INNOVATORS' SUMMIT

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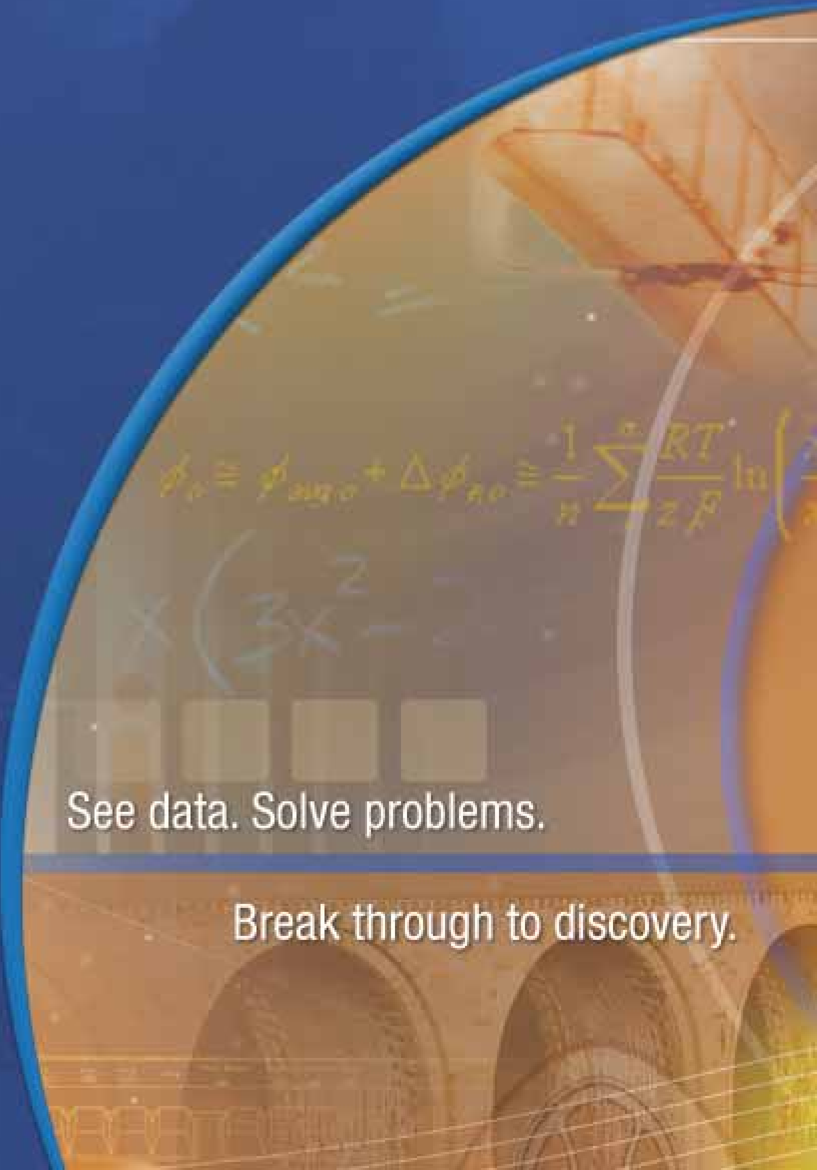

Custom Designing with JMP: A New New Paradigm for DOE

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Overview

> Why DOE?
> What is “custom design”?
> Why is this a new paradigm for DOE
> 2 examples contrasting new and old approaches
> What drives this engine?
> Concluding remarks

What is DOE? (Chapter 15, ALSM)

Design of Experiments (DOE):

Problem solving methodology (invented by Fisher) for efficiently identifying cause-and-effect relationships

George Box (invented RSM):

"To discover what happens to a process when a factor X is changed, you must actually change it!"

Observational versus Experimental Studies

In an ***experimental study***,

Treatments randomly assigned to experimental units (subjects, beakers, batches, PCBs, etc.), and the results are compared.

Cause and effect can be demonstrated in an experimental study.

Observational versus Experimental Studies

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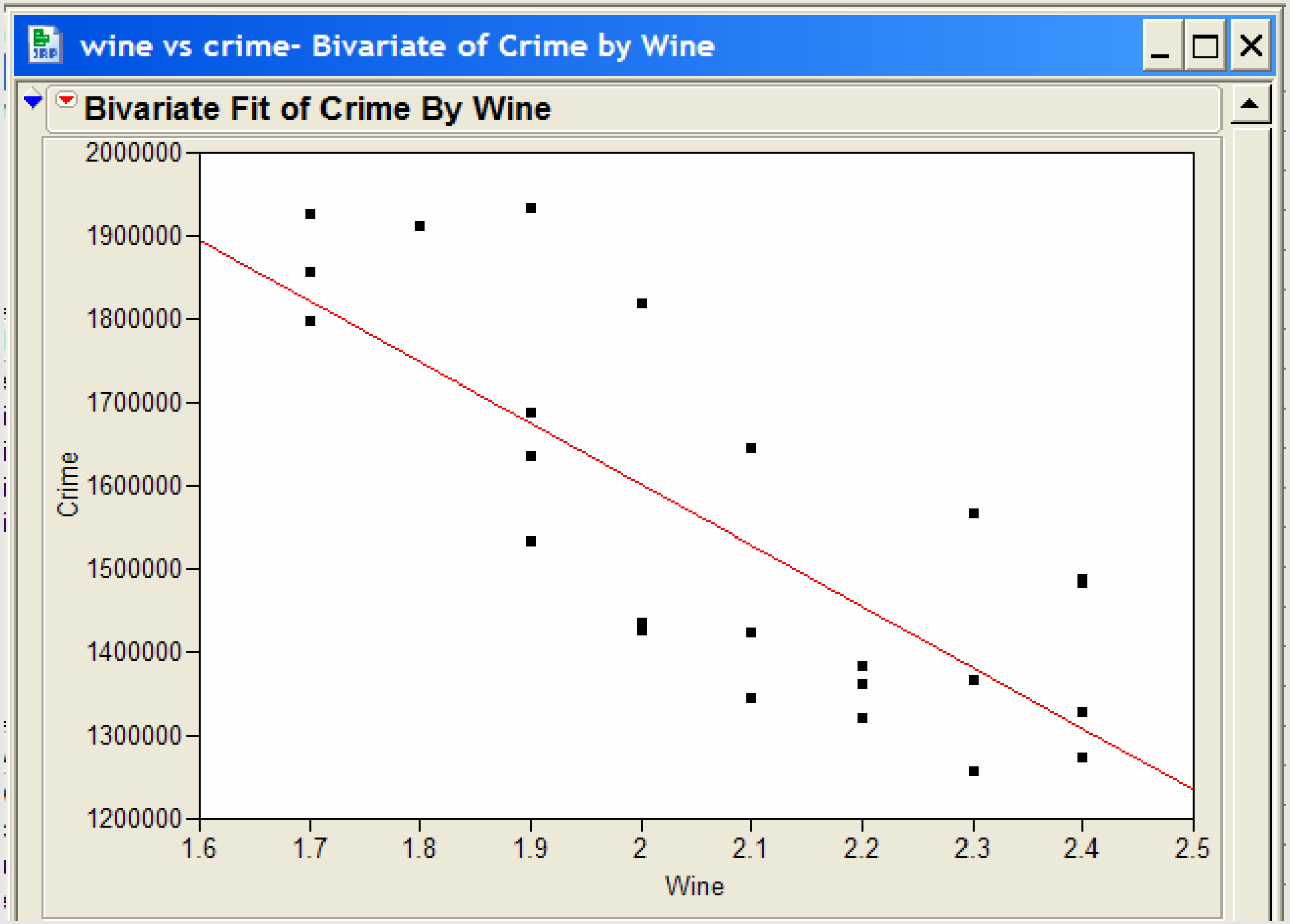
In an *observational study*,

