Practical DOE – "Tricks of the Trade"

Presentation is posted at www.statease.com/webinar.html

***There are many attendees today!** To avoid disrupting the Voice over Internet Protocol (VoIP) system, I will mute all. Please email Questions to me which I answer after the presentation.*

-- Pat

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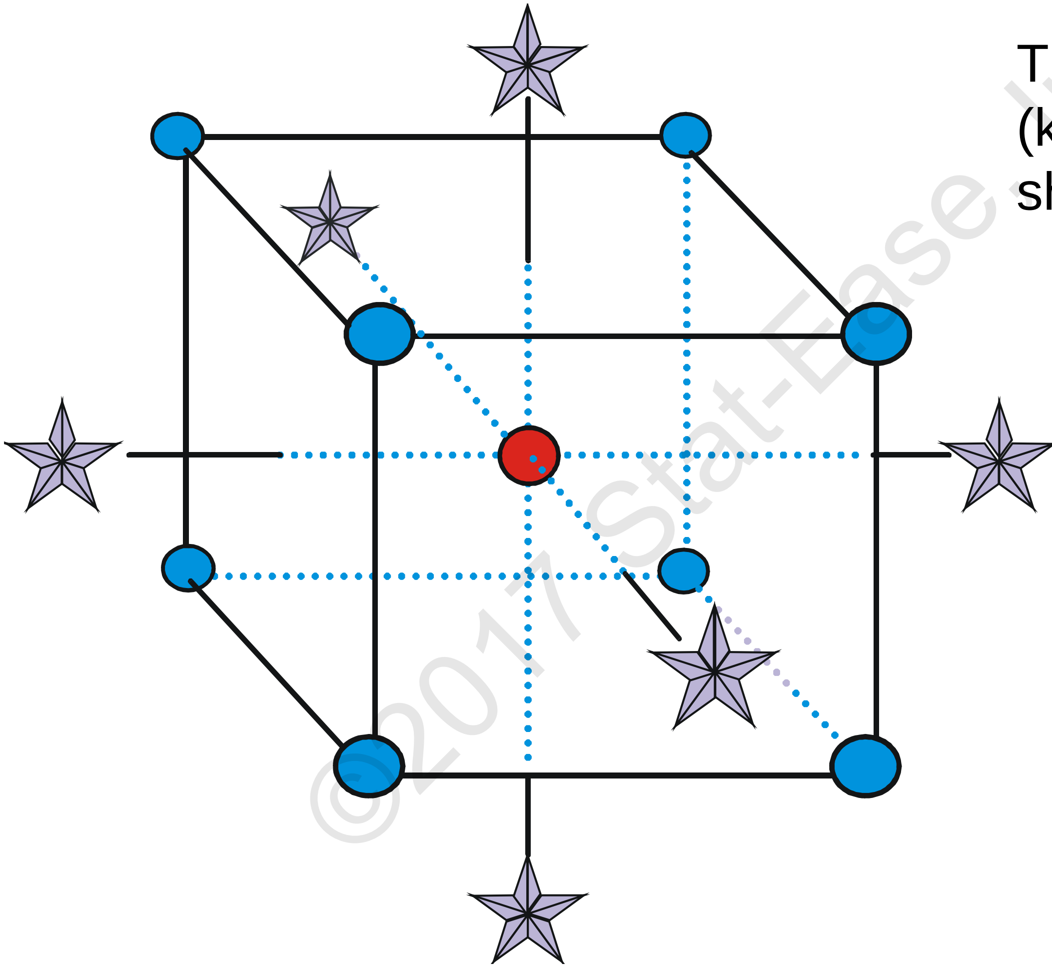
Practical DOE "Tricks of the Trade"

- Using standard error to constrain optimization
- Employing C_{pk} (or P_{pk}) to optimize your DOE
- Combining categoric factors
- A Couple of Case Studies
    - The Loose Collet
    - A Case to Test Your Metal

Practical DOE “Tricks of the Trade”

- **Using standard error to constrain optimization**
  Expand your search without sacrificing precision.
  5 times the volume with no loss in precision!
- Employing C_{pk} (or P_{pk}) to optimize your DOE
- Combining categoric factors
- A Couple of Case Studies
  - The Loose Collet
  - A Case to Test Your Metal

Four Factor CCD – Case Study #1
alpha = 2.0 *(rotatable and spherical)*



There are four factors (k=4), but picture only shows three factors.

Four Factor CCD – Case Study #1
Standard Error of the Mean

Prediction standard error of the expected value:

$$PV(x_0) = \mathrm{var}(\hat{\bar{y}}_0) = \left(x_0^T \left(X^T X\right)^{-1} x_0\right) s^2$$

$$StdErr(x_0) = s_{\hat{\bar{y}}_0} = \sqrt{PV(x_0)}$$

x_0 – the location in the design space (i.e. the x coordinates for all model terms).

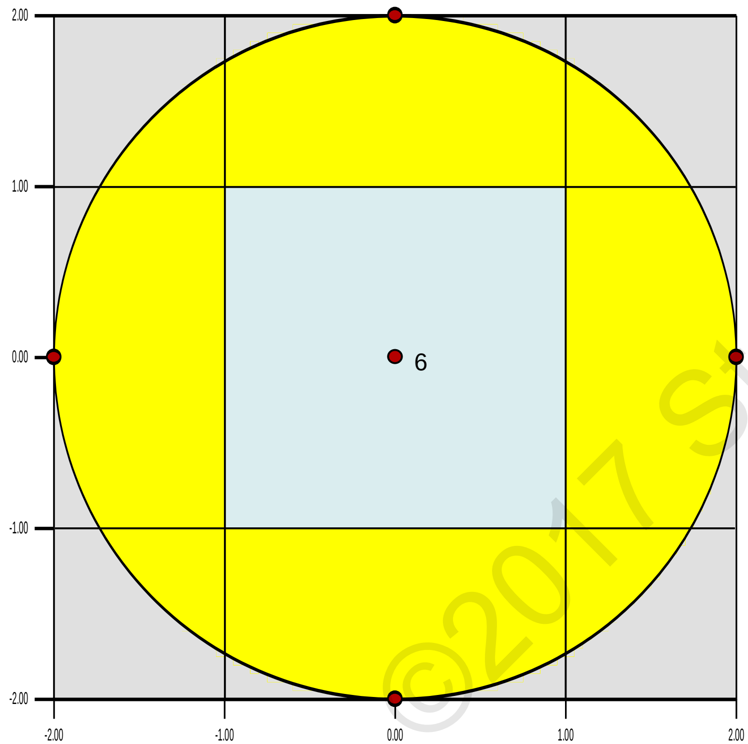
X – the experimental design (i.e. where the runs are in the design space).

In this four factor CCD, the factorial and axial points have:

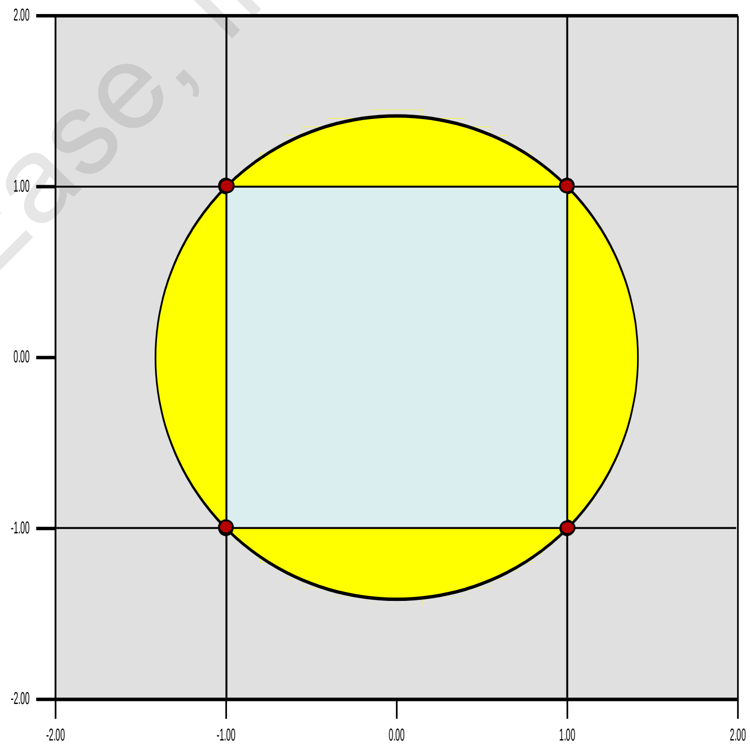
StdErr = 3.43744

Four Factor CCD – Case Study #1
alpha = 2.0 *(rotatable and spherical)*

Slice at: C = 0, D = 0

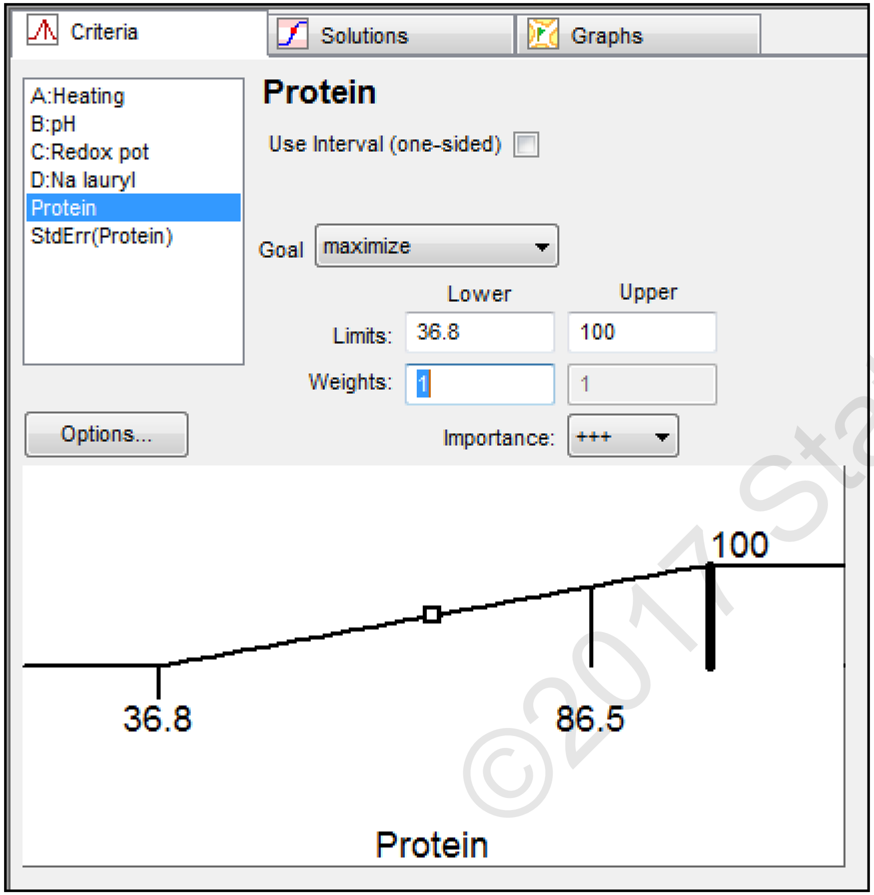


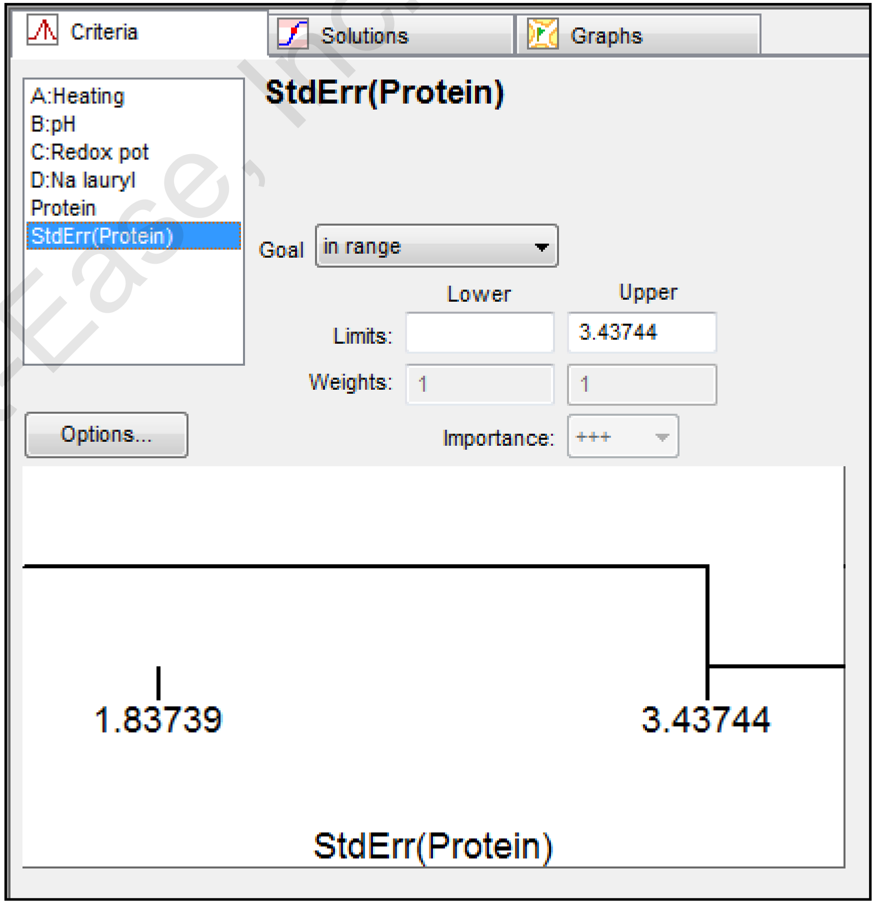
Slice at: C = +1, D = +1



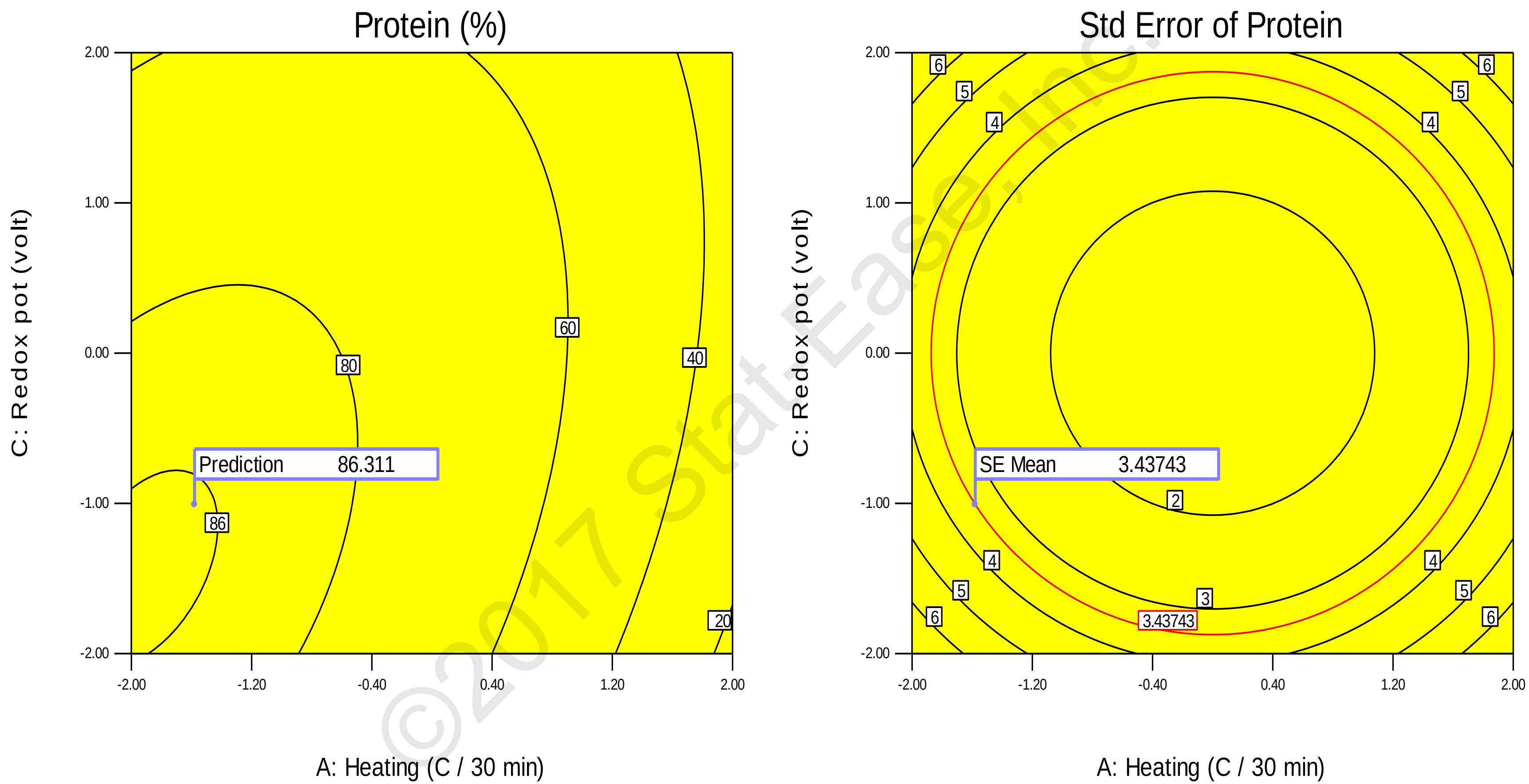
Yellow border at StdErr = 3.43744

Four Factor CCD – Case Study #1
Maximize Protein with StdErr ≤ 3.43744





Four Factor CCD – Case Study #1
Maximize Protein with StdErr ≤ 3.43744



A: Heating	B: pH	C: Redox pot	D: Na lauryl	Protein	StdErr
-1.579	0.234	-1.008	-0.660	86.311	3.437

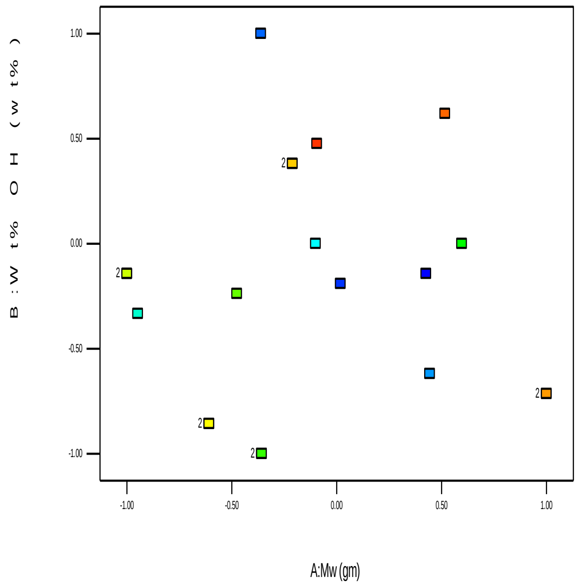
Four Factor CCD – Case Study #1
Maximize Protein

A Heating	B pH	C Redox pot	D Na lauryl	y Protein	StdErr
Factor range ±1.00 cube		**(too restrictive)**		(max SE = 3.43744)	
-1.000	-0.157	-0.870	-0.999	84.696	2.595
Factor range ±2.00 cube		**(too liberal)**		(max SE = 13.3764)	
-2.000	0.636	-2.000	-2.000	89.644	**10.321**
SE ≤ 3.43744 sphere		**(just right)**		(max SE = 3.43744)	
-1.579	0.234	-1.008	-0.660	86.311	3.437

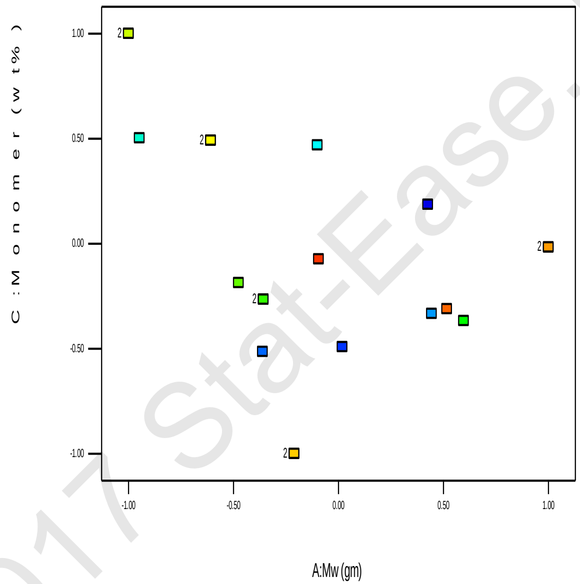
increases volume of search by 393% over ±1 cube

Historical Data – Case Study #2
Not Space Filling for Cube or Sphere

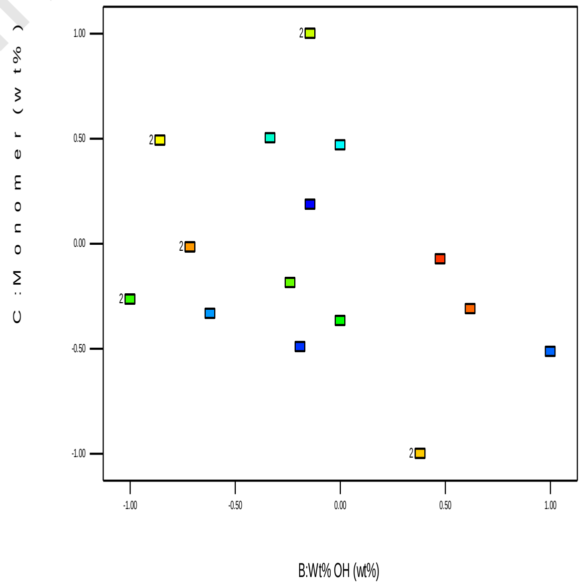
AB



AC



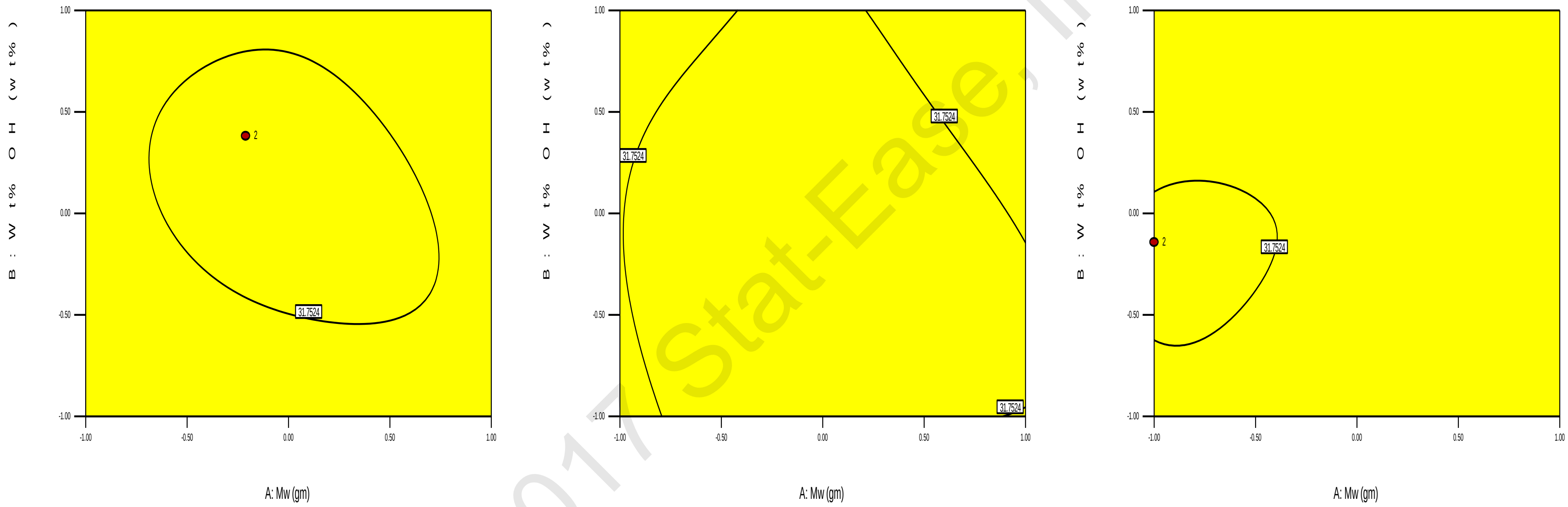
BC



Points projected in two-dimensional planes.

