Optimizing Processes Using Designed Experiments

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Agenda

30-MINUTE PRESENTATION & 15-MINUTE Q & A

- Multiple Response Optimization

  Trade-Space Analysis – Why we do Design of Experiments (DOE)

- Six step framework for creating a successful DOE
  & important questions to consider

- Real-World Experimental Issues – Custom DOE is all about

  Making Designs Fit the Problem –
  NOT Making Problems Fit the Designs!

- Two Example Designs – 1^{st} Quick (slide), 2^{nd} Detailed (run JMP)

  1. Four continuous factors, three responses, and 2^{nd} order RSM model
  2. Continuous, discrete numeric, categorical, and hard-to-change factors, plus added constraints, and 2^{nd} order RSM model

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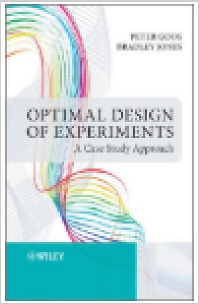
DOE BOOKS

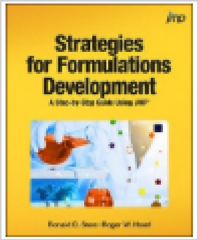
WWW.JMP.COM/BOOKS



› Optimal Design of Experiments: A Case Study Approach

by Peter Goos and Bradley Jones

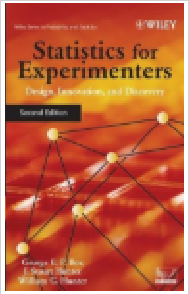
2011 (John Wiley Sons Inc.)



› Strategies for Formulations Development: A Step-by-Step Guide Using JMP

by Ronald Snee and Roger Hoerl

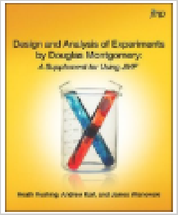
2016 (SAS Institute)



› Statistics for Experimenters: Design, Innovation, and Discovery, 2nd Edition

by George E. P. Box, J. Stuart Hunter, and William G. Hunter

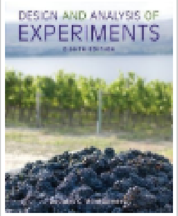
2005 (Wiley)



› Design and Analysis of Experiments by Douglas Montgomery: A Supplement for Using JMP

by Heath Rushing, James Wisnowski, and Andrew Karl

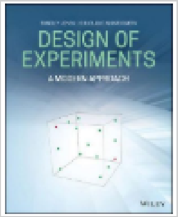
2013 (SAS Institute)



› Design and Analysis of Experiments, 8th Edition

by Douglas C. Montgomery

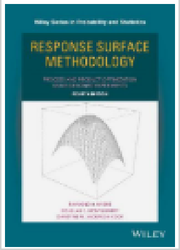
2012 (Wiley)



› Design of Experiments: A Modern Approach

by Bradley Jones and Douglas C. Montgomery

2019 (SAS Institute)



› Response Surface Methodology: Process and Product Optimization Using Designed Experiments, 4th Edition

by Raymond H. Myers, Douglas C. Montgomery, and Christine M. Anderson-Cook

2016 (Wiley)

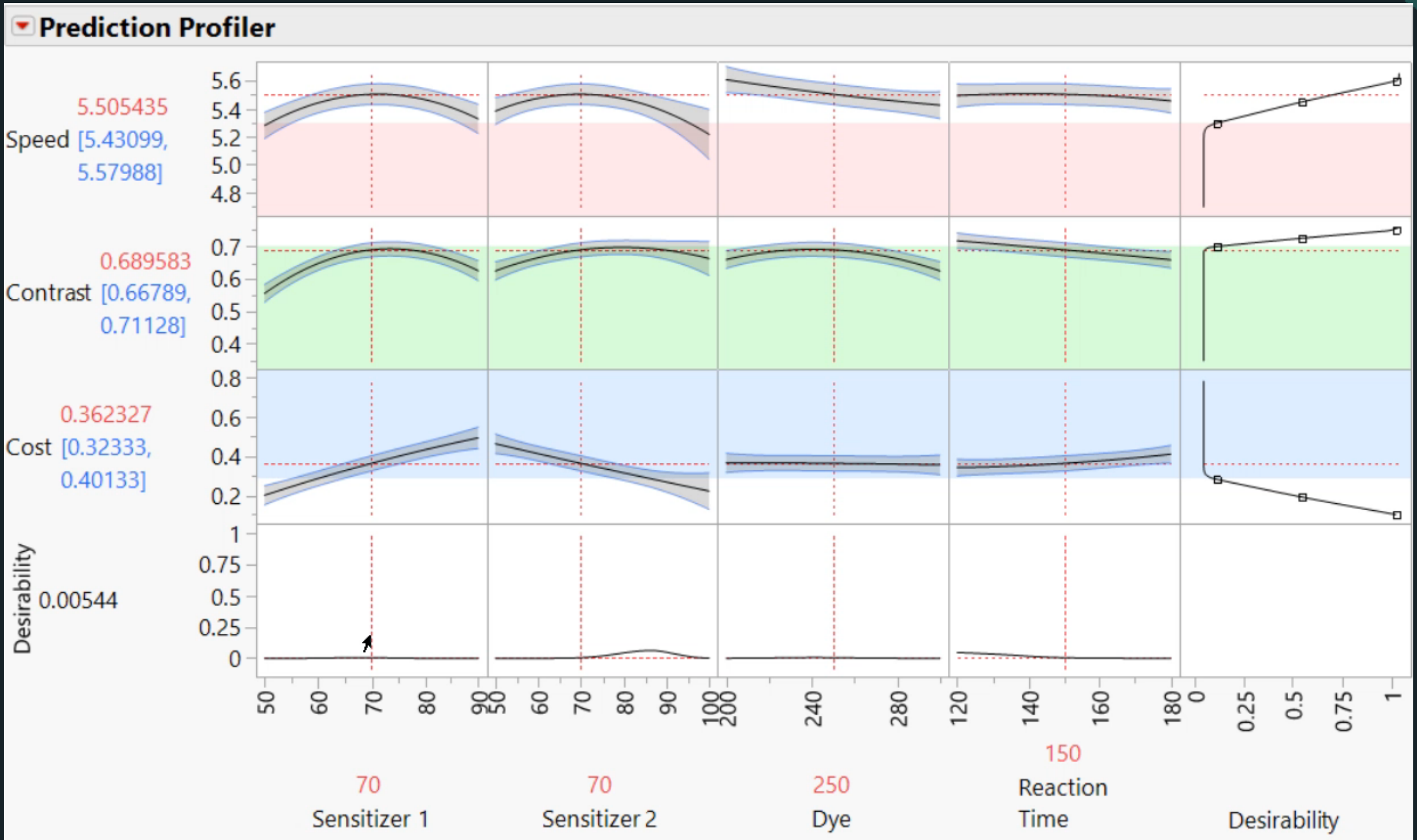
Why use DOE?