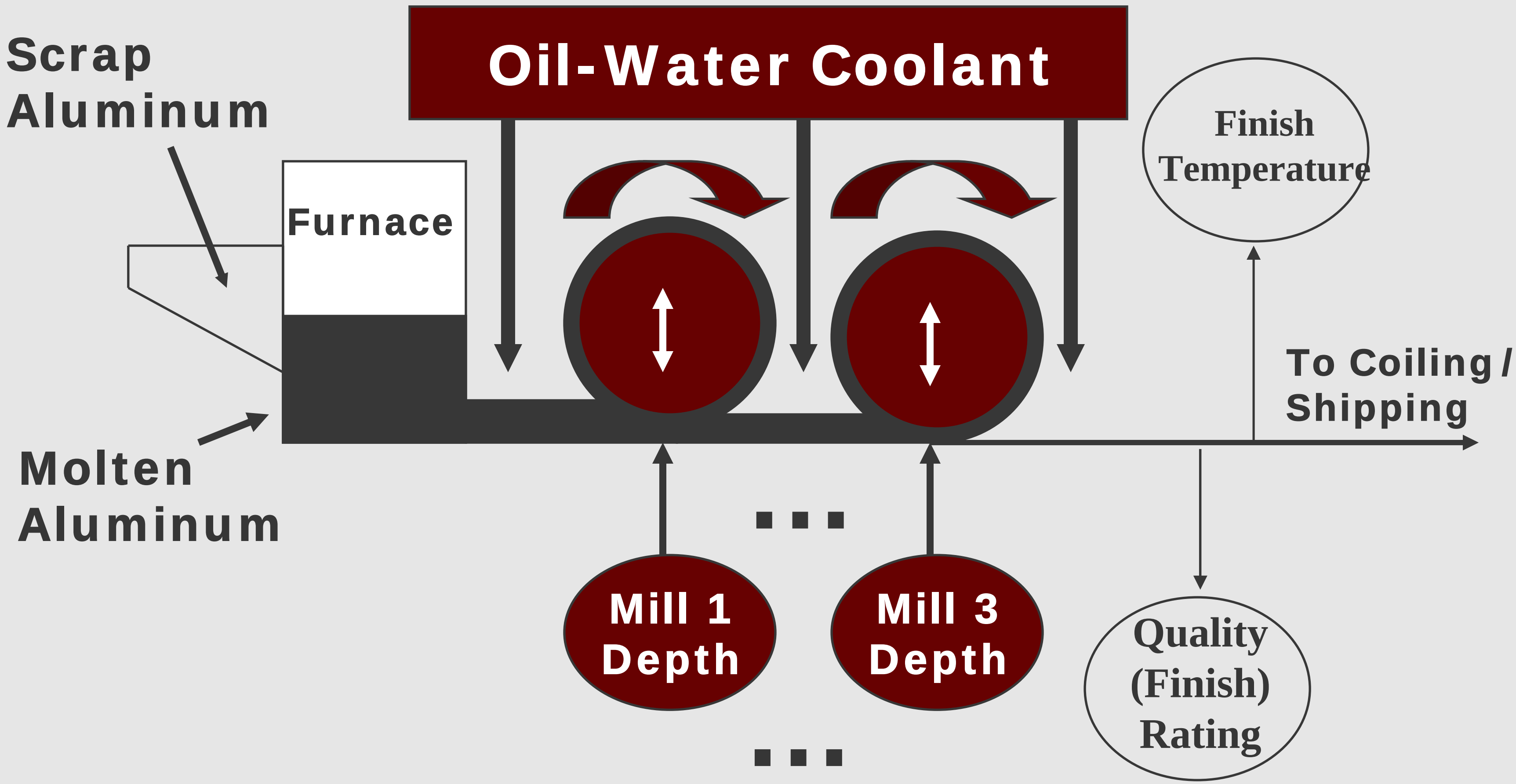
Acquired data. Note that the investigator is passively involved, and does not actively change treatments. Randomization is not employed.

Cause and effect cannot be proven in an observational study.

Wine Consumption vs Crime Rate in US: Observational or Experimental Study?



