DESIGN OF EXPERIMENTS: USING DEFINITIVE SCREENING DESIGNS TO GET MORE INFORMATION FROM FEWER TRIALS

Mastering JMP Webcast
November 1, 2013

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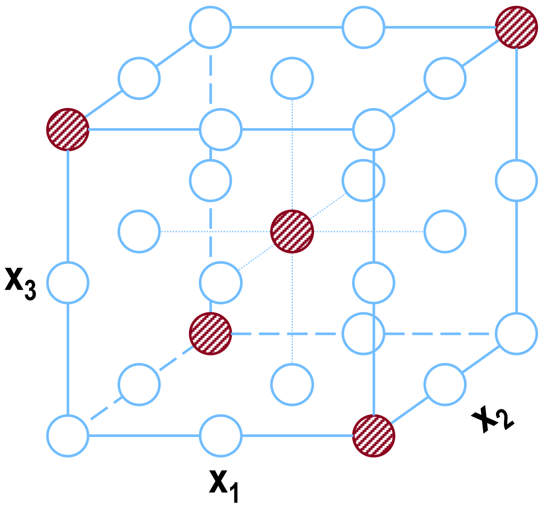
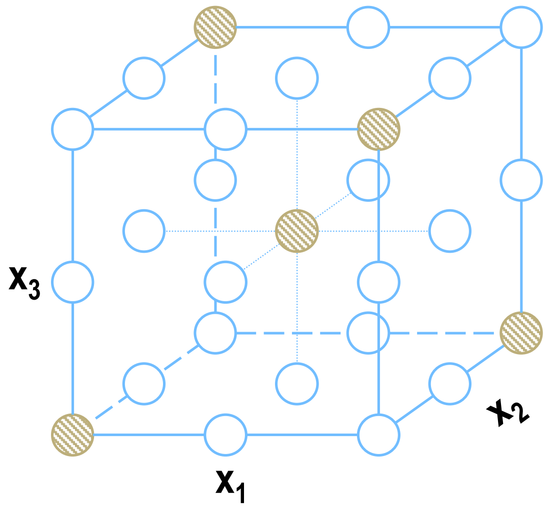
Systems Engineer & Co-insurrectionist
JMP Federal Government Team

CLASSIC RESPONSE-SURFACE DOE IN A NUTSHELL

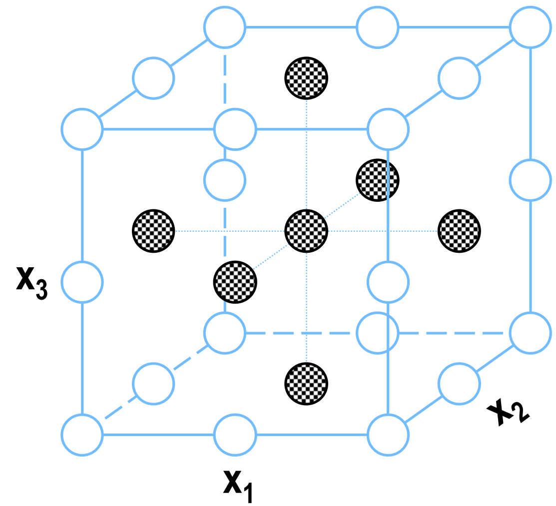
Block 1



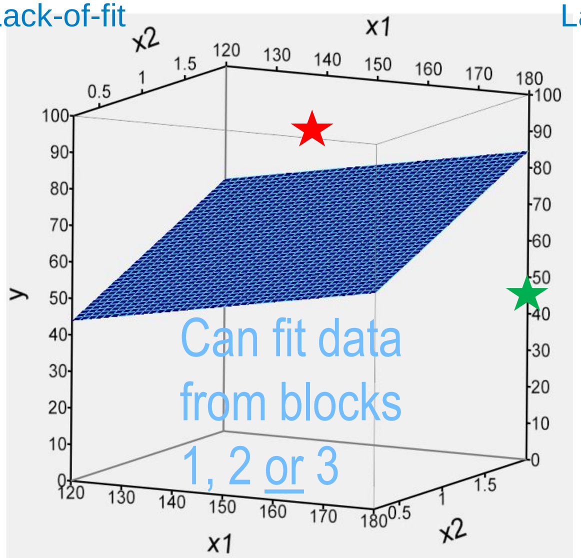
Block 2



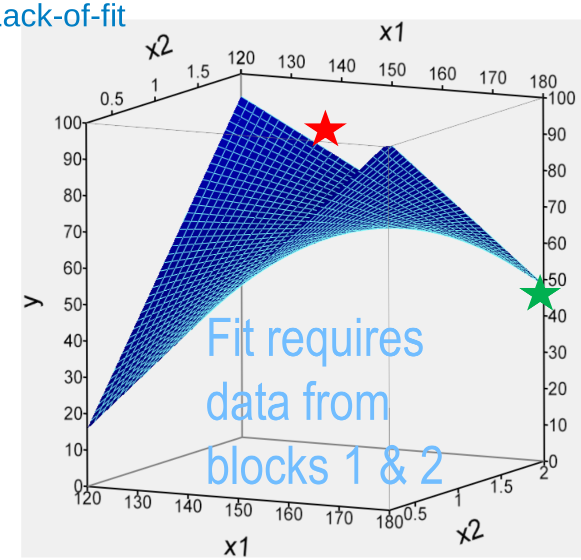
Block 3

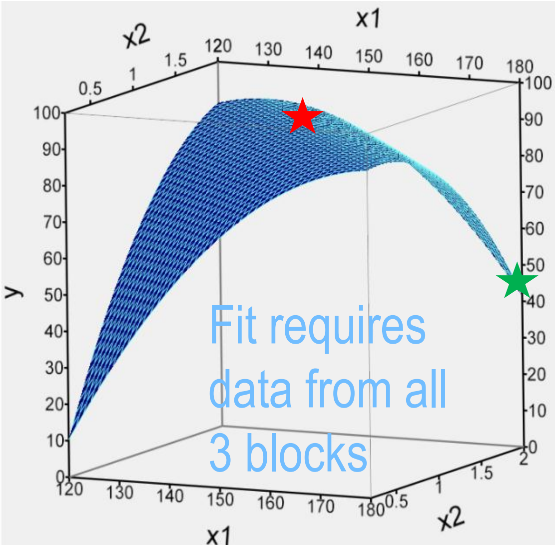


Lack-of-fit



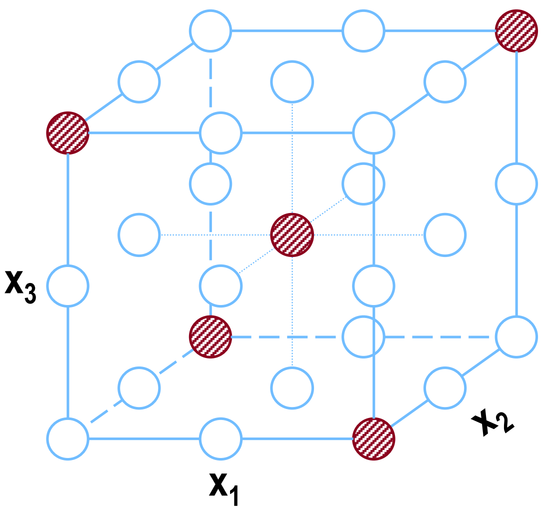
Lack-of-fit





POLYNOMIAL MODELS USED TO CALCULATE SURFACES

Block 1

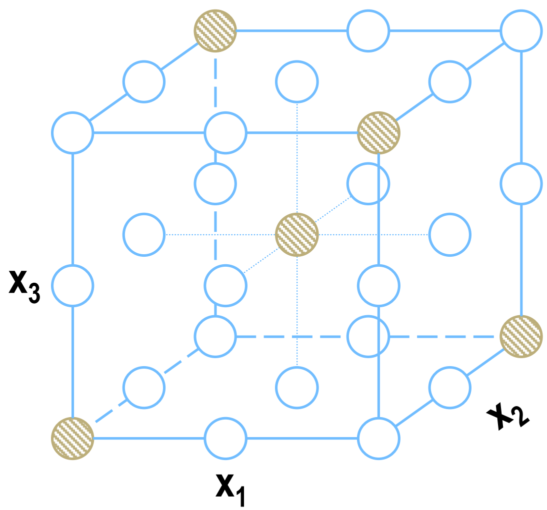


$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3$$

Run this block 1st to:

(i) estimate the main effects*
(ii) use center point to check for curvature.

Block 2

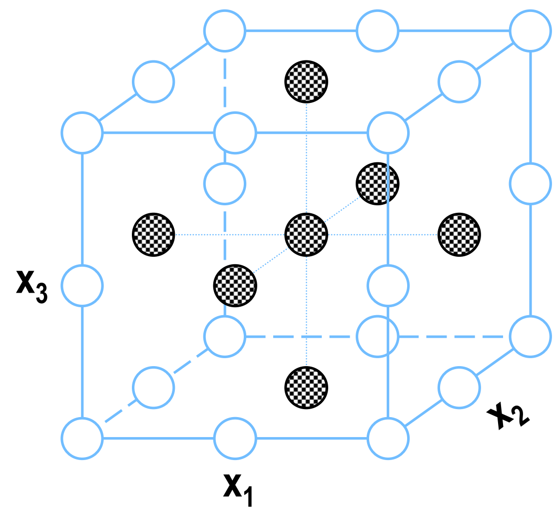


$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3$$
$$+ a_{12}x_1x_2 + a_{13}x_1x_3 + a_{23}x_2x_3$$

Run this block 2nd to:

(i) repeat main effects estimate,
(ii) check if process has shifted
(iii) add interaction effects to model <u>if needed.</u>

Block 3

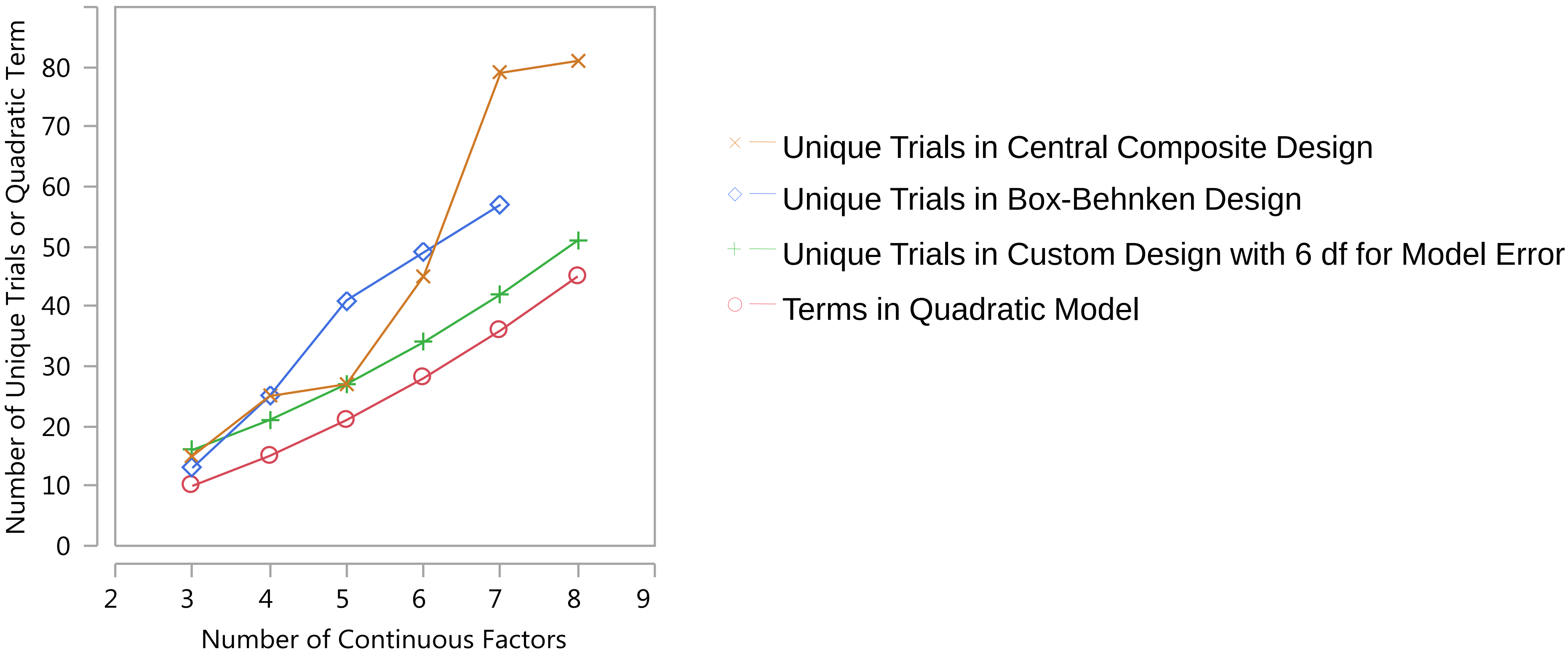


$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3$$
$$+ a_{12}x_1x_2 + a_{13}x_1x_3 + a_{23}x_2x_3$$
$$+ a_{11}x_1^2 + a_{22}x_2^2 + a_{33}x_3^2$$

Run this block 3rd to:

(i) repeat main effects estimate,
(ii) check if process has shifted
(iii) add curvature effects to model <u>if needed.</u>

NUMBER OF UNIQUE TRIALS FOR 3 RESPONSE-SURFACE DESIGNS AND NUMBER OF QUADRATIC MODEL TERMS VS. NUMBER OF CONTINUOUS FACTORS



If generally running 3, 4 or 5-factor fractional-factorial designs…

1. How many interactions are you not investigating?
2. How many more trials needed to fit curvature?
3. Consider two stages: Definitive Screening + Augmentation

- ***Definitive Screening Designs***
  - Efficiently estimate main and quadratic effects for no more and **often fewer trials than traditional designs**
  - If only a few factors are important the design may collapse into a **"one-shot"** design that supports a response-surface model
  - If many factors are important the design can be **augmented** to support a response-surface model
  - Case study for a **10-variable process** shows that it can be **optimized in just 23 unique trials**

Definitive Screening Designs

- For continuous factors only - three levels

Jones, B., and C. J. Nachtsheim (2011). “A Class of Three-Level Designs for Definitive Screening in the Presence of Second-Order Effects," Journal of Quality Technology, 43 pp. 1-14

- Construction via Conference Matrices

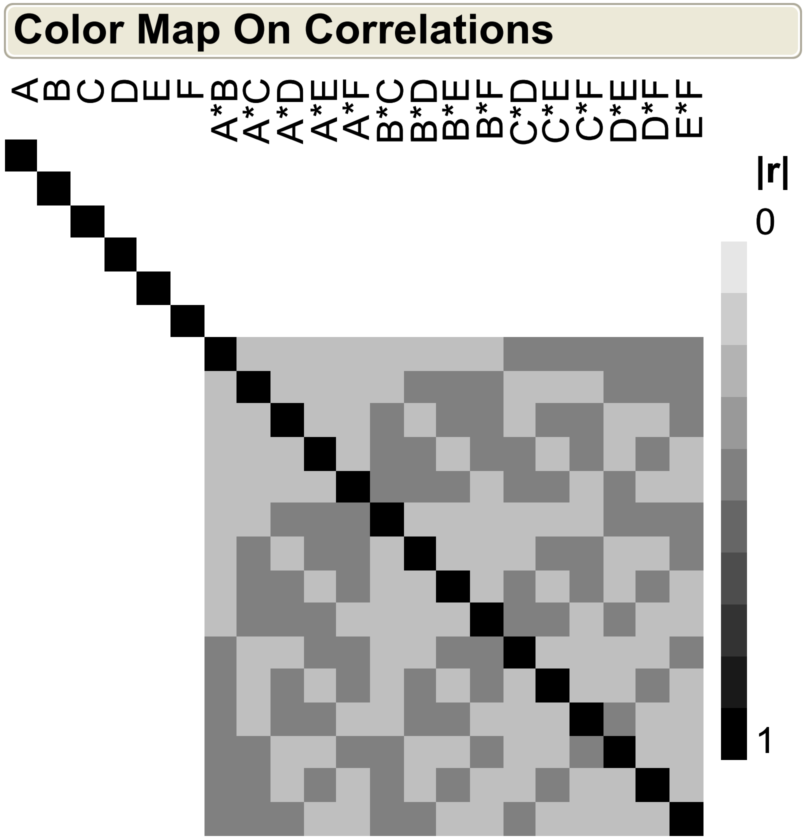
Xiao, L, Lin, D. K.J., and B. Fengshan (2012). “Constructing Definitive Screening Designs Using Conference Matrices,” Journal of Quality Technology, 44, pp. 1-7.

