Testing the Limits of Designed Experiments

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The Value of Replication in Experimentation

- A single good result may look nice in your thesis, but.....
  - Was it a lucky coincidence that you can never repeat?
  - Will other labs confirm the result, or will they prove that it's misleading?
  - Will it have any impact on high-volume manufacturing?
- Some rules for estimating whether a result is "real" or just a fluke:
  - It takes three *independent* replicates to give a trustworthy average
  - It takes ten *independent* replicates to give a trustworthy standard deviation
- *Independent* data capture the sources of uncontrollable variation
  - Cell-to-cell
  - Wafer-to-wafer
  - Day-to-day
  - Tool-to-tool? Person-to-person? Lab-to-lab?
- Example: 8 small cells on each of 10 wafers processed in 2 lots of 5
  - For multi-Si, typically every cell is independent (80 replicates)
  - For mono-Si, probably only every lot is independent (2 replicates!)

Statistical Significance: A-B Comparison

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- Common definition of "statistically significant difference":
  - There is less than a 5% chance that the observed difference between the two things being compared is just due to random noise (p value).
  - If $p<0.05$, the better process will likely be the better process in the long run.
  - If $p>0.05$, you may need more data, or the difference may not be important.
- Conclusions that are based on results that are not statistically significant:
  - Usually lead to a great deal of wasted time and effort!
  - Commonly occur when the first result is the desired result.
  - People like to see what they expect. People don't like repetition.

One-way ANOVA: Reflectance(%) versus Process (3 runs each)

```
Source    DF      SS      MS      F      P
Process    1   5.134   5.134  10.00  0.034
Error      4   2.053   0.513
Total      5   7.187

S = 0.7164   R-Sq = 71.43%   R-Sq(adj) = 64.29%

                             Individual 95% CIs For Mean Based on
                             Pooled StDev
Level  N    Mean  StDev   ---------+---------+---------+---------+
New    3  13.307  0.374   (---------*--------)
Old    3  15.157  0.942                   (--------*---------)
```

Mean of each process lies beyond the 95% confidence limit for the mean of the other process -> Stat Sig!

D-I-Y 95% Confidence Intervals

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df	$t_{.025}$	df	$t_{.025}$	df	$t_{.025}$	df	$t_{.025}$
1	12.71	6	2.45	12	2.18	25	2.06
2	4.30	7	2.36	14	2.14	30	2.04
3	3.18	8	2.31	16	2.12	40	2.02
4	2.78	9	2.26	18	2.10	60	2.00
5	2.57	10	2.23	20	2.09	120	1.98

With 95% confidence, the *true mean* lies within the range given by this expression →

$$m \pm \frac{t_{.025} s_p}{\sqrt{n}}$$

Where:
- m is the measured average (mean) value of the data
- $t_{.025}$ is from the above table (Student's-t)
- S_p is the pooled standard deviation of the available data*
- n is the number of data points averaged to obtain m

For A-B comparison example:
df = 4**, so $t_{.025}$=2.78
s_{old} = .94, s_{new}= .37, s_p=.72
n_{old}=3, n_{new}=3
m_{old}=15.2, m_{new}=13.3

*Can be based on more data than just what was used to calculate m (if all data should have same Stdev)
**df = total number of data points used minus the number of different mean values represented

Choosing Experimental Factors

- Think of all of the factors that might affect your result
  - It's better to be all-inclusive to avoid overlooking something important
  - Decide which factors are readily controllable and which are not
  - Rank controllable factors by significance (performance, cost, repeatability)
  - Design experiment to uniformly and randomly sample uncontrollable factors
- Pick several (e.g. four to six) of the most significant controllable factors
  - For each factor, pick a nominal *midpoint* value (often the current best practice)
  - Pick a range for each, within which you are confident the process won't fail
  - Adjust the midpoint to either the arithmetic mean or the geometric mean
- Example: Alkaline Texturing
  - Controllable and important: KOH concentration, Time, Temperature
  - Controllable but less important: Additive concentration, Number of wafers
  - Uncontrollable: Silicate concentration, Wafer orientation, Surface roughness
- Screen the factors to find the most important ones
  - Vary one factor at a time – OK on limited budget, but not optimal
  - Full factorial (all high/low combinations) – Thorough, but time consuming
  - Fractional factorial (resolution IV) - Usually the most efficient approach

Screening Experimental Factors

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O Designing a "resolution-IV" fractional-factorial experiment

- Tests a fraction of the corners of the multi-dimensional "cube" of factor space
- This design finds the effect of each factor, undistorted by factor interactions
- Add three replicates of the center point at beginning, middle and end
- Table below shows this design for a four-factor screening experiment
  - ✓ The range for each factor is normalized to -1, 0, +1 for the low, mid, high values

Factor A	Factor B	Factor C	Factor D
0	0	0	0
-1	1	-1	1
1	1	-1	-1
1	1	1	1
-1	1	1	-1
0	0	0	0
-1	-1	1	1
1	-1	-1	1
-1	-1	-1	-1
1	-1	1	-1
0	0	0	0

