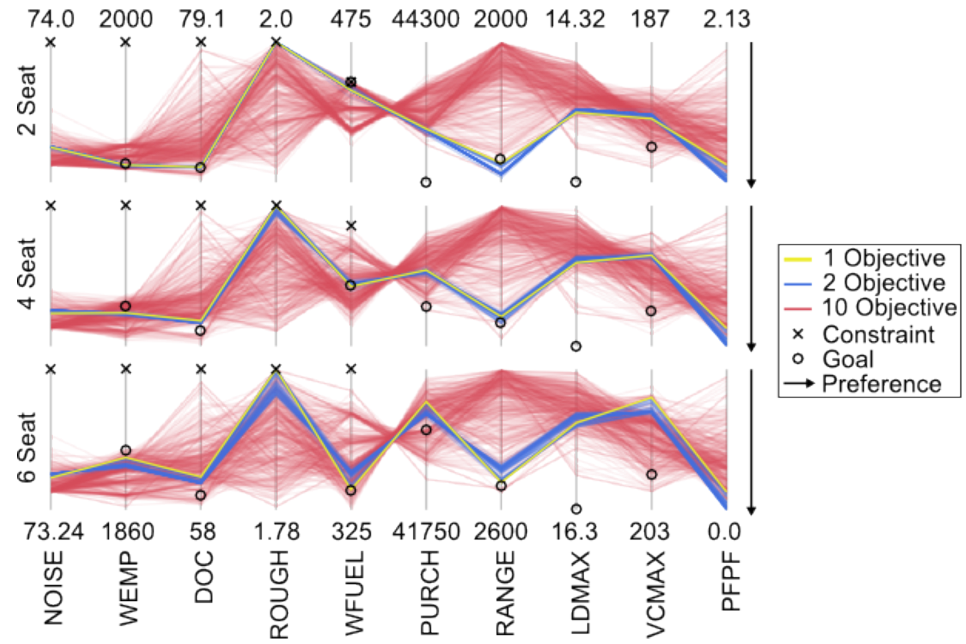
- Comparison
  - Fewer objectives, *a priori* decision about priorities
  - More objectives, opportunistic *a posteriori* selection of design in context of alternatives.

Arrow's Paradox

"If there are at least three alternatives among which the members of the society are free to order in any way, then every social welfare function... must be either imposed or dictatorial."

Arrow, J. Political Economy (1950)

- Formally equivalent to engineering design[1]
  - States of society = design alternatives
  - Voters = performance criteria
  - Social welfare function = aggregate objective function
- Aggregation—cannot predict controlling criteria and lost design opportunities



[1] Franssen, Research in Eng. Design (2005)

MOEA DIAGNOSTICS ON THE GAA

General Aviation Aircraft Problem

- Many-objective
- Severely constrained
  - Probability of randomly generating feasible point = 0.00000714%
- Non-separable
  - Decision variables are highly interactive

DESIGN PARAMETERS AND THEIR RESPECTIVE RANGES.

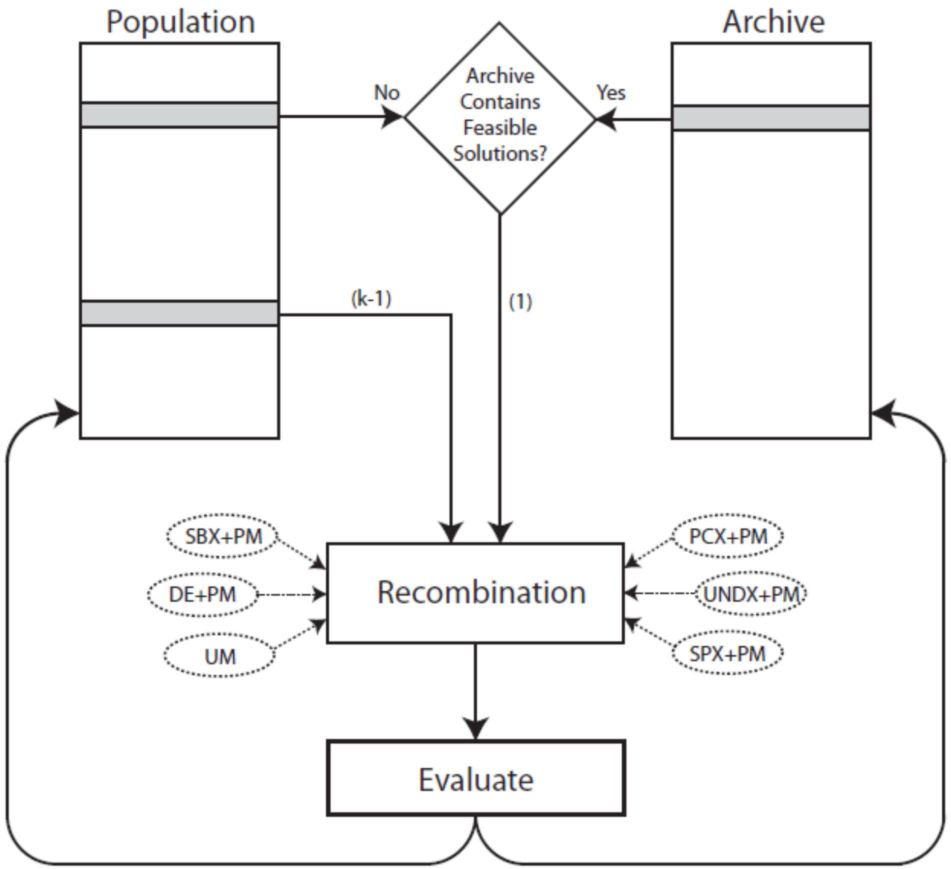
Design Variable	Units	Min	Max
Cruise Speed	Mach	0.24	0.48
Aspect Ratio	-	7	11
Sweep Angle	-	0	6
Propeller Diameter	ft	5.5	5.968
Wing Loading	lb/ft^2	19	25
Engine Activity Factor	-	85	110
Seat Width	inch	14	20
Tail Length/Diameter Ratio	-	3	3.75
Taper Ratio	-	0.46	1

OBJECTIVES AND ϵ VALUES.

Objective	Units	Min/Max	ϵ
Takeoff Noise	dB	min	0.15
Empty Weight	lb	min	30
Direct Operating Cost	$/hour	min	6
Ride Roughness	-	min	0.03
Fuel Weight	lb	min	30
Purchase Price	1970 $	min	3000
Flight Range	nm	max	150
Max Lift/Drag Ratio	-	max	0.3
Max Cruise Speed	kts	max	3
Product Family Penalty Function	-	min	0.3

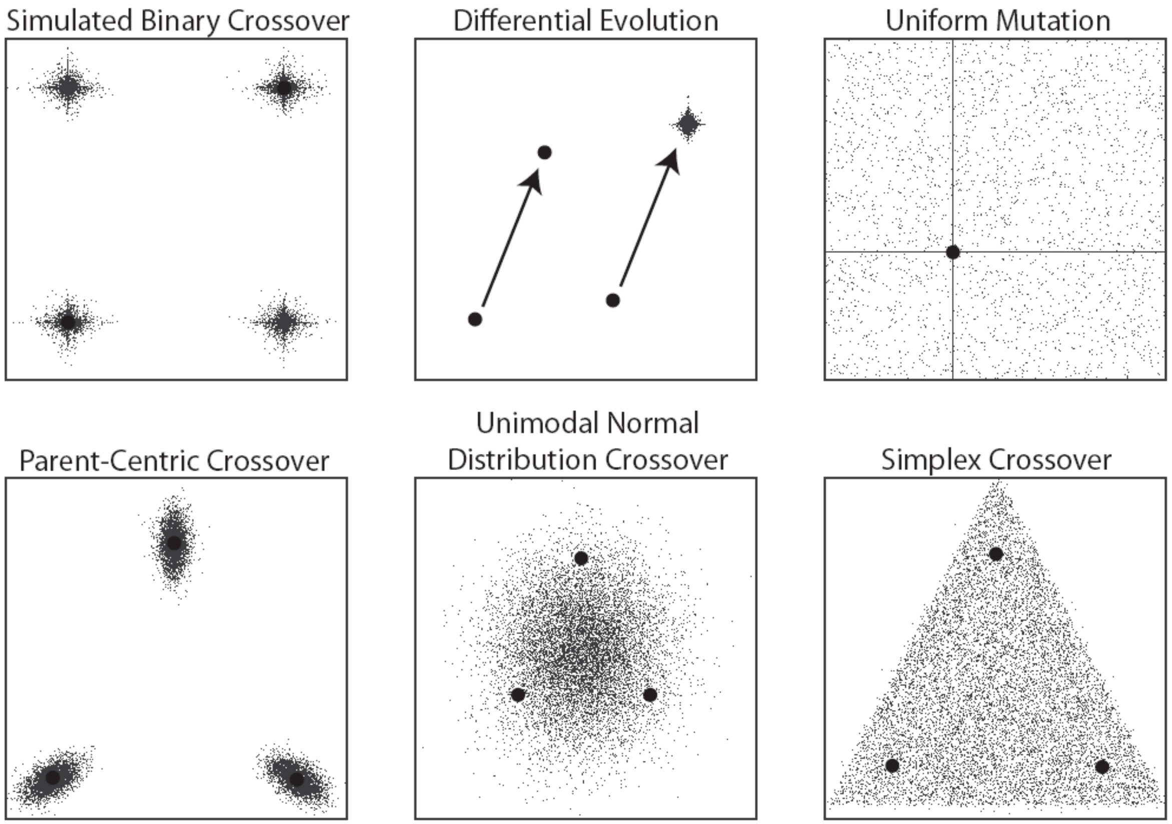
The Borg Search Framework

- Favor search operators based on performance
  - At runtime
  - Tailor to specific problem
  - Adapts to local search landscape
- Framework vs. algorithm



