Overview of Design of Experiments

ASQ Meeting
January 12th 2010

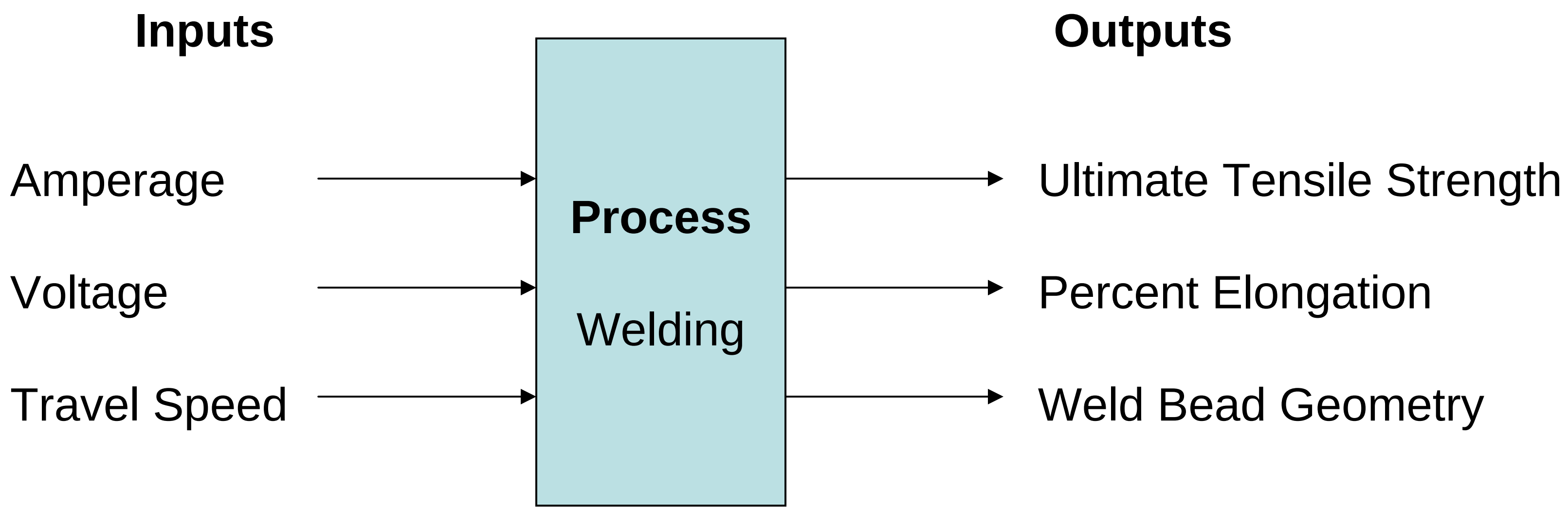
Presented by Jerry Majors

Agenda

- DOE introduction
- Overview
  - Factorial Designs
    - Plackett-Burman
    - Full Factorial
  - Response Surface
    - Central Composite Design
    - Box Benkhen
  - Mixture Designs
    - Simplex Centroid
  - Taguchi Designs
    - L27
- Example of a Central Composite Design
- Common Mistakes

What are Design of Experiments?

- Intended changes to inputs (factors) to a process or activity in order to achieve (measure) changes in the outputs (responses)



Why Use DOE's?

- Efficiently collect process data & make decisions
  - gain an understanding of inputs vs. outputs and their relationships
  - optimize results or minimize variation
- To collect data one factor at a time is an inefficient and ineffective use of time, money and resources

Why are DOE's so good?

- Well structured and randomized process of experimentation
- Based on sampling
- Mitigates outside influences
- Highly effective if followed

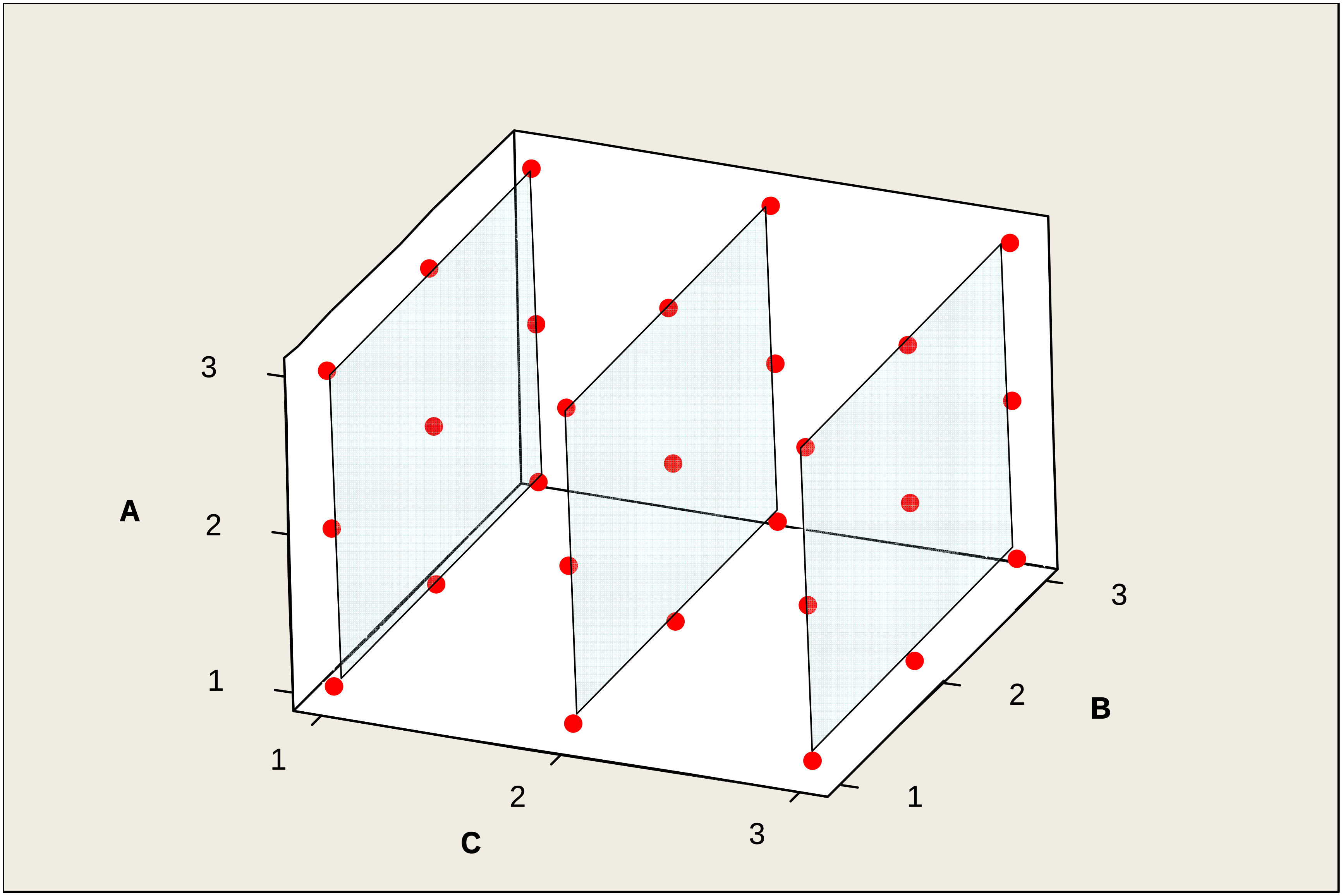
Getting Started

- Identify the problem
- Identify the objective(s)
- Select the response(s)
- Select the factors
- Select DOE approach
  - Select best design for your situation

