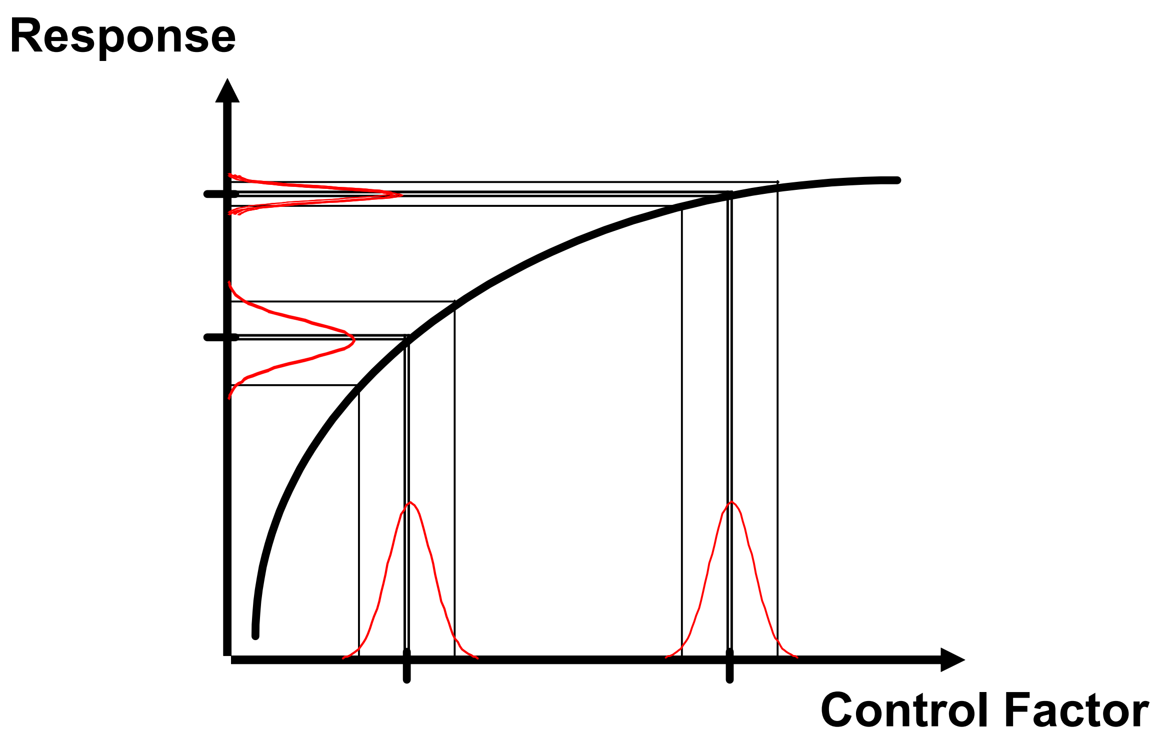
ESD.33 -- Systems Engineering

Session #13
Robust Design



Dan Frey

Plan for the Session

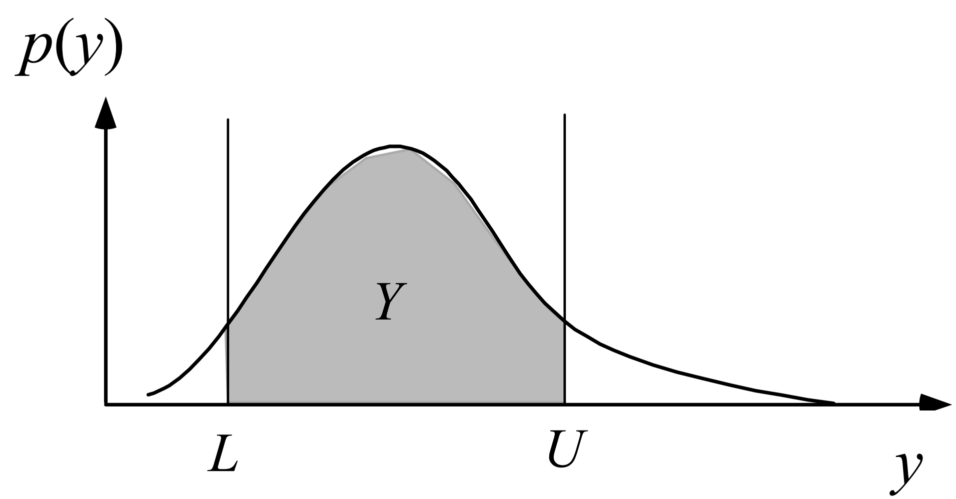
- Taguchi's Quality Philosophy
  - Taguchi_Clausing Robust Quality.pdf
- Implementing Robust Design
  - Ulrich_Eppinger Robust Design.pdf
- Research topics
  - Comparing effectiveness of RD methods
  - Computer aided RD
  - Robustness invention
- Next steps

Robust Design

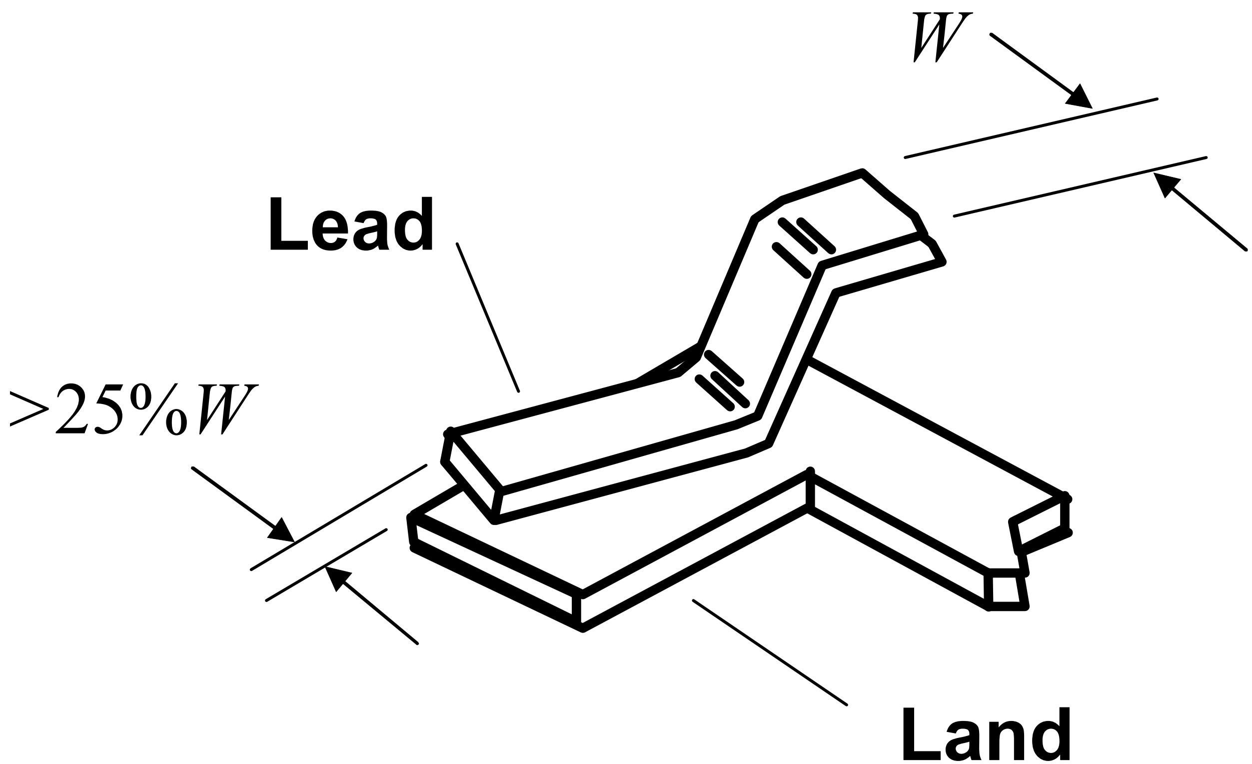
- A set of design methods that
  - Improve the quality of a product
  - Without eliminating the sources of variation (noise factors)
  - By *minimizing sensitivity* to noise factors
  - Most often through parameter design

Engineering Tolerances

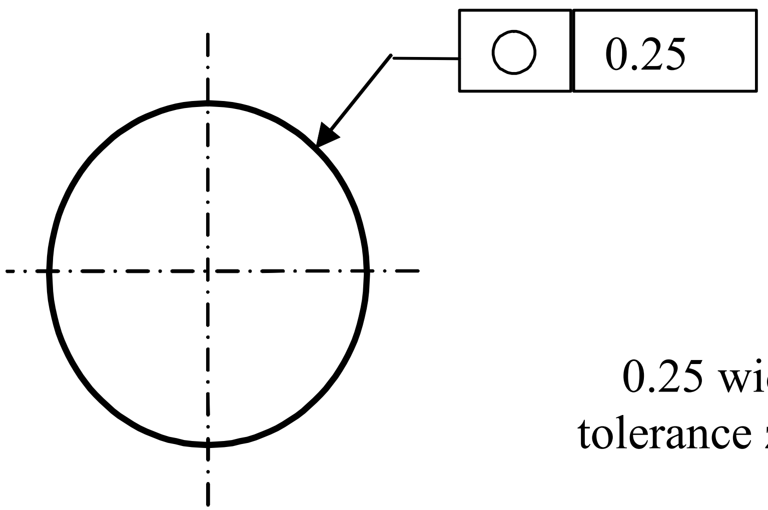
- Tolerance --The total amount by which a specified dimension is *permitted to vary* (ANSI Y14.5M)
- Every component within spec adds to the yield (Y)