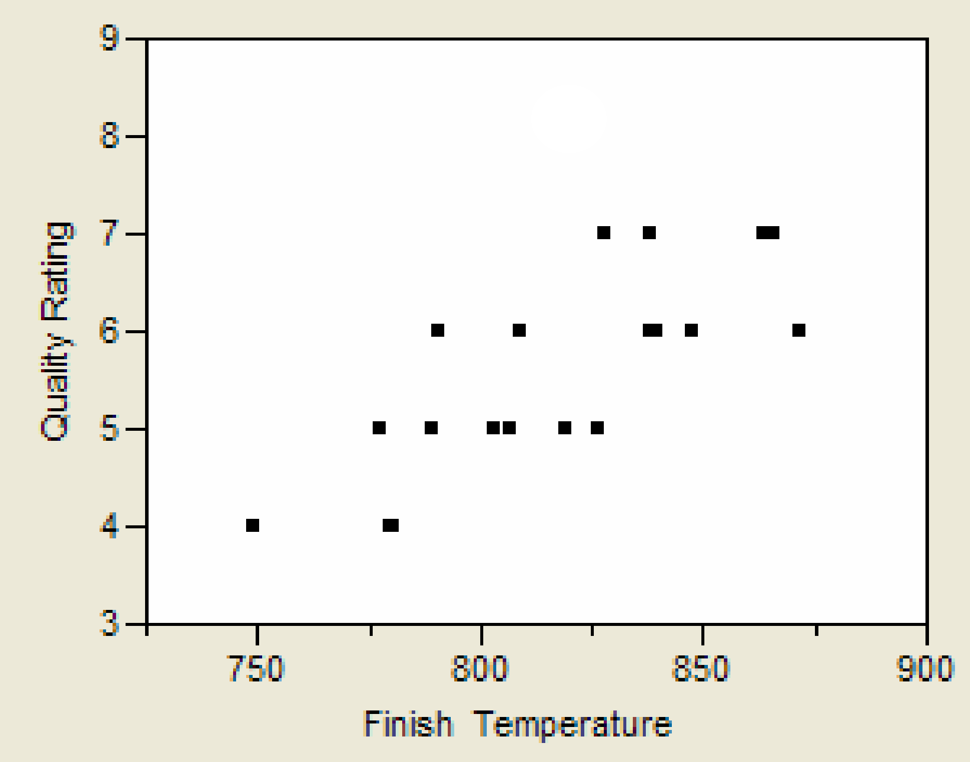
Example 2:
Sheet Aluminum Rolling Mill



Results sample of from 20 Batches

The quality specification limit is: Rating > 5.5

What might you conclude?

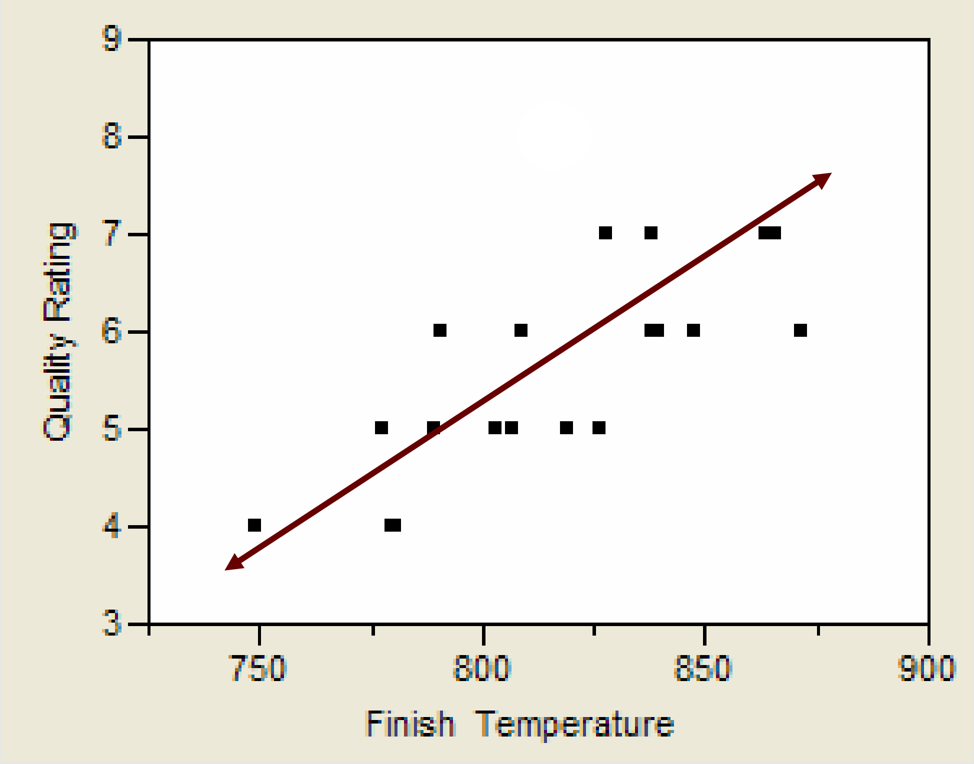


What happens to quality as temperature increases?

Results sample of from 20 Batches

The quality specification limit is: Rating > 5.5

What might you conclude?



What happens to quality as temperature increases?

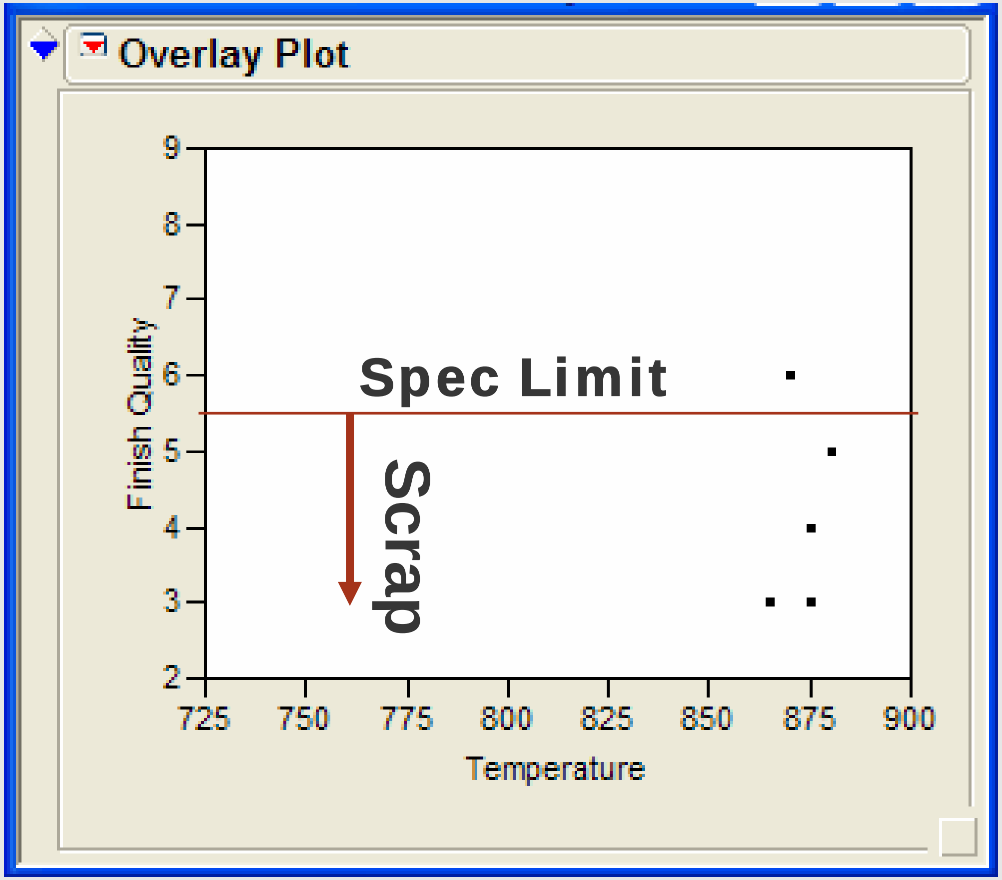
Questions

- Does increasing temperature increase quality?
- Was this an observational or an experimental study?
- How could the study be improved?
- What should management do?