Factorial Designs

- Plackett-Burman and Fractional Factorial designs
  - typically utilized to study main effects and identify which factors are important
- 2 Level (settings) Factorial Designs
  - provide direction for further experimentation
- General Full Factorial designs allow for simultaneous study of:
  - effects of multiple factors
  - The study of interactions between factors
  - May have multiple levels for each factor

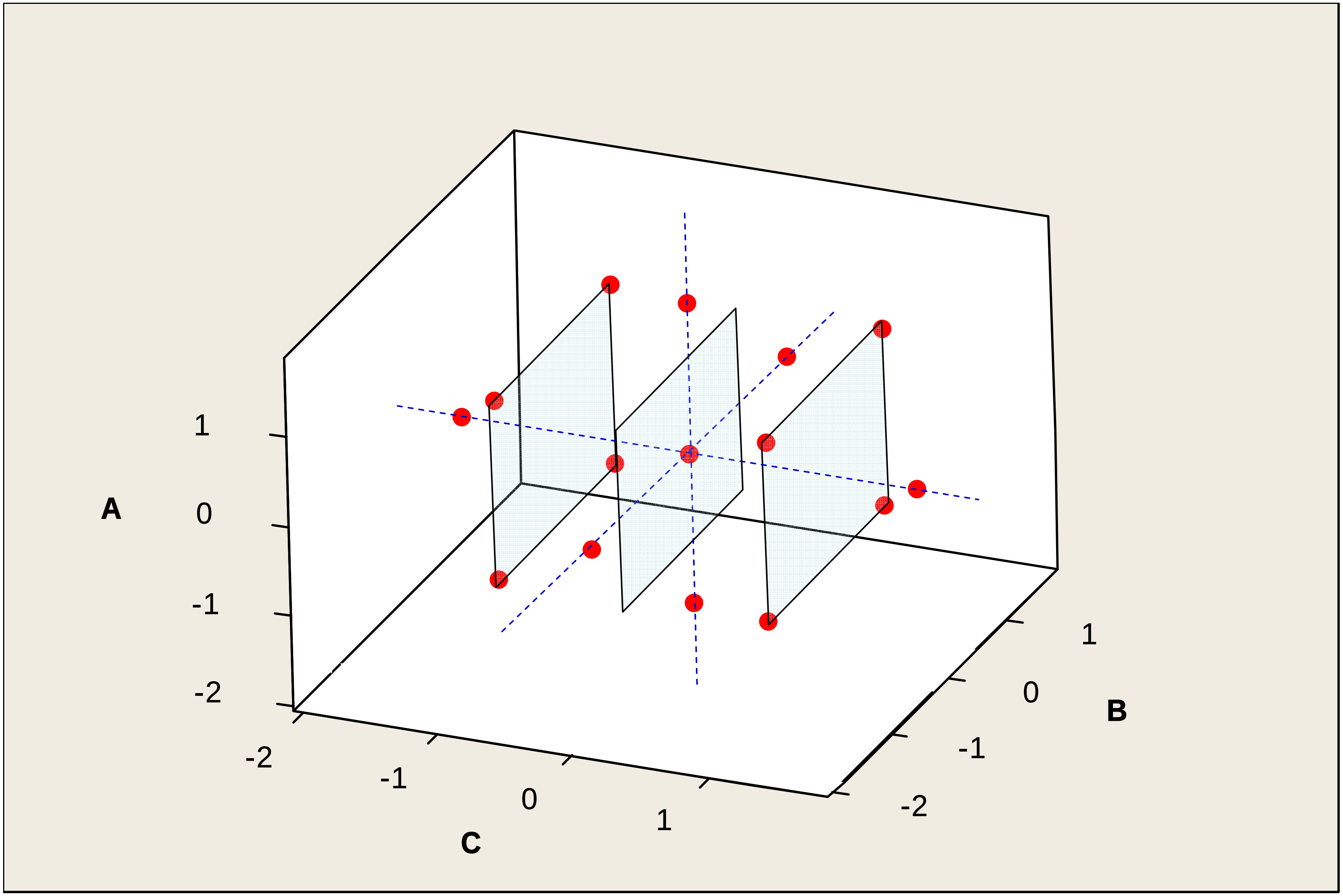
Full Factorial Designs



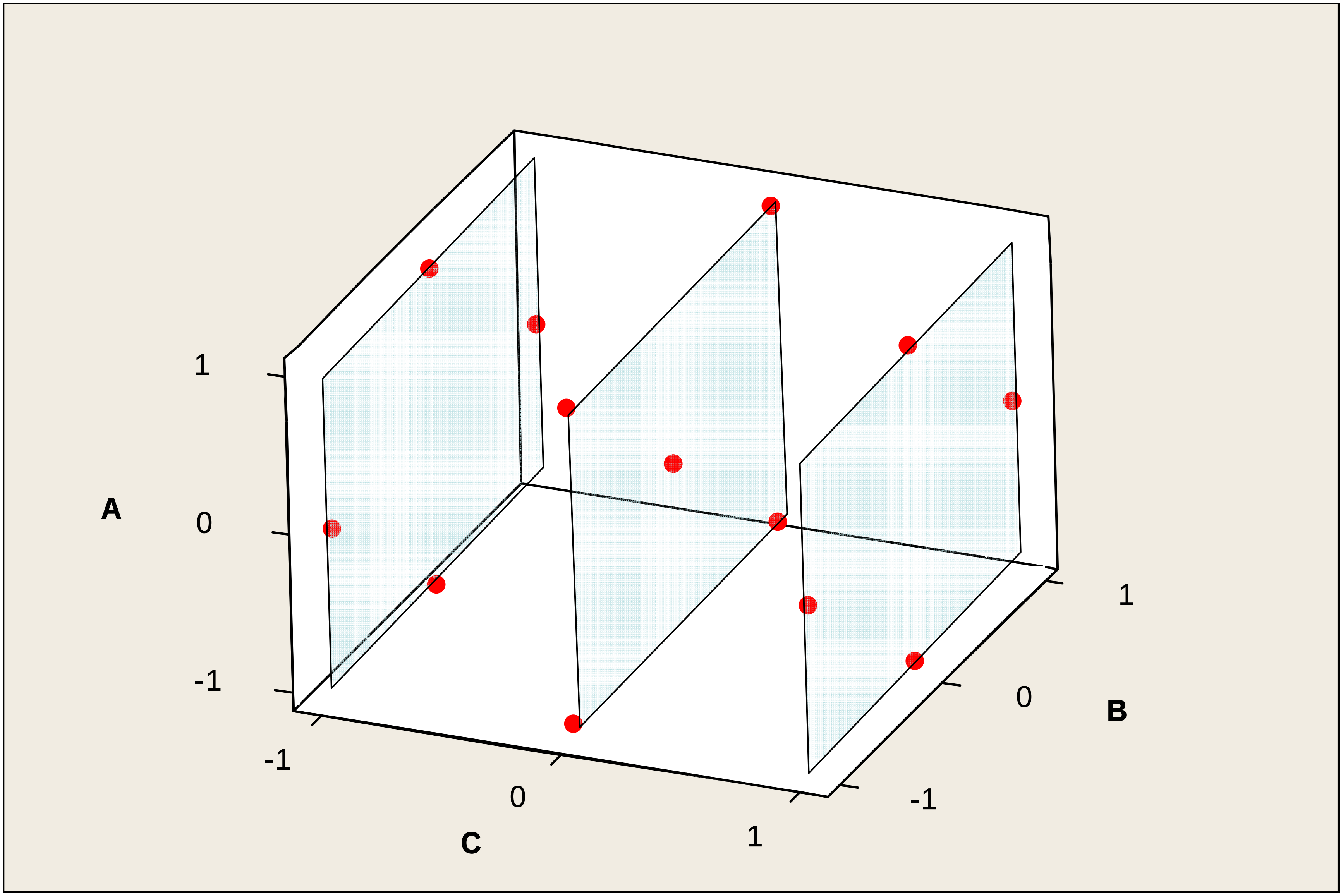
Response Surface Methods

- Examine the relationship between one or more response variables and a set of quantitative input factors.