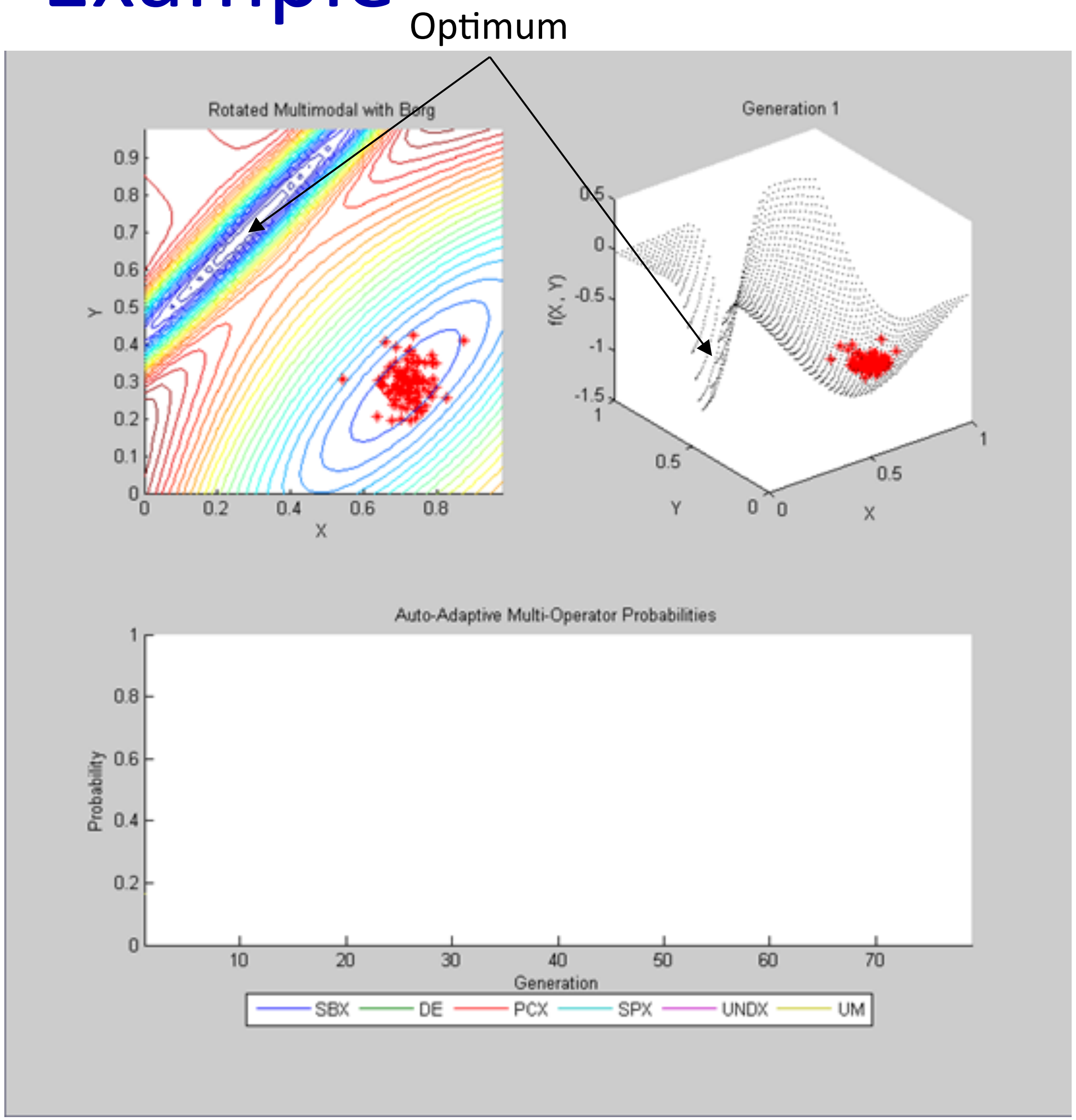
Auto-Adaptive Operators

- Different search operators result in a range of offspring distributions



Example

- Two valleys
- Initialized at suboptimal valley



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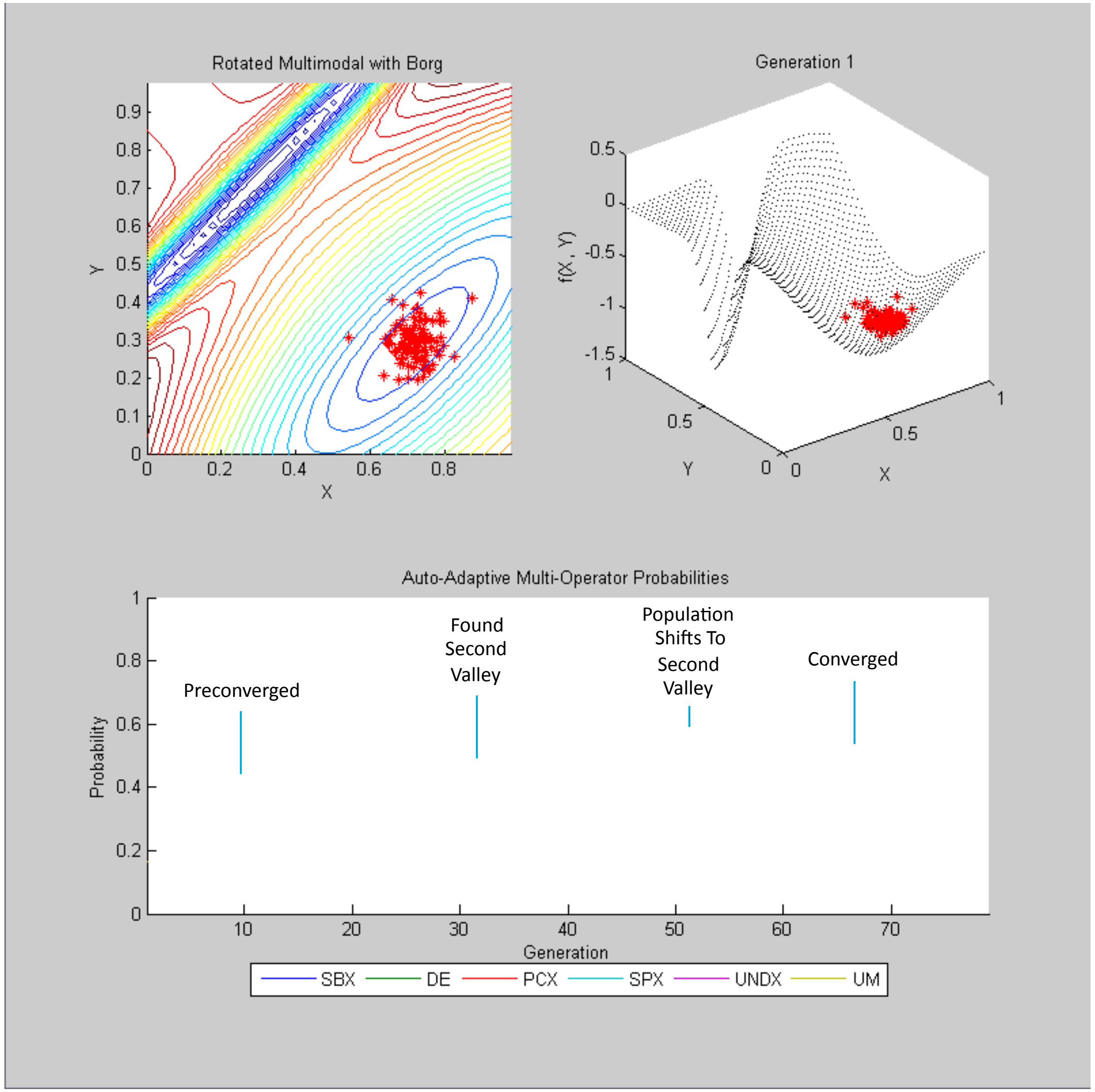
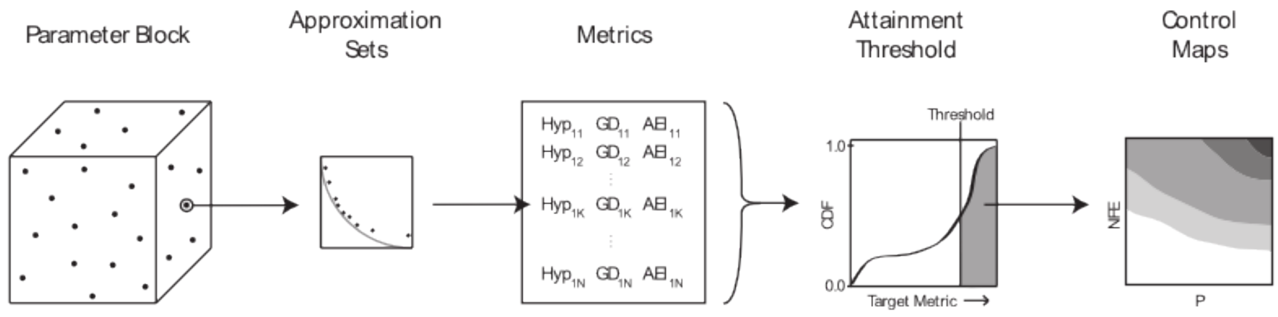


Experimental Design



- Eliminate parameterization bias
- Rigorous diagnostics
- Analyze parameter control sensitivities

Experimental Design

- 6 MOEAs
  - Borg MOEA
  - ε-MOEA
  - ε-NSGA-II
  - GDE3
  - NSGA-II
  - MOEA/D
- Parameter set samples:
  - 20,000
- Replications:
  - 50
- Total evaluations:
  - 176.75 billion

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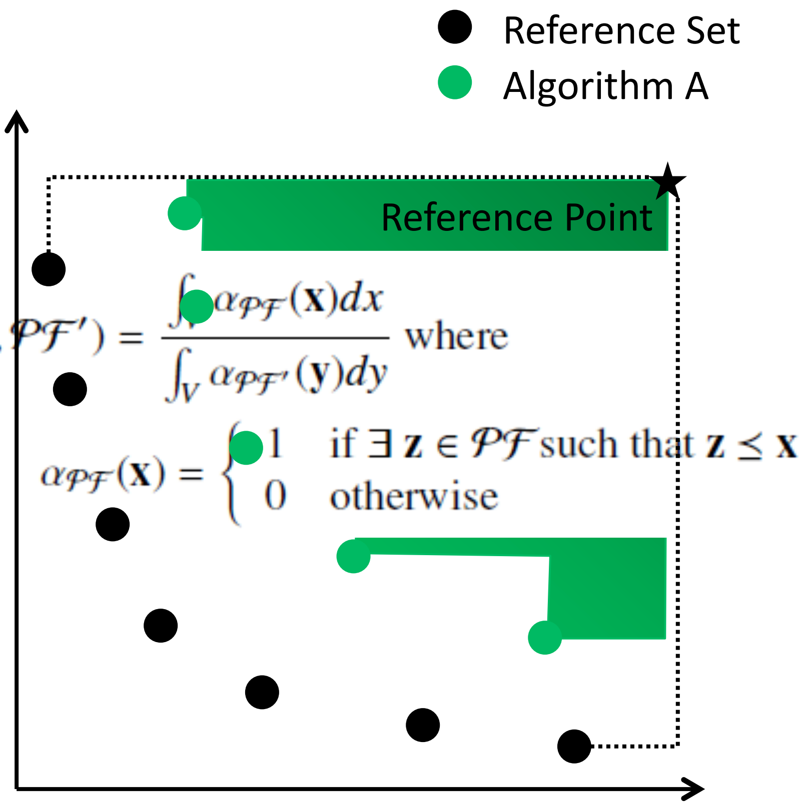
Hypervolume

- How well do we capture the entire optimal set?

- Volume of objective space dominated by an approximation set



$$I_H(\mathcal{PF}, \mathcal{PF}') = \frac{\int \alpha_{\mathcal{PF}}(\mathbf{x})dx}{\int_V \alpha_{\mathcal{PF}'}(\mathbf{y})dy} \quad \text{where}$$

$$\alpha_{\mathcal{PF}}(\mathbf{x}) = \begin{cases} 1 & \text{if } \exists\, \mathbf{z} \in \mathcal{PF} \text{ such that } \mathbf{z} \preceq \mathbf{x} \\ 0 & \text{otherwise} \end{cases}$$

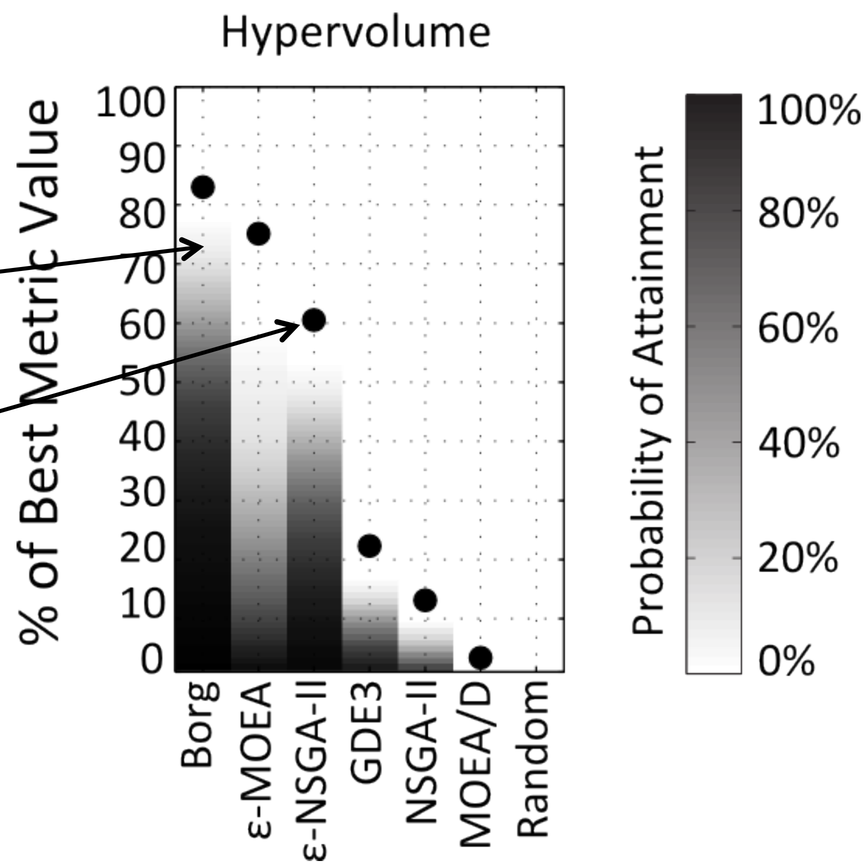
Results - Attainment

- How reliably did the MOEA attain high-quality solutions?

