

July 13, 2004

Guest Lecture ESD.33

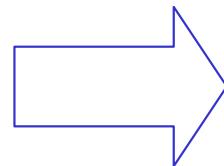
“Isoperformance”

Olivier de Weck

MIT esd Why not performance-optimal ?

“The experience of the 1960’s has shown that for military aircraft the cost of the final increment of performance usually is excessive in terms of other characteristics and that the overall system must be optimized, not just performance”

Ref: Current State of the Art of Multidisciplinary Design Optimization (MDO TC) - AIAA White Paper, Jan 15, 1991



TRW Experience

Industry designs not for optimal performance, but according to targets specified by a requirements document or contract - thus, optimize design for a set of GOALS.

Lecture Outline

- Motivation - why isoperformance ?
- Example: Goal Seeking in Excel
- Case 1: Target vector \mathbf{T} in Range
= Isoperformance
- Case 2: Target vector \mathbf{T} out of Range
= Goal Programming
- Application to Spacecraft Design
- Stochastic Example: Baseball

Forward Perspective

Choose \mathbf{x} \longrightarrow What is \mathbf{J} ?

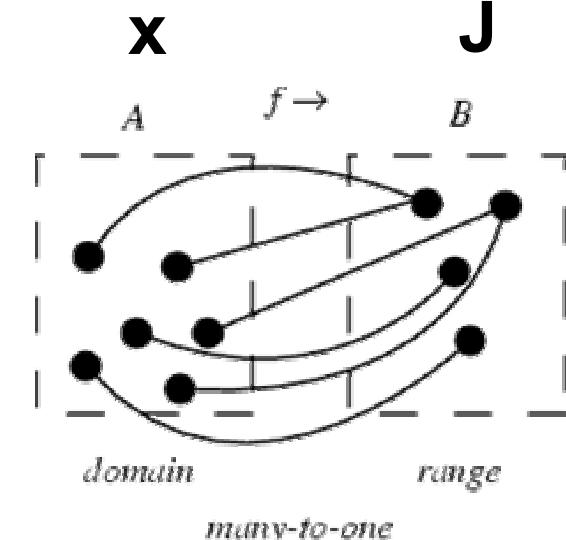
Backward Perspective

Choose \mathbf{J} \longrightarrow What \mathbf{x} satisfy this?

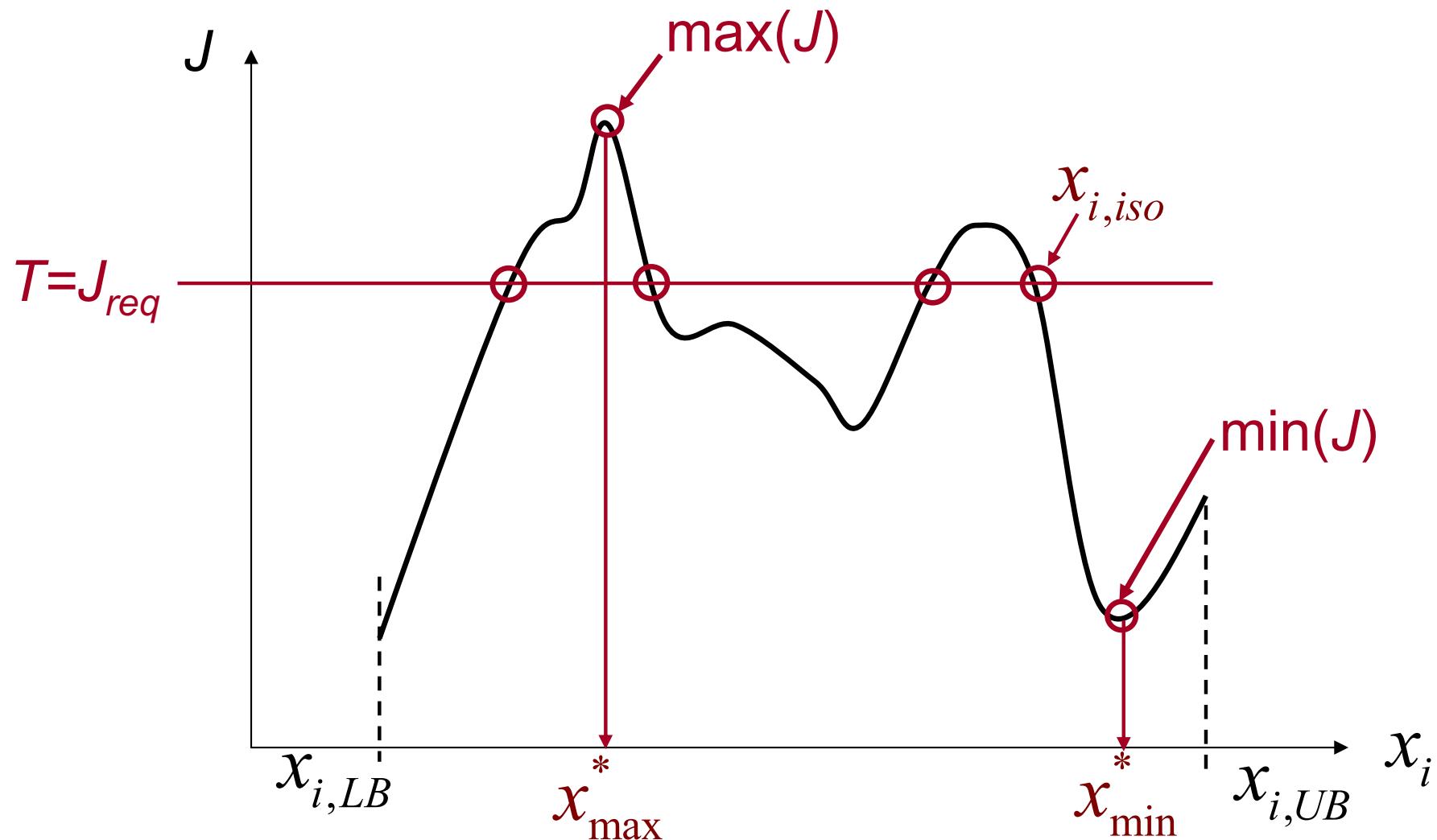
Target
Vector

\mathbf{T}

\mathbf{J}



Goal Seeking



About Goal Seek

Goal Seek is part of a suite of commands sometimes called **what-if analysis** tools. When you know the desired result of a single **formula** but not the input value the formula needs to determine the result, you can use the Goal Seek feature available by clicking **Goal Seek** on the **Tools** menu. When **goal seeking**, Microsoft Excel varies the value in one specific cell until a formula that's dependent on that cell returns the result you want.

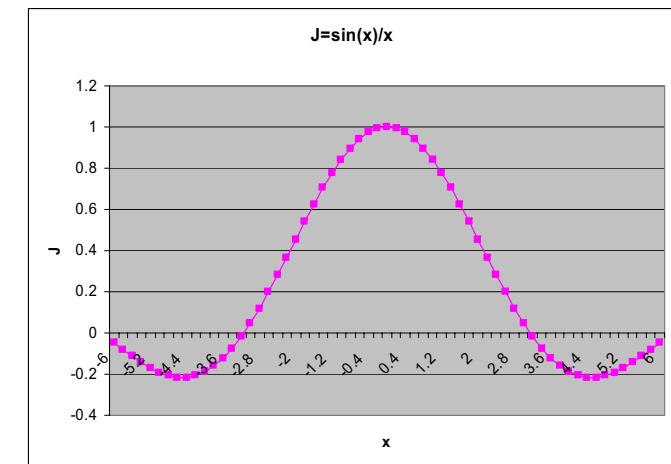
The value in cell B4 is the result of the formula =PMT(B3/12,B2,B1).

	A	B
1	Loan Amount	\$ 100,000
2	Term in Months	180
3	Interest Rate	7.02%
4	Payment	(\$900.00)

Goal seek to determine the interest rate in cell B3 based on the payment in cell B4.

For example, use Goal Seek to change the interest rate in cell B3 incrementally until the payment value in B4 equals \$900.00.

Excel - example



sin(x)/x - example

- single variable x
- no solution if T is out of range

MIT esd Goal Seeking and Equality Constraints

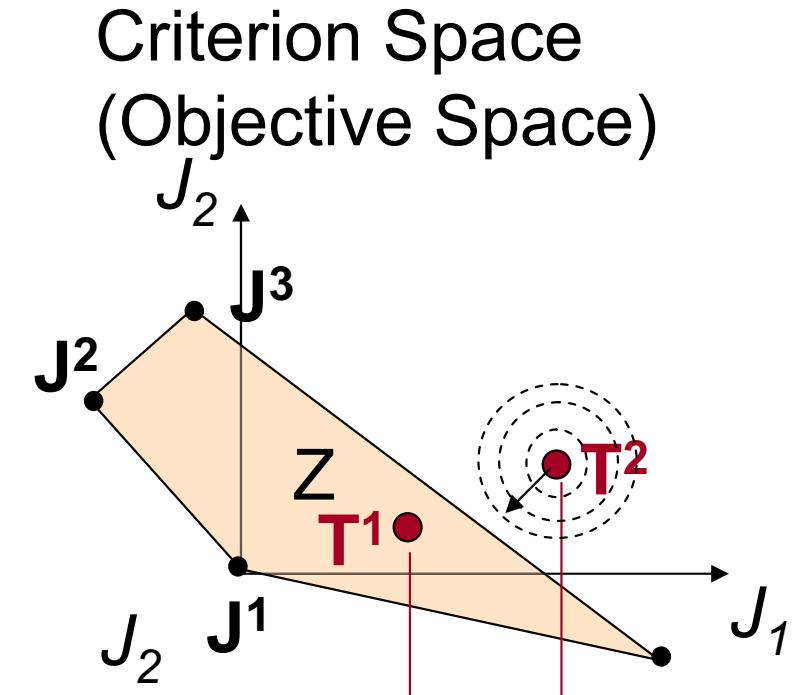
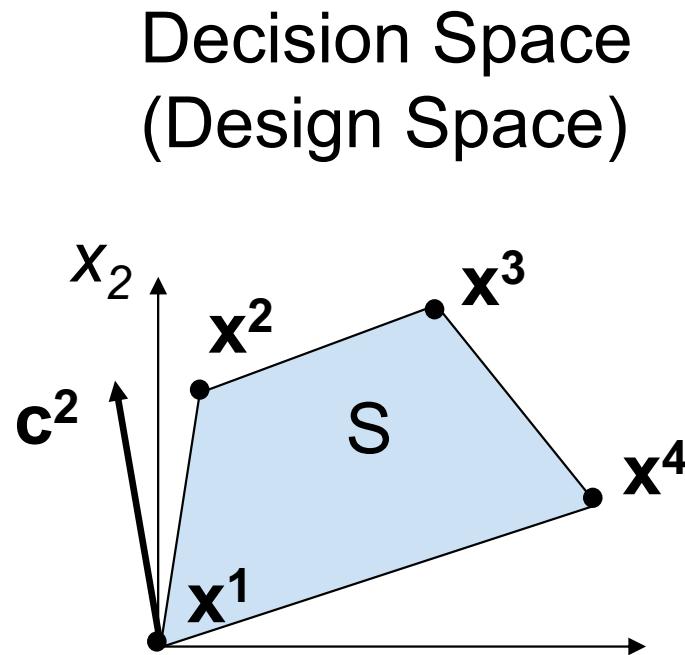
- Goal Seeking – is essentially the same as finding the set of points \mathbf{x} that will satisfy the following “soft” equality constraint on the objective:

Find all \mathbf{x} such that $\left| \frac{J(\mathbf{x}) - J_{req}}{J_{req}} \right| \leq \varepsilon$

Example
Target
Vector:

$$J_{req}(\mathbf{x}) = \begin{bmatrix} m_{sat} \\ R_{data} \\ C_{sc} \end{bmatrix} \equiv \begin{bmatrix} 1000\text{kg} \\ 1.5\text{Mbps} \\ 15\text{M\$} \end{bmatrix} \quad \begin{array}{l} \xleftarrow{\hspace{1cm}} \text{Target mass} \\ \xleftarrow{\hspace{1cm}} \text{Target data rate} \\ \xleftarrow{\hspace{1cm}} \text{Target Cost} \end{array}$$

MIT esd Goal Programming vs. Isoperformance



Case 1: The target (goal) vector
is in Z - usually get non-unique solutions
= Isoperformance

Case 2: The target (goal) vector
is not in Z - don't get a solution - find closest
= Goal Programming

