A Multiobjective, Multidisciplinary Design Optimization Methodology for the Conceptual Design of Distributed Satellite Systems

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SSPARC IAB Meeting
May 16, 2002

Motivation

- **Objective:** **To develop a methodology for mathematically modeling the Distributed Satellite System (DSS) conceptual design problem as an optimization problem to enable an efficient search for the best families of solutions within the system trade space.**

- **Motivation:**
  - The trade-space for DSS's is ***enormous*** - too large to enumerate, analyze, and compare all possible system architectures.
  - MDO techniques have been applied successfully across many fields to find the solutions to ***complex*** problems.
  - "… the conceptual space systems design process is very ***unstructured*** … designers often pursue a ***single*** design concept, patching and repairing their original idea rather than generating new alternatives." - Proceedings of the 1998 IEEE Aerospace Conference
  - A design that is ***globally*** optimized on the basis of a system metric(s) is likely to vary drastically from a design that has been developed by optimizing each ***subsystem***.
  - A methodology is needed that will enable a greater search of the trade space and explore design options that might not otherwise be considered during the ***Conceptual Design*** Phase (when ***lifecycle cost*** gets locked in).

Case Studies

- **Name:** Terrestrial Planet Finder
- **Mission:** Terrestrial Planet Detection/ Characterization
- **Sector:** Civil
- **Sponsor:** NASA
- **TS Size:** 640 Architectures

Image removed due to copyright considerations.

[Beichman et al, 1999]

- **Name:** TechSat 21
- **Mission:** Ground Moving Target Indicator (GMTI)
- **Sector:** Military
- **Sponsor:** AFRL
- **TS Size:** 732,160

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[Martin, 2000]

- **Name:** Broadband Communication
- **Mission:** High Data Rate Communication Services
- **Sector:** Commercial
- **Sponsor:** Private Company
- **TS Size:** 42,400 Architectures

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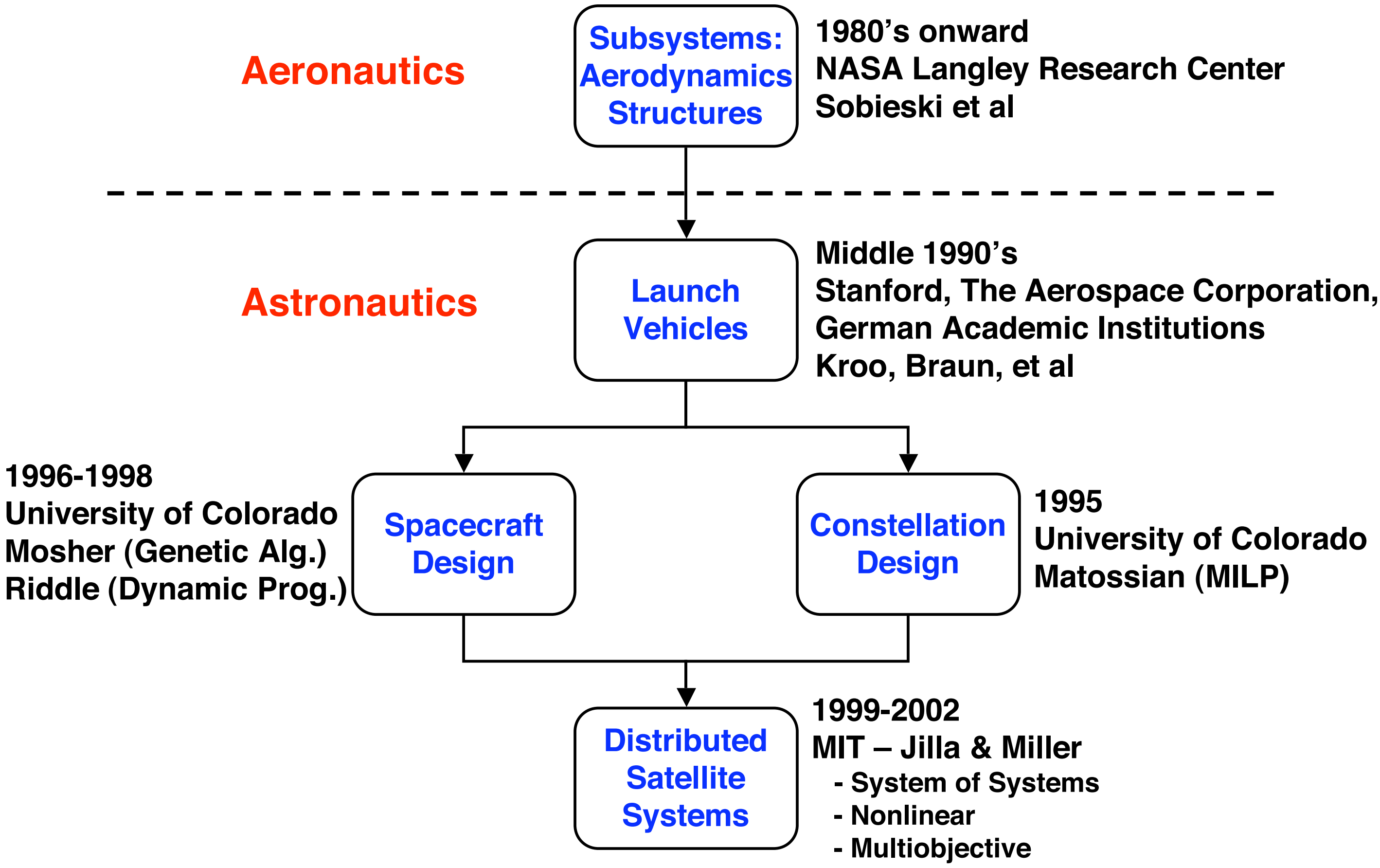
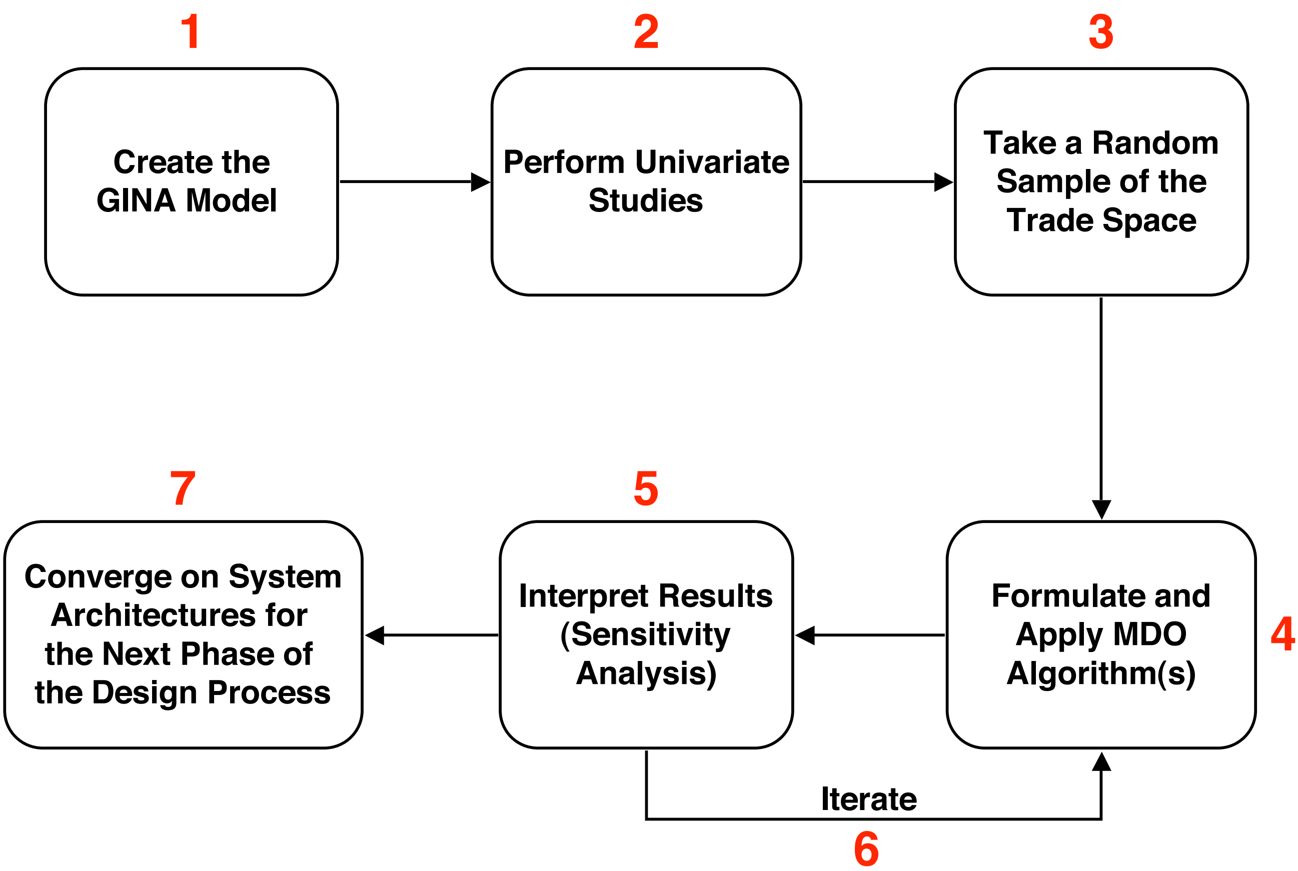
[Boeing, 2002]

