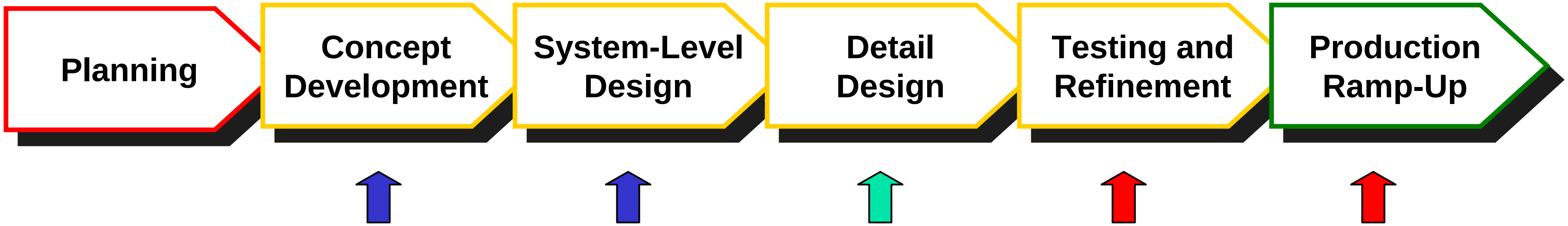
Robust Design: Experiments for Better Products

