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# Good Enough Designs: *A Practitioner's View of Optimality*

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Julia O'Neill

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# Translating Theory Into Practice

Remember this?

$$\frac{[iiii]}{[ijjj]} = \frac{F + 2\alpha^4}{F}$$

Graduate Student's Design Moment



Practitioner's Design Moment

# Purpose of this talk

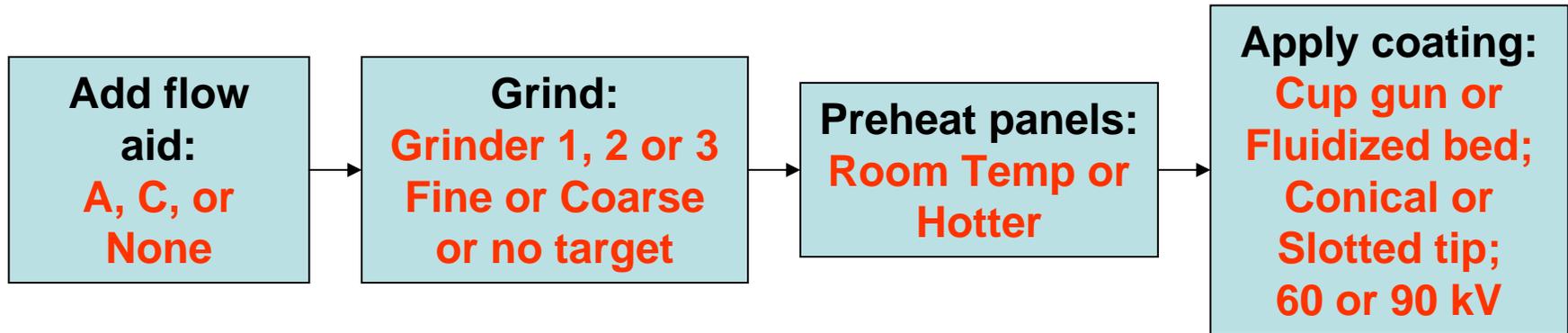
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Using industrial application examples,

illustrate the challenges of  
designing experiments in industry,

and define optimality criteria  
from the practitioner's viewpoint.

# Coating example



## – Variables:

- Formulation variables:
  - Grinding equipment (3 types)
  - Particle size (3 distributions)
  - Additive (A, B, or none)
- Application variables:
  - Spray gun tip (conical or slot)
  - Powder charge (60 or 90 kV)
  - Gun feed (cup or fluid bed)

# Original design



Challenge:  
You don't always get the design points you ask for!

Grinder	Speed	Post Blend	Preheat Temp (F)	Spray	Gun Tip	Charge (kV)
Strand	slow	Aluminum Oxide	150	fluid bed	cone	90
Strand	slow	none	150	fluid bed	slot	60
Strand	slow	Cabosil	75	cup gun	slot	90
Strand	slow	none	75	cup gun	cone	60
Strand	fast	Aluminum Oxide	75	fluid bed	slot	60
Strand	fast	Cabosil	150	cup gun	cone	60
Strand	fast	none	150	cup gun	slot	90
Strand	fast	none	75	fluid bed	cone	90
Brinkman	slow	Cabosil	75	fluid bed	cone	60
Brinkman	slow	none	75	fluid bed	slot	90
Brinkman	slow	Aluminum Oxide	150	cup gun	slot	60
Brinkman	slow	none	150	cup gun	cone	90
Brinkman	fast	none	75	cup gun	slot	60
Brinkman	fast	Cabosil	150	fluid bed	slot	90
Brinkman	fast	Aluminum Oxide	75	cup gun	cone	90
Brinkman	fast	none	150	fluid bed	cone	60