Past Work – Literature Review



The MMDOSA Methodology



Step 1 – Create the GINA Model

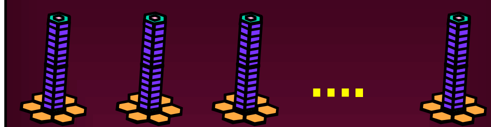
Top Trades / Capability Metrics	Number of Satellites Per Cluster	Number of Clusters	Altitude	Aperture Diameter	Transmission Power
Isolation	N/A	N/A	MDV and maximum cluster baseline	N/A	N/A
Rate	N/A	Minimum revisit time	Revisit time and area search rate	Footprint coverage area	Required dwell time
Integrity	Antenna gain pattern from cluster projection	N/A	Received signal strength	Mainlobe vs. sidelobe gain	Impacts the signal-to-noise ratio
Availability	Overall system reliability	Overall system reliability	N/A	N/A	Time required to scan a target area
Cost per Function	Learning curve effects	Learning curve effects	Launch, eclipse, & drag	Antenna mass & cost	Size of spacecraft

Constellation Radar Payload S/C Bus Deploy/Ops System Analysis

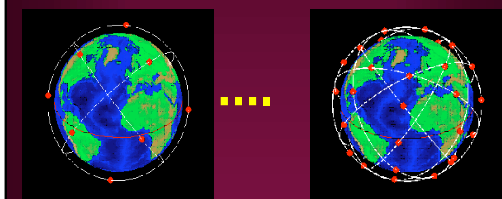
Step 1 – Develop Simulation Software

Inputs (Design Vector)

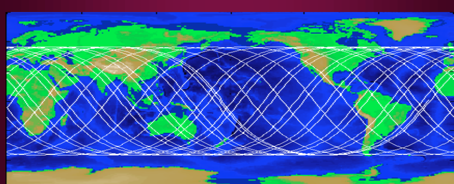
S/C per Cluster



Clusters

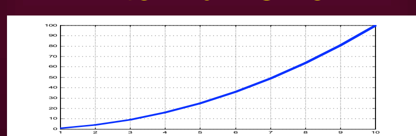


Constellation Altitude



Aperture Diameter

Antenna Power



MATLAB Models

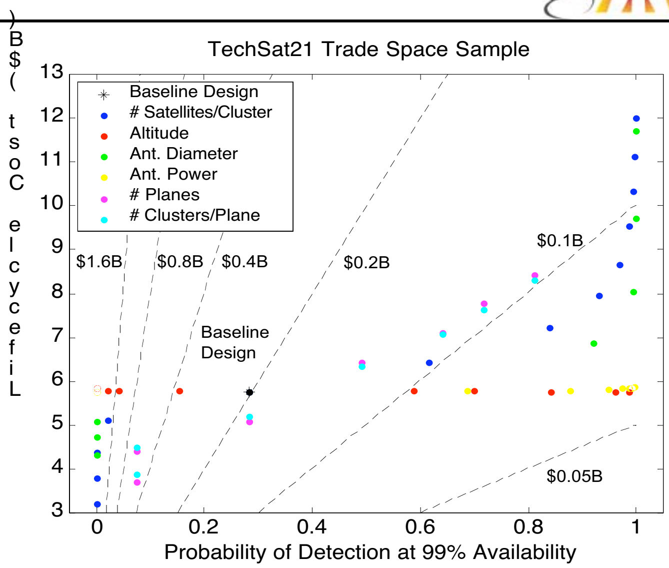
Constellation → Radar → Payload → S/C Bus → Launch & Operations → System Analysis

Key Outputs

- Lifecycle Cost
- Availability
- Probability of Detection
- Revisit Rate
- Resolution & MDV

Step 2 – Perform Univariate Studies

- **Univariate Studies**
  - Select a baseline Γ. Holding everything else constant, **vary an individual γ_i** over its entire range of values and observe how the system attributes vary.
- **Strengths**
  - Provides the systems engineer with an **initial feel** of the trade space.
  - Further assessment of **model fidelity**.
- **Weaknesses**
  - **Ignores couplings** between elements of the design vector.
  - Focuses on only a **local** portion of the global trade space.



