

Modern Design of Experiments for Rapid and Active Learning

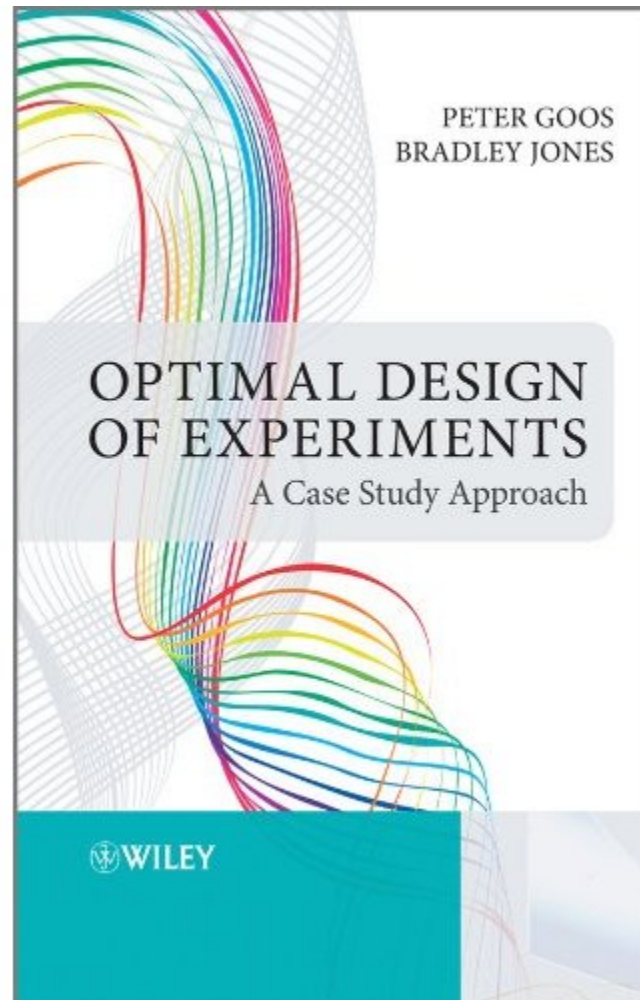
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Statistical Discovery. From SAS[®]

Outline

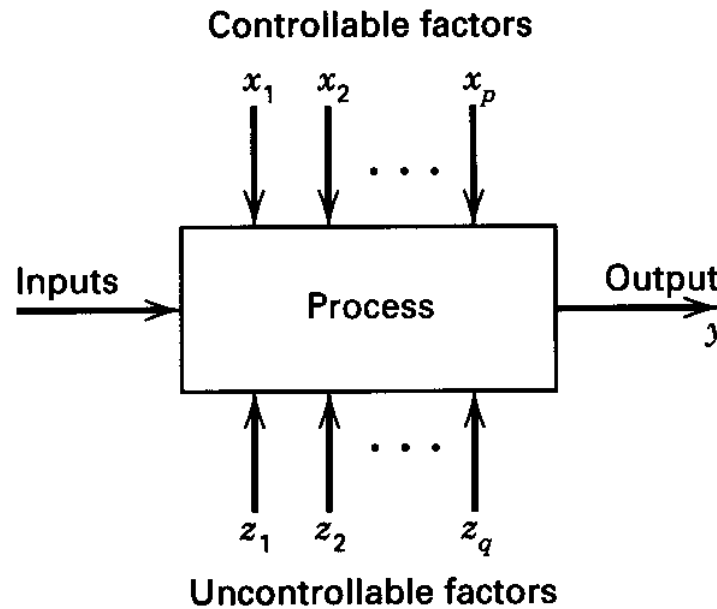
1. Introduction
2. Textbook Designs – restrictions and limitations
3. Examples of Computer Generated Designs
 - a. When the region of interest is not regular
 - b. When design runs need to be run in groups – blocking
 - c. When characteristics of the experimental material are known in advance

Most examples are based on this book.



What Is a Designed Experiment?

a structured set of tests of a system or process



Fundamental to designed experiments are...

1. Response(s) - outputs
2. Factor(s) - inputs
3. Mathematical Model

Why design experiments?

1. To establish causal relationships between inputs & outputs
2. To use this understanding to match desired outputs
3. To do the above efficiently & inexpensively

How do you start doing designed experiments?

The most frequently used industrial experiment is a factor screening experiment.

Screening experiments are a useful starting point.

What is a screening experiment?