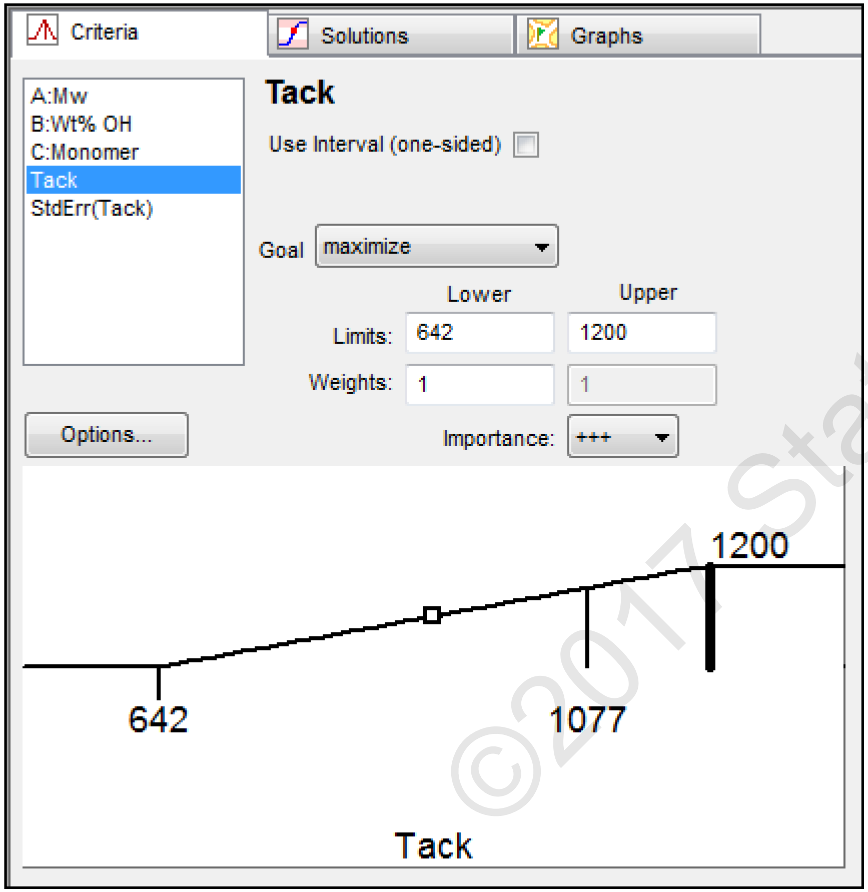
Historical Data – Case Study #2
Limit Search to StdErr ≤ 31.7524

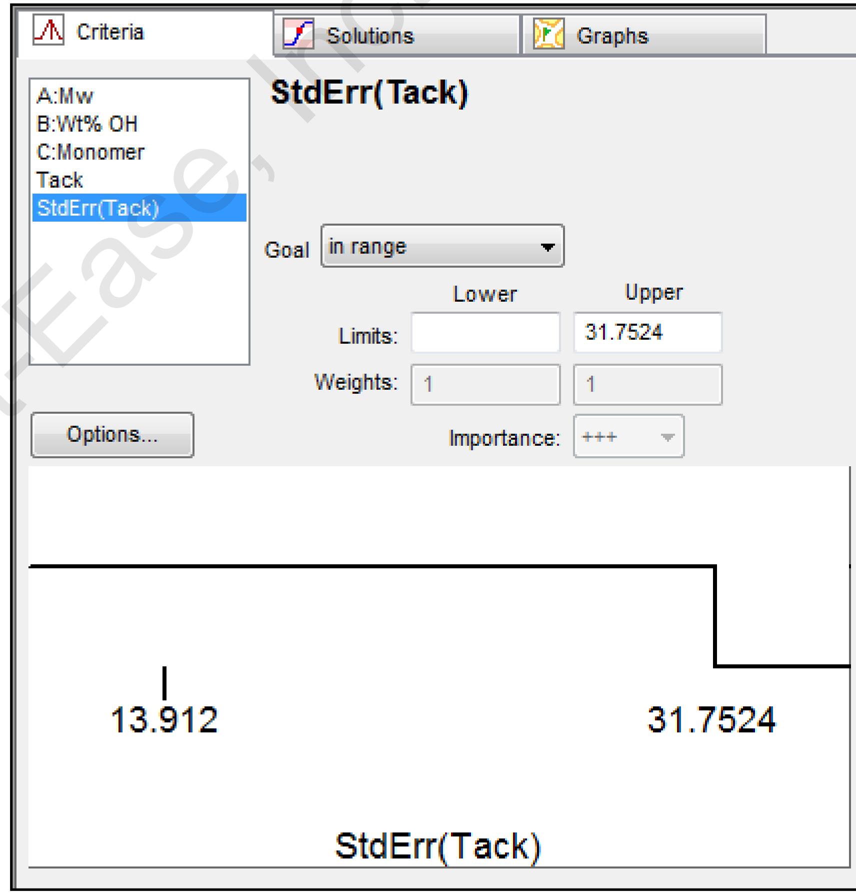
C = -1 C = 0 C = +1



Highest Standard Error at a design point = 31.7524

Historical Data – Case Study #2
Maximize Tack with StdErr ≤ 31.7524





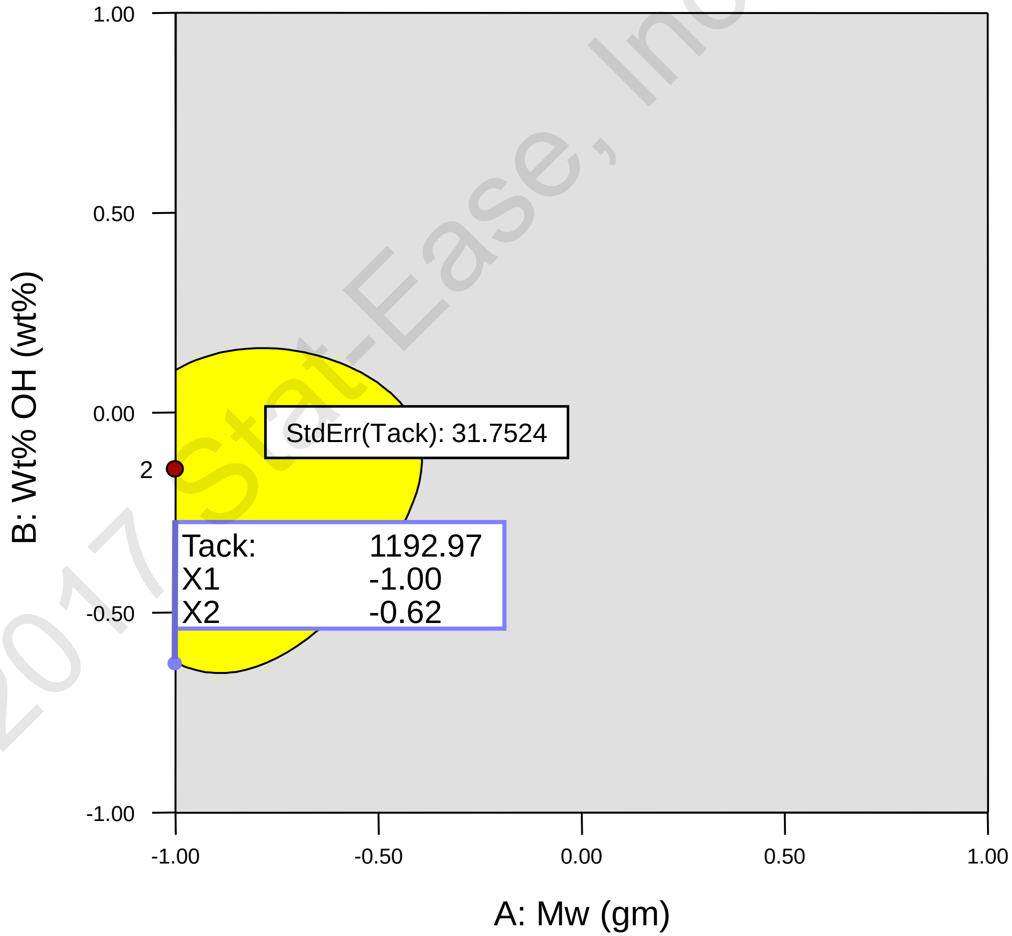
Historical Data – Case Study #2
Maximum Tack with StdErr ≤ 31.7524

Design-Expert® Software
Factor Coding: Coded
Overlay Plot

Tack
StdErr(Tack)
● Design Points

X1 = A: Mw
X2 = B: Wt% OH

Coded Factor
C: Monomer = 1.000



Conclusions: Using Standard Error to Constrain Optimization

Advantages:

- Defines a search area that matches design properties:
  - Spheres for rotatable CCDs.
  - Cubes for face centered CCDs.
  - Irregular shapes for optimal designs and historical data.
- Modifies search area for reduced models and missing data.

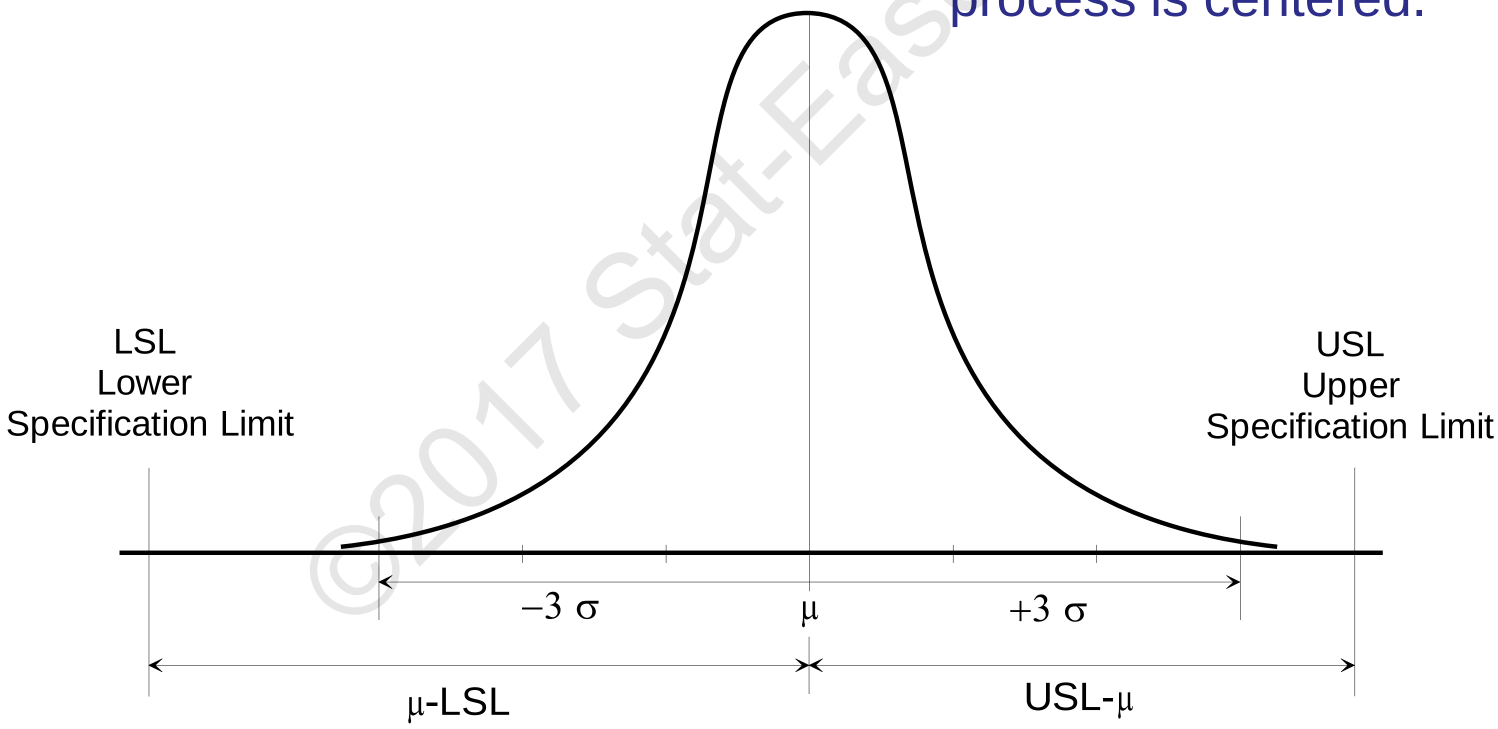
Practical DOE "Tricks of the Trade"

- Using standard error to constrain optimization
- **Employing C_{pk} (or P_{pk}) to optimize your DOE**
  Incorporate specifications in your optimization.
- Combining categoric factors
- A Couple of Case Studies
  - The Loose Collet
  - A Case to Test Your Metal

Process Capability Refresher
C_{pk} statistic

$$C_{pk} = \frac{\text{Minimum}\left(\text{USL} - \mu, \mu - \text{LSL}\right)}{3\hat{\sigma}}$$

C_{pk} defines the potential capability of the process, with regard to where the process is centered.