- For continuous factors AND two-level categorical factors

Jones, B., and C. J. Nachtsheim (2013). “Definitive Screening Designs with Added Two-Level Categorical Factors,” Journal of Quality Technology, 45 pp. 121-129

6-FACTOR, 13-TRIAL, DEFINITIVE SCREENING DESIGN

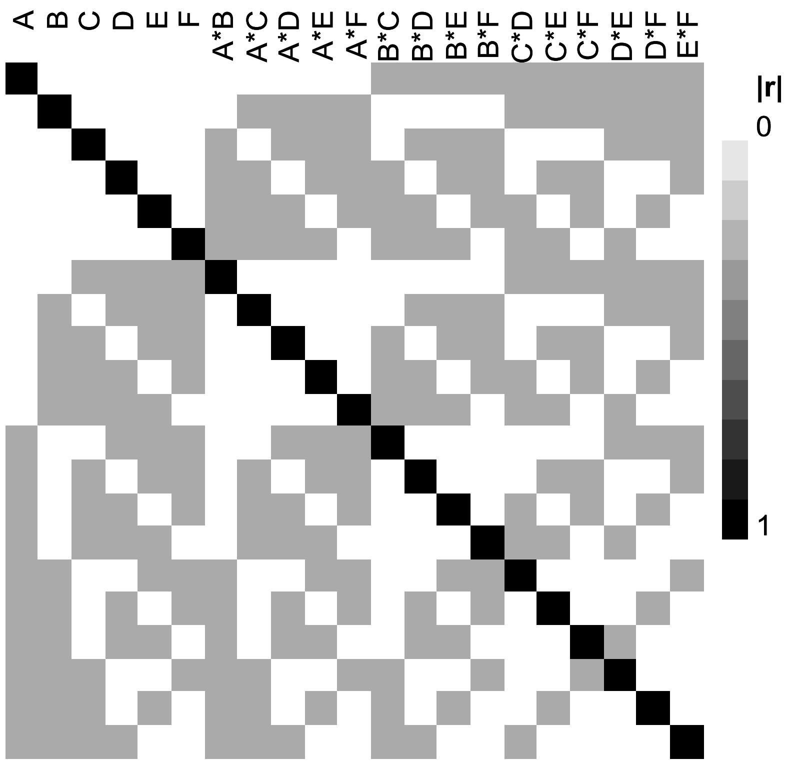
	A	B	C	D	E	F
1	0	1	-1	-1	-1	-1
2	0	-1	1	1	1	1
3	1	0	-1	1	1	-1
4	-1	0	1	-1	-1	1
5	-1	-1	0	1	-1	-1
6	1	1	0	-1	1	1
7	-1	1	1	0	1	-1
8	1	-1	-1	0	-1	1
9	1	-1	1	-1	0	-1
10	-1	1	-1	1	0	1
11	1	1	1	1	-1	0
12	-1	-1	-1	-1	1	0
13	0	0	0	0	0	0



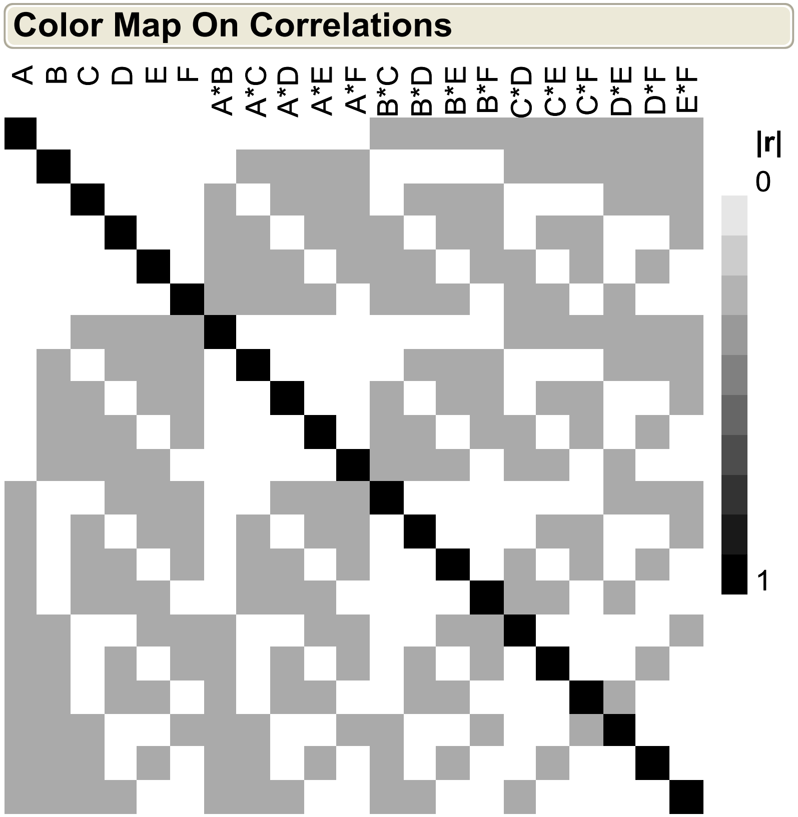
6-FACTOR, 12-TRIAL, PLACKETT-BURMAN DESIGN

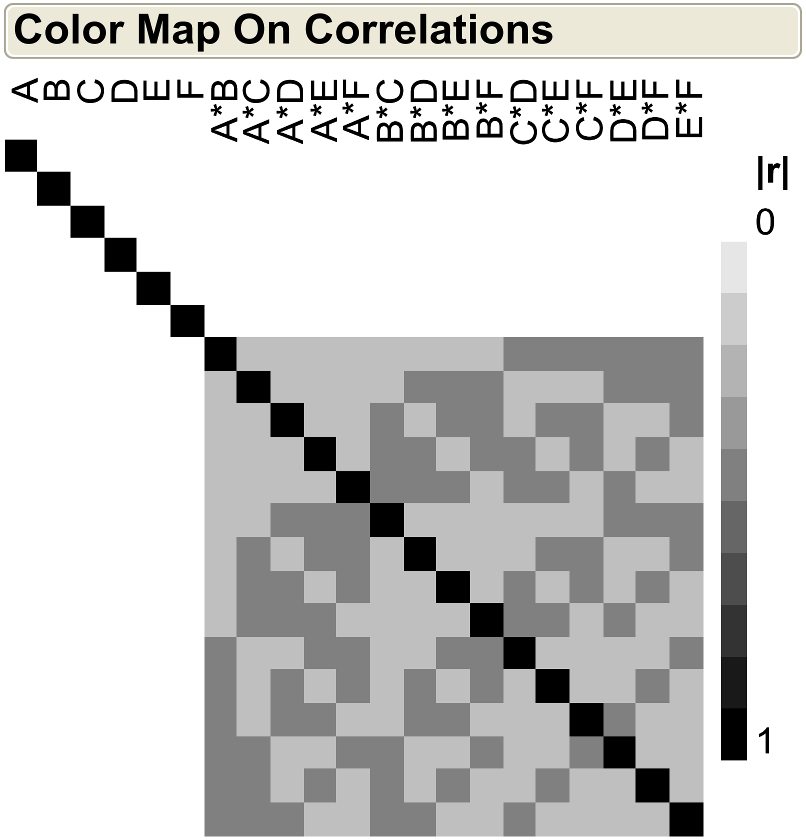
	A	B	C	D	E	F
1	1	-1	1	-1	1	1
2	-1	-1	1	-1	-1	1
3	1	1	1	-1	-1	-1
4	-1	1	-1	-1	1	-1
5	-1	-1	-1	-1	1	-1
6	1	-1	1	1	1	-1
7	1	1	-1	-1	-1	1
8	1	1	-1	1	1	1
9	-1	-1	-1	1	-1	1
10	1	-1	-1	1	-1	-1
11	-1	1	1	1	-1	-1
12	-1	1	1	1	1	1

Color Map On Correlations



COLOR MAPS FOR 6-FACTOR, PLACKETT-BURMAN (LEFT) AND DEFINITIVE SCREENING DESIGN (RIGHT)





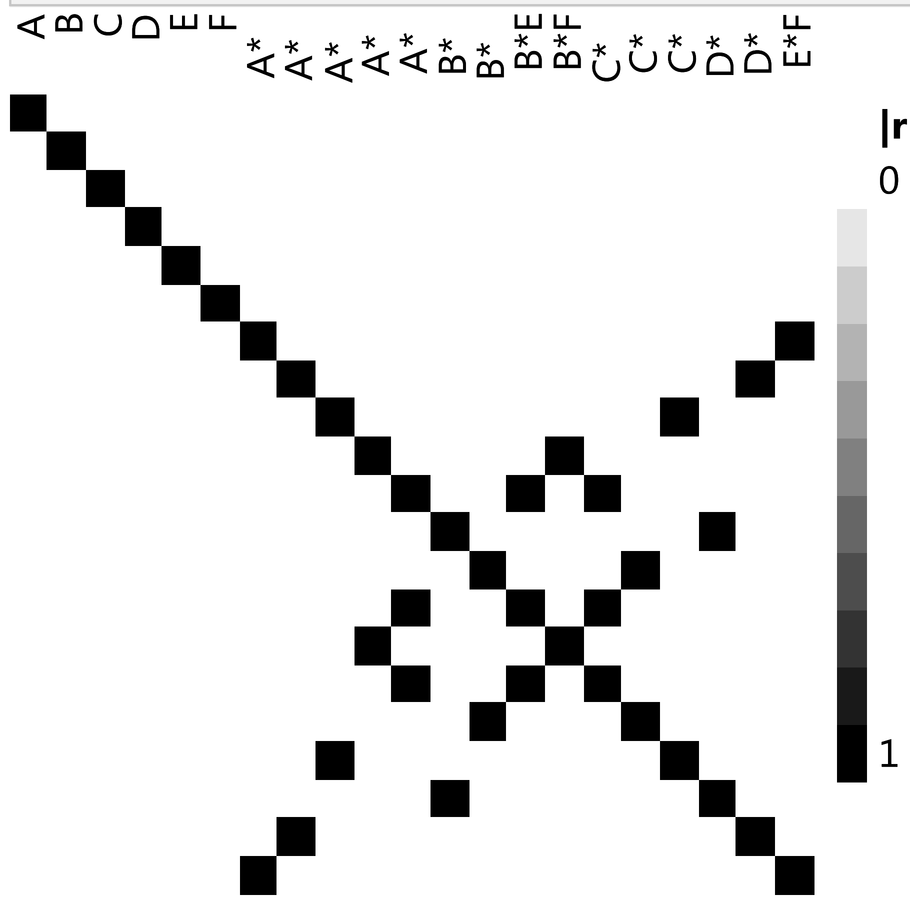
Including center point with Plackett-Burman, these two designs are both 13 trials

Same size BUT Definitive Screening can test for curvature in each factor

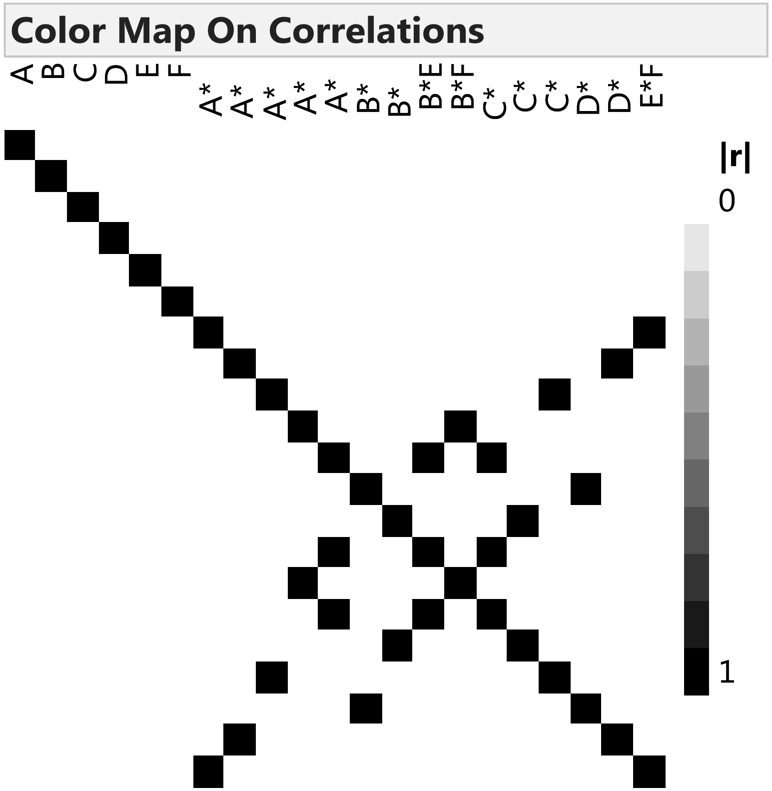
6-FACTOR, 16-TRIAL, REGULAR FRACTIONAL FACTORIAL

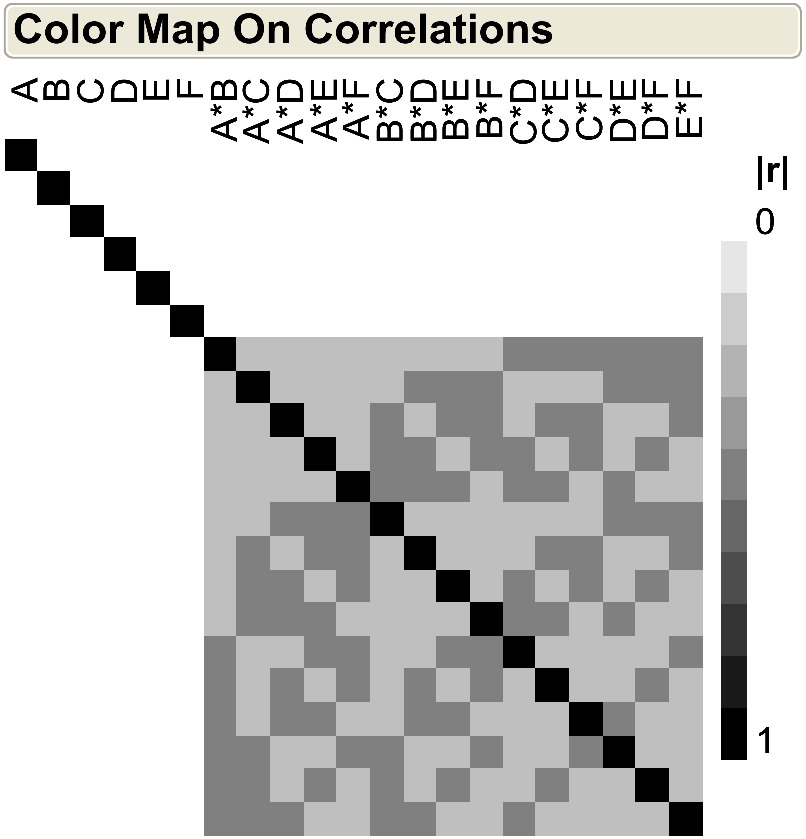
	Pattern	A	B	C	D	E	F
1	−−−−−−	-1	-1	-1	-1	-1	-1
2	−−−+++	-1	-1	-1	1	1	1
3	−−+−++	-1	-1	1	-1	1	1
4	−−++−−	-1	-1	1	1	-1	-1
5	−+−−+−	-1	1	-1	-1	1	-1
6	−+−+−+	-1	1	-1	1	-1	1
7	−++−−+	-1	1	1	-1	-1	1
8	−++++−	-1	1	1	1	1	-1
9	+−−−−+	1	-1	-1	-1	-1	1
10	+−−++−	1	-1	-1	1	1	-1
11	+−+−+−	1	-1	1	-1	1	-1
12	+−++−+	1	-1	1	1	-1	1
13	++−−++	1	1	-1	-1	1	1
14	++−+−−	1	1	-1	1	-1	-1
15	+++−−−	1	1	1	-1	-1	-1
16	++++++	1	1	1	1	1	1