... screening experiments – [are] experiments in which many factors are considered and the objective is to identify those factors (if any) that have large effects.

Montgomery, D.C. (2005) Design and Analysis of Experiments, Wiley, New York, page 283.

A textbook screening design

| Run | Methanol x_1 | Ethanol x_2 | Propanol x_3 | Butanol x_4 | pH x_5 | Time x_6 | Yield (mg) |
|-----|-------------------|------------------|-------------------|------------------|-------------|---------------|---------------|
| 1 | 0 | 0 | 0 | 10 | 6 | 1 | 10.94 |
| 2 | 0 | 10 | 0 | 0 | 9 | 1 | 15.79 |
| 3 | 0 | 10 | 0 | 10 | 9 | 2 | 25.96 |
| 4 | 10 | 10 | 10 | 0 | 6 | 1 | 35.92 |
| 5 | 0 | 0 | 10 | 0 | 6 | 2 | 22.92 |
| 6 | 0 | 10 | 10 | 10 | 6 | 1 | 23.54 |
| 7 | 10 | 10 | 0 | 0 | 6 | 2 | 47.44 |
| 8 | 10 | 0 | 0 | 0 | 9 | 1 | 19.80 |
| 9 | 10 | 0 | 10 | 10 | 9 | 1 | 29.48 |
| 10 | 0 | 0 | 10 | 0 | 9 | 2 | 17.13 |
| 11 | 10 | 10 | 10 | 10 | 9 | 2 | 43.75 |
| 12 | 10 | 0 | 0 | 10 | 6 | 2 | 40.86 |

Bie, Xiaomei, et. al. "Screening the main factors affecting extraction of the antimicrobial substance from *Bacillus* sp. fmbJ using the Plackett–Burman method" *World Journal of Microbiology & Biotechnology* (2005) 21: 925–928 Springer 2005

Implicit Restrictive Assumptions

1. Factor effects are linear

Why? – Every factor has only two settings

2. All factor combinations are feasible

Why? – All pairs of low and high factor settings appear

More textbook design limitations

1. Designs are prespecified – the number of required runs is fixed
2. Applicable models are limited
3. Lack of flexibility in numbers of runs in a group
4. Lack of flexibility in the types of factors
5. Lack of flexibility in dealing with hard-to-change factors
6. No ability to use knowledge about the experimental material
7. Lack of flexibility for replicating runs to estimate error variance

Consequence of Textbook Design Limitation

Experimenters simplify the problem description to accommodate the use of a prespecified design.

Preferable alternative to textbook design

use computer algorithms to construct designs that match all the problem specific requirements

“Design to fit the problem – Don’t change the problem to fit the design”

Software Demonstration

All Main Effects Model

Parameter Estimates

| Term | Estimate | Std Error | t Ratio | Prob> t |
|----------------|----------|-----------|---------|---------|
| Intercept | 27.79 | 0.71 | 39.0 | <.0001* |
| Methanol(0,10) | 8.41 | 0.71 | 11.8 | <.0001* |
| Ethanol(0,10) | 4.27 | 0.71 | 6.0 | 0.0019* |
| Propanol(0,10) | 1.00 | 0.71 | 1.4 | 0.2214 |
| Butanol(0,10) | 1.29 | 0.71 | 1.8 | 0.1292 |
| pH(6,9) | -2.48 | 0.71 | -3.5 | 0.0178* |
| Time(1,2) | 5.22 | 0.71 | 7.3 | 0.0007* |

DOE when not all factor combinations are feasible

Accommodating a Constrained Factor Space

Goals

1. Show the practical need for design when there are restrictions on the factor settings.
2. Provide an example of an experiment with factor constraints that also accommodates curvature in the factor-response relationship.

Reasons to Impose Factor Constraints

1. Certain combinations of factor settings may not work and you know this in advance.
2. Other combinations of factor settings may be dangerous.
3. Other combinations could damage the processing system.