# 20 Panels Evaluated

Charge	Additive	Grinder	PSD		
100	none	production	fine		
100	none	lab	lab		
60	none	lab	lab		
60	B	production	fine		
60	none	lab	lab		
60	A	production	coarse		
100	A	lab	lab		
60	A	production	fine	cup	slotted
60	A	lab	lab	cup	slotted
100	B	production	coarse	fluid	slotted
100	none	production	coarse	cup	slotted
100	none	production	coarse	cup	conical
100	B	production	fine	fluid	conical
60	none	production	fine	cup	slotted
100	none	production	fine	cup	conical
100	A	production	fine	fluid	slotted
100	A	lab	lab	cup	conical
100	B	lab	lab	cup	slotted
100	A	production	fine	cup	conical
100	A	production	coarse	fluid	conical

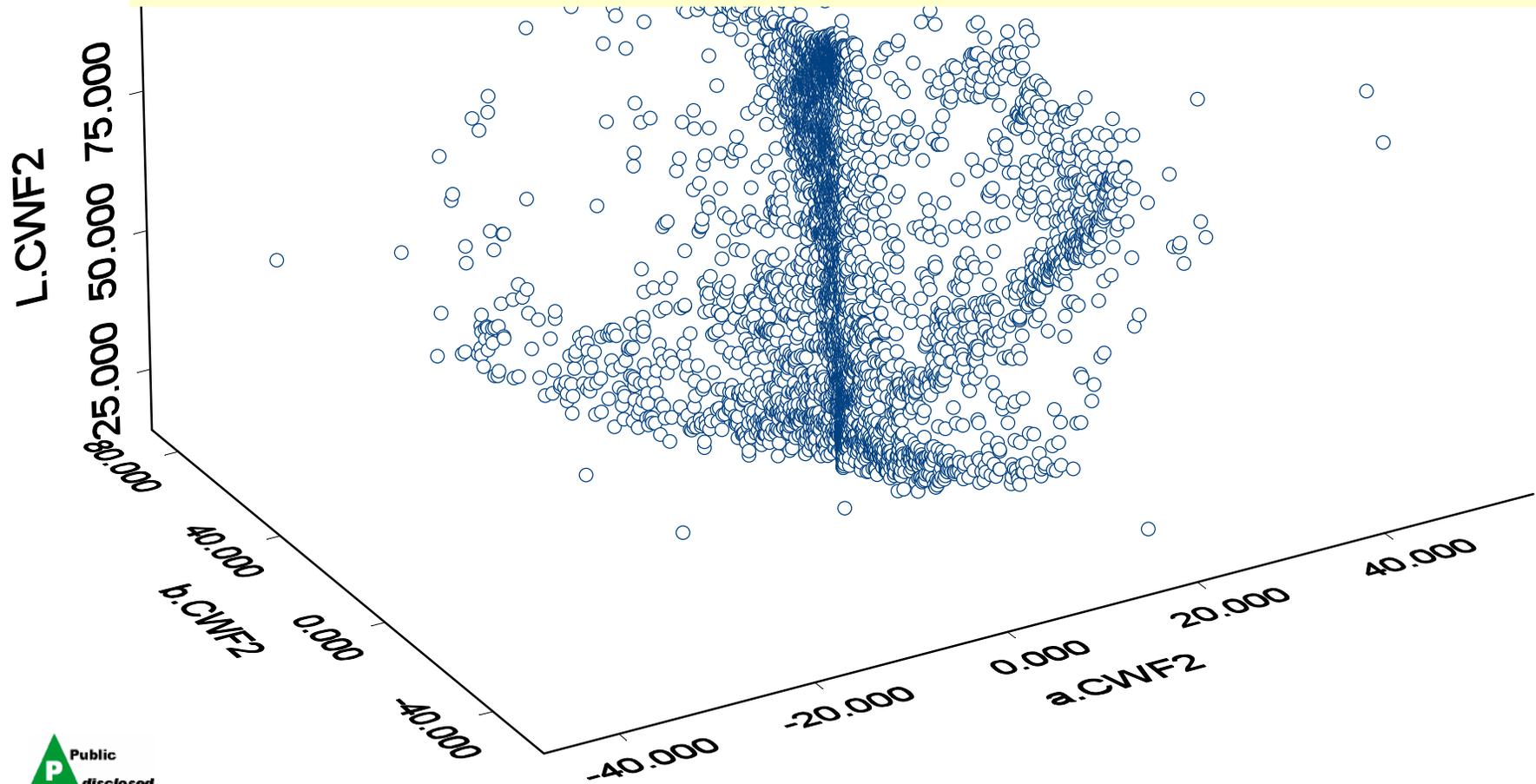
Challenge:  
110 panels were sprayed,  
but not all 16 original design panels were feasible.