QUICKER ANSWERS,
LOWER COSTS,
SOLVE BIGGER PROBLEMS

- More rapidly answer "what if?" questions
- Identify important factors when faced with many
- Do sensitivity and trade-space analysis
- Optimize across multiple responses
- By running efficient subsets of all possible combinations, one can – for the same resources and constraints – *solve bigger problems*
- By running sequences of designs one can be as *cost effective as possible* and *run no more trials than needed* to get a useful answer

Agent Fate 10,000+, USAF Sim Study 648

TRADE-OFF AND OPTIMIZATION (1-MIN RECORDING)



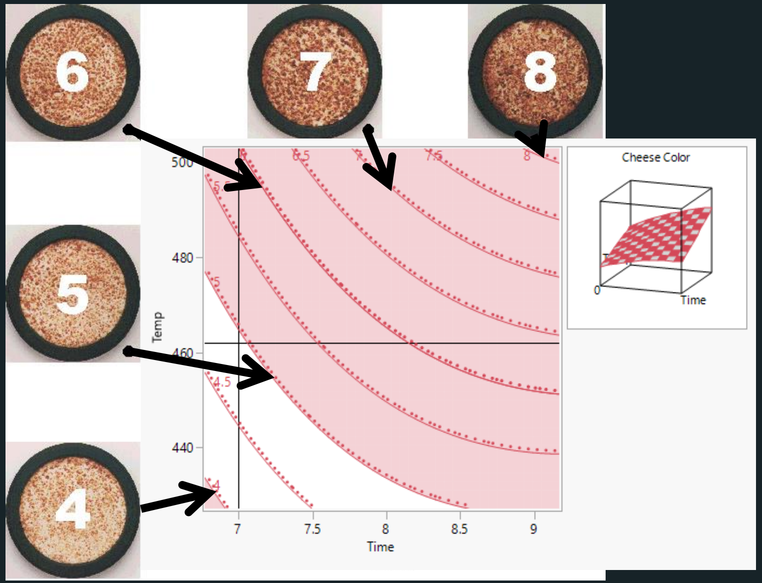
Remembered Settings

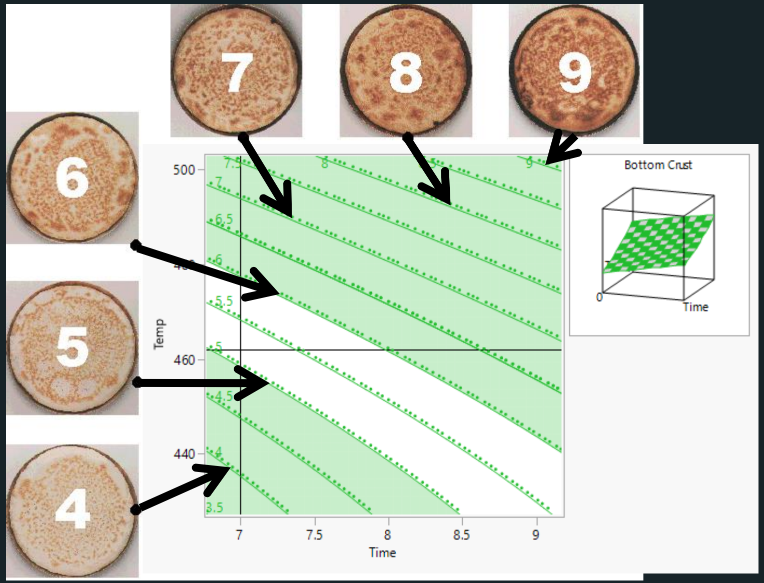
Setting	Sensitizer 1	Sensitizer 2	Dye	Reaction Time	Speed	Contrast	Cost	Desirability
Equal Importance Opt	80.753574	91.269729	250.57625	120	5.3542877	0.7466933	0.2504014	0.347702
Mid Point Settings	70	70	250	150	5.5054353	0.6895831	0.3623274	0.004875
Cost 6X Speed & Contrast	84.016038	93.725925	283.02514	120	5.2902084	0.72549	0.1991539	0.214425
Opt Spd3X-Cntr1X-Cost6X	81.958309	90.706277	286.82246	120	5.3269582	0.7177857	0.2211116	0.264298