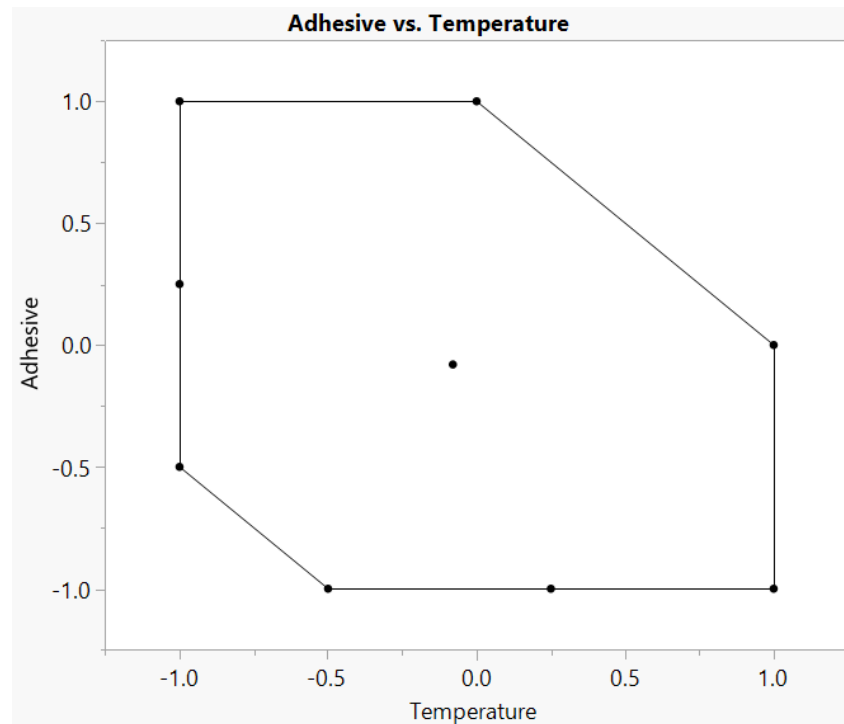
Design employing constrained factors

Scenario – Bonding electronic chip to a pacemaker

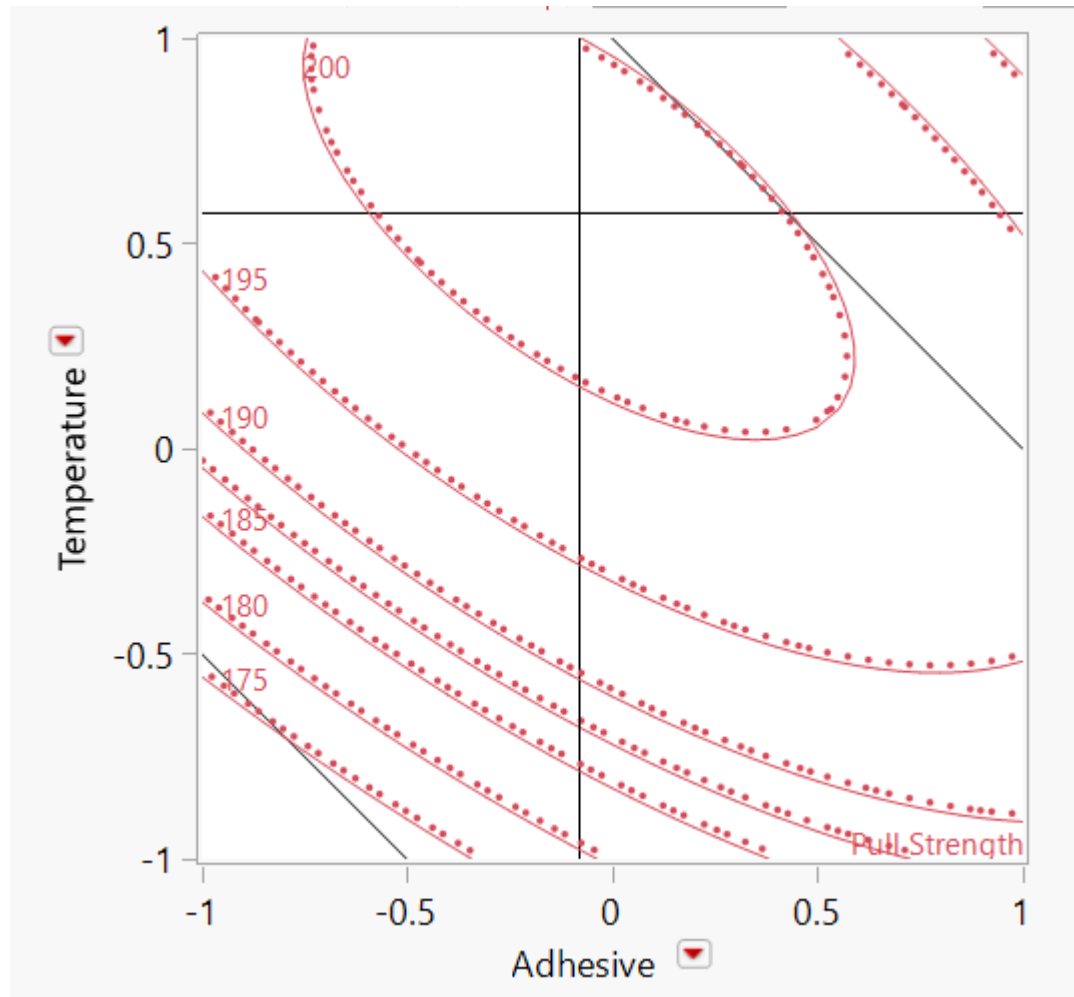
1. Two factors – adhesive and temperature
2. Response is peel strength of the bond
3. Combinations involving high settings of both factors or low settings of both factors are known to result in low yield.

