

Goals for Designed Experiments

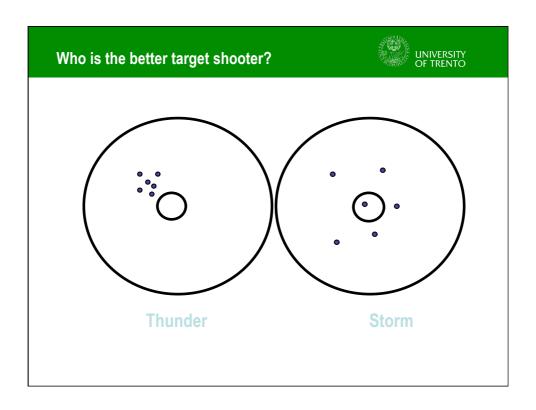


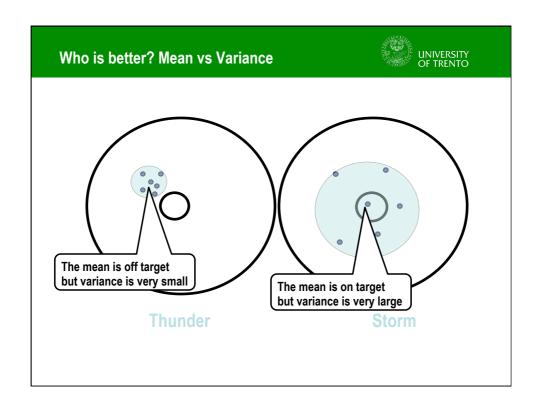
- Modeling
 - Understanding relationships between design parameters and product performance
 - Understanding effects of noise factors
- Optimizing
 - Reducing product or process variations
 - Optimizing nominal performance

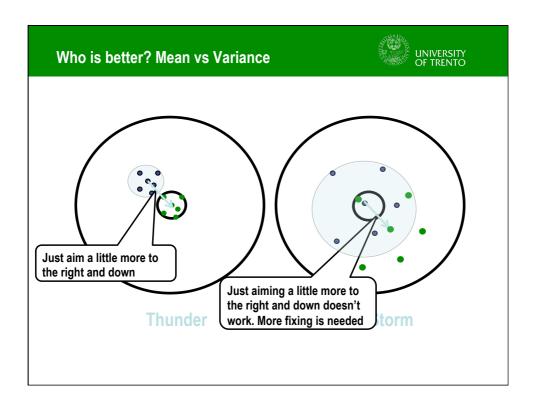
Esercise: the gun shooter



- · Testing a laser-guided rifle
 - Thunder
 - Storm
- Experiment
 - Ask 6 soldiers to take aim and shoot
 - Identify best gun
- Decide what to do in response



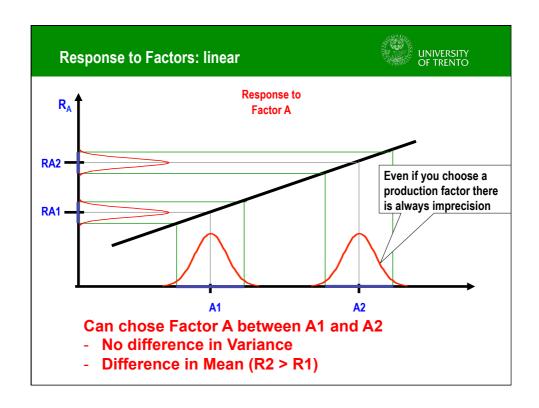


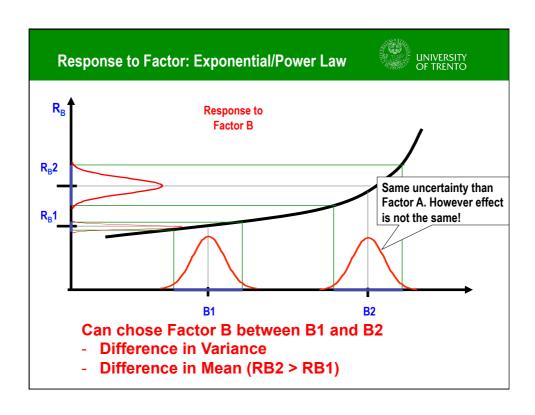


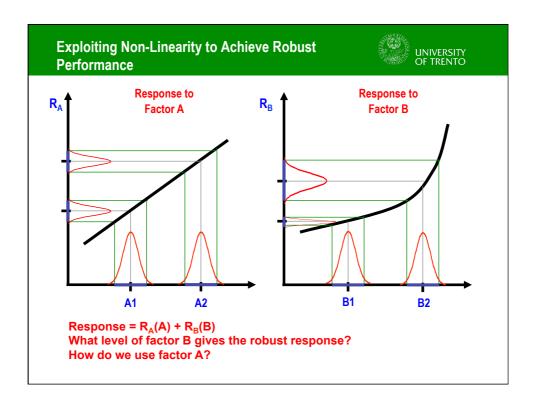
Robust Designs



- A robust product or process performs correctly, even in the presence of noise factors
- e.g. shooters (aka users)
- Noise factors may include:
 - parameter variations
 - environmental changes
 - operating conditions
 - manufacturing variations







