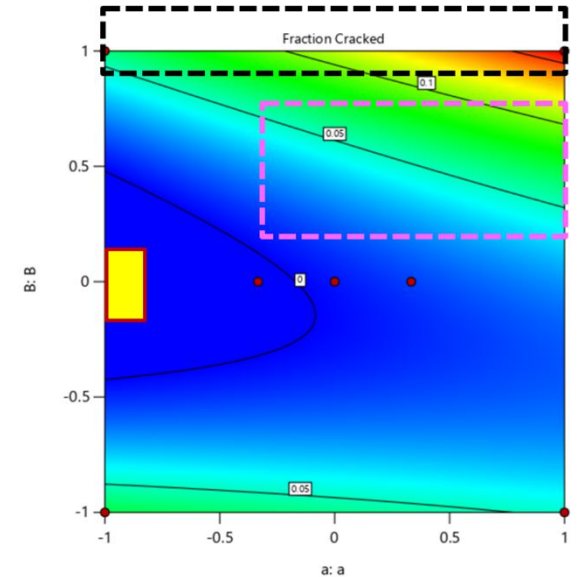


# Case Cracked: Setting Process Windows with Design Expert

Solving a Major Customer Crack Issue Using Statistically-Based Process Windows from a Split Plot Experiment using Design Expert



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# ◆ Agenda

- **The Customer Crack Problem**
- **Don't Jump Immediately Into a DOE**
  - Describe the Problem
  - Use Data Mining to Get Clues
  - Institute Interim Containment Actions if Necessary
  - Ensure Measurement Systems are Valid
- **Find the Process Drivers**

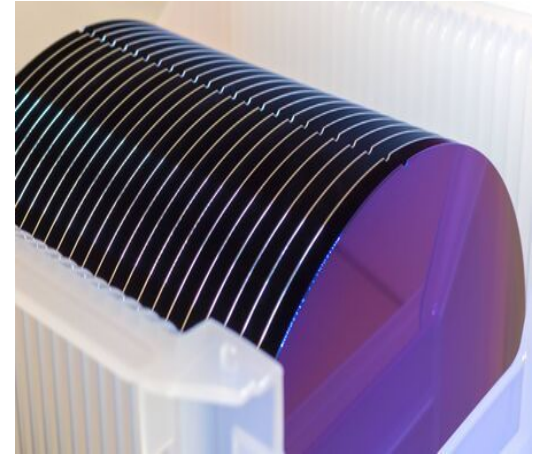
(2FI Split Plot Experiment Using Design Expert)
- **Set Statistically-Based Process Windows**

Conduct a Response Surface Experiment to Set Process Windows (Quadratic Split Plot Experiment Using Design Expert)

# ◆ The Problem

# ◆ The Problem

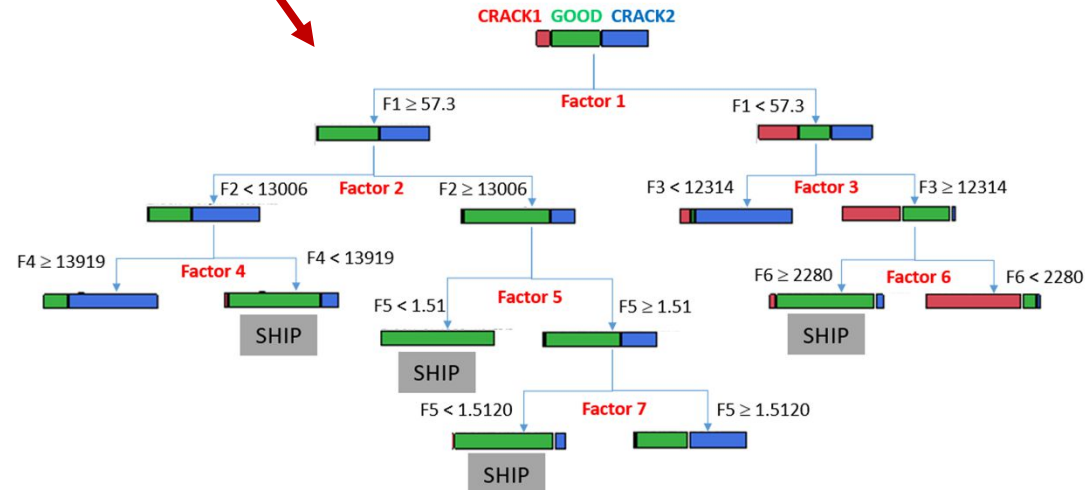
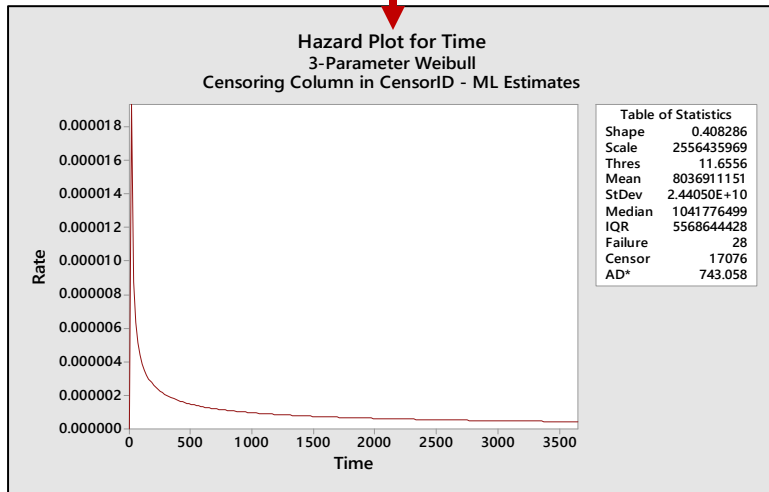
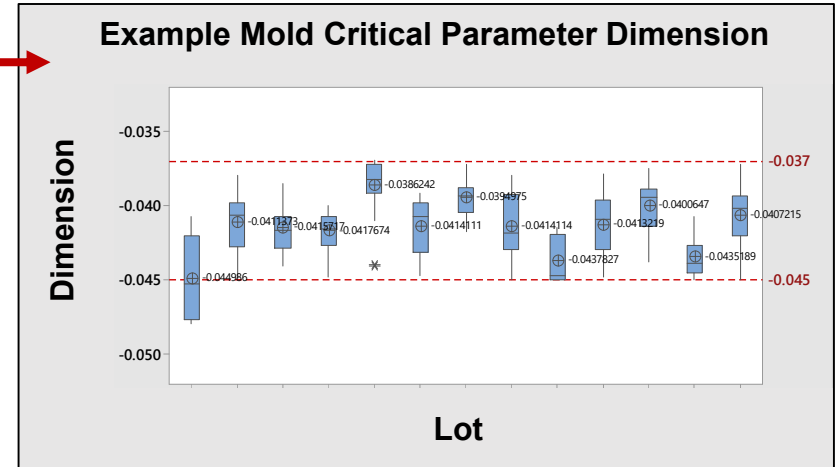
- Second time latent crack problem occurred for the same customer in 2 years.
- Cracks cause line stoppage, delays, cleanings and extra handling resulting in damage and lost revenue for the customer.
- Due to the history of this problem and the customer sensitivity, this is a problem that needs to be resolved quickly.
- Issue is known to be a material issue (resin batch), but qualifying a new design with a new material is a long-term solution. A solution is needed now.
- Constraint: Can only detect cracks after some time used at the wafer fab.