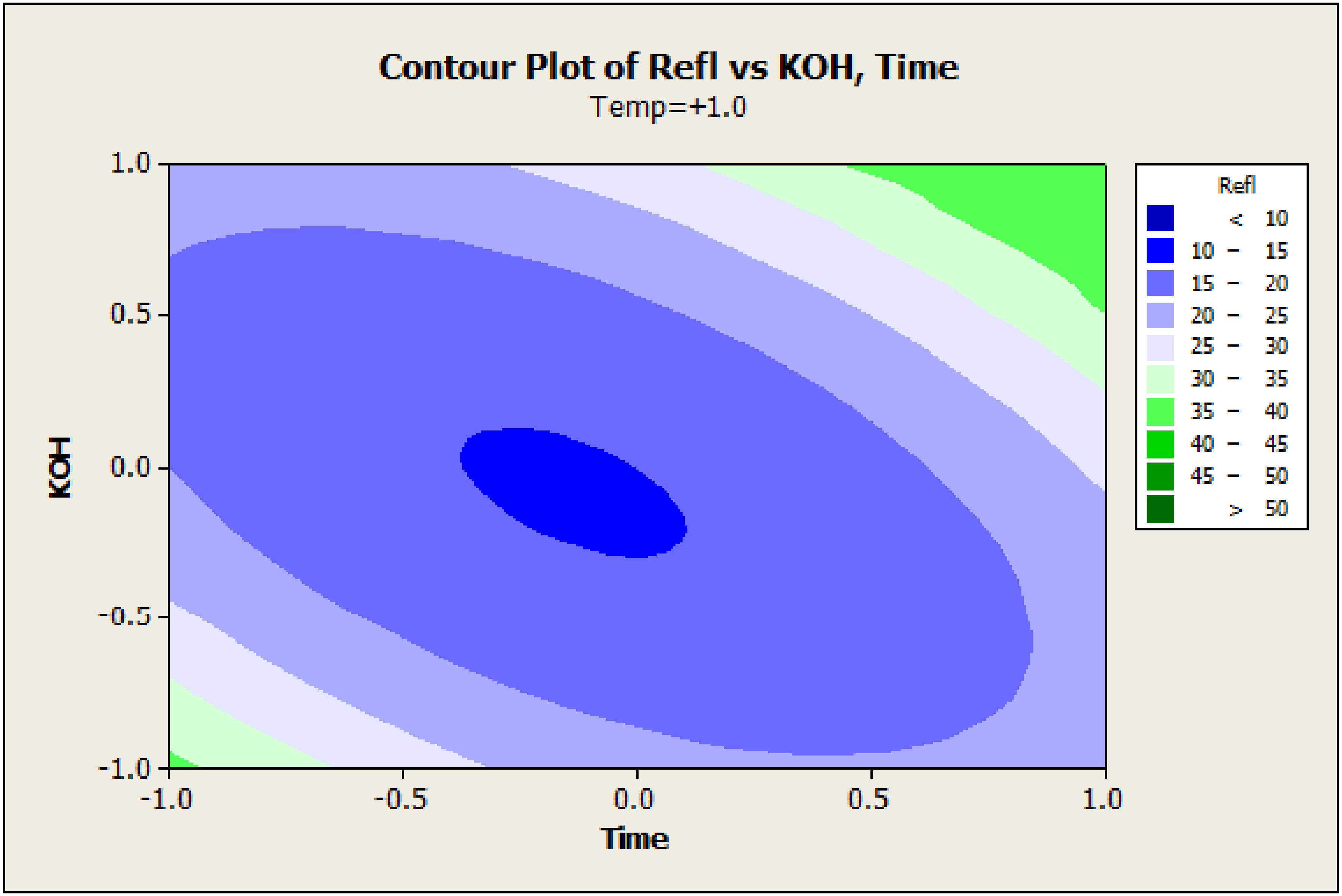
For this design, 11 runs are needed to screen these four factors to determine:

- Which factors have the most effect
- Consistency of the midpoint process
- Deviation of midpoint from linear model