Design with Response Data

| Adhesive | Temperature | Pull Strength |
|----------|-------------|---------------|
| -0.5 | -1 | 173.9 |
| 1 | 0 | 195.9 |
| -0.08 | -0.08 | 201.2 |
| -1 | 1 | 199.3 |
| 1 | -1 | 190.3 |
| 0 | 1 | 198.5 |
| -1 | 0.25 | 190.5 |
| 0.25 | -1 | 179.5 |
| -1 | -0.5 | 176.7 |
| 1 | 0 | 198.1 |
| 0 | 1 | 200.5 |
| -0.08 | -0.08 | 197.1 |



Software Demonstration



A design with homogeneous groups of runs - blocks

1. Many processes have sources of variability that are not controllable factors.
2. Example: day-to-day variability
3. This leads to groups of observations.
4. The groups are called **blocks**.
5. The grouping variable, day, in this case is called a **blocking factor**.
6. We expect that runs within a day are more similar than runs between days

Vitamin Stability Experiment



Journal of Pharmaceutical and
Biomedical Analysis

Volume 16, Issue 2, October 1997, Pages 275-
280



Evaluation of the methods for the
determination of the stability constant of
cyclodextrin–chlorambucil inclusion
complexes

Yannis L. Loukas 

Vitamin Stability Experiment

Vitamins degrade when exposed to light

Can be stabilized when embedded in a fatty molecule

Five different fatty molecule possibilities

Binding with sugar might help as well to stabilize the vitamins

Day-to-day variation due to calibration of measurement apparatus

The data

Data Stability Improvement Experiment Chapter 8 - JMP Pro

File Edit Tables Rows Cols DOE Analyze Graph SAS Tools Add-Ins View Window Help

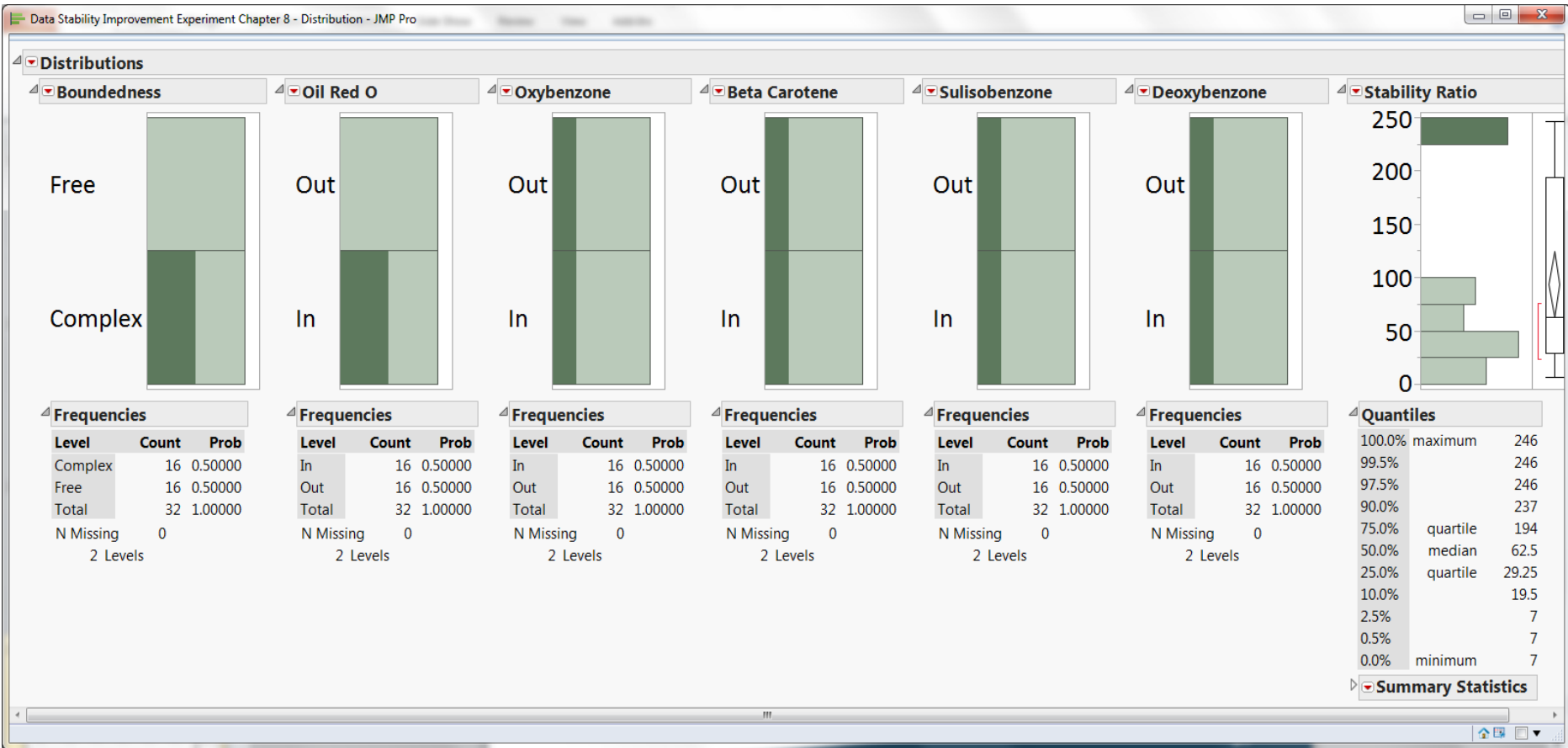
Data Stability I...
 Design Custom Desig
 Criterion D Optimal
 Screening
 Model
 Design Matrix
 Fixed Blocks Mode
 Random Blocks Mc

Columns (8/0)
 Block *
 Boundedness *
 Oil Red O *
 Oxybenzone *
 Beta Carotene *
 Sulisobenzene *
 Deoxybenzone *
 Stability Ratio *

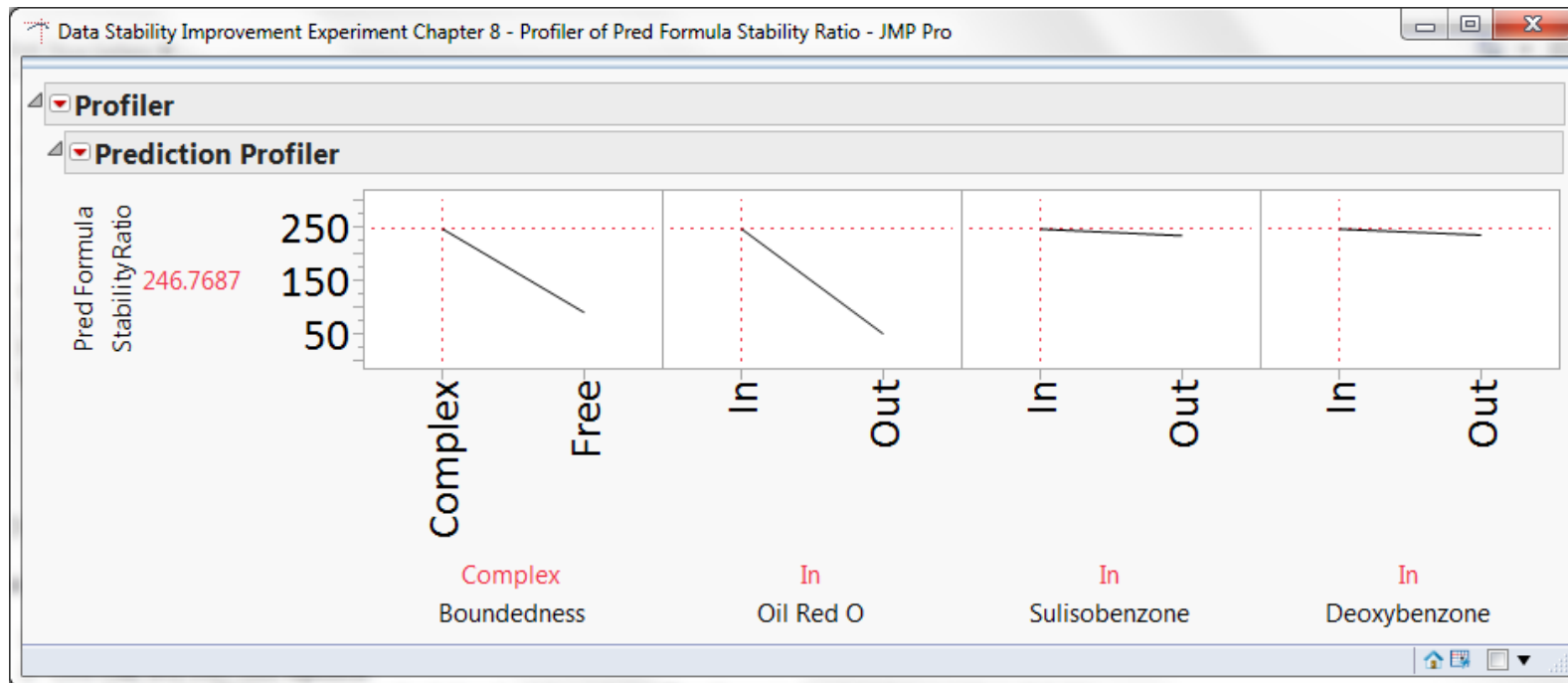
Rows
 All rows 32
 Selected 0
 Excluded 0
 Hidden 0
 Labelled 0