  - Usually employed after you have identified the "vital few" controllable factors
  - and you want to find the factor settings that optimize the response.
  - suspect curvature in the response surface.

Central Composite Design



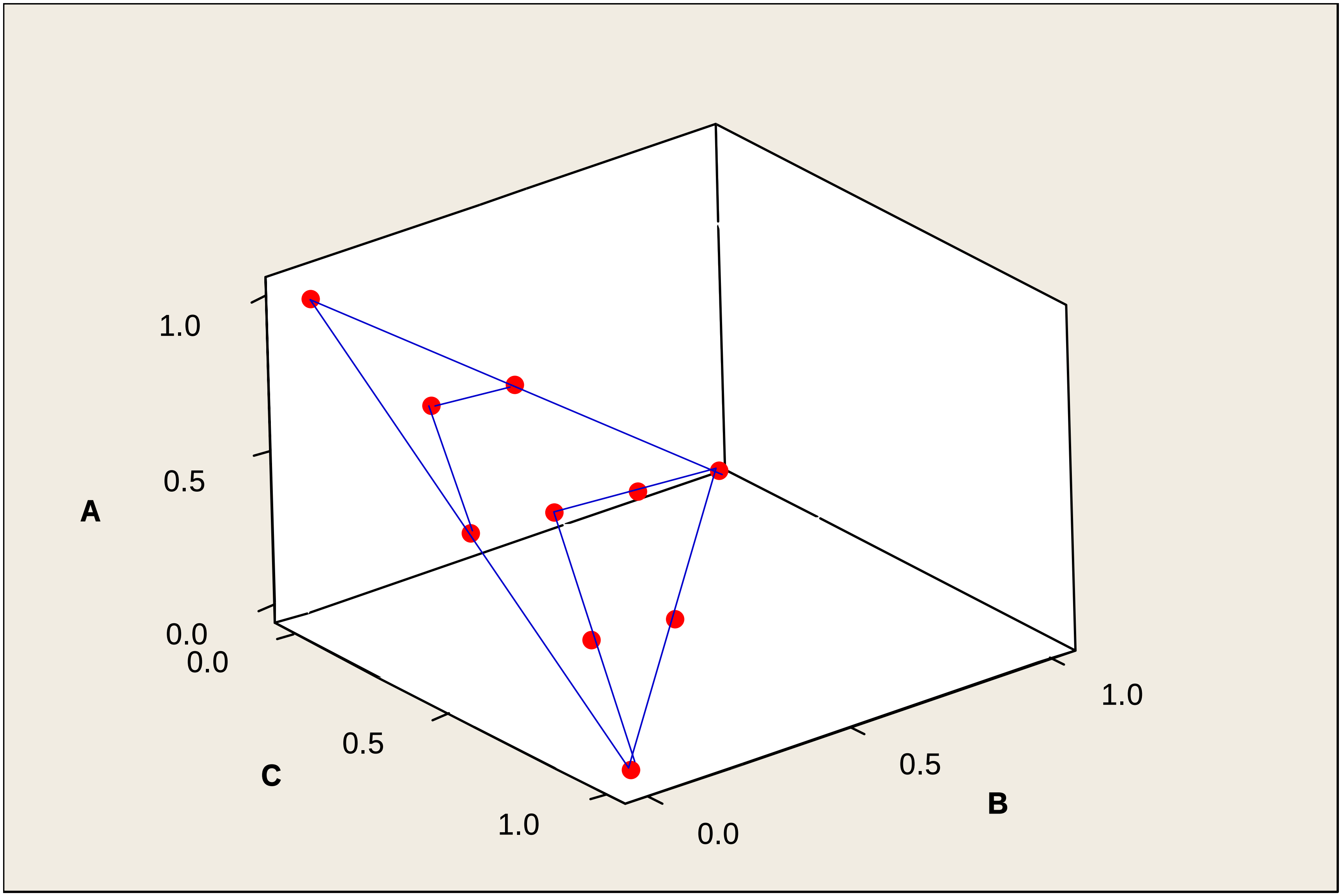
Box-Behnken



Mixture Experiments

- A special class of response surface designs where the product under investigation is made up of several components or ingredients
  - situations involving formulations or mixtures
  - the response is a function of the proportions of the different ingredients in the mixture