Robust Designs

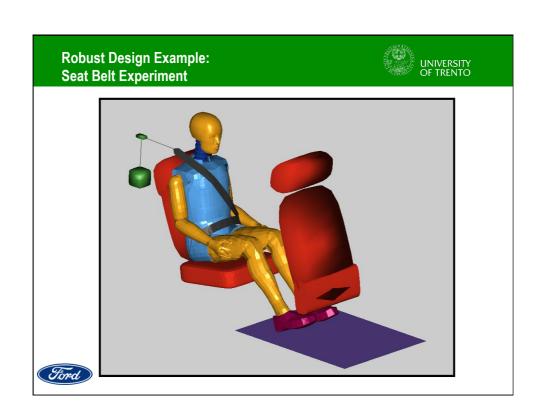


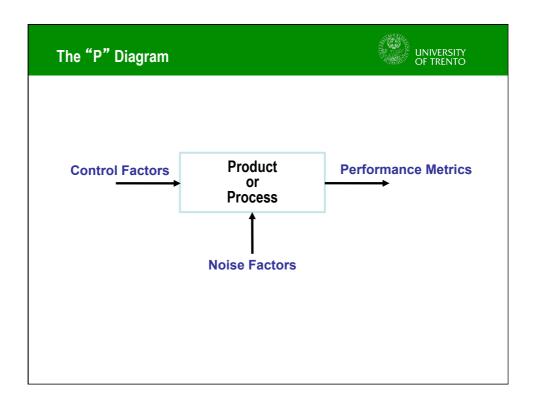
- A robust product or process performs correctly, even in the presence of noise factors
- e.g. shooters (aka users)
- Noise factors may include:
 - parameter variations
 - environmental changes
 - operating conditions
 - manufacturing variations
- · How do we find the robust design?

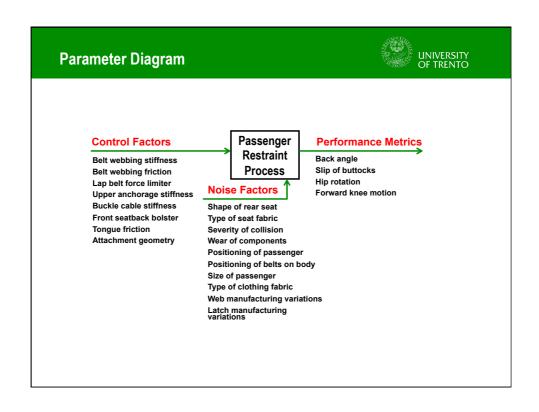
Robust Design Procedure Step 1: Parameter Diagram



- Step 1: Select appropriate controls, response, and noise factors to explore experimentally.
- Control factors (input parameters)
- Noise factors (uncontrollable)
- Performance metrics (response)









Example: Brownie Mix

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

Robust Design Procedure



Step 2: Objective Function

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

- maximize desired performance
- minimize variations
- target value
- signal-to-noise ratio

Types of Objective Functions



Larger-the-Better

e.g. performance $\eta = \mu^2$

Nominal-the-Best

e.g. target $\eta = 1/(\mu - t)^2$

Smaller-the-Better

e.g. variance $\eta = 1/\sigma^2$

Signal-to-Noise

e.g. trade-off $\eta = 10\log[\mu^2/\sigma^2]$

Robust Design Procedure Step 3: Plan the Experiment



- Step 3: Plan experimental runs to 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 interactions.

Expt #	Param A	Param B				
1	A1	B1				
2	A1	B2				
3	A1	В3				
4	A2	B1				
5	A2	B2				
6	A2	В3				
7	A3	B1				
8	A3	B2				
9	A3	В3				

2 factors, 3 levels each: $n^k = 3^2 = 9 \text{ trials}$

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 unbalanced experiment design.