Compromise solution:  
Optimal set of 20 panels were selected  
from 110 panels available..

# Color Calibration example

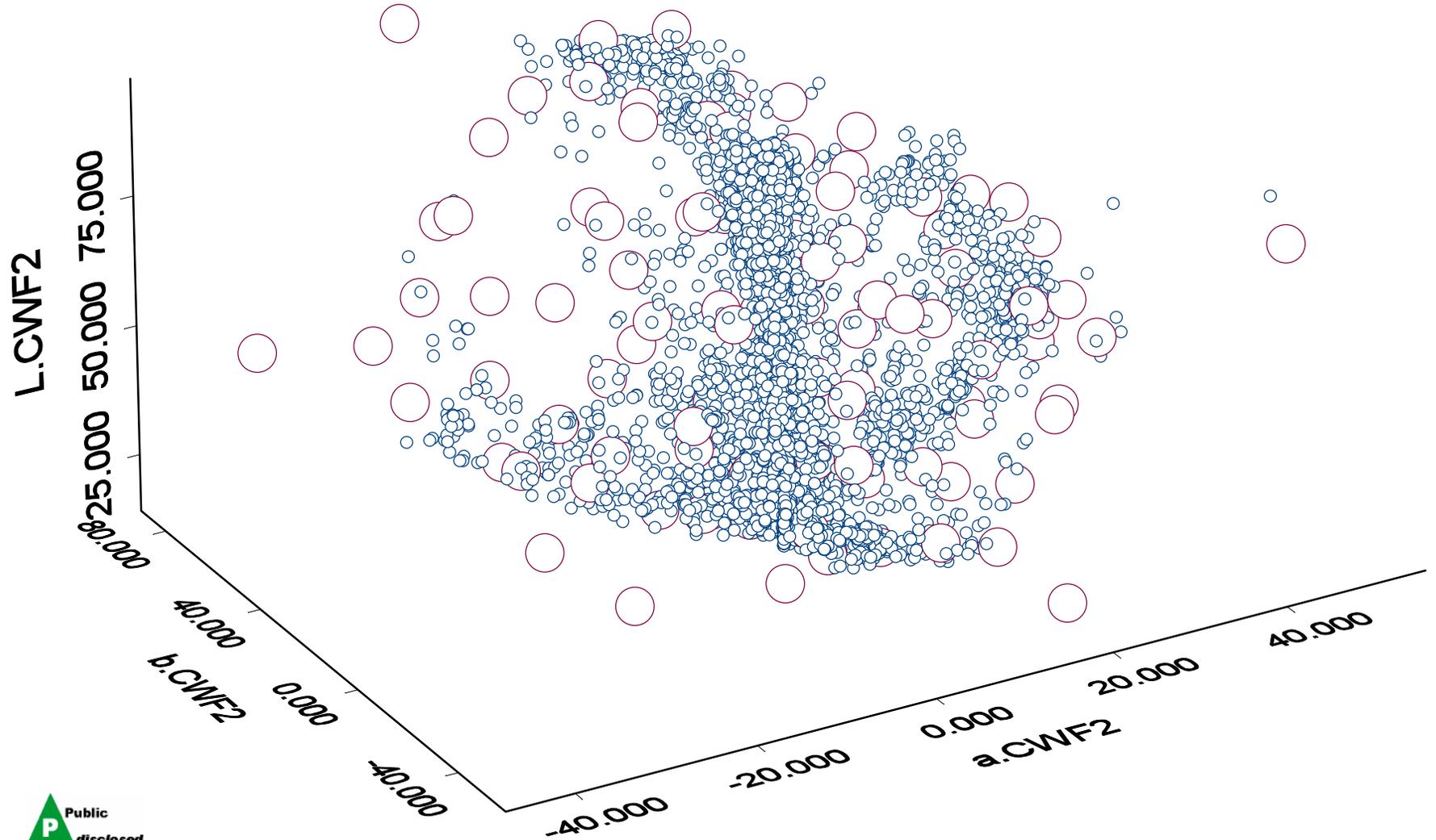


Challenges:  
6050 colored samples to choose from.  
Can't dial in color values, must select from irregular, constrained sample region.  
Can't assume a simple, smooth model throughout color space.



# Distance-based Optimal Design

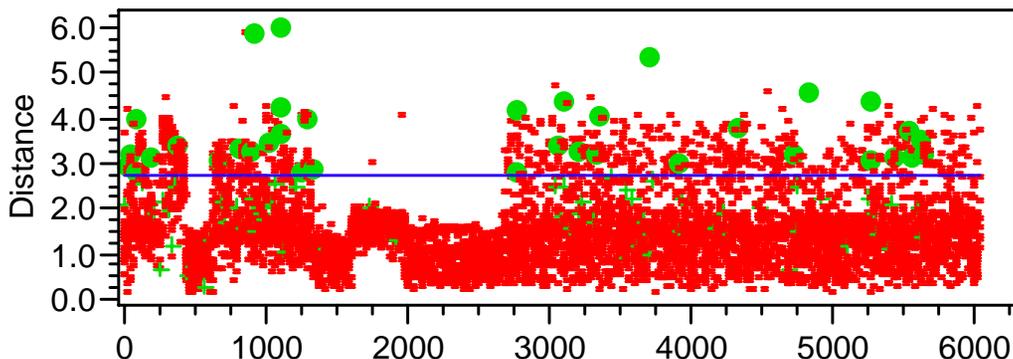
based on  $L^*$ ,  $a^*$ , and  $b^*$



# Distance-based Optimal Design

- Pro's
  - Fills the region of colors used