- ◆ Don't Jump  
Immediately  
Into a DOE

# Describe the Problem and Institute Interim Containment Actions

1. **SPC** review of production charts.
2. **Data Mining** determined short list of factors that are associated with cracking.
3. **Recursive Partition Screening Model** for product at the customer, in transit or in warehouses. Used to set initial containment process windows.
4. **Reliability Weibull Model** built to show that the failure mechanism is infant mortality.



# ◆ Develop a Way to Detect Likelihood of Cracking Inside the Factory

- Tried drop tests and vibration tests without success.
- Developed a destructive chemical test which would release built in stress in the molded part and correlated to cracking in the customer application. Time to cracking is also collected.
- Validated the test on known high defect rate lots and known no defect lots. Achieved a low false positive and false negative rate.

- ◆ Finding  
Process Drivers



# ◆ Screening DOE 1 for Process Drivers

- Screening Design in 5 factors.
- One factor is a temperature which is hard-to-vary in that it requires a time to stabilize and make initialization shots through the mold. To completely randomize this factor would result in delays and too much lost production time.
- Thus, we will restrict the randomization of this factor by using a Split Plot Design recommended by Design Expert to support a two factor interaction model. Since the experiment is to be run over 2 days, we block on day-to-day variation.

# ◆ Concept of a Split Plot Experiment

Fertilizers are applied by a crop duster on an entire field. By contrast, seed variety can be planted manually in smaller plots.

Fertilizer: Whole Plot Factor

Seed Variety: Sub-Plot Factor

Fields (Groups): Provide Whole Plot Replicates; Rep 1 = Fields 1 & 2; Rep 2 = Fields 3 & 4.

Note different sized Experimental Units. Whole Plots have been “split” into smaller Experimental Units for the sub-plot factor. Care must be taken to use the correct error terms for testing factors.

## Fertilizer 1

### Field 1

Seed 1	Seed 2
Seed 2	Seed 1
Seed 1	Seed 2

### Field 3

Seed 2	Seed 1
Seed 1	Seed 2
Seed 1	Seed 2

## Fertilizer 2

### Field 2

Seed 2	Seed 1
Seed 2	Seed 1
Seed 1	Seed 2

### Field 4

Seed 1	Seed 2
Seed 1	Seed 2
Seed 2	Seed 1

In manufacturing, randomly decide which level of the whole plot factor (temperature) goes first, then randomize the remaining factors (B and C) within that whole plot. Repeat with the next whole plot factor level (temperature). Then replicate.

# ◆ DOE 1 for Process Drivers

## Optimal (Custom) Design

Use the Optimal Design for Response Surface Designs with 5 factors (a 6<sup>th</sup> is known to be active so is not included in screening). Since interactions in molding are common, we use a 2FI model.