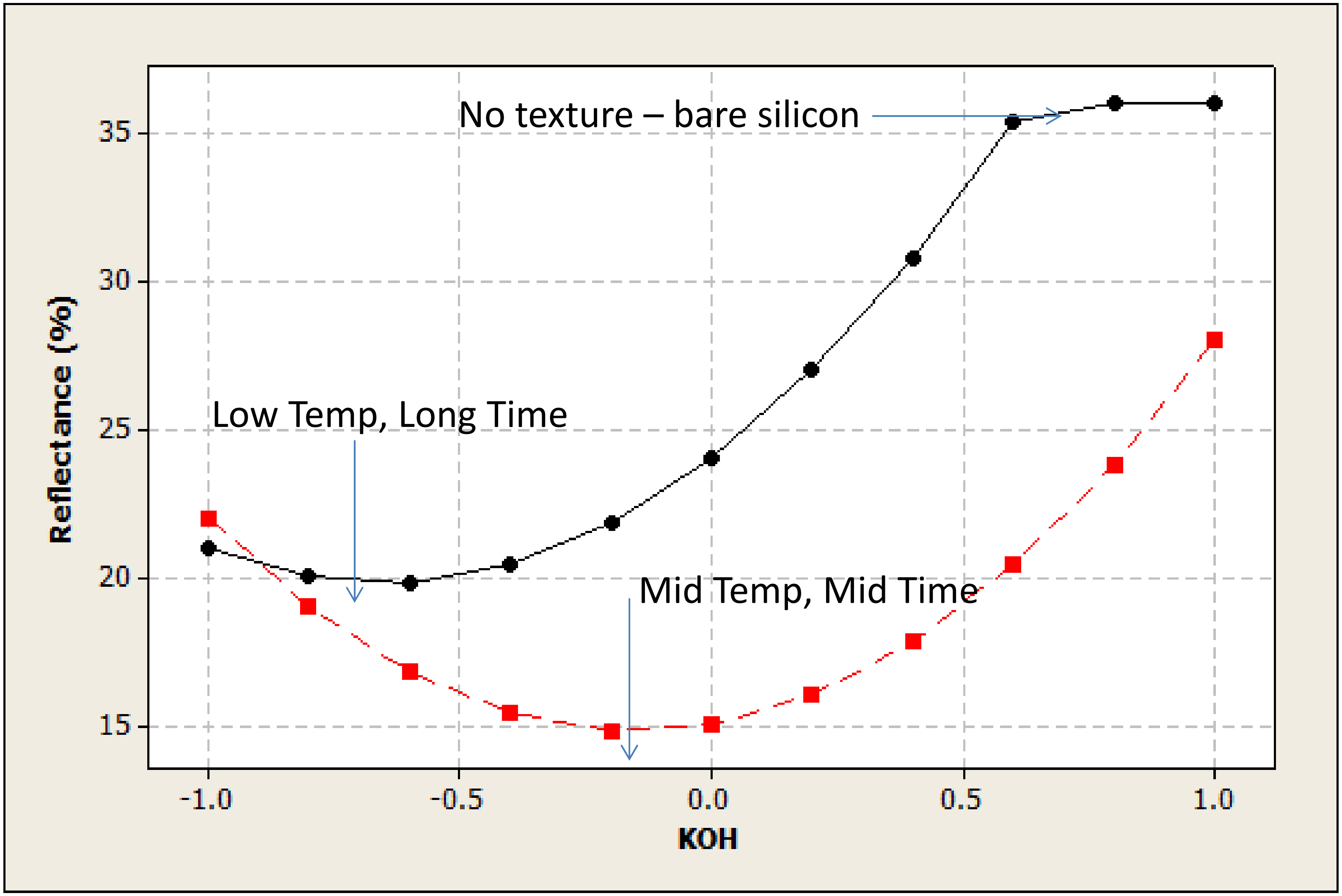
↓

If the average at the midpoint is significantly different than the average of the corners, then expect a maximum/minimum within this space. Non-linear (squared) terms must be included in the model if you want to locate this optimum.

Alkaline Texture Process (3 factors)



One Factor at a Time (KOH)

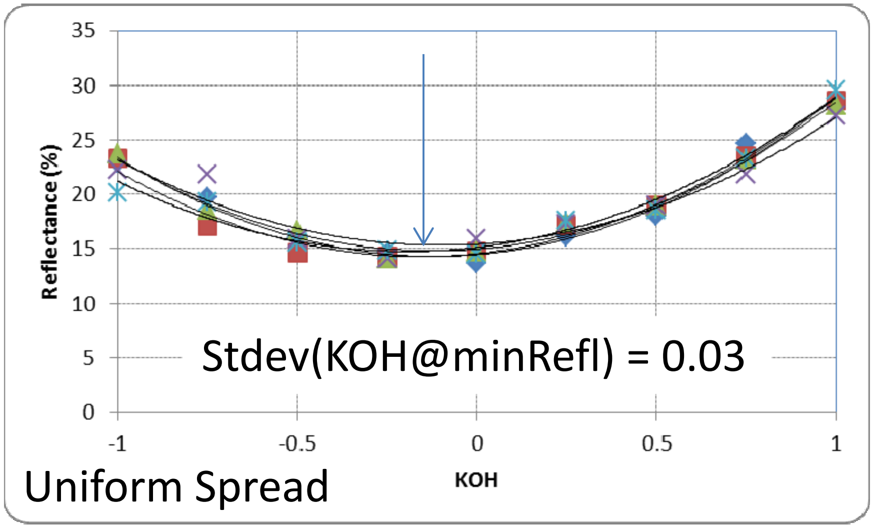


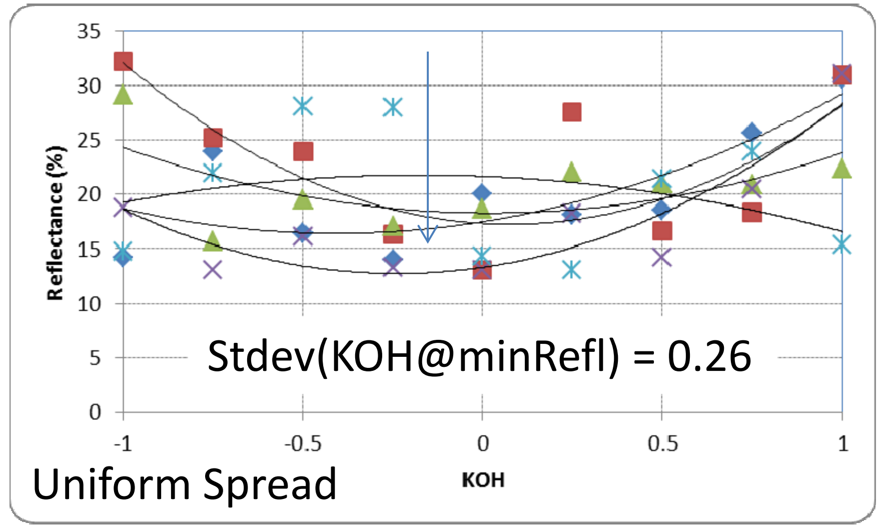
Now add experimental noise: y' = MIN(36,MAX(13,y+StDev*NORM.INV(RAND(),0,1)))