- Con's
  - Picks many extreme colors
    - 36 of 100 points selected are at edges

**Mahalanobis Distances**



# Wood Treatment Example

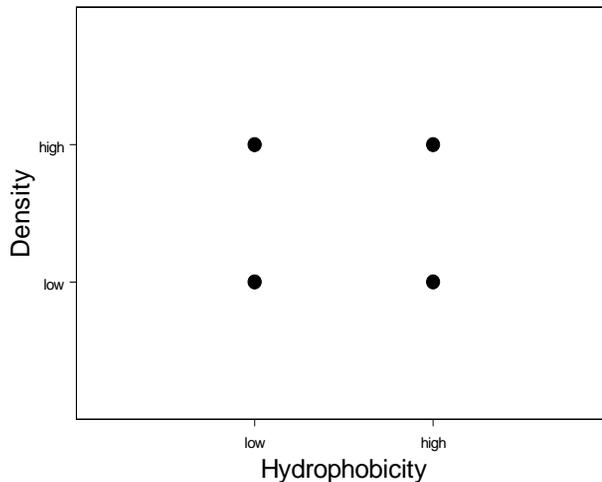
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- Purpose: To compare formulations for a protective coating for wood intended for outdoor use.
- Challenges:
  - **Variation among wood samples is greater than variation across treatments, making it difficult to distinguish treatment effects.**
  - **Can't dial in factor levels for wood samples.**