Search:  Optimality:

2FI

Blocks:  (1 to 1000)

Variance ratio:  (0.0 to 1000.0)

Groups

Required groups:

Additional groups:

Center point groups:

Center point group size:

Total groups: 6

Runs

Required model points:

Additional model points:

Center points:

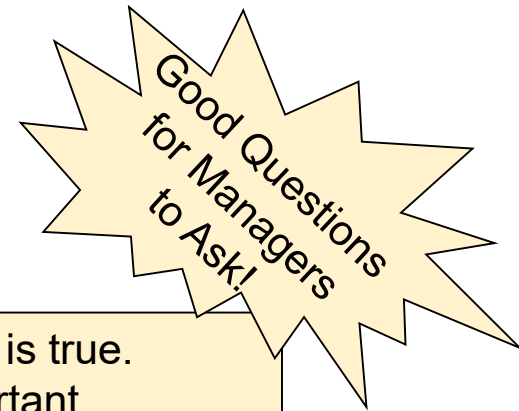
Total runs: 23

	Name	Units	Change	Type	Levels	L[1]	L[2]
a [Numeric]	a		Hard	Continuous	N/A	-1	1
B [Numeric]	B		Easy	Continuous	N/A	-1	1
C [Numeric]	C		Easy	Continuous	N/A	-1	1
D [Numeric]	D		Easy	Continuous	N/A	-1	1
E [Categoric]	E		Easy	Nominal	2	1	2

Block	Group	Run	Factor 1 a:a	Factor 2 B:B	Factor 3 C:C	Factor 4 D:D	Factor 5 E:E	Response 1 Fraction of Level...
Block 1	1	1	1	1	-1	1	2	0.105882
Block 1	1	2	1	1	1	1	1	0.178571
Block 1	1	3	1	-1	1	1	2	0.205882
Block 1	1	4	1	-1	1	-1	2	0.205882
Block 1	2	5	-1	1	1	-1	1	0.178571
Block 1	2	6	-1	1	-1	-1	2	0.205882
Block 1	2	7	-1	-1	-1	1	2	0.0714286
Block 1	2	8	-1	-1	1	1	1	0.0294118
Block 1	3	9	1	1	-1	1	1	0.178571
Block 1	3	10	1	-1	-1	1	1	0.178571
Block 1	3	11	1	1	-1	-1	1	0.205882
Block 1	3	12	1	-1	1	-1	1	0.178571
Block 2	4	13	-1	1	-1	1	2	0.392857
Block 2	4	14	-1	1	-1	1	1	0.454545
Block 2	4	15	-1	1	1	1	2	0.636364
Block 2	4	16	-1	-1	-1	-1	1	0.178571
Block 2	5	17	-1	1	1	-1	2	0.454545
Block 2	5	18	-1	-1	1	-1	2	0.214286
Block 2	5	19	-1	1	1	1	1	0.178571
Block 2	6	20	1	-1	-1	-1	2	0.392857
Block 2	6	21	1	1	1	-1	2	0.441176
Block 2	6	22	1	1	1	-1	1	0.214286
Block 2	6	23	1	-1	-1	1	2	0.441176

Term	Standard Error*	Error df†	VIF	Restricted‡ VIF	Power
<b>Whole-Plot</b>					
a	0.4836	3	1.12092	1.02751	30.4 %
<b>Subplot</b>					
B	0.2336	3	1.10394	1.18985	80.4 %
C	0.2753	3	1.12092	1.38736	68.1 %
D	0.2497	3	1.12092	1.26457	75.6 %
E	0.3179	3	1.12092	1.79589	56.9 %
aB	0.2433	3	1.10394	1.29063	77.5 %
aC	0.2689	3	1.12092	1.32334	69.9 %
aD	0.2558	3	1.12092	1.32198	73.8 %
aE	0.2807	3	1.12092	1.40953	66.6 %
BC	0.2674	3	1.12092	1.24588	70.4 %
BD	0.3172	3	1.12092	1.46589	57.0 %
BE	0.2461	3	1.10394	1.22658	76.7 %
CD	0.2296	3	1.06997	1.10247	81.6 %
CE	0.3257	3	1.12092	1.81191	55.0 %
DE	0.2658	3	1.12092	1.40664	70.8 %

# ◆ 5 Conditions to Accept a Conclusion from Data



- 1. Stability:** Data are stable (in-control);  
Any unusually large or small values (outliers)? Any unusual conditions when the data were taken? Trends? Shifts? Non-random patterns?
- 2. Real:** p-value supports conclusion and assumptions for test are OK;  
The p-value from a statistical test shows the result is real and not noise.
- 3. Important:** There is practical significance;  
Does the magnitude of the result help to make it practically worthwhile.
- 4. Why True:** Understand why the result is true;  
Can you explain why it is true? Do you have a theory?  
Does the conclusion fit with subject matter knowledge?
- 5. Equitable Sample:** The sample is collected fairly.  
Sample is representative. No bias or confounding with the sample.  
The sample size is sufficiently large so we are not being fooled.

**W**hy it is true.  
**I**mportant.  
**S**tability.  
**E**quitable Sample.  
**R**eal, not Noise.

**Ask the right questions**  
⇒ **Collect Data** ⇒ **Analysis**

- ↓
1. H0: Factor not Active  
H1: Factor is active

2. Test Statistic
3. P-value

- Assumptions: (t-tests, ANOVA, Regression, DOE)
1. Independent Data
  2. Equal Variation
  3. Normality

4. Conclusion
- ← {
1. Stability
  2. Real (not Noise)
  3. Important
  4. Why True
  5. Sample is Fair

# ◆ DOE 1 for Process Drivers

Source	Term	df	Error df	F-value	p-value	
<b>Whole-plot</b>		1	2.05	2.09	0.2819	not significant
a-a		1	2.05	2.09	0.2819	
<b>Subplot</b>		5	13.07	9.75	0.0005	significant
B-B		1	11.98	14.75	0.0024	
C-C		1	14.93	0.1489	0.7050	
E-E		1	15.02	5.43	0.0341	
aB		1	12.82	20.59	0.0006	
CE		1	15.00	5.63	0.0315	

**ANOVA to confirm statistical significance.**

## 1. What did you learn?

AB & CE interactions are active.