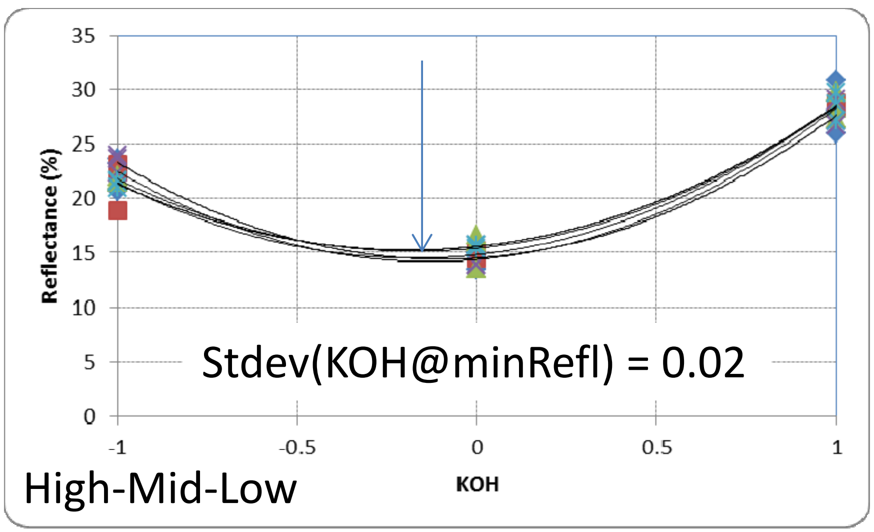
Uniform Spread, or High-Mid-Low?

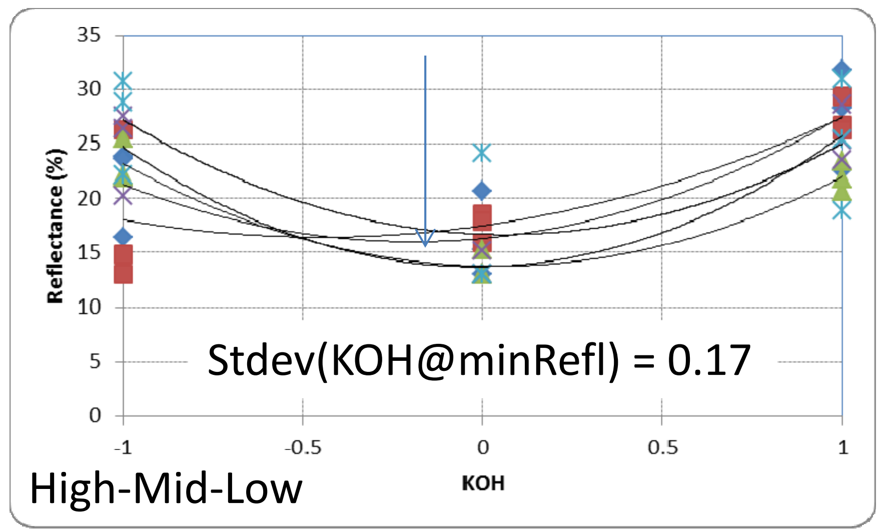
Stdev(Refl) = 1 percentage point

Stdev(Refl) = 5 percentage points



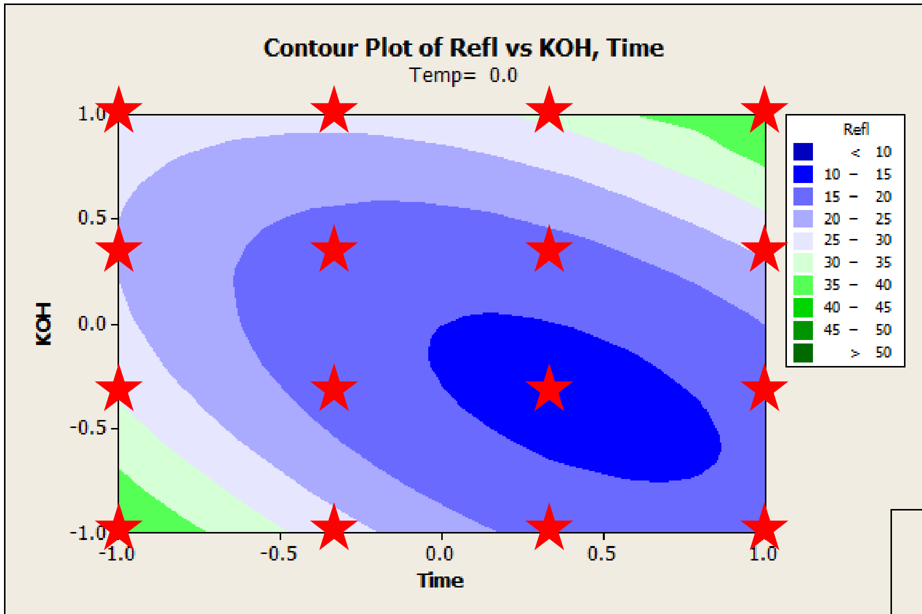






☞ High-Mid-Low better than Uniform Spread for normal distribution, smooth variation