*** Family Baseline Design Vector**

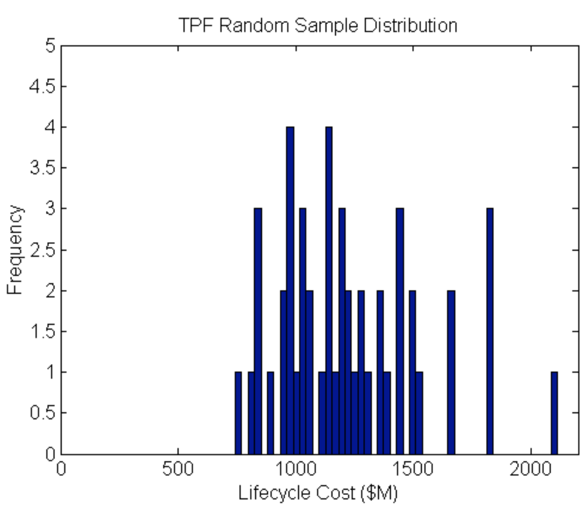
# Satellites Per Cluster:	8
Aperture Diameter:	2 m
Radar Transmission Power:	300 W
Constellation Altitude:	1000 km
# Clusters Per Orbital Plane:	6
# Orbital Planes:	6

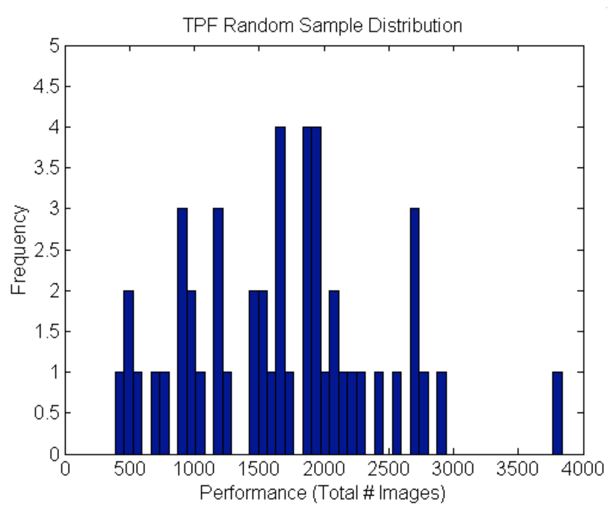
Step 3 – Random Sample

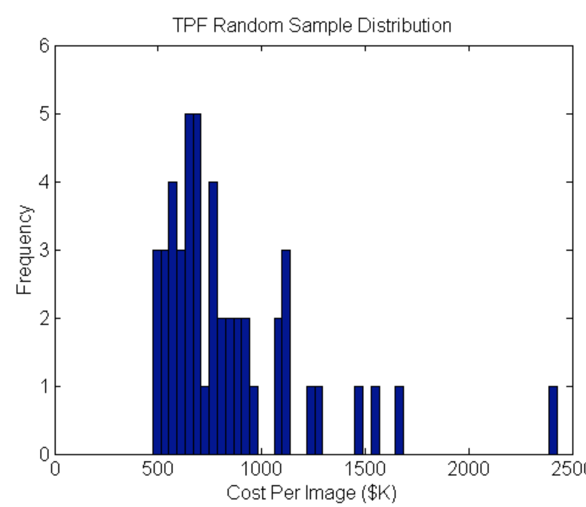
- **Random Sampling**
  - Collecting and deriving data on a population (i.e. the complete set of architectures in the DSS global trade space) after measuring only a small subset of the population in such a way that every architecture in the trade space is **equally likely** to be selected.
- **95% Confidence Intervals**
  - "Average" vs. Optimized Designs
- **Initial Optimization Bounds**
  - LP Relaxation Analogy
- **Gather Data to be Used Downstream to Tailor MDO Algorithms**
  - Simulated Annealing Δ Parameter

TPF Random Sample (n=48)

Parameter	Lifecycle Cost ($B)	Performance (# Images)	Cost Per Image ($K)
Maximum	2.11	3839	2429
Minimum	0.74	390	474
Range	1.37	3449	4955
Mean	1.23	1681	849
Standard Deviation	0.30	731	367

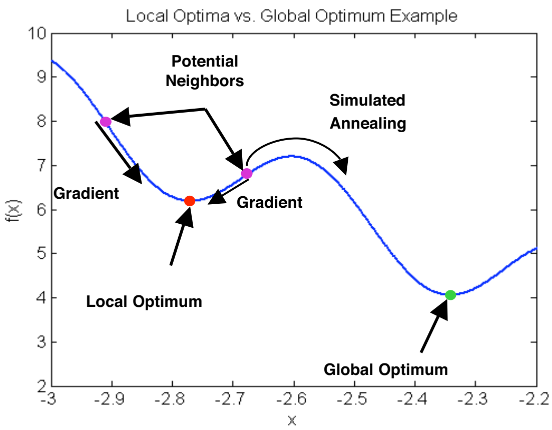






Step 4 – Apply MDO Algorithms: Single Objective Optimization

- Application of **4 MDO Techniques**
  - Taguchi Methods
  - Simulated Annealing
  - Pseudo-Gradient Search
  - Univariate Search
- **Heuristic techniques** found to be the least susceptible to getting stuck in the local optima present in the trade space of DSS's.
- **Simulated Annealing** forms the core algorithm within MMDOSA.

