



Multidisciplinary System Design Optimization (MSDO)

Optimization of a Hybrid Satellite Constellation System

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- Introduction
 - Satellite constellation design
- Simulation
 - Modeling
 - Benchmarking
- Optimization
 - Single objective
 - Gradient based
 - Heuristic: Simulated Annealing
 - Multi-objective
- Conclusions and Future Research



Motivation/Background

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Past attempts at mobile satellite communication systems have failed as there has been an inability to match user demand with the provided capacity in a cost-efficient manner (e.g. Iridium & Globalstar)

Two main assumptions:

- Circular orbits and a common altitude for all the satellites in the constellation
- Uniform distribution of customer demand around the globe

Given a non-uniform market model, can the incorporation of elliptical orbits with repeated ground tracks expand the cost-performance trade space favorably?

Aspects of the satellite constellation design problem previously researched:

-T Kashitani (MEng Thesis, 2002, MIT)

-M. Parker (MEng Thesis, 2001, MIT)

-O. de Weck and D. Chang (AIAA 2002-1866)



Market Distribution Estimation

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0

0.01

0.02

0.03

0.04

0.05

0.06

0.07

0.08

0.09

0.1

Reduced Resolution for Simulation



Problem Formulation

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• A circular LEO satellite backbone constellation designed to provide minimum capacity global communication coverage,

• An elliptical (Molniya) satellite constellation engineered to meet high-capacity demand at strategic locations around the globe (in particular, the United States, Europe and East Asia).

Single Objective J: min the lifecycle cost of the total hybrid satellite constellation sys.

Constraints :

- * the total lifecycle cost must be strictly positive
- * the data rate market demand must be met at least 90% of the time
 - the satellites must service 100% of the users 90% of the time
 - data rate provided by the satellites >= to the demand
 - all satellites must be deployable from current launch vehicles

Design Vector for Polar Backbone Constellation:

<C [polar/walker], emin [deg], MA, ISL [0/1], h [km], Pt [W], DA [m]>

Design Vector for Elliptical Constellation:

<T [day], e [-], Np [-], Pt [W], Da [m]>



Simulation Model

1	6.	8	88	B
E	S	D.	7	7





Tradespace Exploration

- An orthogonal array was implemented for the elliptical constellation DOE
- The recommended initial start point for the numerical optimization of the elliptical constellation is

Xo_{init} =[T=1/6,e=0.6,NP=4,Pt=500,DA=3]^T

- In order to analyze the tradespace of the Polar constellation backbone, a full factorial search was conducted, the Pareto front of non dominated solutions was then defined
- The lowest cost Polar constellation was found to have the following design vector values

X = [C=polar,emin=5 deg,MA=QPSK,ISL=1, h=2000,Pt=0.25,DA=0.5]^T

Factor	Level	Effect
T	4	-207.3
Т	6	159.8
Т	12	131.13
т	24	-95.5
E	0	53.8
E	0.2	-13.98
E	0.4	217.93
E	0.6	-515.55
NP	1	-262.0
NP	2	-36.85
NP	3	717.57
NP	4	-319.13
Pt	500	-975.78
Pt	1000	-849.5
Pt	5000	532.03
Pt	10000	1441.1
DA	1.5	315.8
DA	2.0	25.15
DA	2.5	166.25
DA	3.0	-571.0

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Code Validation



LEO BACKBONE :

- Simulation created by de Weck and Chang (2002)
 - Code benchmarked against a number of existing satellite systems
 - Outputs within 20% of the benchmark's values
- Slight modifications made to suit the broadband market demand
 - # of subscribers, required data rate per user, avg. monthly usage etc...

CODE VALIDATION:

- Orbit and constellation calculations
 - Validated by plotting and visually confirming orbits



Elliptical Benchmarking

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ELLIPTICAL CONSTELLATION :

Simulation benchmarked against Ellipso

- Ellipso
 - Elliptical satellite constellation system proposed to the FCC in 1990
 - (T = 24, NP = 4, phasing of planes = 90 degrees apart)
- System benchmarked on modular basis

• Ellipso didn't use the same demand model, thus a constraint benchmark process was not conducted.