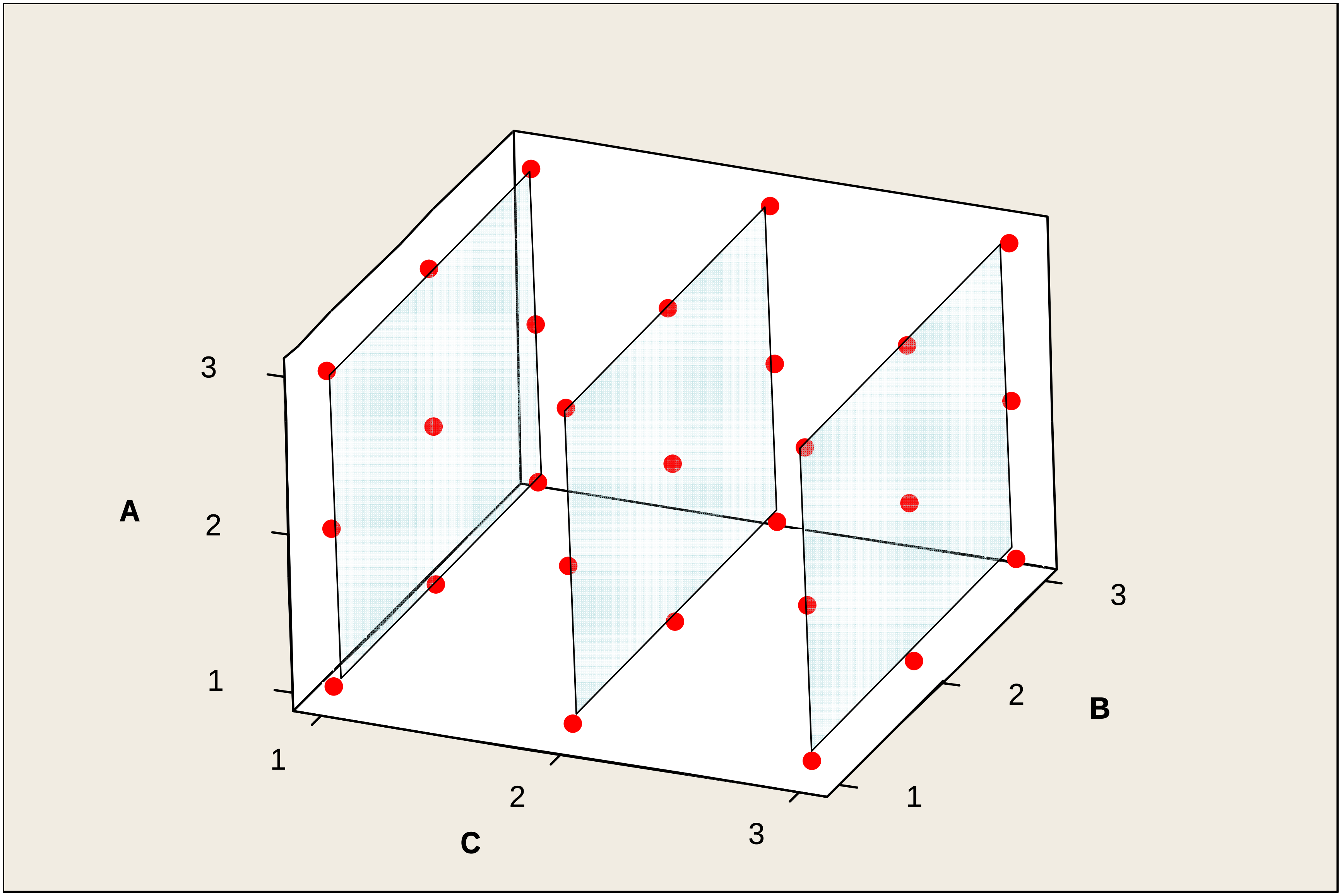
Simplex Centroid



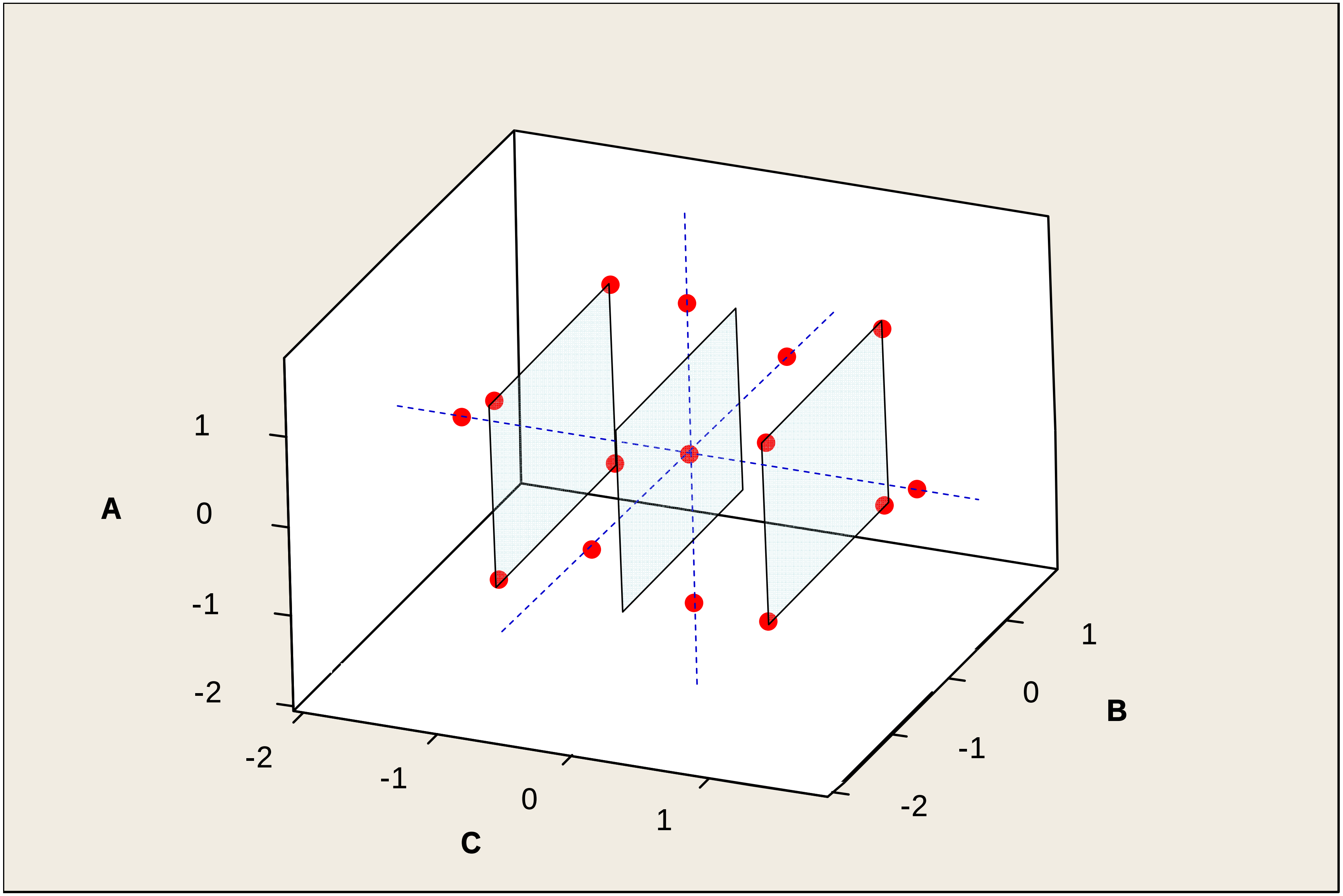
Taguchi Designs

- Focuses on minimizing variation and/or sensitivity to noise
  - these designs provide a method for designing products that operate consistently and optimally over a variety of conditions; i.e. the primary goal is to find factor settings that minimize response variation while keeping the process on target

Taguchi Design (L27)



Central Composite Design Example



Analysis of the DOE

- Mathematical treatment of the data
  - ANOVA
  - Graphical Displays
- Confirmations runs
- Common sense