Taguchi Techniques

Robust Design and Quality in the Product Development Process

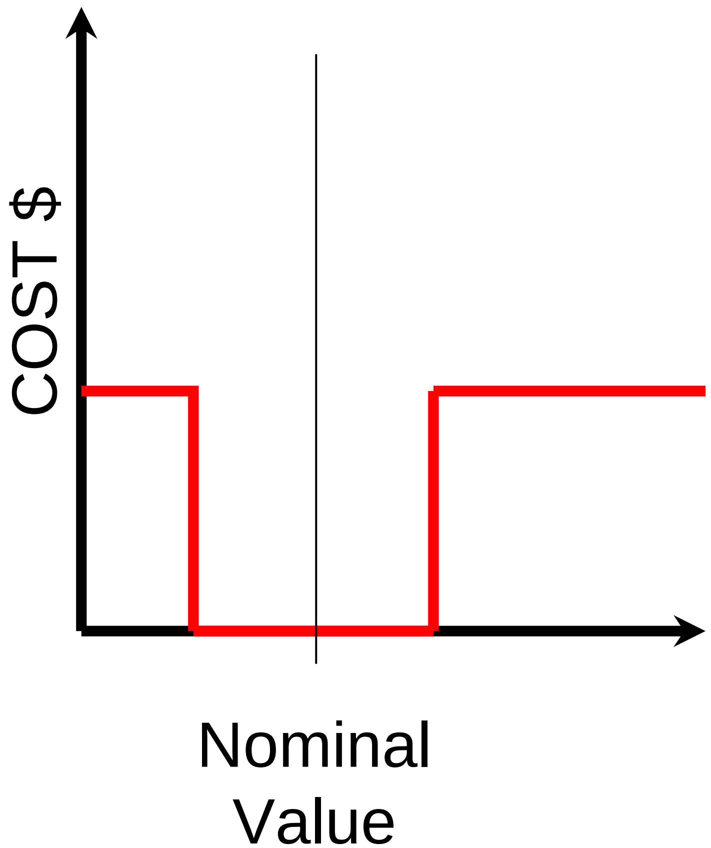


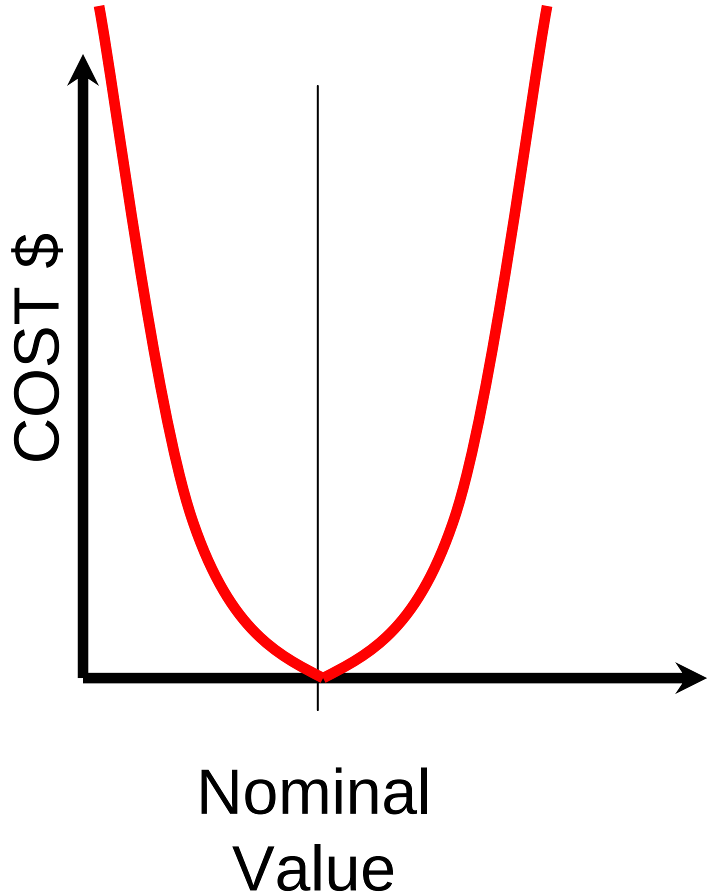
Robust Concept and System Design

Robust Parameter & Tolerance Design

Quality efforts are typically made here, when it is too late.

Goalpost vs Taguchi View





General Loss Function

$$k \cdot \left[\sigma^2 + (\mu - m)^2 \right]$$

Product & Process Engineer (a priori)

Manufacturing (daily)