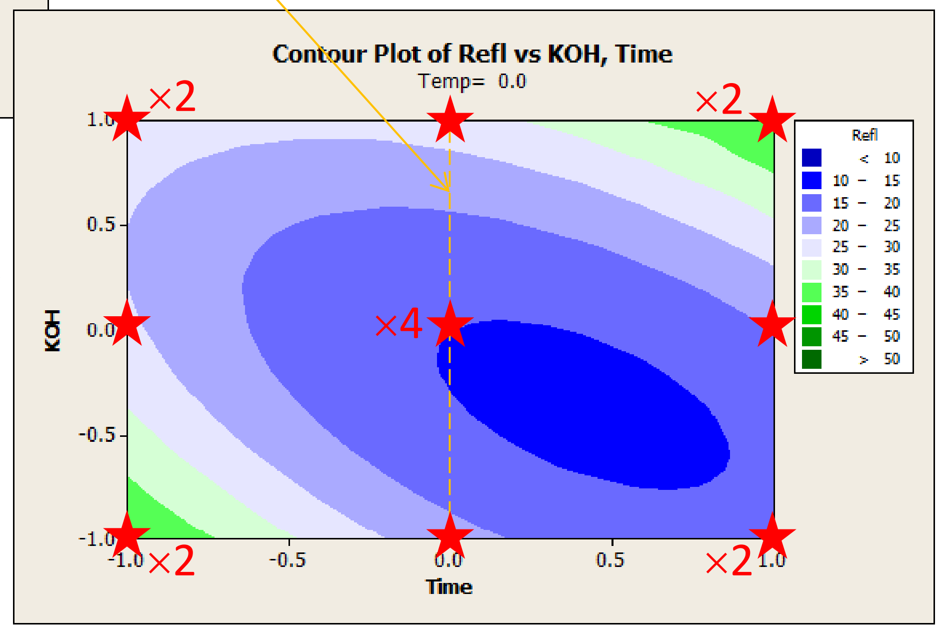
Picking Points in Two Dimensions



16 points distributed uniformly: "Uniform Spread"

Trace of previous 1D example

16 points concentrated around perimeter and at center: "Corner-Edge-Center"



Note texture failure at two corners!