Dark, tall bars indicate an MOEA reached a near-optimal value with high probability

Black dots indicate the best result produced by the MOEA

- Borg ... qual... **high probability**

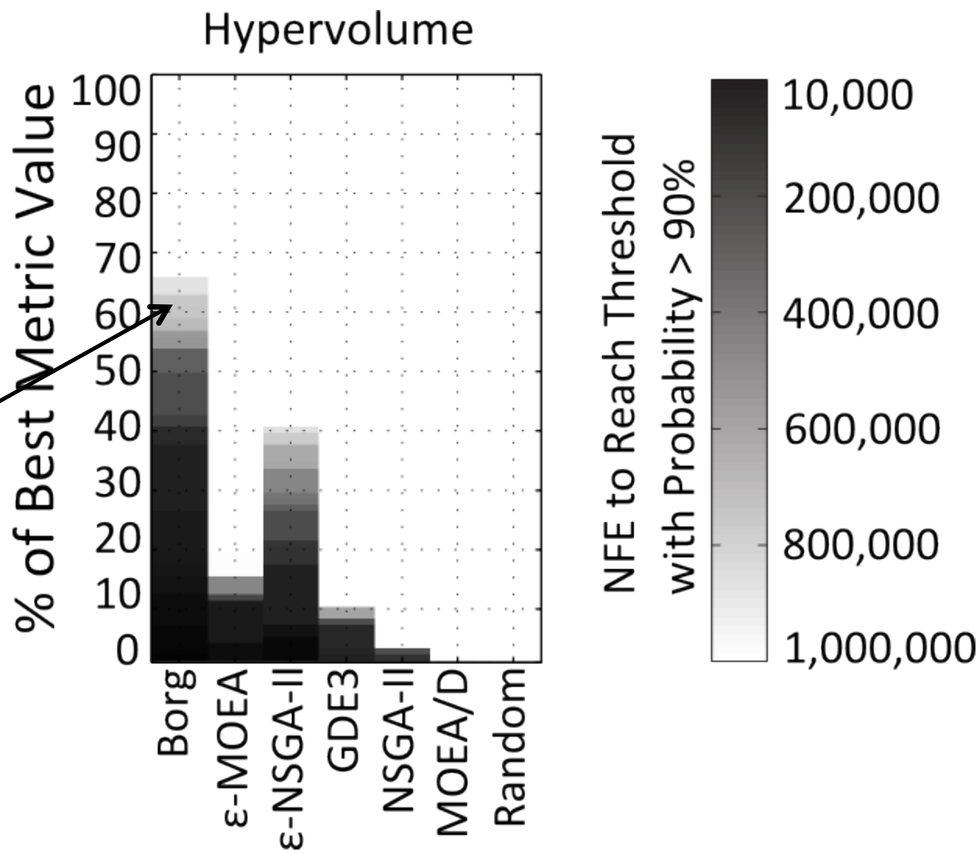


Results - Efficiency

- How quickly did the MOEA find high-quality solutions?

- Bo
qu
fewer NFE

Dark, tall bars indicate an MOEA reached a near-optimal value with fewer NFE

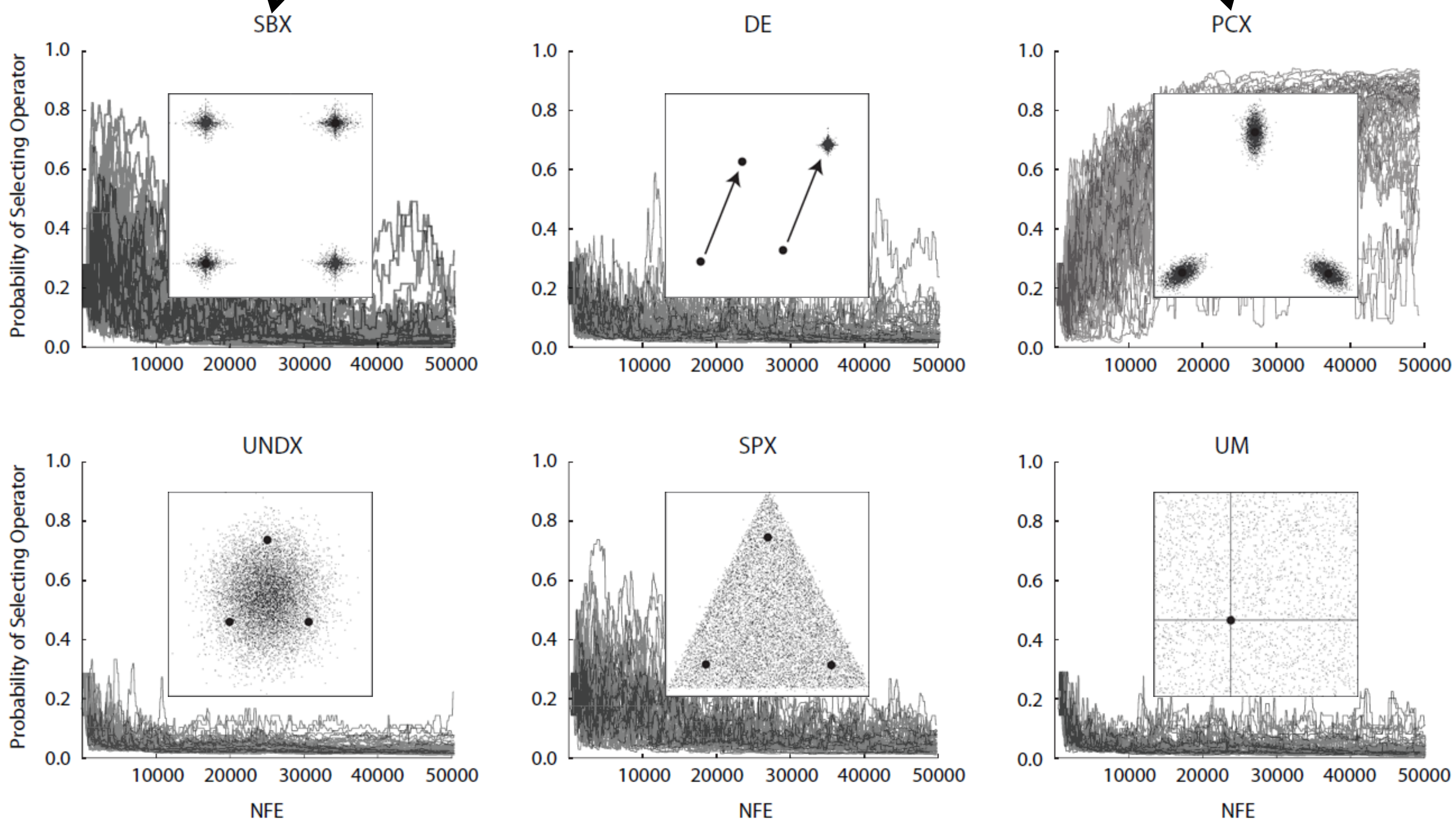


Borg – Operator Probabilities

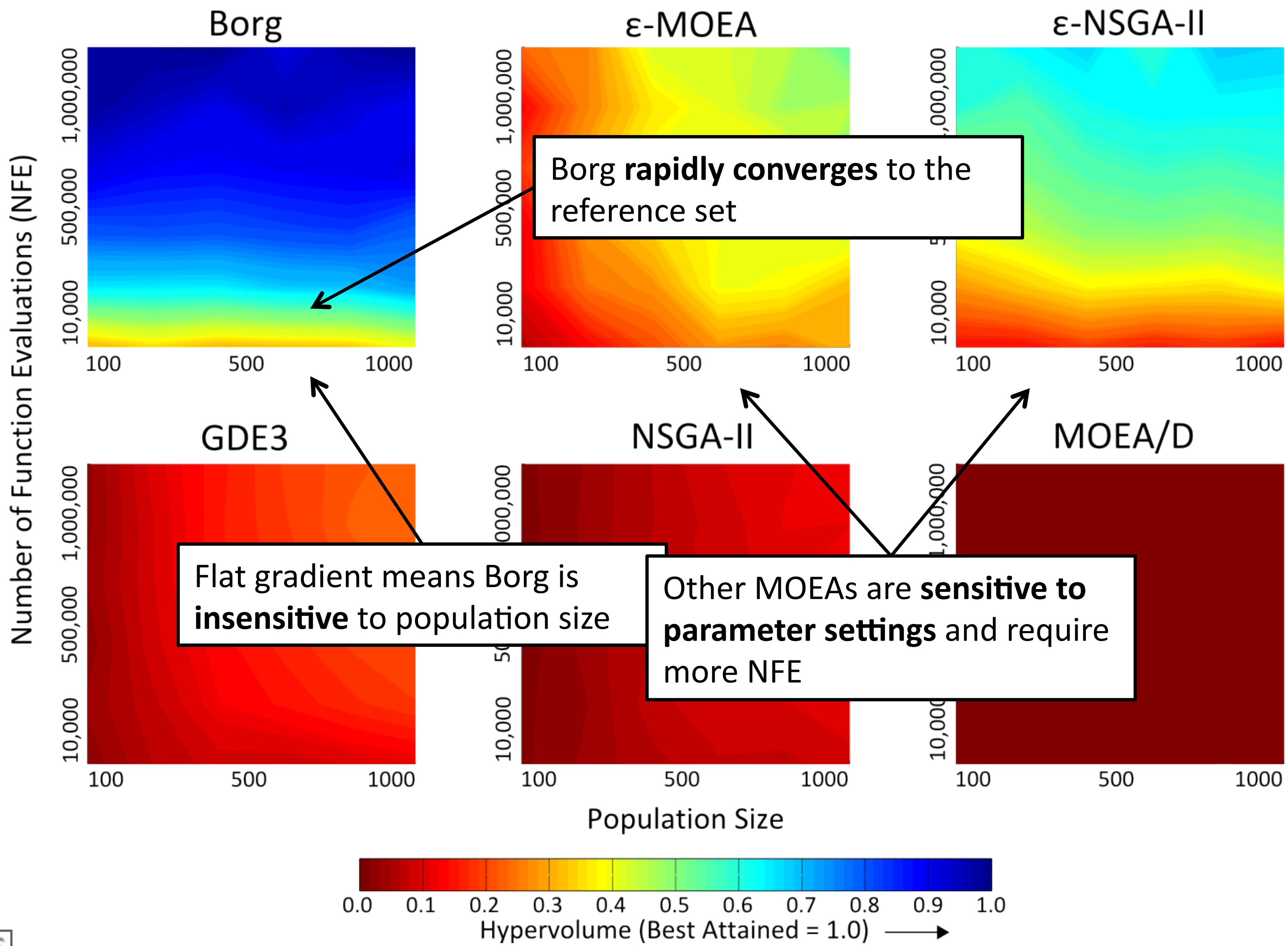
SBX is the most used operator for real-

But PCX clearly dominates on

MOEAs unable to auto-adapt search operators are stuck using *a priori* assumptions!



Results – Control Map



Quantifying Parameter Sensitivities

- Sobol global variance decomposition
  - First-order
  - Second-order
  - Total-order

$$Y = f(X_1, X_2, \ldots, X_n)$$

$$f = f_0 + \sum_i f_i + \sum_{i<j} f_{ij} + \sum_{i<j<k} f_{ijk} + \cdots + f_{ijk\ldots n}$$

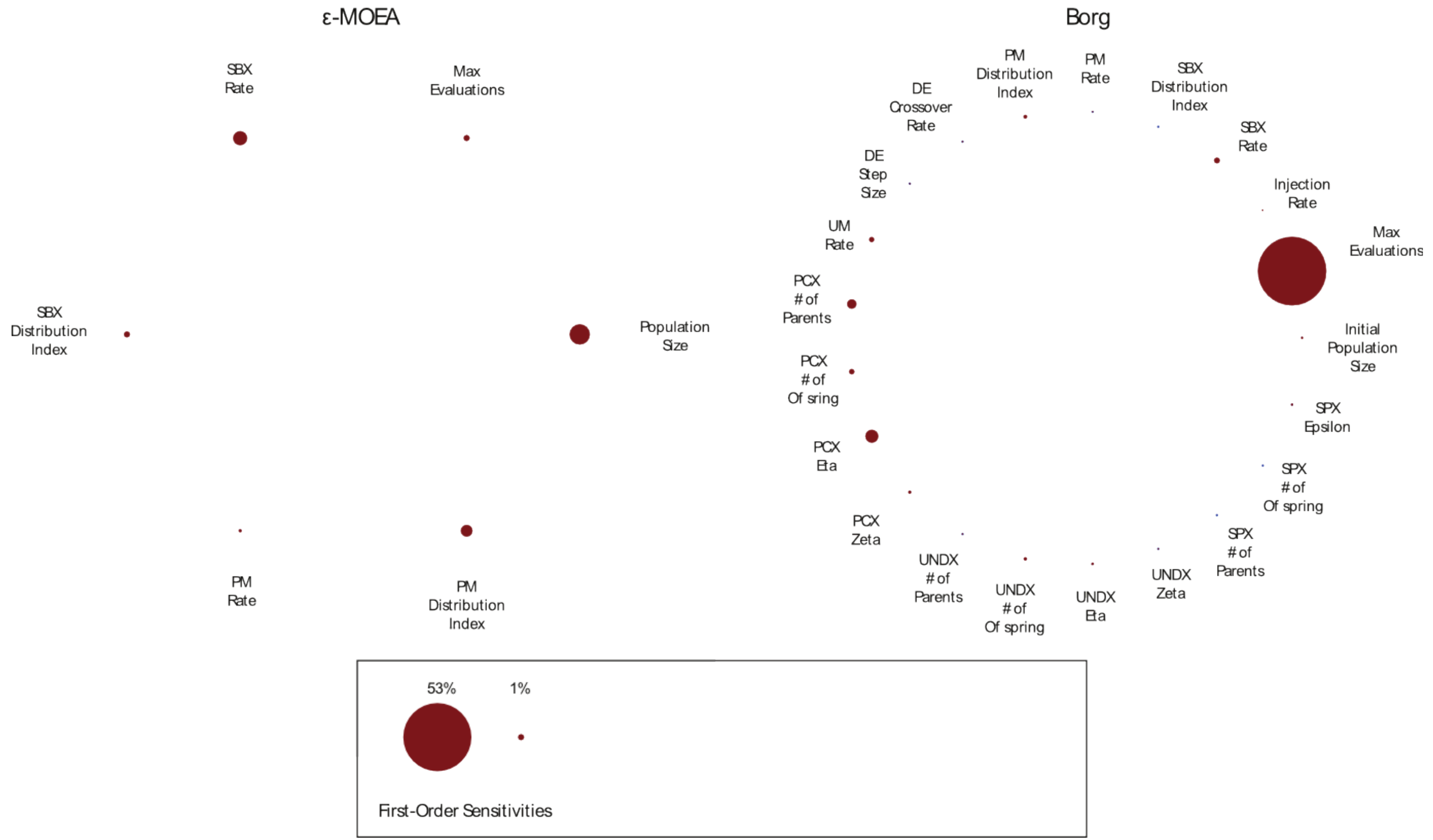
$$S_i = \frac{V[f_i(X_i)]}{V[Y]} = \frac{V[E(Y|X_i)]}{V[Y]}$$