Isoperformance Analogy

Non-Uniqueness of Design if $n > z$

Performance: Buckling Load

Constants: $l=15$ [m], $c=2.05$

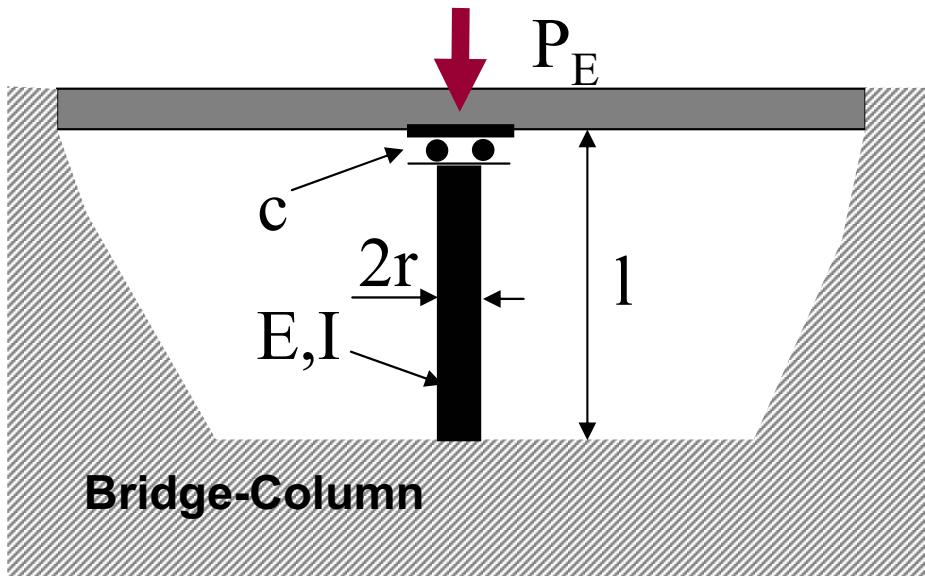
$$P_E = \frac{c\pi^2 EI}{l^2}$$

Variable Parameters: $E, I(r)$

Requirement: $P_{E,REQ} = 1000$ metric tons

Solution 1: V2A steel, $r=10$ cm, $E=19.1e+10$

Solution 2: Al(99.9%), $r=12.8$ cm, $E=7.1e+10$

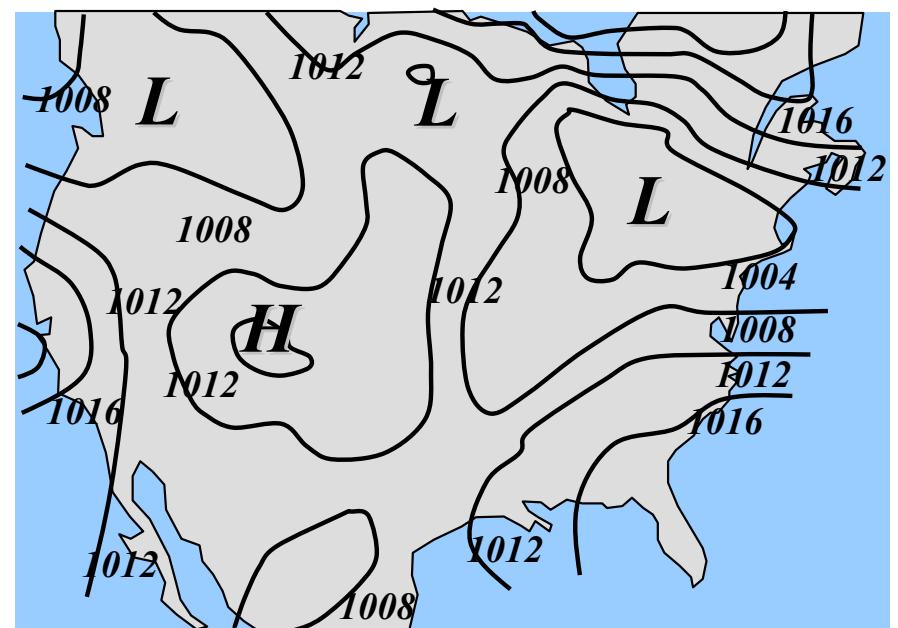


Analogy: Sea Level Pressure [mbar]

Chart: 1600 Z, Tue 9 May 2000

Isobars = Contours of Equal Pressure

Parameters = Longitude and Latitude

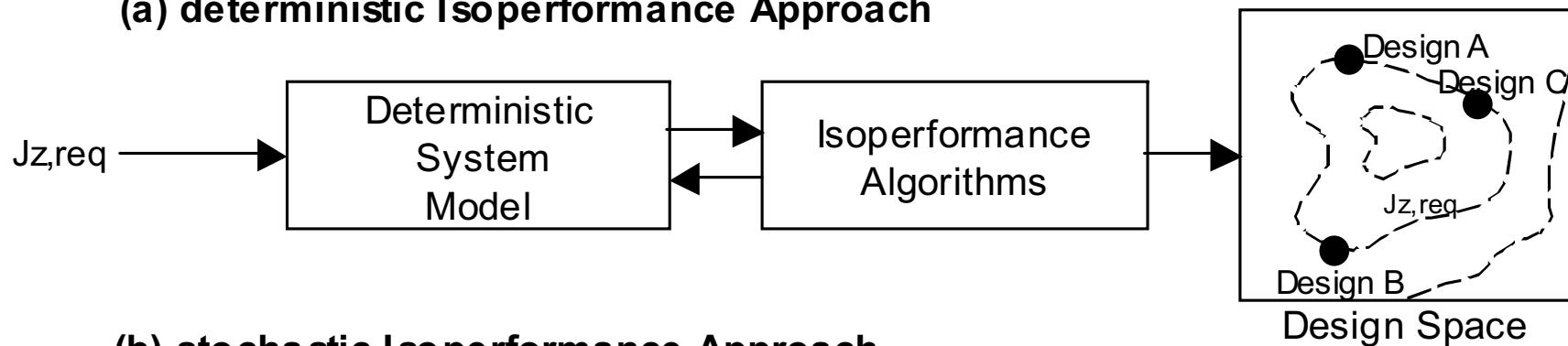


Isoperformance Contours = Locus of constant system performance

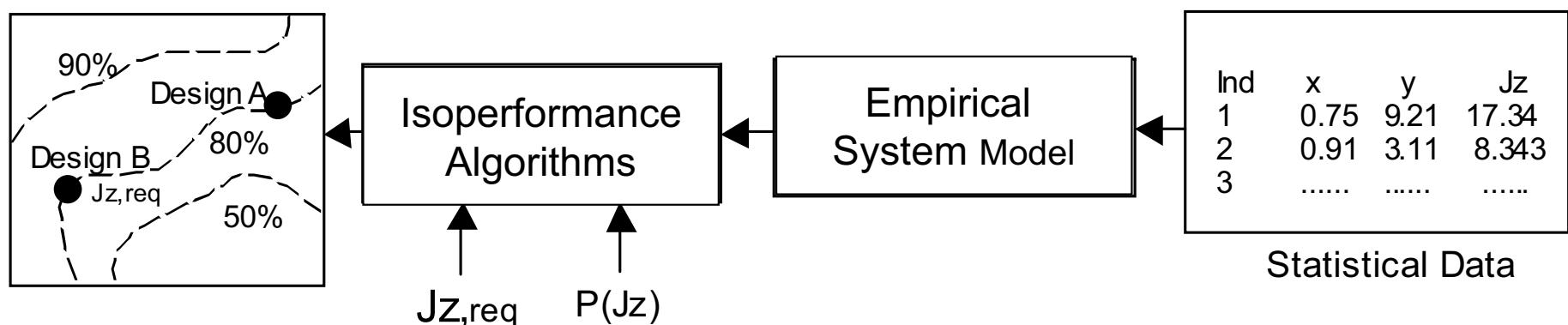
Parameters = e.g. Wheel Imbalance U_s , Support Beam I_{xx} , Control Bandwidth ω_c

Isoperformance Approaches

(a) deterministic Isoperformance Approach



(b) stochastic Isoperformance Approach

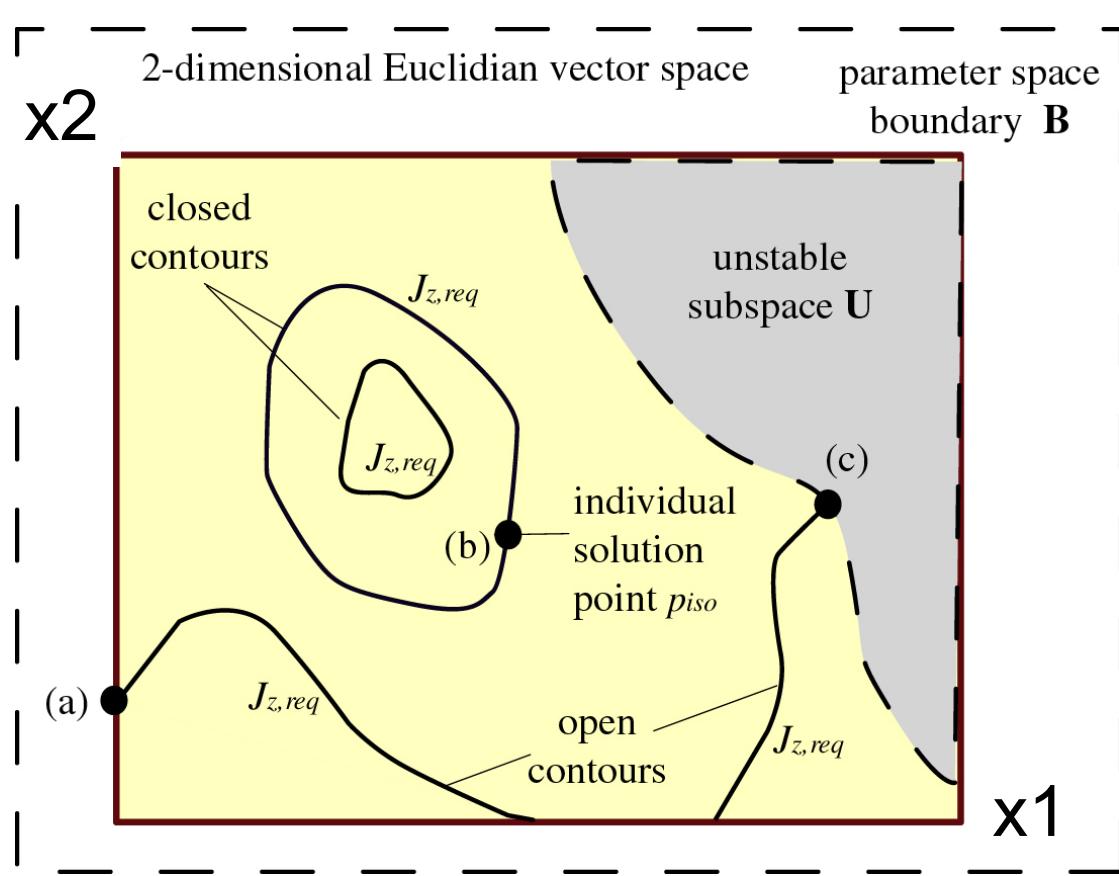


Bivariate Exhaustive Search (2D)

“Simple” Start: Bivariate Isoperformance Problem

Performance $J_z(x_1, x_2)$: $z = 1$

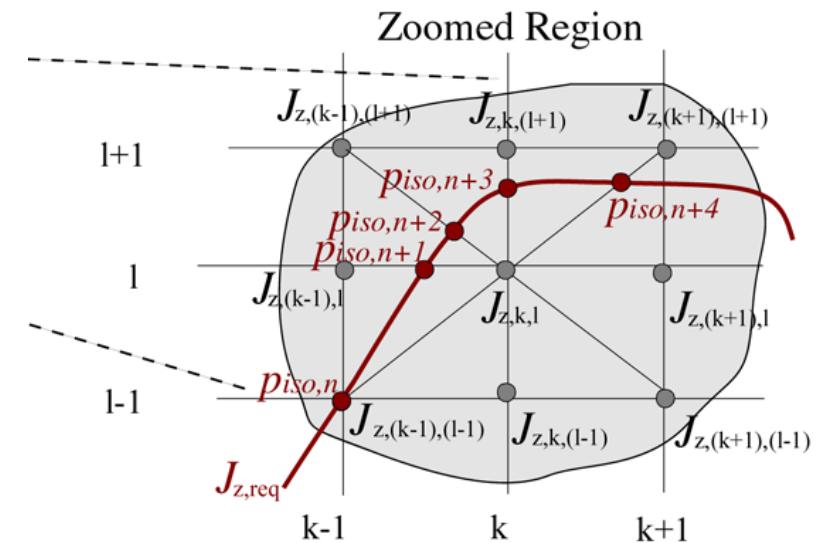
Variables $x_j, j = 1, 2$: $n = 2$



First Algorithm: **Exhaustive Search**
coupled with bilinear interpolation

Number of points along j-th axis:

$$n_j = \left\lceil \frac{x_{j,UB} - x_{j,LB}}{\Delta x} \right\rceil$$



Can also use standard contouring code like MATLAB `contourc.m`

Contour Following (2D)

k-th isoperformance point:

$$\mathbf{x}^k \mapsto J(\mathbf{x}^k), \text{ where } \mathbb{R}^2 \mapsto \mathbb{R}$$

Taylor series expansion

$$J_z(x) = J_z(x^k) + \underbrace{\nabla J_z^T \Big|_{x^k} \Delta x}_{\text{first order term}} + \underbrace{\frac{1}{2} \Delta x^T H \Big|_{x^k} \Delta x}_{\text{second order term}} + \text{H.O.T.}$$

$$\nabla J_z = \begin{bmatrix} \frac{\partial J_z}{\partial x_1} \\ \frac{\partial J_z}{\partial x_2} \end{bmatrix}$$

$$\nabla J_z^T \Big|_{p^k} \Delta x \equiv 0$$

$$t^k = \mathfrak{R} \cdot \underbrace{\frac{-\nabla J_z}{\|\nabla J_z\|}}_{n^k} \Big|_{p^k} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \cdot n^k$$

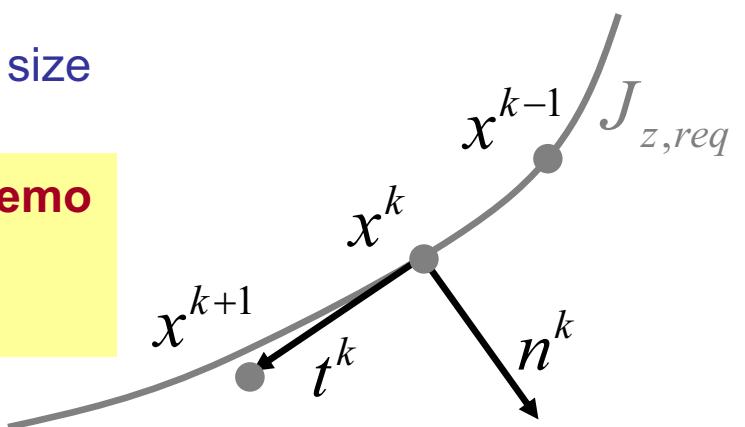
t^k : tangential step direction

$$\alpha_k = \left[2 \frac{\tau J_{z,req}}{100} \left(t_k^T H \Big|_{x^k} t_k \right)^{-1} \right]^{1/2}$$