Color Map On Correlations



COLOR MAPS FOR 6-FACTOR, FRACTIONAL FACTORIAL (LEFT) AND DEFINITIVE SCREENING DESIGN (RIGHT)





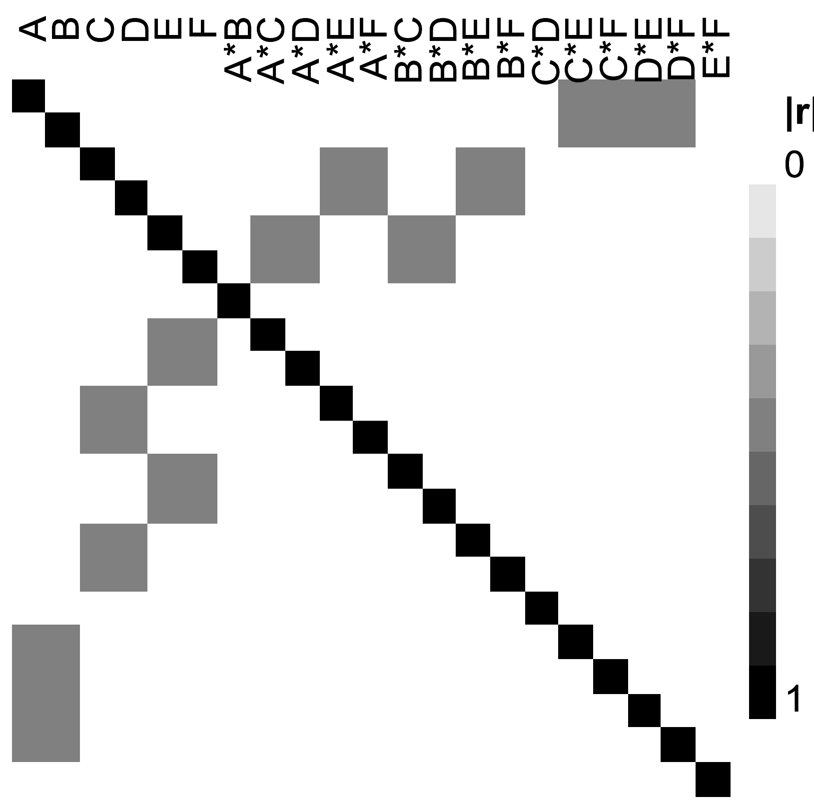
Including center point with FF increases size to 17 trials - 13-trial Definitive Screening Design is **4 fewer tests AND can test for curvature in each factor**

6-FACTOR, 16-TRIAL, NON-REGULAR FRACTIONAL FACTORIAL ("NO CONFOUNDING" DESIGN)

Jones, B. and Montgomery, D., (2010) "Alternatives to Resolution IV Screening Designs in 16 Runs." *International Journal of Experimental Design and Process Optimization*, 2010; Vol. 1 No. 4: 285-295.

	A	B	C	D	E	F
1	1	1	1	1	1	1
2	1	1	-1	-1	-1	-1
3	-1	-1	1	1	-1	-1
4	-1	-1	-1	-1	1	1
5	1	1	1	-1	1	-1
6	1	1	-1	1	-1	1
7	-1	-1	1	-1	-1	1
8	-1	-1	-1	1	1	-1
9	1	-1	1	1	1	-1
10	1	-1	-1	-1	-1	1
11	-1	1	1	1	-1	1
12	-1	1	-1	-1	1	-1
13	1	-1	1	-1	-1	-1
14	1	-1	-1	1	1	1
15	-1	1	1	-1	1	1
16	-1	1	-1	1	-1	-1

Color Map On Correlations



July 22, 2010

Secretary Chu Announces Six Projects to Convert Captured CO2 Emissions from Industrial Sources into Useful Products

$106 Million Recovery Act Investment will Reduce CO2 Emissions and Mitigate Climate Change

Washington, D.C. - U.S. Energy Secretary Steven Chu announced today the selections of six projects that aim to find ways of converting captured carbon dioxide (CO2) emissions from industrial sources into useful products such as fuel, plastics, cement, and fertilizers. Funded with $106 million from the American Recovery and Reinvestment Act -matched with $156 million in private cost-share -today's selections demonstrate the potential opportunity to use CO2 as an inexpensive raw material that can help reduce carbon dioxide emissions while producing useful by-products that Americans can use.

"These innovative projects convert carbon pollution from a climate threat to an economic resource," said Secretary Chu. "This is part of our broad commitment to unleash the American innovation machine and build the thriving, clean energy economy of the future."

23/1	Yield @ Time t	A	B	C	D	E	F	G	H	I	J
1	1.38	-1	1	1	0	1	-1	1	-1	1	1
2	6.44	1	-1	-1	-1	1	-1	1	1	0	1
3	5.96	-1	-1	1	-1	-1	1	-1	1	1	0
4	4.34	0	-1	1	1	1	1	1	1	-1	-1
5	10.46	-1	-1	-1	-1	-1	0	1	-1	-1	-1
6	6.95	-1	-1	1	-1	1	-1	-1	0	-1	-1
7	8.58	1	0	-1	1	1	-1	-1	-1	1	-1
8	2.69	0	1	-1	-1	-1	-1	-1	-1	1	1
9	4.3	-1	1	-1	1	0	-1	-1	1	-1	1
10	0.77	1	-1	1	-1	0	1	1	-1	1	-1
11	2.87	-1	1	1	1	-1	1	-1	-1	0	-1
12	1.01	1	1	1	1	1	0	-1	1	1	1
13	9.47	-1	-1	-1	1	1	1	0	-1	1	1
14	7.49	0	0	0	0	0	0	0	0	0	0
15	0.98	1	1	-1	1	1	-1	1	-1	-1	0
16	0.86	1	1	1	-1	-1	-1	0	1	-1	-1
17	1.25	-1	1	-1	-1	1	1	1	1	1	-1
18	1.03	1	-1	1	1	-1	-1	-1	-1	-1	1
19	1.07	1	1	0	-1	1	1	-1	-1	-1	1
20	7.33	0	0	0	0	0	0	0	0	0	0
21	2.61	1	-1	-1	0	-1	1	-1	1	-1	-1
22	11.39	-1	-1	0	1	-1	-1	1	1	1	-1
23	12.96	-1	0	1	-1	-1	1	1	1	-1	1
24	1.18	1	1	-1	1	-1	1	1	0	1	1

Original design was for 11 variables with 23 unique trials and the center point replicated once.

IN ORIGINAL 2011 JQT PAPER - DESIGN SIZE IS 2M + 1

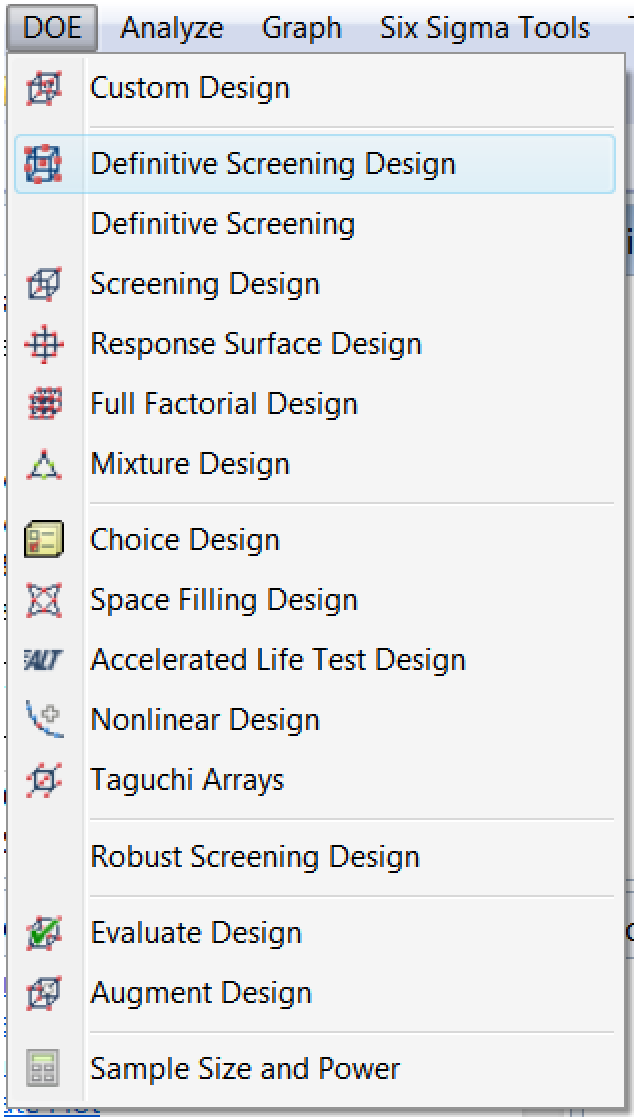
	m = 9
1	0++++++++
2	0--------
3	+0+-+--+-
4	-0-+-++-+
5	-+0-+-+--
6	+-0+-+-++
7	--+0+---+
8	++-0-+++-
9	+-+-0++--
10	-+-+0--++
11	----+0+++
12	++++-0---
13	++--++0-+
14	--++--0+-
15	---+++-0-
16	+++---+0+
17	-++--+-+0
18	+--++-+-0
19	000000000

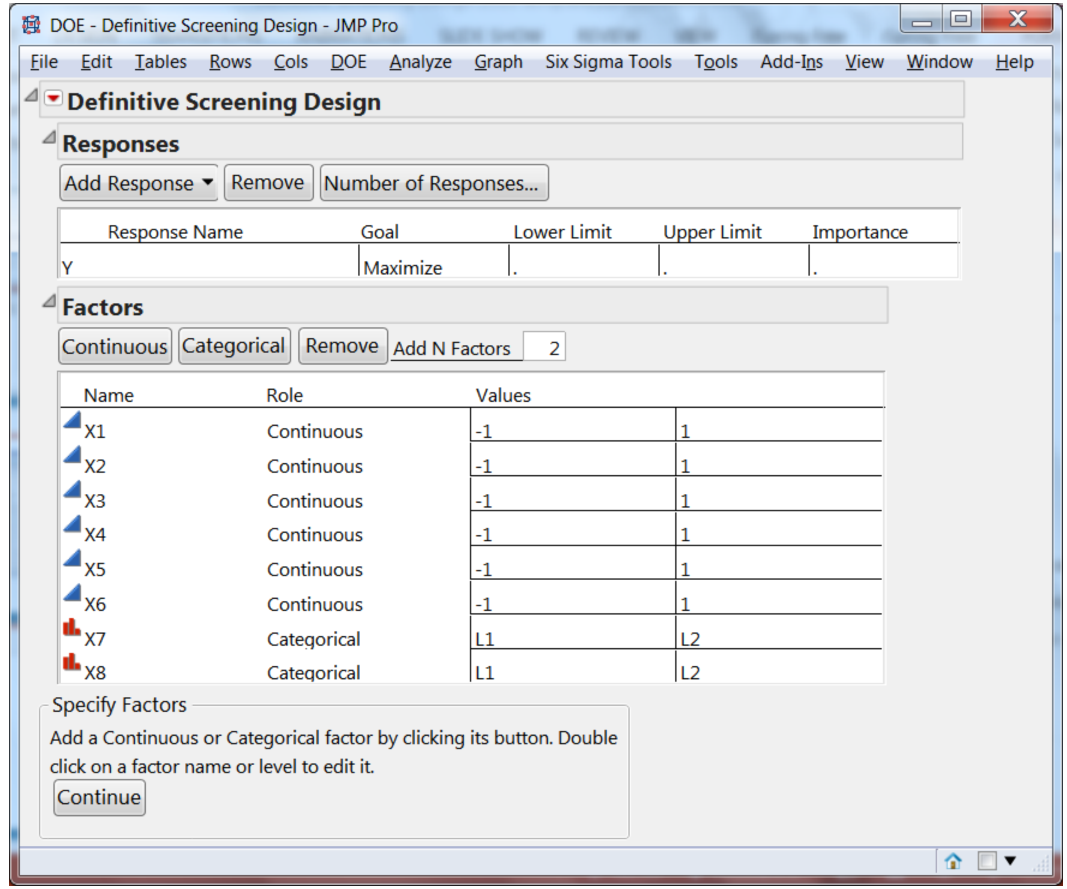
	m = 10
1	0++-++++-+
2	0--+----+-
3	+0-++-++--
4	-0+--+--++
5	-+0---+---
6	+-0+++-+++
7	-++0+--++-
8	+--0-++--+
9	----0++++-
10	++++0----+
11	-+-++0+-++
12	+-+--0-+--
13	++----0+++
14	--++++0---
15	++++-++0+-
16	----+--0-+
17	++--++--0-
18	--++--++0+
19	+-+-+-+-+0
20	-+-+-+-+-0
21	0000000000