- Strong first order sensitivities → easy to control

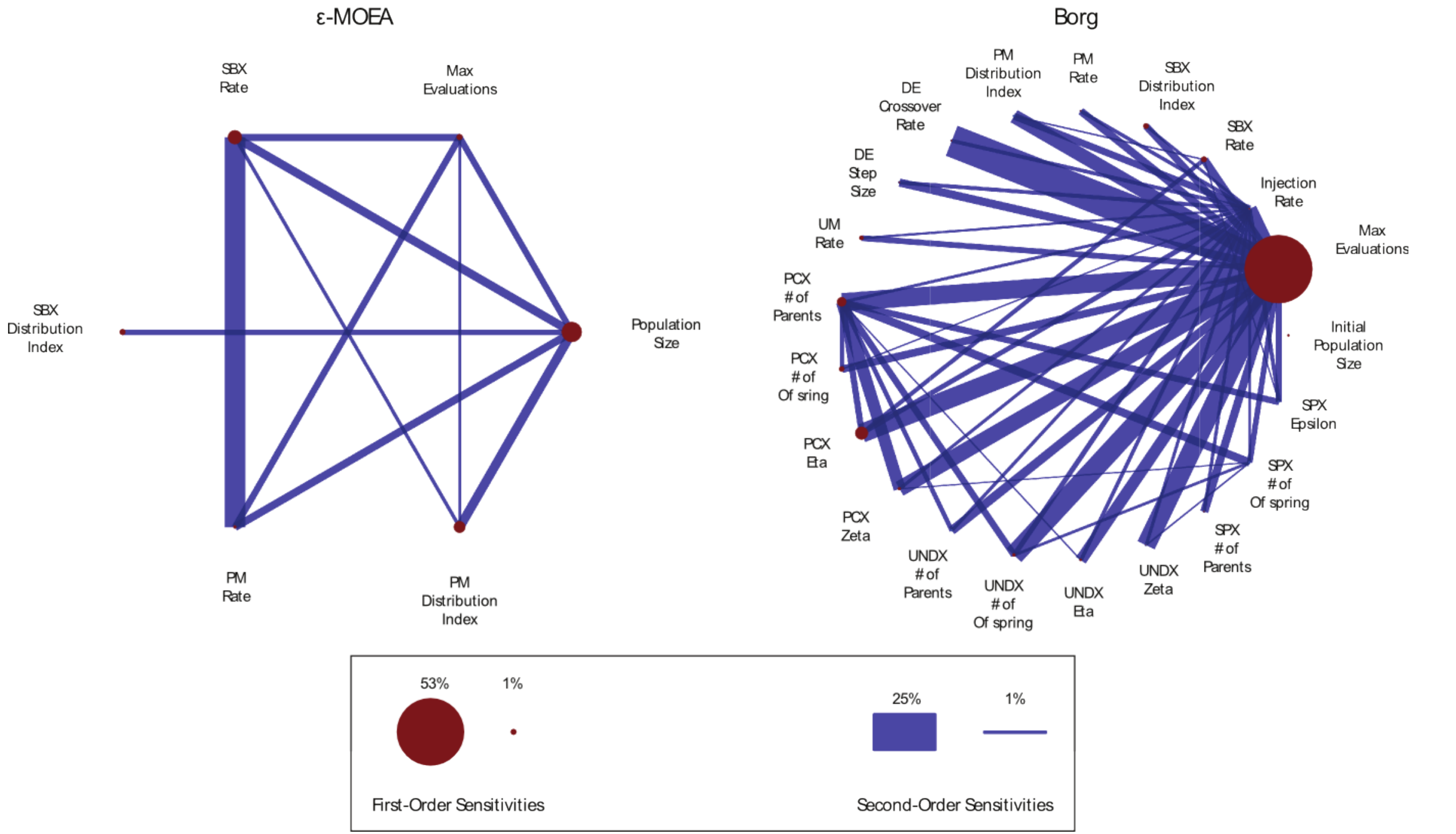
$$\begin{aligned} S_{ij} &= \frac{V[f_{ij}(X_i, X_j)]}{V[Y]} \\ &= \frac{V[E(Y|X_i, X_j)]}{V[Y]} - S_i - S_j \end{aligned}$$

$$S_i^T = 1 - \frac{V[E(Y|X_{\sim i})]}{V[Y]}$$

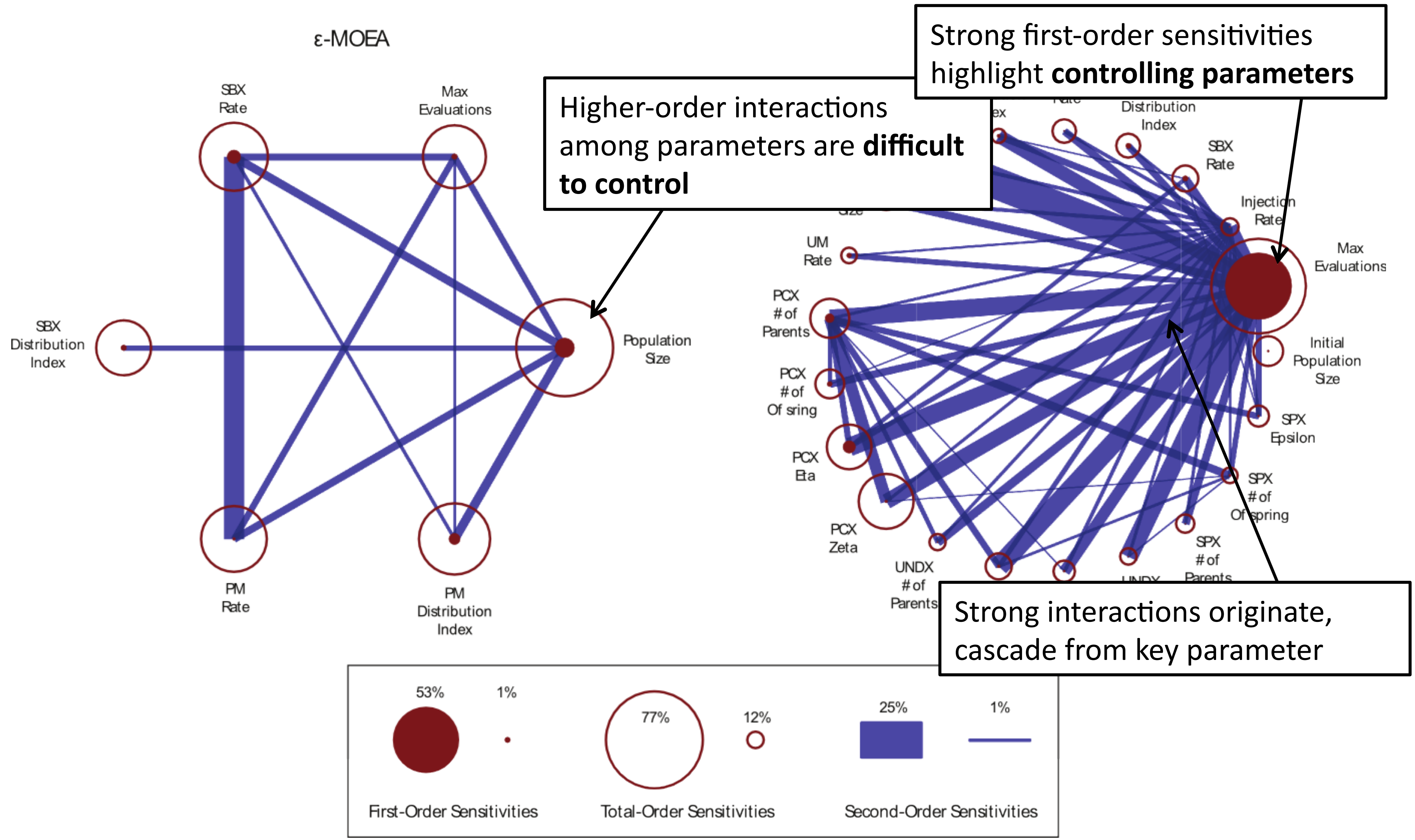
MOEA Controls



MOEA Controls



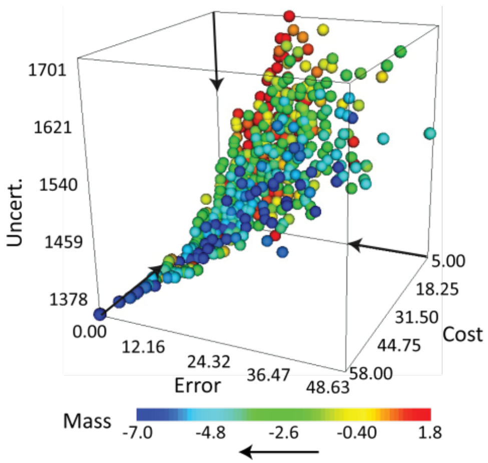
MOEA Controls

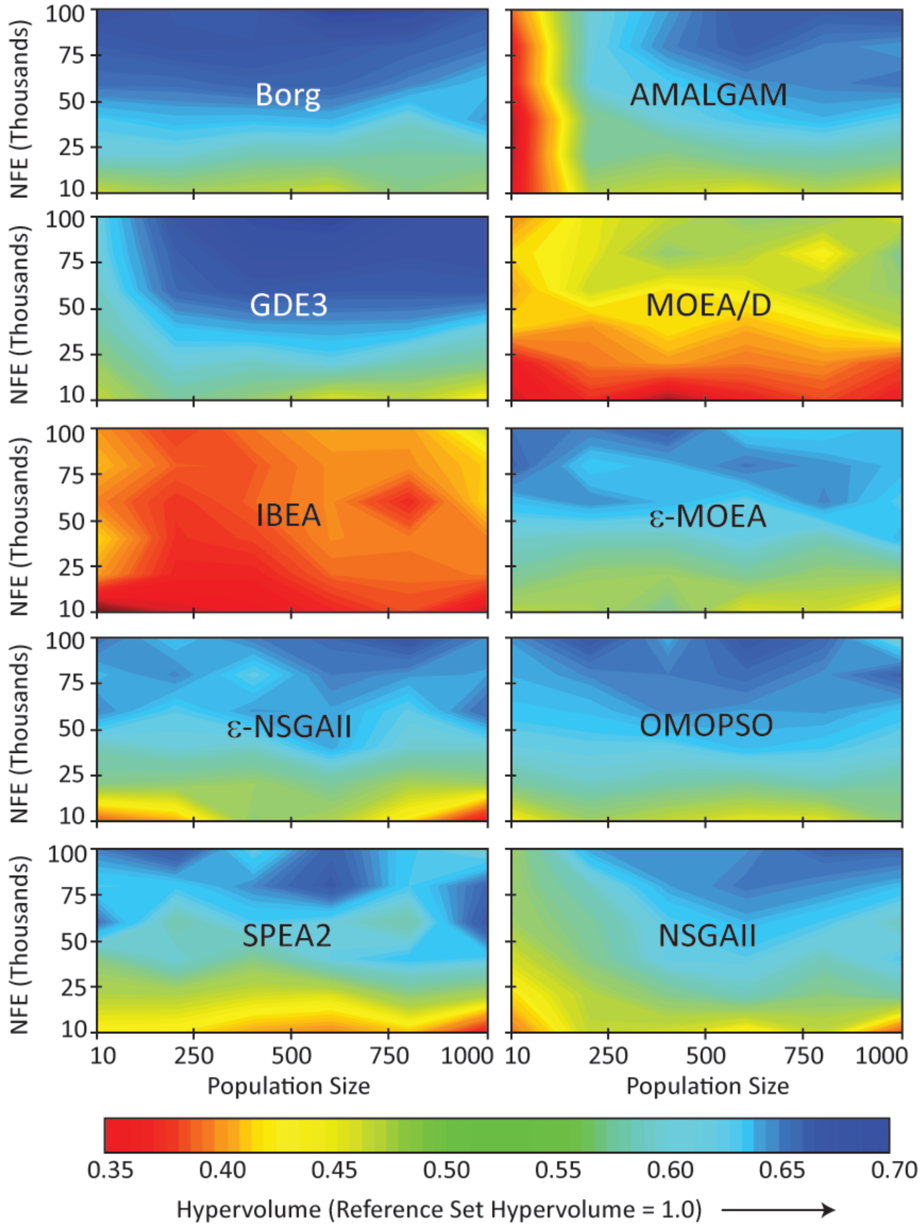


TALES FROM THE REAL-WORLD

Control maps show the robustness of search to parameter choice.