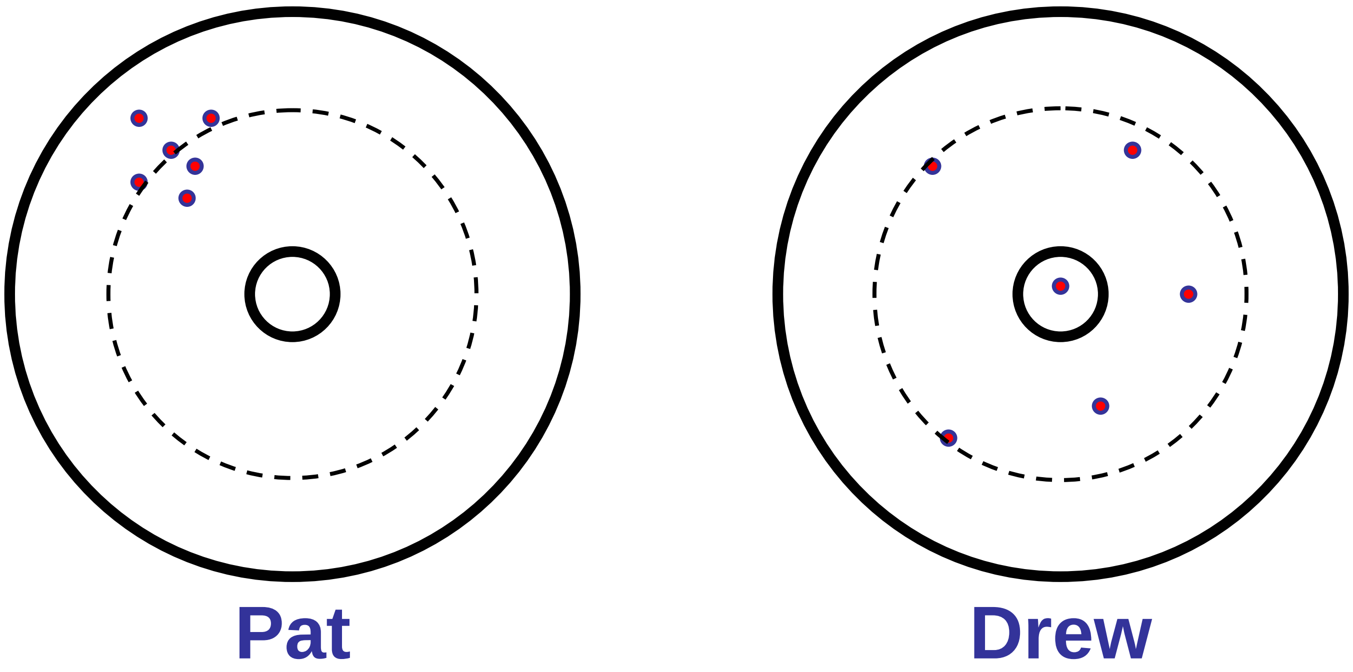
Nominal Value

Average Value

Variance

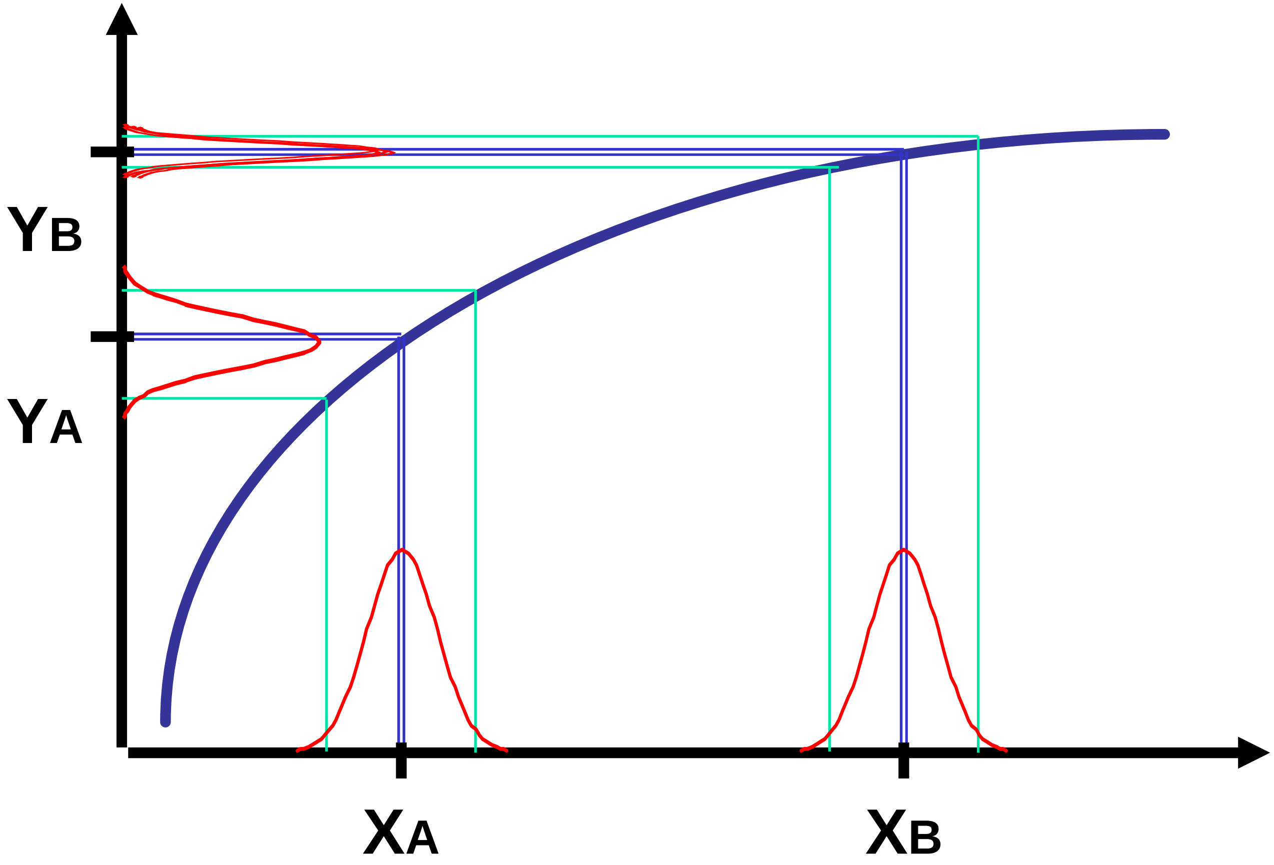
Cost Factor

Who is the better target shooter?



Adapted from: Clausing, Don, and Genichi Taquchi. “Robust Quality.”
Boston, MA: *Harvard Business Review*, 1990. Reprint No. 90114.