Management tested 5 batches at at approximately 875ºC. Results: Results:

Increasing furnace temperature had no effect!

Why not?



DOE Solved the Problem

- A 5-factor experiment was conducted
- Factors included mill depth 1, mill depth 2, spray volume, spray oil content, molten aluminum temperature (input temperature)
- Result: When mill depth 3 increased, it increased output temperature.
- It also increased the quality of the surface

Output temperature was not a causal factor—mill depth 3 was the causal factor!

Scrap reduced from 50% to 10%

OK, So how was the design chosen?

Standard Approach to DOE

1. State the objectives and your constraints
2. Find a design from a book or a table or a software program the most closely matches your objectives (requires DOE expertise)
3. Implement the design
4. Analyze results

What DOE Expertise is Needed?

- Full factorial designs
- Interactions
- 2^k factorial designs
- 2^{k-p} fractional factorial designs
- Confounding schemes and aliasing
- Resolution
- Screening designs (Plackett Burman, Res III FF)

What DOE Expertise (continued)?

> Response surface experiments
> Blocked experiments
> Nested designs
> Repeated measures and split plot designs
> Incomplete block designs
> Mixture experiments and mixture models
> Supersaturated designs

Complications not covered!

- Constraints on factor-level combinations
- Qualitative factors
- Mixed qualitative by quantitative factors
- Mixed mixture by non-mixture factors
- Known experimental unit heterogeneity (fixed covariates)
- Non-standard sample sizes (limited budget)

Rolling Mill Example—Screening DOE

Knowledge Requirements:

- Main effects, interactions (model terms)
- Confounding schemes
- Resolution
- Fractional factorials
- Plackett-Burman designs

Factor Summary

	Factor	Low	High
1	Mill depth 1	0.2	0.8
2	Mill depth 2	0.2	0.8
3	Mill depth 3	0.2	0.8
4	Spray volume	0.7	1.0
5	Spray oil content	0.02	0.05
6	Furnace temperature	L	H

Typical Software Input…

DOE- Screening Design

Screening Design

Responses

Add Response | Remove | N Responses...

Response Name	Goal	Lower Limit	Upper Limit	Importance
Quality Score	Maximize	1	10	.

Factors

Name	Role	Values	
Mill Depth 1	Continuous	0.2	0.8
Mill Depth 2	Continuous	0.2	0.8
Mill Depth 3	Continuous	0.2	0.8
Spray Volume	Continuous	0.7	1
Spray Oil Content	Continuous	0.02	0.05
Furnace Temp	Categorical	Low	High

Now Select!

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Choose a Design

Number Of Runs	Block Size	Design Type	Resolution - what is estimable
8		Fractional Factorial	3 - Main Effects Only
8	4	Fractional Factorial	3 - Main Effects Only
12		Plackett-Burman	3 - Main Effects Only
16		Fractional Factorial	4 - Some 2-factor interactic
16	8	Fractional Factorial	4 - Some 2-factor interactic
16	4	Fractional Factorial	4 - Some 2-factor interactic
16	2	Fractional Factorial	4 - Some 2-factor interactic
32		Fractional Factorial	5+ - All 2-factor interaction:
32	16	Fractional Factorial	5+ - All 2-factor interaction:
32	8	Fractional Factorial	4 - Some 2-factor interactic
32	4	Fractional Factorial	4 - Some 2-factor interactic
32	2	Fractional Factorial	4 - Some 2-factor interactic
64		Full Factorial	>6 - Full Resolution
64	32	Full Factorial	5+ - All 2-factor interaction:

But there is a problem:

We have constrained mill depths (MDs):

$$MD1 + MD2 + MD3 = 1$$

$$.2 < MD1 < .8$$

$$.2 < MD1 < .8$$

$$.2 < MD1 < .8$$

None of the tabled designs work!

MDs are mixture factors: proportions that sum to 1.0

Factors

Add Factor | Remove | Add N Factors 1

Name	Role	Changes	Values	
Mill Depth 1	Mixture	Easy	0.2	0.8
Mill Depth 2	Mixture	Easy	0.2	0.8
Mill Depth 3	Mixture	Easy	0.2	0.8
Spray Volume	Continuous	Easy	0.7	1
Spray Oil Content	Continuous	Easy	0.02	0.05
Furnace Temp	Categorical	Easy	L1	L2

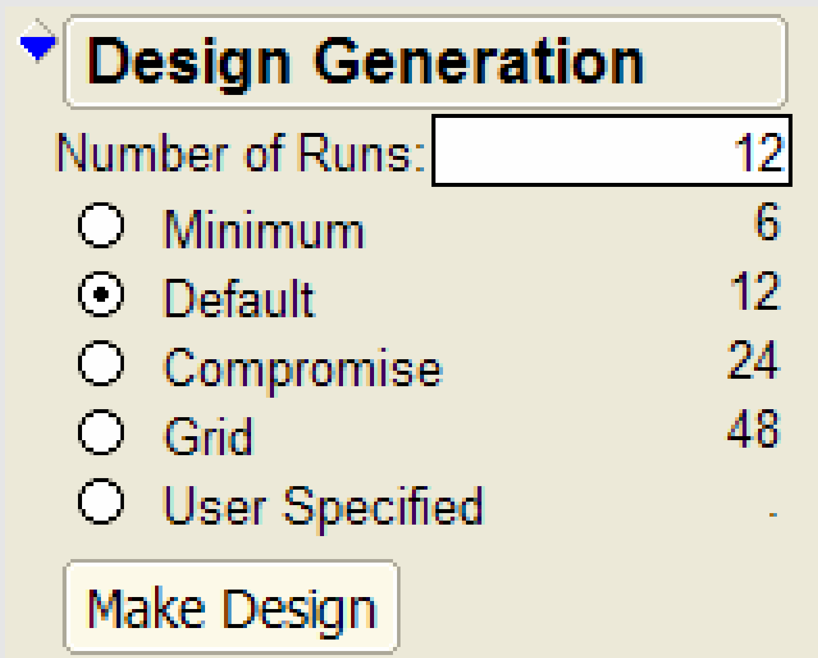
Main effects only model assumed:

Model

Main Effects | Interactions | Cross | Powers | Scheffe Cubic | Remove Term

Name	Estimability
Mill Depth 1	Necessary
Mill Depth 2	Necessary
Mill Depth 3	Necessary
Spray Volume	Necessary
Spray Oil Content	Necessary
Furnace Temp	Necessary