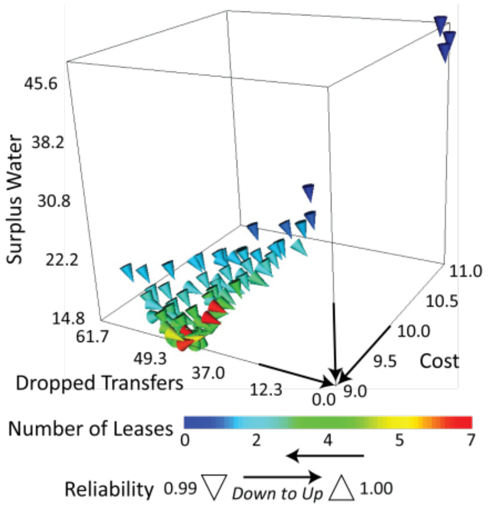
LTM
Test Problem
(Equally Difficult)

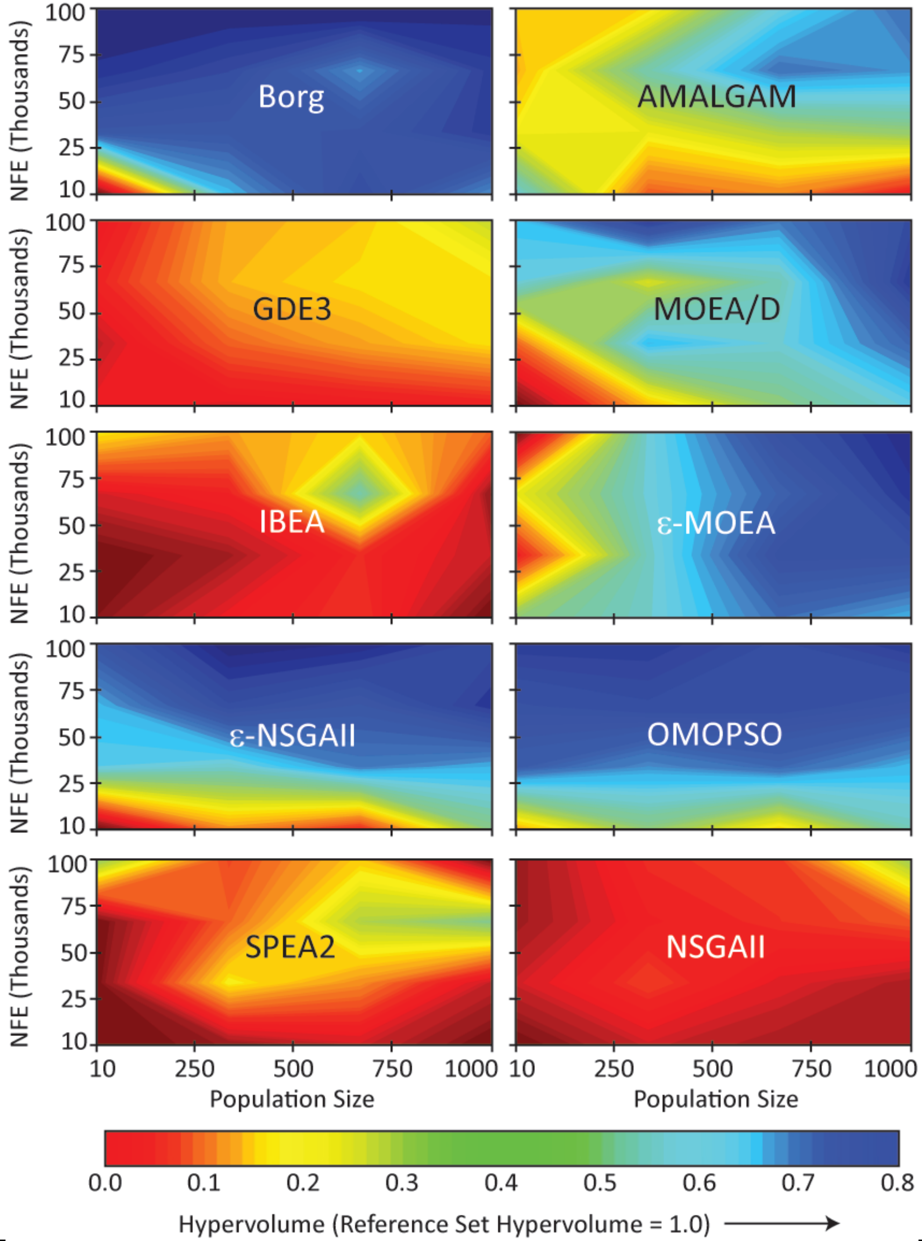




Control maps show the robustness of search to parameter choice.

LRGV
Test Problem
(Just Plain Difficult)

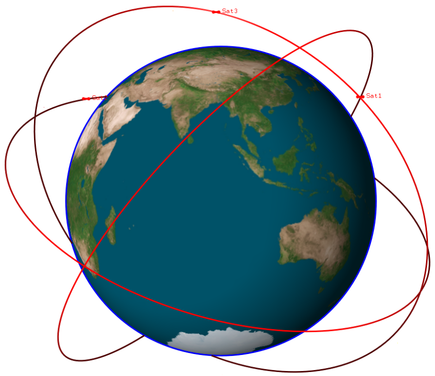




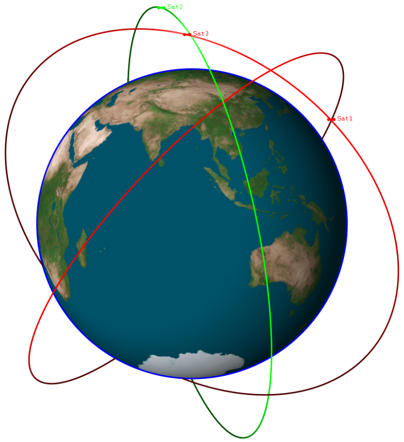
Earth Science Satellite Constellation Design Challenges

Launch image reprinted courtesy of NASA

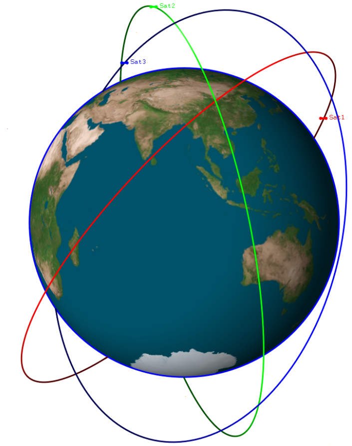
- Problem Properties:
  - Near-term decisions impact future performance
  - Adaptive observations to capture periods of time key tradeoff decisions must be made
  - Build-up → reconfiguration → replenishment



Current Constellation



Optimized Configuration in 2012

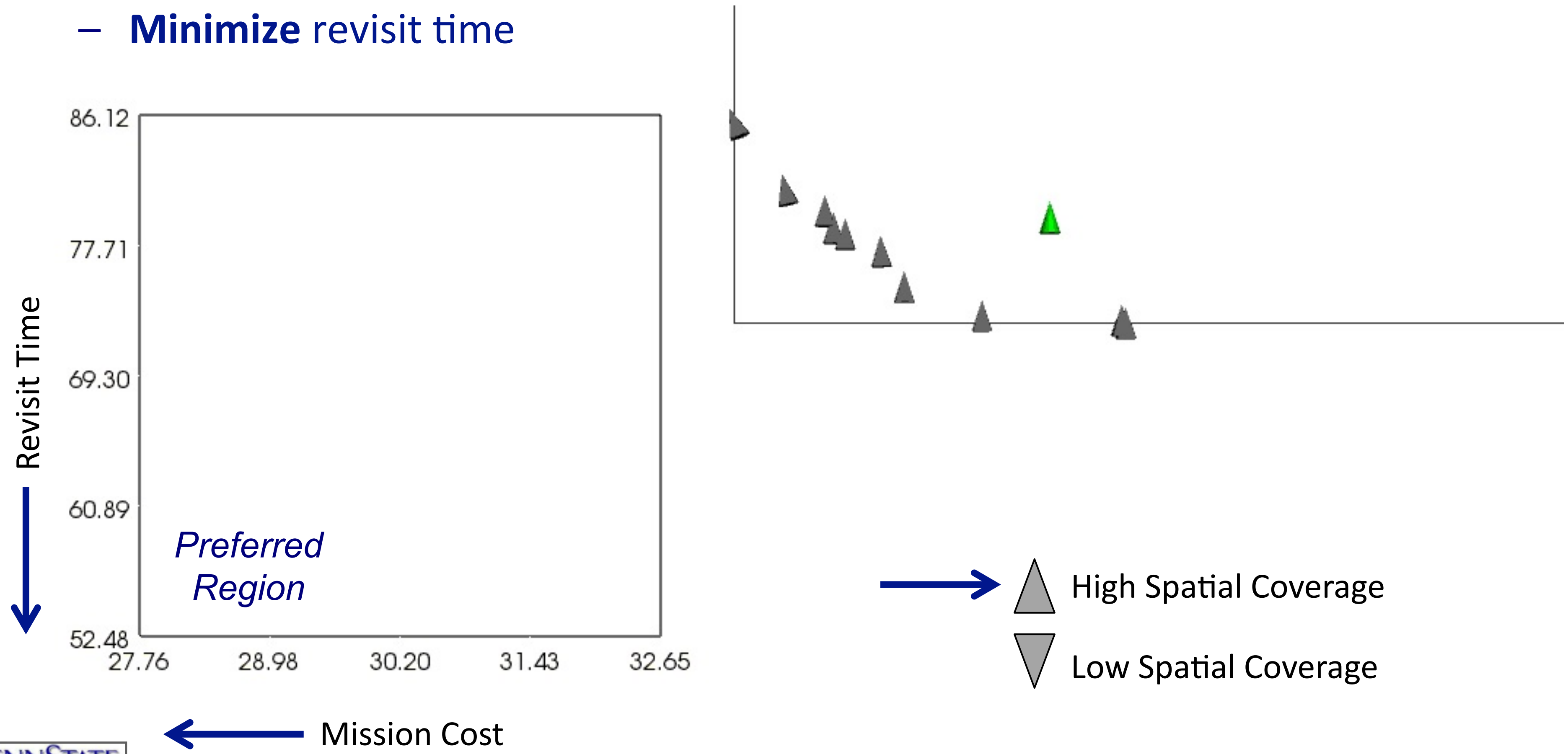


Optimized Configuration in 2018

Time

Earth Science Satellite Constellation (Hypothetical Example)

- Design Objectives:
  - **Minimize** mission cost
  - **Maximize** spatial coverage
  - **Minimize** revisit time



Earth Science Satellite Constellation (Hypothetical Example)