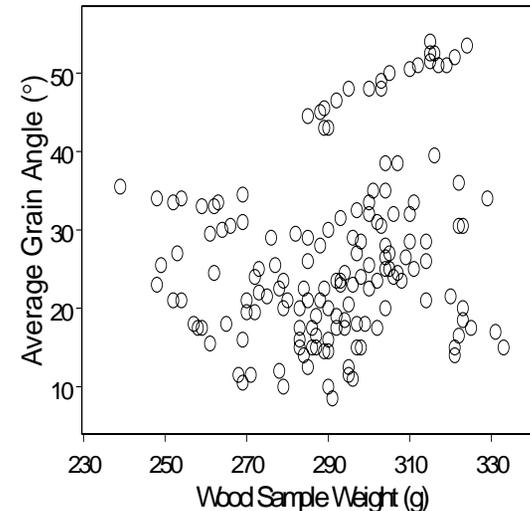
# Design Challenge



- Classical approach:
  - Hypothesize important variables, e.g.:
    - Hydrophobicity of treatments
    - Density of wood
  - Choose low and high levels
  - Run combinations of low's and high's for each variable



- Complications:
  - Cannot control the levels of wood properties
  - Can only select from the samples available
  - Do not know which properties are most important



# Alternative Design Approaches

## Competitive advantage

- Formulate treatments to be robust to wood variations
  - Wood expert characterizes each sample
  - Test as wide a range of samples as possible
  - Use optimal design to create a crossed array of wood properties by treatment levels
- Lumber industry approach:
  - Throw out wood samples which are different
  - Test as homogeneous a set of samples as possible
  - Ignore the variation among the samples

# Raw Material Screening example

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- Two different treatments are applied to a raw material, with two possible levels for each treatment:
  - Treatment 1 is either “normal” or “high”.
  - Treatment 2 is either “treated” or “not treated”.
- Raw material is used at two process stages.
  - Concentration at each stage can be different.
    - First Stage: 5, 10, or 15%
    - Second Stage: 1, 2, 4, or 8%
- Maximum block size is 12.
- Sequential designs are not practical because cycle time for an experiment is long.

# Original Screening design

Run Number	Block Number	RM Treatment 1	RM Treatment 2	Conc Stage 1 (%)	Conc Stage 2 (%)	Run Number	Block Number	RM Treatment 1	RM Treatment 2	Conc Stage 1 (%)	Conc Stage 2 (%)
1	1	normal	treated	5	1	25	3	normal	not	5	1
2	1	high	treated	5	2	26	3	high	not	5	2
3	1	normal	not	5	4	27	3	normal	treated	5	4
4	1	high	not	5	8	28	3	high	treated	5	8
5	1	high	treated	10	1	29	3	high	not	10	1
6	1	normal	not	10	2	30	3	normal	treated	10	2
7	1	high	not	10	4	31	3	high	treated	10	4
8	1	normal	treated	10	8	32	3	normal	not	10	8
9	1	normal	not	15	1	33	3	normal	treated	15	1
10	1	high	not	15	2	34	3	high	treated	15	2
11	1	normal	treated	15	4	35	3	normal	not	15	4
12	1	high	treated	15	8	36	3	high	not	15	8
13	2	high	treated	5	1	37	4	high	not	5	1
14	2	normal	not	5	2	38	4	normal	treated	5	2
15	2	high	not	5	4	39	4	high	treated	5	4
16	2	normal	treated	5	8	40	4	normal	not	5	8
17	2	normal	not	10	1	41	4	normal	treated	10	1
18	2	high	not	10	2	42	4	high	treated	10	2
19	2	normal	treated	10	4	43	4	normal	not	10	4
20	2	high	treated	10	8	44	4	high	not	10	8
21	2	high	not	15	1	45	4	high	treated	15	1
22	2	normal	treated	15	2	46	4	normal	not	15	2
23	2	high	treated	15	4	47	4	high	not	15	4
24	2	normal	not	15	8	48	4	normal	treated	15	8

*What if resources are diverted before all blocks can be completed?*

Classic Youden square from Kempthorne (1957)