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	В3	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-1) =

1+4x2 = 9 trials

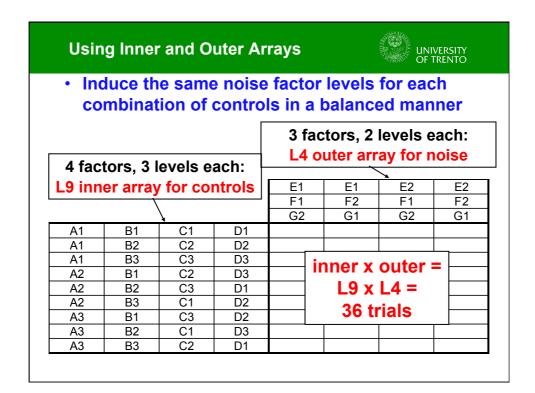
Experiment Design: Orthogonal Array

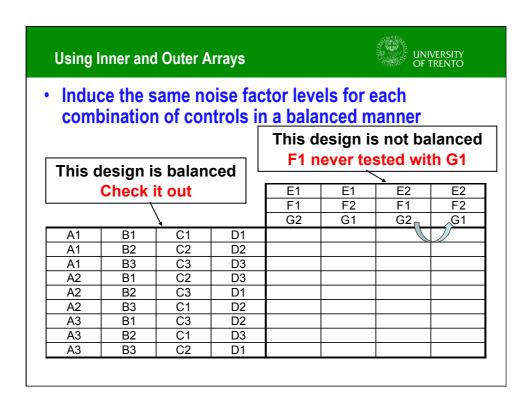


- · Consider k factors, n levels each.
- For every pair of factors each level of one factor is paired with all levels of the other factors
- The number of experiments is order of (k-1)n.
- This is the smallest balanced experiment design.
- Trade-off effects and interactions are confounded.

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	В3	C1	D2
7	A3	B1	C3	D2
8	A3	B2	C1	D3
9	A3	B3	C2	D1

4 factors, 3 levels each: (k-1)n = (4-1)3 = 9 trials

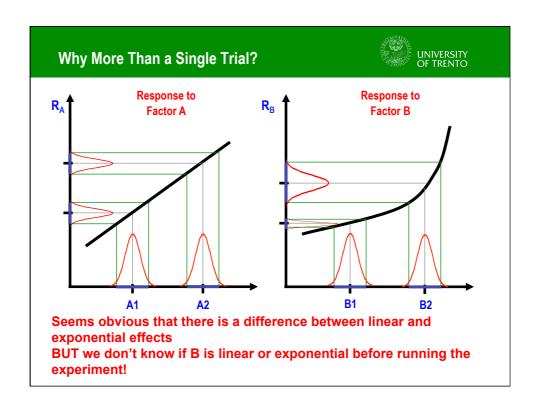


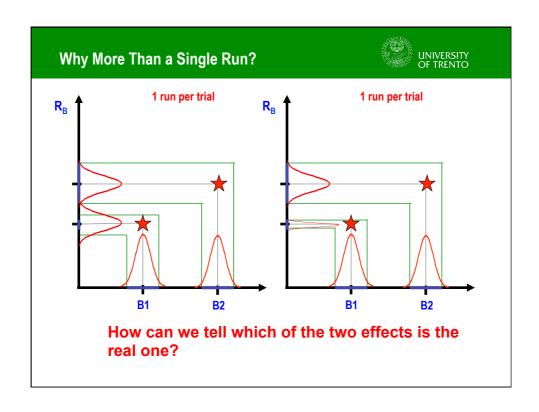


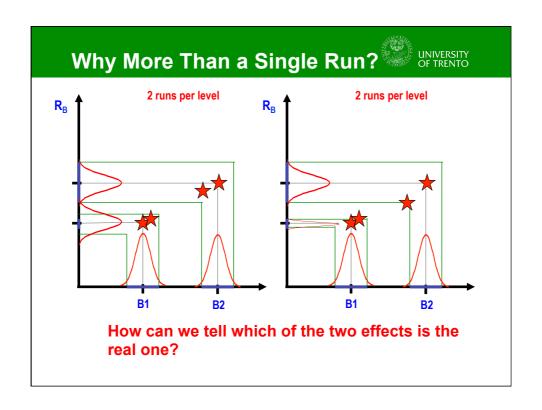
Robust Design Procedure Step 4: Run the Experiment