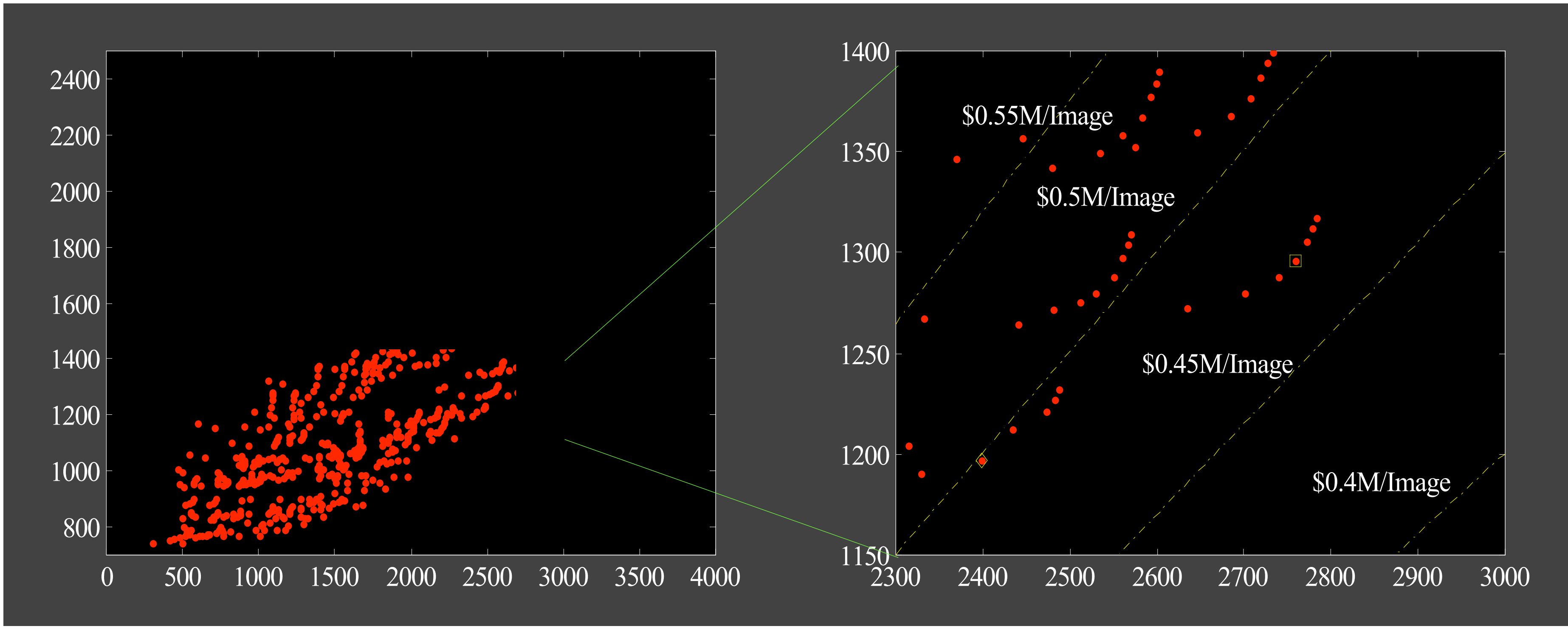


MDO Technique Performance

Trial	Simulated Annealing ($K/Image)	Pseudo-Gradient Search ($K/Image)	Univariate Algorithm ($K/Image)
1	493.8	470.8	469.6
2	470.0	470.0	469.6
3	469.6	469.6	513.8
4	505.1	520.9	469.6
5	470.8	469.6	526.0
6	470.8	469.6	513.8
7	493.8	532.6	470.8
8	470.0	469.6	525.9
9	498.2	470.8	469.6
10	496.4	483.0	473.9
MSE ($K/Image)^2	**397.1**	**678.3**	**1027.8**

(*)

Step 4 – Apply MDO Algorithms: Single Objective Optimization



"Optimal" Solution

Orbit	**4 AU**	Number of Images	**2759**
Interf.	**SCI-2D**	Total Cost	**$1.3 Billion**
# Apert.	**8**	Cost Per Image	**$469,000**
Apert.	**4 m**		

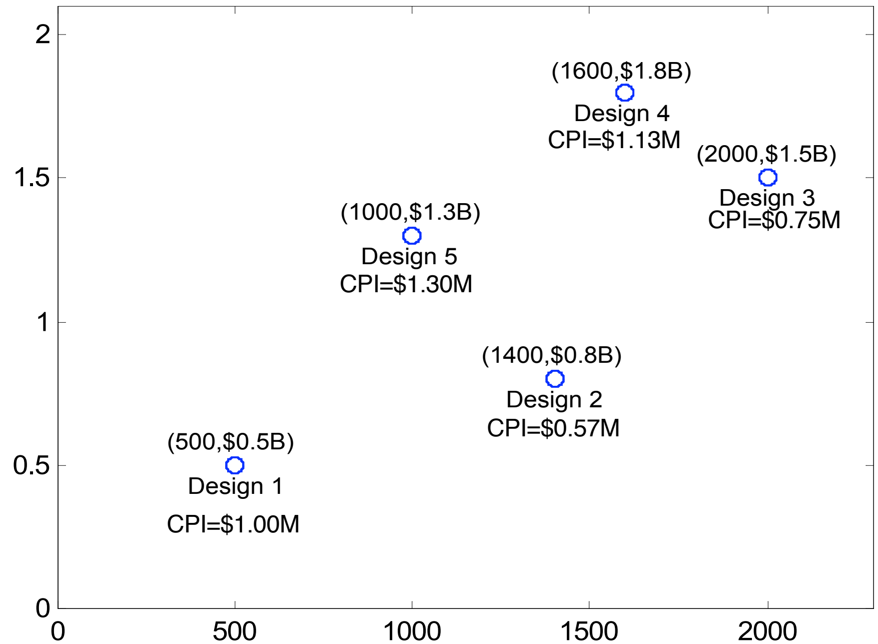
Step 4 – Apply MDO Algorithms: Multiobjective Optimization

- **Motivation:** True systems methods handles **trades**, not just a single metric. In real-world systems engineering problems, one has to **balance** multiple requirements while simultaneously trying to achieve **multiple** goals.

- **Differences** between single objective and multiobjective problems.
  - **Single objective** problems have only **one** true solution.
  - **Multiobjective** problems can have **more than one solution**.

- **Terminology:**
  - Dominated Solutions
  - Non-Dominated Solutions
  - Pareto Optimal Set

$$O_j(x_i) < O_j(y) \ \text{ for all } i \text{ and } j$$



Step 4 – Apply MDO Algorithms: Multiobjective Multiple Solution Algorithm

Goal:

To find multiple architectures in the Pareto optimal set.