Optimum Process from Parabolic Fit

Results from 100 16-point experiments

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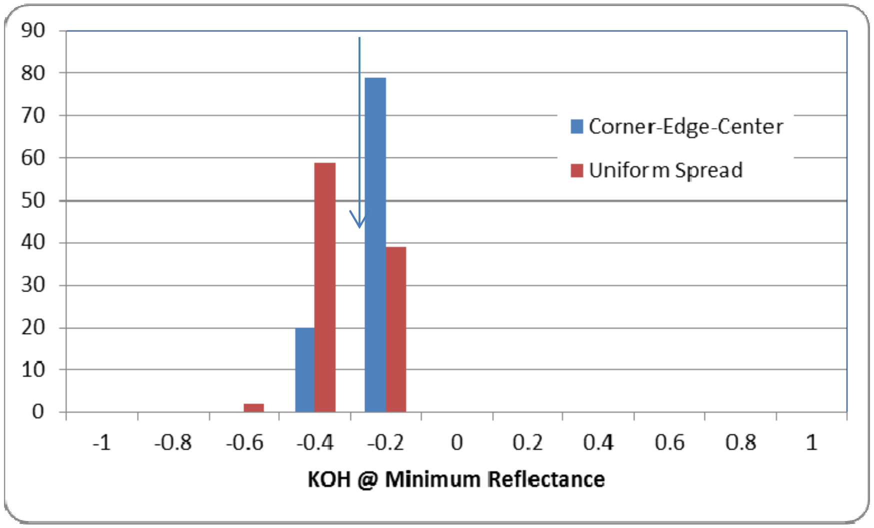
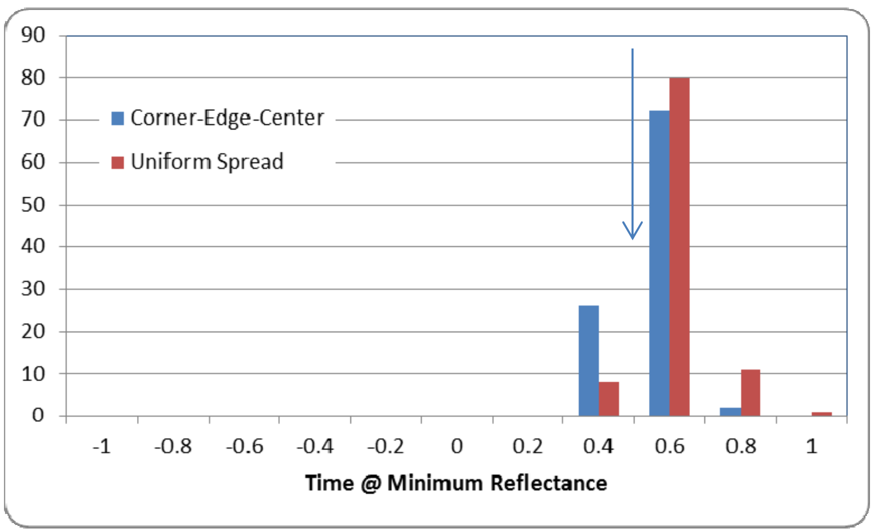
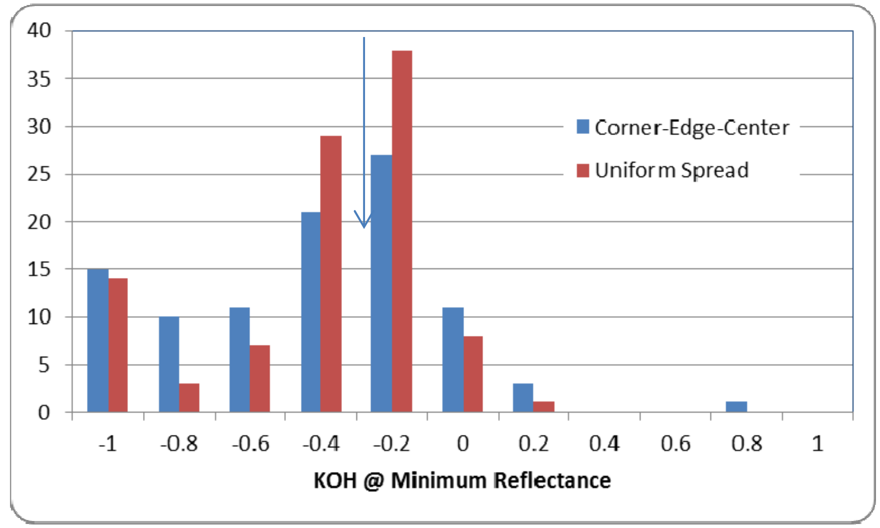
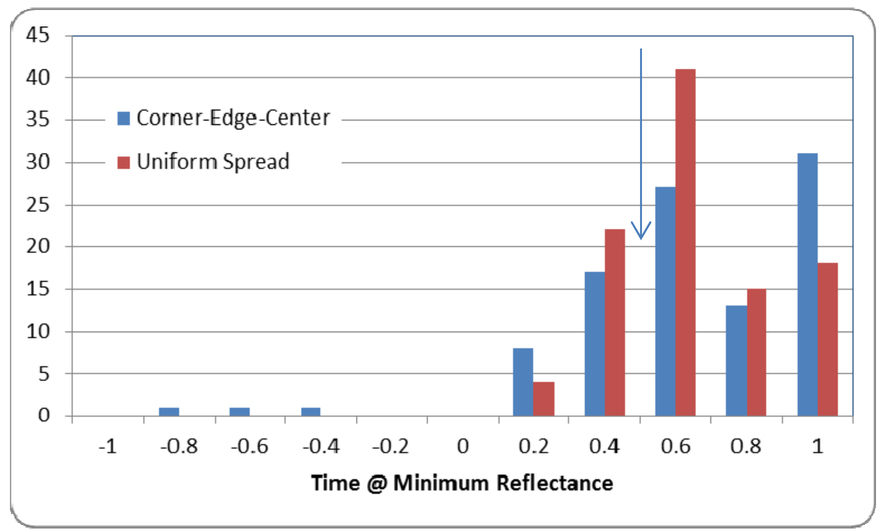
Stdev(Refl) = 1 percentage point





Stdev(Refl) = 5 percentage points





☞ Corner-Edge-Center still slightly better despite process failure in two corners

3D: Corners-Faces-Center (8+6+2=16 pts)

Response Surface Regression:
Reflectance versus Time, Temp, KOH

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The analysis was done using coded units.

Estimated Regression Coefficients for Reflectance

Term          Coef   SE Coef       T      P
Constant    16.793     1.622  10.354  0.000
Time        -2.188     1.083  -2.020  0.090
Temp        -2.534     1.083  -2.339  0.058
KOH          2.432     1.083   2.245  0.066
Time*Time    5.765     2.110   2.732  0.034
Temp*Temp    1.836     2.110   0.870  0.418
KOH*KOH      6.486     2.110   3.074  0.022
Time*Temp    1.687     1.211   1.393  0.213
Time*KOH     5.285     1.211   4.363  0.005
Temp*KOH    -1.666     1.211  -1.376  0.218