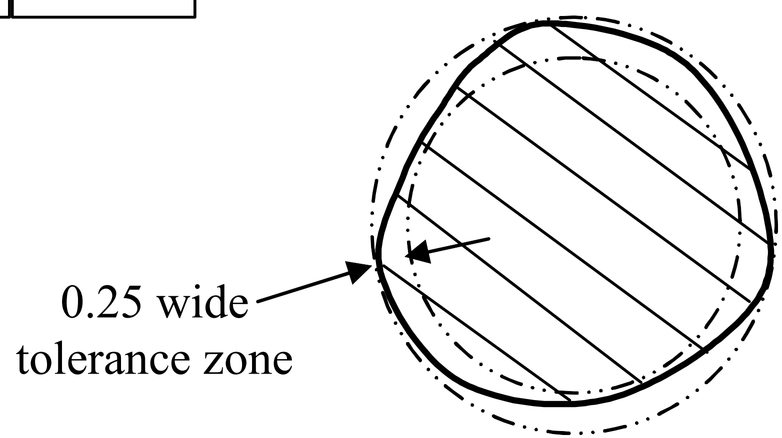
Tolerance on Position



Tolerance of Form



THIS ON A DRAWING

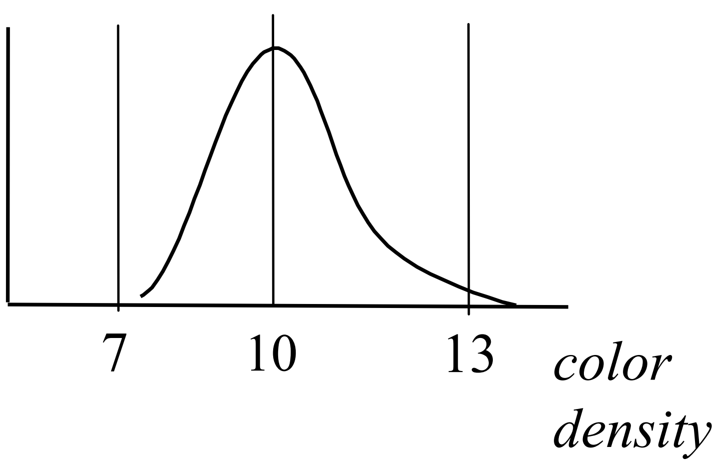


MEANS THIS

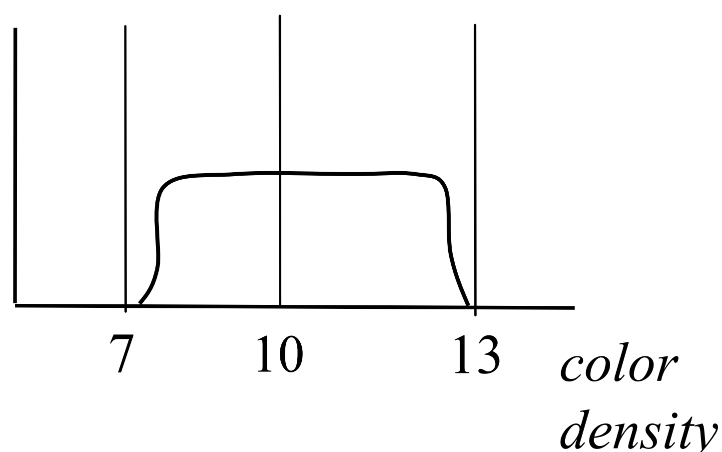
Sony Televisions

- Manufactured in two sites
- Which has lower defect rates?
- Which one has better quality?