New Decision Logic

$$\text{IF } E_n(\tilde{A}_k) < E_n(\tilde{A}_i) \text{ for ALL } n = 1,2,\ldots,N$$

$$\tilde{A}_i \notin P \qquad\qquad k = 1,2,\ldots,i-1$$

ELSE

$$\tilde{A}_i \in P$$

END

$$\text{IF } \tilde{A}_{i+1} \in \text{P OR } \chi < e^{-\frac{\Delta}{T}}$$

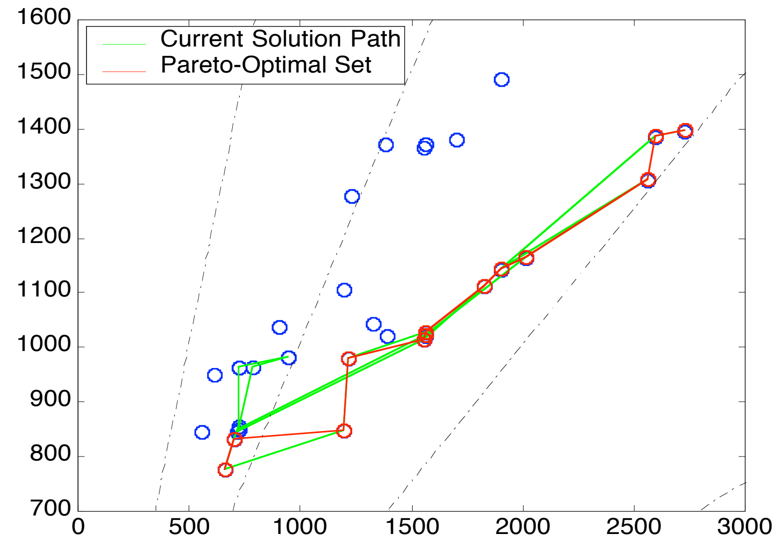
$$\tilde{A}_b = \tilde{A}_{i+1}$$

ELSE

$$\tilde{A}_b = \tilde{A}_i$$

END

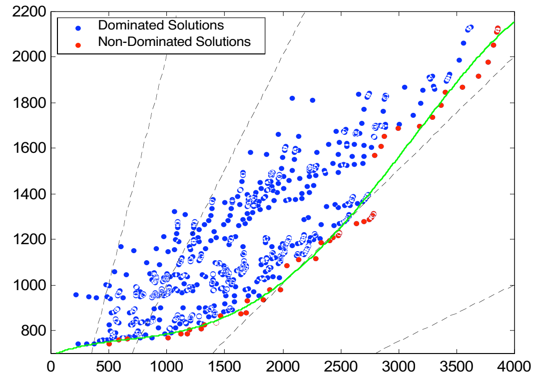
Pareto Front

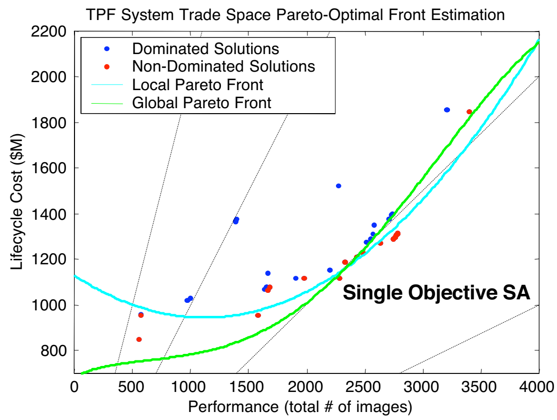


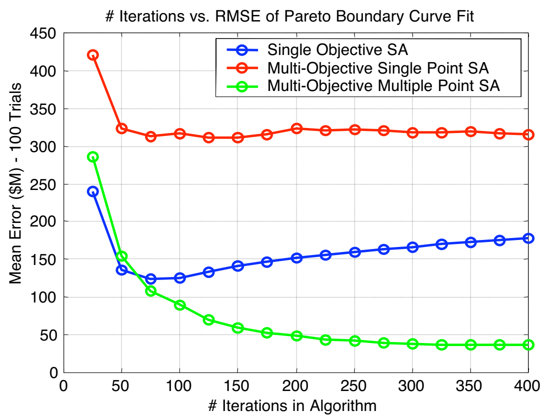
Observations:

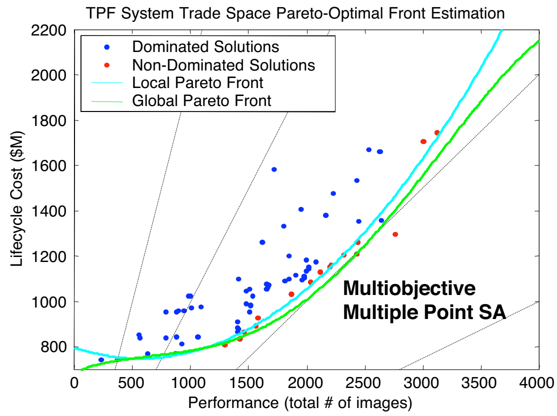
- Along this boundary, the systems engineer cannot improve the **performance** of the design without also increasing lifecycle **cost**.
- This boundary **quantitatively** captures the **trades** between the DSS design criteria.