ANOVA Output

Estimated Regression Coefficients for Response 1

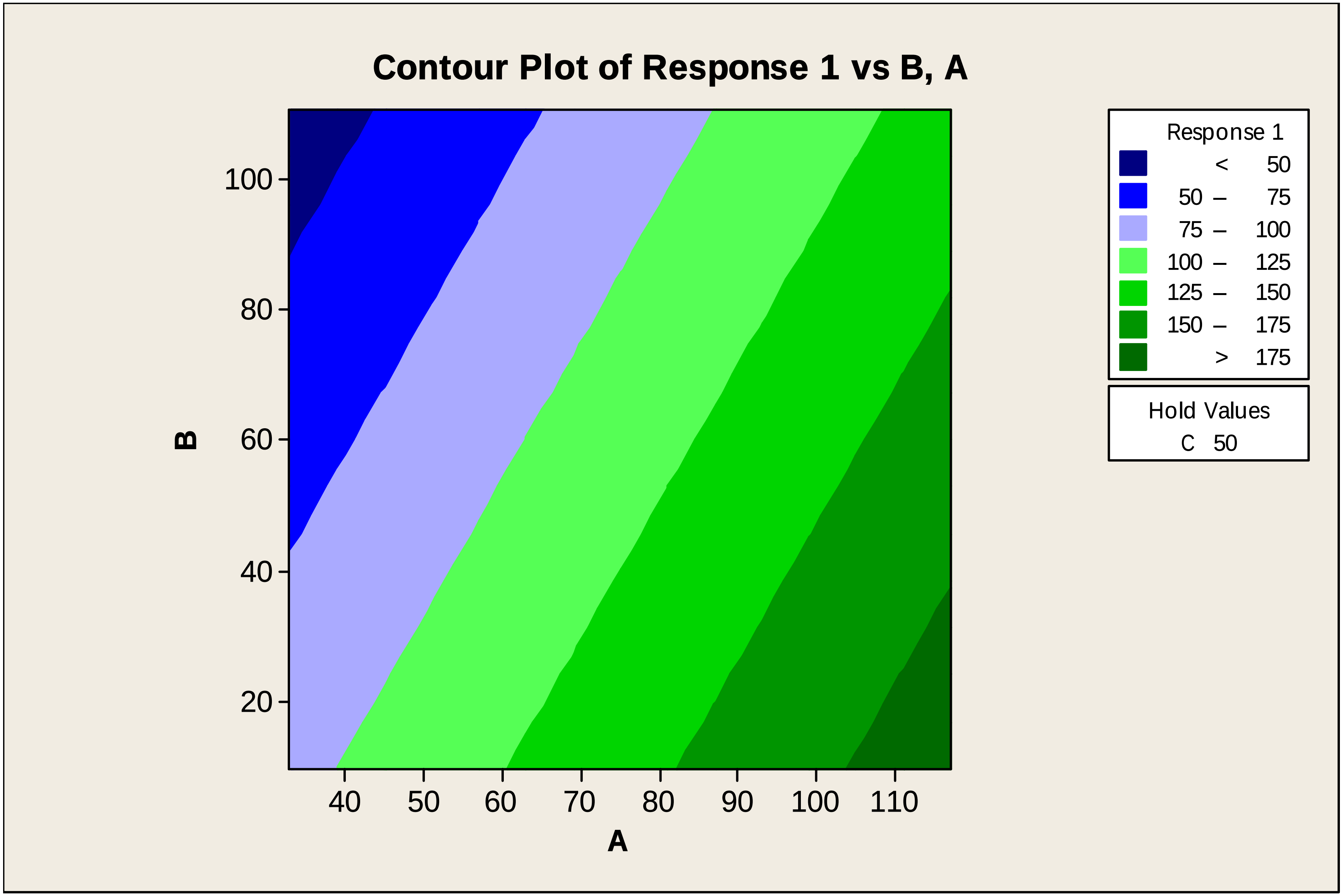
Term	Coef	SE Coef	T	P
Constant	114.028	1.549	73.624	0.000
Block 1	-3.415	2.190	-1.559	0.125
Block 2	3.048	2.190	1.392	0.170
A	28.843	1.874	15.389	0.000
B	-16.508	1.874	-8.807	0.000
C	24.607	.874	13.129	0.000

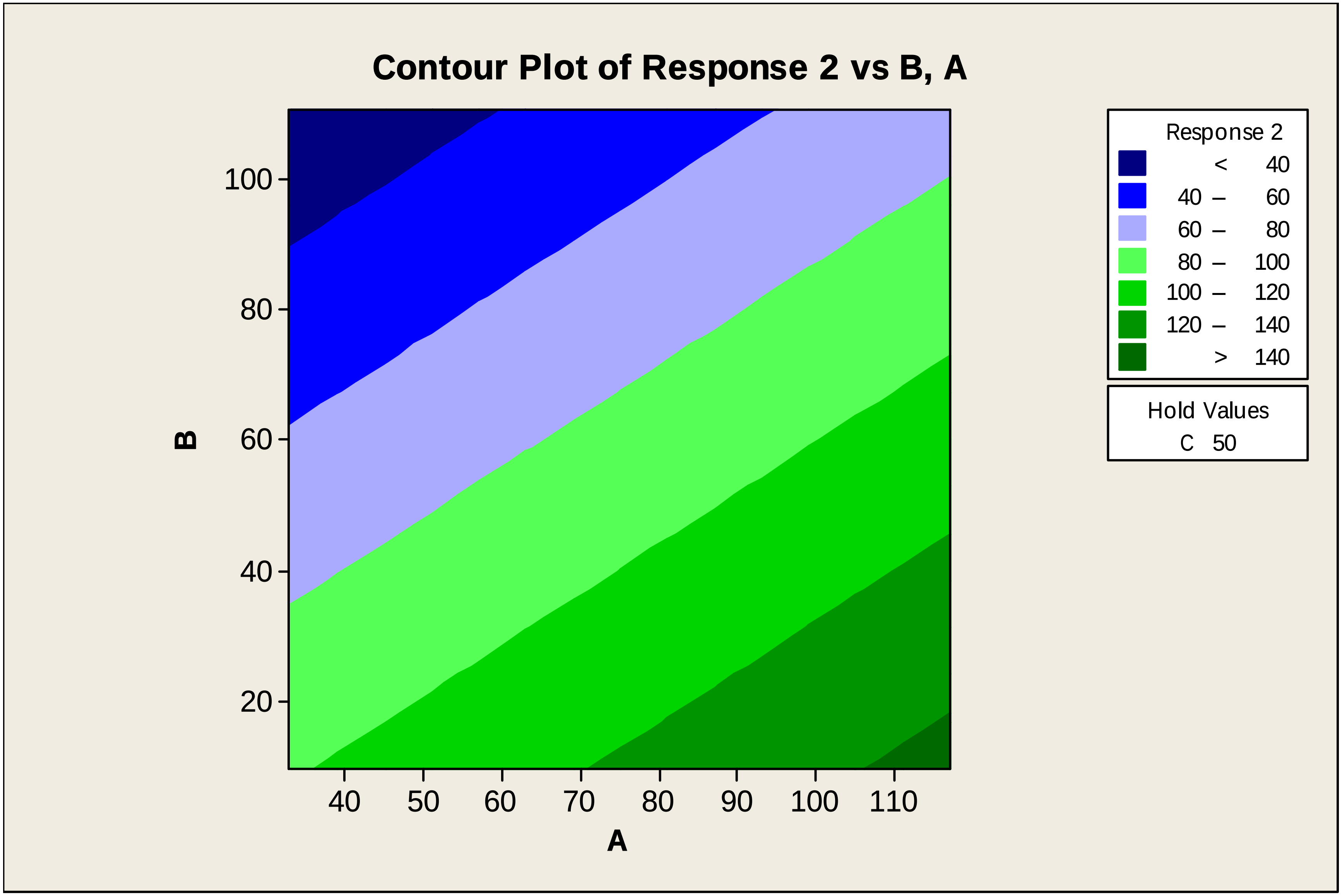
- S = 11.9969   PRESS = 9692.21
- R-Sq = 90.07%
- R-Sq(pred) = 87.61%
- R-Sq(adj) = 89.15%