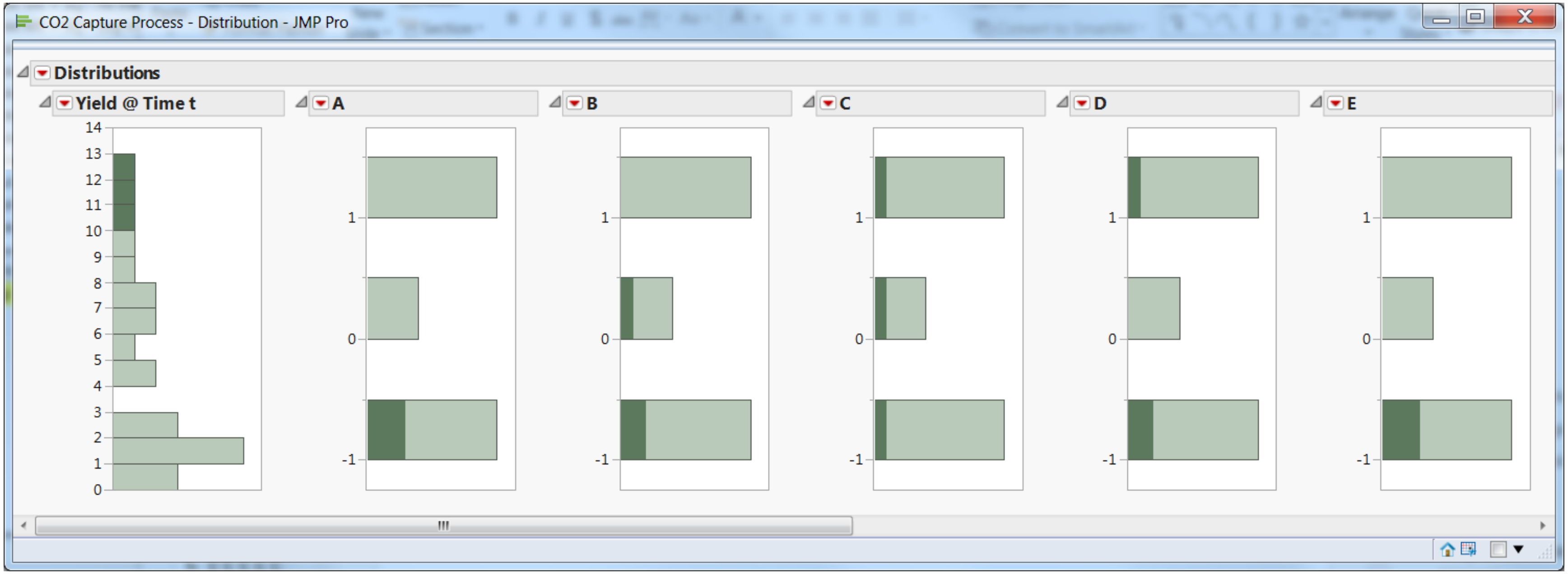
	m = 11
1	0-+-----+-+
2	0+-+++++-+-
3	-0--+----++
4	+0++-++++--
5	--0++++---+
6	++0----+++-
7	---0-++-++-
8	+++0+--+--+
9	+--+0+-++++
10	-++-0-+----
11	--++-0-+-+-
12	++--+0+-+-+
13	---++-0++--
14	+++--+0--++
15	-+++--+0+++
16	+---++-0---
17	-+---+-+0-+
18	+-+++-+-0+-
19	+-----++-0+
20	-+++++--+0-
21	++-+------0
22	--+-++++++0
23	00000000000

	m = 12
1	0--+-+-+++-+
2	0++-+-+---+-
3	-0+++++++---
4	+0-------+++
5	++0-++-++-++
6	--0+--+--+--
7	+--0+-+-+--+
8	-++0-+-+-++-
9	++++0-++++++
10	----0+------
11	+-+-+0++-+-+
12	-+-+-0--+-+-
13	++++-+0----+
14	----+-0++++-
15	--+++--0--++
16	++---++0++--
17	+-++++--0++-
18	-+----++0--+
19	++-++--+-0--
20	--+--++-+0++
21	-+-++++--+0+
22	+-+----++-0-
23	+--+-+++--+0
24	-++-+---++-0
25	000000000000

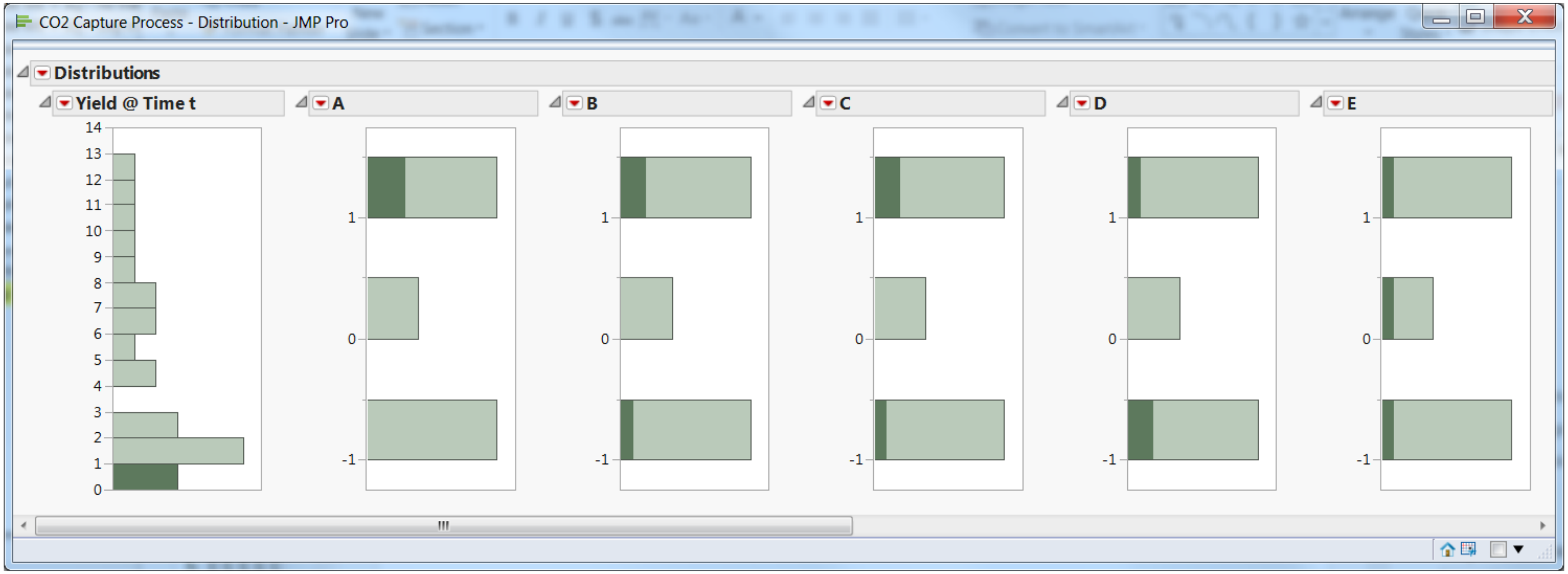
WITH JMP 11 USE DEFINITIVE SCREENING ON DOE MENU





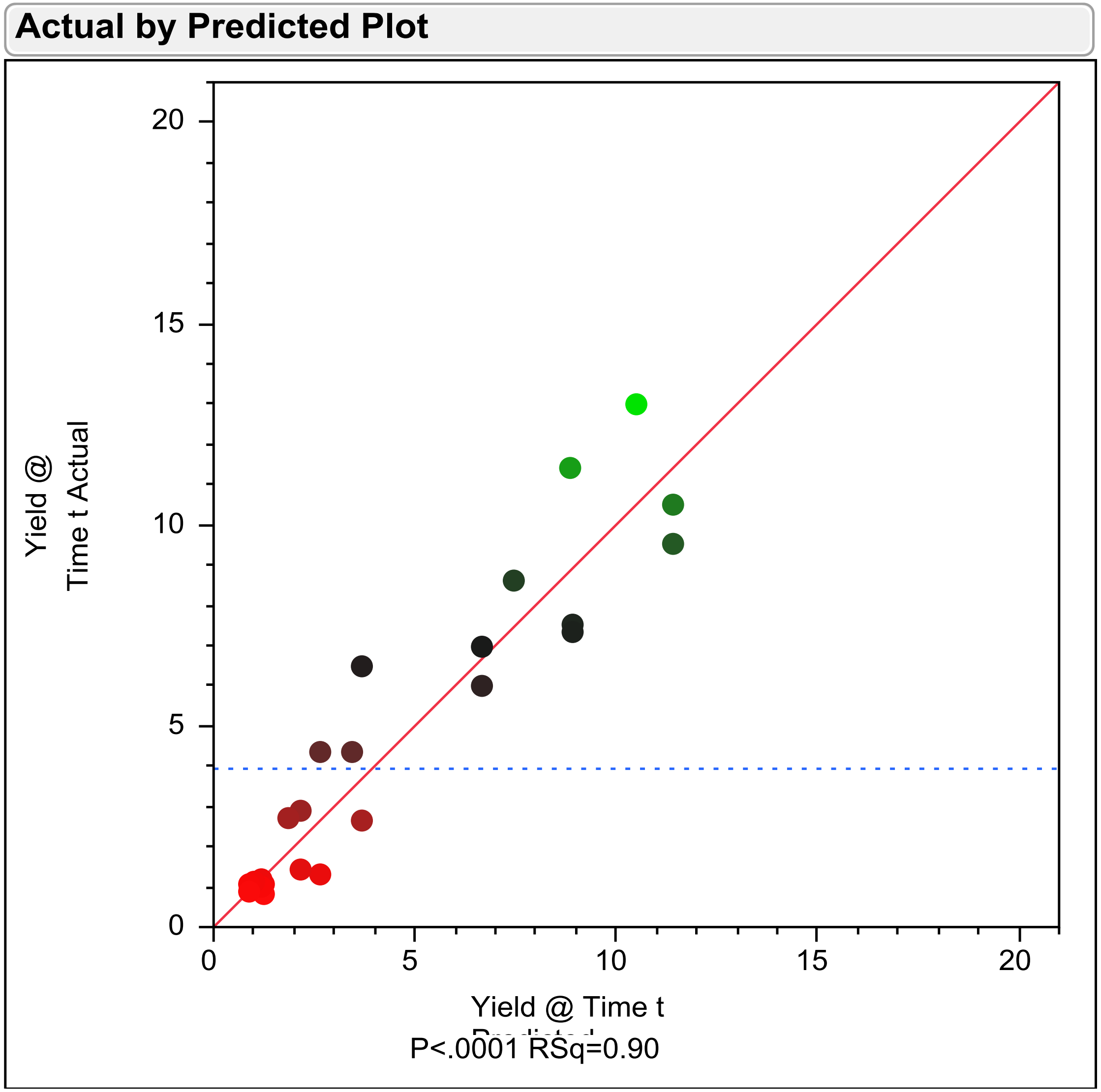


CO2 Capture Process - Distribution - JMP Pro
Distributions
Yield @ Time t
A
B
C
D
E

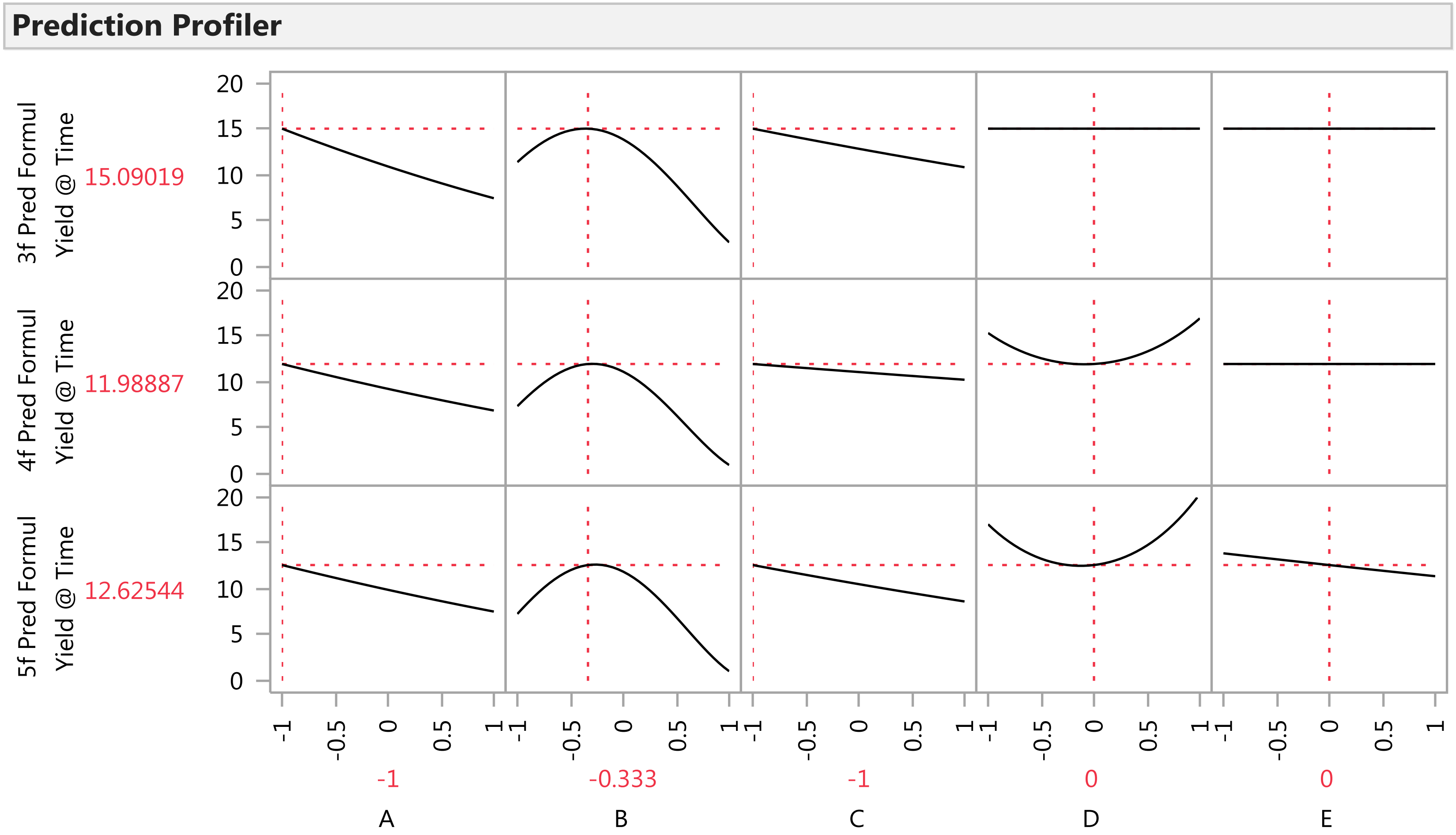


CO2 Capture Process - Distribution - JMP Pro
Distributions
Yield @ Time t
A
B
C
D
E