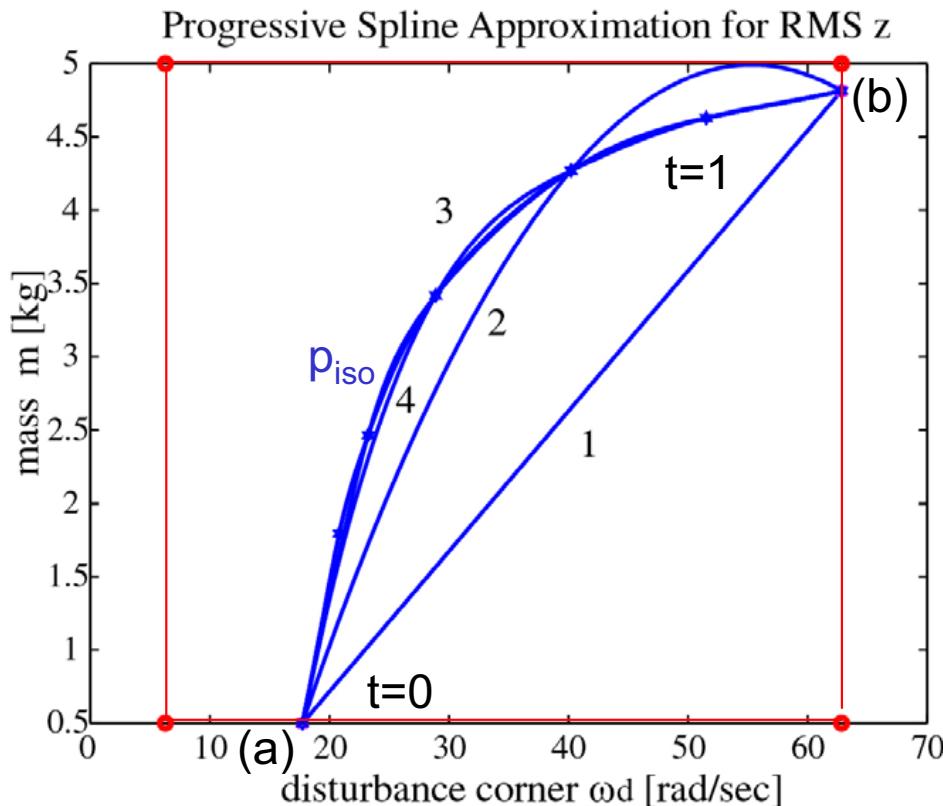
H: Hessian

α^k : Step size

$$\text{k+1-th isoperformance point: } x^{k+1} = x^k + \Delta x$$



Progressive Spline Approximation (III)



- First find iso-points on boundary
- Then progressive spline approximation via segment-wise bisection
- Makes use of MATLAB spline toolbox , e.g. function `csape.m`

$$t \mapsto P_l(t) = \begin{bmatrix} x_{iso,1}(t) \\ x_{iso,2}(t) \end{bmatrix} = \begin{bmatrix} f_1(t) \\ f_2(t) \end{bmatrix}$$

$$t \in [0,1] \mapsto P_l(t) \in [a,b]$$

Demo

Use cubic splines: $k=4$

$$f_{j,l}(t) = \sum_{i=1}^k \frac{(t - \zeta_l)^{k-i}}{(k-i)!} c_{j,l,k}, \quad t \in [\zeta_l \dots \zeta_{l+1}]$$

Bivariate Algorithm Comparison

Metric	Exhaustive Search (I)	Contour Follow (II)	Spline Approx (III)
FLOPS	2,140,897	783,761	377,196
CPU time [sec]	1.15	0.55	0.33
Tolerance τ	1.0%	1.0%	1.0%
Actual Error γ_{iso}	0.057%	0.347%	0.087%
# of isopoints	35	45	7

Results for SDOF Problem

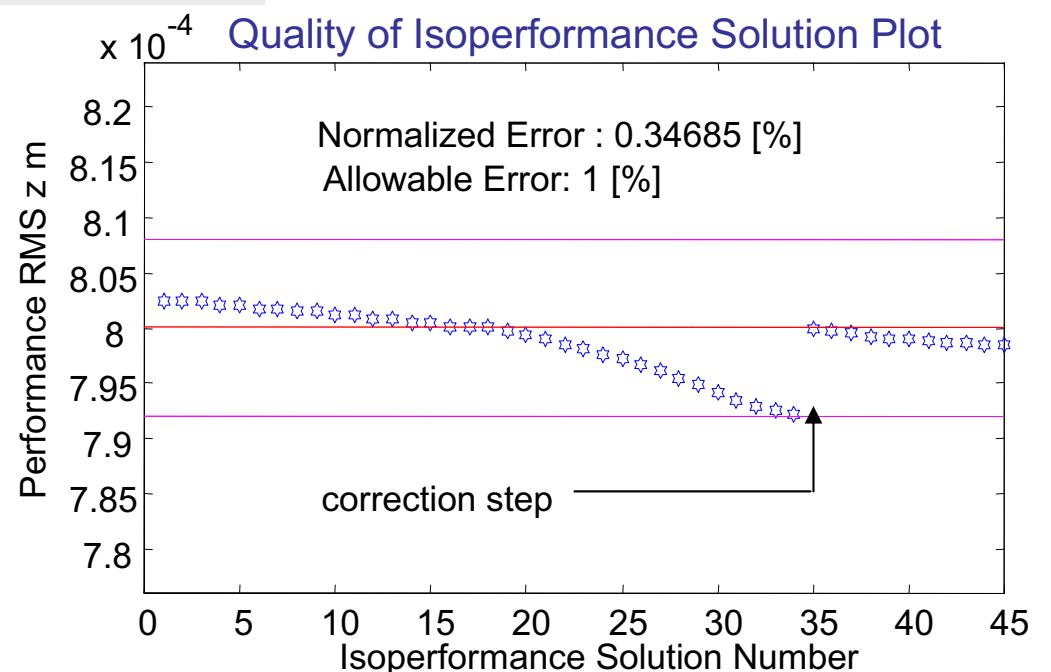
Conclusions:

- (I) most general but expensive
- (II) robust, but requires guesses
- (III) most efficient, but requires monotonic performance J_z

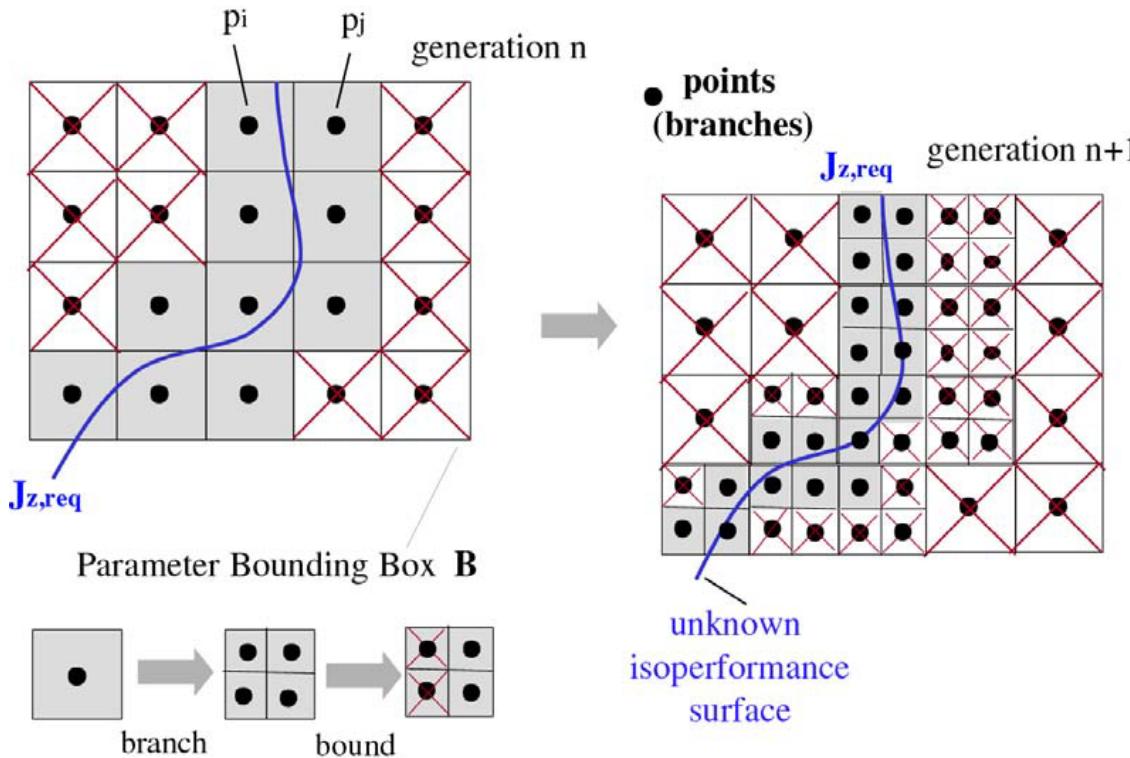
Isoperformance Quality Metric

“Normalized Error”

$$\Upsilon_{iso} = \frac{100}{J_{z,req}} \left[\frac{\sum_{r=1}^{n_{iso}} (J_z(x_{iso,k}) - J_{z,req})^2}{n_{iso}} \right]^{1/2}$$



MIT esd Multivariable Branch-and-Bound



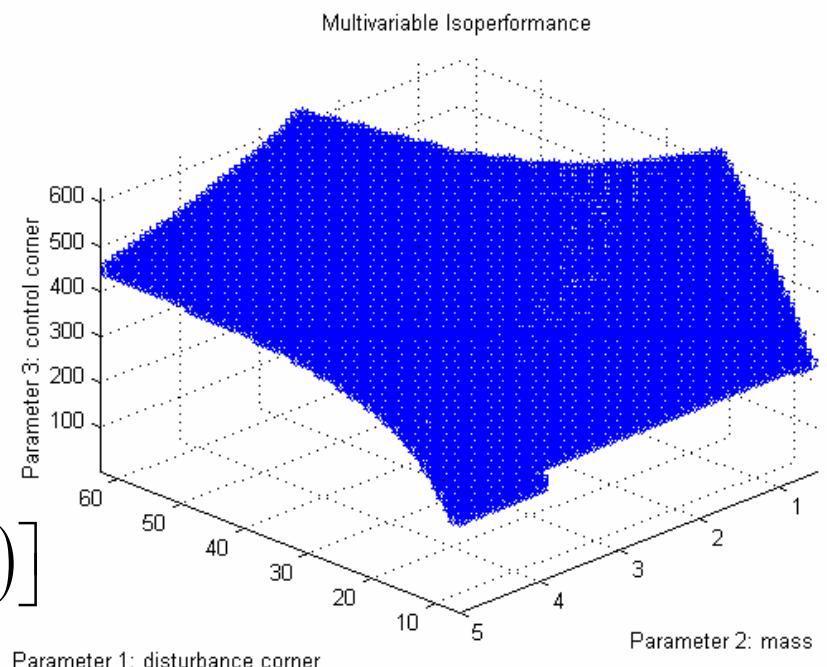
Branch-and-Bound only retains points/branches which meet the condition:

$$[J_z(x_i) \geq J_{z,req} \geq J_z(x_j)] \cup [J_z(x_i) \leq J_{z,req} \leq J_z(x_j)]$$

Expensive for small tolerance τ
Need initial branches to be fine enough

Exhaustive Search requires n_p -nested loops \rightarrow NP-cost: e.g.

$$N = \prod_{j=1}^{n_p} \left\lceil \frac{x_{UB,j} - x_{LB,j}}{\Delta x_j} \right\rceil$$

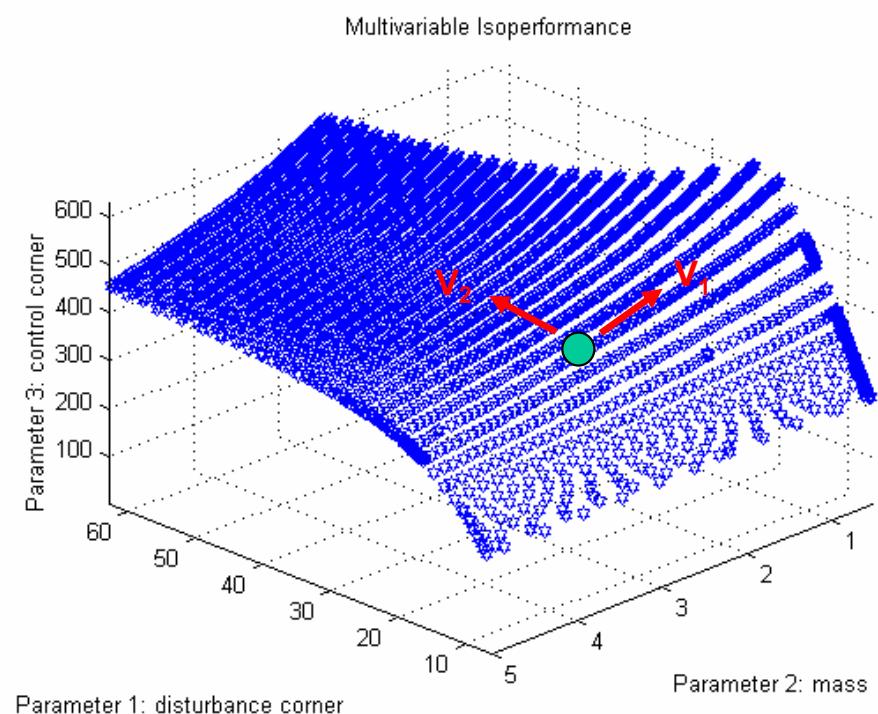


Tangential Front Following

The diagram illustrates the Singular Value Decomposition (SVD) of a matrix A as $A = U\Sigma V^T$, where U is orthogonal, Σ is diagonal, and V has orthonormal columns. The matrix Σ is shown as a block-diagonal matrix with a $z \times z$ block of $\sigma_1, \dots, \sigma_{n_z}$ and a $n_z \times (n_p - n_z)$ zero block. The matrix V is partitioned into a $z \times n$ block of column vectors v_1, \dots, v_z and a $(n-p) \times n$ block of nullspace vectors v_{z+1}, \dots, v_n . A yellow box highlights the equation $U\Sigma V^T = \nabla J_z^T$, which relates the SVD to the gradient of a performance function J_z . To the right, the gradient ∇J_z is shown as a vector of partial derivatives $\frac{\partial J_1}{\partial x_1}, \dots, \frac{\partial J_z}{\partial x_z}$. Below this, a 3D surface plot shows a blue surface representing a multivariable isoperformance surface, with axes labeled 'corner' (vertical), x_1 (horizontal), and x_2 (depth). Red arrows point from the vectors v_1 and v_2 in the nullspace direction towards the surface.