# Modified Screening design



Run Number	Block Number	RM Treatment 1	RM Treatment 2	Conc Stage 1 (%)	Conc Stage 2 (%)
1	1	normal	treated	5	1
2	1	high	treated	5	1
3	1	normal	not	5	1
4	1	high	not	5	1
5	1	high	treated	10	2
6	1	normal	not	10	2
7	1	high	not	10	2
8	1	normal	treated	10	2
9	1	normal	not	15	4
10	1	high	not	15	4
11	1	normal	treated	15	4
12	1	high	treated	15	4
13	2	high	treated	5	8
14	2	normal	not	5	8
15	2	high	not	5	8
16	2	normal	treated	5	8
17	2	normal	not	10	1
18	2	high	not	10	1
19	2	normal	treated	10	1
20	2	high	treated	10	1
21	2	high	not	15	2
22	2	normal	treated	15	2
23	2	high	treated	15	2
24	2	normal	not	15	2

Run Number	Block Number	RM Treatment 1	RM Treatment 2	Conc Stage 1 (%)	Conc Stage 2 (%)
25	3	normal	not	5	4
26	3	high	not	5	4
27	3	normal	treated	5	4
28	3	high	treated	5	4
29	3	high	not	10	8
30	3	normal	treated	10	8
31	3	high	treated	10	8
32	3	normal	not	10	8
33	3	normal	treated	15	1
34	3	high	treated	15	1
35	3	normal	not	15	1
36	3	high	not	15	1
37	4	high	not	5	2
38	4	normal	treated	5	2
39	4	high	treated	5	2
40	4	normal	not	5	2
41	4	normal	treated	10	4
42	4	high	treated	10	4
43	4	normal	not	10	4
44	4	high	not	10	4
45	4	high	treated	15	8
46	4	normal	not	15	8
47	4	high	not	15	8
48	4	normal	treated	15	8

Current or "control" concentrations

Each block gives estimates of treatment effects and interaction.  
Most interested in treatment effects for certain concentrations.

# From Interviews with 20 Statistically Excellent Researchers



- Software is crucial. Researchers need useful, easy-to-use statistics software with good manuals. Many practitioners learn statistical methods from software manuals.
  - When asked to describe a challenging statistics problem, many of the examples cited were challenging because of a lack of software.
- Management support is not necessary for using statistics. It is sufficient for successful use of statistics if the manager just “gets out of the way”.
- Most scientists are very willing to try new ideas. We should continually look for ways to support and encourage this attitude.

# “Good” Response Surface Designs\*

1. Generate useful information throughout region of interest
2. Ensure fitted values close to true values
3. Detect lack-of-fit
4. Allow estimation of transformations
5. Permit blocking
6. Allow sequential buildup of design order
7. Provide internal estimate of error
8. Insensitive to outliers and nonnormality
9. Require minimum number of points
10. Provide data that allow visual analysis
11. Ensure simplicity of calculation
12. Insensitive to errors in settings of  $x$ 's
13. Require a practical number of variable levels
14. Provide check for constancy of variance

\* **Box and Draper (1975).**

# Shortcomings of optimality criteria\*

- Design statistics are meaningless if the assumed model is inadequate.
  - In some situations, we cannot even assume smoothness.
- May require large amounts of replication at certain design points

Use the “Boss” Option:

There is no requirement that you must run all the points selected by the algorithm or that you can't run some points that the algorithm failed to choose.

# Optimality Criteria

## from this Practitioner's Viewpoint

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- ✓ Does the experimenter have software to construct the design and analyze the results?
- ✓ Is the design simple enough to be executed according to the plan?
- ✓ Will the experimenter be able to make simple plots of the results?
- ✓ Has the experimenter already been trained on or used either classical or optimal designs?
- ✓ If some of the runs cannot be completed, can the results still be analyzed?
- ✓ If the results from the first set of runs are ambiguous, how easy is it to add runs?
- ✓ Does it really matter – is the optimal design much different from the classical design?

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