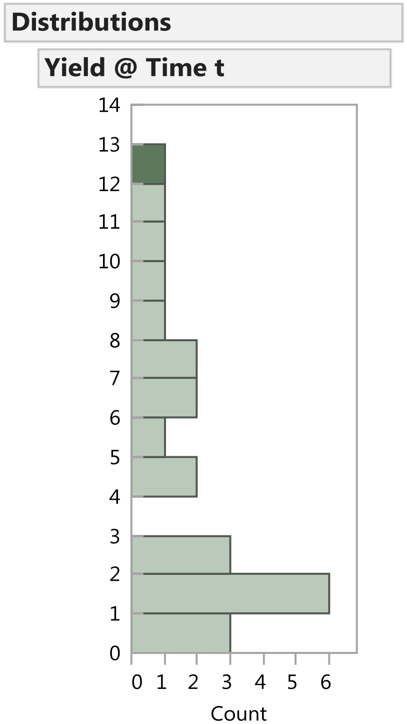
ACTUAL BY PREDICTED PLOT FOR FINAL 3-FACTOR MODEL FOR THE 24 DESIGN TRIALS

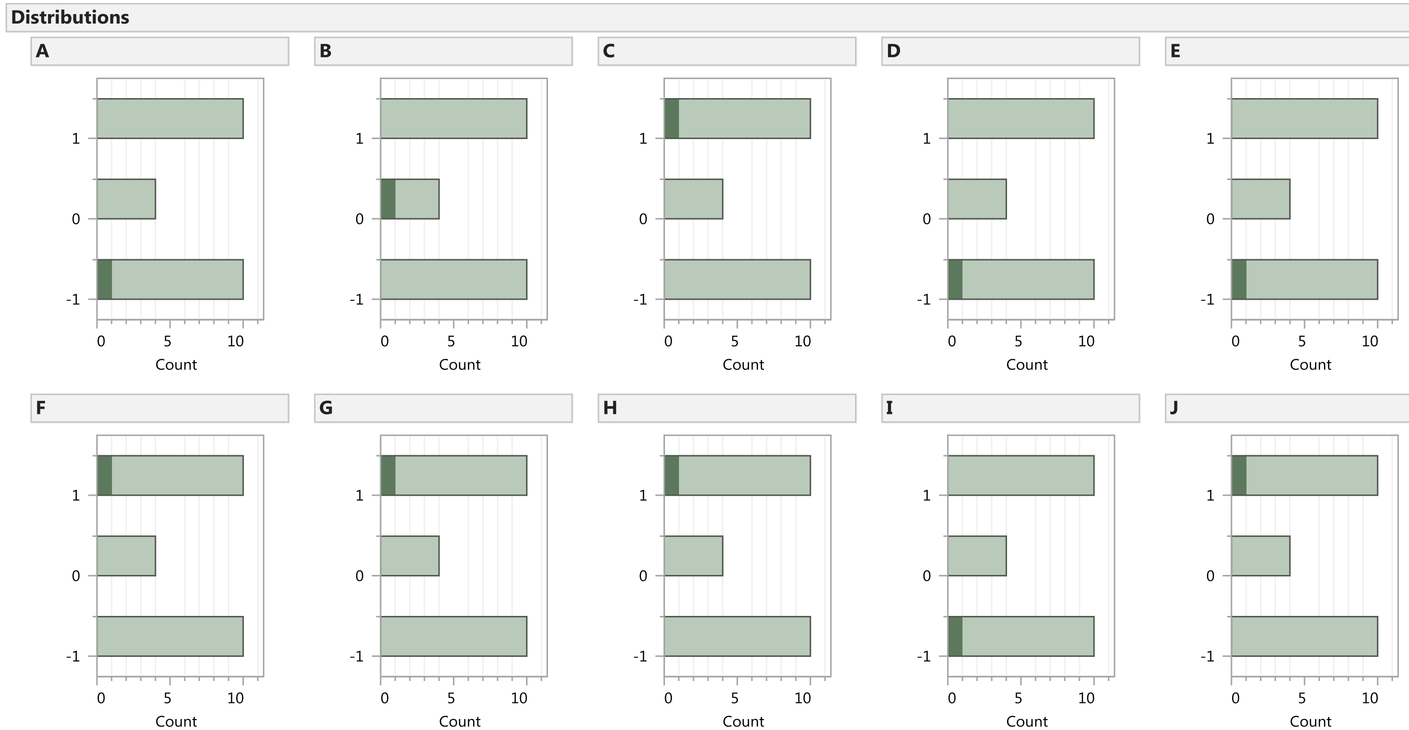


PREDICTING WITH 3, 4 AND 5-FACTOR MODELS

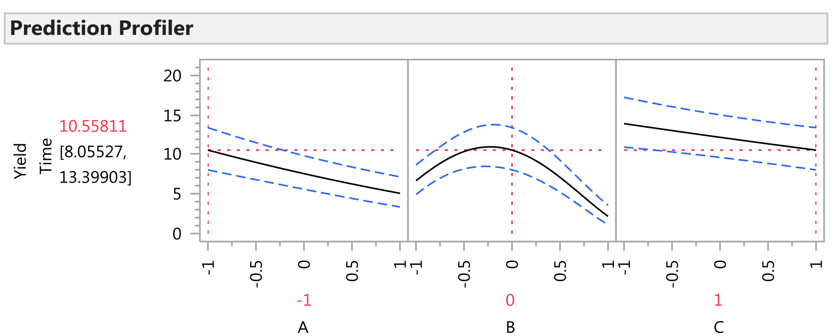


SETTINGS OF BEST OBSERVATION OF YIELD = 12.96

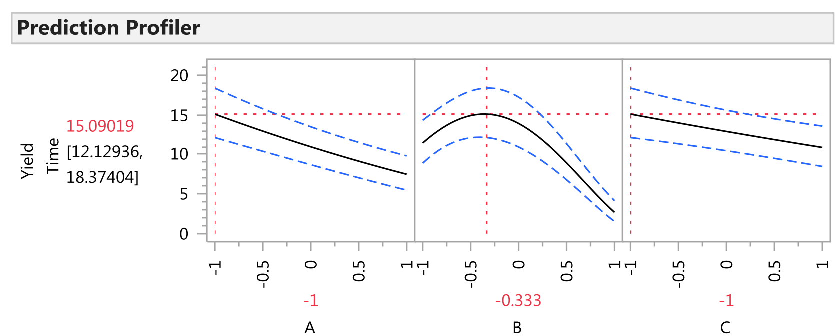




Prediction at settings of best observation

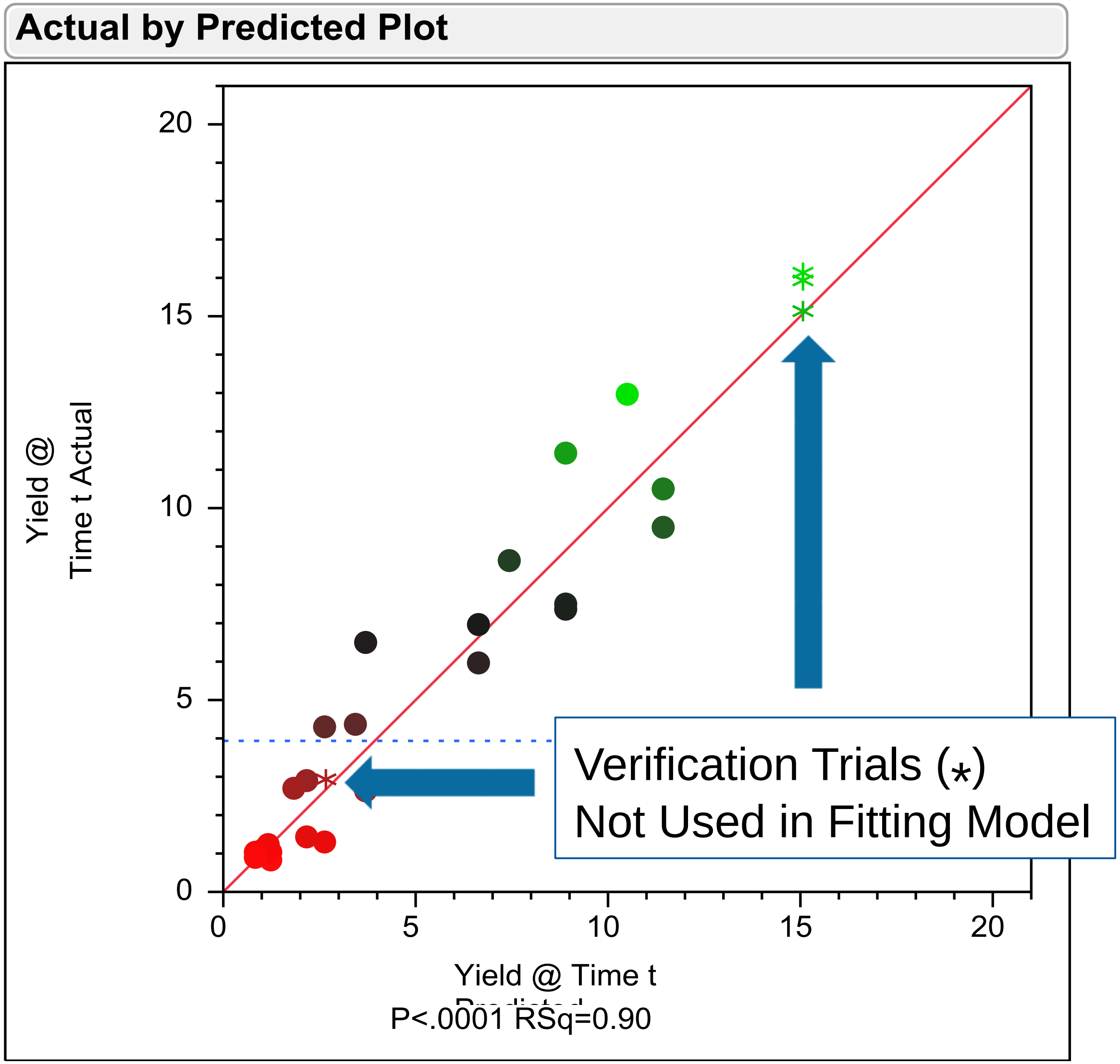


Prediction at best settings – run this checkpoint



23/1	Yield @ Time t	A	B	C	D	E	F	G	H	I	J
1	1.38	-1	1	1	0	1	-1	1	-1	1	1
2	6.44	1	-1	-1	-1	1	-1	1	1	0	1
3	5.96	-1	-1	1	-1	-1	1	-1	1	1	0
4	4.34	0	-1	1	1	1	1	1	1	-1	-1
5	10.46	-1	-1	-1	-1	-1	0	1	-1	-1	-1
6	6.95	-1	-1	1	-1	1	-1	-1	0	-1	-1
7	8.58	1	0	-1	1	1	-1	-1	-1	1	-1
8	2.69	0	1	-1	-1	-1	-1	-1	-1	1	1
9	4.3	-1	1	-1	1	0	-1	-1	1	-1	1
10	0.77	1	-1	1	-1	0	1	1	-1	1	-1
11	2.87	-1	1	1	1	-1	1	-1	-1	0	-1
12	1.01	1	1	1	1	1	0	-1	1	1	1
13	9.47	-1	-1	-1	1	1	1	0	-1	1	1
14	7.49	0	0	0	0	0	0	0	0	0	0
15	0.98	1	1	-1	1	1	-1	1	-1	-1	0
16	0.86	1	1	1	-1	-1	-1	0	1	-1	-1
17	1.25	-1	1	-1	-1	1	1	1	1	1	-1
18	1.03	1	-1	1	1	-1	-1	-1	-1	-1	1
19	1.07	1	1	0	-1	1	1	-1	-1	-1	1
20	7.33	0	0	0	0	0	0	0	0	0	0
21	2.61	1	-1	-1	0	-1	1	-1	1	-1	-1
22	11.39	-1	-1	0	1	-1	-1	1	1	1	-1
23	12.96	-1	0	1	-1	-1	1	1	1	-1	1
24	1.18	1	1	-1	1	-1	1	1	0	1	1
25	15.93	-1	-0.333	-1	1	-1	-1	1	1	1	1
26	2.9	-1	1	-1	1	-1	-1	1	1	1	1
27	16.16	-1	-0.333	-1	-1	-1	-1	1	1	1	1
28	15.1	-1	-0.333	-1	0	-1	-1	1	1	1	1

ACTUAL BY PREDICTED PLOT FOR FINAL 3-FACTOR MODEL FOR THE 24 DESIGN TRIALS AND 4 VERIFICATION TRIALS

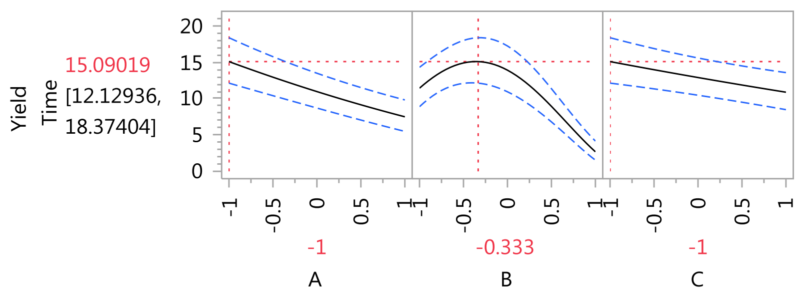


STEPWISE 3-FACTOR MODEL (7 TERMS) - LEFT
FULL QUADRATIC 3-FACTOR MODEL (10 TERMS) - RIGHT

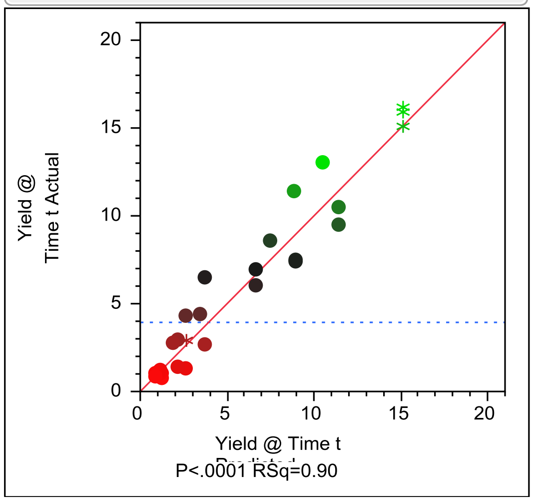
Sorted Parameter Estimates (Stepwise, 7 terms)

Term	Estimate	Std Error	t Ratio	Prob>|t|
B*B	-1.218717	0.182702	-6.67	<.0001 *
A	-0.496169	0.075133	-6.60	<.0001 *
B	-0.481867	0.075133	-6.41	<.0001 *
C	-0.240181	0.075133	-3.20	0.0053 *
A*B	0.2306449	0.078918	2.92	0.0095 *
C*B	0.1585526	0.078918	2.01	0.0607

Prediction Profiler



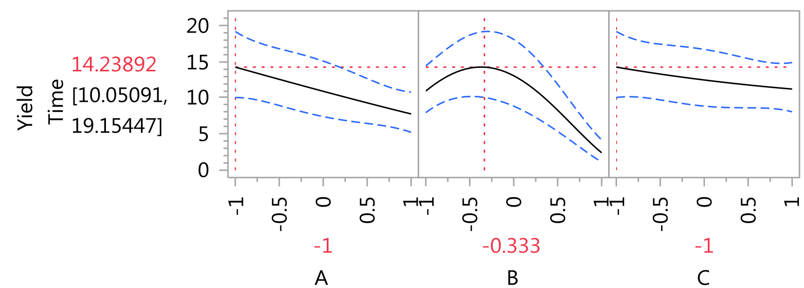
Actual by Predicted Plot



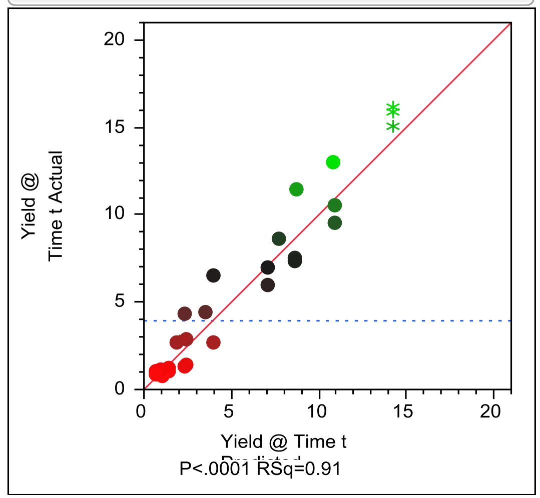
Sorted Parameter Estimates (Full Quadratic, 10 terms)

Term	Estimate	Std Error	t Ratio	Prob>|t|
A	-0.496169	0.080197	-6.19	<.0001 *
B	-0.481867	0.080197	-6.01	<.0001 *
B*B	-1.181941	0.233332	-5.07	0.0002 *
C	-0.240181	0.080197	-2.99	0.0096 *
A*B	0.2339616	0.087698	2.67	0.0184 *
C*B	0.1610152	0.087698	1.84	0.0877
A*C	-0.08124	0.087698	-0.93	0.3700
C*C	0.0307046	0.233332	0.13	0.8972
A*A	-0.021309	0.233332	-0.09	0.9285