- Estimated Regression Coefficients for Response 2

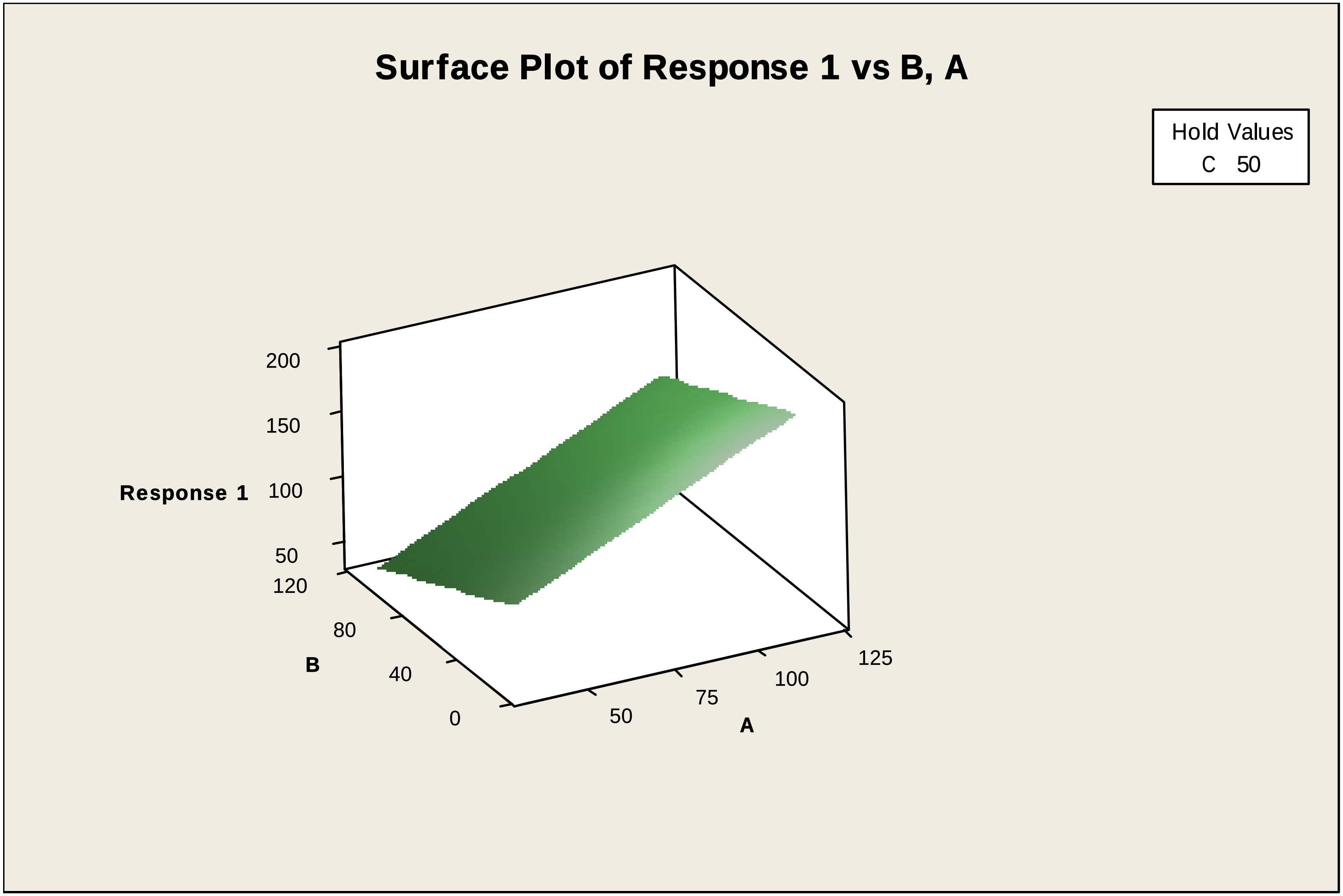
Term	Coef	SE Coef	T	P
Constant	85.459	3.023	28.271	0.000
Block 1	5.479	4.275	1.282	0.205
Block 2	-7.001	4.275	-1.638	0.107
A	14.222	3.658	3.888	0.000
B	-21.899	3.658	-5.986	0.000
C	42.726	3.658	11.680	0.000

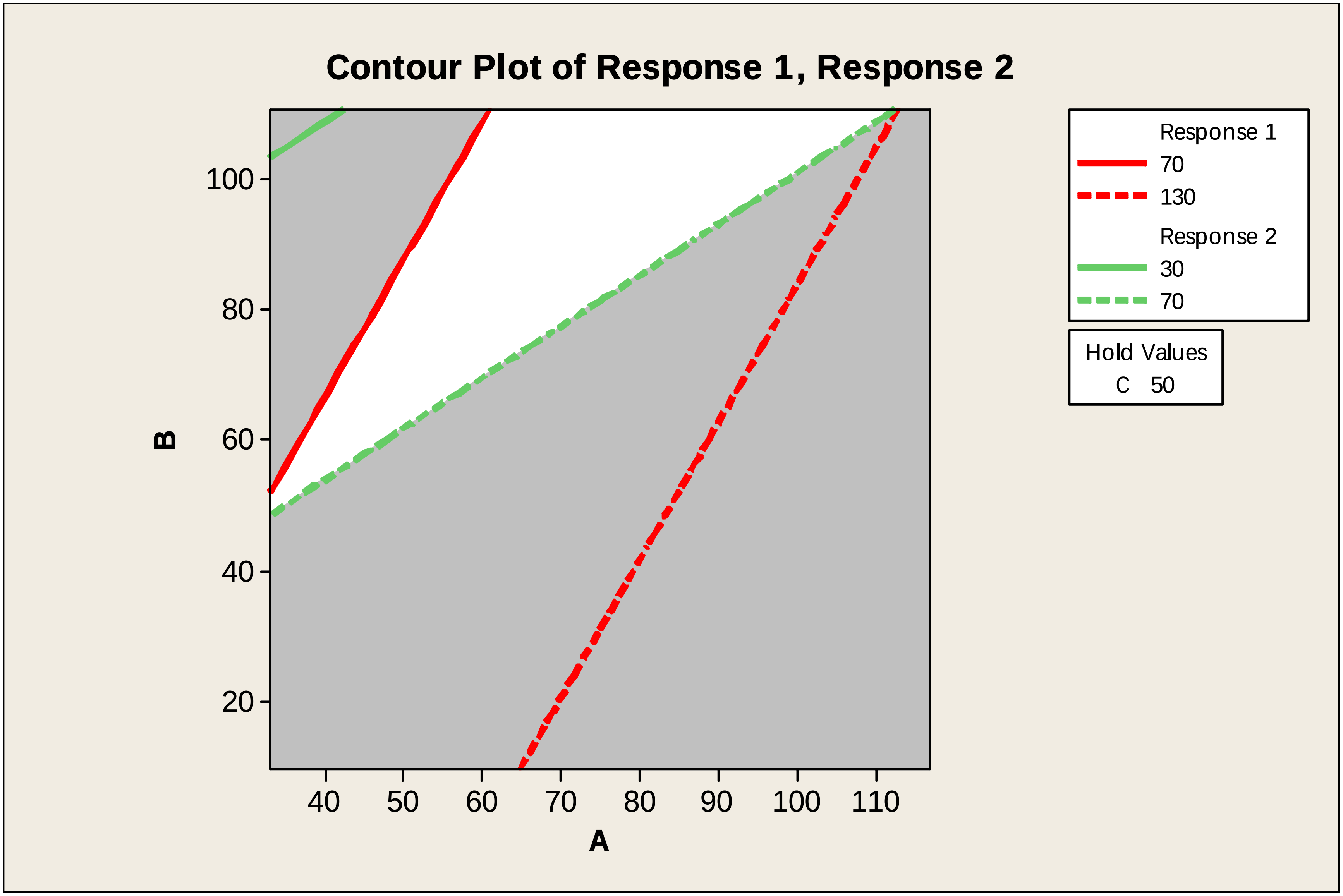
- S = 23.4149   PRESS = 36427.4
- R-Sq = 77.90%
- R-Sq(pred) = 72.81%
- R-Sq(adj) = 75.85%