Step 4 – Apply MDO Algorithms: Approximating the Global Pareto Boundary



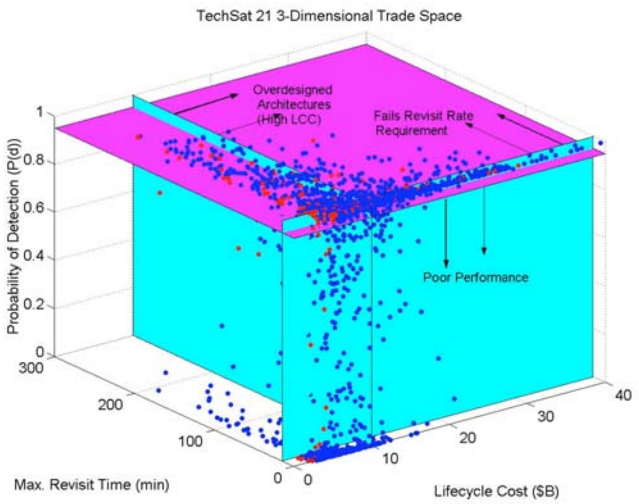


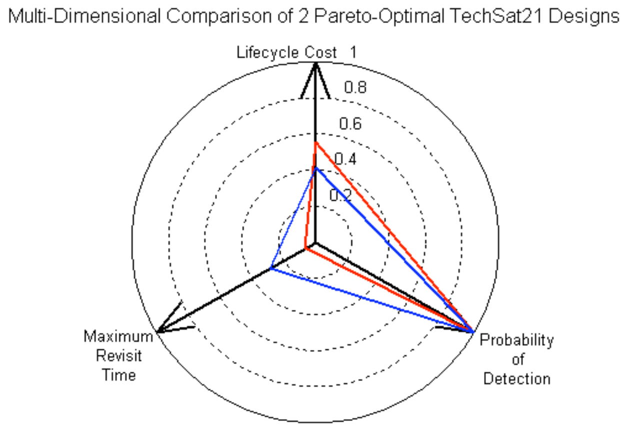




Step 4 – Apply MDO Algorithms: Multiobjective Optimization

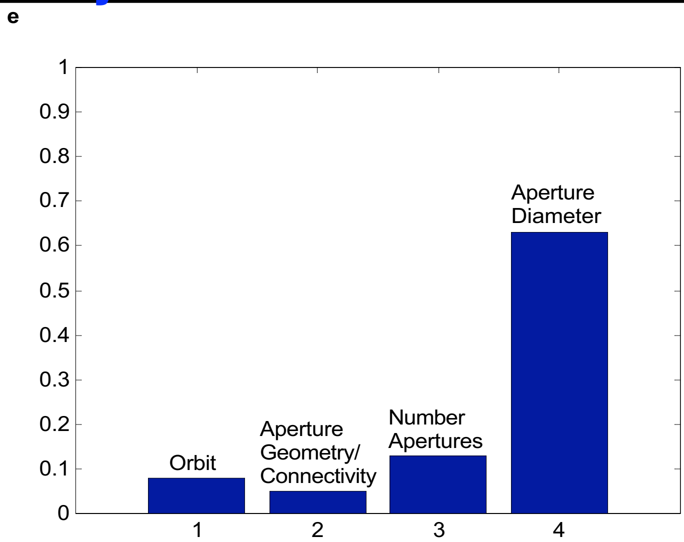
- In a **two-dimensional trade space**, the Pareto Optimal set represents the **boundary** of the most design efficient solutions.
- The same principles of Pareto Optimality hold for a trade space with **any number *n* dimensions** (ie. any number of decision criteria).
- **3 Criteria Example for Space-Based Radar**
  - Minimize(Lifecycle Cost) AND
  - Minimize(Maximum Revisit Time) AND
  - Maximize(Target Probability of Detection)





Step 5 – Interpret Results: Sensitivity Analysis

- **Finite Differencing**
  - Computationally expensive
  - Local Sensitivity
- **Key Question:** Which **variables** in the design vector have the most significant **effect** on the **metrics** of interest for **system**?
- **Analysis of Variance (ANOVA)**
  - A **statistical technique** used to detect differences in the average performance of groups of items tested.
- **ANOVA** provides the systems engineer with a tool to identify key models and guide **technology investment strategies** during the **Conceptual Design Phase** of a program.



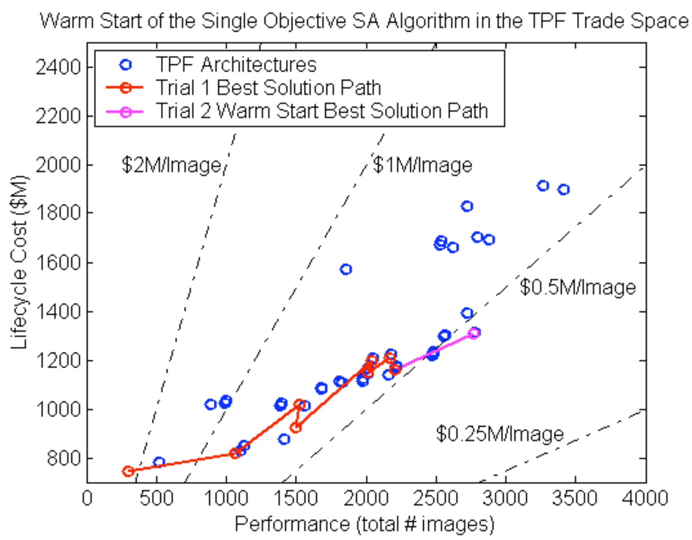
$$SS_T = \sum_{i=1}^{N} \left(y_i - \bar{T}\right)^2$$

$$SS_\gamma = \sum_{i=1}^{n} n_{\gamma_i} \left(\bar{y}_{\gamma_i} - \bar{T}\right)^2$$

$$RI = \left[\frac{SS_\gamma}{SS_T}\right] \times 100$$

Step 6 – Iterate

- Model Fidelity
- Simulated Annealing Algorithm Parameters
  - Cooling Schedule
  - DOF
- "Warm Starting"
- Run additional trials

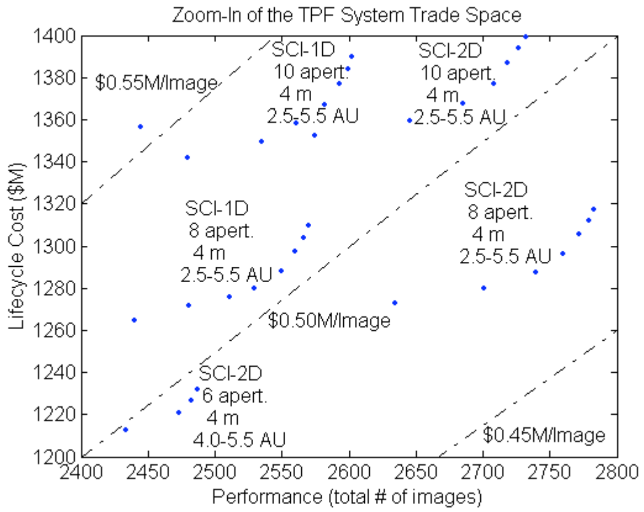


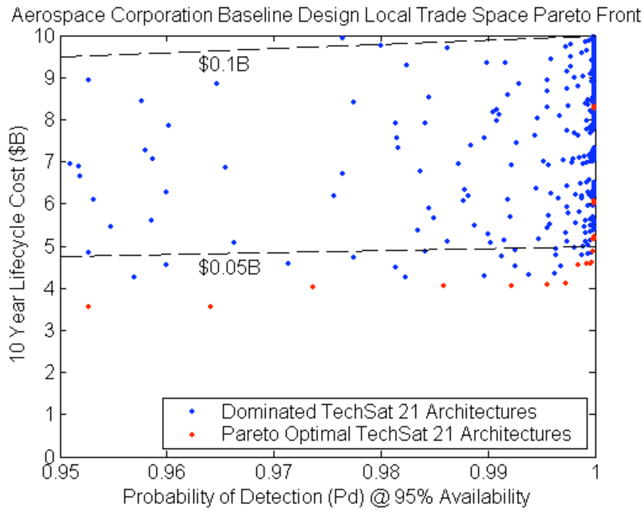
Warm Start Example

State	Orbit (AU)	Number Apertures	Collector Connectivity/ Geometry	Aperture Diameter (m)	Cost Per Image ($K)
Trial 1 Initial Architecture	1	4	SCI-1D	1	2475
Trial 1 Final Architecture	4.5	8	SCI-2D	3	526
Trial 2 Warm Start Initial Architecture	4.5	8	SCI-2D	3	526
Trial 2 Warm Start Final Architecture	4.5	8	SCI-2D	4	471