Process Capability Refresher
P_{pk} statistic

P_{pk} statistic is used to determine how "in control" the process has been over time.

$$Z_{upper} = \frac{USL - \bar{\bar{Y}}}{3\hat{\sigma}_s}, \quad Z_{lower} = \frac{\bar{\bar{Y}} - LSL}{3\hat{\sigma}_s}$$

$$P_{pk} = \text{minimum}(Z_{upper}, Z_{lower})$$

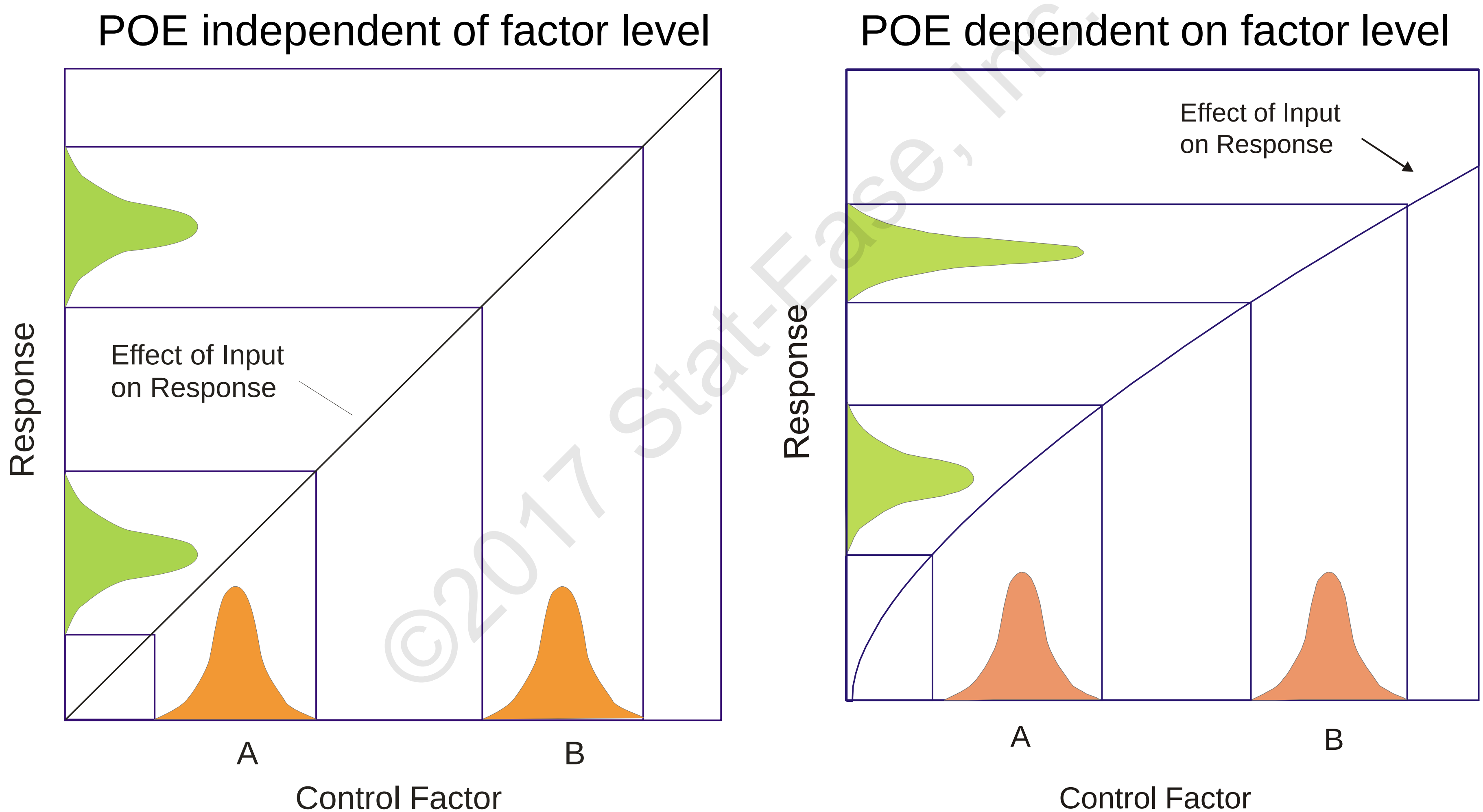
P_{pk} allows for variation from a centered process.

$\hat{\sigma}_s$ is calculated from data gathered over time to capture long term variation.

The difference between C_{pk} and P_{pk} is the estimate of sigma:

- C_{pk} uses a **short** term estimate of sigma
- P_{pk} uses a **long** term estimate of sigma

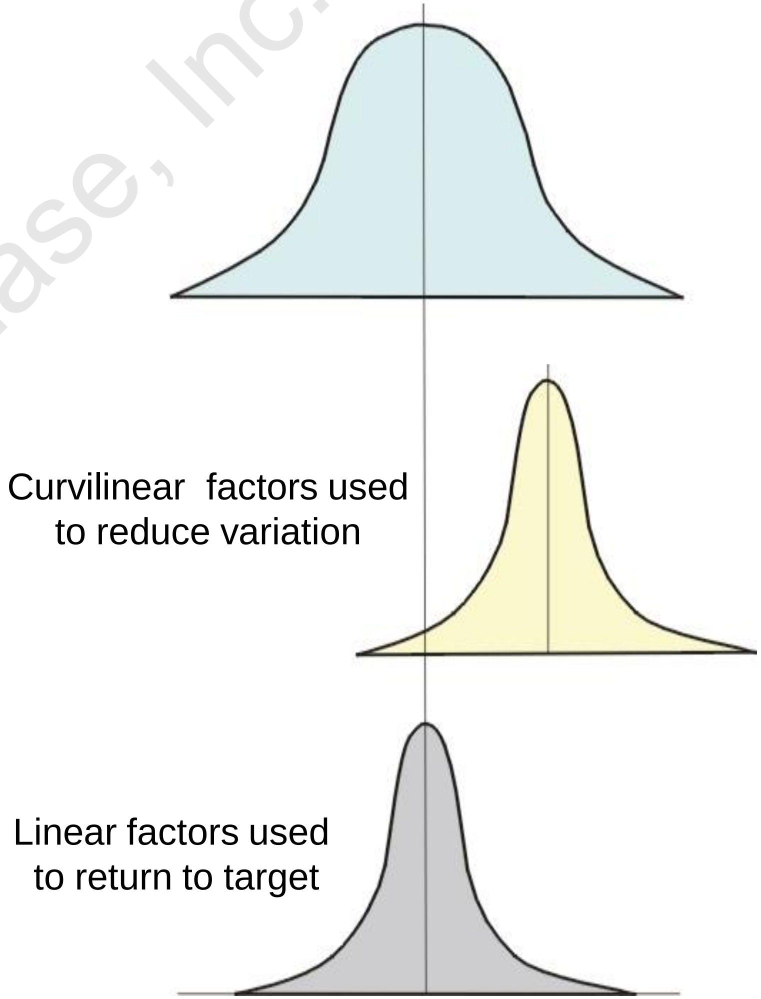
Propagation of Error
Tool to Improve C_{pk} & P_{pk}



Propagation of Error
Achieve Target with Less Variation

To illustrate the theory, the control factors were used in two steps: first to decrease variation and second to move back on target.

In practice, numerical optimization can be used to simultaneously obtain all the goals.



Propagation of Error
Goal: Minimize Propagated Error (POE)

Statistical detail

First order:

$$\sigma^2_{\hat{Y}} = \sum_i \left(\frac{\partial f}{\partial x_i} \right)^2 \sigma^2_{x_i} + \sigma^2_e$$

$$\hat{y} = f\left(x_1, \ldots, x_k\right)$$

Second order:

$$\sigma^2_{\hat{Y}} = \sum_{i=1}^{k} \left(\frac{\partial f}{\partial x_i} \right)^2 \sigma^2_{ii} + \frac{1}{2} \sum_{i=1}^{k} \left(\frac{\partial^2 f}{\partial x_i^2} \right)^2 \sigma^4_{ii} + \sum_{i<j}^{k} \left(\frac{\partial^2 f}{\partial x_i \partial x_j} \right)^2 \sigma^2_{ii}\sigma^2_{jj} + \sigma^2_e$$

$$\hat{y} = f\left(x_1, \ldots, x_k\right) + \frac{1}{2} \sum_{i=1}^{k} \left(\frac{\partial^2 f}{\partial x_i^2} \right) \sigma^2_{ii}$$

$\sigma^2_e = MS_{residual}$ from the ANOVA and $POE = \sqrt{\sigma^2_{\hat{Y}}}$

Process Capability Refresher

C_{pk} versus P_{pk} statistic

The difference between C_{pk} and P_{pk} is the estimate of sigma:

- C_{pk} uses a **short** term estimate of sigma
- P_{pk} uses a **long** term estimate of sigma

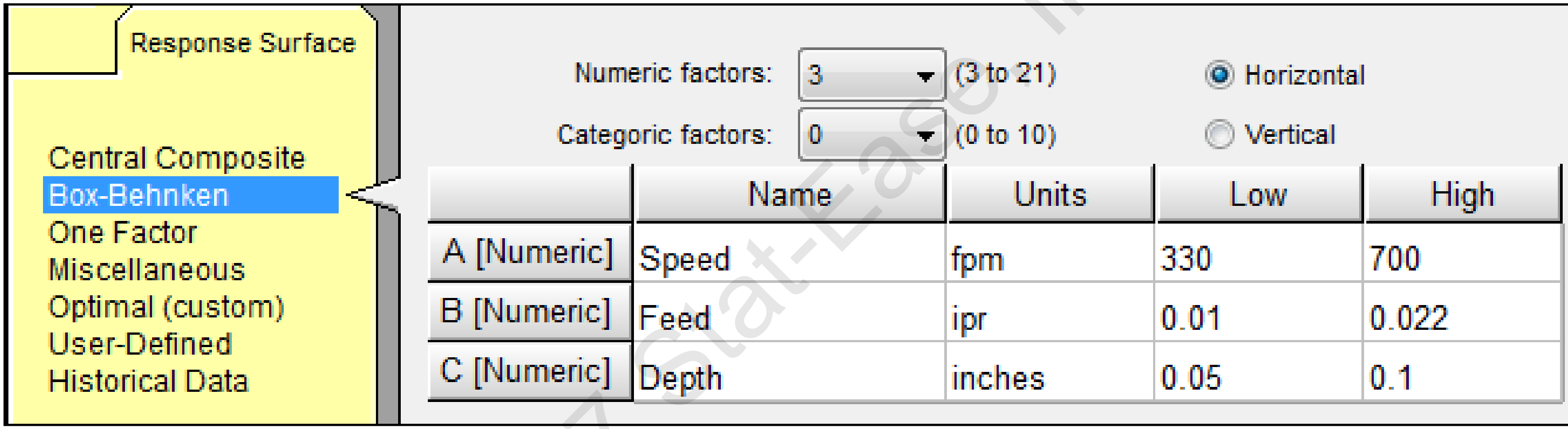
Design of Experiments (DOE):

- The residual MSE (σ_e^2) estimates short variation (C_{pk})
- Propagation of error estimates long term variation (P_{pk} like)

$$\sigma^2_{\hat{Y}} = \sum_{i=1}^{k}\left(\frac{\partial f}{\partial x_i}\right)^2 \sigma_{ii}^2 + \frac{1}{2}\sum_{i=1}^{k}\left(\frac{\partial^2 f}{\partial x_i^2}\right)^2 \sigma_{ii}^4 + \sum_{i<j}^{k}\left(\frac{\partial^2 f}{\partial x_i \partial x_j}\right)^2 \sigma_{ii}^2\sigma_{jj}^2 + \sigma_e^2$$

Employing C_{pk} (or P_{pk}) to optimize your DOE Lathe Case Study

The experimenters run a three factor Box-Behnken design:



The key response is delta, i.e. the deviation of the finished part's dimension from its nominal value. Delta is measured in mils, 1 mil = 0.001 inches.