Tokyo



San Diego

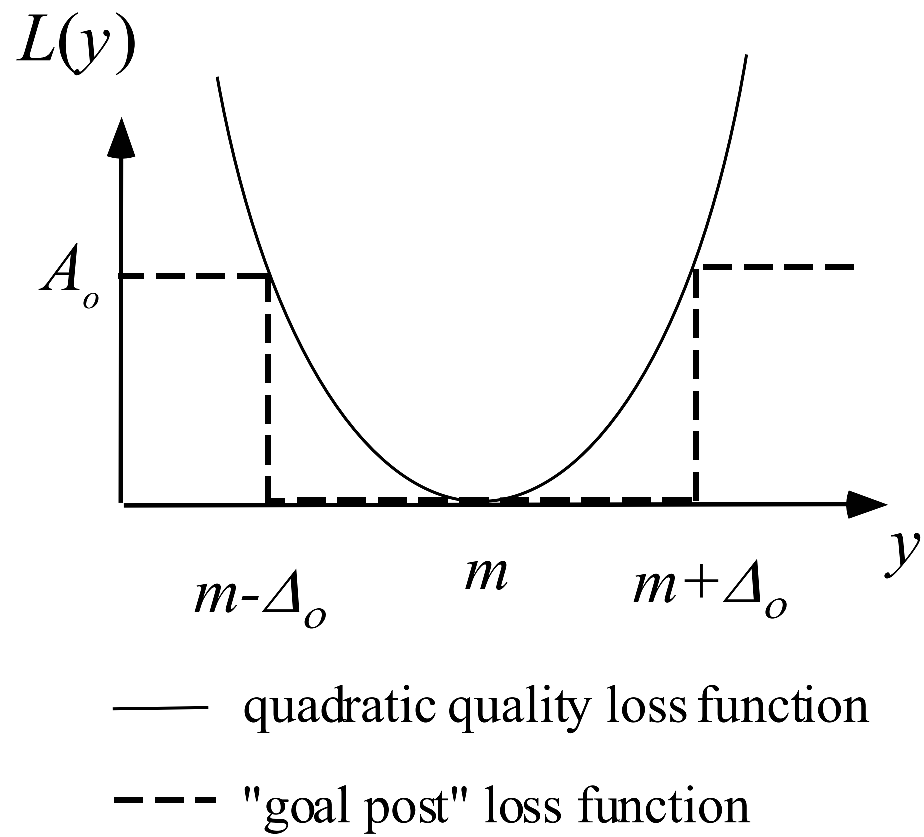


Quadratic loss function

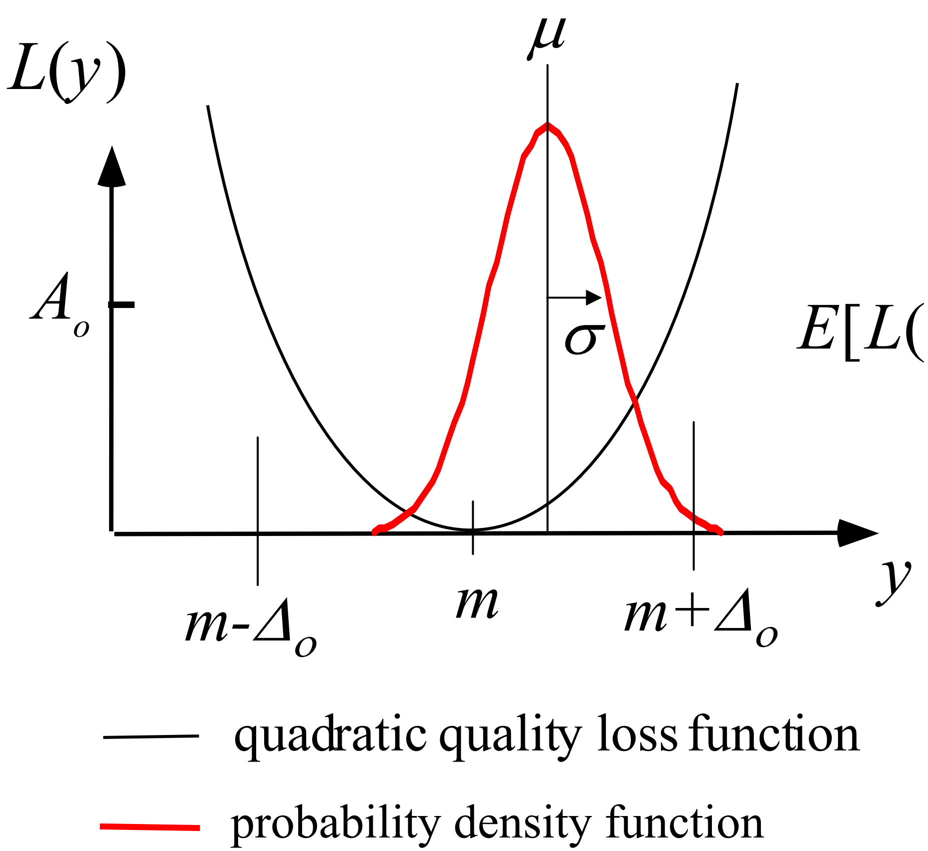
- Defined as

$$L(y) = \frac{A_o}{\Delta_o^{\ 2}}(y - m)^2$$

- Zero at the target value
- Equal to scrap cost at the tolerance limits



Average Quality Loss



$$E[L(y)] = \frac{A_o}{\Delta_o^{\ 2}}\left[\sigma^2 + (\mu - m)^2\right]$$

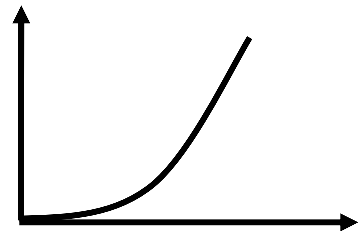
reduce variance

get on target

Other Loss Functions

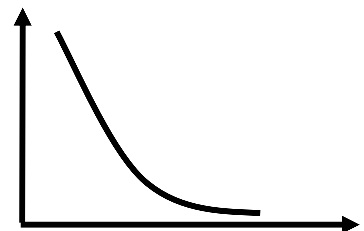
- Smaller the better

$$L(y) = \frac{A_o}{\Delta_o{}^2} y^2$$



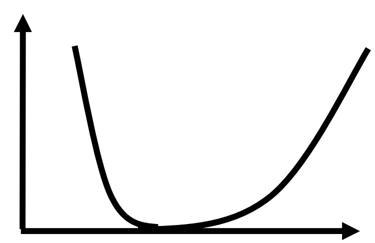
- Larger-the better

$$L(y) = A_o \Delta_o{}^2 \frac{1}{y^2}$$

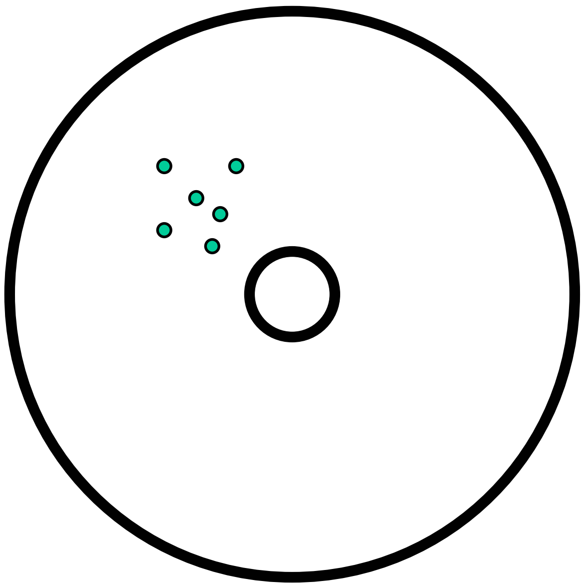


- Asymmetric

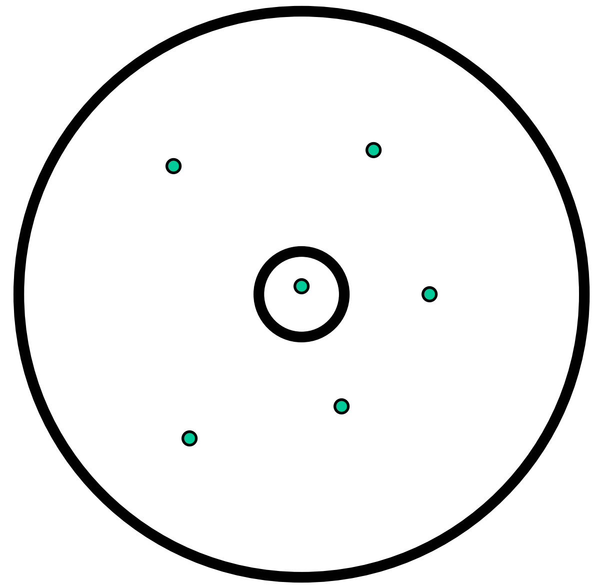
$$L(y) = \begin{cases} \dfrac{A_o}{\Delta_{Upper}{}^2}(y-m)^2 \text{ if } y > m \\ \dfrac{A_o}{\Delta_{Lower}{}^2}(y-m)^2 \text{ if } y \le m \end{cases}$$



Who is the better target shooter?

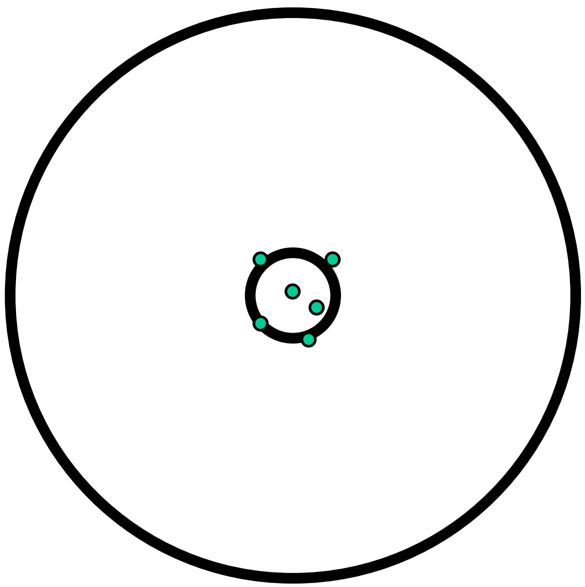


Sam

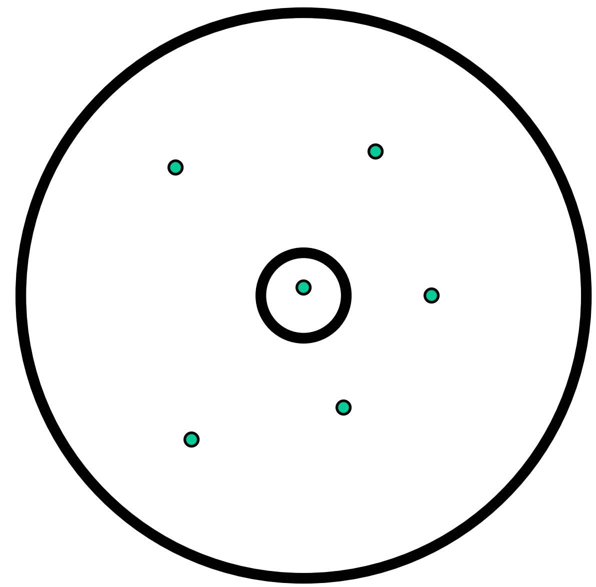


John

Who is the better target shooter?



Sam

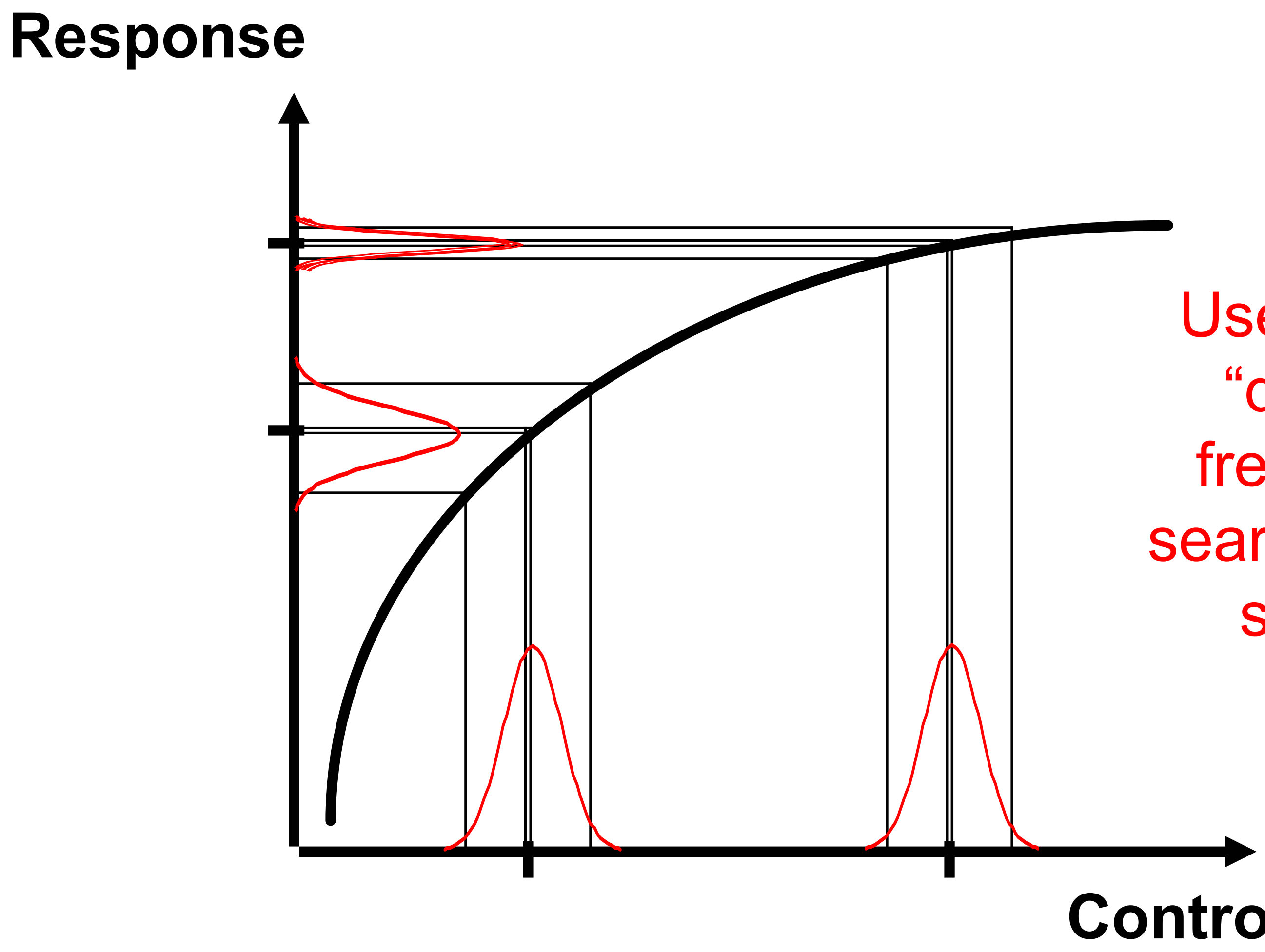


John

Sam can just adjust his sights

John requires lengthy training

Exploiting Non-linearity



Use your extra "degrees of freedom" and search for robust set points.