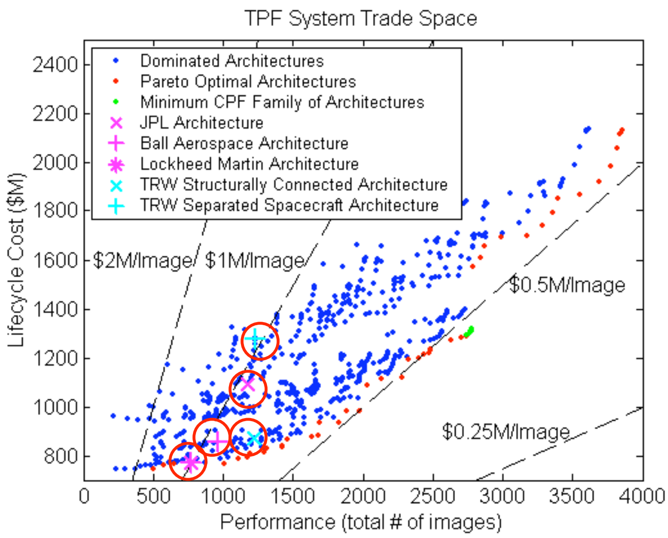
Step 7 – Recommended Architectures

- **Single Objective DSS Conceptual Design Problem**
  - The best **family(s)** of architectures with respect to the metric of interest found by the single objective simulated annealing algorithm.
- **Multiobjective DSS Conceptual Design Problem**
  - The **Pareto optimal set** with respect to the selected decision criteria as found by the multiobjective, multiple solution simulated annealing algorithm.
  - Budget Capping, Multiattribute Utility Theory, Uncertainty Analysis, Flexibility, and Policy Implications





Terrestrial Planet Finder Case Study – Results (1)



Architecture	MMDOSA Minimum CPF (% Improvement)	Pareto Optimal Equivalent Performance (% Improvement)	Pareto Optimal Equivalent LCC (% Improvement)
JPL	49%	28%	73%
Ball Aerospace	47%	10%	52%
Lockheed Martin	53%	0%	31%
TRW SCI	34%	7%	20%
TRW SSI	55%	37%	119%

Terrestrial Planet Finder Case Study – Results (2)

Mission Cost & Performance

Low

Medium

High

Family
4 ap.
SCI-1D
2 m Diam.

Family
6 ap.
SCI-2D
4 m Diam.

Family
6 ap.
SSI-2D
4 m Diam.

Family
10 ap.
SSI-1D
4 m Diam.

# "Images"	LCC ($B)	Orbit (AU)	# Apert.'s	Architecture	Apert. Diam. (m)
502	0.743	1.5	4	SCI-1D	1
577	0.762	2.0	4	SCI-1D	1
651	0.767	2.5	4	SCI-1D	1
1005	0.768	1.5	4	SCI-1D	2
1114	0.788	2.0	4	SCI-1D	2
1171	0.790	2.5	4	SCI-1D	2
1195	0.807	1.5	6	SCI-1D	2
1292	0.811	1.5	6	SCI-2D	2
1317	0.830	1.5	8	SCI-1D	2
1424	0.836	2.0	4	SCI-1D	3
1426	0.838	1.5	8	SCI-2D	2
1464	0.867	2.5	6	SCI-2D	2
1631	0.877	1.5	6	SCI-1D	3
1684	0.881	1.5	6	SCI-2D	3
1687	0.932	2.0	6	SCI-1D	3
1828	0.936	2.0	6	SCI-2D	3
1881	0.980	1.5	8	SCI-2D	3
1978	0.982	1.5	6	SCI-1D	4
2035	1.086	2.0	8	SCI-2D	3
2132	1.112	1.5	8	SCI-1D	4
2285	1.120	1.5	8	SCI-2D	4
2328	1.190	2.5	6	SCI-2D	4
2398	1197	3.0	6	SCI-2D	4
2433	1.212	4.0	6	SCI-2D	4
2472	1.221	4.5	6	SCI-2D	4
2482	1.227	5.0	6	SCI-2D	4
2487	1.232	5.5	6	SCI-2D	4
2634	1.273	2.5	8	SCI-2D	4
2700	1.280	3.0	8	SCI-2D	4
2739	1.288	3.5	8	SCI-2D	4
2759	1.296	4.0	8	SCI-2D	4
2772	1.305	4.5	8	SCI-2D	4
2779	1.312	5.0	8	SCI-2D	4
2783	1.317	5.5	8	SCI-2D	4
2788	1.569	3.0	6	SSI-2D	4
2844	1.609	3.5	6	SSI-2D	4
2872	1.655	4.0	6	SSI-2D	4
2988	1.691	2.0	8	SSI-1D	4
3177	1.698	2.5	8	SSI-1D	4
3289	1.739	3.0	8	SSI-1D	4
3360	1790	3.5	8	SSI-1D	4
3395	1.850	4.0	8	SSI-1D	4
3551	1.868	2.5	10	SSI-1D	4
3690	1.919	3.0	10	SSI-1D	4

Family
4 ap.
SCI-1D
1 m Diam.