No outliers.

Significant p-value with assumptions satisfied.

Important (see contour plot)

Understand why this is true.

Equitable data collection.

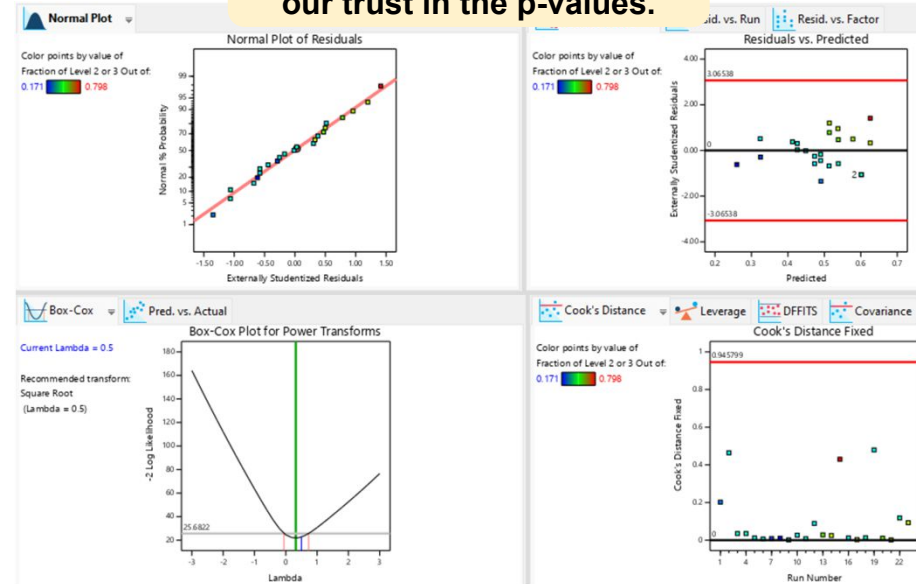
## 2. What action are you going to take?

Fix the categorical factor E = 1 and fix C = 1.

Keep factors A and B. Also add a new factor C which is known by engineering to be active.

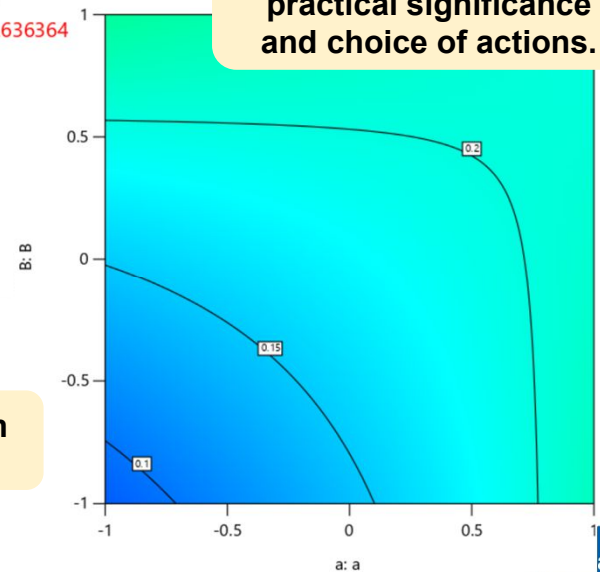
Fit a quadratic model to determine process windows for Factors A, B and C.

**Diagnostics: To confirm our trust in the p-values.**



**Plots to confirm practical significance and choice of actions.**

Factor Coding: Actual  
 0.0294118 0.636364  
 X1 = a  
 X2 = B  
**Actual Factors**  
 C = 1  
 D = 0  
 E = 1



**Optimizer: To confirm the best solution.**

Number	a	B	C	D	E	Fraction of Level 2 or 3 Out of	Desirability
1	-1.000	-1.000	1.000	0.000	1	0.085	0.674 Selected

- ◆ Setting  
Statistically-  
Based Process  
Windows

# ◆ Concept of Statistically-Based Process Windows for 2 Factors

Converting a Contour Plot on the Average Response into Process Windows on the Individual Responses.

1. A statistical model is always a model for the average.
2. Suppose points vary according to a normal distribution with standard deviation  $s$ , above and below the surface specified by  $A$  and  $B$ .
3. Then  $Y + ks$  and  $Y - ks$  raises and lowers this surface according to where the individual points may vary. The overlaid contour plot for  $Y + ks$  and  $Y - ks$ , using specs for  $Y$ , then shows where individual readings satisfy the specs on  $Y$ . ( $k$  may be chosen using a Z-score rough approximation value or a tolerance interval factor).
4. Drawing a rectangle within this region then determines statistically based process windows for  $A$  and  $B$ .