System Verification Test

- AFTER maximizing robustness
- Make a system prototype
- Get a benchmark (e.g., a good competitor's product)
- Subject BOTH to the same harsh conditions

Taguchi’s Quality Imperatives

- Quality losses result from poor design
- Signal to noise ratios should be improved
- Expose your system to noises systematically
- Two step process – reduce variance first THEN get on target
- Tolerance design – select processes based on total cost (manufacturing cost AND quality)
- Robustness in the field / robustness in the factory

Plan for the Session

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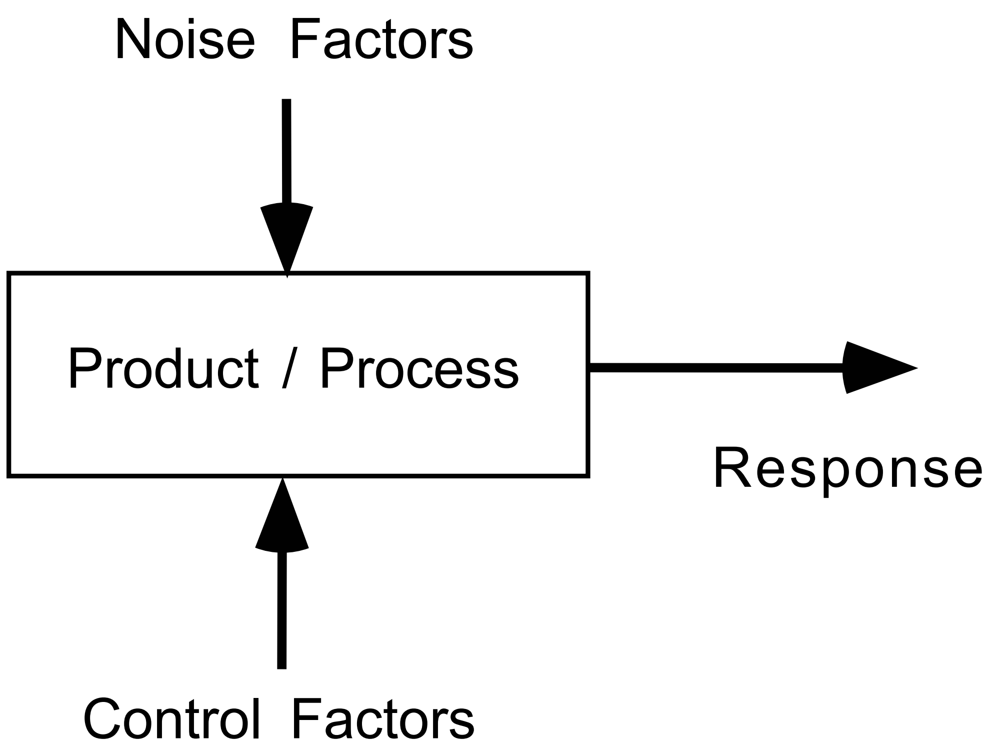
Robust Design Process

- Identify Control Factors, Noise Factors, and Performance Metrics
- Formulate an objective function
- Develop an experimental plan
- Run the experiment
- Conduct the analysis
- Select and confirm factor setpoints
- Reflect and repeat

The "P" Diagram

There are probably lots of noise factors, but a few are usually dominant



There are usually more control factors than responses

Full Factorial Experiments

- For example, if only two factors (A and B) are explored

Control Factors	
A	B
1	1
1	2
1	3
2	1
2	2
2	3
3	1
3	2
3	3

This is called a

full factorial design

$$p^k = 3^2$$

The number of experiments quickly becomes untenable

Orthogonal Array

- Explore the effects of ALL 4 factors in a balanced fashion

Control Factors			
A	B	C	D
1	1	1	1
1	2	2	2
1	3	3	3
2	1	2	3
2	2	3	1
2	3	1	2
3	1	3	2
3	2	1	3
3	3	2	1

requires only

$k(p-1)+1=9$

But main effects and interactions are confounded

Outer Array

- Induce the same noise factor levels for each row in a balanced manner

				E1	E1	E2	E2
				F1	F2	F1	F2
				G1	G2	G2	G1
A1	B1	C1	D1	*1*	*2*	*3*	*4*
A1	B2	C2	D2	*5*	*6*	*7*	*8*
A1	B3	C3	D3	*9*	*10*	*11*	*12*
A2	B1	C2	D3	*13*	*14*	*15*	*16*
A2	B2	C3	D1	*17*	*18*	*19*	*20*
A2	B3	C1	D2	*21*	*22*	*23*	*24*
A3	B1	C3	D2	*25*	*26*	*27*	*28*
A3	B2	C1	D3	*29*	*30*	*31*	*32*
A3	B3	C2	D1	*33*	*34*	*35*	*36*

inner x outer = L9xL4= 36

Compounding Noise

- If the physics are understood qualitatively, worst case combinations may be identified *a priori*

				E1	~~E1~~	~~E2~~	~~E2~~
				F1	F2	~~F1~~	~~F2~~
				G1	G2	~~G2~~	~~G1~~
A1	B1	C1	D1	*1*	*2*	*3*	*4*
A1	B2	C2	D2	*5*	*6*	*7*	*8*
A1	B3	C3	D3	*9*	*10*	*11*	*12*
A2	B1	C2	D3	*13*	*14*	*15*	*16*
A2	B2	C3	D1	*17*	*18*	*19*	*20*
A2	B3	C1	D2	*21*	*22*	*23*	*24*
A3	B1	C3	D2	*25*	*26*	*27*	*28*
A3	B2	C1	D3	*29*	*30*	*31*	*32*
A3	B3	C2	D1	*33*	*34*	*35*	*36*

inner x outer = L9xL4= ~~36~~ 18

Signal to Noise Ratio

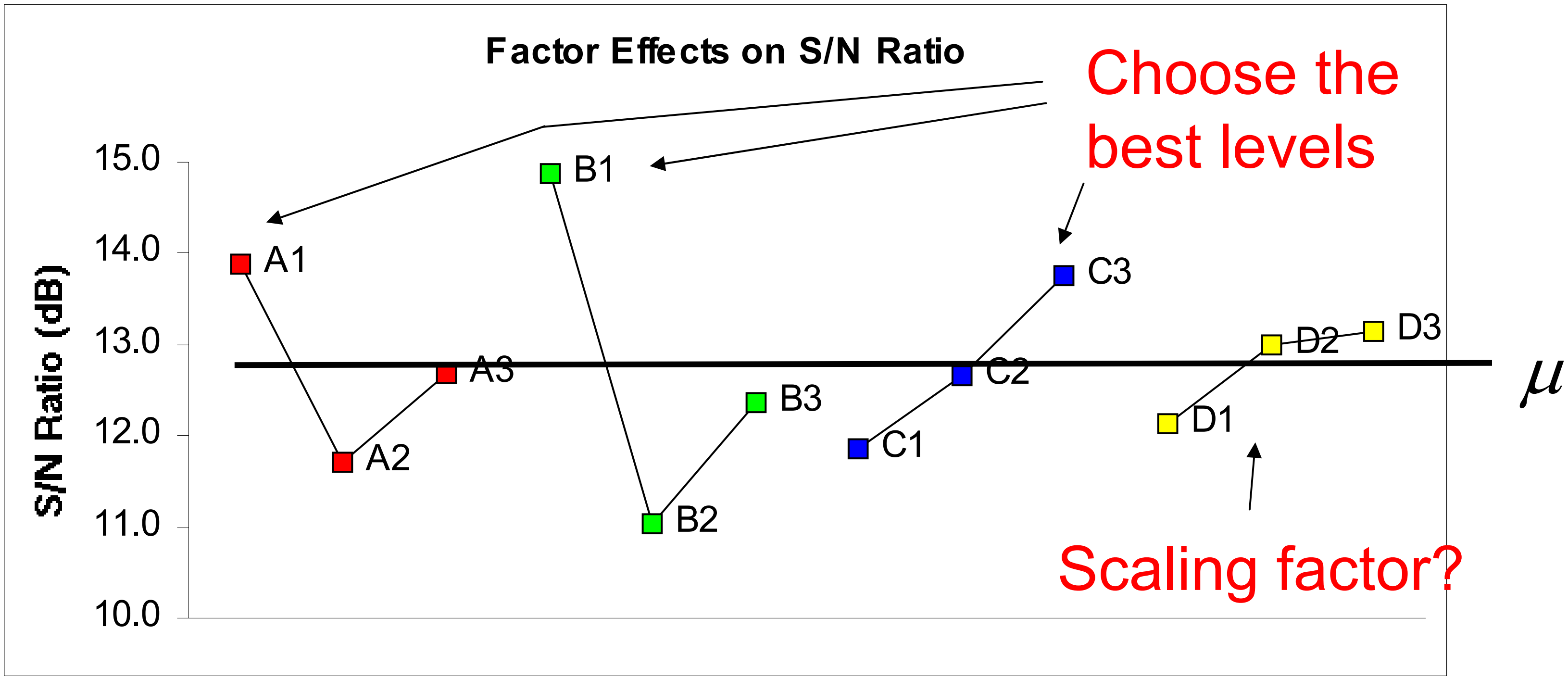
- PERformance Measure Independent of Adjustment *PERMIA* (two-step optimization)

				E1	E1	E2	E2
				F1	F2	F1	F2
				G1	G2	G2	G1
A1	B1	C1	D1	*1*	*2*	*3*	*4*
A1	B2	C2	D2				
A1	B3	C3	D3				
A2	B1	C2	D3				
A2	B2	C3	D1				
A2	B3	C1	D2				
A3	B1	C3	D2				
A3	B2	C1	D3				
A3	B3	C2	D1				

For each row, take an average μ and standard deviation σ

$$\eta = 10\log_{10}\left[\frac{\mu^2}{\sigma^2}\right]$$

Factor Effect Plots



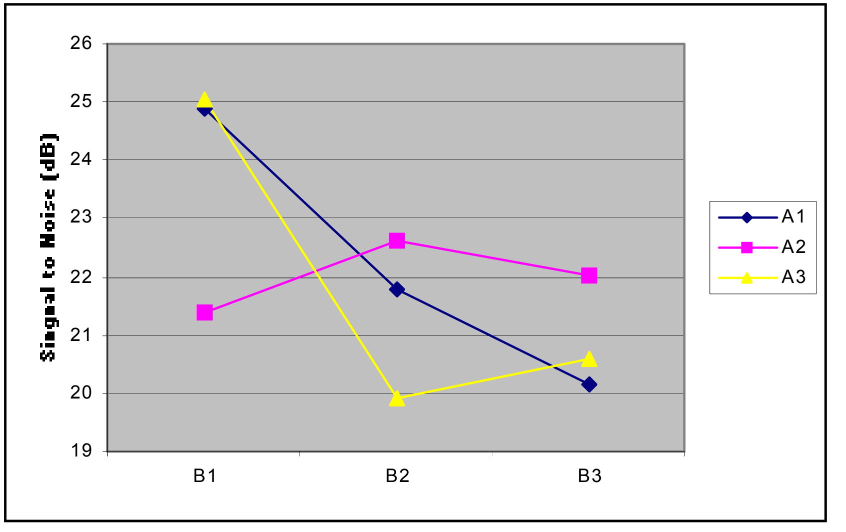
Prediction Equation

$$\eta(A_i, B_j, C_k, D_i) = \mu + a_i + b_j + c_k + d_i + e$$

What is an Interaction?