Employing C_{pk} (or P_{pk}) to optimize your DOE Lathe Case Study

ANOVA for Response Surface Reduced Quadratic model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	1.36	7	0.19	42.65	< 0.0001
A-Speed	*0.037*	*1*	*0.037*	*8.17*	*0.0189*
B-Feed	*0.15*	*1*	*0.15*	*32.42*	*0.0003*
C-Depth	*0.35*	*1*	*0.35*	*77.80*	*< 0.0001*
AB	*0.27*	*1*	*0.27*	*59.70*	*< 0.0001*
AC	*0.24*	*1*	*0.24*	*53.21*	*< 0.0001*
A^2	*0.025*	*1*	*0.025*	*5.52*	*0.0434*
C^2	*0.27*	*1*	*0.27*	*59.53*	*< 0.0001*
Residual	0.041	9	4.558E-003		
Lack of Fit	*0.019*	*5*	*3.740E-003*	*0.67*	*0.6689*
Pure Error	*0.022*	*4*	*5.582E-003*		
Cor Total	1.40	16			

Std. Dev.	0.068	R-Squared	0.9707
Mean	-3.535E-003	Adj R-Squarec	0.9480
C.V. %	1909.78	Pred R-Square	0.8906
PRESS	0.15	Adeq Precisio	20.957

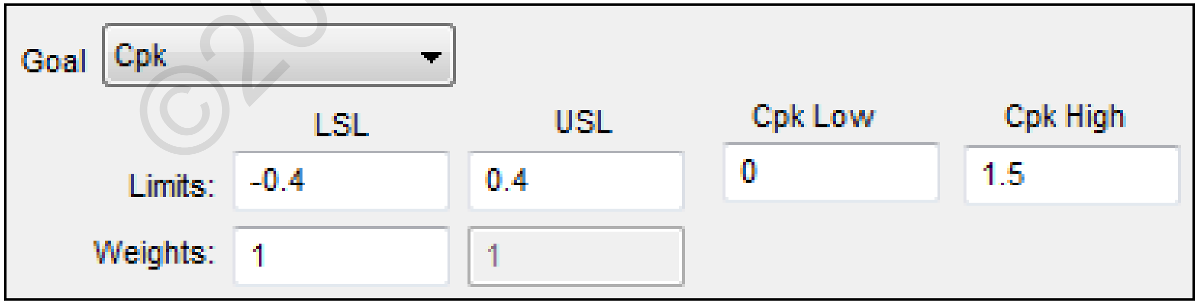
Employing C_{pk} (or P_{pk}) to optimize your DOE Lathe Case Study

Variation of Inputs:

Variable	Std Dev: $\hat{\sigma}_{ii}$
A – Speed	5 fpm
B – Feed	0.00175 ipr
C – Depth	0.0125 inches

Specifications: Delta = 0.000 ± 0.400

Goal is to maximize P_{pk}:



Employing C_{pk} (or P_{pk}) to optimize your DOE Lathe Case Study

Factor	Name	Level	Low Level	High Level	Std. Dev.	Coding				
A	Speed	8.187E-003	-1.00	1.00	5.00	Coded				
B	Feed	1.00	-1.00	1.00	1.750E-003	Coded				
C	Depth	-0.41	-1.00	1.00	0.013	Coded				
	Predicted	Predicted				CI for Mean		99% of Population		
Response	Mean	Median¹	Observed	Std Dev	SE Mean	95% CI low	95% CI high	95% TI low	95% TI high	Cpk
delta	-0.0634	-0.0634	-	0.0675	0.0354	-0.144	0.0167	-0.414	0.288	1.66
delta (POE)	2.02E-008	2.02E-008	-	0.12	0.0629	-0.142	0.142	-0.623	0.623	1.11

delta: $C_{pk} = 1.66$

delta (POE): $C_{pk} = 1.11$ *(more like P_{pk})*

Conclusions: Employing C_{pk} (or P_{pk}) to optimize your DOE

Advantages:

- Brings specifications into the optimization.
- Can use POE to better represent long term variability.
- In multiple response optimization the various process capabilities can be weighted by importance of response.
- Can explore what if questions, e.g. what if there was better control of various factors; e.g. compare C_{pk} without POE to C_{pk} with POE (P_{pk}).

Practical DOE “Tricks of the Trade”

- Using standard error to constrain optimization
- Employing C_{pk} (or P_{pk}) to optimize your DOE
- **Combining categoric factors**
  Reduce redundancy and number of runs.
- A Couple of Case Studies
  - The Loose Collet
  - A Case to Test Your Metal

Combining Categoric Factors
CWA detection Case Study

Goal: Prove effectiveness of a remote detection system for a chemical-warfare agent (CWA).

Factors and levels:

A.	CWA	(Threshold, Objective)
B.	Interferent	(None, Burning diesel, Burning plastic)
C.	Time	(Day, Night)
D.	Distance	(1 km, 3 km, 5 km)
E.	Environment	(Desert, Tropical, Arctic, Urban, Forest)
F.	Season	(Summer, Winter)
G.	Temperature	(High, Low)
H.	Humidity	(High, Low)

Combining Categoric Factors

CWA detection Case Study

Looking at the last four factors, there are too many combinations (40) and not all of these combinations are meaningful:

- E. Environment (Desert, Tropical, Arctic, Urban, Forest)
- F. Season (Summer, Winter)
- G. Temperature (High, Low)
- H. Humidity (High, Low)

Not meaningful: Tropical with low temperature and low humidity
Arctic with high temperature and high humidity

Solution is to combine these four categorical factors into one.

Combining Categoric Factors
CWA detection Case Study

The eight most meaningful combinations:

Background	Temperature	Humidity
Desert Winter	Low	Low
Desert Summer	High	Low
Tropical	High	High
Arctic	Low	Low
Urban Winter	Low	Low
Urban Summer	High	High
Forest Winter	Low	Low
Forest Summer	High	High

Conclusions:
Combining Categoric Factors

Advantages:

- Number of runs reduced.
  - Runs reduced by 80% (1,440 to 288) for CWA.
- All the combinations can be run and result in meaningful results.
- Can fit a full model.
  Preventing meaningless (or impossible) runs that result in missing data thereby creating an aliased model.

Practical DOE "Tricks of the Trade"

- Using standard error to constrain optimization
- Employing C_{pk} (or P_{pk}) to optimize your DOE
- Combining categoric factors
- **A Couple of Case Studies**
  - **The Loose Collet**
    Diagnostics plus subject matter knowledge save the day.
  - A Case to Test Your Metal

The Loose Collet *

Background *(page 1 of 2)*

1. A computer controlled lathe feeds in bar stock, cuts it, machines the surface and releases a part. The collet holds the part in place as it is being machined. The operator programs the speed (rate of spin) and feed (depth of cut). The operator hand tightens the collet.

2. The response is surface finish, measured on the same one inch section of each part. The higher the reading the rougher the surface. Low readings (a smooth surface) are desirable.

* William H. Collins and Carol B. Collins, *Quality Engineering*, Vol. 6, No.4, 1994, p. 547.

The Loose Collet
Background *(page 1 of 2)*

3. The factors studied are:

	Factor	-1	+1	Units
A	Speed	2500	4500	rpm
B	Feed	0.003	0.009	in/rev
C	Collet	Loose	Tight	
D	Tool wear	New	after 250 parts	

4. The design run was a 2^4 replicated factorial.

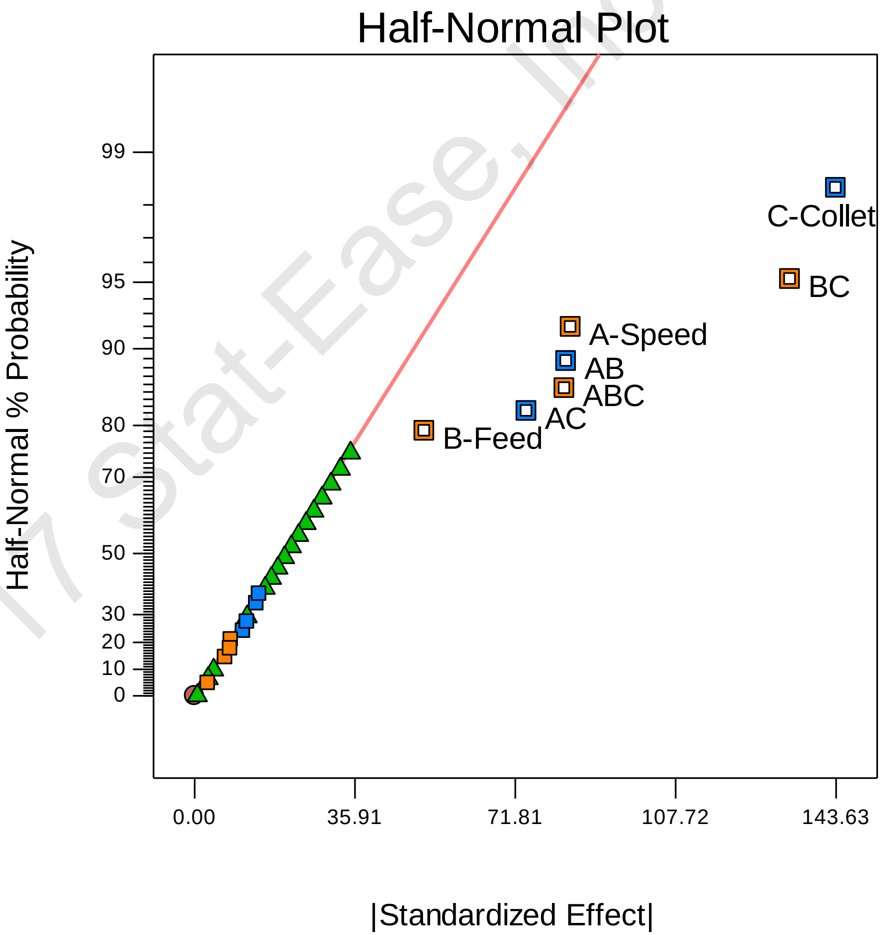
5. Determine what is causing rough surface?