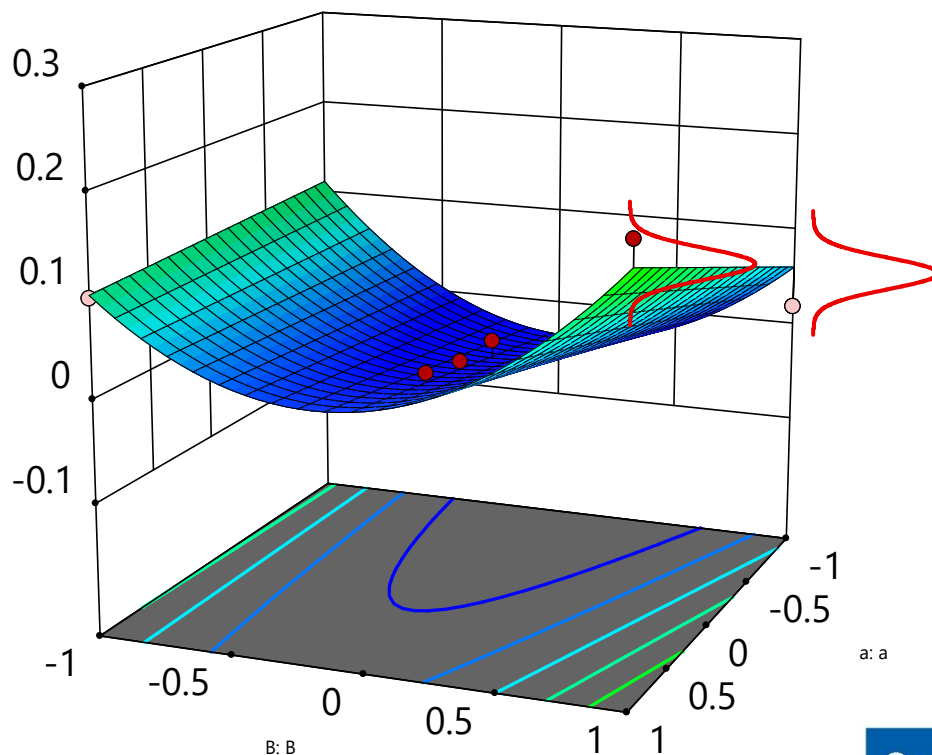
*Model:*  $Y = \beta_0 + \beta_1A + \beta_2B + \beta_{12}AB + \beta_{11}A^2 + \beta_{22}B^2 + \epsilon$

*Ave(Y):*  $E(Y) = \beta_0 + \beta_1A + \beta_2B + \beta_{12}AB + \beta_{11}A^2 + \beta_{22}B^2$

*Fitted Model Prediction:*  $\hat{Y} = b_0 + b_1A + b_2B + b_{12}AB + b_{11}A^2 + b_{22}B^2$

*Formally,*  $E(Y) = \hat{Y}$

*Showing the model prediction is a prediction for the mean response.*



a: a



# ◆ DOE 2 for Setting Process Windows

Factors A and B are to have statistically based process windows. Factor C is categorical, known to be active, and will be included in case there are interactions with the other factors.

## Procedure

1. Fit a response surface model  $Y = f(A,B,C)$  for the average response  $Y$  and determine optimum values for A, B and C with  $s = \text{stdev}$  of pts around the model prediction for the average response. Model domain should include good and degraded performance regions.
2. Fit the models  $Y+ks = f(A,B,C)$  and  $Y-ks = f(A,B,C)$ . Tolerance limit values can also be used in place of the standard deviation  $s$ .
3. With C fixed at its optimum value, construct an overlaid contour plot for  $Y+ks$  and  $Y-ks$  using the desired specs on  $Y$ .
4. Draw the largest rectangle for A and B which is contained within the feasible region on the overlaid contour plot satisfying the specs on  $Y$ .

k Values for $k \times \text{Sigma}$ (Z-Score) Limits	One-Sided Prob	Two-Sided Prob
3	99.865%	99.73%
2 (or 1.96)	97.5%	95%
1.645	95%	90%



# ◆ DOE 2 Setting Process Windows for A and B

**Optimal (Custom) Design**

A flexible design structure to accommodate custom models, categoric factors, and irregular (constrained) regions. Runs are determined by a selection criterion chosen during the build.

Numeric factors: 2 (1 to 30)  Horizontal  
 Categoric factors: 1 (0 to 10)  Vertical

	Name	Units	Change	Type	Levels	L[1]	L[2]
a [Numeric]	a		Hard	Continuous	N/A	-1	1
B [Numeric]	B		Easy	Continuous	N/A	-1	1
C [Categoric]	C		Easy	Nominal	2	1	2

## Optimal (Custom) Design

Search: Both Exchanges Optimality: 1

Edit model... Quadratic

Blocks: 1 (1 to 1000)

Variance ratio: 1 (0.0 to 1000.0)

Groups

Required groups: 3  
 Additional groups: 2  
 Center point groups: 0  
 Center point group size: 0  
 Total groups: 5

Runs

Required model points: 9  
 Additional model points: 5  
 Center points: 0  
 Total runs: 14

Group	Run	Factor 1 a:a	Factor 2 B:B	Factor 3 C:C	Response 1 Fraction Cracked
1	1	0.333333	0	1	0.01
1	2	0.333333	1	2	0.14
1	3	0.333333	-1	2	0.06
2	4	-0.333333	1	2	0.1
2	5	-0.333333	-1	2	0.07
2	6	-0.333333	0	1	0
3	7	1	-1	1	0.05
3	8	1	0	2	0.02
3	9	1	1	1	0.16
4	10	0	0	2	0
4	11	0	0	1	0
5	12	-1	1	1	0.06
5	13	-1	-1	1	0.07
5	14	-1	0	2	0.01

Optimal Split Plot Design to Handle a Hard-to-Vary Factor with wider factor ranges to show degradation in the response.