Exploiting Non-Linearities



Source: Ross, Phillip J. "Taguchi Techniques for Quality Engineering (2nd Edition)." New York, NY: McGraw Hill, 1996.

Goals for Designed Experiments

- Understanding relationships between design parameters and product performance
- Understanding effects of noise factors
- Reducing product or process variations

Robust Designs

A Robust Product or Process performs correctly, even in the presence of noise factors.

- Outer Noise

  Environmental changes, Operating conditions, People
- Inner Noise
  - Function & Time related (Wear, Deterioration)
- Product Noise
  - Part-to-Part Variations

Parameter Design

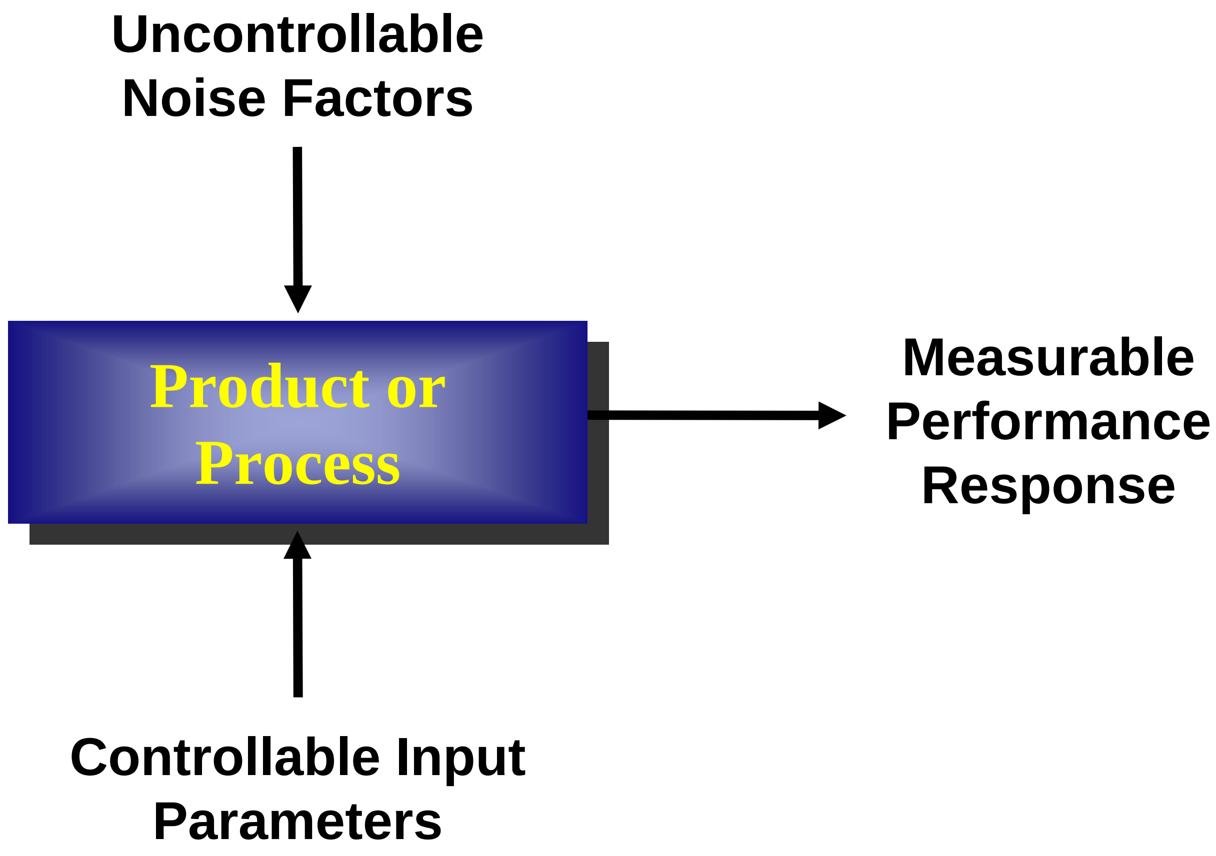
Procedure

Step 1: P-Diagram

Step 1: Select appropriate controls, response, and noise factors to explore experimentally.