Contour Plot of Response 1 vs B, A
B
100
80
60
40
20
40
50
60
70
80
90
100
110
A
Response 1
< 50
50 – 75
75 – 100
100 – 125
125 – 150
150 – 175
> 175
Hold Values
C 50

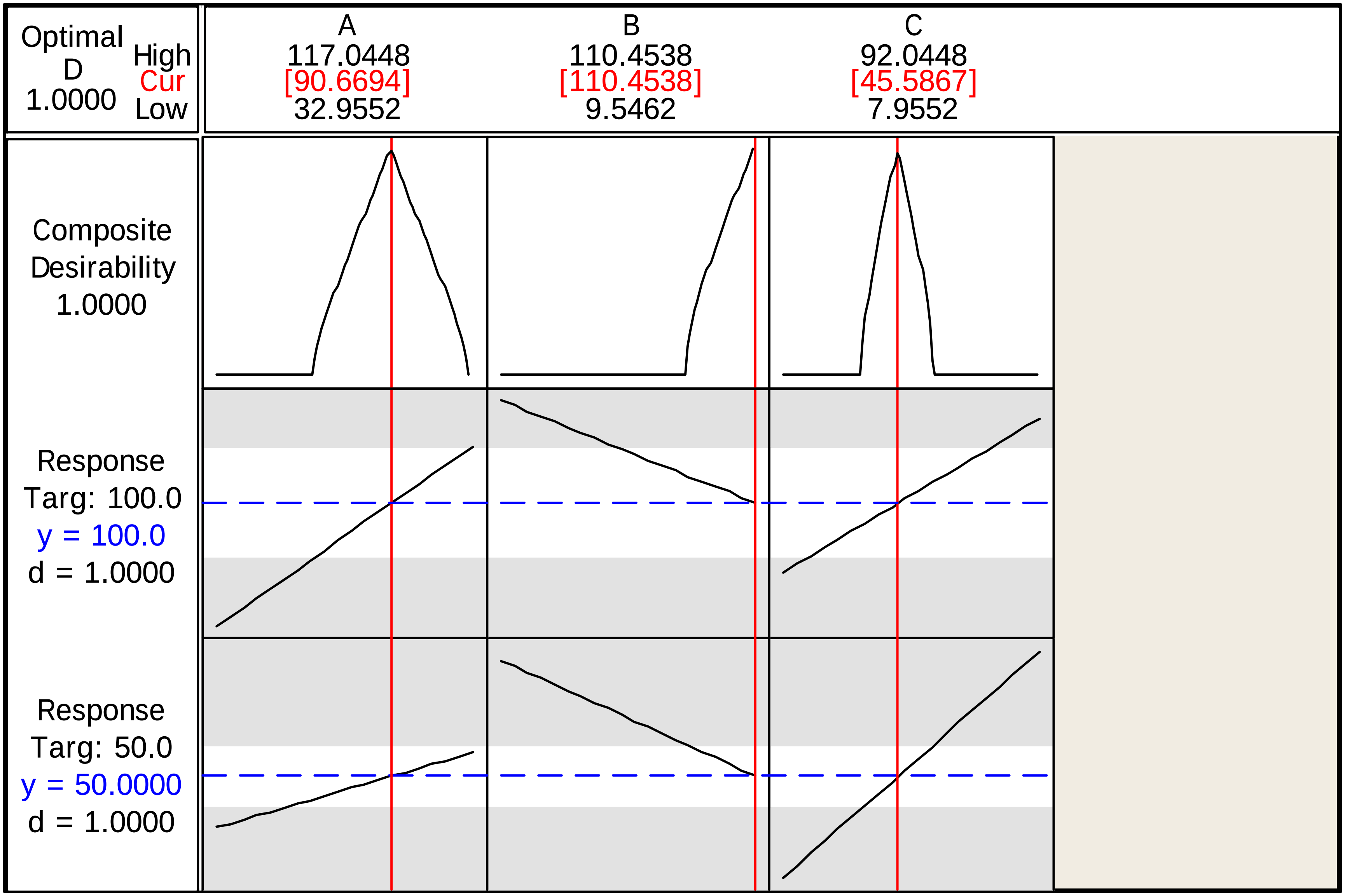


Contour Plot of Response 2 vs B, A
B
100
80
60
40
20
A
40
50
60
70
80
90
100
110
Response 2
< 40
40 – 60
60 – 80
80 – 100
100 – 120
120 – 140
> 140
Hold Values
C 50


Surface Plot of Response 1 vs B, A
Hold Values
C 50
Response 1
200
150
100
50
120
80
B
40
0
50
75
100
125
A



Contour Plot of Response 1, Response 2
Response 1
70
130
Response 2
30
70
Hold Values
C 50
100
80
60
40
20
B
40
50
60
70
80
90
100
110
A


Optimal
D
1.0000
High
Cur
Low
A
117.0448
[90.6694]
32.9552
B
110.4538
[110.4538]
9.5462
C
92.0448
[45.5867]
7.9552
Composite
Desirability
1.0000
Response
Targ: 100.0
y = 100.0
d = 1.0000
Response
Targ: 50.0
y = 50.0000
d = 1.0000

Common Mistakes

- Don’t use attribute data as input factors or response variable
  - Good/Bad
- Not randomized
- Review ANOVA table
  - $P<.05$
- Beware of correlations between inputs
- Look at the data graphically to make sure the data really does fit
- Human error or lack of understanding

Are the Inputs Significant?