S = 3.42584
```

Probability that each factor could actually be zero (P)

Maybe significant (Time, Temp, KOH)

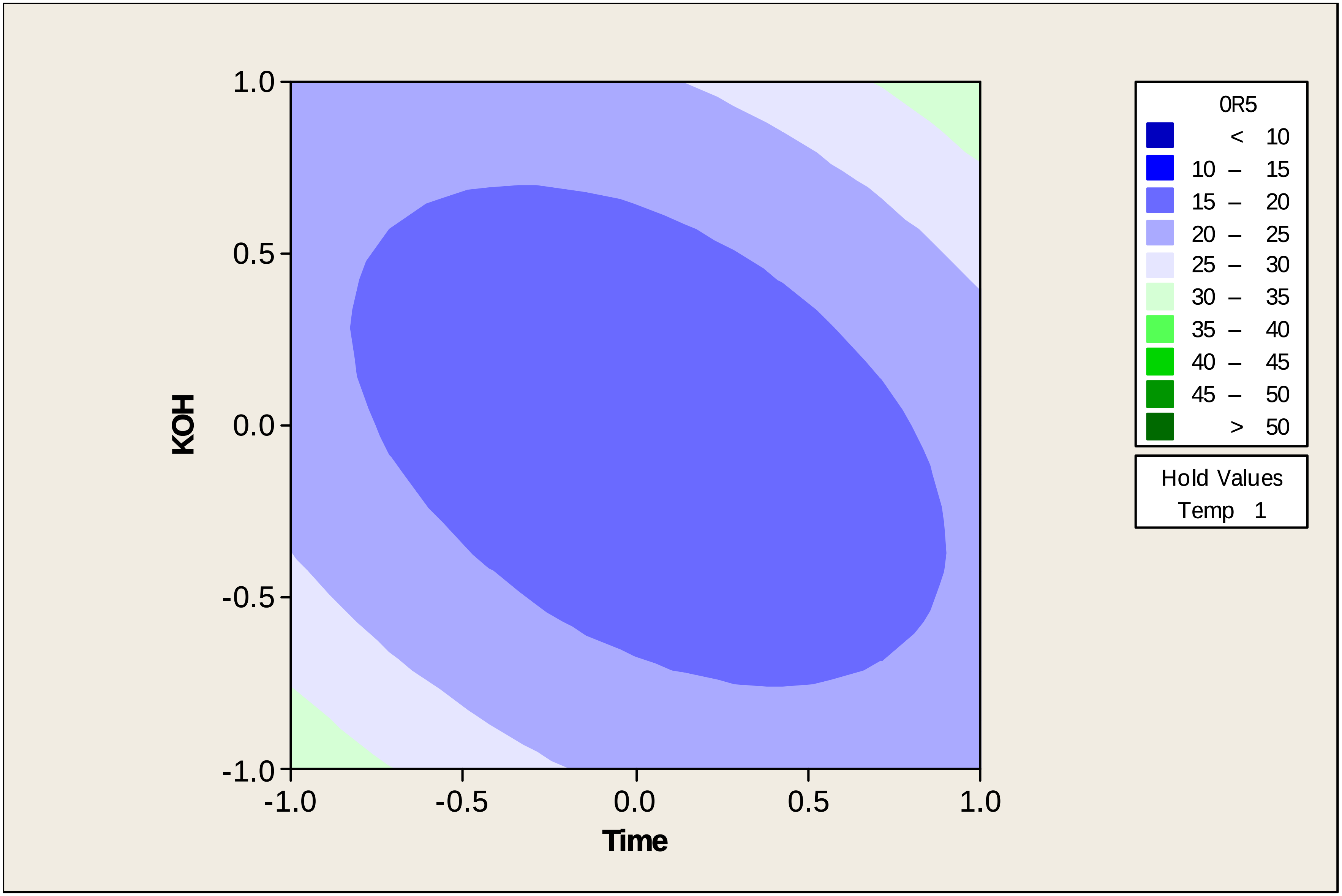
Statistically significant (Time*Time, KOH*KOH, Time*KOH)

Not significant (Temp*Temp, Time*Temp, Temp*KOH)

S: Stdev of the deviation of reflectance(%) from the model after accounting for the effect of the factors – due to both modeling error (3.3%) and random noise (1%).

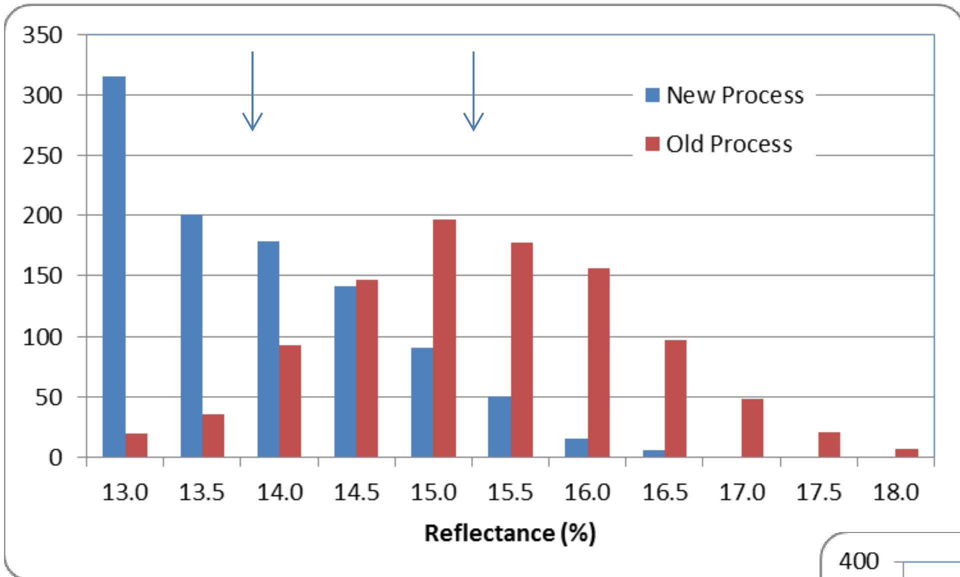
Here, due mostly to process failure in some regions of the parameter space

3D Response Surface from Regression Fit

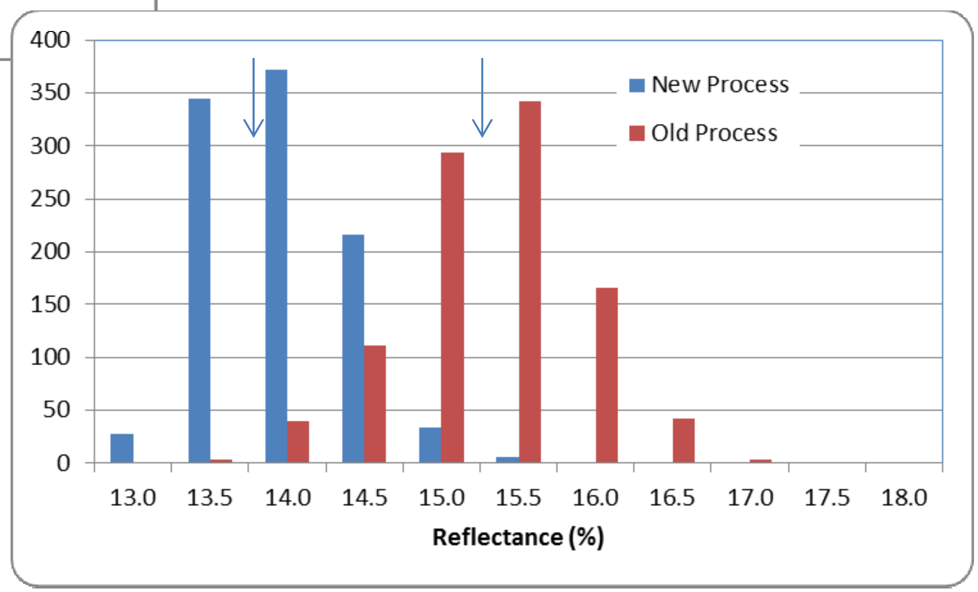


Old Process: Time=0, Temp=0, KOH=0 New Process: Time=0.25, Temp=0.31, KOH=-0.19

Validation



Do one run each of the Old Process and the New Process. This is the distribution of 1000 such attempts. The new process will appear better only 86% of the time.



Compare average of three runs each of Old Process and New Process. The new process will be better 97% of the time. Note the effect of Central Limit Theorem!

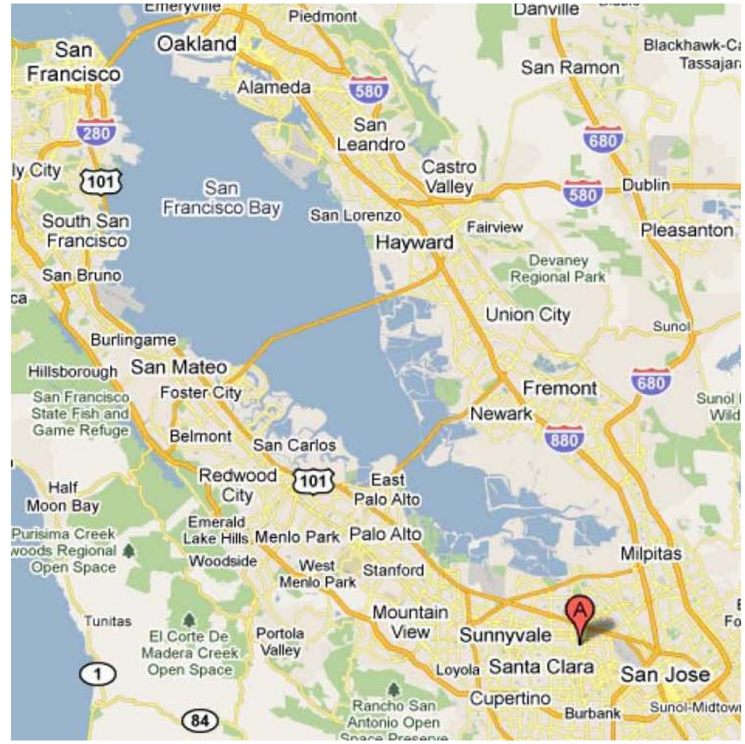
The above simulations used Stdev(Reflectance) of 1 percentage point.

Final Words of Caution

- If a result is statistically significant, still *heed the scope of the comparison*
  - If all data was collected on Monday, the conclusion may only apply on Monday
  - If all data was from a single tool, the conclusion may only apply to that tool
  - If all data used identical wafers, the conclusion may only apply to those wafers
  - If one person did all of the processing, the conclusion may only apply to them
- Rigorously keeping everything the same except the experimental factors?
  - Most likely to give a statistically significant result, *but with a narrow scope*
  - The result may not be repeatable under slightly difference circumstances!
    - ✓ Spread your replicates across multiple days
    - ✓ Randomize the run order to avoid misinterpretation of process drift over time
    - ✓ If wafer quality is the main source of variability, use an assortment of wafers
    - ✓ If you can, obtain replicates using different people, tools and process materials
- <u>The most valuable results are those that others can replicate</u>
  - In PV, unless it gets put into high-volume manufacturing, what's the point?
  - Collaboration between different R&D labs is a good thing!

In publications, show statistical significance and clarify the scope of your results

When in the Bay Area, Visit the ARDL!



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