Now press the button:



Design is created:

Custom Design

Responses

Factors

Define Factor Constraints

Model

Design

Run	Mill Depth 1	Mill Depth 2	Mill Depth 3	Spray Volume	Spray Oil Content	Furnace Temp	Quality Score
1	0.6	0.2	0.2	1	0.02	High	.
2	0.6	0.2	0.2	1	0.02	Low	.
3	0.2	0.2	0.6	0.7	0.02	High	.
4	0.2	0.6	0.2	1	0.02	Low	.
5	0.2	0.2	0.6	1	0.05	High	.
6	0.6	0.2	0.2	0.7	0.05	High	.
7	0.2	0.2	0.6	1	0.05	Low	.
8	0.6	0.2	0.2	0.7	0.05	Low	.
9	0.2	0.6	0.2	1	0.05	High	.
10	0.2	0.6	0.2	0.7	0.05	Low	.
11	0.2	0.6	0.2	0.7	0.02	High	.
12	0.2	0.2	0.6	0.7	0.02	Low	.

Summary: Custom Design Approach

- **Custom design is very easy to do and to teach. One, unified approach to (nearly) all design problems:**

  1. **Describe your responses**
  2. **Describe your factors**
  3. **Describe your objectives (model terms)**
  4. **Tell me your budget (n)**
  5. **Press button to create the design**
  6. **Manually alter as with classical**
  7. **Check diagnostics, do sensitivity analysis**

- **Can eliminate a barrier to entry for users, and that’s the objective!**

Example 5: ALSM Response Surface

Problem: Market researcher wishes to understand factors that affect recall of television commercials

Objective: Maximize recall

Example 5: ALSM p1293

*30.11. **Television commercial recall.** A three-factor, face-centered central composite design was carried out to study the effects of length of commercial, frequency of viewing, and length of recall on the ability of subjects to recall an advertised product. Subjects were shown a video containing a number of programs with advertisements for three products. The factors of interest are all quantitative: commercial length ($X_1 = -1$: 10 seconds; $X_1 = 0$: 20 seconds; $X_1 = 1$: 30 seconds), number of repetitions of commercial ($X_2 = -1$: 1 viewing; $X_2 = 0$: 2 viewings; $X_2 = 1$: 3 viewings), delay between time of viewing and time of recall ($X_3 = -1$: 1 week; $X_3 = 0$: 3 weeks, $X_3 = 1$: 5 weeks). Each of the 15 treatments in the central composite design was assigned at random to 20 subjects. The response of interest (Y) is the average number of products recalled (out of three) by the 20 subjects that received a particular treatment. The observed responses and the design matrix follow.

Example 5: ALSM p1293

	Factor	Low	High
1	Commercial Length	10	30
2	Viewings	1	3
3	Delay for recall	1 week	5 weeks

Knowledge Requirements:

- Main effects, interactions, second-order powers (model terms)
- Confounding and resolution (for corners)
- Fractional factorials (for corners)
- CCDs, Box-Behnken designs
- Blocking (sort of)
- Axial points

RSM design dialog

Response Surface Design
3 Factors

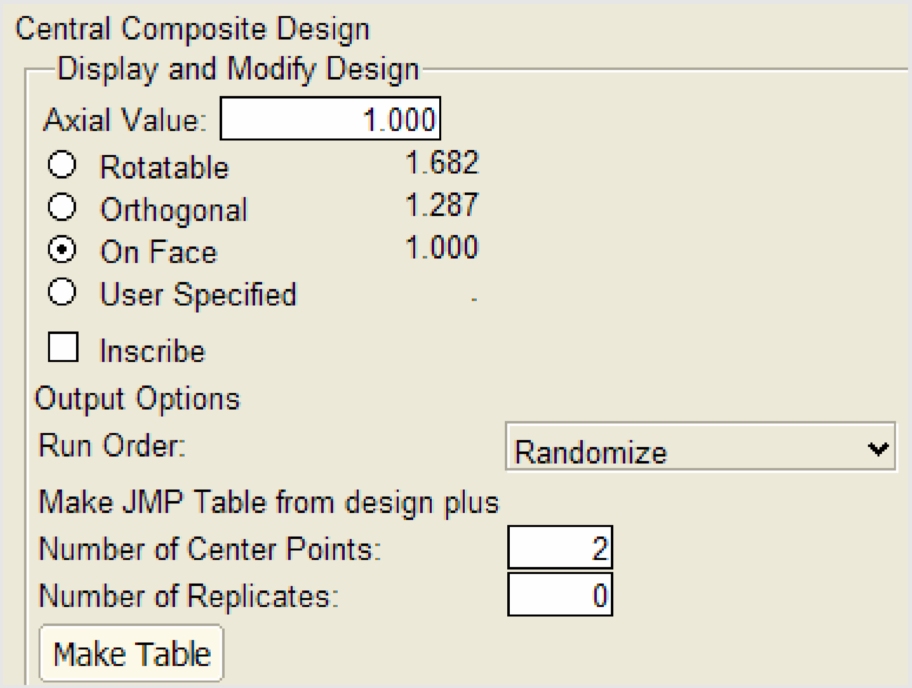
Choose a Design

Number Of Runs	Block Size	Center Points	Design Type
15		3	Box-Behnken
16		2	Central Composite Design
20		6	CCD-Uniform Precision
20	6	6	CCD-Orthogonal Blocks
23		9	CCD-Orthogonal
optional item			

Continue

Selecting a central composite design.

RSM design dialog



Selecting a central composite design.

RSM design dialog

	Pattern	Length	Viewings	Delay	Recall
1	00a	20	2	1	•
2	000	20	2	3	•
3	a00	10	2	3	•
4	0a0	20	1	3	•
5	−+−	10	3	1	•
6	−−−	10	1	1	•
7	+−−	30	1	1	•
8	++−	30	3	1	•
9	−++	10	3	5	•
10	+−+	30	1	5	•
11	A00	30	2	3	•
12	−−+	10	1	5	•
13	00A	20	2	5	•
14	000	20	2	3	•
15	0A0	20	3	3	•
16	+++	30	3	5	•

Contrast: Custom Design Approach

Knowledge Requirements:

1. Main effects, interactions, second-order powers (RSM button)

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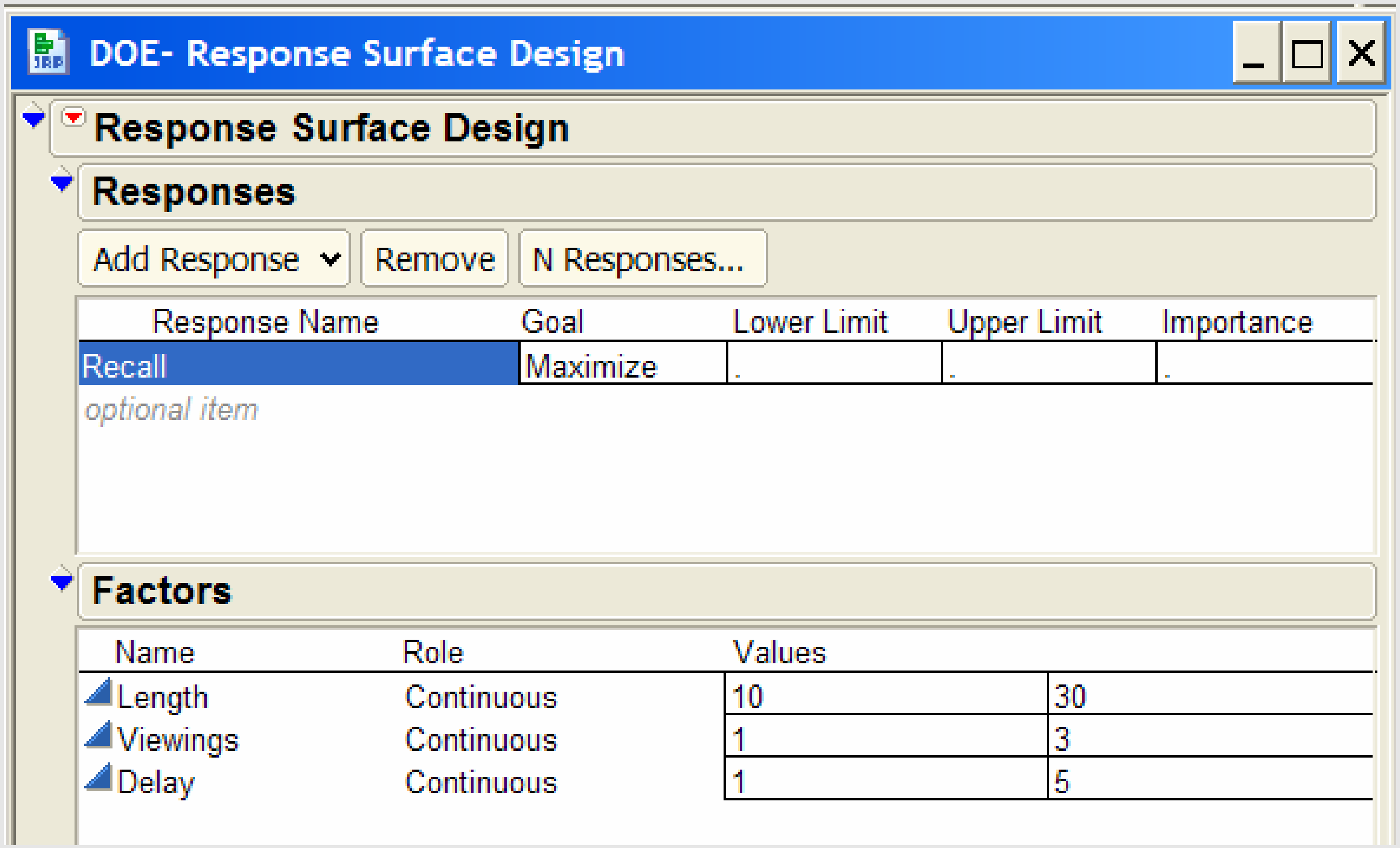
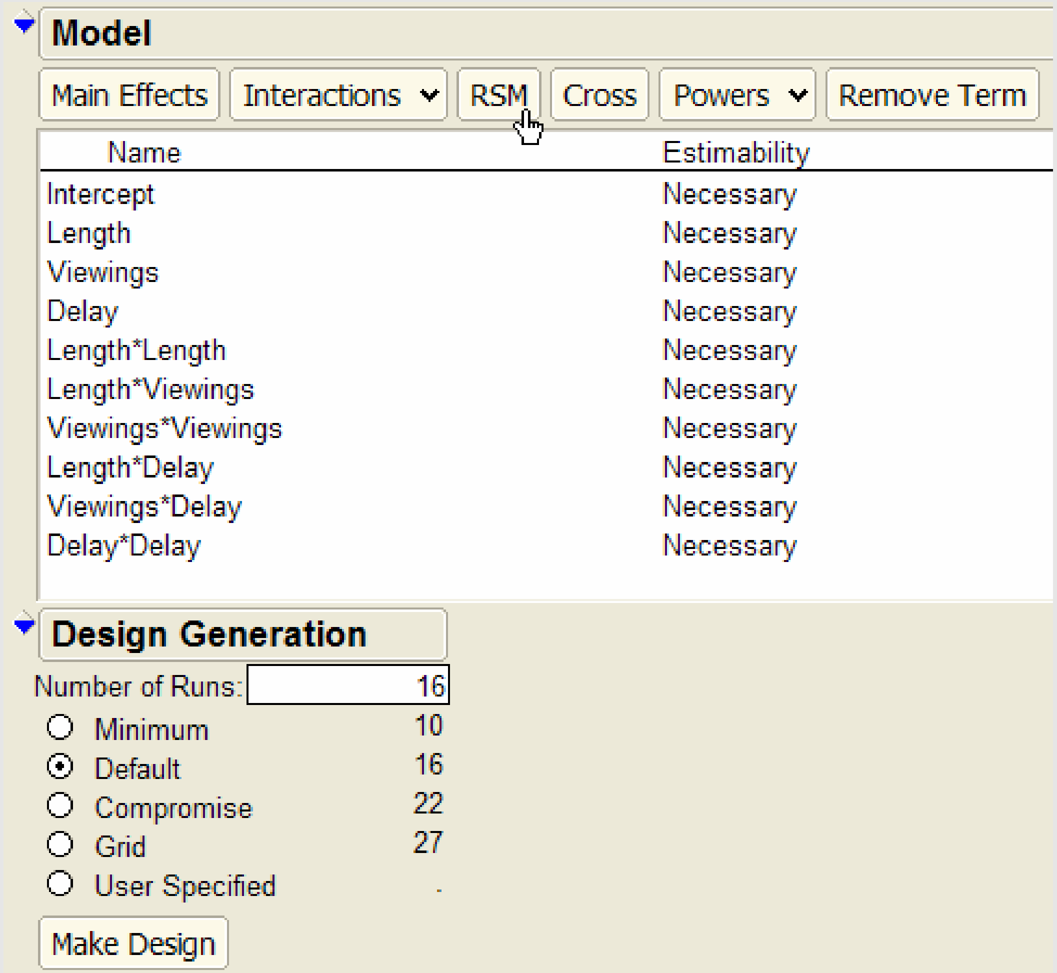
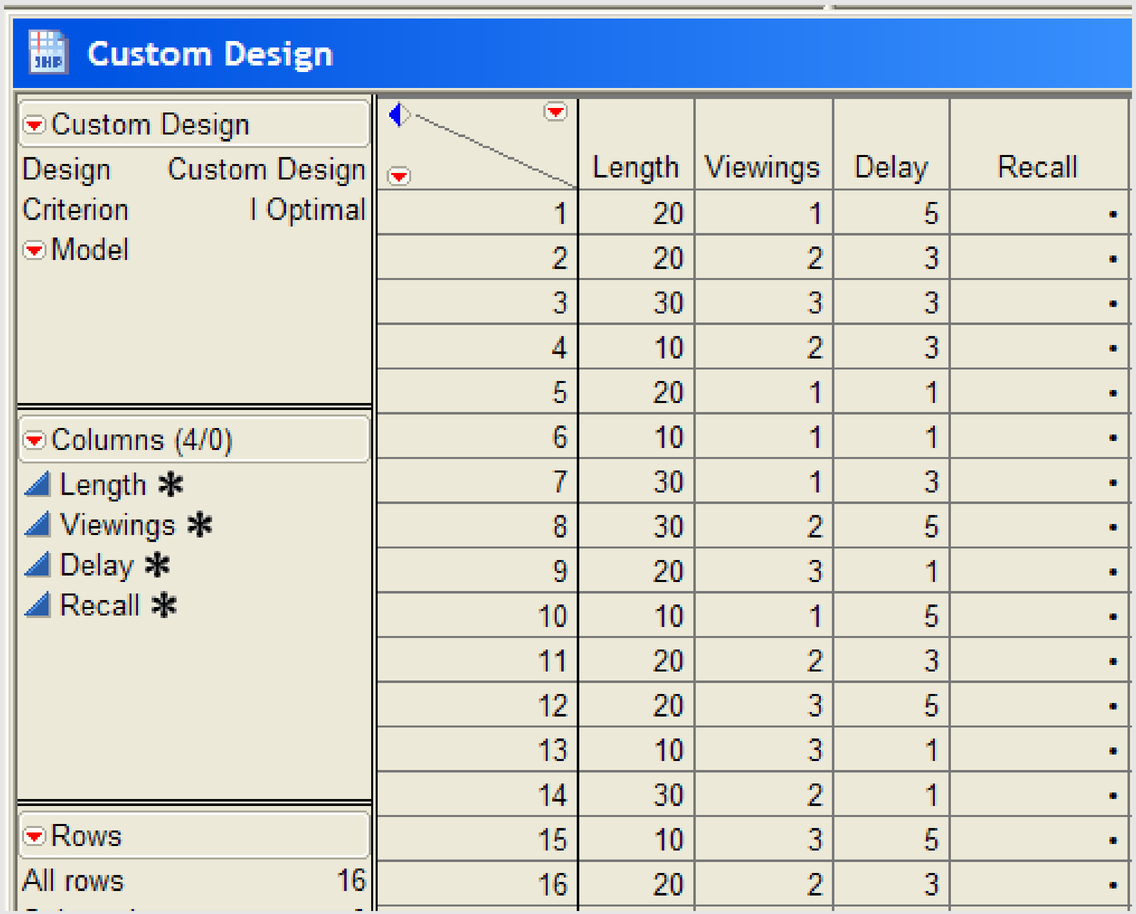
Enter response and factor information information