- controllable input parameters
- measurable performance response
- uncontrollable noise factors

The “P” Diagram



Example: Brownie Mix

- Controllable Input Parameters
  - Recipe Ingredients (quantity of eggs, flour, chocolate)
  - Recipe Directions (mixing, baking, cooling)
  - Equipment (bowls, pans, oven)
- Uncontrollable Noise Factors
  - Quality of Ingredients (size of eggs, type of oil)
  - Following Directions (stirring time, measuring)
  - Equipment Variations (pan shape, oven temp)
- Measurable Performance Response
  - Taste Testing by Customers
  - Sweetness, Moisture, Density

Step 2: Objective Function

Step 2: Define an objective function (of the response) to optimize.

- maximize desired performance
- minimize variations
- quadratic loss
- signal-to-noise ratio

Types of Objective Functions

Larger-the-Better
e.g. performance
$f(y) = y^2$

Smaller-the-Better
e.g. variance
$f(y) = 1/y^2$

Nominal-the-Best
e.g. target
$f(y) = 1/(y-t)^2$

Signal-to-Noise
e.g. trade-off
$f(y) = 10\log[\mu^2/\sigma^2]$

Step 3: Plan the Experiment

Elicit desired effects:

- Use full or fractional factorial designs to identify interactions.
- Use an orthogonal array to identify main effects with minimum of trials.
- Use inner and outer arrays to see the effects of noise factors.

Experiment Design: Full Factorial

- Consider k factors, n levels each.
- Test all combinations of the factors.
- The number of experiments is n^k .
- Generally this is too many experiments, but we are able to reveal all of the interactions.

Experiment Design: Full Factorial

Expt #	Param A	Param B
1	A1	B1
2	A1	B2
3	A1	B3
4	A2	B1
5	A2	B2
6	A2	B3
7	A3	B1
8	A3	B2
9	A3	B3

2 factors, 3 levels each:

$n^k = 3^2 = 9$ trials

4 factors, 3 levels each:

$n^k = 3^4 = 81$ trials

Experiment Design: One Factor at a Time

- Consider k factors, n levels each.
- Test all levels of each factor while freezing the others at nominal level.
- The number of experiments is $1+k(n-1)$.
- BUT this is an <u>unbalanced</u> experiment design.

Experiment Design: One Factor at a Time

Expt #	Param A	Param B	Param C	Param D
1	A2	B2	C2	D2
2	A1	B2	C2	D2
3	A3	B2	C2	D2
4	A2	B1	C2	D2
5	A2	B3	C2	D2
6	A2	B2	C1	D2
7	A2	B2	C3	D2
8	A2	B2	C2	D1
9	A2	B2	C2	D3

4 factors, 3 levels each:

$1+k(n\text{-}1) = 1+4(3\text{-}1) = 9$ trials

Experiment Design: Orthogonal Array

- Consider k factors, n levels each.
- Test all levels of each factor in a balanced way.
- The number of experiments is $n(k\text{-}1)$.
- This is the smallest balanced experiment design.
- BUT main effects and interactions are confounded.

Experiment Design: Orthogonal Array

Expt #	Param A	Param B	Param C	Param D
1	A1	B1	C1	D1
2	A1	B2	C2	D2
3	A1	B3	C3	D3
4	A2	B1	C2	D3
5	A2	B2	C3	D1
6	A2	B3	C1	D2
7	A3	B1	C3	D2
8	A3	B2	C1	D3
9	A3	B3	C2	D1

4 factors, 3 levels each:

$n(k-1) = 3(4-1) = 9$ trials

Using Inner and Outer Arrays

- Induce the same noise factor levels for each combination of controls in a balanced manner

4 factors, 3 levels each:
L9 inner array for controls

3 factors, 2 levels each:
L4 outer array for noise

				E1	E1	E2	E2
				F1	F2	F1	F2
				G2	G1	G2	G1
A1	B1	C1	D1				
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				

inner x outer =
L9 x L4 =
36 trials

Step 4: Run the Experiment

Step 4: Conduct the experiment.