# ◆ DOE 2 Setting Process Windows for A and B

## Fixed Effects [Type III]

### Response 1: Fraction Cracked

REML (REstricted Maximum Likelihood) analysis  
Kenward-Roger p-values

Fit reduced model.  
Found  $s = 0.0068$ .  
Optimal setting for Factor C = 1.  
Computed  $Y + 1.645s$  and  $Y - 1.645s$ .

	Source	Term	df	Error df	F-value	p-value	
Whole-plot			1	1.60	20.11	0.0684	significant
	a-a		1	1.60	20.11	0.0684	
Subplot			5	3.44	125.45	0.0005	significant
	B-B		1	3.01	143.96	0.0012	
	C-C		1	3.66	3.47	0.1427	
	aB		1	3.01	109.75	0.0018	
	aC		1	3.28	4.97	0.1044	
	B <sup>2</sup>		1	4.56	369.06	< 0.0001	

## Fit Statistics

Std. Dev.	0.0068	R <sup>2</sup>	0.9913
Mean	0.0536	Adjusted R <sup>2</sup>	0.9775
C.V. %	12.62		

Group	Run	Factor 1 a:a	Factor 2 B:B	Factor 3 C:C	Response 1 Fraction Cracked	Response 2 Fraction Cracked - 1.645s	Response 3 Fraction Cracked + 1.645s
1	1	0.333333	0	1	0.01	0.001186	0.021186
1	2	0.333333	1	2	0.14	0.128814	0.151186
1	3	0.333333	-1	2	0.06	0.048814	0.071186
2	4	-0.333333	1	2	0.1	0.088814	0.111186
2	5	-0.333333	-1	2	0.07	0.058814	0.081186
2	6	-0.333333	0	1	0	-0.011186	0.011186
3	7	1	-1	1	0.05	0.038814	0.061186
3	8	1	0	2	0.02	0.008814	0.031186
3	9	1	1	1	0.16	0.148814	0.171186
4	10	0	0	2	0	-0.011186	0.011186
4	11	0	0	1	0	-0.011186	0.011186
5	12	-1	1	1	0.06	0.048814	0.071186
5	13	-1	-1	1	0.07	0.058814	0.081186
5	14	-1	0	2	0.01	-0.001186	0.021186