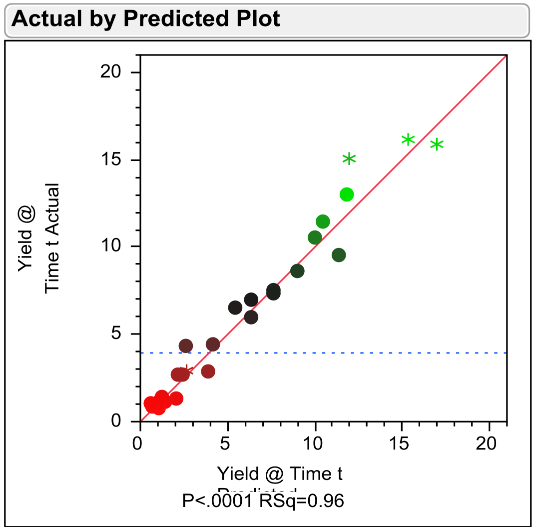
Prediction Profiler

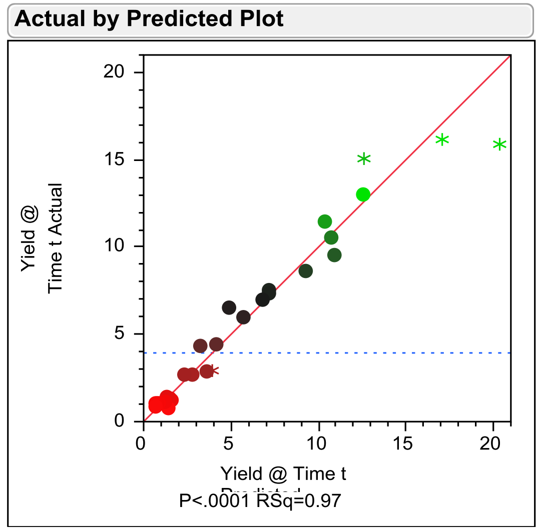


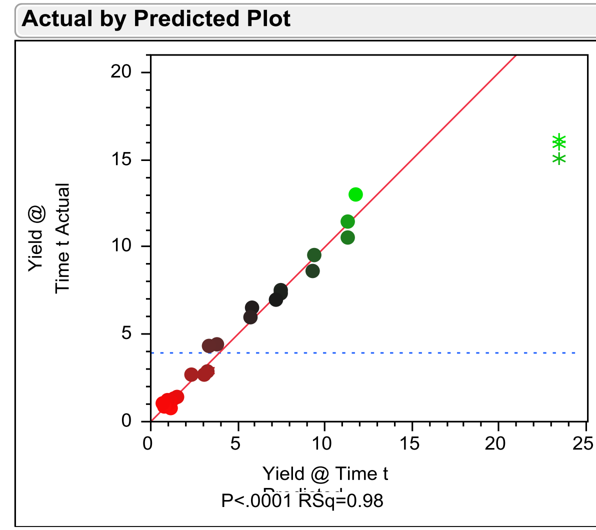
Actual by Predicted Plot

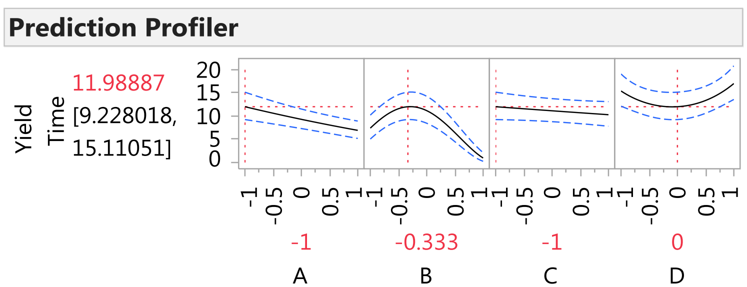


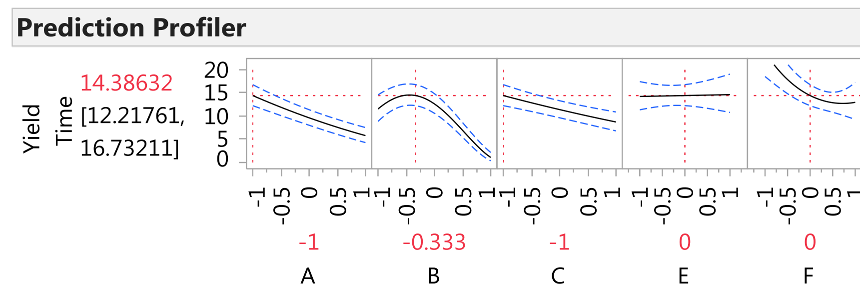
STEPWISE MODELS:
4-FACTOR (12 TERMS), 5-FACTOR (13 TERMS), 6-FACTOR (15 TERMS)

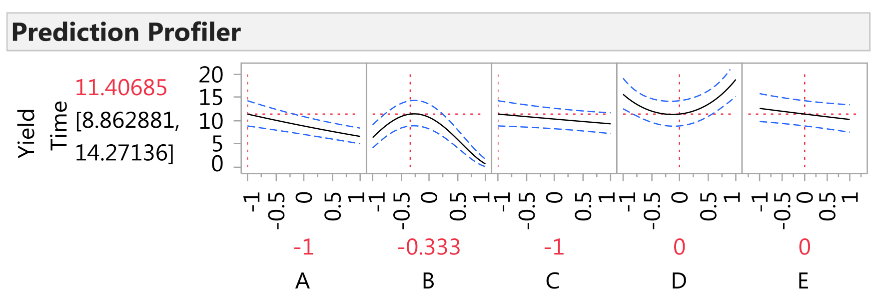




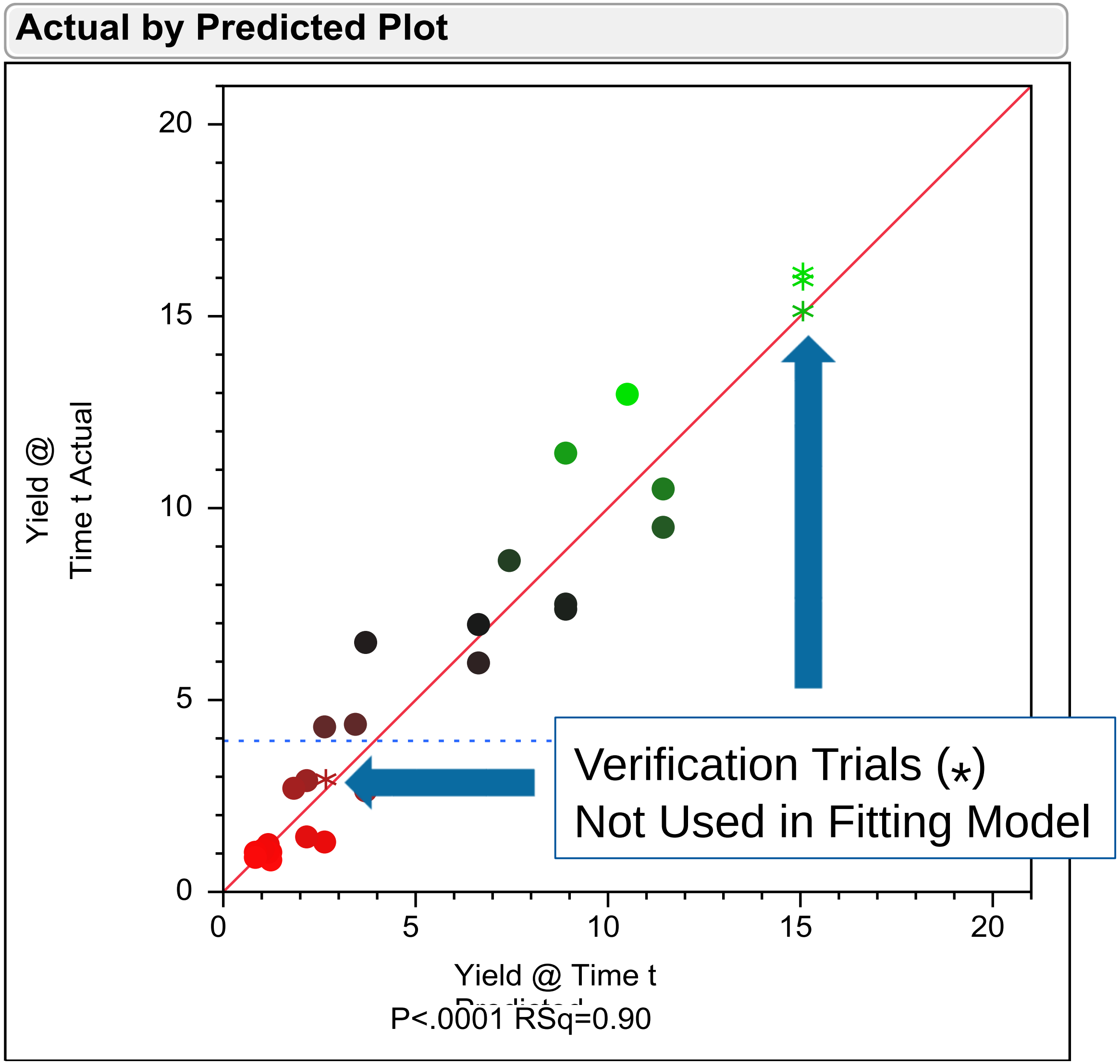








ACTUAL BY PREDICTED PLOT FOR FINAL 3-FACTOR MODEL FOR THE 24 DESIGN TRIALS AND 4 VERIFICATION TRIALS



A Class of Three-Level Designs for Definitive Screening in the Presence of Second-Order Effects

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PAPER AND CATALOGUE OF DEFINITIVE SCREENING DESIGNS FOR 4 TO 30 FACTORS AVAILABLE AT ASQ WEBSITE: HTTP://ASQ.ORG/QIC/DISPLAY-ITEM/INDEX.HTML?ITEM=33051

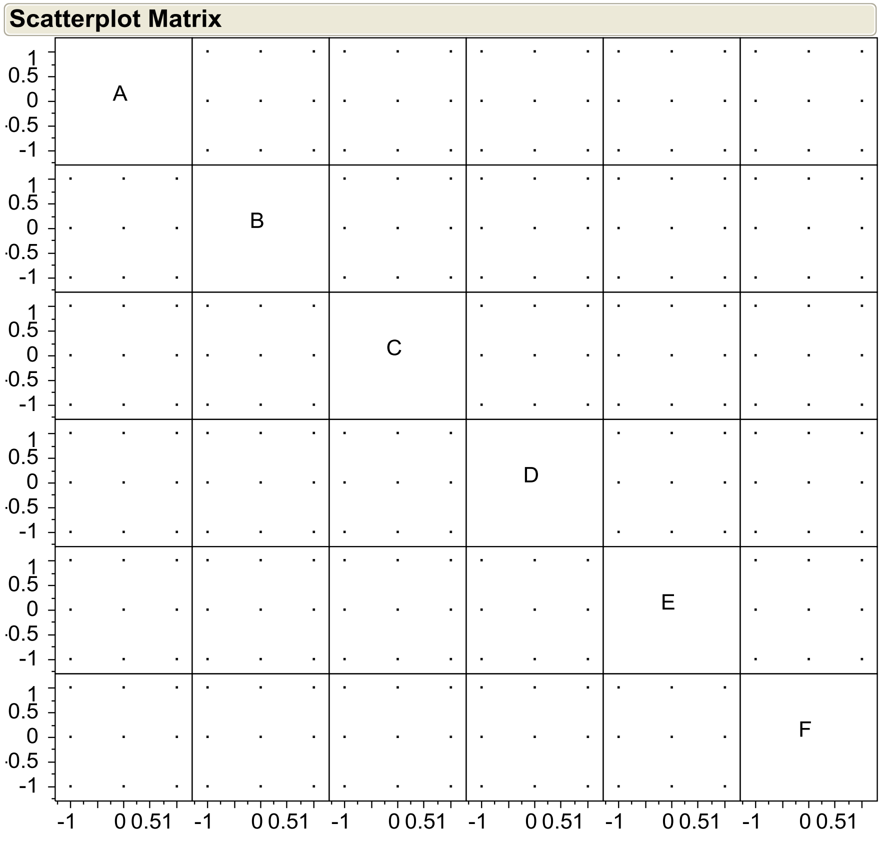
DEFINITIVE SCREENING DESIGNS FROM CONFERENCE MATRICES XIAO, BAI AND LIN (JQT, 2012)

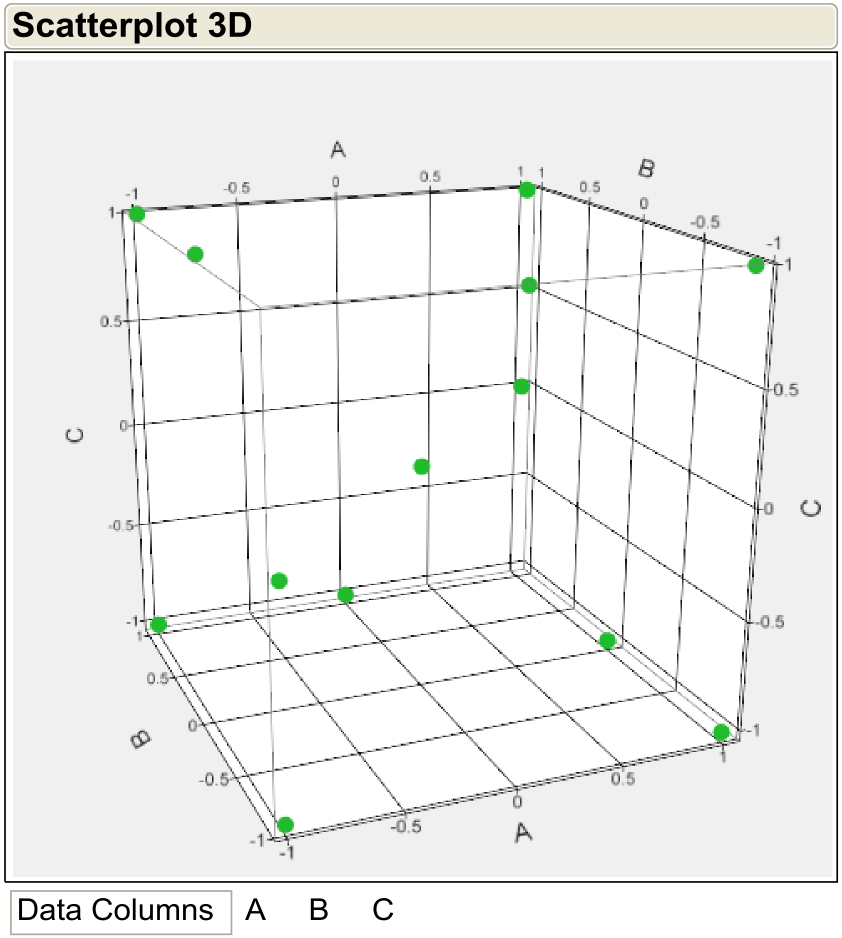
The D-efficiency is 92.3%, higher than 89.8% for the design given in Jones and Nachtsheim (2011).

$$
\mathrm{D} = \begin{pmatrix} \mathrm{C} \\ -\mathrm{C} \\ 0 \end{pmatrix} = \begin{array}{c} \begin{array}{cccccccccccc} x_1 & x_2 & x_3 & x_4 & x_5 & x_6 & x_7 & x_8 & x_9 & x_{10} & x_{11} & x_{12} \end{array} \\ \left(\begin{array}{rrrrrrrrrrrr}
0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 0 & -1 & -1 & -1 & -1 & 1 & -1 & 1 & 1 & 1 & 1 \\
1 & 1 & 0 & 1 & 1 & -1 & 1 & -1 & -1 & 1 & -1 & -1 \\
1 & 1 & -1 & 0 & 1 & 1 & -1 & -1 & -1 & -1 & 1 & 1 \\
1 & 1 & -1 & -1 & 0 & 1 & -1 & 1 & 1 & 1 & -1 & -1 \\
1 & 1 & 1 & -1 & -1 & 0 & 1 & 1 & -1 & -1 & 1 & -1 \\
1 & -1 & -1 & 1 & 1 & -1 & 0 & 1 & 1 & -1 & 1 & -1 \\
1 & 1 & 1 & 1 & -1 & -1 & -1 & 0 & 1 & -1 & -1 & 1 \\
1 & -1 & 1 & 1 & -1 & 1 & -1 & -1 & 0 & 1 & 1 & -1 \\
1 & -1 & -1 & 1 & -1 & 1 & 1 & 1 & -1 & 0 & -1 & 1 \\
1 & -1 & 1 & -1 & 1 & -1 & -1 & 1 & -1 & 1 & 0 & 1 \\
1 & -1 & 1 & -1 & 1 & 1 & 1 & -1 & 1 & -1 & -1 & 0 \\
\hdashline
0 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\
-1 & 0 & 1 & 1 & 1 & 1 & -1 & 1 & -1 & -1 & -1 & -1 \\
-1 & -1 & 0 & -1 & -1 & 1 & -1 & 1 & 1 & -1 & 1 & 1 \\
-1 & -1 & 1 & 0 & -1 & -1 & 1 & 1 & 1 & 1 & -1 & -1 \\
-1 & -1 & 1 & 1 & 0 & -1 & 1 & -1 & -1 & -1 & 1 & 1 \\
-1 & -1 & -1 & 1 & 1 & 0 & -1 & -1 & 1 & 1 & -1 & 1 \\
-1 & 1 & 1 & -1 & -1 & 1 & 0 & -1 & -1 & 1 & -1 & 1 \\
-1 & -1 & -1 & -1 & 1 & 1 & 1 & 0 & -1 & 1 & 1 & -1 \\
-1 & 1 & -1 & -1 & 1 & -1 & 1 & 1 & 0 & -1 & -1 & 1 \\
-1 & 1 & 1 & -1 & 1 & -1 & -1 & -1 & 1 & 0 & 1 & -1 \\
-1 & 1 & -1 & 1 & -1 & 1 & 1 & -1 & 1 & -1 & 0 & -1 \\
-1 & 1 & -1 & 1 & -1 & -1 & -1 & 1 & -1 & 1 & 1 & 0 \\
\hdashline
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{array} \right) \end{array}
$$