Scan QR code for HTML, phone-sized, interactive version on JMP Public

Multiple Response Optimization – Best Trade-Off of Three Target Values

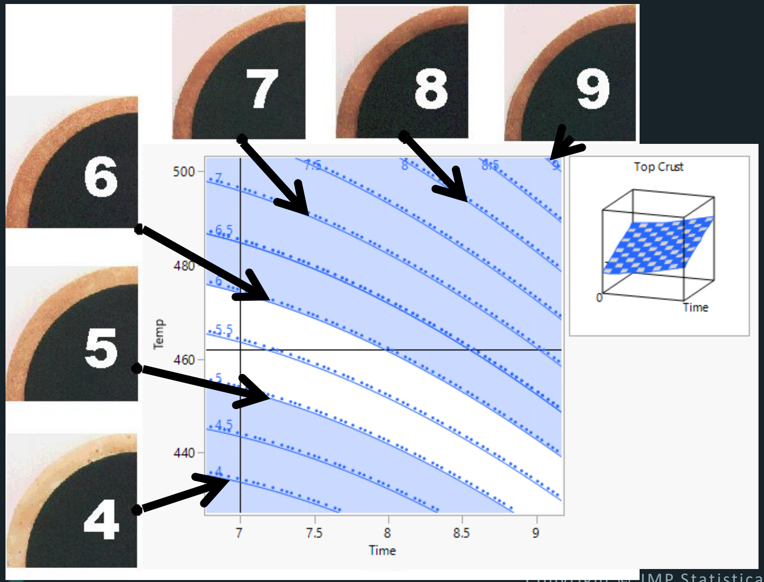
Cheese Color
Target Value
4.5 ± 0.5

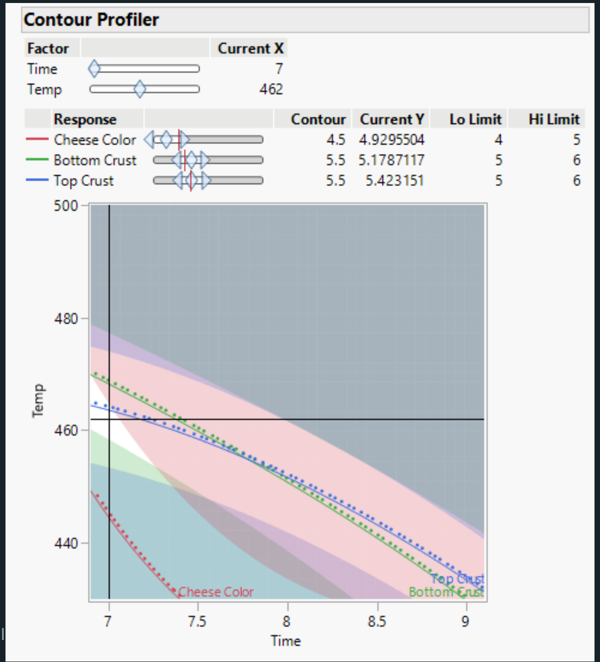




Bottom Crust
Target Value
5.5 ± 0.5

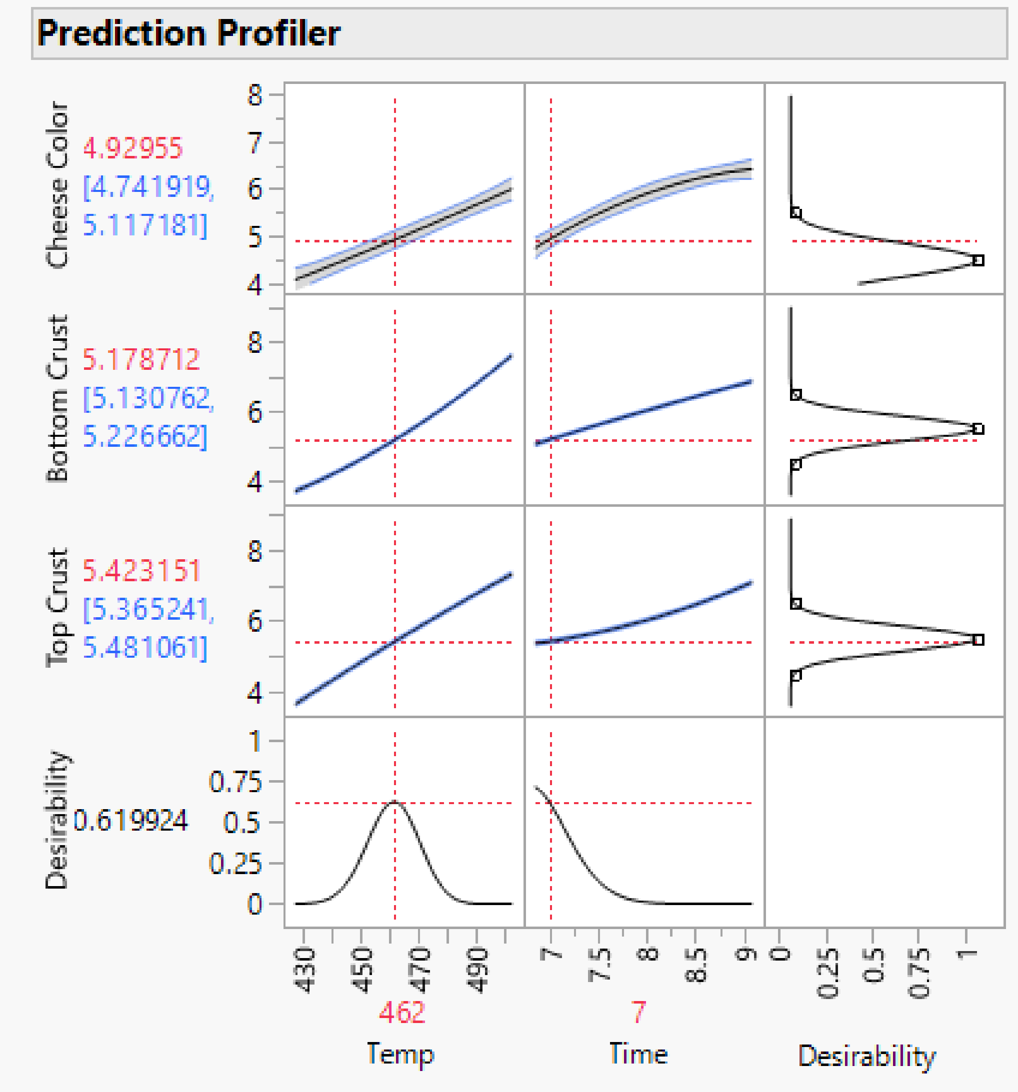
Top Crust
Target Value
5.5 ± 0.5

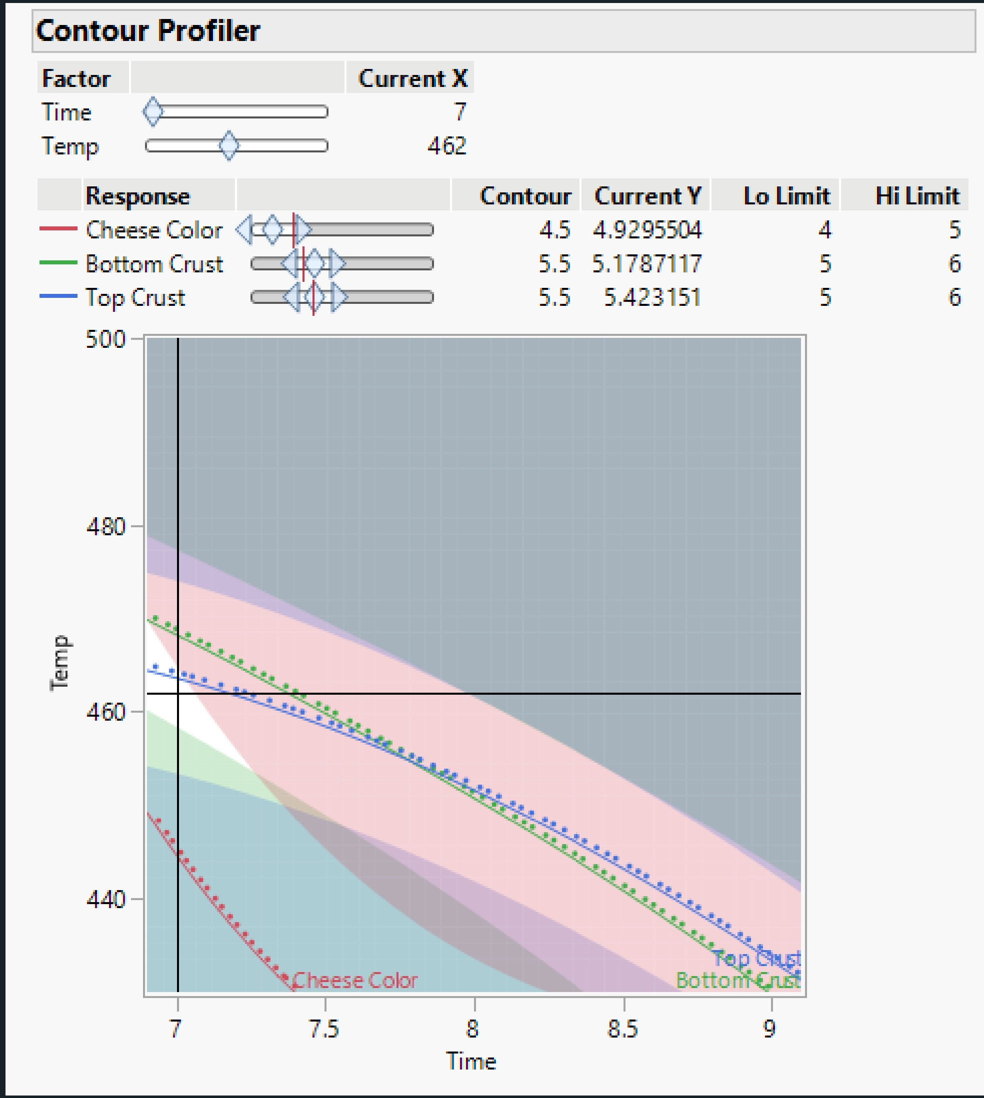




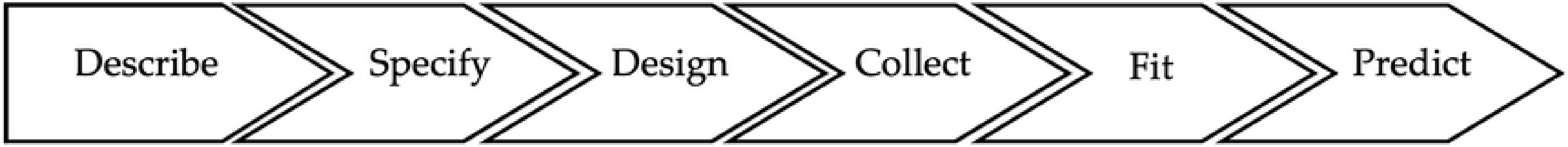
Overlay of
Contour Plots
Acceptable
Region is White

Multiple Response Optimization –
Best Trade-Off of Three Target Values





6-Step DOE Process



- **Describe:** Identify goal, responses, and factors. Ranges require SME!
- **Specify:** Identify effects for an assumed model. Propose 1st or 2nd order?
- **Design:** Generate a design and evaluate it for suitability.
- **Collect:** Run trials using design settings. Measure response for each run.
- **Fit:** Determine a model that best fits experimental data.
- **Predict:** Use the model to optimize factor settings or to predict process performance.

Loads of Questions to Ask

Describe

1. What is the goal of the experimentation?
2. How do you measure success?
3. What response variables do you measure?
4. If more than one response needs to be characterized for your process, what are the relative levels of importance?
5. What kind of control factors do you have?
    1. Continuous (Quantitative) – varies over a range.
    2. Categorical (Qualitative) – varies as different levels.
    3. Discrete Numeric – analyzes like a continuous factor, but only available at discrete levels, like an ordinal categorical factor.