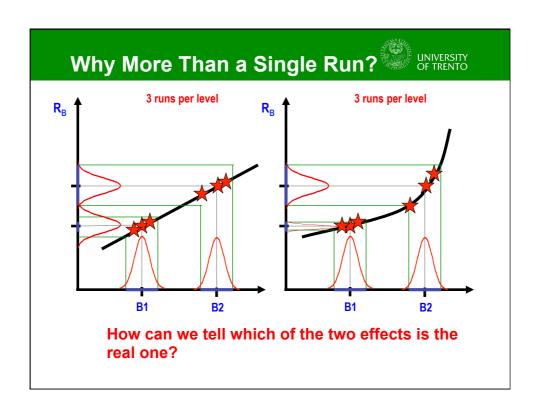


- Step 4: Conduct the experiment.
- Vary the control and noise factors
- Record the performance metrics
- Compute the objective function
- Possibly more than one single run for each trial!
 - So total is (k-1) factors * n levels * m runs





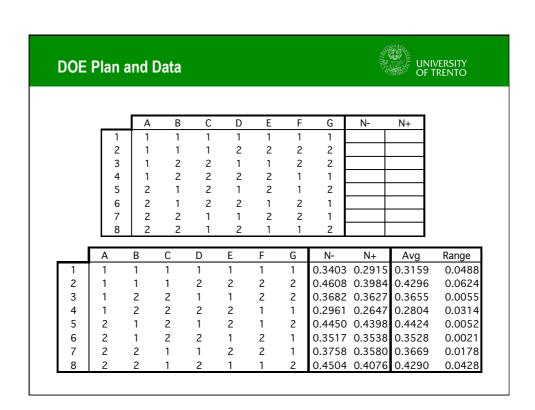


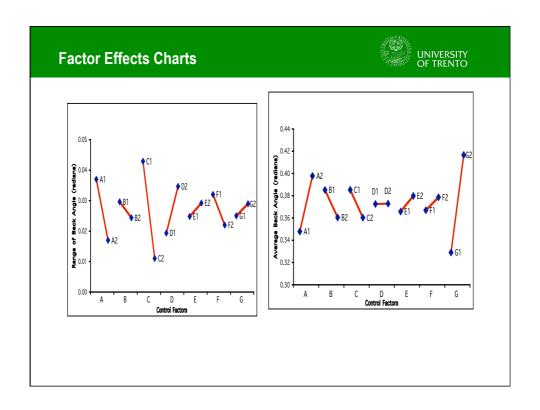


Robust Design Procedure Step 5: Conduct Analysis



- Step 5: Perform analysis of means and variance.
 - Compute the mean value of the objective function for each factor setting.
 - Identify which control factors reduce the effects of noise and which ones can be used to scale the response. (2-Step Optimization)





Robust Design Procedure Step 6: Select Setpoints

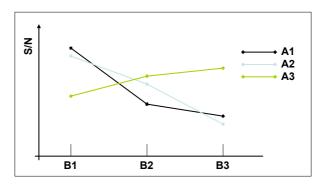


- Step 6: Select control factor setpoints.
 - Choose settings to maximize or minimize objective function.
 - Consider variations carefully. (Use means or variance to understand variation explicitly.)
- · Advanced use:
 - Conduct confirming experiments.
 - Set scaling factors to tune response.
 - Iterate to find optimal point.
 - Use higher fractions to find interaction effects.
- Test additional control and noise factors.

Confounding Interactions



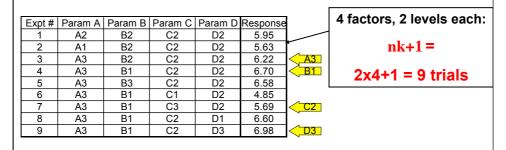
- Generally the main effects dominate the response.
 BUT sometimes <u>interactions</u> are important. This is generally the case when the confirming trial fails.
- To explore interactions, use a fractional factorial experiment design.



Adaptive Factor: Hill Climbing



- · Consider k factors, n levels each.
- · Start at nominal levels.
- Test each level of each factor one at a time, while freezing the previous ones at best level so far.
- The number of experiments is nk+1.
- Since this is an unbalanced experiment design, you can stop anytime (you have no info anyway).
- · Helpful to sequence factors for strongest effects first.
- · In some cases it work well when interactions are present.



Key Concepts of Robust Design



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

References



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- Phadke, Madhav S.
 Quality Engineering Using Robust Design Prentice Hall, Englewood Cliffs, 1989.
- Ross, Phillip J.
 Taguchi Techniques for Quality Engineering McGraw-Hill, New York, 1988.

UNIVERSITY OF TRENTO **Paper Airplane Experiment** Wing Expt # Weight Winglet Nose Trials Mean Std Dev S/N D1 В1 C1 Α1 C2 D2 2 B2 Α1 3 В3 C3 D3 Α1 C2 D3 4 A2 В1 C3 5 A2 В2 D1 D2 6 A2 В3 C1 А3 В1 C3 D2 8 А3 B2 C1 D3 9 А3 В3 C2 D1