SVD of Jacobian provides V-matrix
V-matrix contains the orthonormal
vectors of the nullspace.

Isoperformance set I is obtained by following the nullspace of the Jacobian !



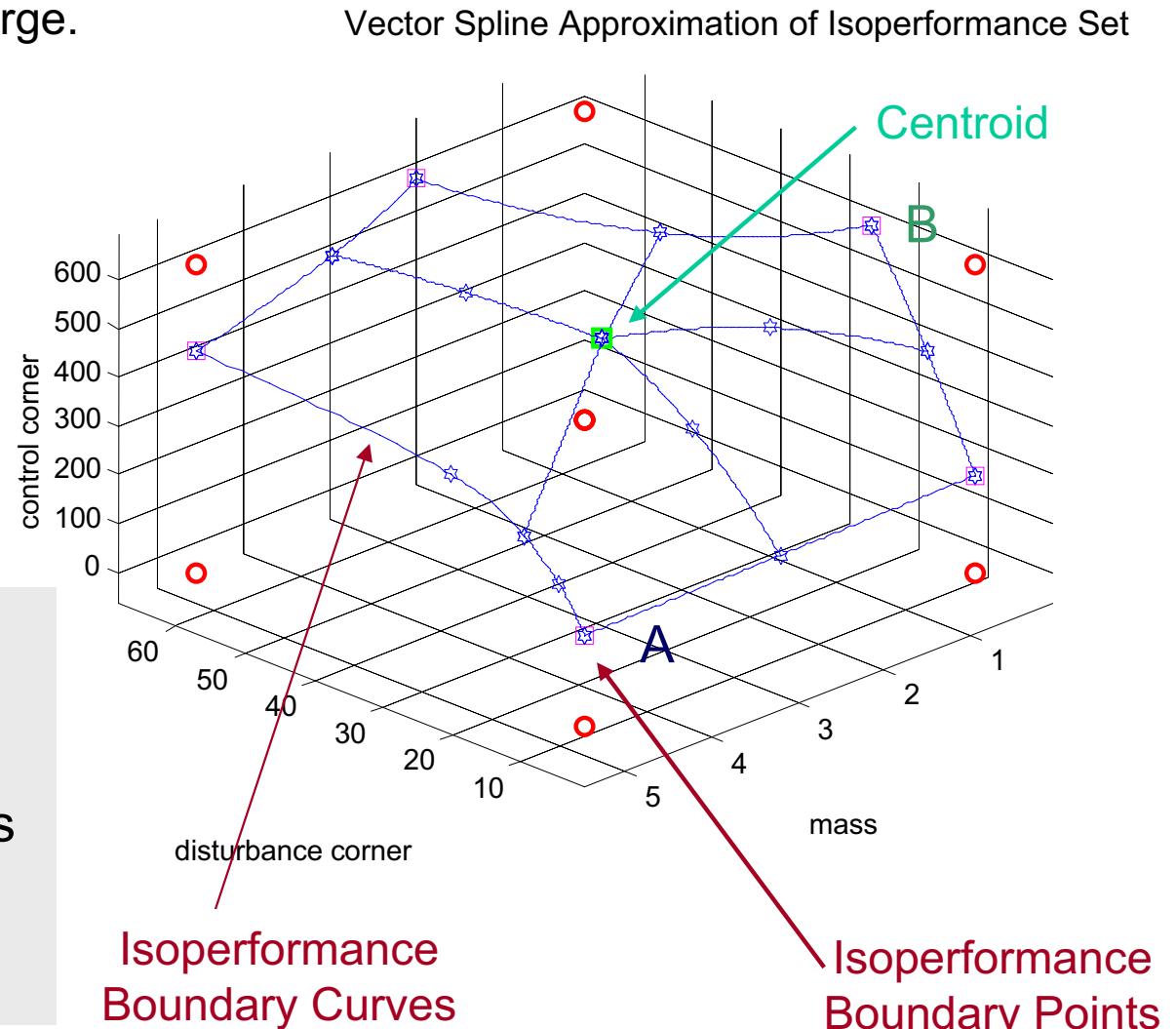
Tangential front following is more efficient than branch-and-bound but can still be expensive for n_p large.

Idea: Find a representative subset off all isoperformance points, which are different from other.

“Frame-but-not-panels” analogy in construction

Algorithm:

1. Find Boundary (Edge) Points
2. Approximate Boundary curves
3. Find Centroid point
4. Approximate Internal curves



Multivariable Algorithm Comparison

Challenges if $n_p > 2$

Problem Size:

$z = \# \text{ of performances}$

$d = \# \text{ of disturbances}$

$n = \# \text{ of variables}$

$n_s = \# \text{ of states}$

- Computational complexity as a function of [$n_z \ n_d \ n_p \ n_s$]
- Visualization of isoperformance set in n_p -space

Table: Multivariable Algorithm Comparison for SDOF ($n_p=3$)

Metric	Exhaustive Search	Branch-and-Bound	Tang Front Following	V-Spline Approx
MFLOPS	6,163.72	891.35	106.04	1.49
CPU [sec]	5078.19	498.56	69.59	4.45
Error Y_{iso}	0.87 %	2.43%	0.22%	0.42%
# of points	2073	7421	4999	20

From Complexity Theory: Asymptotic Cost [FLOPS]

$$\text{Exhaustive Search: } \log(J_{exs}) \rightarrow n_p \log \alpha + 3 \log n_s + c$$

$$\text{Branch-and-Bound: } \log(J_{bab}) \rightarrow n_g (n_p \log 2 + \log \beta) + 3 \log n_s + c$$

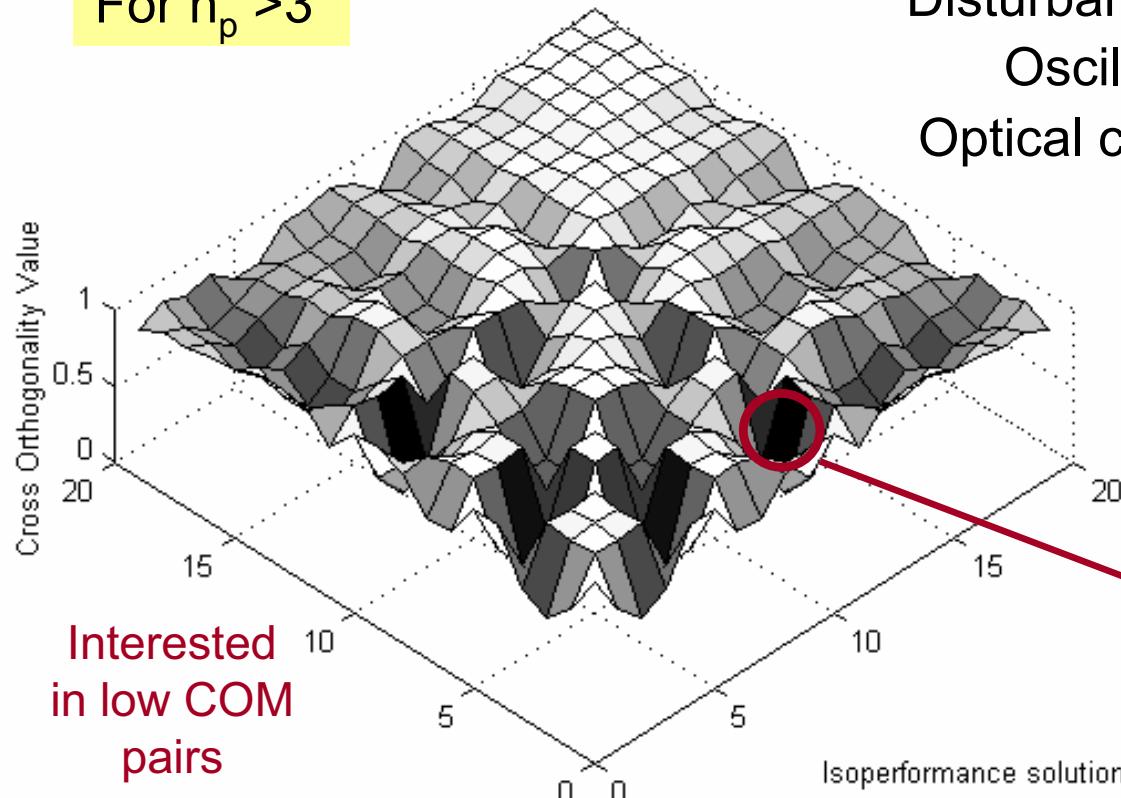
$$\text{Tang Front Follow: } \log(J_{tff}) \rightarrow (n_p - n_z) \log \gamma + \log(1 + n_z) + 3 \log n_s + c$$

$$\text{V-Spline Approx: } \log(J_{vsap}) \rightarrow n_p \log 2 + 3 \log n_s + \log(n_z + 1) + c$$

Conclusion: Isoperformance problem is non-polynomial in n_p

Graphics: Radar Plots

For $n_p > 3$

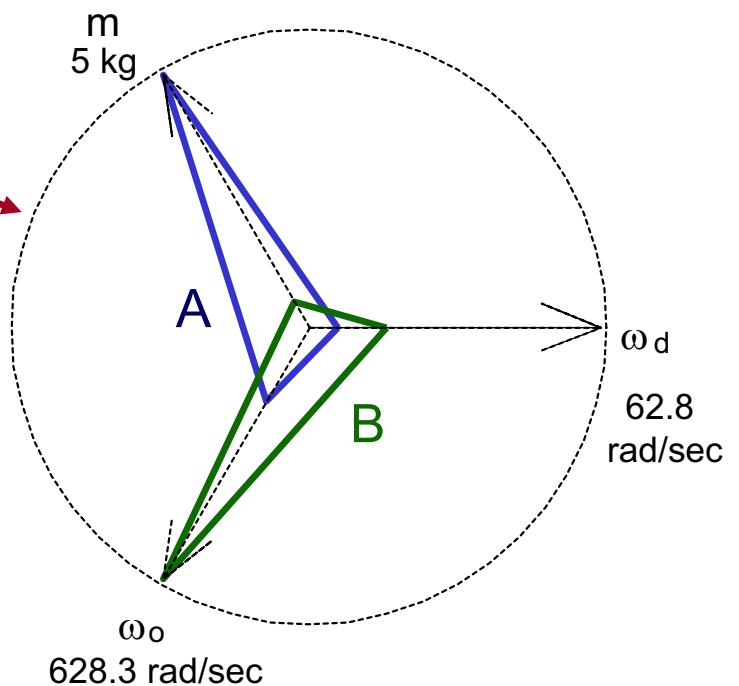


$$COM(i, j) = \frac{p_{iso,i} \cdot p_{iso,j}}{|p_{iso,i}| \cdot |p_{iso,j}|}$$

Disturbance corner ω_d	6.2832	21.3705
Oscillator mass m	5.0000	0.5000
Optical control bw ω_o	186.5751	628.3185

A B

Multi-Dimensional Comparison
of Isoperformance Points



Nexus Case Study

Purpose of this case study:

Demonstrate the usefulness of Isoperformance on a realistic conceptual design model of a high-performance spacecraft

The following results are shown:

- Integrated Modeling
- Nexus Block Diagram
- Baseline Performance Assessment
- Sensitivity Analysis
- Isoperformance Analysis (2)
- Multiobjective Optimization
- Error Budgeting