    4. Mixture or formulation factor – behaves like a continuous factor, but all mixture component proportions are constrained to sum to (typically) 1.00.
    5. Blocking factors – groupings of trials such as *day* or *batch* that should not have an effect. We add blocking factors to see if the process shifts between groups as an indicator of unknown or lurking factors being correlated with the blocks.
6. Over what ranges does it make sense to operate the control factors?
    1. Too bold may break the process.
    2. Too timid may not generate a sufficiently large effect.
    3. Don't know? Involve subject matter experts on the process.
7. Are there potentially important factors that can't be controlled?
8. Can any uncontrollable factors be monitored so that the settings can be captured and recorded (e.g., ambient temperature, humidity, operator at time of trial)? These can be treated as covariate factors.
9. Does the process drift over the course of the day or period being measured?
10. How many trials can be run in a day? Will multiple days be required?
11. Do you typically run control samples for this process?
12. Will trials be run in batches or groups?
13. Are there any hard-to-change factors, and if so, which ones?
14. How many devices do you have of each type?
15. Do you have historical data that can be "data mined" for possible factors and to better understand factor ranges?
16. Are these *real* experiments or are they *computer simulations*?
17. If simulations, are they deterministic (same answer every time), or stochastic (randomness built in so answer is slightly different each time)?