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  - **Maximize** spatial coverage
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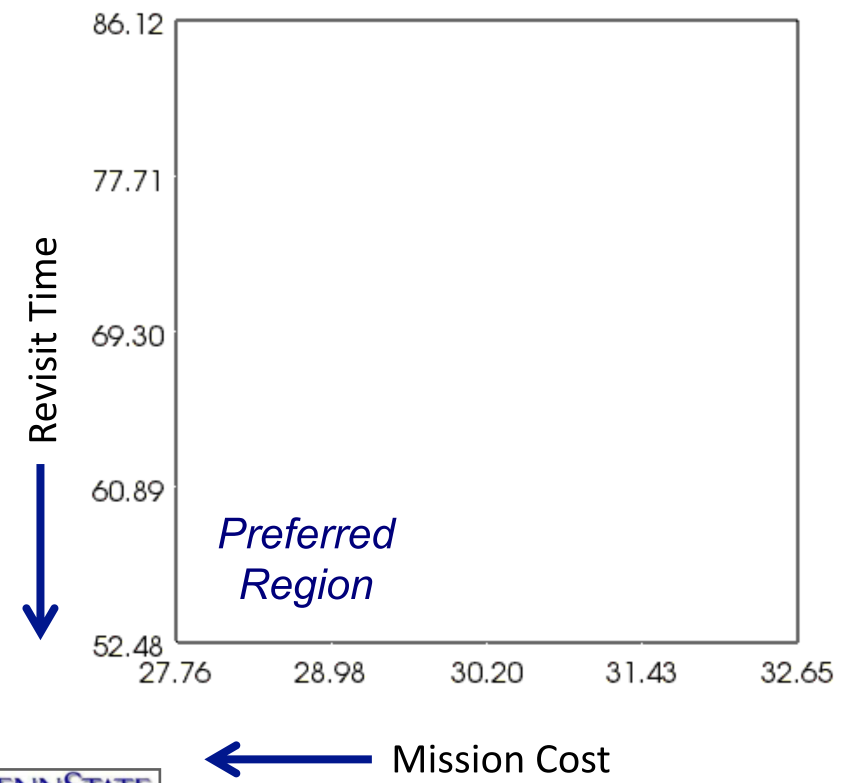
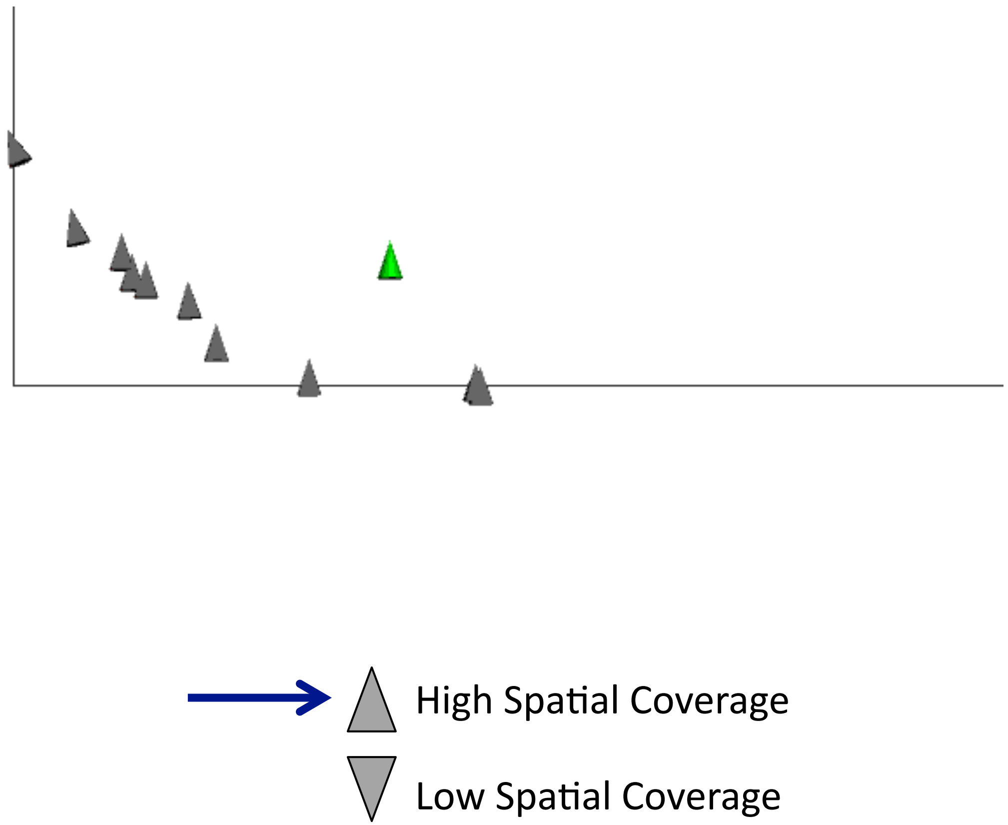
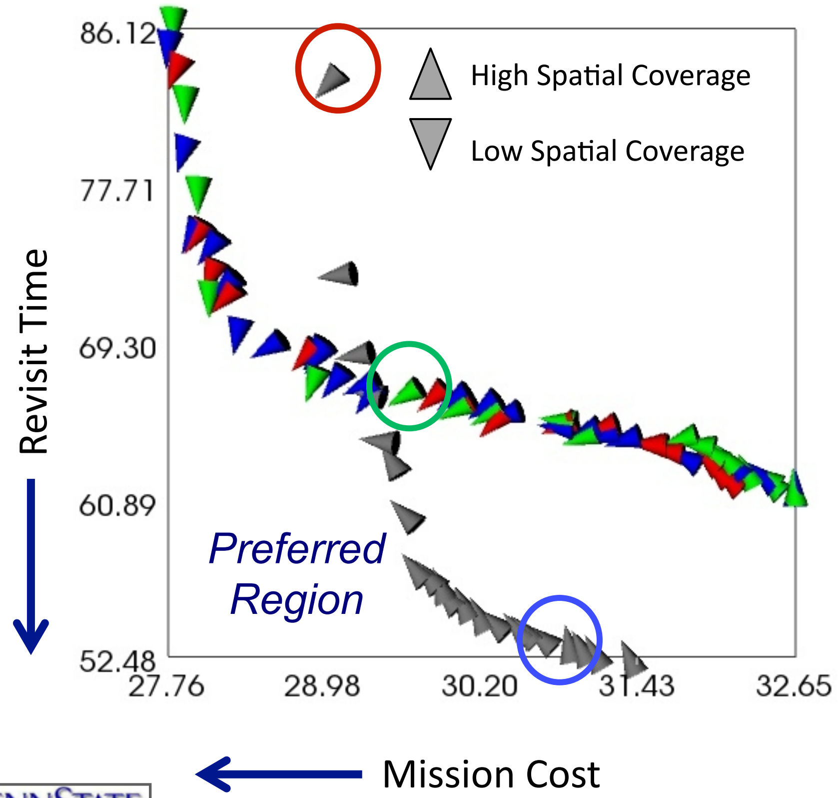




Earth Science Satellite Constellation (Hypothetical Example)

- Analyzing key tradeoffs and performance differences
- Efficient exploration of candidate designs
  - Click on the red, green, and blue solutions to visualize their designs



Earth Science Satellite Constellation (Hypothetical Example)

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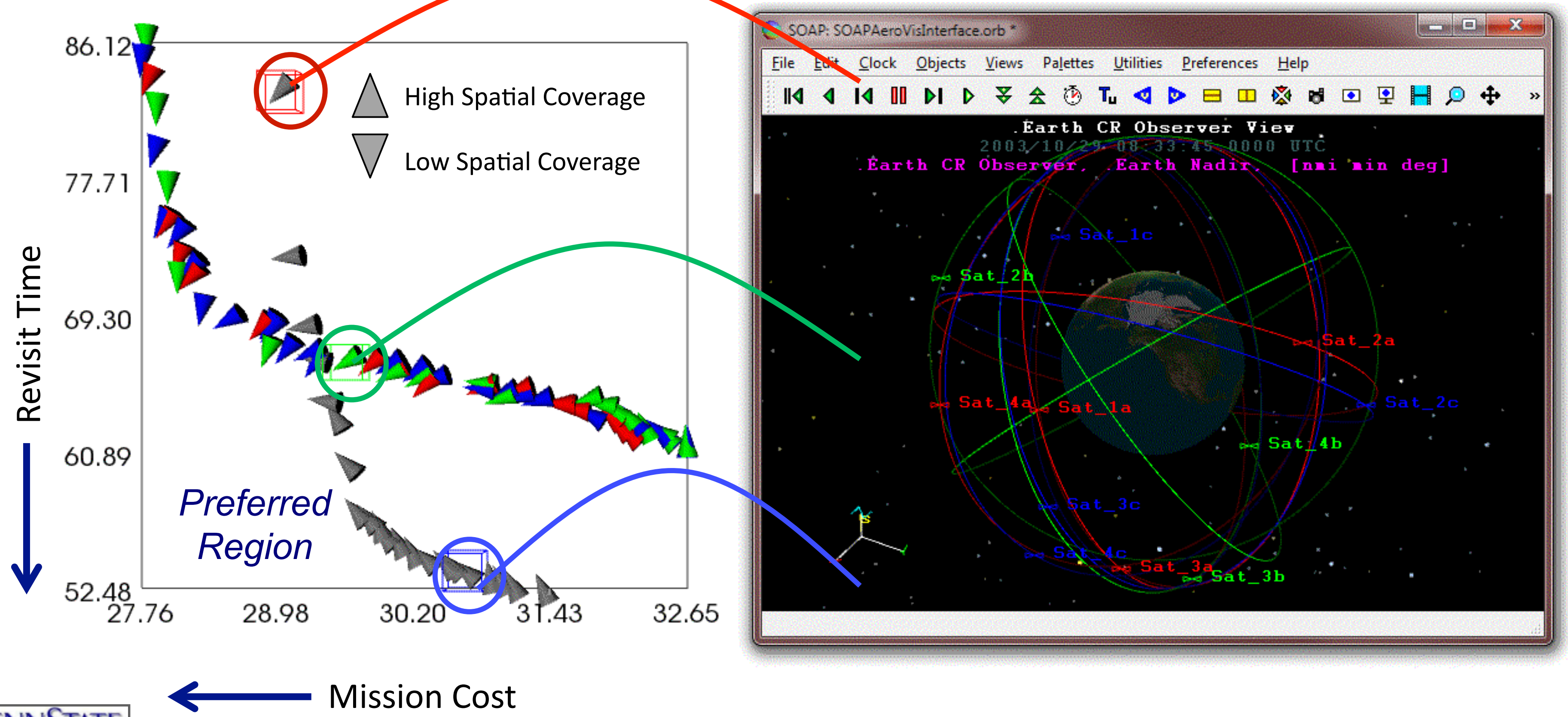


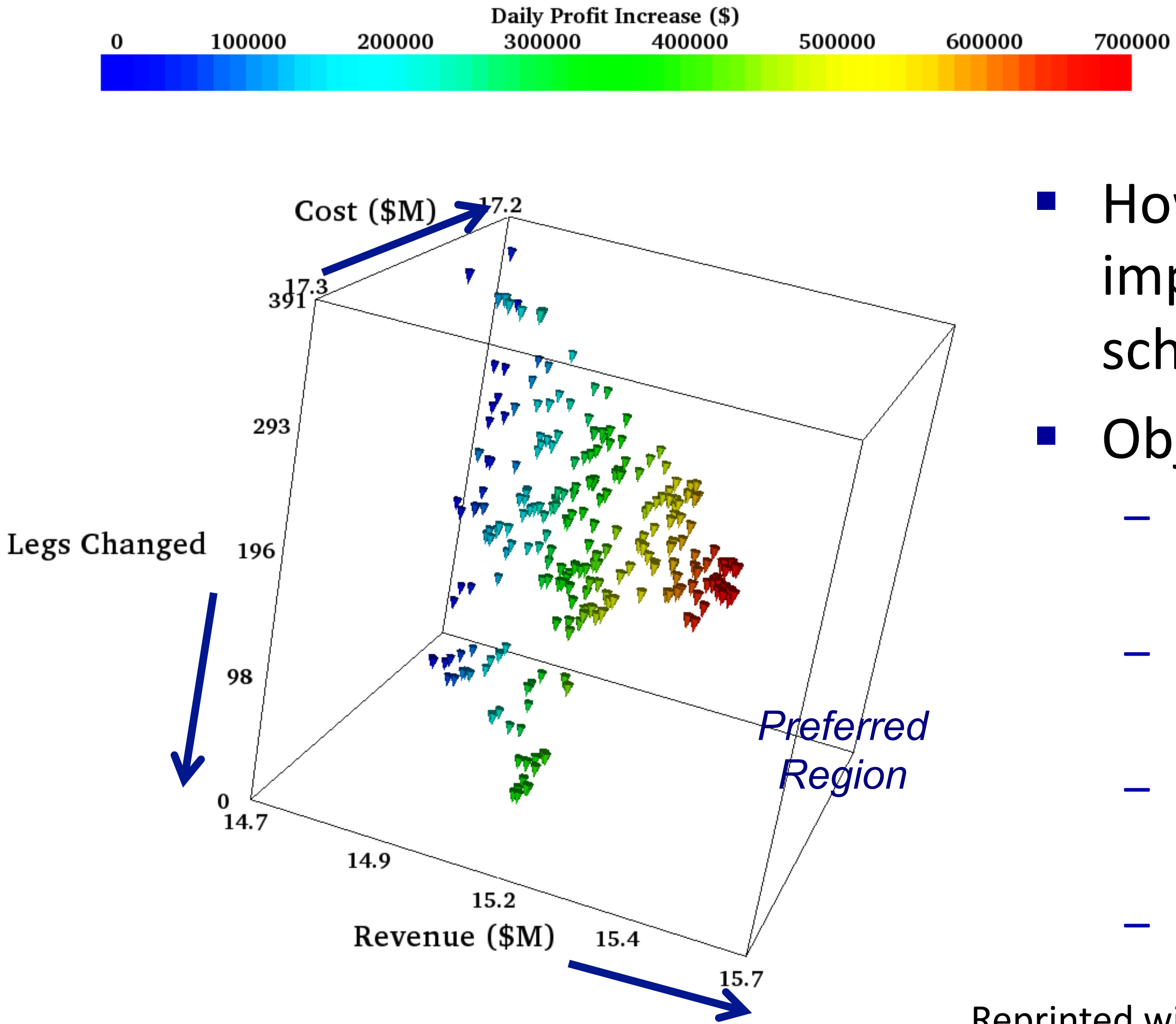
From The Aerospace Corporation 2009 Annual Report*

"While most applications to date have been based on optimizing the performance of space systems architectures, GRIPS permits the explicit trade of system-level parameters in diverse areas, such as orbits, sensor characteristics, and system costs. The GRIPS process provides a new tool to help decision makers understand the impact of system-level decisions."