Details are contained in CH7

Nexus
Spacecraft
Concept

launch
configuration

Deployable
PM petal

Delta II
Fairing

on-orbit
configuration

OTA

Instrument
Module

Sunshield

0 1 2
meters

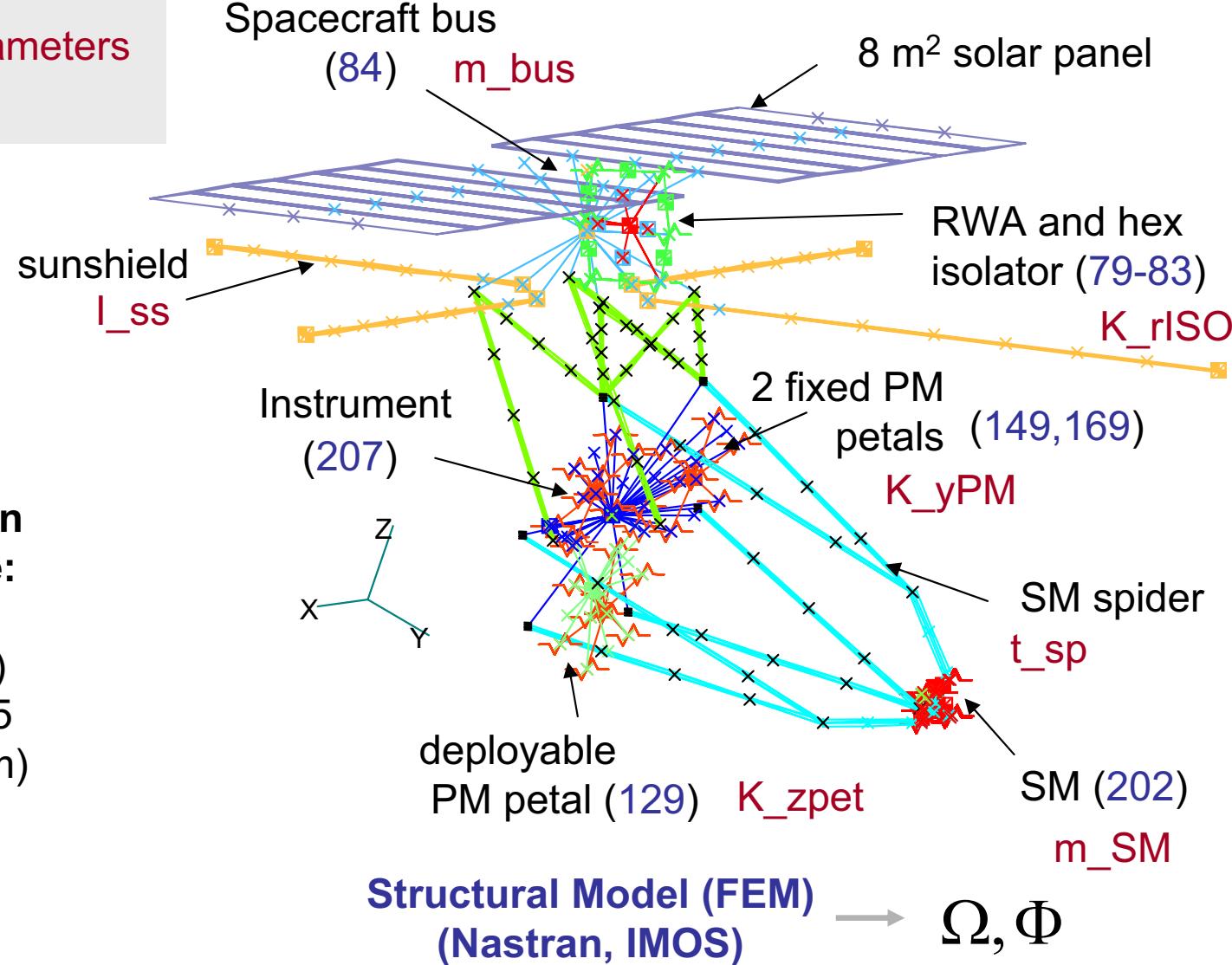
NGST Precursor Mission
2.8 m diameter aperture
Mass: 752.5 kg
Cost: 105.88 M\$ (FY00)
Target Orbit: L2 Sun/Earth
Projected Launch: 2004

Nexus Integrated Model

Legend:
Design Parameters
(I/O Nodes)

Cassegrain Telescope:

PM (2.8 m)
PM f/# 1.25
SM (0.27 m)
f/24 OTA



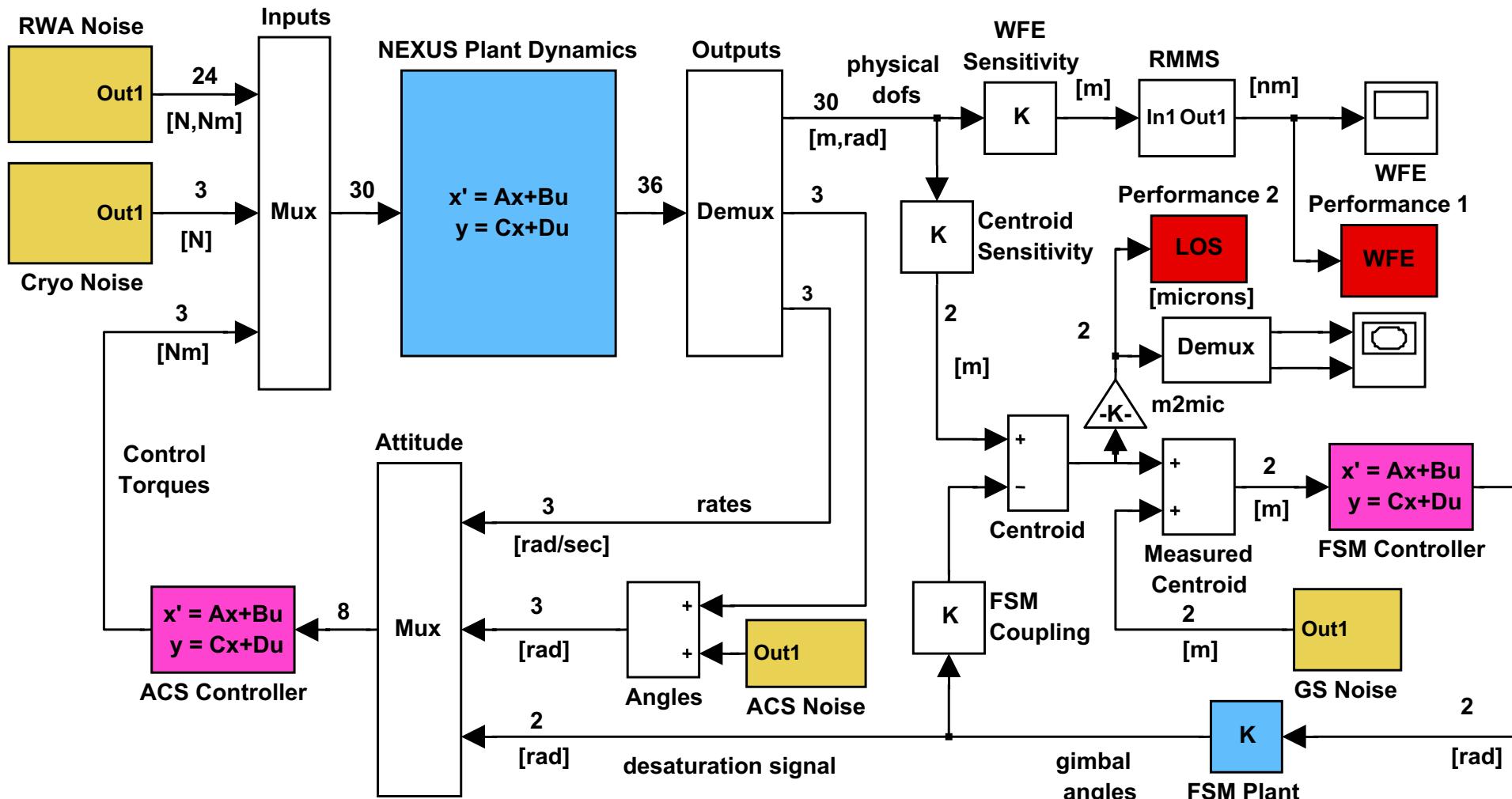
Nexus Block Diagram

Number of performances: $n_z = 2$

Number of design parameters: $n_p = 25$

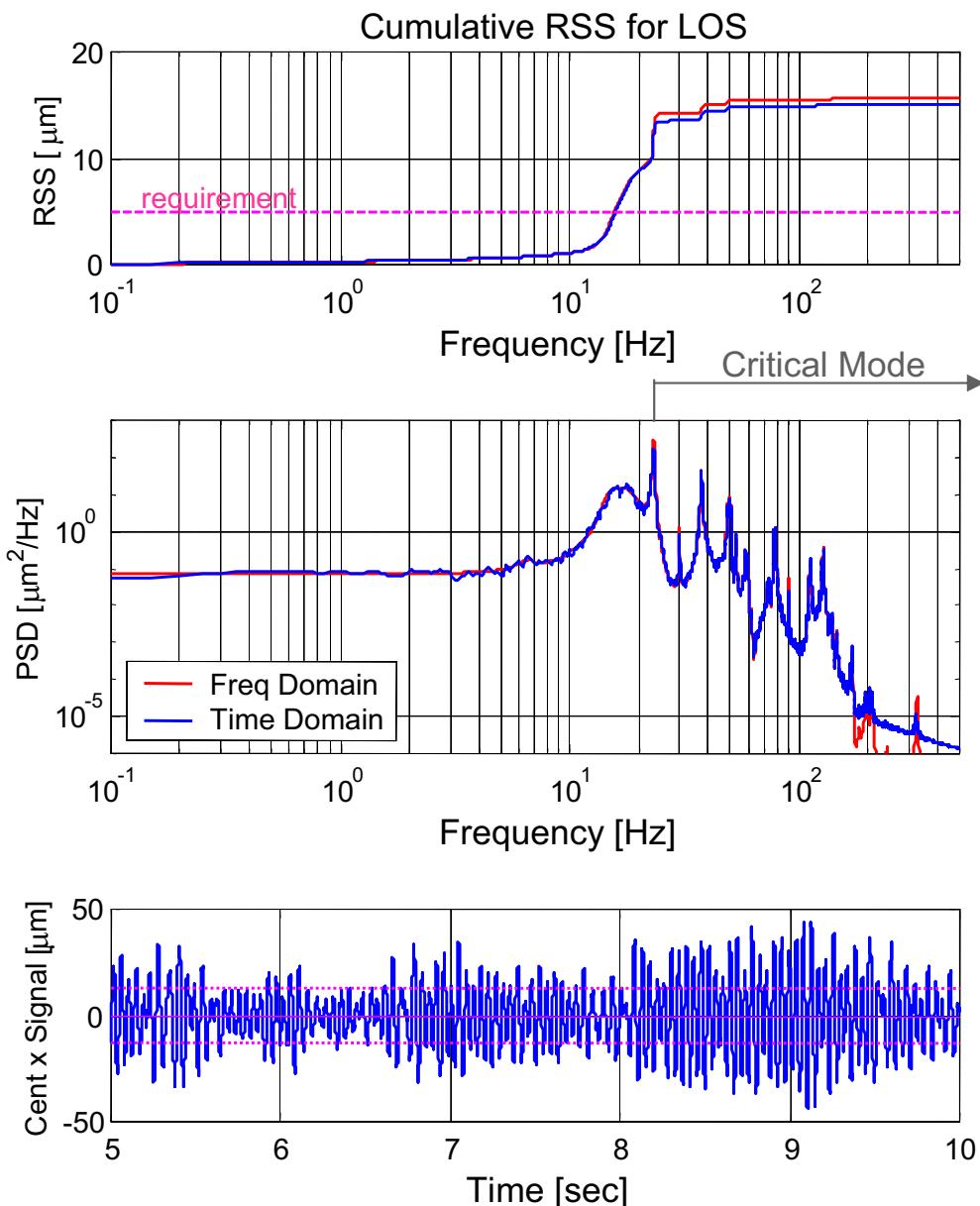
Number of states $n_s = 320$

Number of disturbance sources: $n_d = 4$



Initial Performance Assessment

$J_z(p^\circ)$



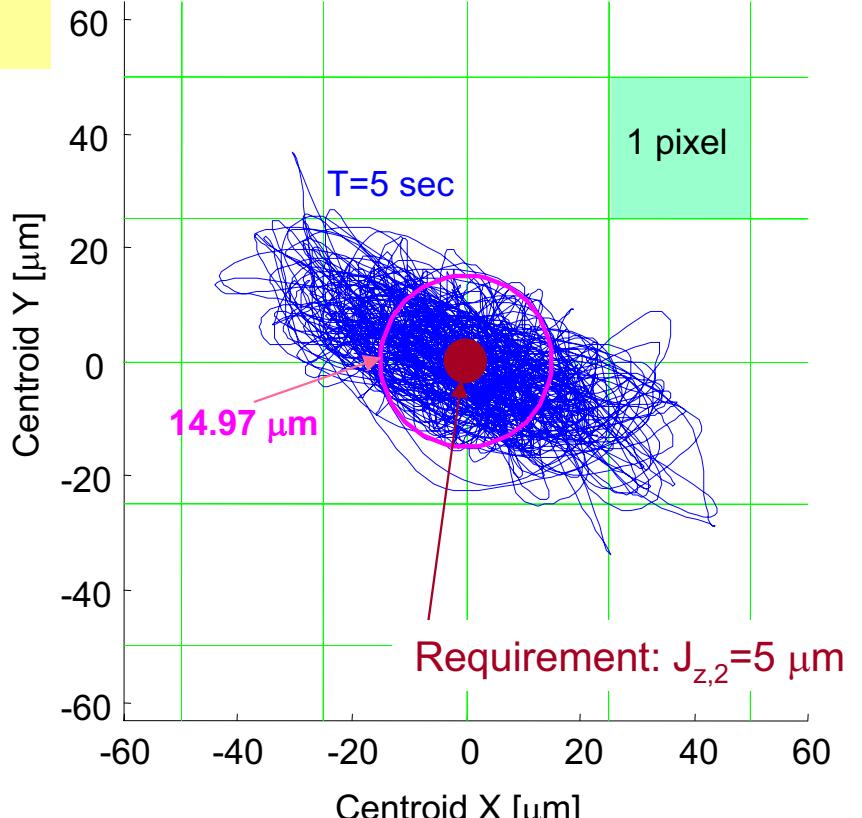
Results

$J_{z,1}$ (RMMS WFE)
 $J_{z,2}$ (RSS LOS)