- If I carry out this experiment, I will find that:

	Control Factors				
Expt. No.	A	B	C	D	η
1	1	1	2	2	24.88
2	1	2	2	2	21.78
3	1	3	2	2	20.17
4	2	1	2	2	21.38
5	2	2	2	2	22.62
6	2	3	2	2	22.02
7	3	1	2	2	25.03
8	3	2	2	2	19.93
9	3	3	2	2	20.58



If there are significant interactions, the prediction may fail to confirm, but you still probably improve the design

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Robust Design References

- Phadke, Madhav S., 1989, *Quality Engineering Using Robust Design* Prentice Hall, Englewood Cliffs, 1989.
- Logothetis and Wynn, *Quality Through Design,* Oxford Series on Advanced Manufacturing, 1994.
- Wu and Hamada, 2000, *Experiments: Planning, Analysis and Parameter Design Optimization,* Wiley & Sons, Inc., NY.

Single Arrays

- Single arrays achieve improved run size economy (or provide advantages in resolving selected effects)
- Selection guided by "effect ordering principle"
- "…those with a larger number of clear control-by-noise interactions, clear control main effects, clear noise main effects, and clear control-by-control interactions are judged to be good arrays."
- "Some of the single arrays … are uniformly better than corresponding cross arrays in terms of the number of clear main effects and two factor interactions"

Wu, C. F. J, and H., M. Hamada, 2000, *Experiments: Planning Analysis, and Parameter Design Optimization,* John Wiley & Sons, New York.

Comparing Crossed & Single Arrays

$$2_{III}^{7-4} \times 2_{III}^{3-1}$$

- 32 runs
- All control factor main effects aliased with CXC
- All noise main effects estimable
- 21 CxN interactions

  clear of 2fi

  clear of CxCxC

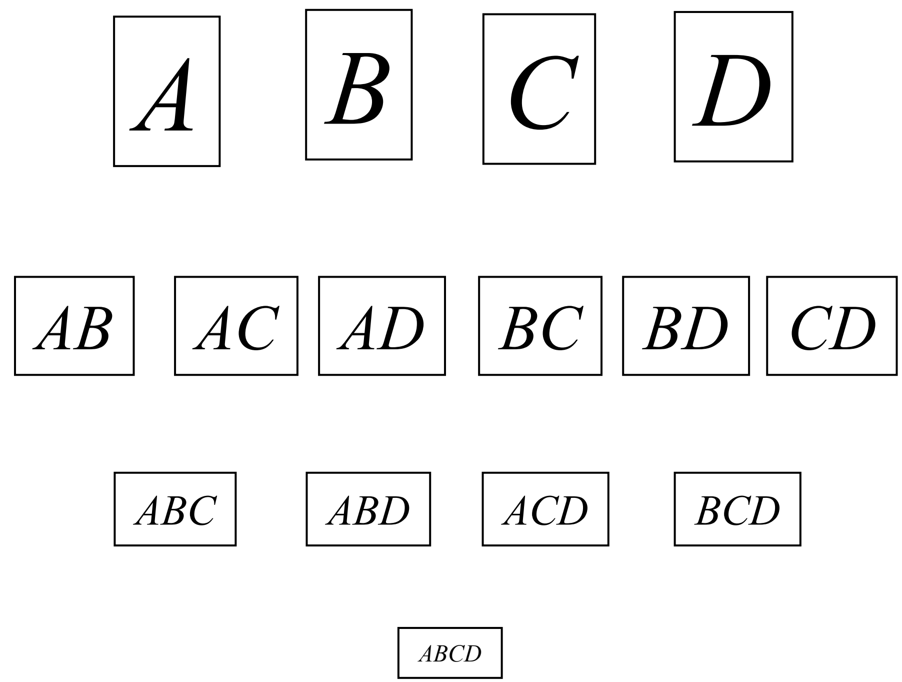
  clear of NxNxN

$$2^{10-5}$$

- 32 runs
- All control factor main effects clear of 2fi
- All noise main effects estimable
- 14 CxN interactions clear of 2fi

Hierarchy

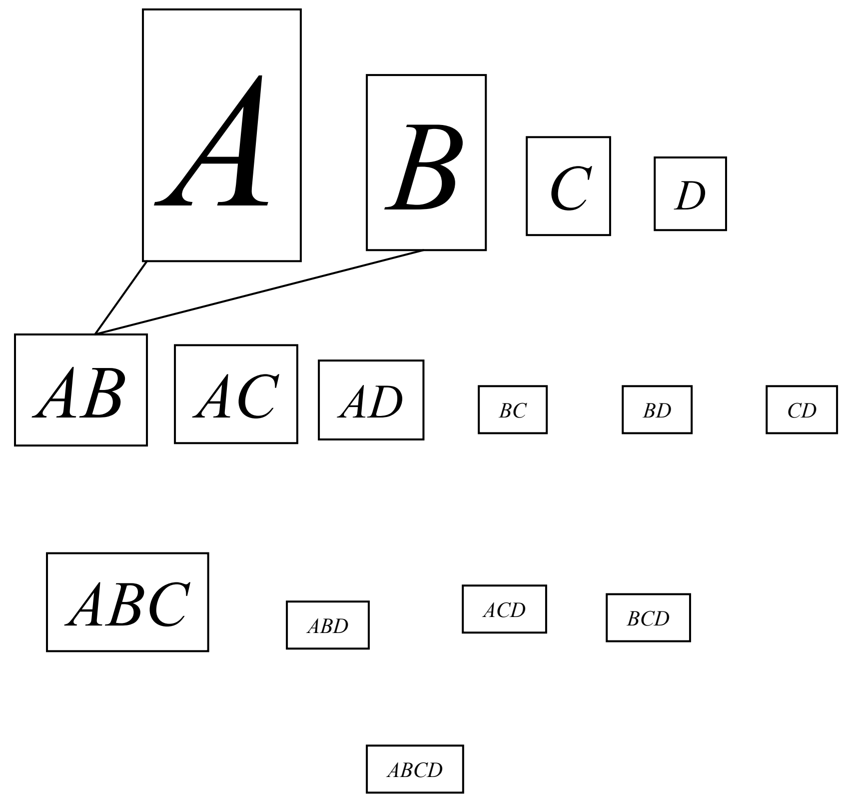
- Main effects are usually more significant than two-factor interactions
- Two-way interactions are usually more significant than three-factor interactions
- And so on



In Robust Design, control by noise interactions are key!

Inheritance

- Two-factor interactions are **most** likely when both participating factors (parents?) are strong
- Two-way interactions are **least** likely when neither parent is strong
- And so on



A Model of Interactions

$$y(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j>i}}^{n} \beta_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j>i}}^{n} \sum_{\substack{k=1 \\ k>j}}^{n} \beta_{ijk} x_i x_j x_k + \varepsilon$$

$$f(\beta_i | \delta_i) = \begin{cases} N(0,1) & \text{if} \quad \delta_{\mathrm{i}} = 0 \\ N(0,c^2) & \text{if} \quad \delta_{\mathrm{i}} = 1 \end{cases}$$

effects are normally distributed
two classes – strong and weak

$$\Pr(\delta_i = 1) = p$$

effect sparsity

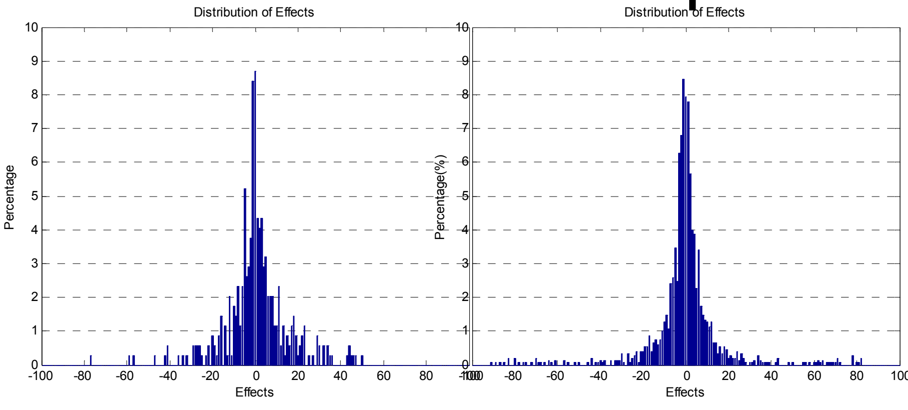
$$\Pr(\delta_{ij} = 1 | \delta_i, \delta_j) = \begin{cases} p_{00} & \text{if} \quad \delta_{\mathrm{i}} + \delta_{\mathrm{j}} = 0 \\ p_{01} & \text{if} \quad \delta_{\mathrm{i}} + \delta_{\mathrm{j}} = 1 \\ p_{11} & \text{if} \quad \delta_{\mathrm{i}} + \delta_{\mathrm{j}} = 2 \end{cases}$$

effect hierarchy & inheritance

Chipman, H., M. Hamada, and C. F. J. Wu, 2001, "A Bayesian Variable Selection Approach for Analyzing Designed Experiments with Complex Aliasing", *Technometrics* 39(4)372-381.