The Loose Collet
Analysis Replicated 2^4

Design-Expert® Software
Finish

▲ Error estimates

Shapiro-Wilk test
W-value = 0.792
p-value = 0.024
A: Speed
B: Feed
C: Collet
D: Tool wear
■ Positive Effects
■ Negative Effects



The Loose Collet
Analysis Replicated 2^4

Transform | Effects | ANOVA | Diagnostics

ANOVA for selected factorial model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	5.400E+005	7	77140.36	15.32	< 0.0001
A-Speed	*56784.50*	*1*	*56784.50*	*11.28*	*0.0026*
B-Feed	*21218.00*	*1*	*21218.00*	*4.21*	*0.0511*
C-Collet	*1.650E+005*	*1*	*1.650E+005*	*32.78*	*< 0.0001*
AB	*55444.50*	*1*	*55444.50*	*11.01*	*0.0029*
AC	*44253.13*	*1*	*44253.13*	*8.79*	*0.0067*
BC	*1.423E+005*	*1*	*1.423E+005*	*28.27*	*< 0.0001*
ABC	*54946.13*	*1*	*54946.13*	*10.91*	*0.0030*
Residual	1.208E+005	24	5034.38		
Lack of Fit	*6763.00*	*8*	*845.38*	*0.12*	*0.9976*
Pure Error	*1.141E+005*	*16*	*7128.88*		
Cor Total	6.608E+005	31			

Std. Dev.	70.95	R-Squared	0.8172
Mean	203.63	Adj R-Squarec	0.7638
C.V. %	34.85	Pred R-Square	0.6749
PRESS	2.148E+005	Adeq Precisio	12.529

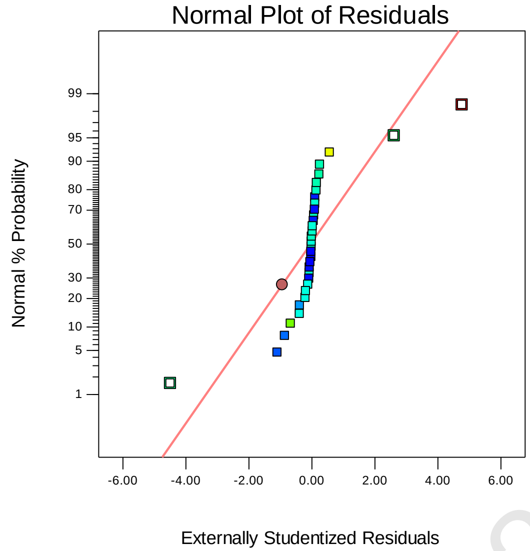
The Loose Collet

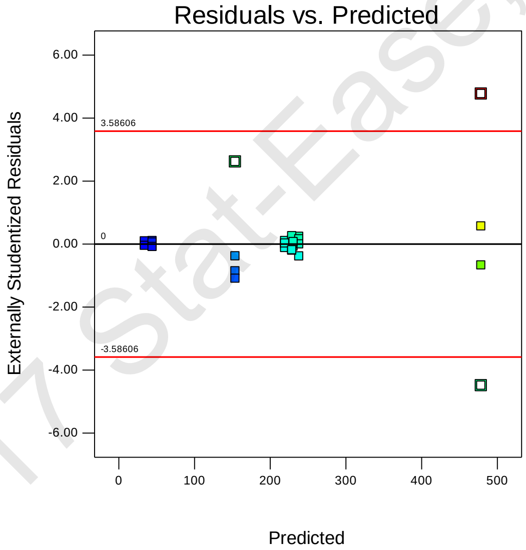
Diagnostic Plots Replicated 2^4

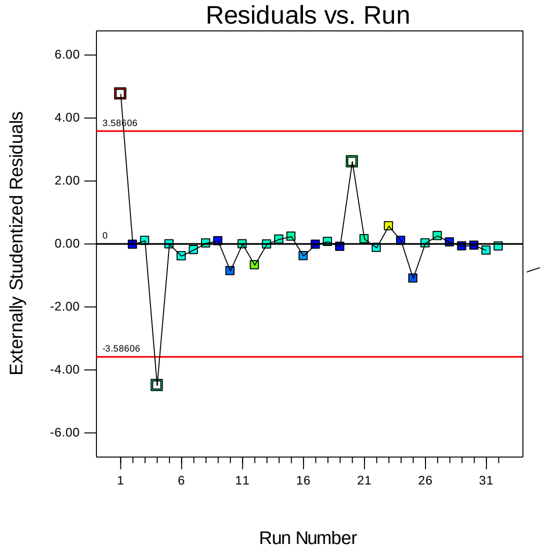
Stat-Ease
statistics made easy

Residual Plots

(runs 1, 4 & 20 are highlighted)







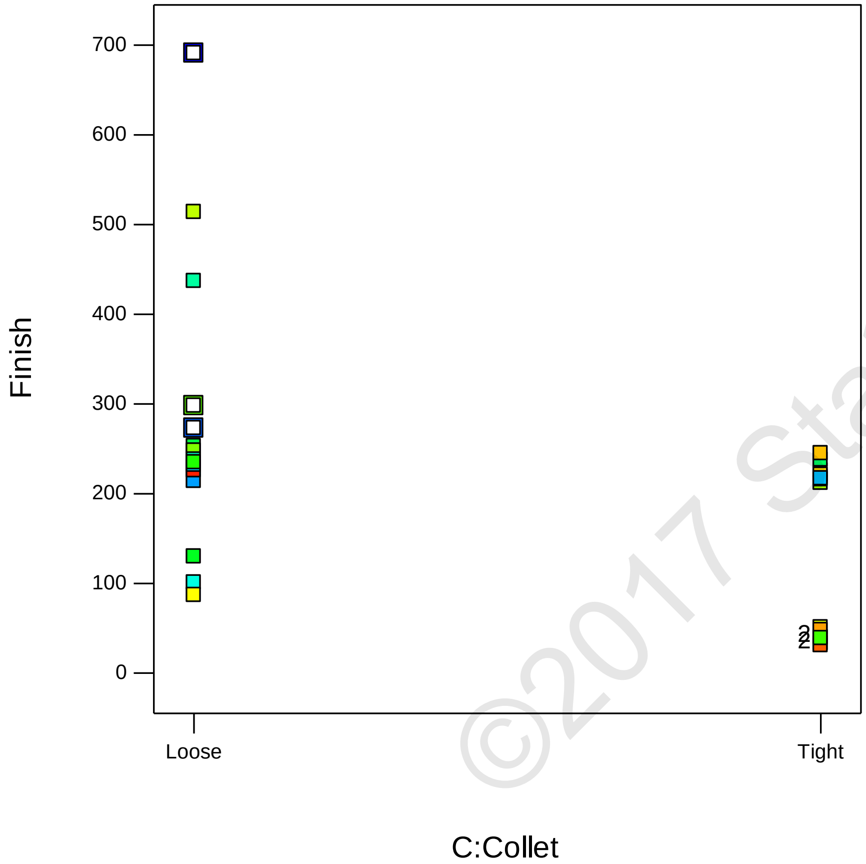
The Loose Collet
Raw Data

The residuals from runs 1, 4 and 20 seem unusually large:

Std	Run	Factor A:Speed rpm	Factor B:Feed in/rev	Factor C:Collet	Factor D:Tool wear	Response Finish
1	10	2500	0.003	Loose	New	101
2	16	2500	0.003	Loose	New	130
3	**4**	**4500**	**0.003**	**Loose**	**New**	**273**
4	**1**	**4500**	**0.003**	**Loose**	**New**	**691**
5	15	2500	0.009	Loose	New	253
			•			
16	27	4500	0.009	Tight	New	245
17	**20**	**2500**	**0.003**	**Loose**	**After 250**	**298**
18	25	2500	0.003	Loose	After 250	87
			•			
31	31	4500	0.009	Tight	After 250	216
32	7	4500	0.009	Tight	After 250	217

These three runs occur when at slow feed and a loose collet. When measuring the surface finish, it was noted that this treatment combination produced an unusual finish. The surface profile looked like a sine wave. The problem is clear; the bar oscillated and caused an uneven cut pattern.

The Loose Collet
Graph Columns



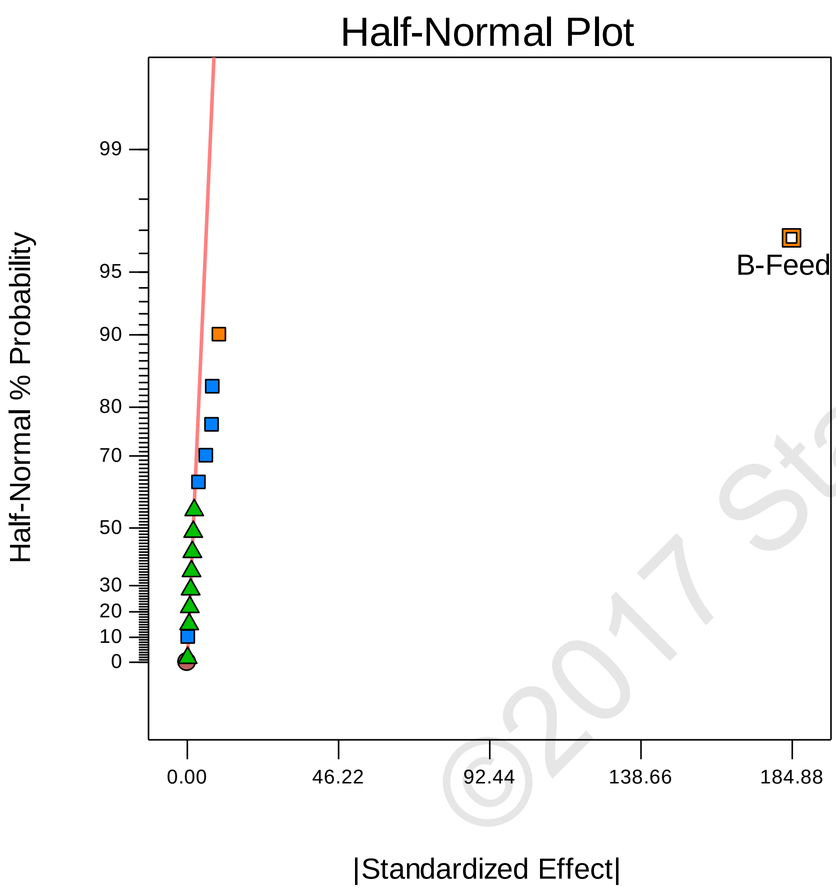
What we've learned so far:

- A loose collet is consistently bad.
- Never use a loose collet in production.

Next steps:

- Ignore loose collet data.
- Reanalyze the remaining data (a replicated 2^3 factorial).

The Loose Collet
Analysis w/o Loose Collet



Transform | Effects | ANOVA | Diagnostics

Response 1 **Finish**

These rows were ignored for this analysis.

10, 16, 4, 1, 15, 6, 13, 32, 20, 25, 23, 12, 21, 11, 8, 18

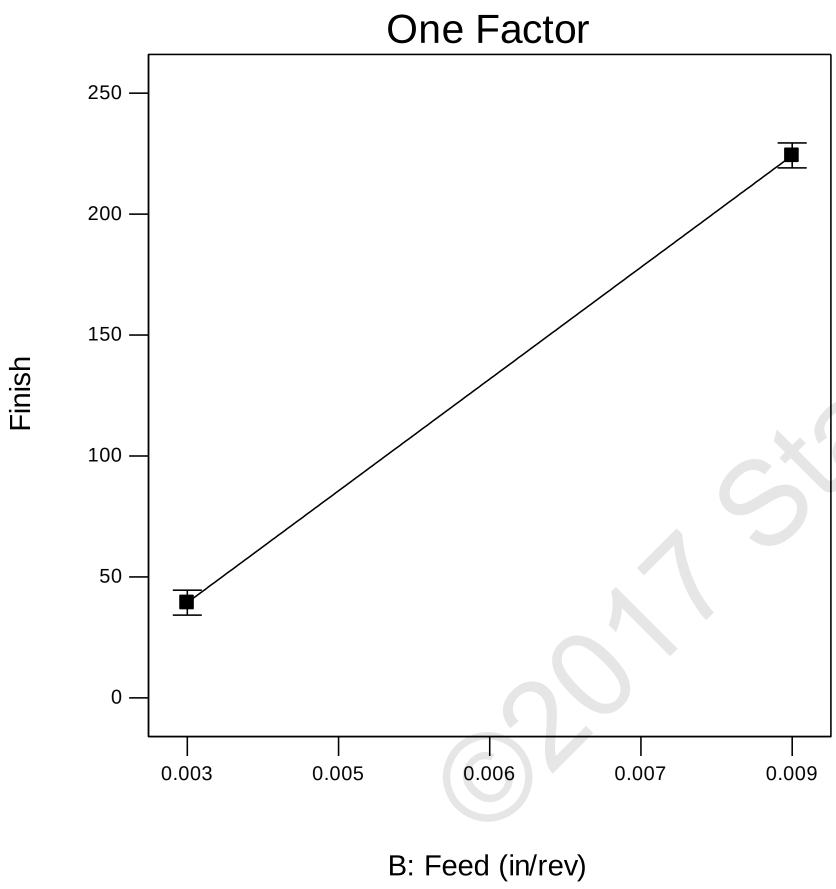
ANOVA for selected factorial model

Analysis of variance table [Partial sum of squares - Type III]

Source	**Sum of Squares**	**df**	**Mean Square**	**F Value**	**p-value Prob > F**
Model	1.367E+005	1	1.367E+005	1479.86	< 0.0001
B-Feed	*1.367E+005*	*1*	*1.367E+005*	*1479.86*	*< 0.0001*
Residual	1293.37	14	92.38		
Lack of Fit	*1061.87*	*6*	*176.98*	*6.12*	*0.0113*
Pure Error	*231.50*	*8*	*28.94*		
Cor Total	1.380E+005	15			

Std. Dev.	9.61	R-Squared	0.9906
Mean	131.81	Adj R-Squarec	0.9900
C.V. %	7.29	Pred R-Square	0.9878
PRESS	1689.31	Adeq Precisio	54.403

The Loose Collet
Analysis w/o Loose Collet



Take Away:

- Feed (depth of cut) is the only factor that affects surface finish when you use a tight collet!
- A simple solution that could have been complicated if we had:
  - Not paid attention to the residual plots.
  - Not used our subject matter knowledge to ignore loose collets!