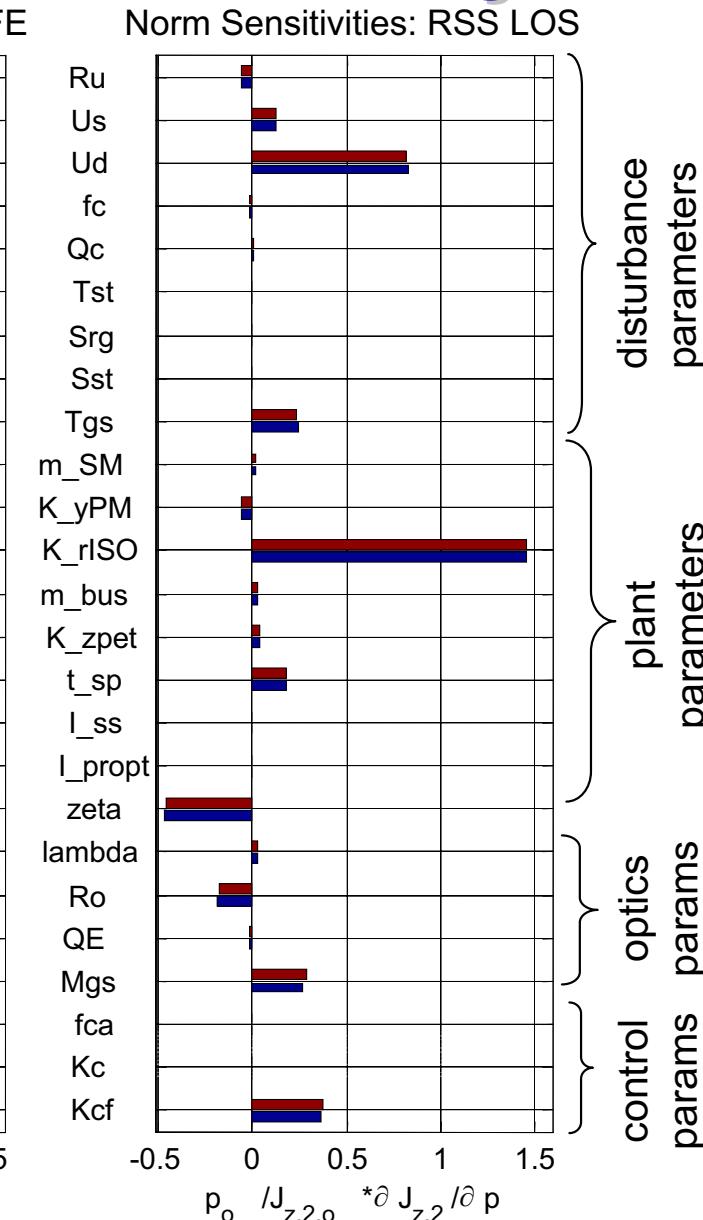
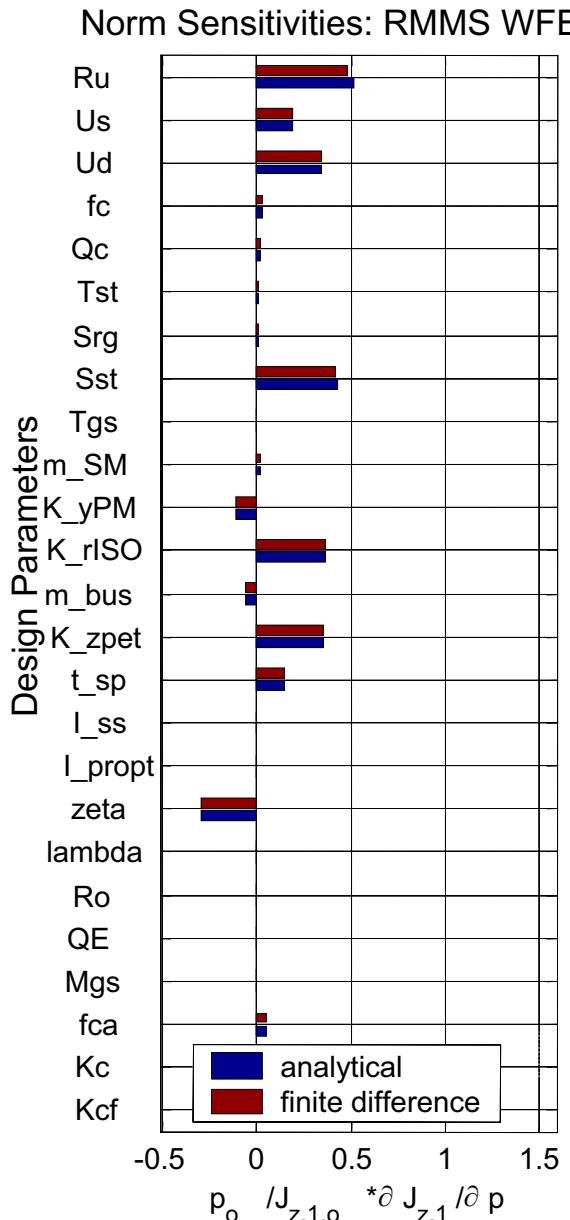
Lyap/Freq	Time	
25.61	19.51	[nm]
15.51	14.97	[μm]

23.1 Hz

Centroid Jitter on Focal Plane [RSS LOS]



Nexus Sensitivity Analysis



Graphical Representation of Jacobian evaluated at design p_o , normalized for comparison.

$$\bar{\nabla}J_z = \frac{p_o}{J_{z,o}} \begin{bmatrix} \frac{\partial J_{z,1}}{\partial R_u} & \frac{\partial J_{z,2}}{\partial R_u} \\ \dots & \dots \\ \frac{\partial J_{z,1}}{\partial K_{cf}} & \frac{\partial J_{z,2}}{\partial K_{cf}} \end{bmatrix}$$

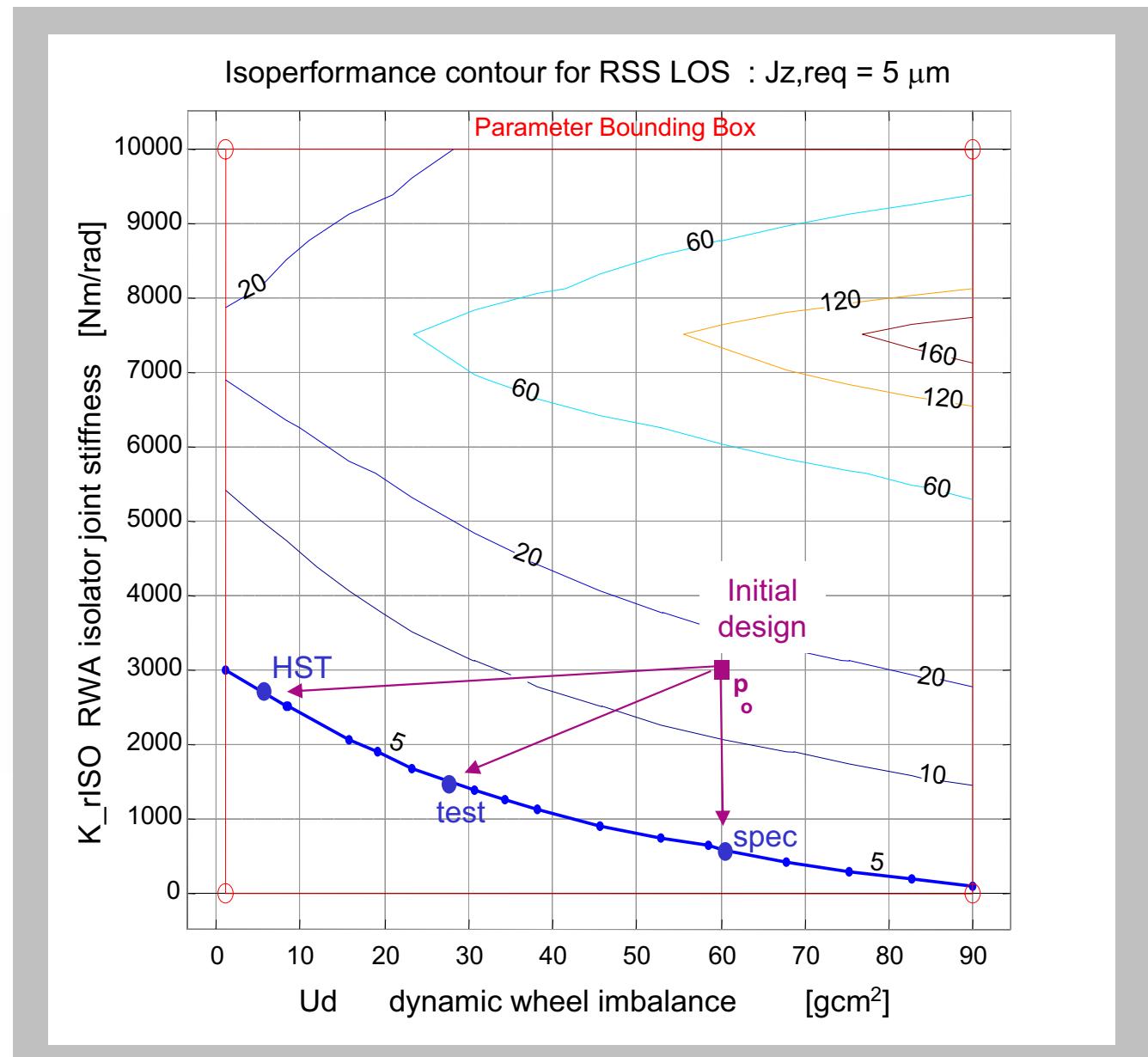
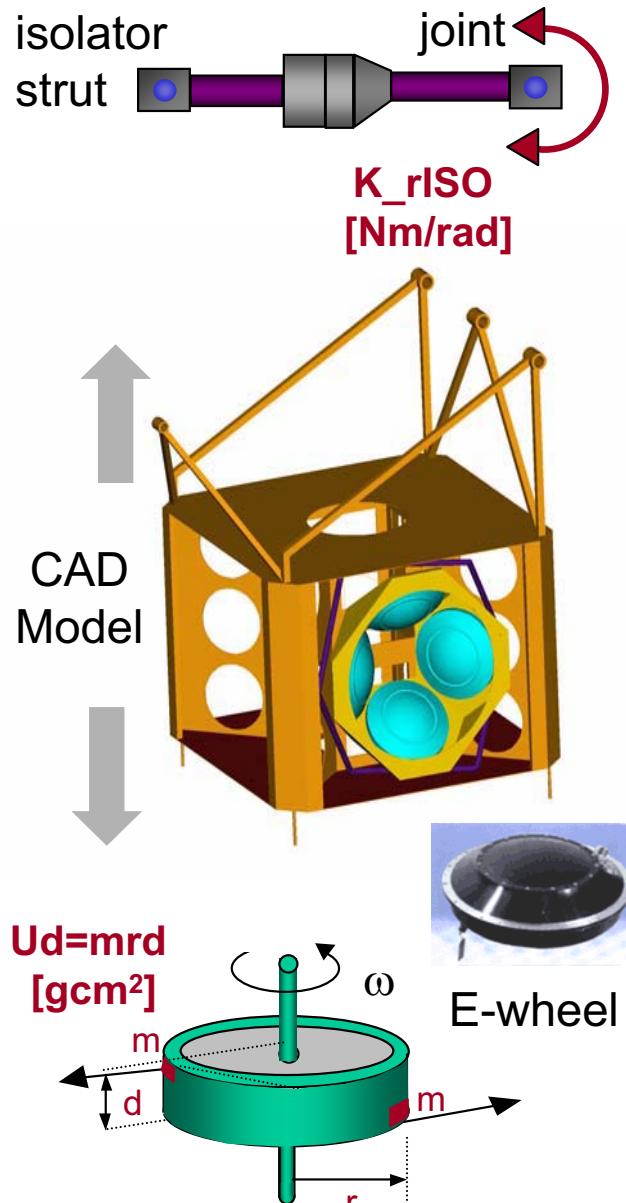
RMMS WFE most sensitive to:

- Ru - upper op wheel speed [RPM]
- Sst - star track noise 1σ [asec]
- K_rISO - isolator joint stiffness [Nm/rad]
- K_zpet - deploy petal stiffness [N/m]

RSS LOS most sensitive to:

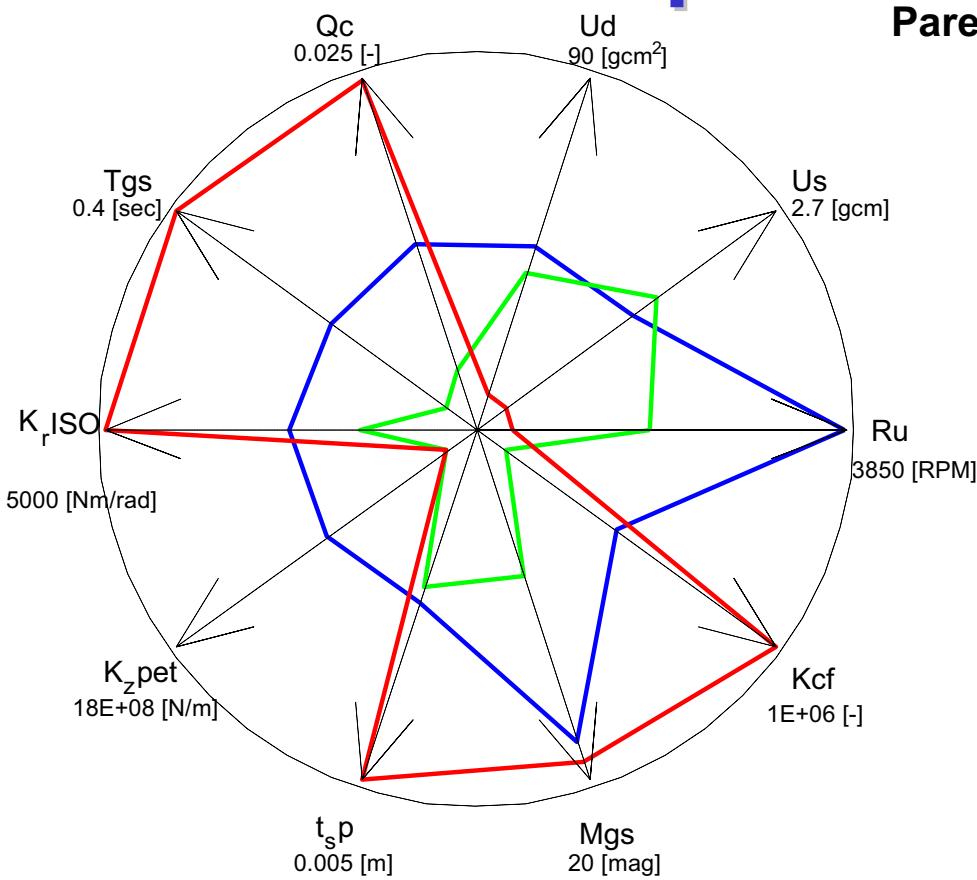
- Ud - dynamic wheel imbalance [gcm^2]
- K_rISO - isolator joint stiffness [Nm/rad]
- zeta - proportional damping ratio [-]
- Mgs - guide star magnitude [mag]
- Kcf - FSM controller gain [-]