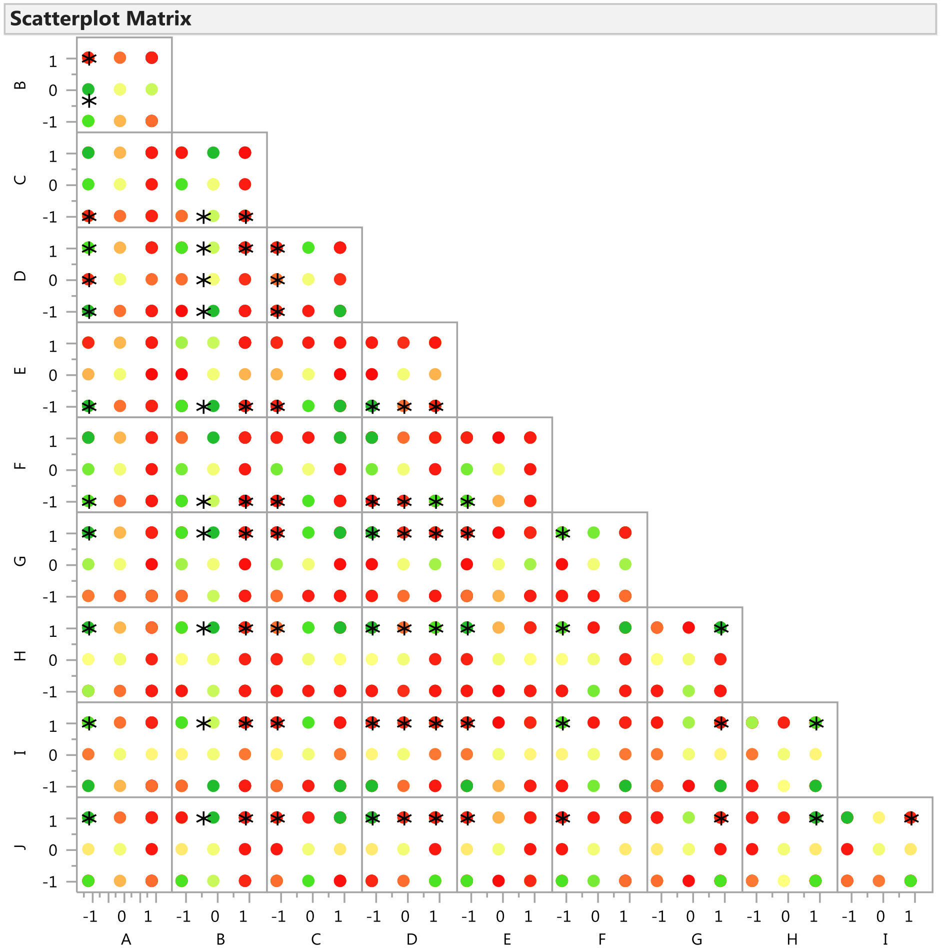
http://www.newton.ac.uk/programmes/DAE/seminars/090209001.pdf

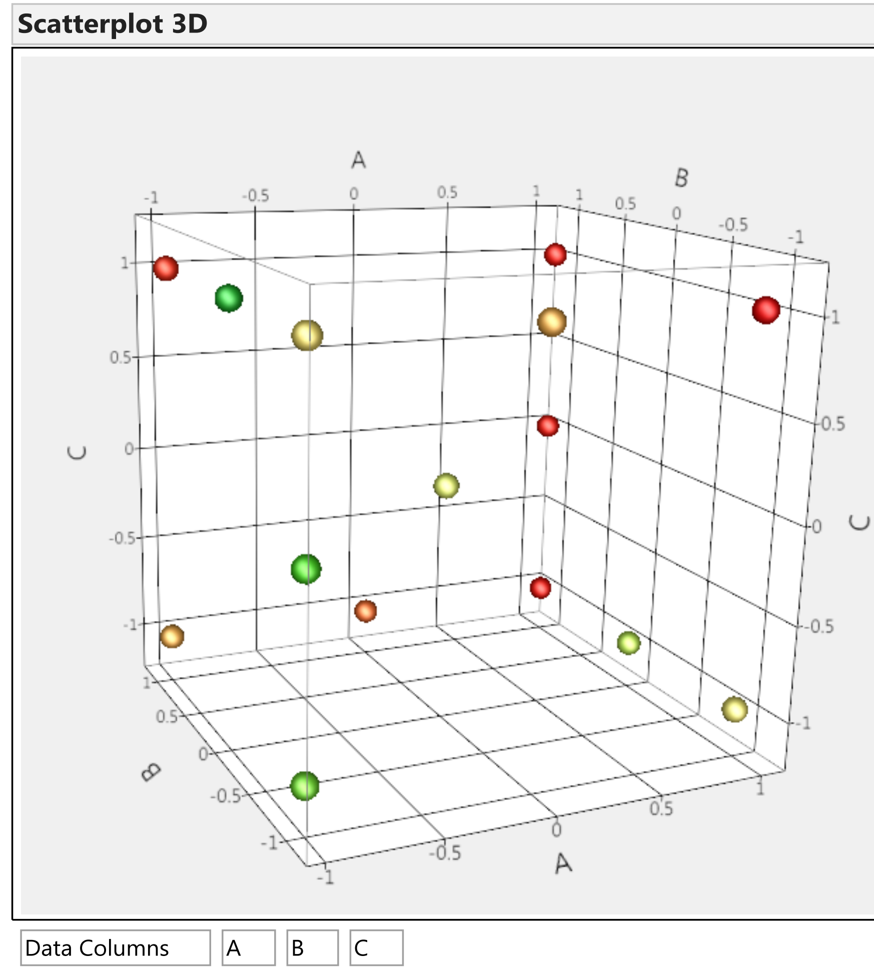
6-FACTOR DEFINITIVE SCREENING DESIGN, PROJECTION IN ALL 2-FACTOR COMBINATIONS (LEFT) AND PROJECTION IN FIRST THREE FACTORS (RIGHT)





10-FACTOR DEFINITIVE SCREENING DESIGN, PROJECTION IN ALL 2-FACTOR COMBINATIONS (LEFT) AND PROJECTION IN FIRST THREE FACTORS (RIGHT)





DEFINITIVE SCREENING DESIGNS HAVE DESIRABLE PROPERTIES

- Main effects are not confounded with 2nd order effects
- Number of trials for even numbers of factors is (2m + 1)

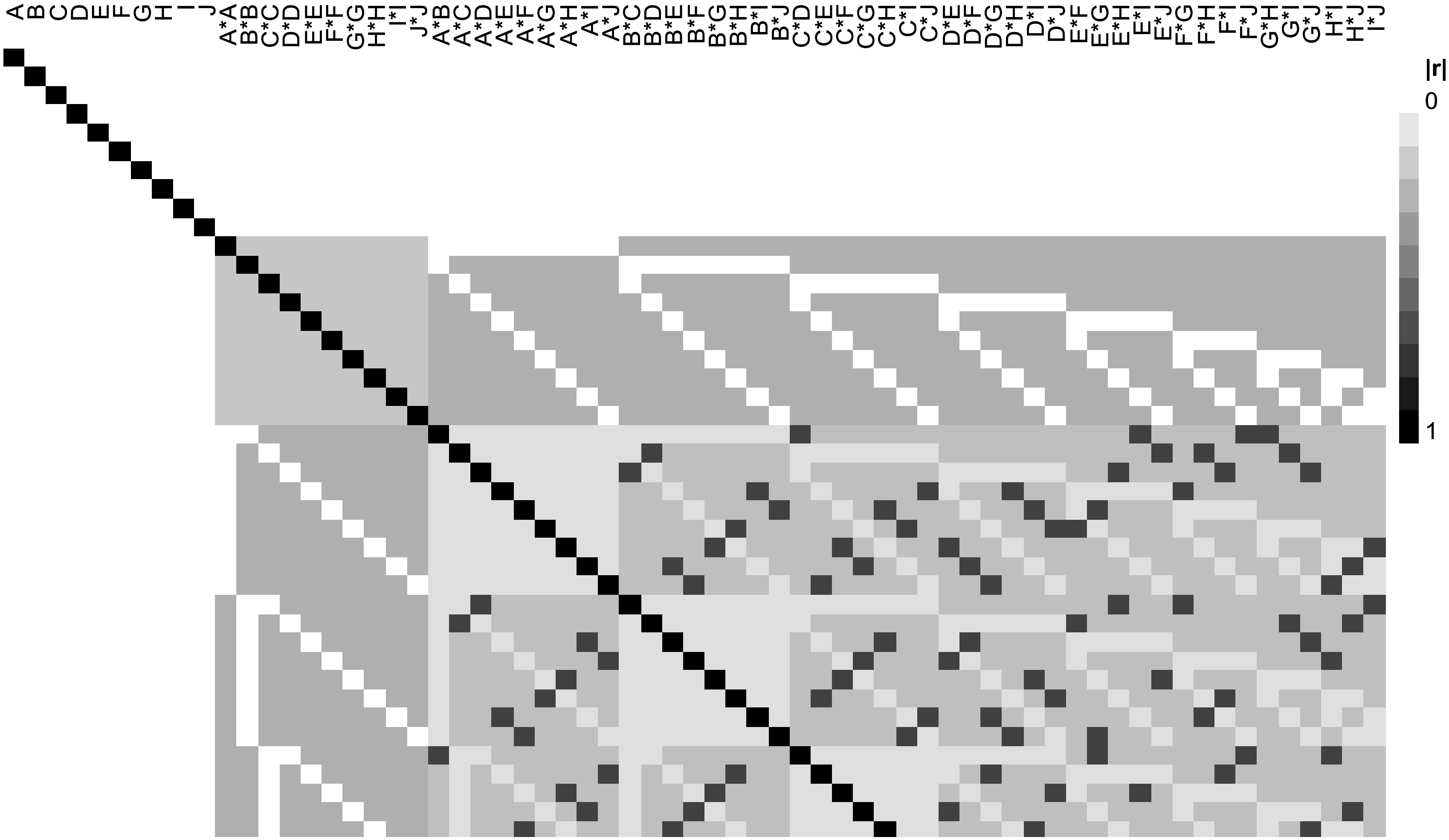
  and for odd numbers of factors it is (2m + 3)

  which is **equal to or smaller** than a Plackett-Burman (Res III) or Fractional Factorial (Res IV) design plus center point
- There are mid-levels for each factor allowing estimation of **curvature individually - not just globally** as with a PB or FF designs plus center point
- Dropping a factor the design retains all its properties
- If a subset of factors are significant there is a good chance that interaction terms may also be fit

  The screening design may even collapse into a response-surface design supporting a 2nd order model in a subset of factors with which one can optimize the process

COLOR MAP FOR 10-FACTOR, 21-TRIAL, DEFINITIVE SCREENING DESIGN

Color Map On Correlations



MORE CONSERVATIVE ANALYSIS STRATEGIES THAN STEPWISE REGRESSION METHOD

- Fit just main effects to rank factors
- Fit main effects and squared effects together to not only identify dominant factors but look for curvature in factors
- Assuming **Factor Sparsity** and **Effect Heredity** principles* hold true - add interactions among dominant factors
  - If three or fewer factors have main effects, fit the full quadratic model for these factors with standard least squares regression.
  - If four or more factors have main effects, fit the full quadratic for these factors using stepwise regression

*Factor Sparsity states only a few variables will be active in a factorial DOE
Effect Heredity states significant interactions will only occur if at least one parent is active
Pg. 112 , Wu & Hamada, "*Experiments, Planning, Analysis and Parameter Design Optimization*"

IF MORE THAN A FEW FACTORS ARE SIGNIFICANT, THEN AUGMENT DESIGN TO SUPPORT 2ND ORDER MODEL

	A	B	C	D	E	F	Block	Yield @ Time t
14	0	0	0	0	0	0	1	7.49
15	1	1	-1	1	1	-1	1	0.98
16	1	1	1	-1	-1	-1	1	0.86
17	-1	1	-1	-1	1	1	1	1.25
18	1	-1	1	1	-1	-1	1	1.03
19	1	1	0	-1	1	1	1	1.07
20	0	0	0	0	0	0	1	7.33
21	1	-1	-1	0	-1	1	1	2.61
22	-1	-1	0	1	-1	-1	1	11.39
23	-1	0	1	-1	-1	1	1	12.96
24	1	1	-1	1	-1	1	1	1.18
25	1	1	-1	-1	-1	1	2	•
26	-1	-1	1	1	1	1	2	•
27	1	1	1	1	-1	-1	2	•
28	1	-1	1	-1	1	-1	2	•
29	1	0	-1	-1	1	1	2	•
30	-1	1	-1	1	-1	-1	2	•
31	-1	-1	-1	-1	1	-1	2	•
32	-1	1	1	-1	1	1	2	•
33	1	0	1	1	-1	-1	2	•
34	-1	0	-1	-1	-1	-1	2	•
35	-1	0	1	1	1	1	2	•
36	1	-1	-1	1	-1	1	2	•

NOTE: First 13 rows of original design are not shown.