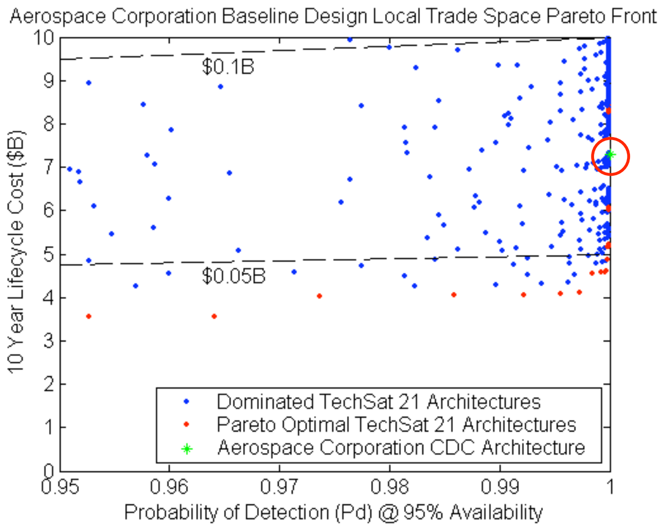
Intersection
of Multiple
Families

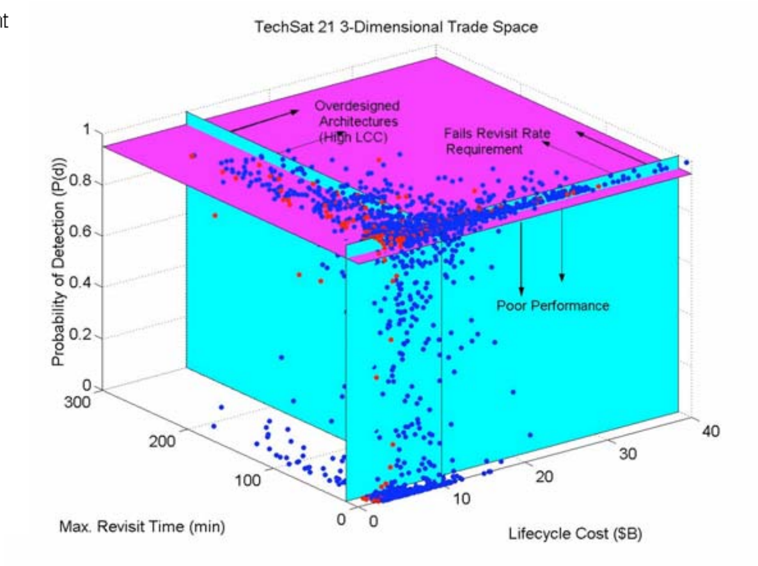
Family
8 ap.
SCI-2D
4 m Diam.

Transition from
SCI to SSI
Designs

Family
8 ap.
SSI-1D
4 m Diam.

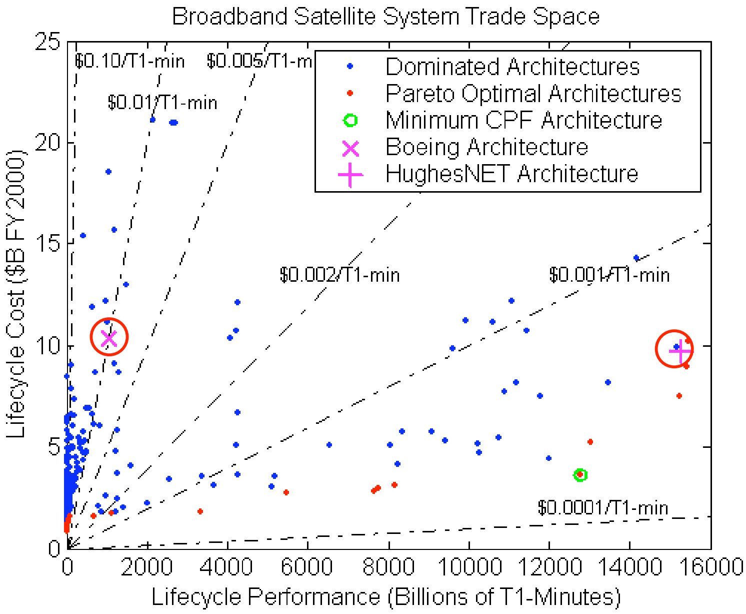
TechSat 21 Case Study – Results





Architecture	CPF % Improvement	Lifecycle Cost % Improvement	Probability of Detection % Improvement	Max. Revisit Time % Improvement
CDC Trade Space	49%	51%	-4%	0%
Global Trade Space - SO	65%	66%	-3%	13%
Global Trade Space - MO	54%	57%	-5%	67%

Broadband Communication Case Study – Results (1)



Architecture	MMDOSA Minimum CPF (% Improvement)	Pareto Optimal Equivalent Performance (% Improvement)	Pareto Optimal Equivalent LCC (% Improvement)
Boeing	97%	85%	1392%
HughesNet	59%	22%	1%

Broadband Communication Case Study – Results (1)

Mission Cost & Performance

Low

Single GEO

Family
Small LEO's
Low Inclination
Low Power

Med.

Family
Big LEO's
High Inclination
High Power

High

# Subscriber Years (M)	LCC ($B)	Const. Altitude	Const. Inclination (°)	# Satellites Per Plane	# Orbital Planes	Payload Transmission Power (kW)	Antenna Transmission Area (m2)
0.00120	0.81	GEO	0	1	1	1	1.0
0.00573	0.83	MEO	0	3	1	1	0.5
0.0140	0.93	MEO	0	7	1	1	0.5
0.0237	0.96	MEO	0	6	1	1	1.0
0.0553	1.12	MEO	0	7	1	1	2.0
0.0676	1.18	MEO	0	5	1	1	3.5
0.0794	1.28	MEO	15	5	2	1	2.0
0.095	1.44	MEO	0	8	1	1	3.0
0.157	1.56	MEO	30	5	2	1	4.0
1.32	1.58	LEO	0	7	1	2	0.5
2.15	1.70	LEO	0	7	1	2	1.5
6.37	1.78	LEO	30	7	4	1	1.0
10.4	2.71	LEO	45	3	10	1	2.0
14.6	2.79	LEO	45	5	8	1	2.0
14.8	2.95	LEO	30	5	6	1	4.0
15.5	3.09	LEO	30	5	6	1	4.5
24.3	3.62	LEO	60	6	10	1	3.5
24.8	5.22	LEO	45	7	10	1	3.0
29.0	7.53	LEO	75	7	8	3	4.0
29.4	8.98	LEO	75	7	8	4	4.0
29.4	10.20	LEO	60	5	10	5	3.0
29.5	20.43	LEO	75	7	8	10	3.5

Transition from GEO to MEO Architectures

Family
Small MEO's
Low Inclination
Low Power

Transition from MEO to LEO Architectures

Family
Big LEO's
High Inclination
Low Power

Thesis Contributions (1)

- Developed a **methodology** for mathematically formulating **DSS** conceptual design problems as **nonlinear multiobjective optimization** problems.
- Determined that a heuristic **simulated annealing** technique finds the best system architectures with **greater consistency** than Taguchi, gradient, and univariate techniques when searching a nonconvex DSS trade space.
- Created **two new multiobjective variants** of the core simulated annealing (SA) algorithm – the multiobjective single solution SA algorithm and the multiobjective multiple solution SA algorithm.
- For each of the **three case study missions**, identified specific architectures that provide **higher levels of performance** for **lower lifecycle costs** than prior proposed designs.

Thesis Contributions (2)

- Created a method for computing the **simulated annealing Δ-parameter**, originally developed and intended for single objective optimization problems, for **multiobjective** optimization problems.
- Gathered empirical evidence that the **2-DOF** variant of the simulated annealing algorithm is the **most effective** at both single objective and multiobjective searches of a DSS trade space.
- Developed an **integer programming** approach to model and solve the DSS **launch vehicle selection** problem as an optimization problem.