"GRIPS is currently being used in support of several National Reconnaissance Office programs within imagery intelligence and signal intelligence. As a result of the insights developed through GRIPS results, system-level specifications are being modified, and decisions that were made decades ago are being reconsidered."

*Source: http://www.aero.org/corporation/AerospaceAR.pdf

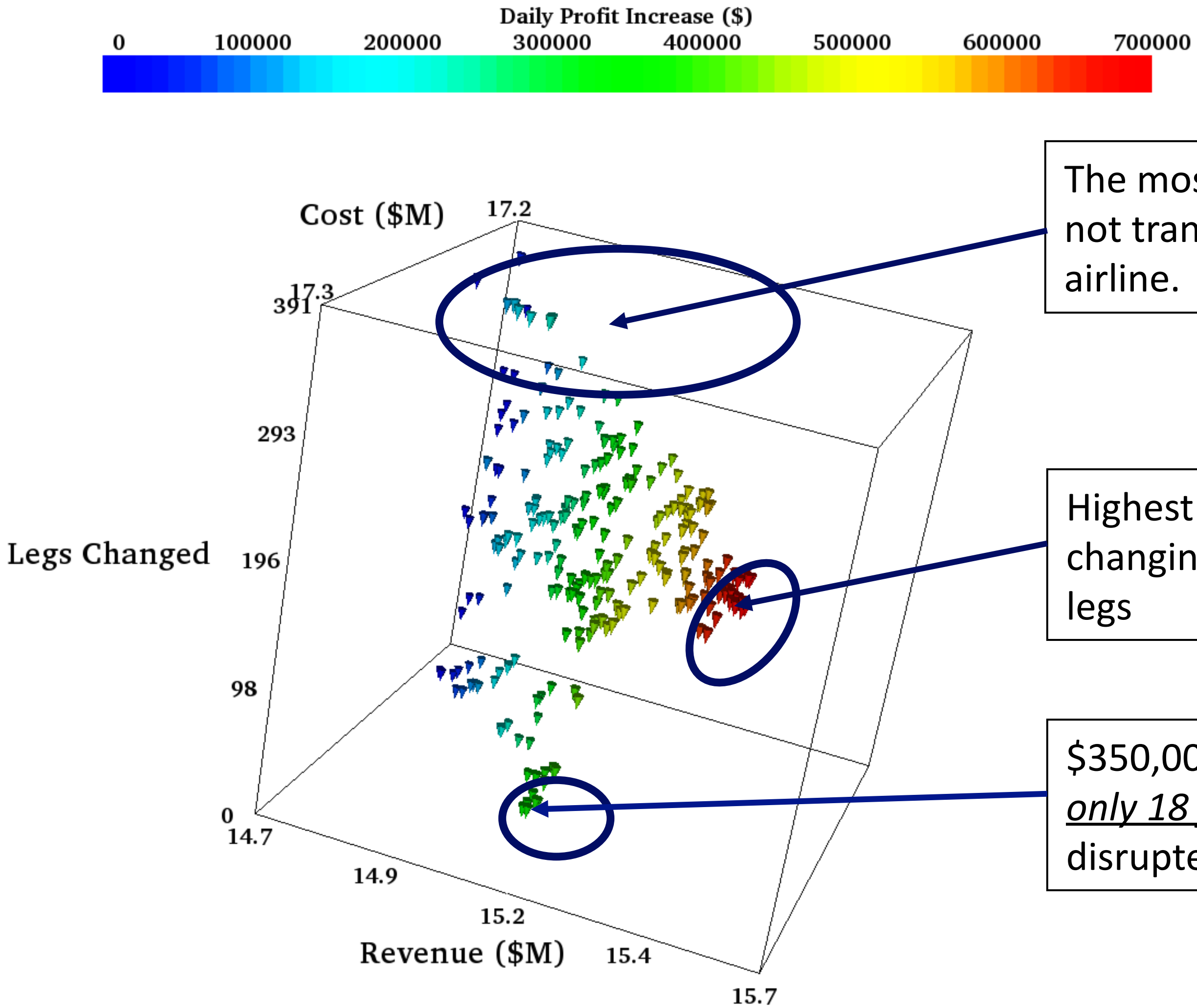
Flight Network Scheduling



- How can we optimally improve flight network scheduling?
- Objectives:
  - Minimize Cost of Changes ($Millions)
  - Minimize Schedule Disruptions (Legs Changed)
  - Maximize Passenger Revenue ($Millions)
  - Maximize Daily Profit ($)

Reprinted with permission of Apptimation LLC apptimation aviation

Flight Network Scheduling

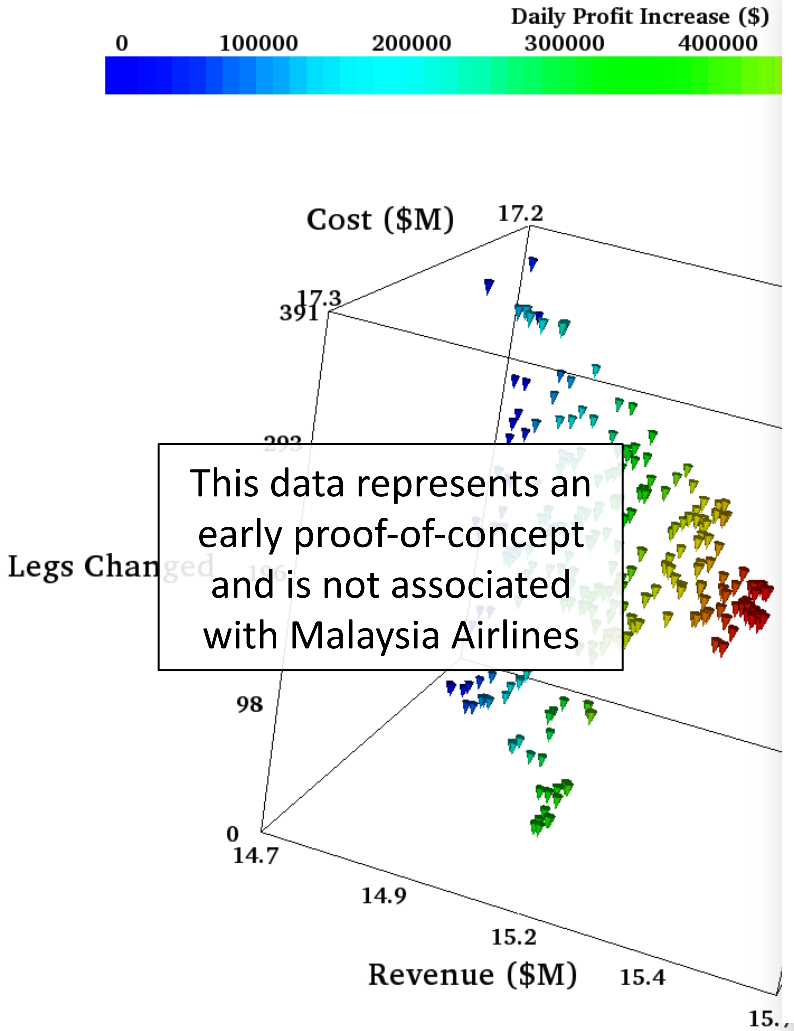


The most disruptive schedule changes do not translate into greater profits for the airline.

Highest profit is very disruptive changing 270 out of the possible 391 legs

$350,000 daily profit increase but with *only 18 flight legs* out of the possible 391 disrupted.

Airline Network Planning



This data represents an early proof-of-concept and is not associated with Malaysia Airlines

Apptimation Completes Proof of Concept with Malaysia Airlines

Apptimation LLC (Apptimation) announces the successful completion of a proof of concept with Malaysia Airlines. The proof of concept focused on Apptimation's revolutionary new airline network planning and optimization product - NetXellerate.

Denver, Colorado (PRWEB) October 13, 2011

ShareThis Email PDF Print

Apptimation LLC (Apptimation) announces the successful completion of a proof of concept with Malaysia Airlines. The proof of concept focused on Apptimation's revolutionary new airline network planning and optimization product - NetXellerate.

Working with Malaysia Airlines, Apptimation has successfully proven the applicability and value of its multi-objective evolutionary algorithm approach to one of the world's most complex problems, that of airline connectivity optimization. "Working with Apptimation introduced us to a whole new way of looking at network planning and in a short period of time NetXellerate produced results that would have taken us years to obtain otherwise," said Dr. Amin Khan – Executive Vice President Commercial Strategy at Malaysia Airlines.

When speaking of the Apptimation proof of concept with Malaysia Airlines, Dr. Matthew Ferringer, a founder of Apptimation stated - "Apptimation is extremely proud of the success we have had with Malaysia Airlines and how well NetXellerate integrated with the existing tools Malaysia Airlines uses today."

Apptimation is releasing NetXellerate to the commercial market in the 4th quarter of 2011.

Evolutionary Optimization

“Working with Apptimation introduced us to a whole new way of looking at network planning...”

About Apptimation LLC - Apptimation LLC (Apptimation) is a wholly owned travel, transportation, finance, and logistics optimization firm. Apptimation specializes in the use of multiple objective genetic algorithms to solve previously intractable problems in the travel, transportation, finance, and logistics domains; airline network connectivity optimization being just one example. For a complete overview or additional information about Apptimation, please contact an Apptimation Solutions Representative – +1-941-447-7923 – info(at)apptimation(dot)com or visit the Apptimation website at http://www.apptimation.com.

Key Points

- (1) Proposing the "**Many-Objective Visual Analytics**" framework for complex engineered systems design.