- Estimated Regression Coefficients for Response 1

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Constant	114.028	1.549	73.624	0.000
Block 1	-3.415	2.190	-1.559	0.125
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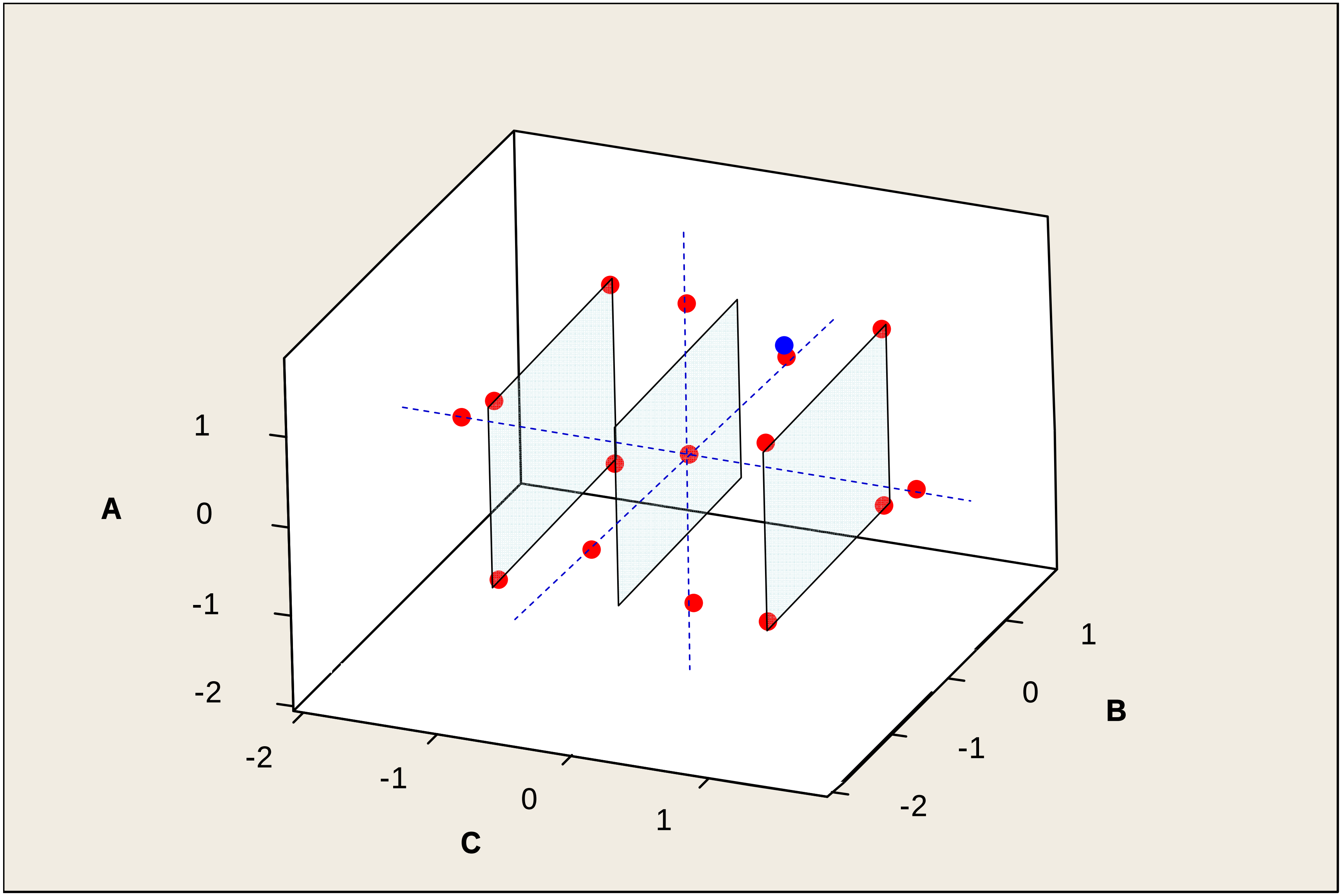
Central Composite Design



Correlation Example

Standard CCD

	A	B	C
A	1	0	0
B	0	1	0
C	0	0	1

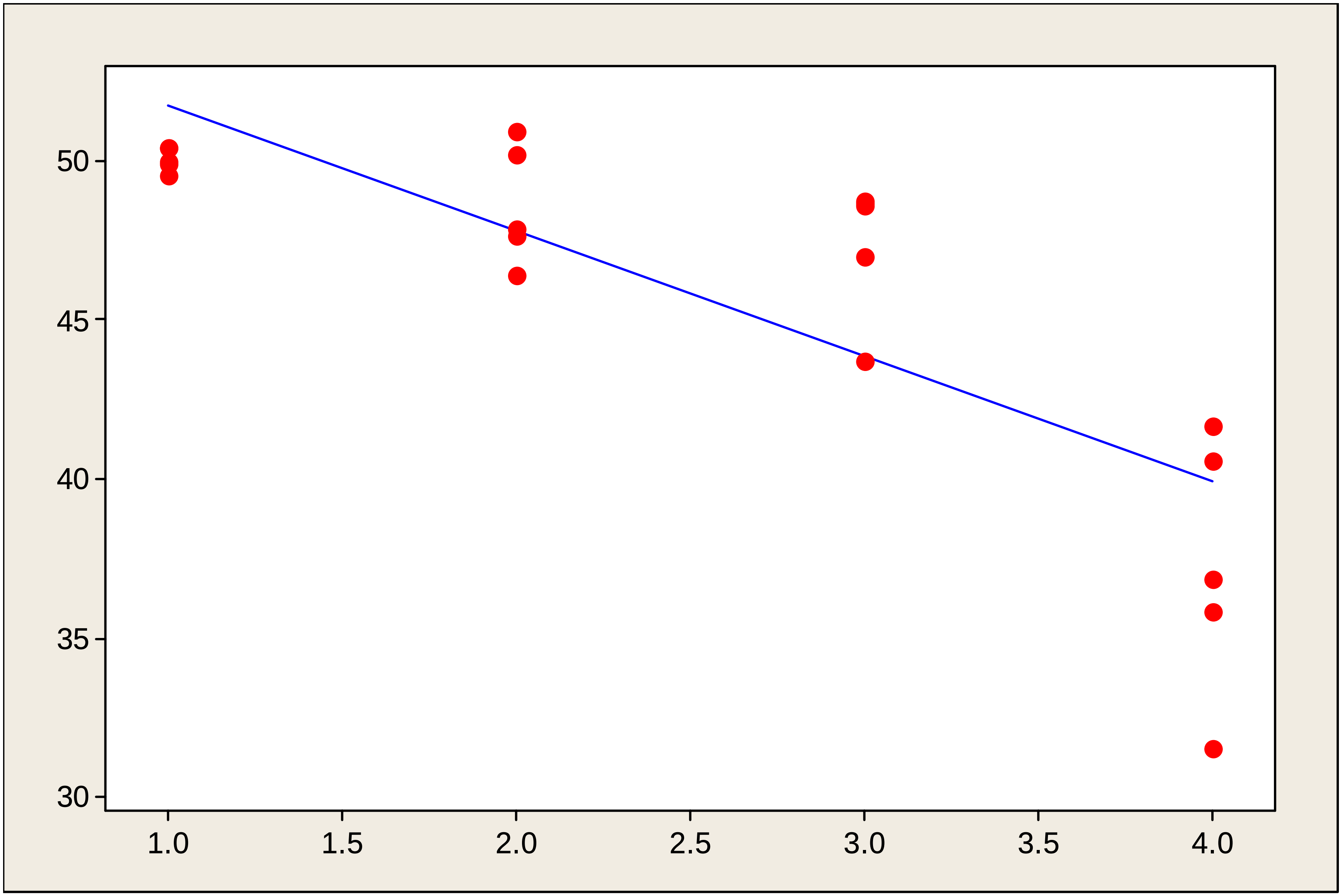
Cell Contents: Pearson correlation

CCD with Additional Run

	A	B	C
A	0.886	0.033	0.033
B	0.033	0.886	0.017
C	0.033	0.017	0.941

Cell Contents: Pearson correlation

Does the Data Fit?



Does the Data Fit?