Specify

1. Are you looking to identify important main effects from a large set (e.g., 6+) of factors?
2. Are you looking to build a predictive model with which to characterize and optimize a process?

    NOTE: These two questions determine if the proposed model will be 1st order or 2nd order.

Design

1. What is your budget?
2. What is your deadline?
3. Does every trial cost about the same (i.e., take the same amount of time to setup and run)?
4. Does getting setup to run the first trial cost substantially more than running the next few? Whenever initial setup is large, consider adding extra trials (replicates or especially checkpoints) while they are cheap to run.
5. Do any combinations of variable settings cause problems (e.g., unsafe, too costly, breaks the equipment/process, impossible to achieve)?
6. Will you need to constrain the design space or disallow certain combinations of factor settings?
7. If you run the same process on separate days, do you ever get obviously/surprisingly different results?
8. Do you have past records of replicated trials for each response?
    1. Are the replicate trial response values close together or spread out over time?
    2. How big is the variability for each response? That is, what is the standard deviation or root-mean squared error (RMSE) of the response?
9. How tiny of a difference for each response is considered practically important?
10. For each response, do you think you are looking for tiny differences in big variability (hard to do because lots of replication is needed) or big differences in small variability (easy to do)?
11. What is the desired level of confidence in detecting effects? This is typically 95%, which leads to setting alpha at 0.05 (Type I error).
12. What are acceptable levels of power for the various types of effects (main, interaction, quadratic, categorical levels)? **NOTE:** This is the desired level of confidence in NOT missing an effect if it is real. It is typically 0.8 for main effects and interactions, and less for quadratic effects (Type II error).
13. How hard is it to come back later to run checkpoint trials? Can you build in checkpoint trials now – especially if they are inexpensive to run? If so, where?
    1. Your guess at where the best performance will occur.
    2. Your guess at where the poorest performance will occur.
    3. Your boss' opinion as to where to run the process.
    4. Add a trial to support the next higher model.
    5. Some points outside the design region.
14. What trial do you think is most likely to break the design? **NOTE:** Perhaps run that trial first.

Readable List in Blog

[Turn many small decisions into one big process optimization success (jmp.com)](https://www.jmp.com)

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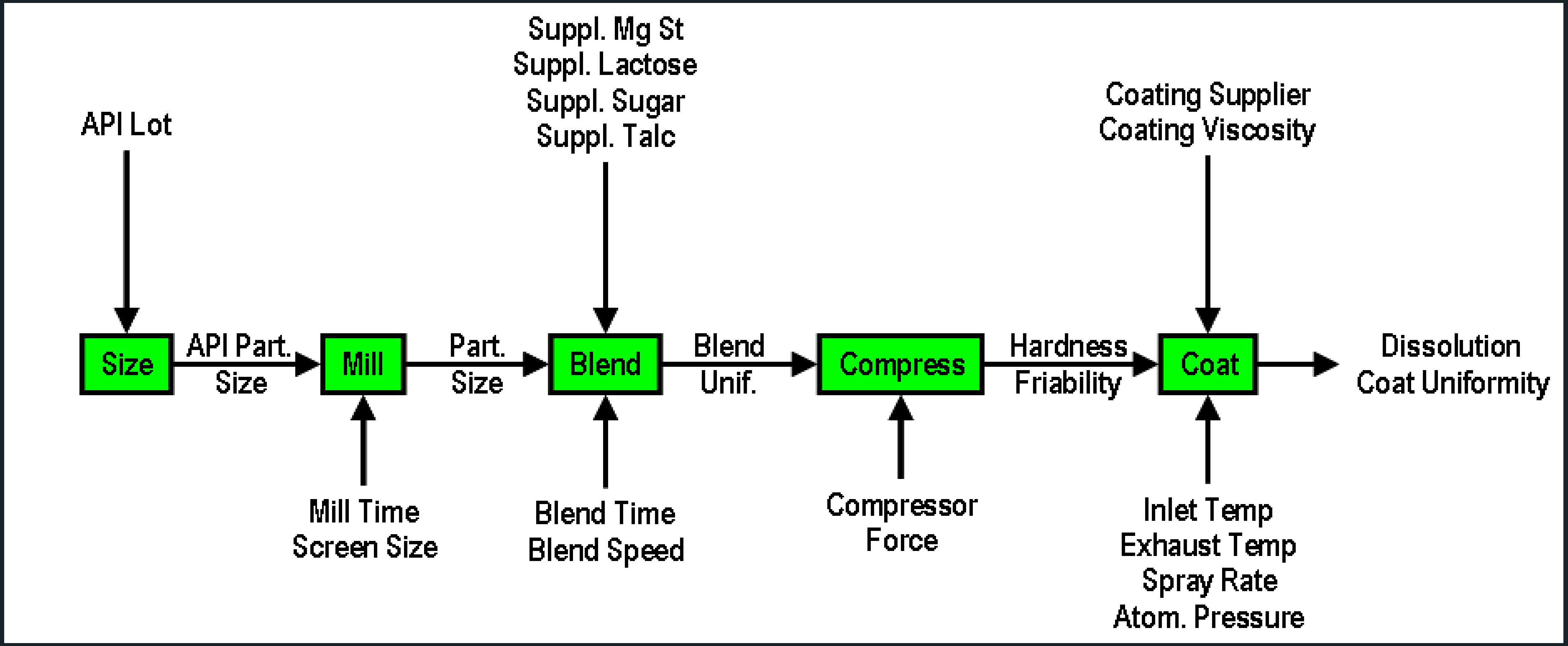
Classic Definition of DOE

PURPOSEFUL CONTROL OF THE INPUTS (FACTORS) IN SUCH A WAY AS TO DEDUCE THEIR RELATIONSHIPS (IF ANY) WITH THE OUTPUT (RESPONSES).