| | Block | Boundedness | Oil Red O | Oxybenzone | Beta Carotene | Sulisobenzene | Deoxybenzone | Stability Ratio |
|----|-------|-------------|-----------|------------|---------------|---------------|--------------|-----------------|
| 1 | 1 | Complex | In | In | In | Out | In | 237 |
| 2 | 1 | Free | Out | In | In | In | In | 42 |
| 3 | 1 | Free | Out | In | Out | Out | In | 29 |
| 4 | 1 | Free | In | Out | In | Out | Out | 72 |
| 5 | 2 | Complex | In | Out | Out | In | Out | 229 |
| 6 | 2 | Free | Out | Out | Out | Out | Out | 11 |
| 7 | 2 | Complex | In | Out | Out | Out | In | 235 |
| 8 | 2 | Free | In | Out | In | In | In | 89 |
| 9 | 3 | Free | In | In | In | In | Out | 76 |
| 10 | 3 | Free | Out | Out | In | Out | In | 18 |
| 11 | 3 | Complex | In | Out | In | In | In | 246 |
| 12 | 3 | Complex | Out | In | In | Out | Out | 23 |
| 13 | 4 | Free | Out | In | Out | In | Out | 29 |
| 14 | 4 | Complex | Out | Out | In | In | Out | 44 |
| 15 | 4 | Complex | In | In | Out | Out | Out | 228 |
| 16 | 4 | Complex | Out | In | In | In | In | 46 |
| 17 | 5 | Free | In | Out | Out | Out | In | 83 |
| 18 | 5 | Free | Out | Out | In | In | Out | 30 |
| 19 | 5 | Complex | Out | Out | Out | In | In | 60 |
| 20 | 5 | Complex | In | Out | In | Out | Out | 228 |
| 21 | 6 | Complex | Out | In | Out | In | Out | 39 |
| 22 | 6 | Free | In | In | Out | In | In | 92 |
| 23 | 6 | Free | In | Out | Out | In | Out | 76 |
| 24 | 6 | Free | Out | In | In | Out | Out | 7 |
| 25 | 7 | Complex | In | In | Out | In | In | 240 |
| 26 | 7 | Complex | Out | Out | In | Out | In | 38 |
| 27 | 7 | Free | In | In | In | Out | In | 74 |
| 28 | 7 | Free | Out | Out | Out | In | In | 24 |

Graphical descriptive analysis



Software Demonstration



DOE With Covariate Factors Known in Advance

Designing around prior information about experimental units

Goals

1. Explain the practical utility of taking information about the experimental units into account in design
2. Provide an example of an experiment with a covariate factor.