Specify model and sample size



Then, “Make Design”



	Length	Viewings	Delay	Recall
1	20	1	5	•
2	20	2	3	•
3	30	3	3	•
4	10	2	3	•
5	20	1	1	•
6	10	1	1	•
7	30	1	3	•
8	30	2	5	•
9	20	3	1	•
10	10	1	5	•
11	20	2	3	•
12	20	3	5	•
13	10	3	1	•
14	30	2	1	•
15	10	3	5	•
16	20	2	3	•

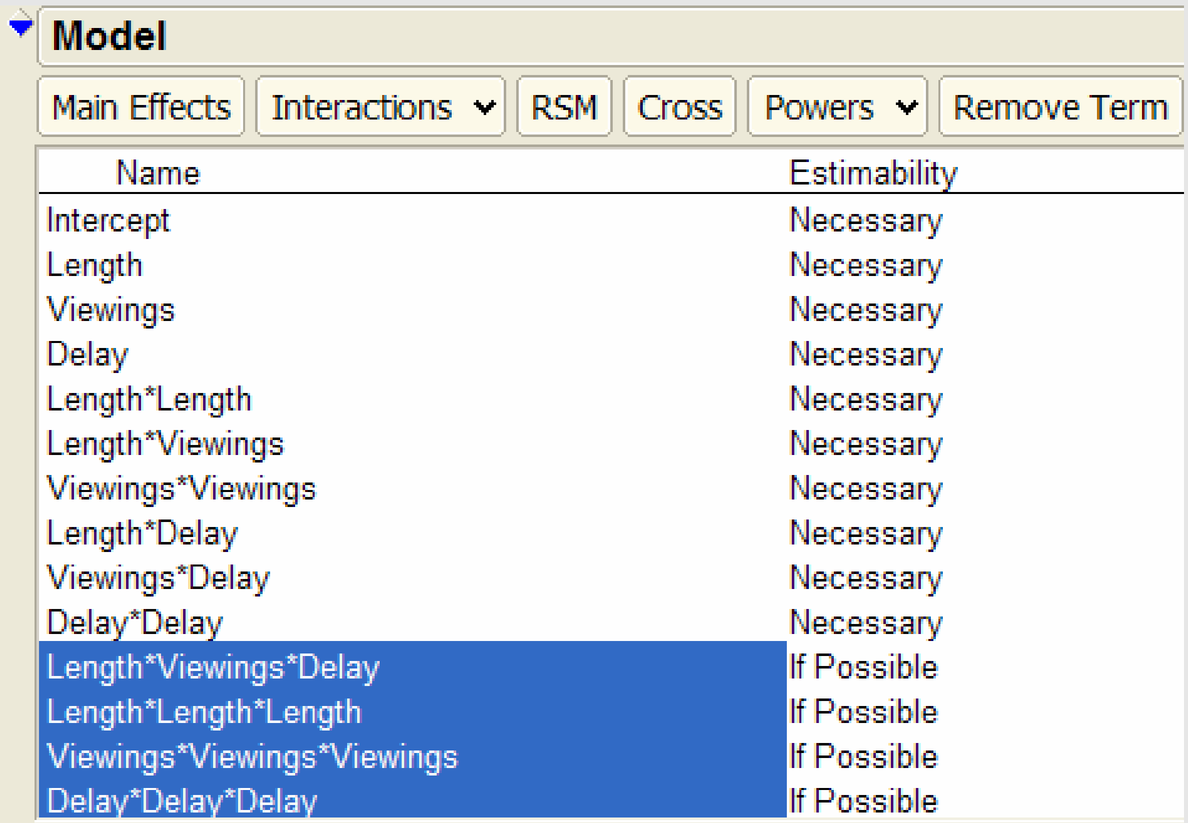
Yes BUT:

- The design employs only 3 levels for each factor
- Can’t check for cubic lack of fit

Custom Design Approach

- Add cubic terms in as “if possible”
- Rest is the same

Adding 3rd-order guys as “if possible”



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Resulting design

Custom Design

Custom Design

Design Custom Design
Criterion I Optimal
Model

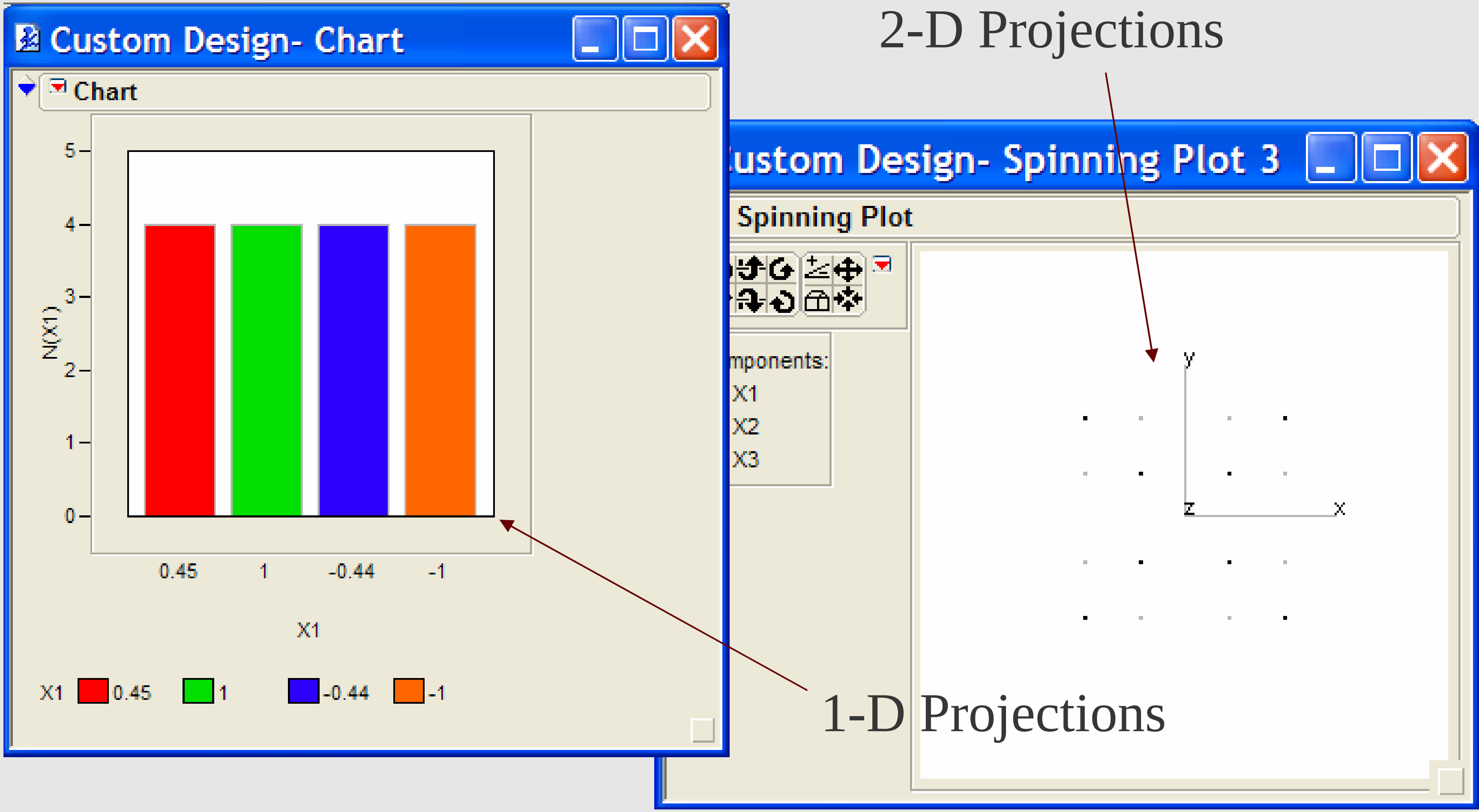
Columns (4/0)
- Length ✱
- Viewings ✱
- Delay ✱
- Recall ✱

Rows
All rows 16

	Length	Viewings	Delay	Recall
1	30	3	2	•
2	30	1	1	•
3	30	1	5	•
4	25	3	5	•
5	15	2.5	3	•
6	25	2.5	1	•
7	15	2.5	2	•
8	25	1.5	2	•
9	30	2.5	4	•
10	10	1	2	•
11	25	1.5	4	•
12	10	1.5	5	•
13	10	3	1	•
14	10	3	4	•
15	15	1	4	•
16	15	1.5	1	•

Design now has four levels:

2-D Projections



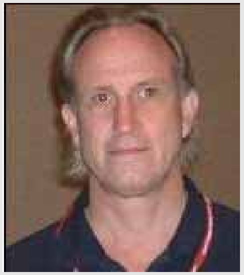
1-D Projections

What's Driving Custom Designer?

Optimal design construction, optimal blocking

- Cook and Nachtsheim (1980, *Technometrics*)
- Johnson and Nachtsheim (1982, *Technometrics*)
- Cook and Nachtsheim (1989, *Technometrics*)
- Meyer and Nachtsheim (1995,*Technometrics*)

Bayesian D-Optimal Designs



- DuMouchel and Jones, *Technometrics* (1994)
- Jones, Lin, Nachtsheim (*Journal of Statistical Planning and Inference*, 2007)

Concluding Remarks

Custom Design: A Paradigm Shift

“Change the problem to fit the tabled design” vs

“Create the design that solves the problem”

Simplifies design, simplifies teaching, removes barriers.

Needed: wider implementation, wider awareness, better texts.