## Solutions

Number	a	B	C
1	-1.000	0.028	1

# ◆ DOE 2 Setting Process Windows for A and B

Factor Coding: Actual

● Design Points

0  0.16

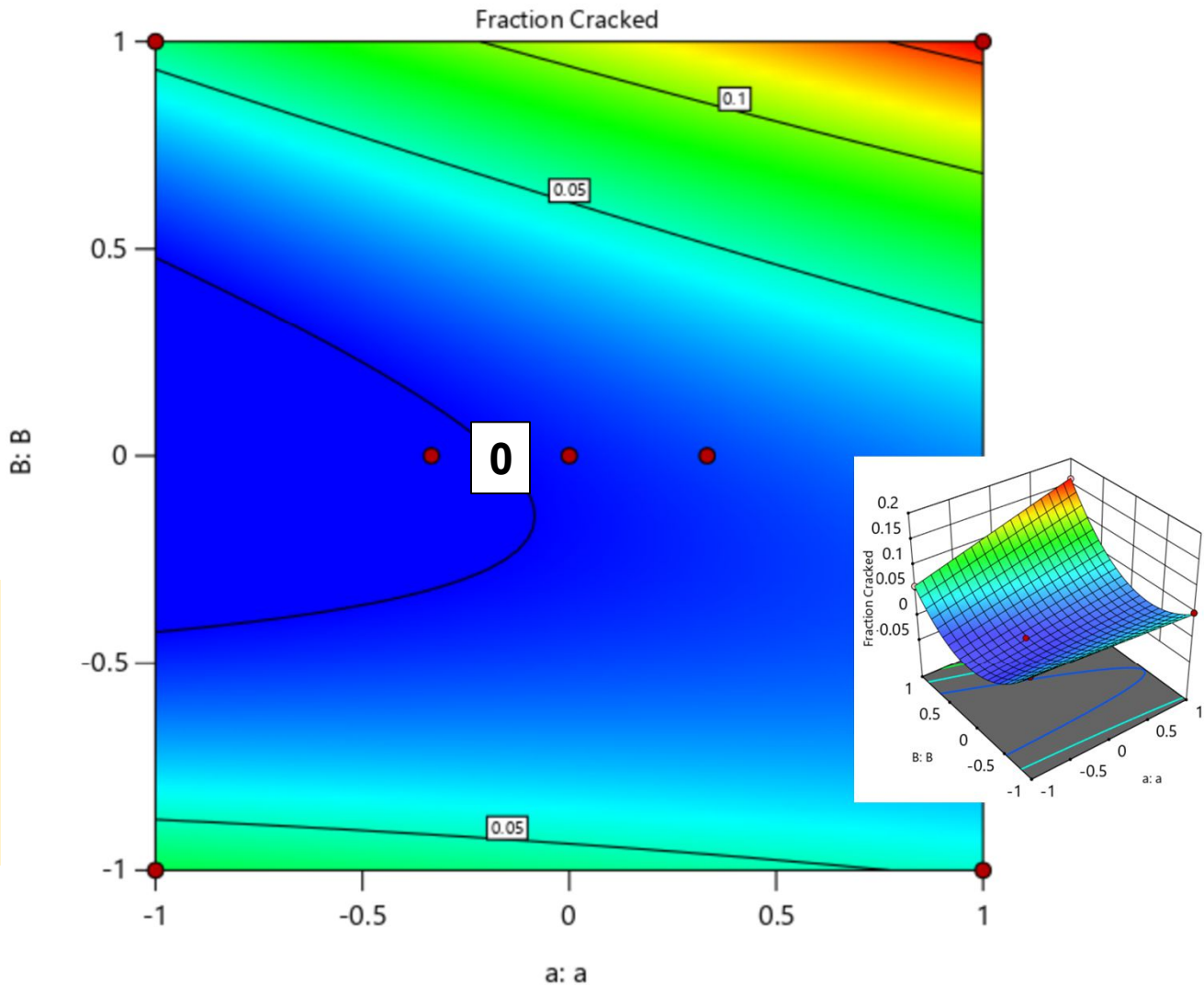
X1 = a

X2 = B

**Actual Factor**

C = 1

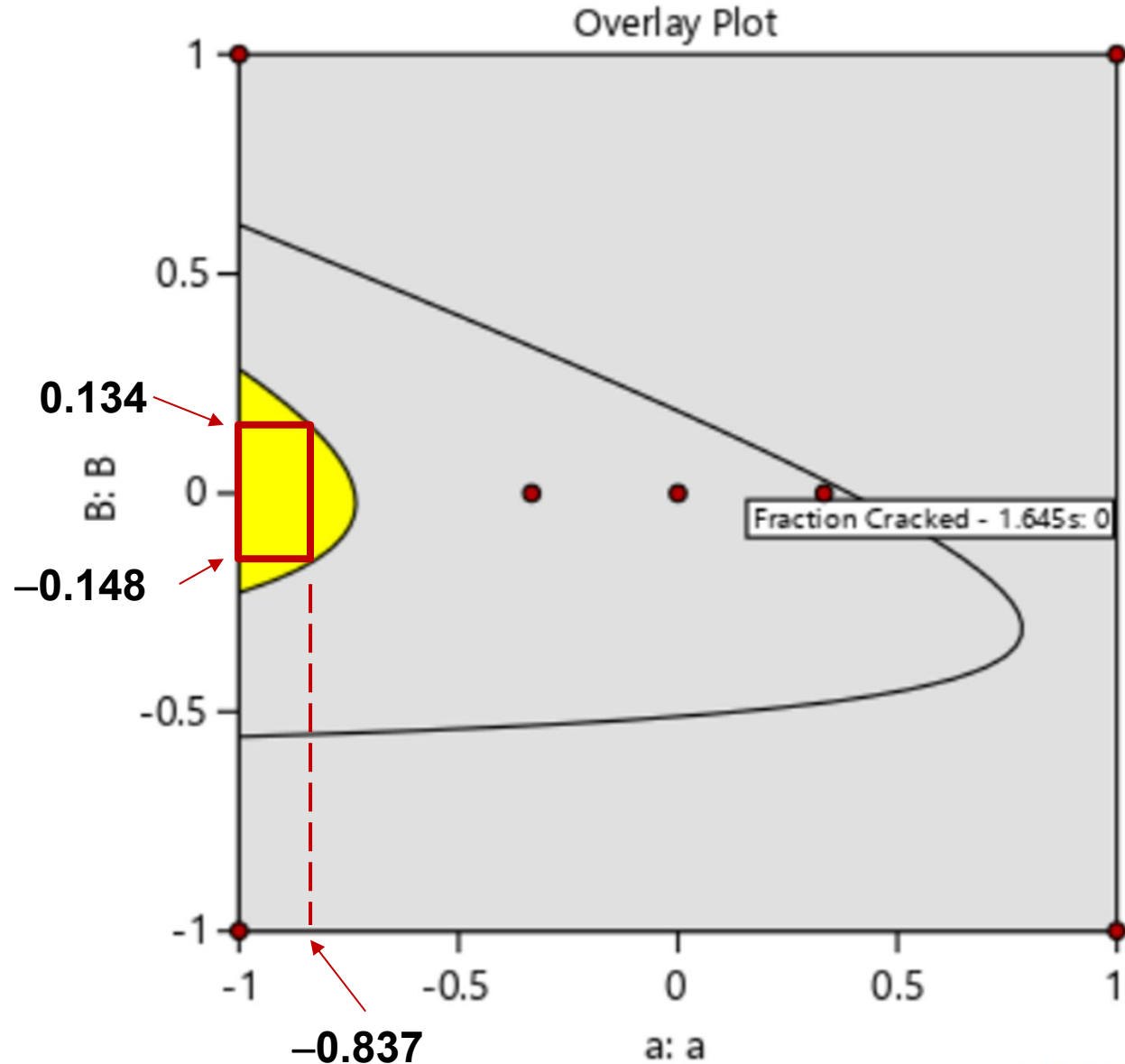
Contour plot on the average response showing where the average will be 0 for the proportion cracked.