System		Ellipso	Simulation	Units
Module				
Link Budget	Antenna Gain	12	11.93	[dBi]
	EIRP	27	24.93	[dBW]
	Data Rate	2.2	1.08	[Mbps]
Spacecraft	Sat Mass	68	98.68	[Kg]
	Sat Volume	0.0008	0.810	m ³
Lifecycle Cost		249.6	290.9	[YR2002 \$M]

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Gradient-Based Optimization

- Sequential Quadratic Programming (SQP)
 - Simplification => number of planes integer
- Objective: minimize lifecycle cost

Initial guess:

Period (T):	0.5 day
Eccentricity (e):	0.01
# Planes (NP):	4
Transmitter Power (Pt):	4000 W
Antenna Diameter (DA):	3 m

J: \$6280.5999 M

Optimal:

Period (T):	0.7 day
Eccentricity (e):	0
# Planes (NP):	4
Transmitter Power (Pt):	3999.7 W
Antenna Diameter (DA):	1.76 m

J*: \$6187.8559 M

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Sensitivity Analysis



Optimal Design, x*:

Period (T):	0.7 day
Eccentricity (e):	0
# Planes (NP):	4
Transmitter Power (Pt):	3999.7 W
Antenna Diameter (DA):	1.76 m

Parameters:

Data Rate: 1000 kbps Step Size: 10 kbps # Subscribers: 1000 users Step Size: 10 users







Heuristic Optimization



- Simulated annealing was used
- Quite sensitive to cooling schedule and starting conditions
- Not very repeatable
 - Low confidence that global optimum was reached
- Total computational cost high
- Abandoned in favor of full-factorial evaluation of the tradespace for the multi-objective case
 - Possibly gain insight into key trends

Sample Simulated Annealing Run ESD.77





Multi-Objective Optimization



- Try to simultaneously:
 - Minimize Lifecycle Cost (LCC)
 - Maximize Time Averaged Over Capacity

```
If % market served > min market share
    Over capacity = ...
    Total capacity - Market served
Else
    Over capacity = 0
End
```

• Min market share chosen to be 90%

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Full Factorial Tradespace

- 1280 designs evaluated
- Interesting trends revealed

Factor	Levels	Units
Т	1,1/2,1/3,1/4,1/5	[days]
е	0.001, 0.1, 0.3 0.4	[-]
NP	2, 3, 4, 6	[-]
Pt	1, 2, 4, 6	[kW]
DA	1.5, 2, 2.5, 3	[m]

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Very high average over

Unrestricted Pareto Front

 Seems counterintuitive that high success does not yield high average

capacity

 Look at the design trade to find an explanation

over capacity



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Restricted Pareto Front



- Much smaller AOC when demand constraint is enforced
- Again explore the tradespace by coloring by DV values

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Restricted Tradespace



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Some Useful Visualizations



- Convex Hulls
 - Smallest convex polygon that contains all points in the tradespace that have a design variable at a particular value
 - Determines regions that are 'closed off' when a design choice is made
- Conditional Pareto Fronts
 - Pareto optimal set of points given that a particular design choice has been made
 - When compared to the unconditioned front, can determine key characteristics of designs on sections of the Pareto front



Convex Hulls





Conditional Pareto Fronts



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Conclusions and Future Work



- Historic mismatch between capacity and demand
- Hybrid constellations
 - First provide baseline service
 - Then supplement backbone to cover high demand
 - Allows for staged deployment that adjusts to an unpredictable market
- Pareto analysis
 - $-\frac{1}{2}$ day period, ~0 eccentricity
 - Transmitter power key to location on Pareto front
 - Number of planes, antenna gain not as important



Future Work

- Coding for radiation shielding due to van Allen belts
 - Current CER for satellite hardening is taken as 2-5% increment in cost
 - Can compute hardening needed using NASA model need to translate hardening requirement into cost increment
- Model hand-off problem
 - Transfer of a 'call' from one satellite to another
 - Not addressed in current simulation
 - Key component of interconnected network satellite simulations
- Increase the fidelity of the simulation modules with less simplifying assumptions
- Increase fidelity of cost module
 - Include table of available motors for the apogee and geo transfer orbit kick motors





Backup Slides

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Demand Distribution Map

GN	P-P	PP
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Population



Demand

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Example Ground Tracks



Sample Ground Track: T=1/2 day; e=0.5

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Sensitivity Analysis: Design Variables