Reasons to Use Covariate Factor Information

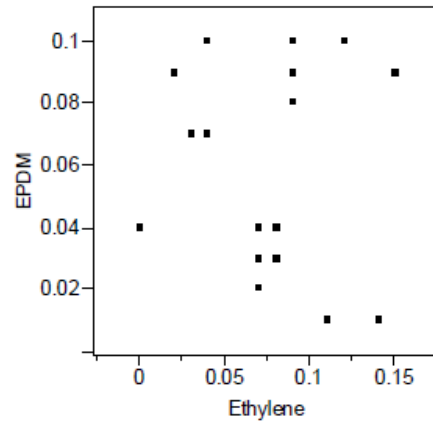
1. You may have more experimental material than necessary and need to choose which material to use.
2. Certain characteristics of the experimental material may strongly influence the response and you want to make sure that these characteristics are as little correlated with the effects of your control factors as possible.

Case Study Using Covariate Information

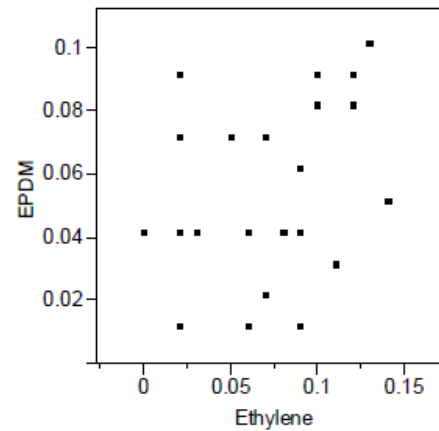
Scenario

1. You have 40 batches of polypropylene to use in your study.
2. You have a budget of 18 runs.
3. You have information about two continuous and one categorical characteristic for each batch.

Graphical View of Covariate Information

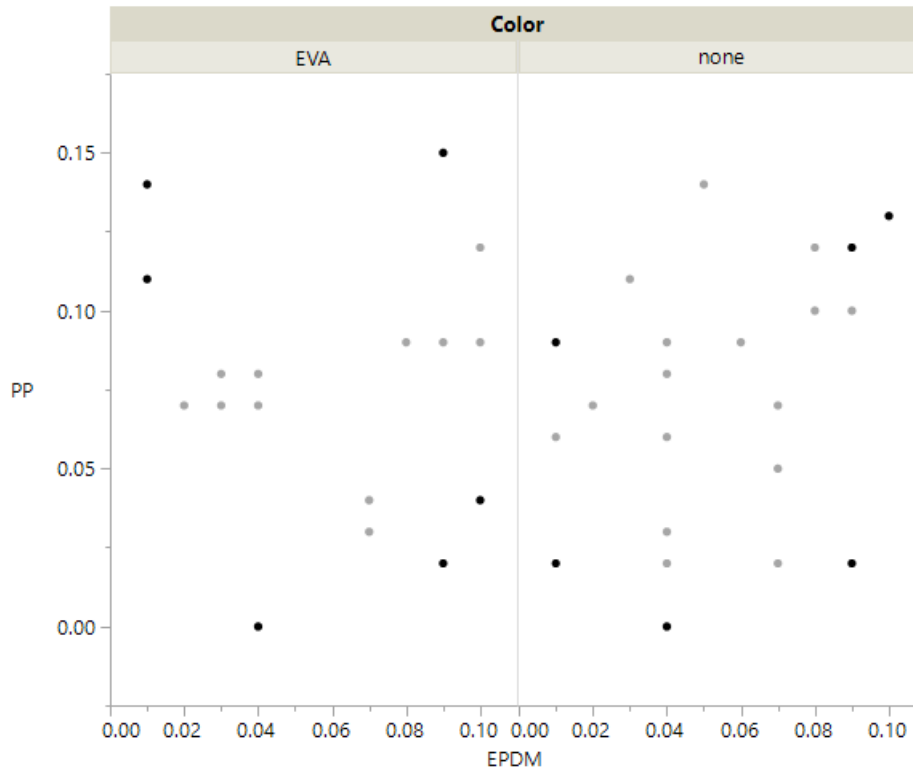


(a) Samples containing EVA



(b) Samples not containing EVA

Software Demonstration



Summary of DOE with Covariate Factors

1. Including covariate information, when it is available, is a powerful way to account for known sources of variability.
2. This approach can also be used to adjust the time order of runs when the response is subject to linear drift over time.

Summary

1. This talk provided a taste of a new approach to industrial design of experiments.
2. Each of the examples emphasizes the approach of designing experiments to solve the problem as stated rather than to change the requirements in order to use a textbook design.