2D-Isoperformance Analysis



Isoperformance $n_p=10$

Pareto-Optimal Designs p^*_iso



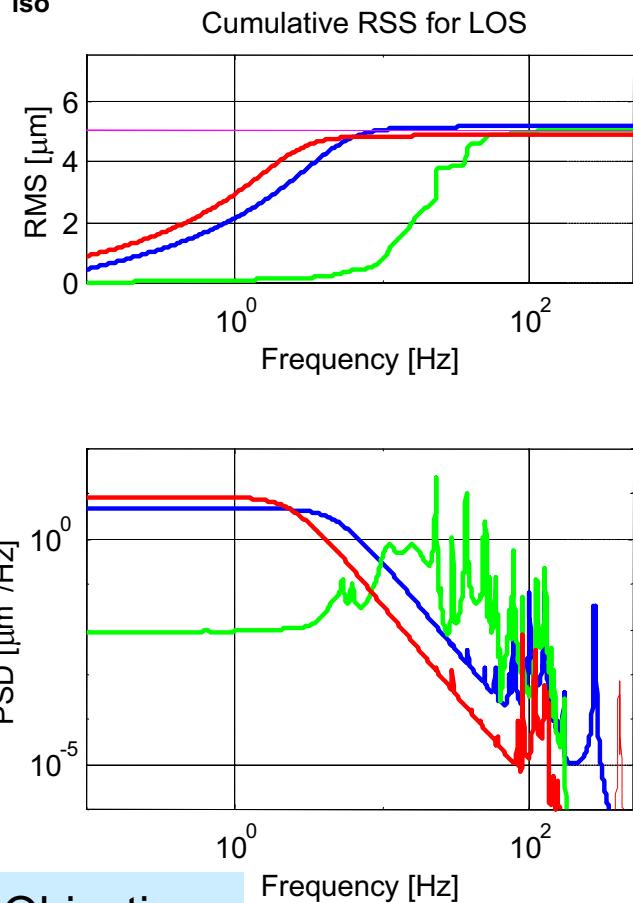
Design A

Best “mid-range” compromise

Design B

Smallest FSM control gain

Design C
Smallest
performance
uncertainty



Performance

Jz.1 Jz.2

20.0000 5.2013

Cost and Risk Objectives

Jc.1 Jc.

-6324 0.4668

Jr. 1

- A: $\min(J_{c1})$
- B: $\min(J_{c2})$
- C: $\min(J_{r1})$

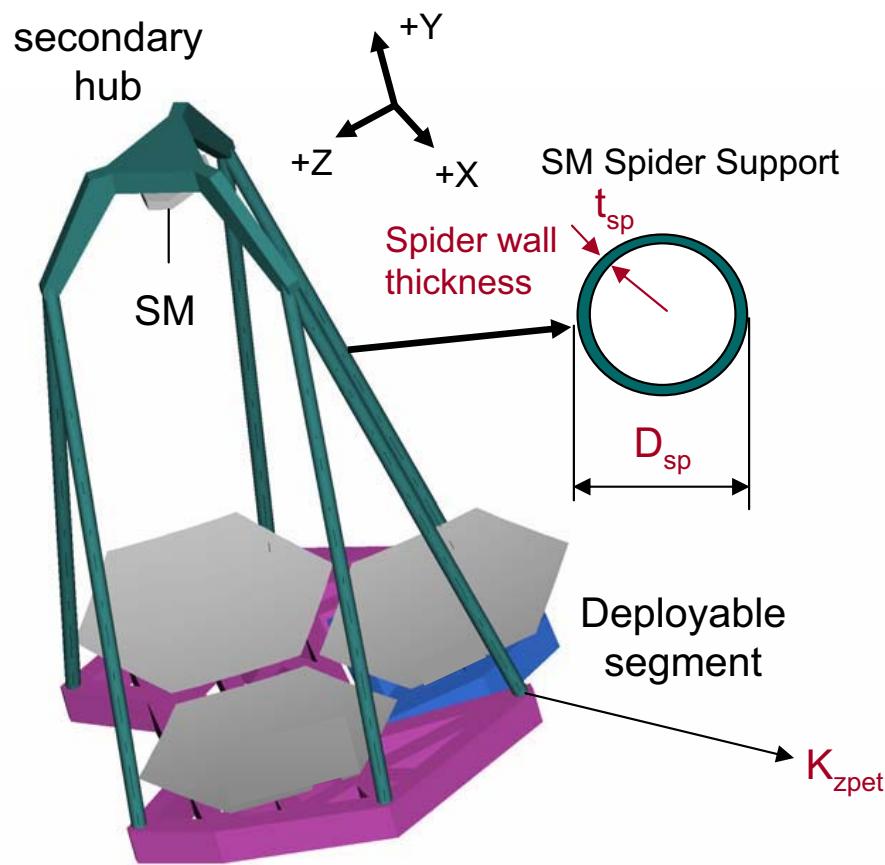
Design A

Design A

Design B

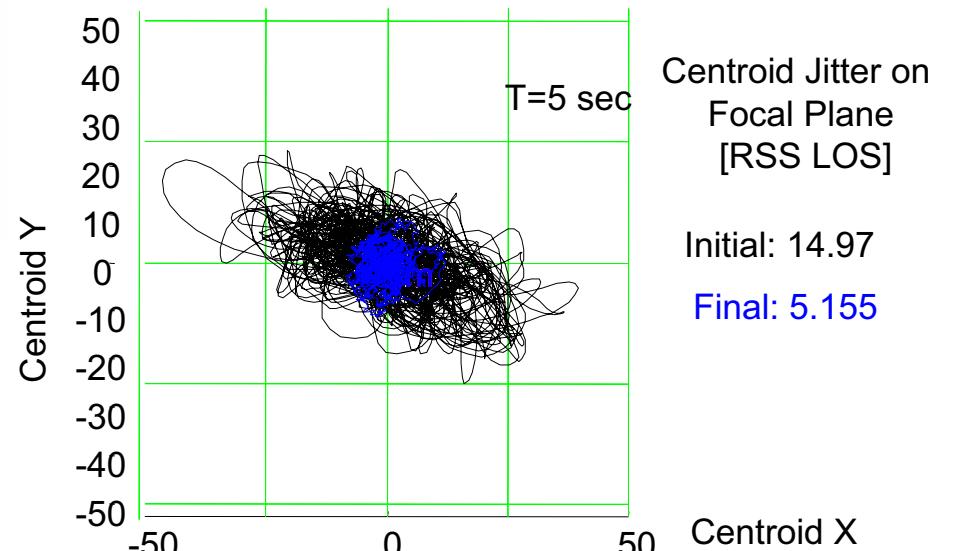
Design B

Design C

Nexus Initial p^o vs. Final Design p^{**}_{iso} 

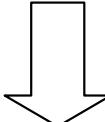
Improvements are achieved by a well balanced mix of changes in the disturbance parameters, structural redesign and increase in control gain of the FSM fine pointing loop.

Parameters	Initial	Final	
R_u	3000	3845	[RPM]
U_s	1.8	1.45	[gcm]
U_d	60	47.2	[gcm ²]
Q_c	0.005	0.014	[⁻]
T_{gs}	0.040	0.196	[sec]
K_{rlISO}	3000	2546	[Nm/rad]
K_{zpet}	0.9E+8	8.9E+8	[N/m]
t_{sp}	0.003	0.003	[m]
M_{gs}	15	18.6	[Mag]
K_{cf}	2E+3	4.7E+5	[⁻]



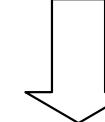
Example: Baseball season has started

What determines success of a team ?

Pitching


ERA

“Earned Run Average”

Batting


RBI

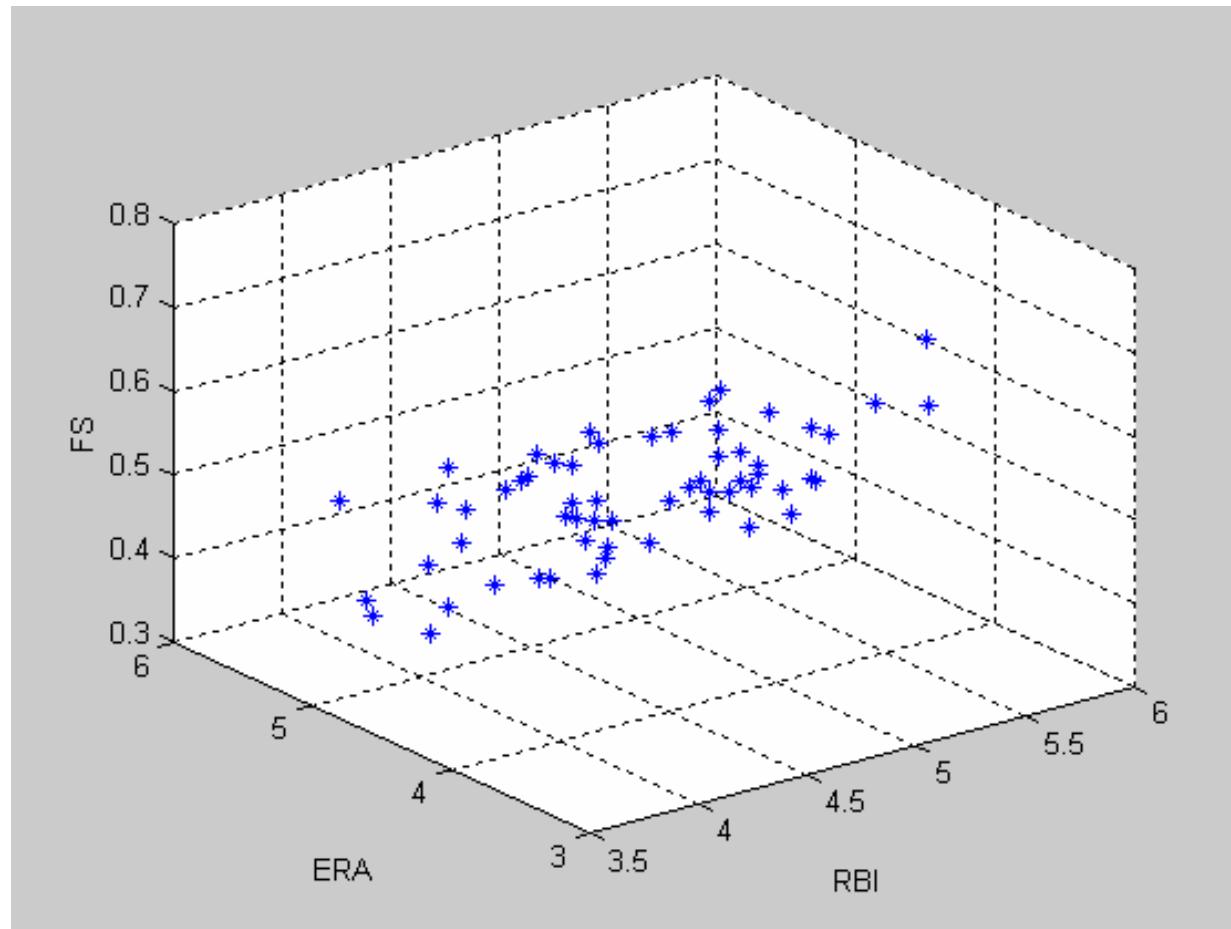
“Runs Batted In”

How is success of team measured ?