These 12 trials added onto original 24 trials to support full quadratic model in 6 most important factors plus a block effect between original and augmented trials

COMPARE AUGMENTED DESIGNS

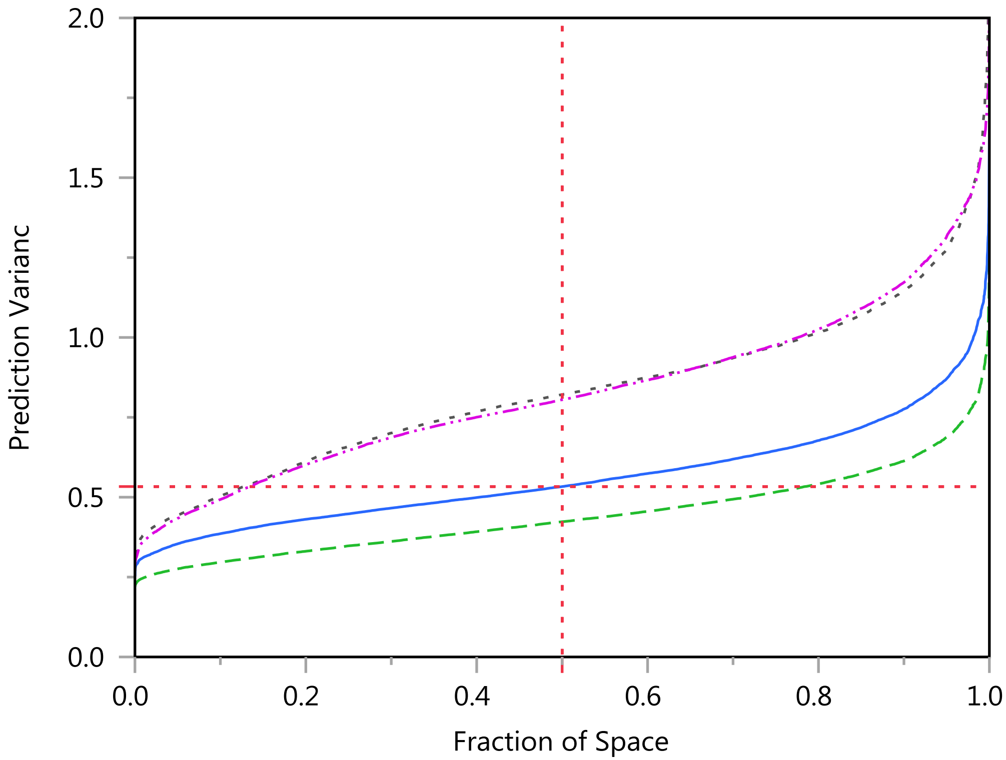
TOP: 10-FACTOR FRACTIONAL FACTORIAL + C.P. AUGMENTED TO SUPPORT FULL QUADRATIC MODEL IN 6 FACTORS
33 + 9 = 42 TOTAL TRIALS

UPPER MIDDLE: 10-FACTOR PLACKET-BURMAN + C.P. AUGMENTED TO SUPPORT FULL QUADRATIC MODEL IN 6 FACTORS
25 + 11 = 36 TOTAL TRIALS

LOWER MIDDLE: 10-FACTOR DEFINITIVE SCREENING AUGMENTED TO SUPPORT FULL QUADRATIC MODEL IN 6 FACTORS
21 + 15 = 36 TOTAL TRIALS

BOTTOM: 6-FACTOR CUSTOM DOE FOR FULL RSM MODEL
34 TOTAL TRIALS

Fraction of Design Space Plot



Design Diagnostics	
I Optimal Design	
D Efficiency	40.729
G Efficiency	56.09719
A Efficiency	12.41717
Average Variance of Prediction	0.82307
Design Creation Time (seconds)	0.05

Design Diagnostics	
I Optimal Design	
D Efficiency	38.46605
G Efficiency	54.33992
A Efficiency	14.61968
Average Variance of Prediction	0.833744
Design Creation Time (seconds)	0.05

Design Diagnostics	
I Optimal Design	
D Efficiency	42.15506
G Efficiency	69.61262
A Efficiency	22.27027
Average Variance of Prediction	0.563765
Design Creation Time (seconds)	0.066667

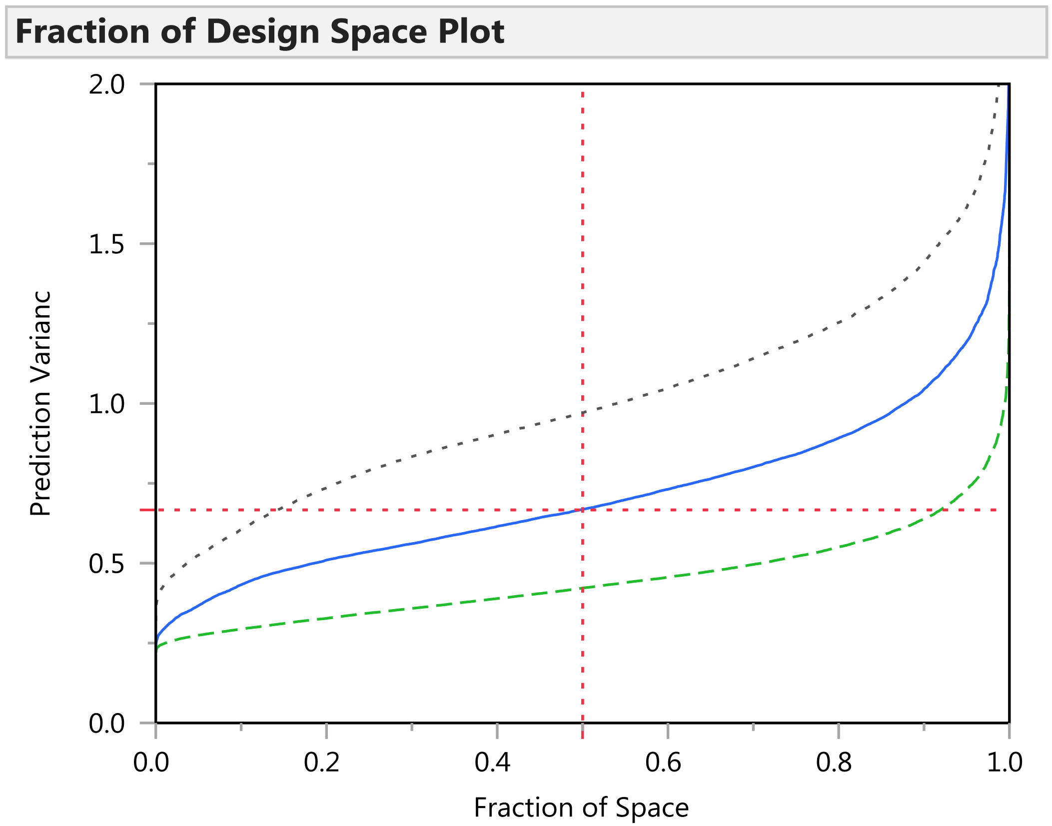
Design Diagnostics	
I Optimal Design	
D Efficiency	42.94028
G Efficiency	75.52931
A Efficiency	27.20305
Average Variance of Prediction	0.44424
Design Creation Time (seconds)	0.066667

COMPARE AUGMENTED DESIGNS

TOP: 14-FACTOR FRACTIONAL FACTORIAL + C.P. AUGMENTED TO SUPPORT FULL QUADRATIC MODEL IN 7 FACTORS
33 + 13 = 46 TOTAL TRIALS

MIDDLE: 14-FACTOR DEFINITIVE SCREENING AUGMENTED TO SUPPORT FULL QUADRATIC MODEL IN 7 FACTORS
29 + 17 = 46 TOTAL TRIALS

BOTTOM: 7-FACTOR CUSTOM DOE FOR FULL RSM MODEL
42 TOTAL TRIALS



Design Diagnostics

I Optimal Design	
D Efficiency	37.352
G Efficiency	48.68453
A Efficiency	11.13939
Average Variance of Prediction	1.006709
Design Creation Time (seconds)	0.133333

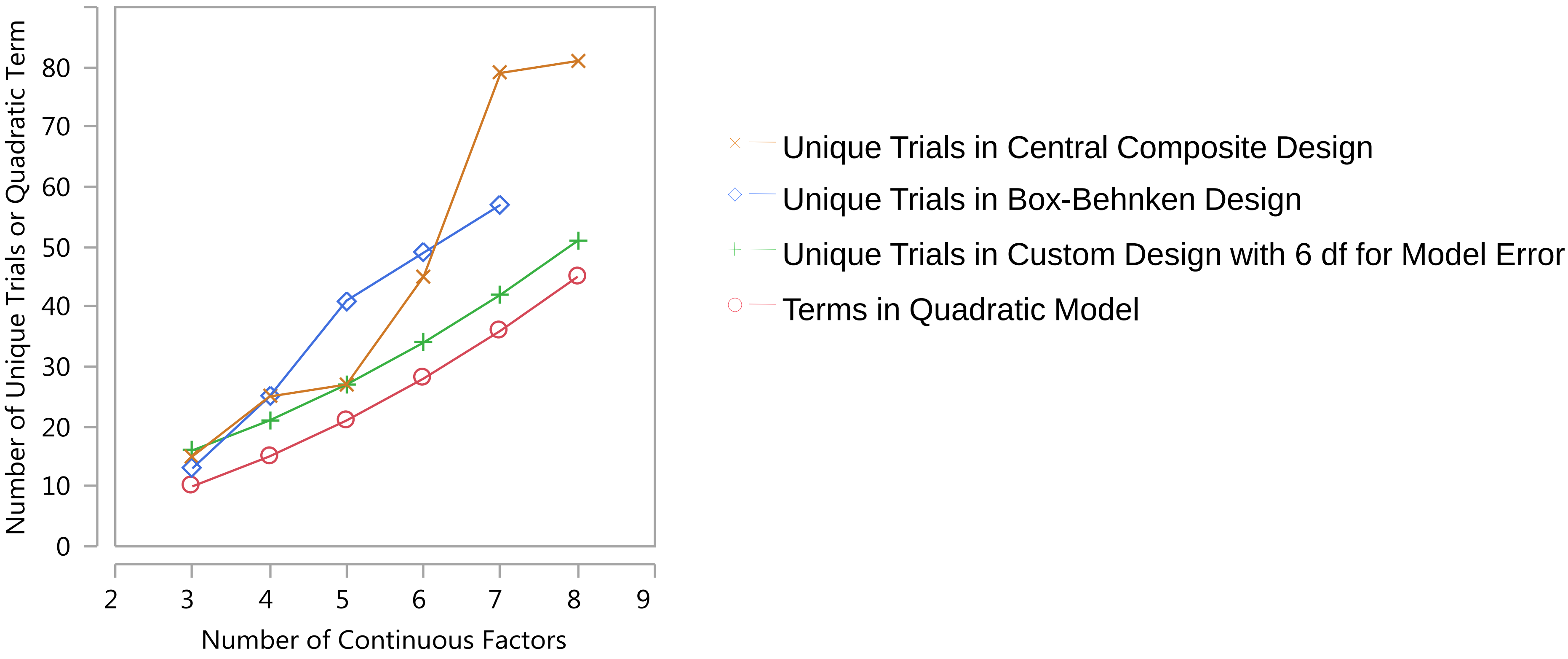
Design Diagnostics

I Optimal Design	
D Efficiency	36.69963
G Efficiency	58.39688
A Efficiency	15.61337
Average Variance of Prediction	0.714178
Design Creation Time (seconds)	0.133333

Design Diagnostics

I Optimal Design	
D Efficiency	41.03495
G Efficiency	71.04153
A Efficiency	27.70772
Average Variance of Prediction	0.449918
Design Creation Time (seconds)	0.216667

NUMBER OF UNIQUE TRIALS FOR 3 RESPONSE-SURFACE DESIGNS AND NUMBER OF QUADRATIC MODEL TERMS VS. NUMBER OF CONTINUOUS FACTORS

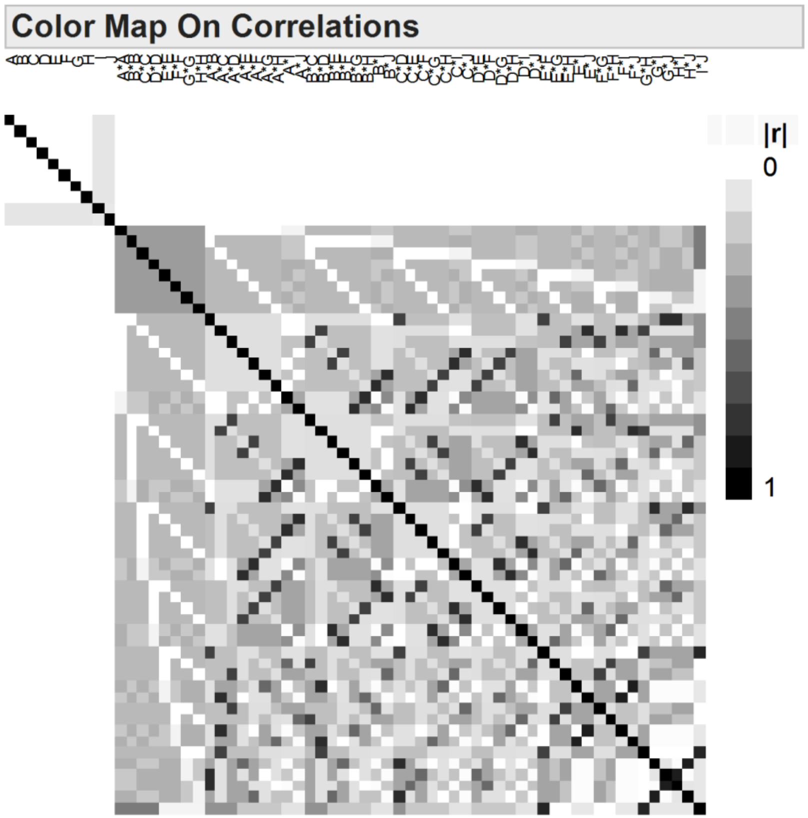


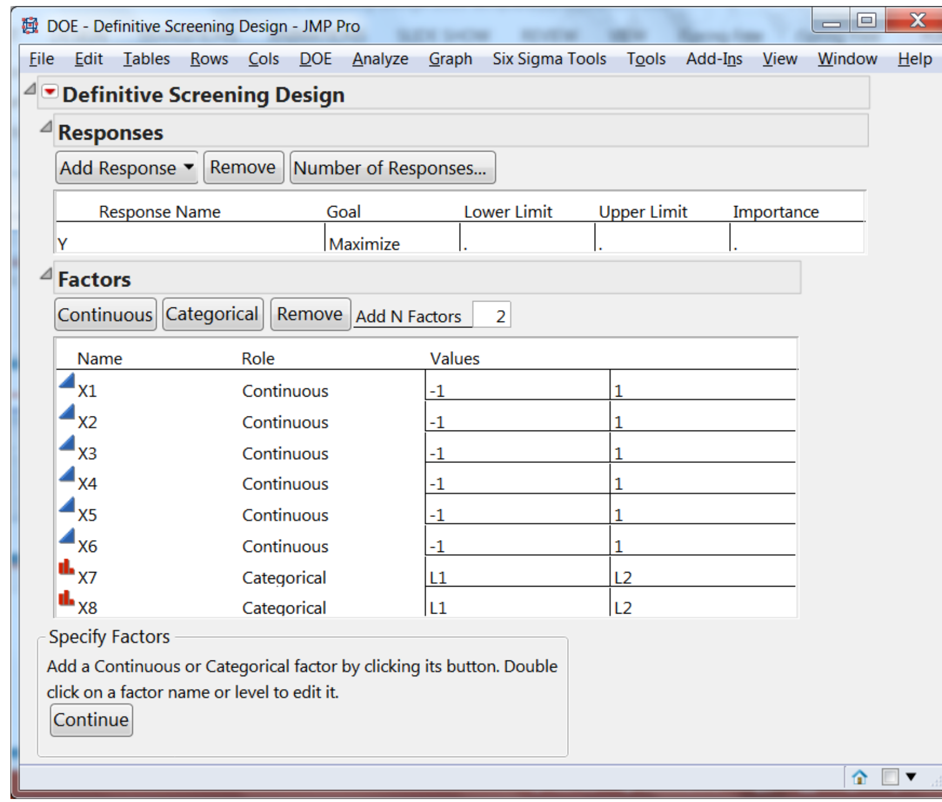
If generally running 3, 4 or 5-factor fractional-factorial designs…

1. How many interactions are you not investigating?
2. How many more trials needed to fit curvature?
3. Consider two stages: Definitive Screening + Augmentation

JMP 11 DEFINITIVE SCREENING DESIGN COLOR MAPS FOR 8-CONTINUOUS, 2-CATEGORICAL FACTOR

De-alias 2-f Interactions and Categorical Factors





- ***Definitive Screening Designs***
  - Efficiently estimate main and quadratic effects for no more and **often fewer trials than traditional designs**
  - If only a few factors are important the design may collapse into a **“one-shot”** design that supports a response-surface model
  - If many factors are important the design can be **augmented** to support a response-surface model
  - Case study for a **10-variable process** shows that it can be **optimized in just 23 unique trials**

Thanks.
Questions or comments?

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