Fitting the Model to Data

- Collect published full factorial data on various engineering systems
  - More than data 100 sets collected so far
- Use Lenth method to sort “active” and “inactive” effects
- Estimate the probabilities in the model
- Use other free parameters to make model pdf fit the data pdf



Different Variants of the Model

	c	s_1	s_2	w_1	w_2
Basic WH	10	1	1	1	1
Basic low w	10	1	1	0.1	0.1
Basic 2nd order	10	1	0	1	1
Fitted WH	15	1/3	2/3	1	1
Fitted low w	15	1/3	2/3	0.1	0.1
Fitted 2nd order	15	1/3	0	1	1

The model that drives much of DOE & Robust Design

The model I think is most realistic

	p	p_{11}	p_{01}	p_{00}	p_{111}	p_{011}	p_{001}	p_{000}
Basic WH	0.25	0.25	0.1	0	0.25	0.1	0	0
Basic low w	0.25	0.25	0.1	0	0.25	0.1	0	0
Basic 2nd order	0.25	0.25	0.1	0	N/A	N/A	N/A	N/A
Fitted WH	0.43	0.31	0.04	0	0.17	0.08	0.02	0
Fitted low w	0.43	0.31	0.04	0	0.17	0.08	0.02	0
Fitted 2nd order	0.43	0.31	0.04	0	N/A	N/A	N/A	N/A

Robust Design Method Evaluation Approach

1. Instantiate models of multiple "engineering systems"
2. For each system, simulate different robust design methods
3. For each system/method pair, perform a confirmation experiment
4. Analyze the data

Frey, D. D., and X. Li, 2004, "Validating Robust Design Methods, accepted for *ASME Design Engineering Technical Conference*, September 28 - October 2, Salt Lake City, UT.

Results

The single array is <u>extremely effective</u> if the typical modeling assumptions of DOE hold

		Basic			Fitted		
Method	Experiments	WH	low w	2^{nd} order	WH	low w	2^{nd} order
$2^7 \times 2^3$	1,024	60%	81%	58%	50%	58%	40%
$2^7 \times 2_{III}^{3-1}$	512	44%	80%	52%	45%	58%	40%
2^{10-4}	64	8%	8%	56%	18%	9%	38%
2^{10-5}	32	9%	3%	33%	16%	9%	17%
$2_{III}^{7-4} \times 2_{III}^{3-1}$	32	12%	8%	51%	16%	25%	38%
$OFAT \times 2_{III}^{3-1}$	32	39%	56%	43%	36%	42%	35%
$OFAT \times OFAT$	32	31%	37%	41%	33%	31%	27%
2^{10-6}	16	4%	4%	8%	4%	2%	0%

Results

The single array is terribly ineffective if the more realistic assumptions are made

		Basic			Fitted		
Method	Experiments	WH	low w	2^{nd} order	WH	low w	2^{nd} order
$2^7 \times 2^3$	1,024	60%	81%	58%	50%	58%	40%
$2^7 \times 2_{III}^{3-1}$	512	44%	80%	52%	45%	58%	40%
2^{10-4}	64	8%	8%	56%	18%	9%	38%
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2^{10-6}	16	4%	4%	8%	4%	2%	0%

Results

Taguchi's crossed arrays are more effective than single arrays

Method	Experiments	Basic WH	Basic low w	Basic 2^{nd} order	Fitted WH	Fitted low w	Fitted 2^{nd} order
$2^7 \times 2^3$	1,024	60%	81%	58%	50%	58%	40%
$2^7 \times 2_{III}^{3-1}$	512	44%	80%	52%	45%	58%	40%
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2^{10-6}	16	4%	4%	8%	4%	2%	0%

A Comparison of Taguchi's Product Array and the Combined Array in Robust Parameter Design

We have run an experiment where we have done both designs simultaneously (*product and combined*). In our experiment, we found that the product array performed better for the identification of effects on the variance. An explanation for this might be that the combined array relies too much on the factor sparsity assumption.

Joachim Kunert, Universitaet Dortmund
The Eleventh Annual Spring Research Conference (SRC) on Statistics in Industry and Technology will be held May 19-21, 2004.

Results

An adaptive approach is quite effective if the more realistic assumptions are made

Method	Experiments	Basic			Fitted		
		WH	low w	2nd order	WH	low w	2nd order
$2^7 \times 2^3$	1,024	60%	81%	58%	50%	58%	40%
$2^7 \times 2^{3-1}_{III}$	512	44%	80%	52%	45%	58%	40%
2^{10-4}	64	8%	8%	56%	18%	9%	38%
2^{10-5}	32	9%	3%	33%	16%	9%	17%
$2^{7-4}_{III} \times 2^{3-1}_{III}$	32	12%	8%	51%	16%	25%	38%
$OFAT \times 2^{3-1}_{III}$	32	39%	56%	43%	36%	42%	35%
$OFAT \times OFAT$	32	31%	37%	41%	33%	31%	27%
2^{10-6}	16	4%	4%	8%	4%	2%	0%

Results

An adaptive approach is <u>a solid choice</u> (among the fast/frugal set) <u>no matter what modeling assumptions are made</u>

		Basic			Fitted		
Method	Experiments	WH	low w	2^{nd} order	WH	low w	2^{nd} order
$2^7 \times 2^3$	1,024	60%	81%	58%	50%	58%	40%
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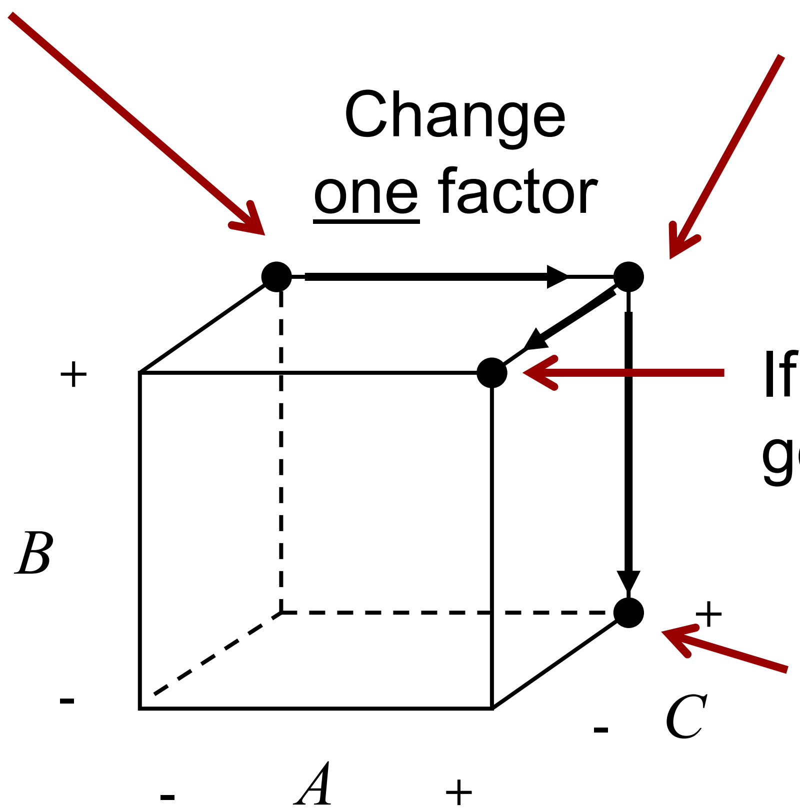
2^{10-6}	16	4%	4%	8%	4%	2%	0%

Adaptive One Factor at a Time Experiments



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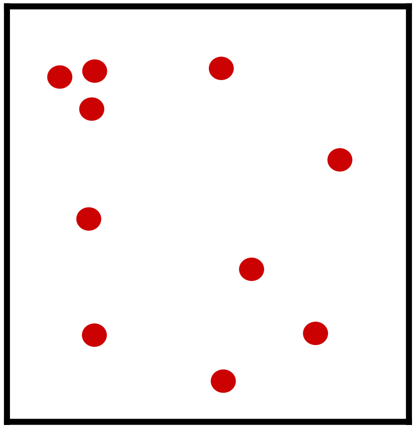
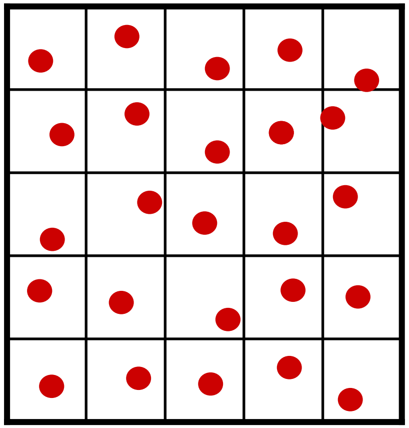
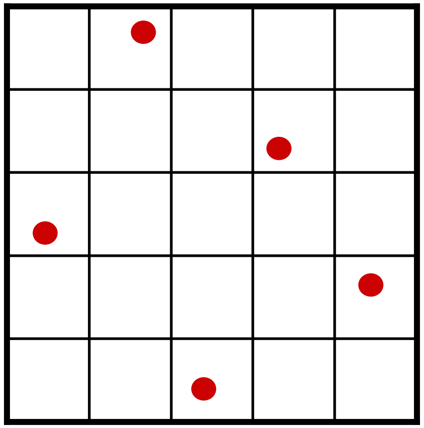
Sampling Techniques for Computer Experiments