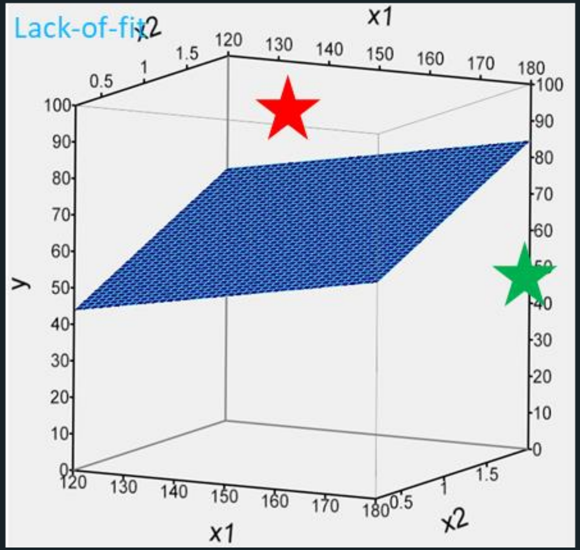


Alternative Definition of DOE

A DOE IS THE SPECIFIC COLLECTION OF TRIALS RUN TO SUPPORT A PROPOSED MODEL.

- If proposed model is *simple* - just main effects or *1st order* terms (x_1 , x_2 , x_3, etc.) - the design is called a *screening* DOE
  - Goals include rank factor importance or **find a "winner" quickly**
  - Used with many (> 6?) factors at start of process characterization
- If the proposed model is *more complex*, the model is *2nd order* so that it includes two-way interaction terms (x_1x_2, x_1x_3, x_2x_3, etc.) and in the case of continuous factors, squared terms (x_1^2, x_2^2, x_3^2 , etc.), the design is called a *response-surface* DOE
  - Goal is generally to develop a predictive model of the process
  - Used with a few (< 6?) factors after a screening DOE

Quadratic model is not much bigger than Interaction model.
If you have continuous factors, choose full 2nd order Quadratic



1st Order

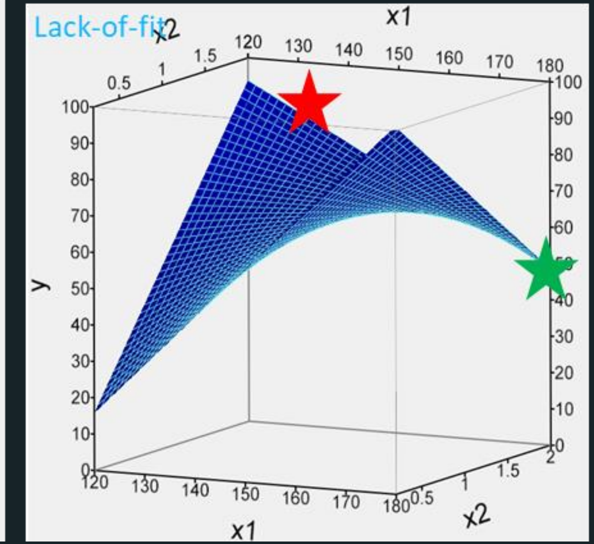
$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3$

For k factors there are
k main effects

For 3 factors Linear Model has 4 terms

For 6 factors Linear Model has 7 terms

For 10 factors Linear Model has 11 terms



2nd Order

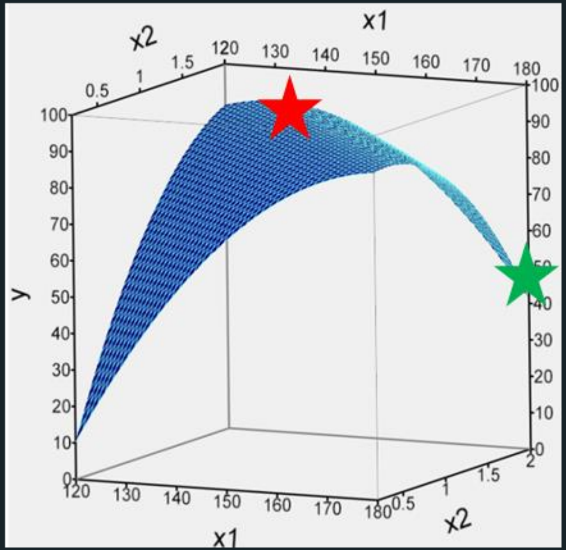
$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3$
$+ a_{12}x_1x_2 + a_{13}x_1x_3 + a_{23}x_2x_3$

For k factors there are
k(k-1)/2 interaction effects

For 3 factors Interaction Model has 7 terms

For 6 factors Interaction Model has 22 terms

For 10 factors Interaction Model has 56 terms



2nd Order

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

For k factors there are
k squared effects

For 3 factors Quadratic Model has 10 terms

For 6 factors Quadratic Model has 28 terms

For 10 factors Quadratic Model has 66 terms

If no squared terms, then optimum can ONLY be a corner!

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Real-World Design Issues

Reasons why classical designs likely will not work…

Making Designs Fit the Problem –
NOT Making Problems Fit the Designs!