- Vary the input and noise parameters
- Record the output response
- Compute the objective function

Paper Airplane Experiment

Expt #	Weight	Winglet	Nose	Wing	Trials	Mean	Std Dev	S/N
1	A1	B1	C1	D1				
2	A1	B2	C2	D2				
3	A1	B3	C3	D3				
4	A2	B1	C2	D3				
5	A2	B2	C3	D1				
6	A2	B3	C1	D2				
7	A3	B1	C3	D2				
8	A3	B2	C1	D3				
9	A3	B3	C2	D1				

Step 5: Conduct Analysis

Step 5: Perform analysis of means.

- Compute the mean value of the objective function for each parameter setting.
- Identify which parameters reduce the effects of noise and which ones can be used to scale the response. (2-Step Optimization)

Parameter Design Procedure Step 6: Select Setpoints

- Parameters can effect
  - Average and Variation (tune S/N)
  - Variation only (tune noise)
  - Average only (tune performance)
  - Neither (reduce costs)

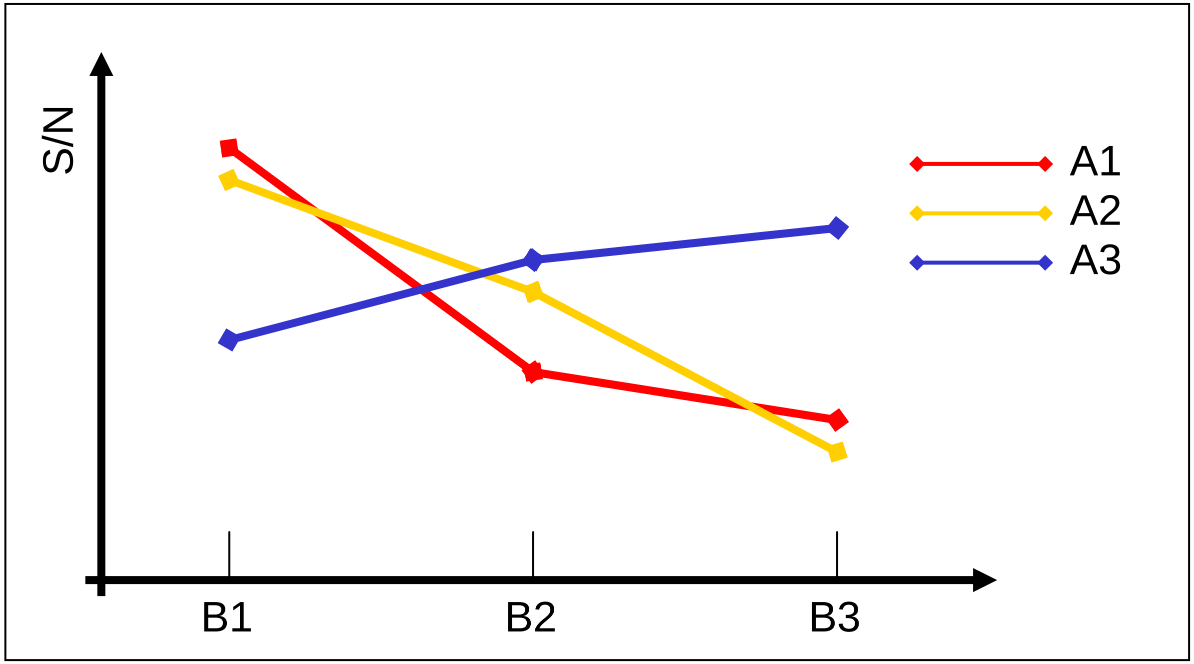
Parameter Design Procedure Step 6: Advanced Use

- Conduct confirming experiments.
- Set scaling parameters to tune response.
- Iterate to find optimal point.
- Use higher fractions to find interaction effects.
- Test additional control and noise factors.

Confounding Interactions

- Generally the main effects dominate the response. BUT sometimes interactions are important. This is generally the case when the confirming trial fails.
- To explore interactions, use a fractional factorial experiment design.

Confounding Interactions



Key Concepts of Robust Design

- Variation causes quality loss
- Parameter Design to reduce Variation
- Matrix experiments (orthogonal arrays)
- Two-step optimization
- Inducing noise (outer array or repetition)
- Data analysis and prediction
- Interactions and confirmation