Random Sampling



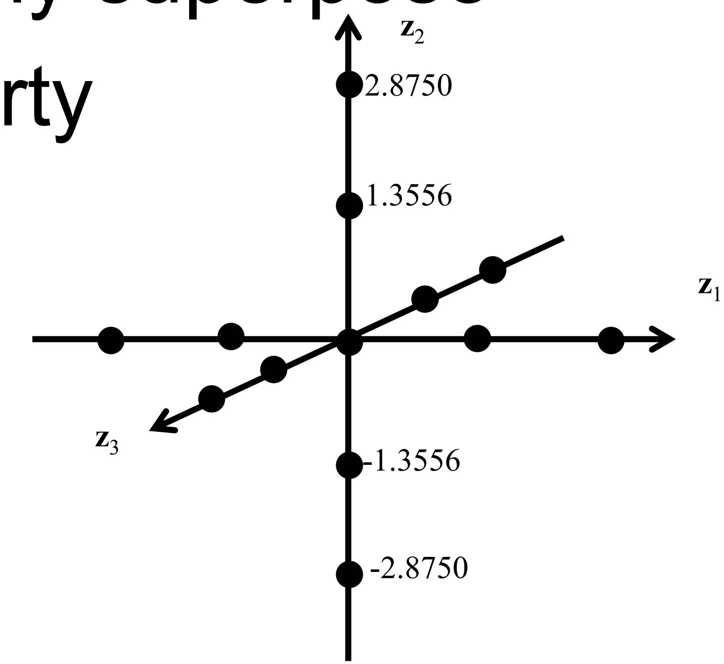
Stratified Sampling



Latin Hypercube Sampling

Proposed Method

- Simply extend quadrature to many variables
- Will be exact to if factor effects of 4th polynomial order linearly superpose
- Lacks projective property
- Poor divergence



Why Neglect Interactions?

$$\eta(\mathbf{z}) = \beta_0 + \sum_{i=1}^{n} \beta_i \mathbf{z}_i + \sum_{j=1}^{n} \sum_{\substack{i=1 \\ i \le j}}^{n} \beta_{ij} \mathbf{z}_i \mathbf{z}_j + \sum_{j=1}^{n} \sum_{\substack{i=1 \\ i \le j}}^{n} \sum_{\substack{k=1 \\ k \le k}}^{n} \beta_{ijk} \mathbf{z}_i \mathbf{z}_j \mathbf{z}_k + \sum_{j=1}^{n} \sum_{\substack{i=1 \\ i \le j}}^{n} \sum_{\substack{k=1 \\ k \le j}}^{n} \sum_{\substack{l=1 \\ l \le k}}^{n} \beta_{ijkl} \mathbf{z}_i \mathbf{z}_j \mathbf{z}_k \mathbf{z}_l$$

If the response is polynomial

$$\sigma^2(\eta(\mathbf{z})) = \sum_{i=1}^{n} \left(\beta_i^{\,2} + 2\beta_{ii}^{\,2} + 6\beta_i \beta_{iii} + 15\beta_{iii}^{\,2} + 24\beta_{ii}\beta_{iiii} + 96\beta_{iiii}^{\,2} \right) +$$

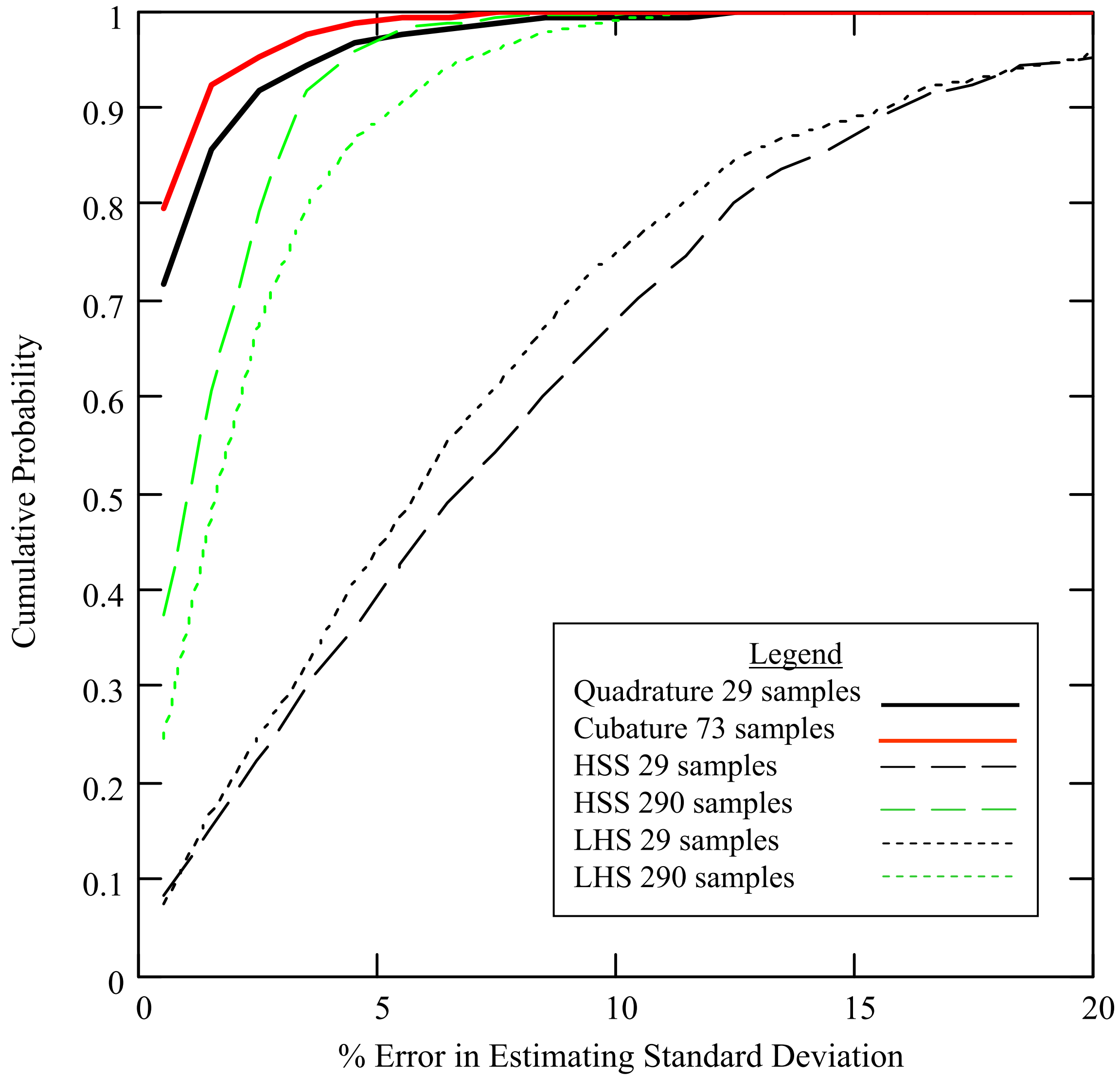
$$\sum_{i=1}^{n} \sum_{\substack{j=1 \\ i<j}}^{n} \begin{pmatrix} \beta_{ij}^{\,2} + 3\beta_{iij}^{\,2} + 3\beta_{ijj}^{\,2} + 15\beta_{iiij}^{\,2} + 15\beta_{ijjj}^{\,2} + 8\beta_{iijj}^{\,2} + \\ 2\beta_i \beta_{ijj} + 2\beta_j \beta_{iij} + 4\beta_{ii}\beta_{iijj} + 4\beta_{jj}\beta_{iijj} + 6\beta_{ij}\beta_{iiij} + \\ 6\beta_{ij}\beta_{ijjj} + 6\beta_{iii}\beta_{ijj} + 6\beta_{jjj}\beta_{iij} + 24\beta_{iiii}\beta_{iijj} + 24\beta_{jjjj}\beta_{iijj} \end{pmatrix} +$$

$$\sum_{i=1}^{n} \sum_{\substack{j=1 \\ i<j}}^{n} \sum_{\substack{k=1 \\ j<k}}^{n} \begin{pmatrix} \beta_{ijk}^{\,2} + 3\beta_{iijk}^{\,2} + 3\beta_{ijjk}^{\,2} + 3\beta_{ijkk}^{\,2} + 2\beta_{iij}\beta_{jkk} + 2\beta_{iik}\beta_{jjk} + \\ 2\beta_{ijj}\beta_{ikk} + 4\beta_{iijj}\beta_{jjkk} + 4\beta_{iijj}\beta_{iikk} + 4\beta_{iikk}\beta_{jjkk} + 6\beta_{iiij}\beta_{ijkk} + \\ 6\beta_{iiik}\beta_{ijjk} + 6\beta_{ijjj}\beta_{ijkk} + 6\beta_{jjjk}\beta_{iijk} + 6\beta_{jkkk}\beta_{iijk} \end{pmatrix} +$$

$$\sum_{i=1}^{n} \sum_{\substack{j=1 \\ i<j}}^{n} \sum_{\substack{k=1 \\ j<k}}^{n} \sum_{\substack{l=1 \\ k<l}}^{n} \begin{pmatrix} \beta_{ijkl}^{\,2} + 2\beta_{iijj}\beta_{kkll} + 2\beta_{iikk}\beta_{jjll} + 2\beta_{iill}\beta_{jjkk} + 2\beta_{iijk}\beta_{jkll} \\ + 2\beta_{ijjk}\beta_{ikll} + 2\beta_{ijkk}\beta_{ijll} + 2\beta_{iijl}\beta_{jkkl} + 2\beta_{ijjl}\beta_{ikkl} + 2\beta_{ijll}\beta_{ijkk} \end{pmatrix}$$

Then the effects of single factors have larger contributions to σ than the mixed terms.