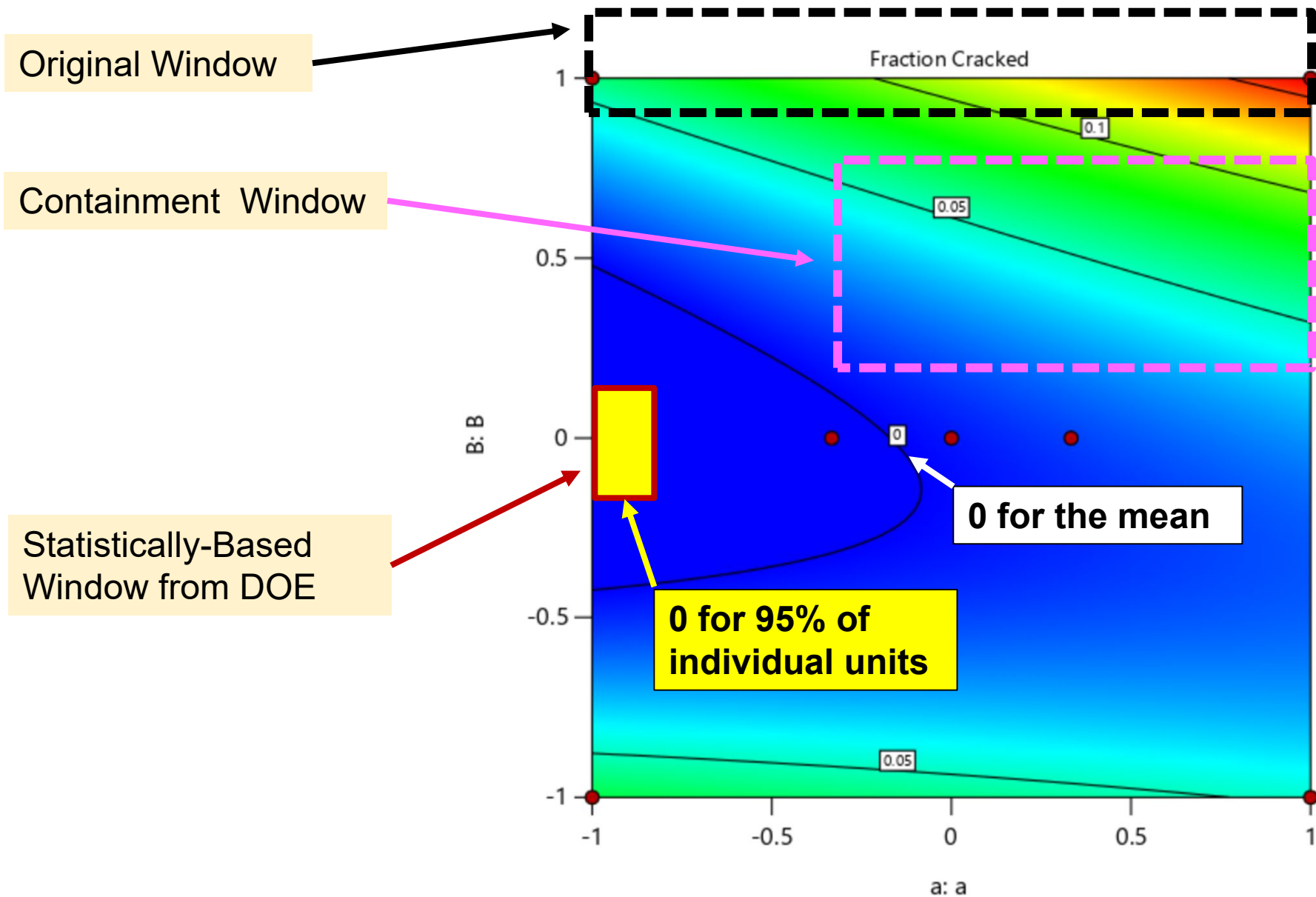
# ◆ DOE 2 Setting Process Windows for A and B

The overlaid contour plot for  $Y \pm 1.645s$  shows a much more restricted region.

Since the one-sided constant 1.645 was used (lowering the surface did not come into play), we can say that with the process window  $[-1, -0.837]$  for A and  $[-0.148, 0.134]$  for B, there is a 95% chance that there will be no cracks.



# ◆ DOE 2 Setting Process Windows for A and B



# ◆ Key Take Aways

- Don't jump into a DOE.
  - Measurement systems must be valid.
  - Use data mining to get clues for factors in a DOE.
- Use DOE to determine process drivers.
  - DOE can expose interactions when a problem is not straightforward.
  - Use an experimental design appropriate for your type of data. E.g. a split plot design for hard-to-vary factors which is simple to design using Design Expert.
- Remember the 5 conditions to accept a conclusion from data (Stable, Real, Important, Why, Equitable Sample)
- Remember the two questions to ask from any DOE (1. Learn? 2. Action?)
- Know how to use a response surface design for 2 Factors using Design Expert to convert a contour plot on the average response into a contour region for the individual data points to set statistically-based process windows. (Specs are usually on the individuals, not on the average.)