Practical DOE "Tricks of the Trade"

- Using standard error to constrain optimization
- Employing C_{pk} (or P_{pk}) to optimize your DOE
- Combining categoric factors
- **A Couple of Case Studies**
  - The Loose Collet
  - **A Case to Test Your Metal**
    Trick to detect outlier and investigation save the day.

A Case to Test Your Metal *

Background *(page 1 of 2)*

A customer of Stat-Ease examined his aluminum casting process using a fractional factorial design. He studied five factors in a 2^{5-1} factorial design:

A) Hot oil temperature

B) Trip in mm

C) Molten aluminum temperature

D) Fast shot velocity

E) Dwell time

The fraction defective out of 100 parts, was recorded for each design point. To his dismay, none of the factors seemed to make any difference.

* From Stat-Ease client files: Dave DeVowe, Tool Products

A Case to Test Your Metal *

Background *(page 2 of 2)*

Look at the Response Data

Select	Std	Run	Factor 1 A:Hot Oil Degrees F	Factor 2 B:Trip mm	Factor 3 C:Metal Degrees F	Factor 4 D:Fast Shot mm	Factor 5 E:Dwell sec	Response 1 Defects Fraction
	13	1	350	390	1300	2.20	5.50	0.30
	15	2	350	410	1300	2.20	3.50	0.22
	6	3	450	390	1300	1.60	5.50	0.90
	14	4	450	390	1300	2.20	3.50	0.06
	11	5	350	410	1260	2.20	5.50	0.38
	16	6	450	410	1300	2.20	5.50	0.38
	4	7	450	410	1260	1.60	5.50	0.42
	8	8	450	410	1300	1.60	3.50	0.14
	1	9	350	390	1260	1.60	5.50	0.14
	9	10	350	390	1260	2.20	3.50	0.22
	12	11	450	410	1260	2.20	3.50	0.12
	2	12	450	390	1260	1.60	3.50	0.98
	7	13	350	410	1300	1.60	5.50	0.28
	3	14	350	410	1260	1.60	3.50	0.36
	10	15	450	390	1260	2.20	5.50	0.26
	5	16	350	390	1300	1.60	3.50	1.00

Note:
Lots of variation in the response!

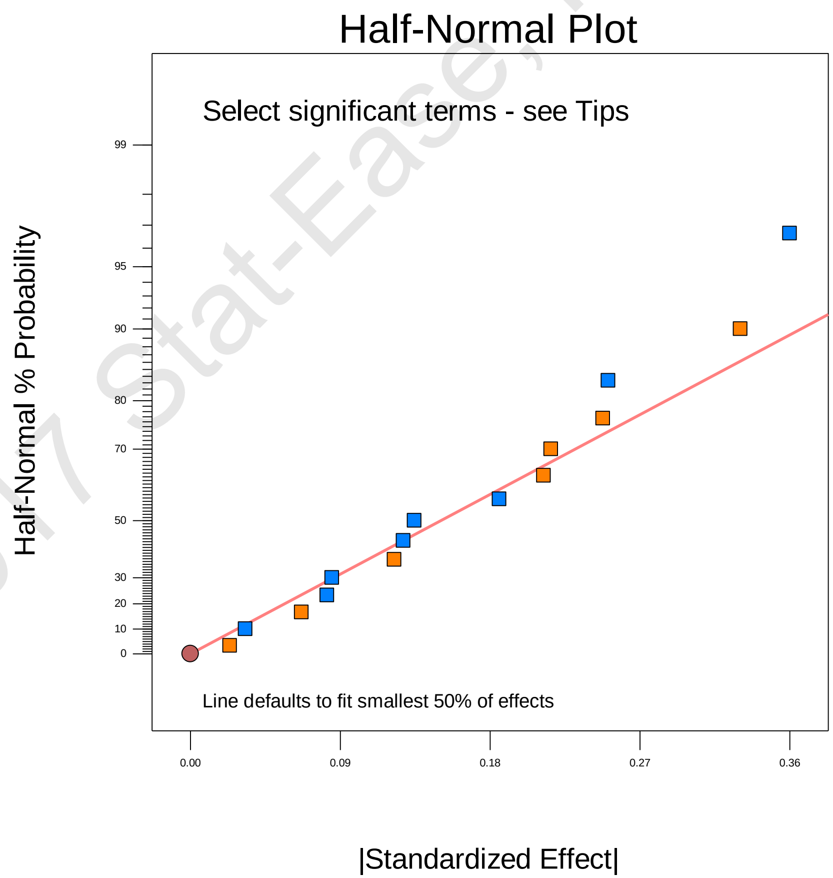
A Case to Test Your Metal

Analysis – First Pass

Notice all the effects fall in a line!

Design-Expert® Software
ArcSin(Sqrt(Defects))

Shapiro-Wilk test
W-value = 0.974
p-value = 0.909
A: Hot Oil
B: Trip
C: Metal
D: Fast Shot
E: Dwell
Positive Effects
Negative Effects



A Case to Test Your Metal
Analysis – Second Pass

Lots of variation in the responses, but no effects!

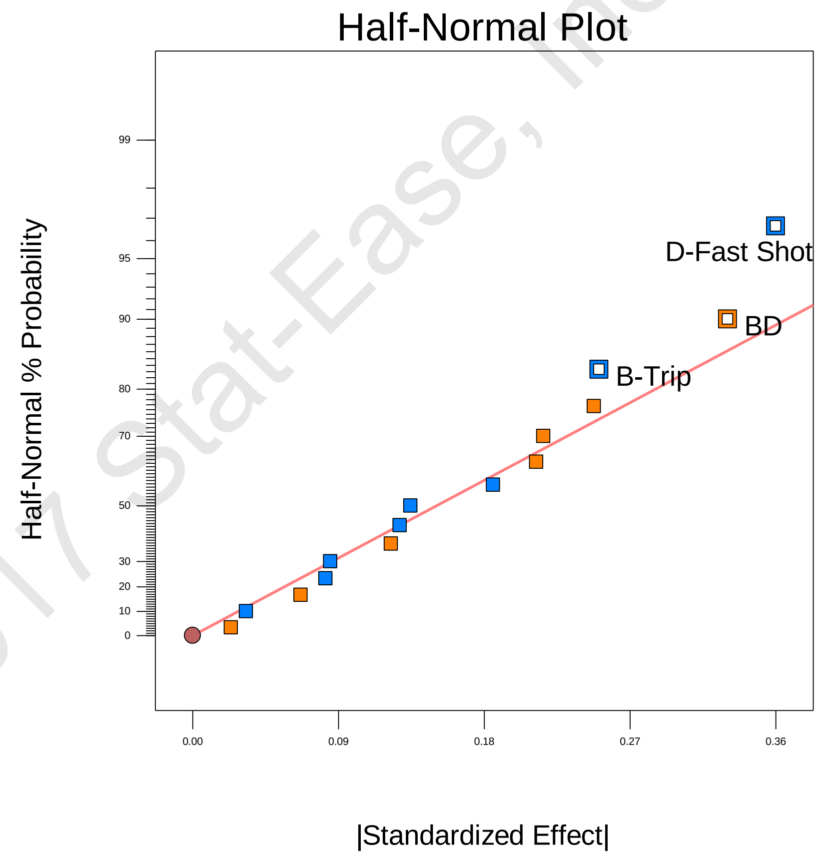
Procedure to detect a possible outlier:

1. Pick a couple of the most extreme effects on the half normal plot.
2. Look for a potential outlier.
3. Judge influence of potential outlier.
4. Investigate the suspected outlier.
5. “Ignore” the outlier and reanalyze the design.

1. Pick a couple of the most extreme effects on the half normal plot.

Design-Expert® Software
ArcSin(Sqrt(Defects))

Shapiro-Wilk test
W-value = 0.921
p-value = 0.295
A: Hot Oil
B: Trip
C: Metal
D: Fast Shot
E: Dwell
Positive Effects
Negative Effects



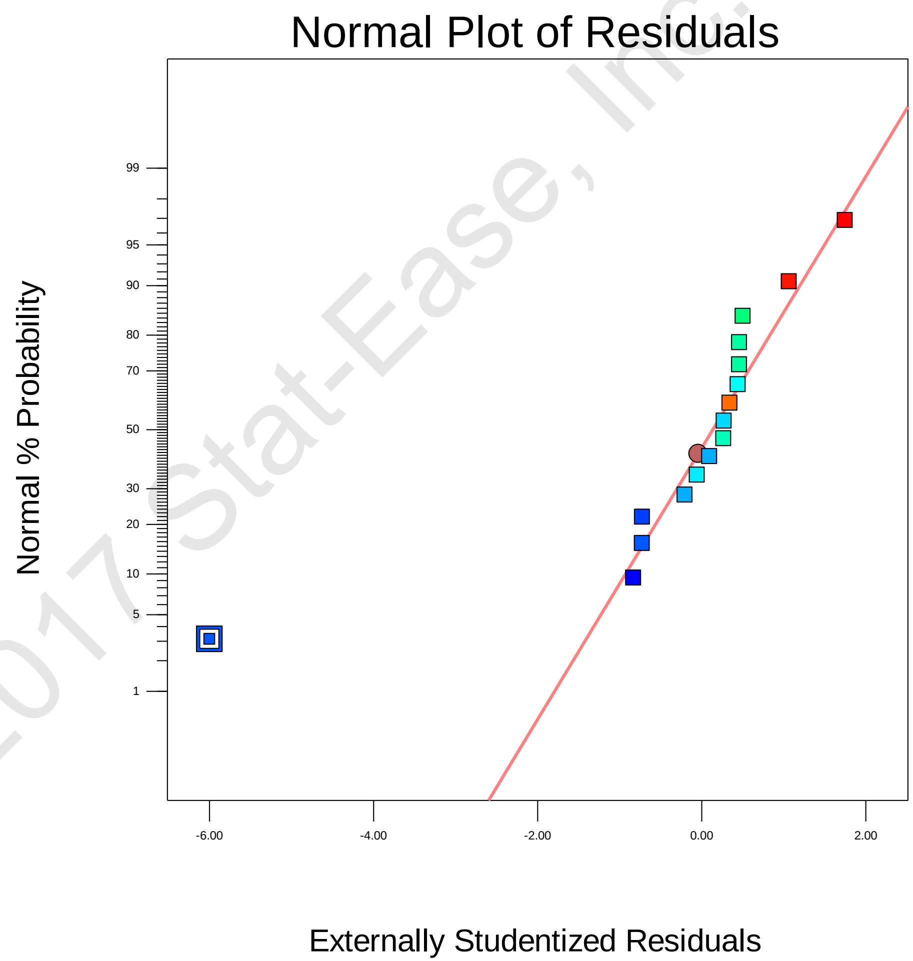
A Case to Test Your Metal

2. Look for a potential outlier. *(page 1 of 2)*

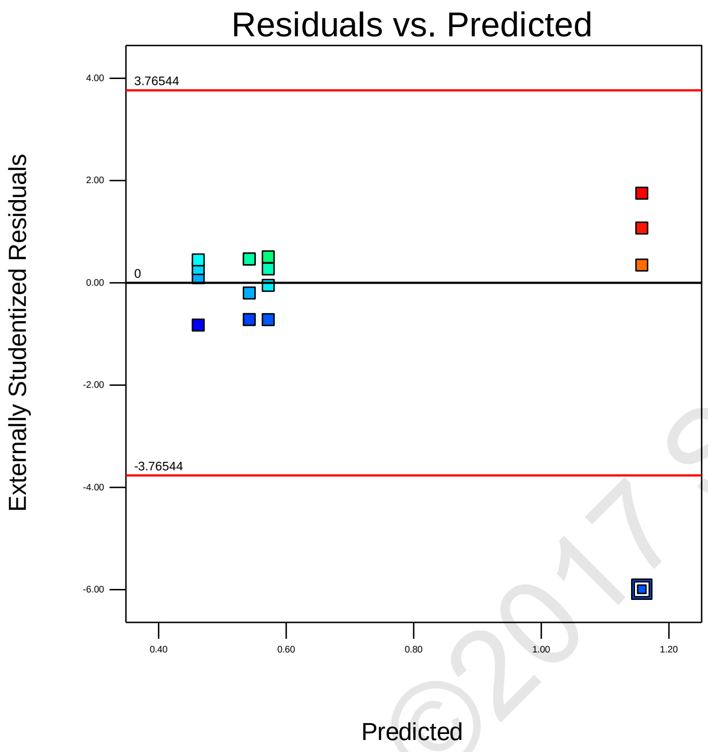
Design-Expert® Software
ArcSin(Sqrt(Defects))