Fourth Order – RWH Model Fit to Data



$d=7$

$4d+1=29$

$d^2+3d+3=73$

Continuous-Stirred Tank Reactor

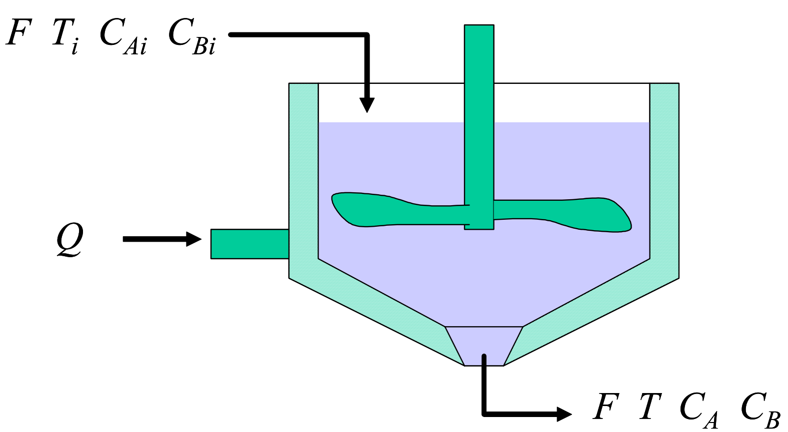
- Objective is to generate chemical species B at a rate of 60 mol/min

$$Q = F\rho C_p (T - T_i) + V(r_A H_{RA} + r_B H_{RB})$$

$$C_A = \frac{C_{Ai}}{1 + k_A^0 e^{-E_A/RT}\tau} \quad C_B = \frac{C_{Bi} + k_A^0 e^{-E_A/RT}\tau C_A}{1 + k_B^0 e^{-EB/RT}\tau}$$

$$-r_A = k_A^0 e^{-E_A/RT} C_A$$

$$-r_B = k_B^0 e^{-E_B/RT} C_B - k_A^0 e^{-E_A/RT} C_A$$

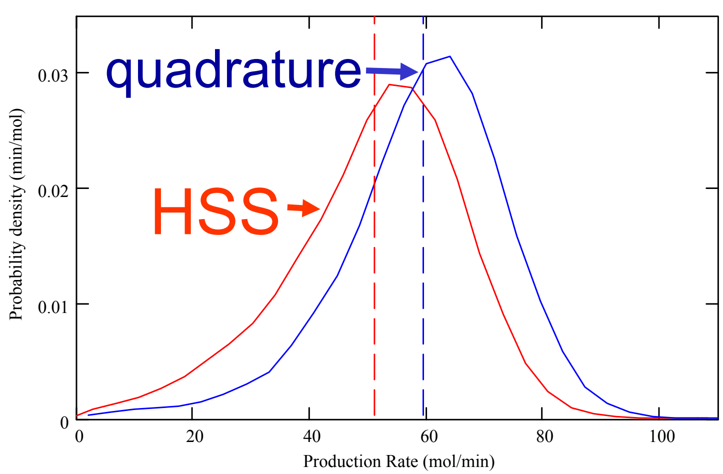


Adapted from Kalagnanam and Diwekar, 1997, "An Efficient Sampling Technique for Off-Line Quality Control", *Technometrics* (39 (3) 308-319.

Comparing HSS and Quadrature

Hammersley Sequence

- Required ~150 points
- 1% accuracy σ^2
- $\downarrow \sigma^2$ from 1,638 to 232
- Nominally on target
- Mean 15% off target



Quadrature

- Used 25 points
- 0.3% accuracy in μ
- 9% accuracy in $(y\text{-}60)^2$ far from optimum
- 0.8% accuracy in $(y\text{-}60)^2$ near to optimum
- Better optimum, on target and slightly lower variance
- $E(L(y)) = 208.458$

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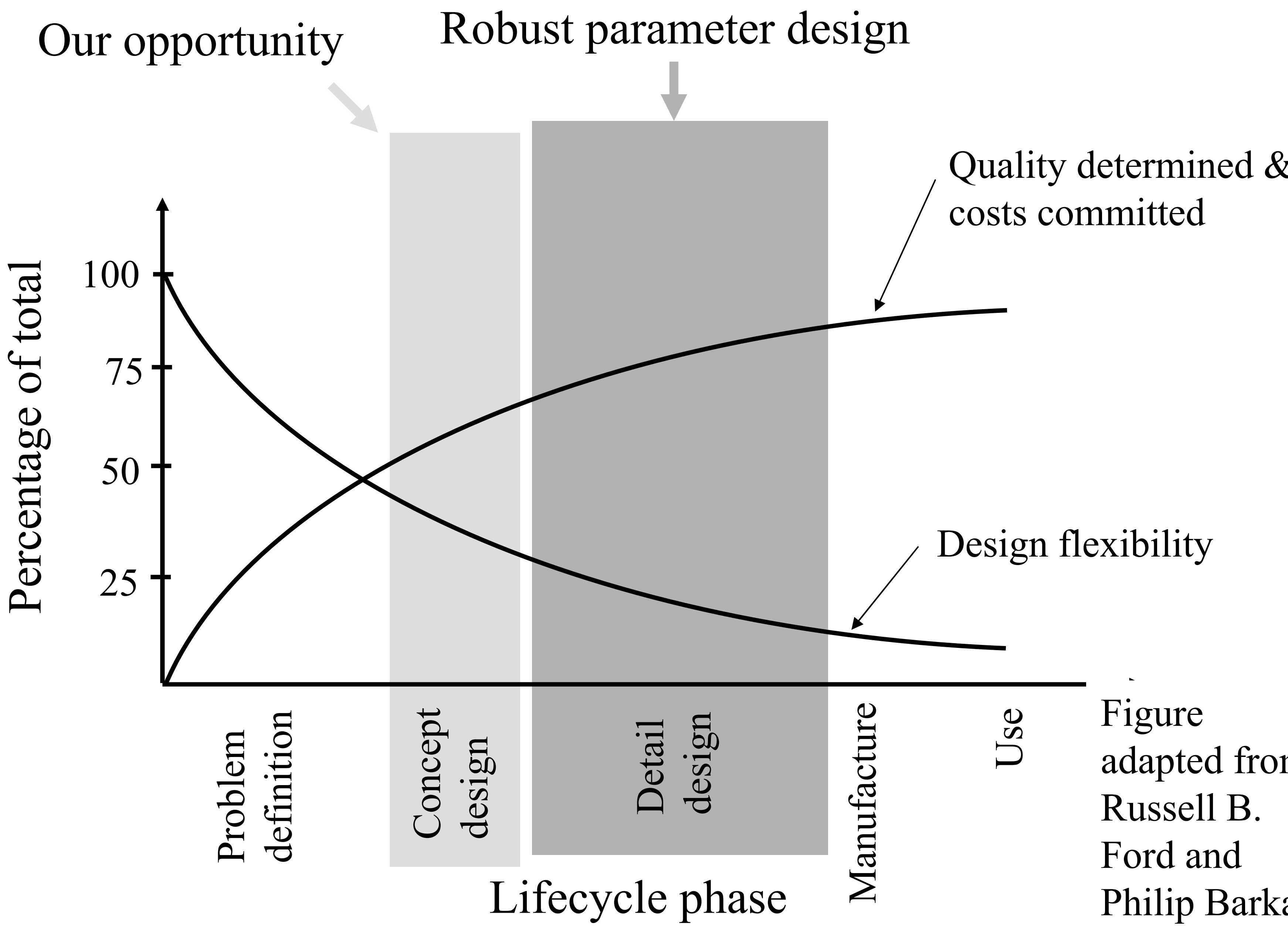


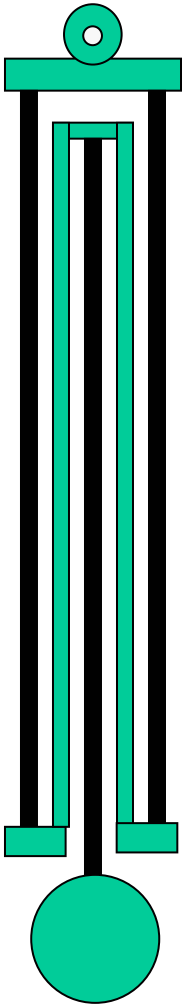
Figure adapted from Russell B. Ford and Philip Barkan

Harrison’s “H1”

- Longitude Act of 1714 promises £20,000
- Accurate nautical timekeeping was one possible key
- But chronometers were not robust to the shipboard environment
- Harrison won through robust design!

Example -- A Pendulum Robust to Temperature Variations

- Period of the swing is affected by length
- Length is affected by temperature
- Consistency is a key to accurate timekeeping
- Using materials with different thermal expansion coefficients, the length can be made insensitive to temp

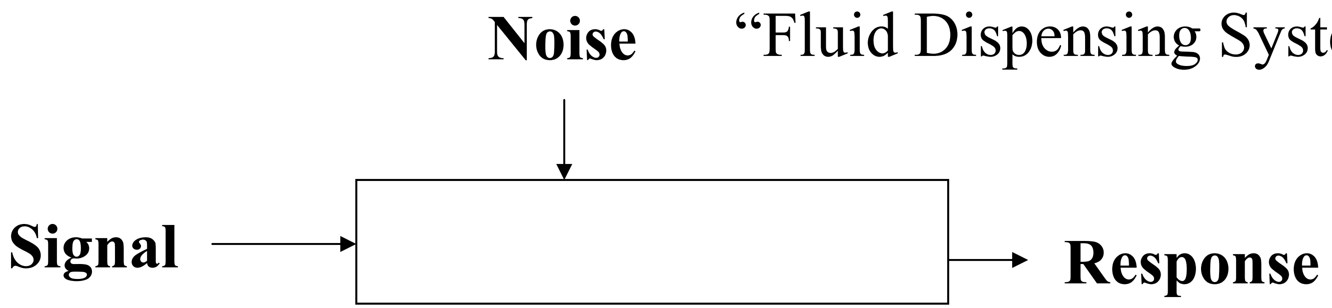


Defining “Robustness Invention”

- A “robustness invention” is a technical or design innovation whose primary purpose is to make performance more consistent despite the influence of noise factors
- The patent summary and prior art sections usually provide clues

Classifying Robustness Inventions

Patent #4,487,333 –
“Fluid Dispensing System”



Patent #5,483,840 –
“System for
Measuring Flow”

Patent #5,024,105 –
Viscosity-insensitive
variable-area flowmeter

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Next Steps

- No HW
- BUT, you should begin preparing for exam
  - Supplemental notes Clausing_TRIZ.pdf
  - When should exam go out?
- See you at Thursday's session
  - On the topic "Extreme Programming"
  - 8:30AM Thursday, 22 July
- Reading assignment for Thursday
  - Beck_Extreme Programming.pdf
  - Williams_Pair Programming.pdf

testable