- Work with these different kinds of control variables/factors:
  - Continuous/quantitative? (Finely adjustable like *temperature*, *speed*, *force*)
  - Categorical/qualitative? (Comes in types, like material = *rubber*, *polycarbonate*, *steel* with mixed # of levels; 3 chemical agents, 4 decontaminants, 8 coupon materials…)
  - Mixture/formulation? (Blend different amounts of *ingredients* and the process performance is dependent on the *proportions* more than on the amounts)
  - Blocking? (e.g. “lots” of the same raw materials, multiple “same” machines, samples get processed in “groups” – like “eight in a tray,” run tests over multiple days – i.e. variables for which there *shouldn’t* be a causal effect
- Work with combinations of these four kinds of variables?
- Certain combinations cannot be run? (too costly, unsafe, breaks the process)
- Certain factors are hard-to-change (temperature takes a day to stabilize)
- Would like to add onto existing trials? (really expensive/time consuming to run, or by adding constraints can repair broken design)

Categorical Factors and Responses

Factors

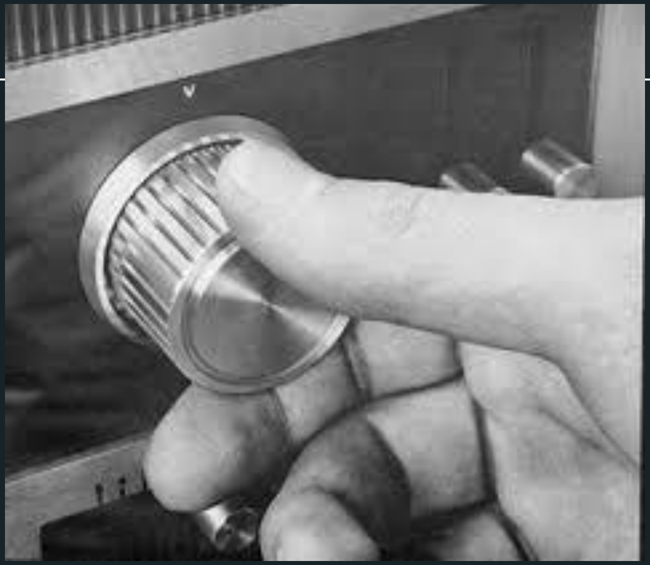
- **Agent**
  - Agent 1
  - Agent 2
  - Agent 3
- **Decontaminant**
  - Decon 1
  - Decon 2
  - Decon 3
  - Decon 4
- **Material**
  - Steel
  - Aluminum
  - Glass
  - Polycarbonate
  - CARC (Paint)
  - Viton
  - Kapton
  - Silicone

Responses

- Pass/Fail
- Yes/No
- Not Cracked/Cracked
- Safe/Caution/Unsafe
- Not Corroded/ Moderately Corroded/ Severely Corroded

Continuous Factors and Responses

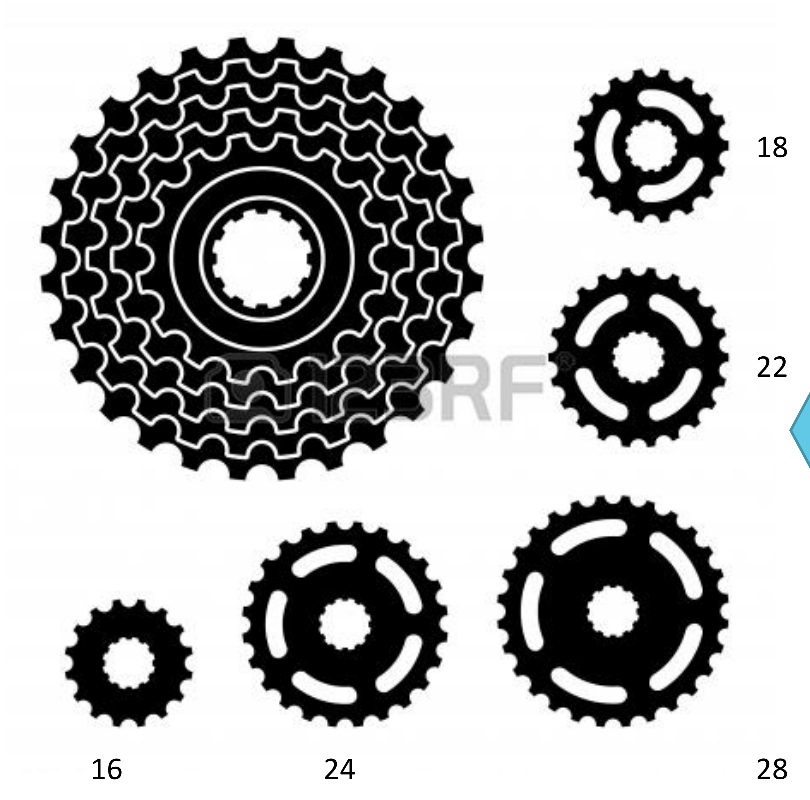
- Factors
  - Time
  - Temperature
  - Amount of Agent/Unit Area
  - Wind Speed
  - Humidity



- Responses
  - Evaporation Rate
  - Absorption
  - Adsorption
  - Residual Concentration

Discrete Numeric Variable

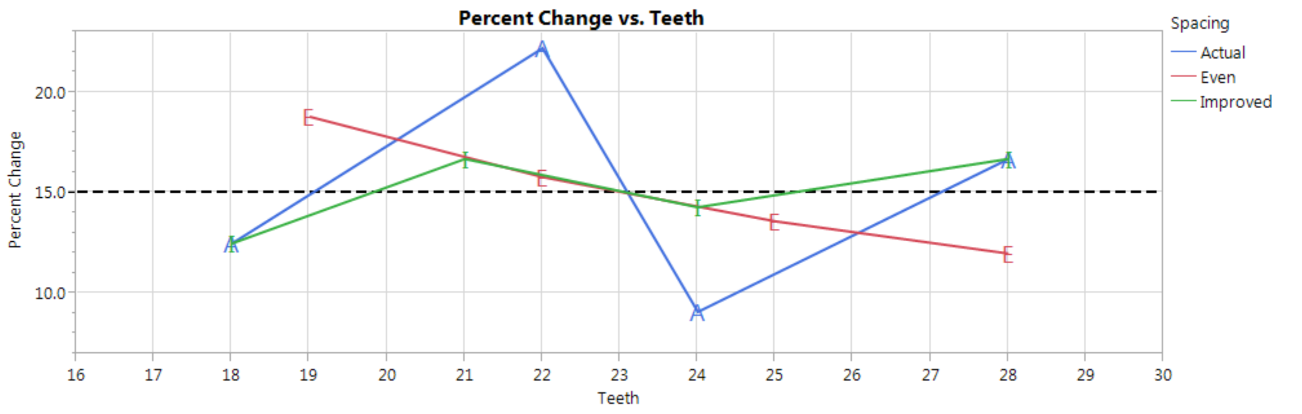
EXAMPLE: NUMBER OF TEETH ON BICYCLE SPROCKETS – INTEGER !!!