$FS = \text{Wins}/\text{Decisions}$

Raw Data

Team results for 2000, 2001 seasons: RBI,ERA,FS



Step-by-step process for obtaining (bivariate) isoperformance curves given statistical data:

Starting point, need:

- Model - derived from empirical data set
- (Performance) Criterion
- Desired Confidence Level

Step 1: Obtain an expression from model for expected performance of a “system” for individual design i as a function of design variables $x_{1,i}$ and $x_{2,i}$

1.1 assumed model

$$E[J_i] = a_0 + a_1(x_{1,i}) + a_2(x_{2,i}) + a_{12}(x_{1,i} - \bar{x}_1)(x_{2,i} - \bar{x}_2) \quad (1)$$

1.2 model fitting

General mean

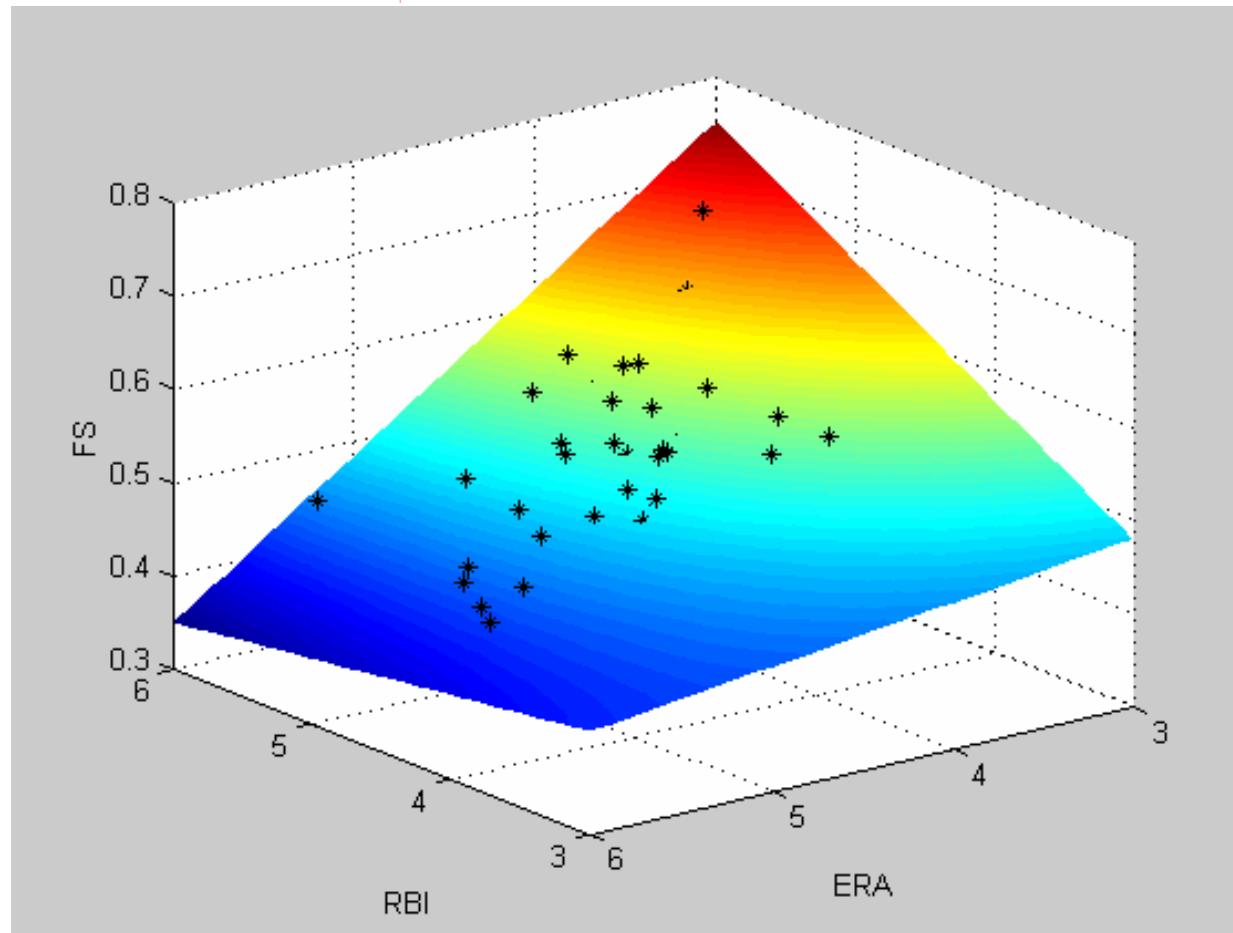
$$a_o = \frac{1}{N} \sum_{j=1}^N J_j$$

Used Matlab
fminunc.m for
optimal surface fit

Baseball: Obtain an expression for expected final standings (FS_i) of individual Team i as a function of RBI_i and ERA_i

$$E[FS_i] = m + a(RBI_i) + b(ERA_i) + c(RBI_i - \bar{RBI})(ERA_i - \bar{ERA})$$

Fitted Model



RMSE:
Error
 $\sigma_e = 0.0493$

Error
Distribution

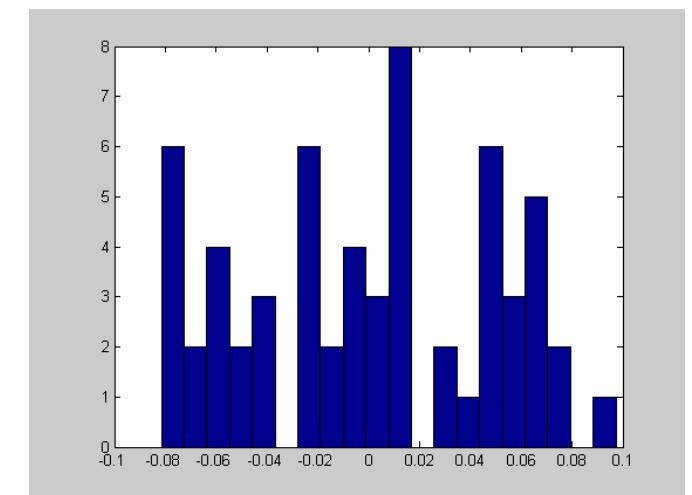
Coefficients:

$$a_0 = 0.7450$$

$$a_1 = 0.0321$$

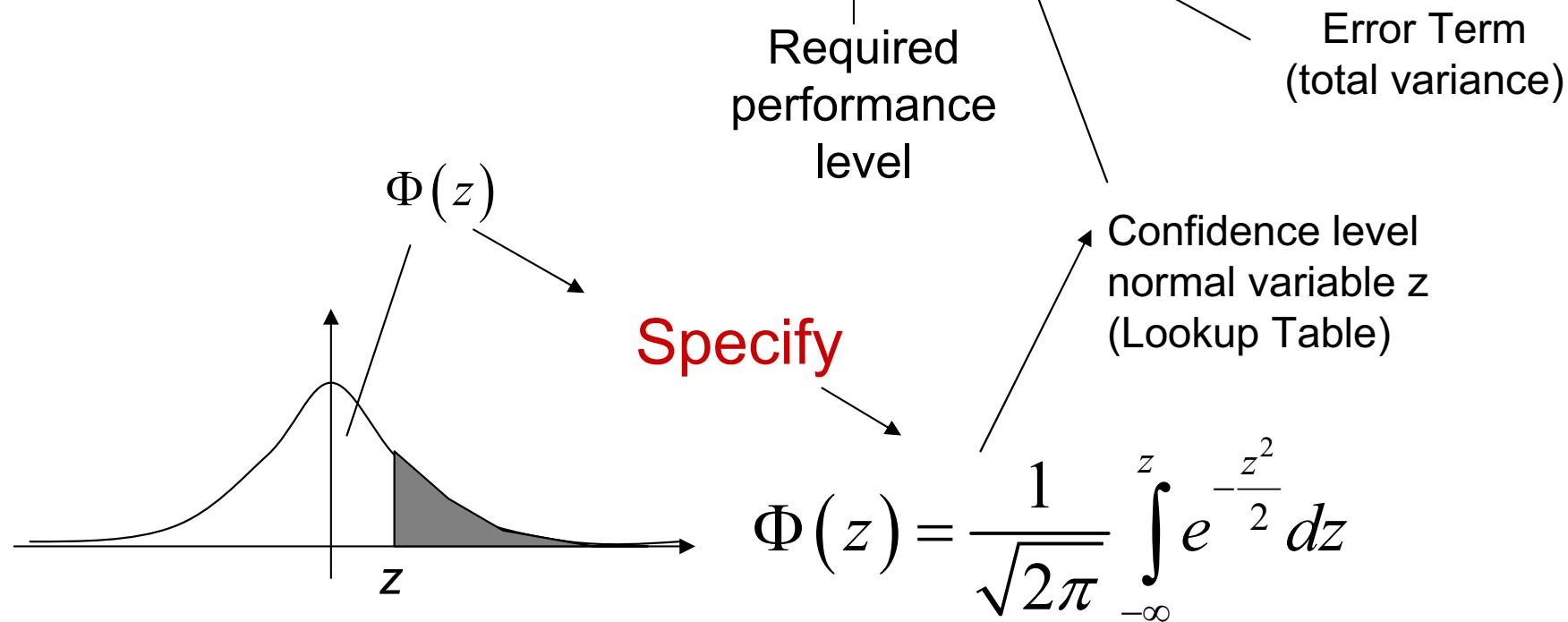
$$a_2 = -0.0869$$

$$a_{12} = -0.0369$$



Step 2: Determine expected level of performance for design i such that the probability of adequate performance is equal to specified confidence level

$$E[J_i] = J_{req} + z\sigma_\varepsilon \quad (2)$$



Baseball:

Performance criterion

- User specifies a final desired standing of $FS_r = 0.550$

Confidence Level

- User specifies a .80 confidence level that this is achieved

Spec is met if for Team i :

$$E[FS_i] = .550 + z\sigma_r = .550 + 0.84(0.0493) = 0.5914$$


The diagram shows two arrows pointing to specific terms in the equation. One arrow points from the text "From normal table lookup" to the term $z\sigma_r$. Another arrow points from the text "Error term from data" to the term 0.0493 .

If the final standing of team i is to equal or exceed .550 with a probability of .80, then the expected final standing for Team i must equal 0.5914

Get Isoperformance Curve

Step 3: Put equations (1) and (2) together

$$J_{req} + z\sigma_r = E[J_i] = a_0 + a_1(x_{1,i}) + a_2(x_{2,i}) + a_{12}(x_{1,i} - \bar{x}_1)(x_{2,i} - \bar{x}_2)$$

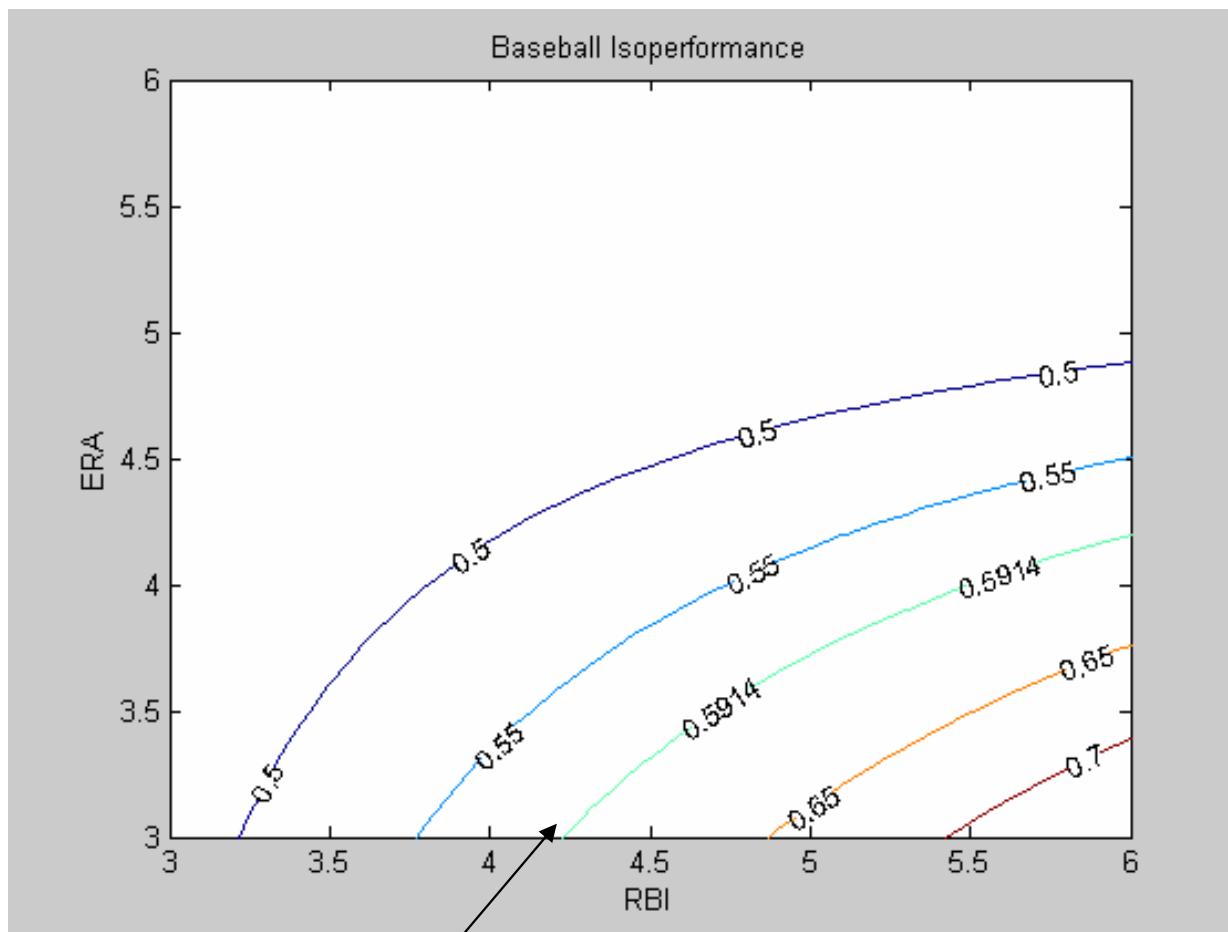
- Four constant parameters: a_0, a_1, a_2, a_{12}
- Two sample statistics: \bar{x}_1, \bar{x}_2
- Two design variables: $x_{1,i}$ and $x_{2,i}$

Then rearrange: $x_{2,i} = f(x_{1,i})$

Baseball: $RBI_i = \frac{.5914 - m - bERA_i + c\overline{RBI}(\overline{ERA} - ERA)}{a + c(ERA_i - \overline{ERA})}$

Equation
for isoperformance
curve

Stochastic Isoperformance



This is our desired tradeoff curve

Summary

- Isoperformance fixes a target level of “expected” performance and finds a set of points (contours) that meet that requirement
- Model can be physics-based or empirical
- Helps to achieve a “balanced” system design, rather than an “optimal design”.