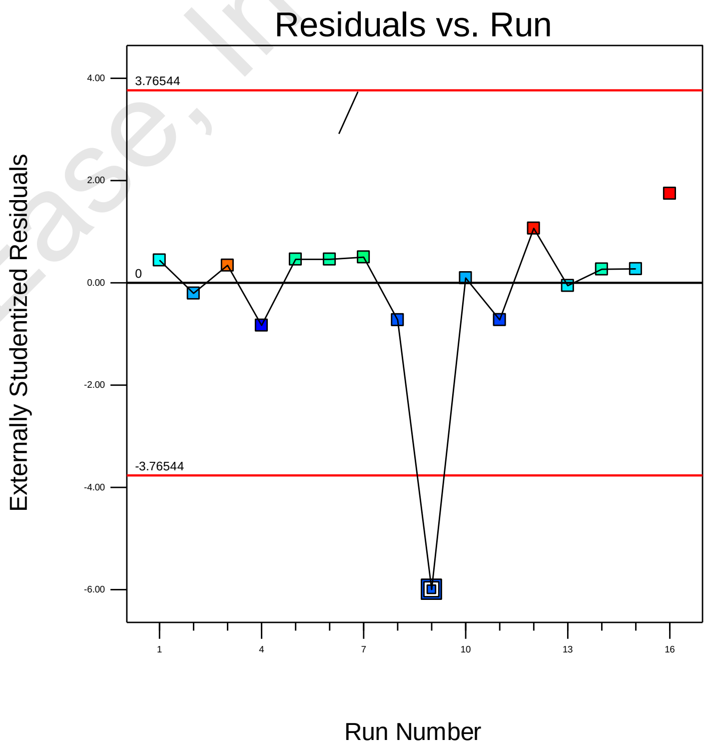
Color points by value of
ArcSin(Sqrt(Defects)):
1.571
0.247

Std # 1 Run # 9
X: -5.997
Y: 3.1

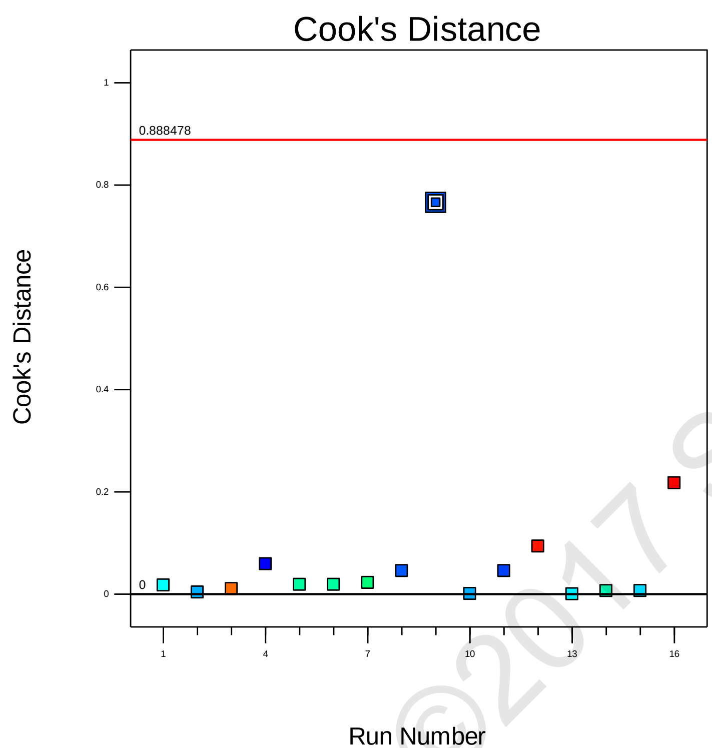


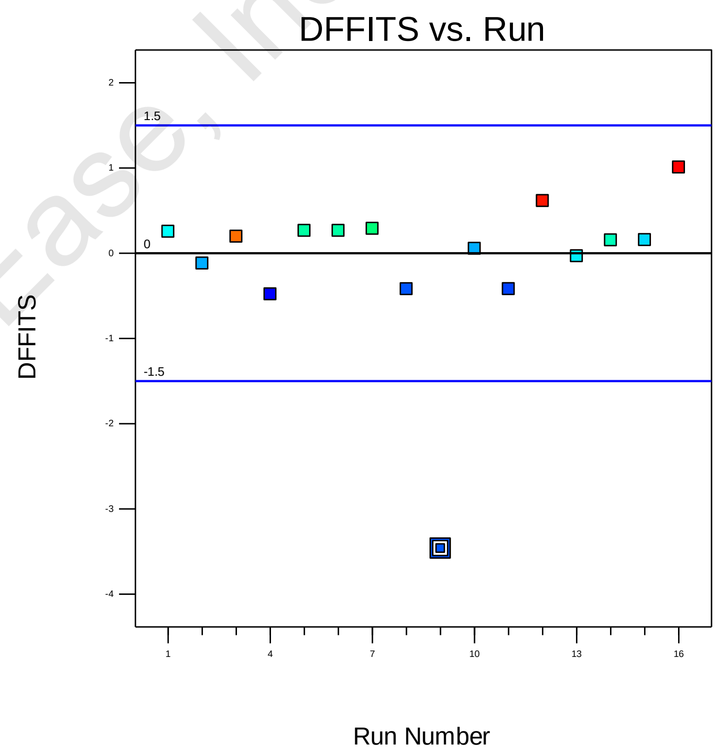
A Case to Test Your Metal
2. Look for a potential outlier. *(page 2 of 2)*





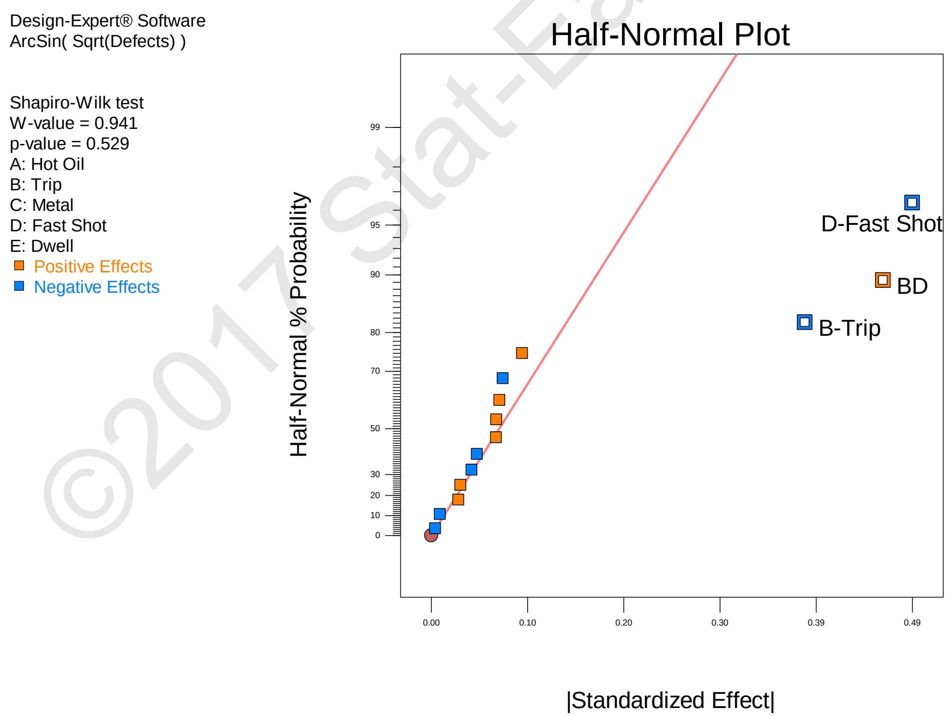
A Case to Test Your Metal
3. Judge influence of potential outlier.





A Case to Test Your Metal

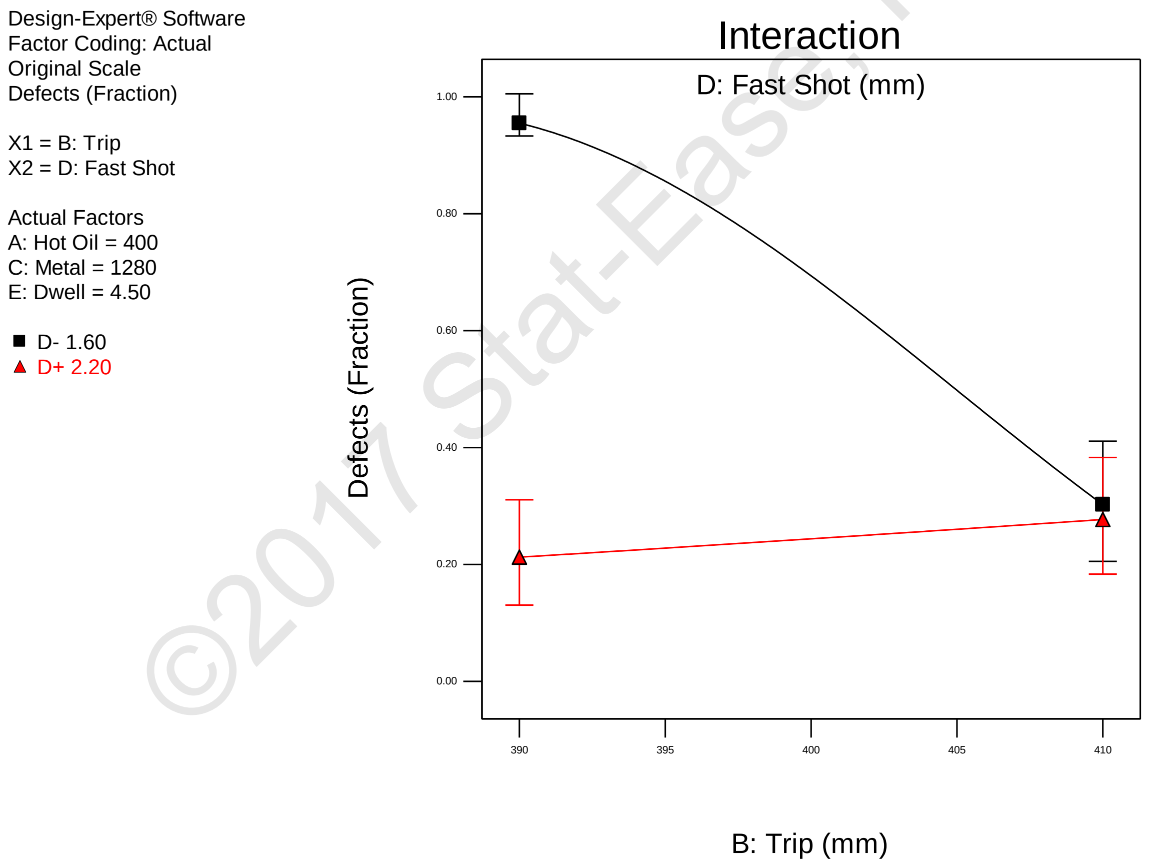
4. Investigate the suspected outlier.
   (The operator confirmed problems with run 9 (std 1))
5. “Ignore” the outlier and reanalyze the design.



A Case to Test Your Metal

Analysis – Second Pass

Do not use a **390** "Trip" with a **1.60** "Fast Shot":



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Practical DOE – “Tricks of the Trade”

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pat@statease.com

Thank you for joining me today!