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Compute Gradient

• Normalize

$$\nabla Jnormalized = \frac{x^*}{J(x^*)} \nabla J = \begin{bmatrix} \frac{\partial J}{\partial T} \\ \frac{\partial J}{\partial \epsilon} \\ \frac{\partial J}{\partial Pt} \\ \frac{\partial J}{\partial DA} \end{bmatrix} = \begin{bmatrix} -102.1317 \\ 114.5666 \\ 204.0848 \\ 0.3328 \\ 40.5873 \end{bmatrix}$$

$$\nabla Jnormalized = \frac{x^*}{J(x^*)} \nabla J = \begin{bmatrix} \left(\frac{0.7}{6187.8559}\right)^* - 102.1317 \\ \left(\frac{0}{6187.8559}\right)^* - 102.1317 \\ \left(\frac{4}{6187.8559}\right)^* 204.0848 \\ \left(\frac{3999.7}{6187.8559}\right)^* 0.3328 \\ \left(\frac{1.8}{6187.8559}\right)^* 40.5873 \\ 12 \text{ May } 2003 - \text{Chan, Samuels, Shah, Underwood} \end{bmatrix}$$



Sensitivity Analysis: Parameters

- Basic Equation
 - Finite Differencing
- Data Rate
 - Step Size: 10 kbps

$$\frac{\Delta J}{\Delta p} = \frac{J(p^{o} + \Delta p) - J(p^{o})}{\Delta p}$$

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$$\frac{\Delta J}{\Delta p} = \frac{J(p^{\circ} + \Delta p) - J(p^{\circ})}{\Delta p} = \frac{2003.884M\$ - 2008.7703M\$}{10} = -0.48863$$

• # Subscribers

- Step Size: 10 users

$$\frac{\Delta J}{\Delta p} = \frac{J(p^{\circ} + \Delta p) - J(p^{\circ})}{\Delta p} = \frac{2003.7966M\$ - 2008.7703M\$}{10} = -0.49737$$



Simulated Annealing Tuning (I)



Nature of Tuning Implemented	J* [\$M]	x* [T, e, NP ,Pt, DA] ^T	Improvement from optimal SA cost of 5389 [\$M]?
1. Geometric progression cooling schedule with a 15% decrease per iteration	\$5753.4 (50 runs)	[1/7, 0.01, 2, 2918.23, 2.33] ^T	No, optimal cost increased by \$364 million dollars
2. Geometric progression cooling schedule with a 25% decrease per iteration	\$5427.9 (50 runs)	[1/7, 0.01, 3, 1581.72, 2.23] ^T	No, optimal cost increased by \$39 million dollars
3. Stepwise reduction cooling schedule with a 25% reduction per iteration	\$6278.7 (50 runs)	[1/2, 0.01, 4, 4000, 3] ^T	No, optimal cost and design vector remained the values they were before optimization
4. Geometric progression cooling schedule with a 15% decrease per iteration but with the added constraint that the result of each iteration has to be better than the one preceding it.	\$5800.1 (41 runs)	[1/2, 0.01, 3, 3256.08, 2.17] ^T	No, optimal cost increased by \$411 million dollars



Simulated Annealing Tuning (II)

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Nature of Tuning Implemented	J* [\$M]	x* [T, e, NP ,Pt, DA] ^T	Improvement from optimal SA cost of 5389 [\$M]?
5. Initial Temperature is doubled (i.e., initial temperature changed from 6278.7 [\$M] to 12557.4 [\$M]	\$6278.7 (50 runs)	[1/2, 0.01, 4 , 4000, 3] ^T	No, optimal cost and design vector remained the values they were before optimization
6. Initial Temperature is halved. (i.e., initial temp changed from 6278.7 [\$M] to 3139.4 [\$M]	\$5622.7 (50 runs)	[1/2, 0.01, 2, 3658.08, 2.3] ^T	No, optimal cost increased by \$234 million dollars
7. Initial design vector is altered such that $x_0 = [1, 0, 3, 3000, 3]^T$	\$5719.1 (50 runs)	[1, 0, 3, 3000, 3] ^T	No, optimal cost increased by \$330 million dollars
8. Initial design vector was altered such that $x_0 = [0.25, 0.5, 5, 3000, 3]^T$	Failed to find a feasible solution		