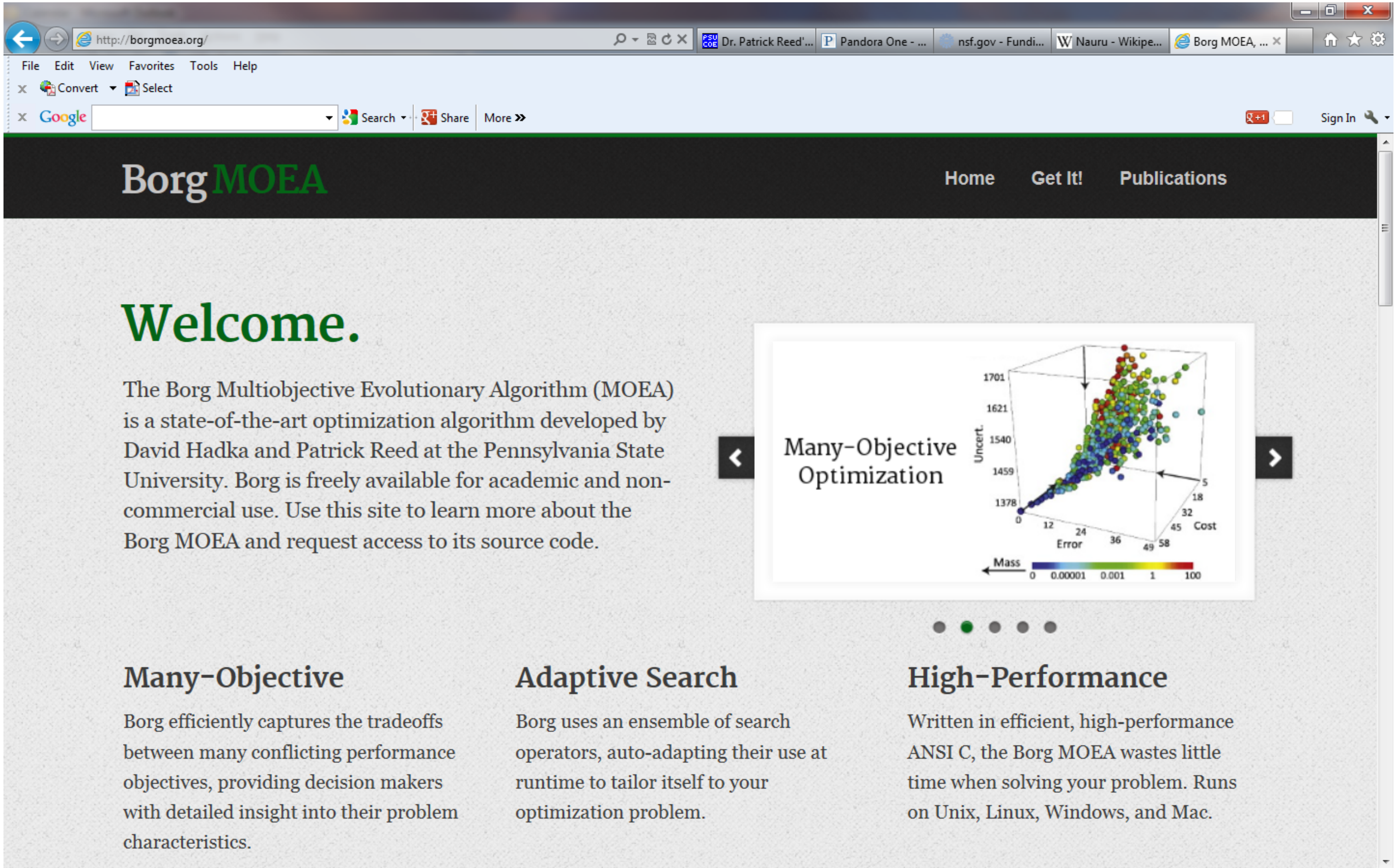
- (2) Seeking to avoid **cognitive myopia** (*too limited a view of optimality*) and **cognitive hysteresis** (*preconceptions limit discoveries*)

- (3) **Arrow's Paradox**: optimizing aggregated performance measures does not optimize individual components in a predictable fashion

- (4) **Preferences develop and evolve opportunistically** in response to how changing formulations provide solutions with desirable characteristics (what is the non-dominated problem?)

- (5) Operational use of MOEAs requires efficiency, effectiveness, reliability, and controllability—proof must be based on **rigorous algorithm diagnostics**

BorgMOEA.org



Borg MOEA

Home Get It! Publications

Welcome.

The Borg Multiobjective Evolutionary Algorithm (MOEA) is a state-of-the-art optimization algorithm developed by David Hadka and Patrick Reed at the Pennsylvania State University. Borg is freely available for academic and non-commercial use. Use this site to learn more about the Borg MOEA and request access to its source code.

Many-Objective

Borg efficiently captures the tradeoffs between many conflicting performance objectives, providing decision makers with detailed insight into their problem characteristics.

Adaptive Search

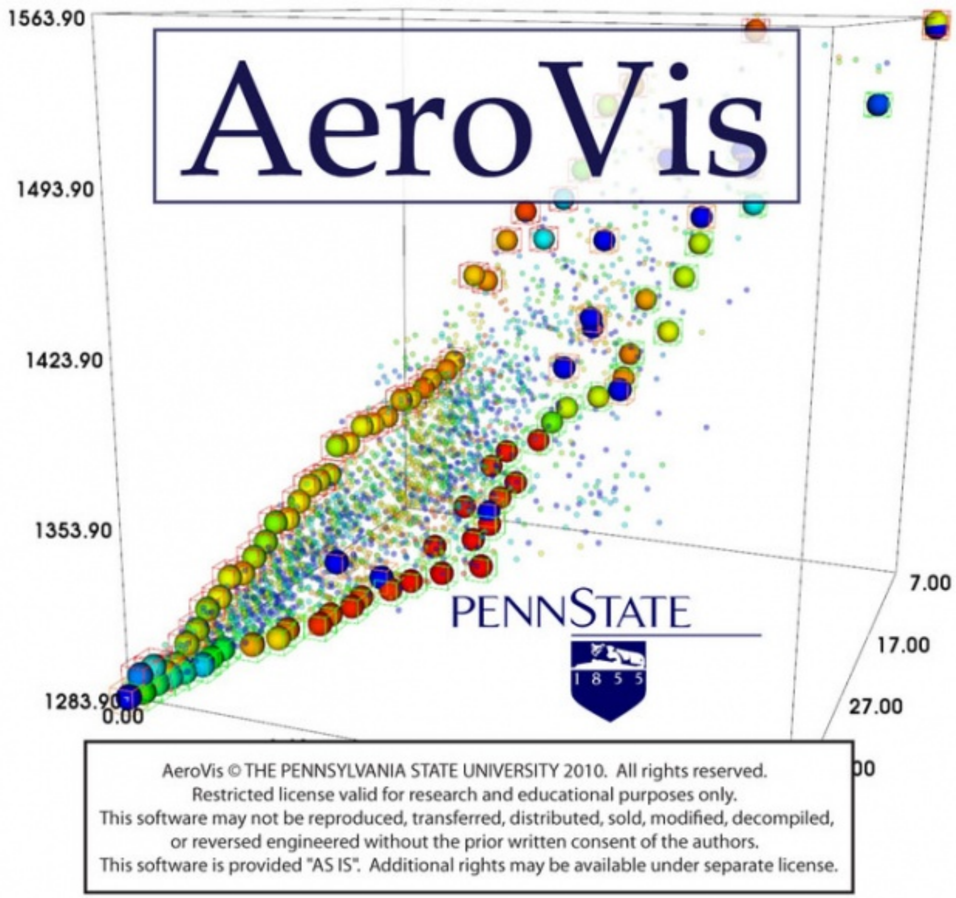
Borg uses an ensemble of search operators, auto-adapting their use at runtime to tailor itself to your optimization problem.

High-Performance

Written in efficient, high-performance ANSI C, the Borg MOEA wastes little time when solving your problem. Runs on Unix, Linux, Windows, and Mac.

Many-Objective Visual Analytics

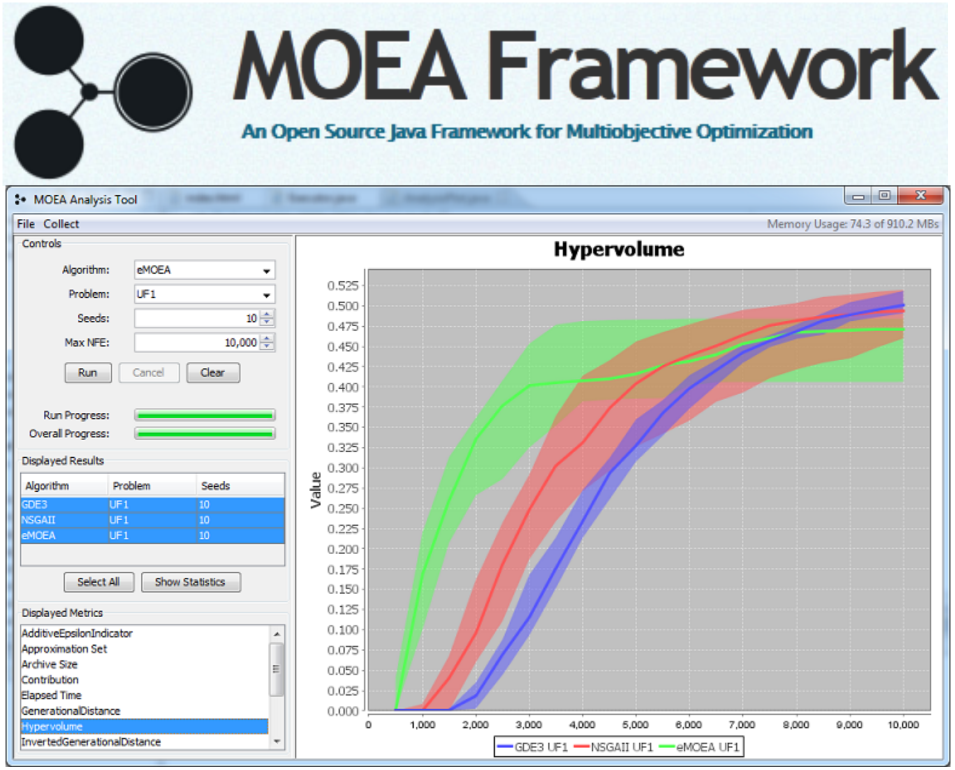
- High-dimensional visualization
- Interactive
- Efficient design space exploration



http://www.coe.psu.edu/water/index.php/Software

MOEA Framework

- Free and open source
- Java
- Features:
  - 24 MOEAs
  - Over 80 MOPs
  - Extensible
  - Run large-scale experiments



http://www.moeaframework.org

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Joshua B. Kollat, Ph.D.

Owner & Founder

Email: jkollat@decisionvis.com

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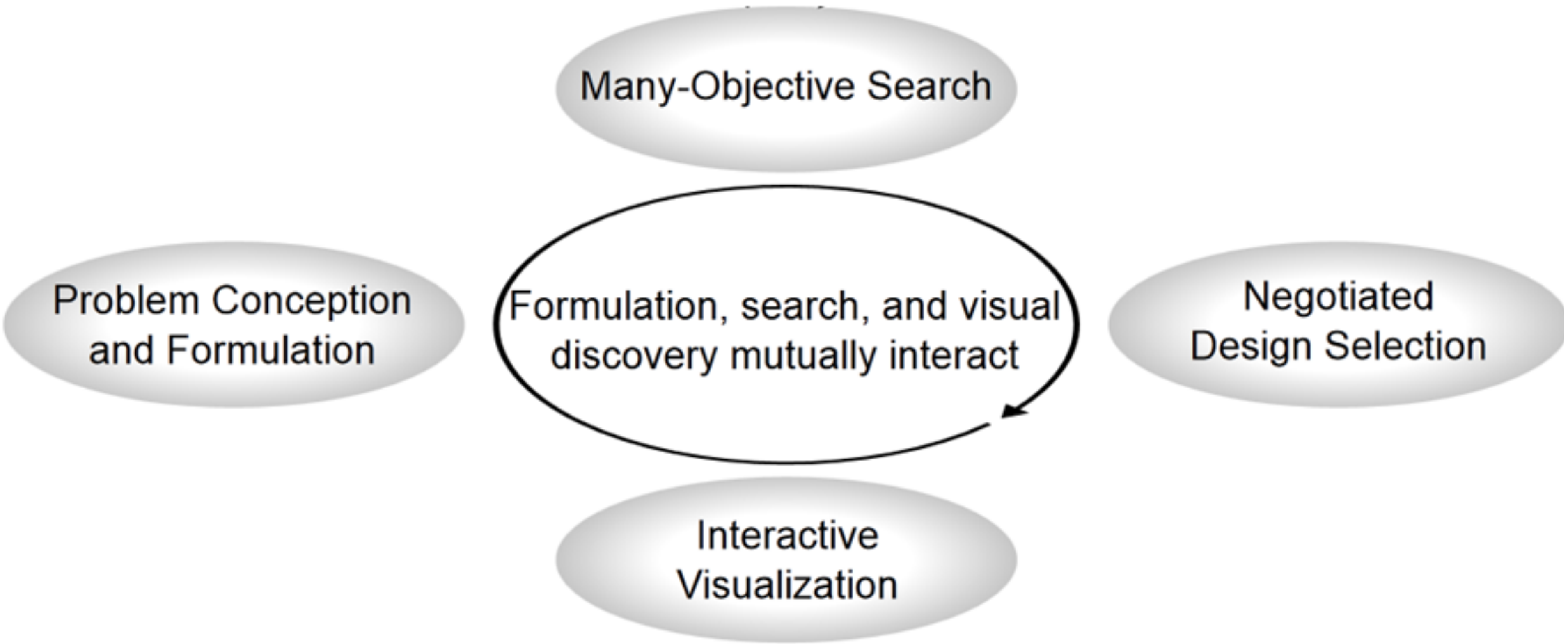
Questions?


Many-Objective Search
Problem Conception and Formulation
Formulation, search, and visual discovery mutually interact
Negotiated Design Selection
Interactive Visualization