Evenly Spaced					
Teeth	16	19	22	25	28
Delta		3	3	3	3
% Change		18.8%	15.8%	13.6%	12.0%

Actual Spacing					
Teeth	16	18	22	24	28
Delta		2	4	2	4
% Change		12.5%	22.2%	9.1%	16.7%

Improved Spacing					
Teeth	16	18	21	24	28
Delta		2	3	3	4
% Change		12.5%	16.7%	14.3%	16.7%



Designs like a categorical factor
Models like a continuous factor

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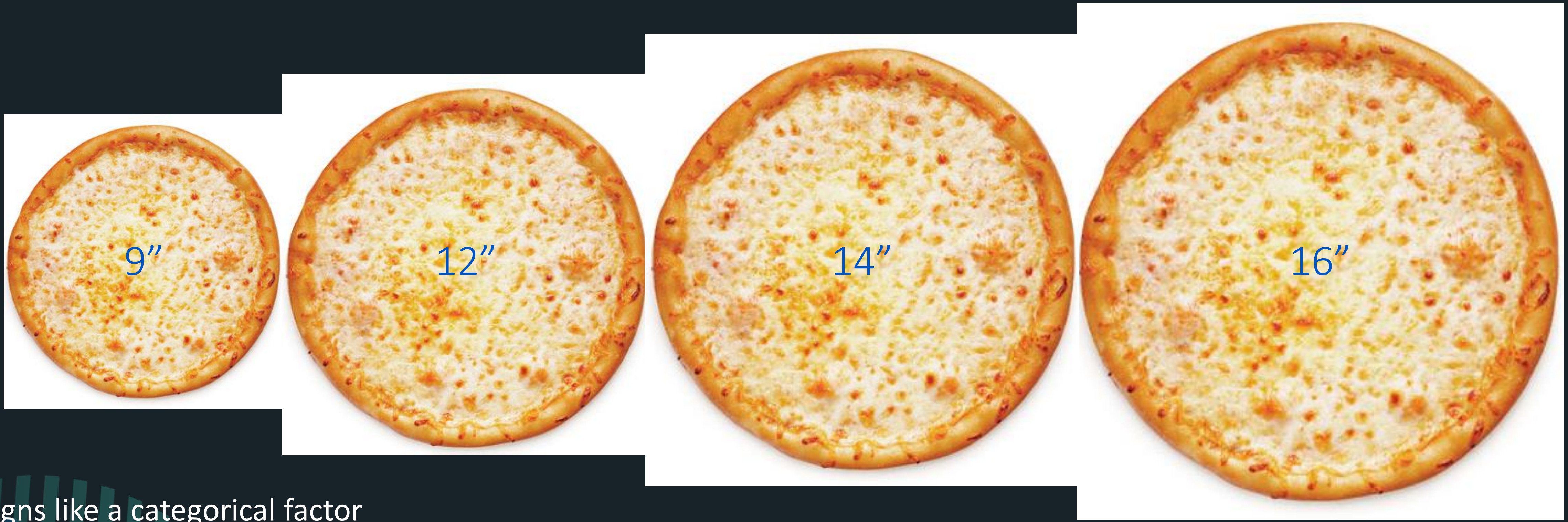
Discrete Numeric Variable

Have only four sizes of pizza pan: 9”, 12”, 14” & 16” in diameter.
Sizes are not evenly spaced and missing mid-point of full range,12.5”.

If size treated as continuous factor, 9” to 16” range entered, & model specified as quadratic, then JMP will produce design with mid-points of 12.5”.

If size treated as discrete numeric factor, all four sizes entered, & model specified as quadratic, then JMP will produce design with all four levels. There will be more 9s & 16s (extremes), than 12s & 14s (more central).



Designs like a categorical factor
Models like a continuous factor

Mixture Variables

SIMPLE MIXTURE – MAKING SALAD DRESSING

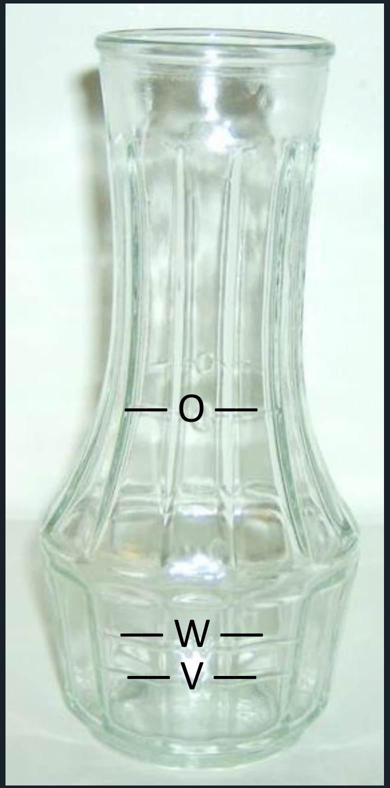
- Relative ***proportions*** of factors or components is more important than actual quantity
- Three liquid components - Oil, Water, and Vinegar
- 8 oz. in Cruet vs. 4 gal. in Jug

5 oz.	"O"	320 oz.	5/8
1 oz.	"W"	64 oz.	1/8
2 oz.	"V"	128 oz.	1/4

- To study these mixture components in a DOE use ranges that are proportions:

O:	0.500 to 0.750	(½ to ¾)
W:	0.000 to 0.250	(0 to ¼)
V:	0.125 to 0.375	(⅛ to ⅜)

- Sum of proportions ***constrained*** to equal 1.



100.0%

37.5%

25.0%

0%

1 = O + W + V so therefore…

W = 1 – (O + V), O = 1 – (V + W), & V = 1 – (O + W)

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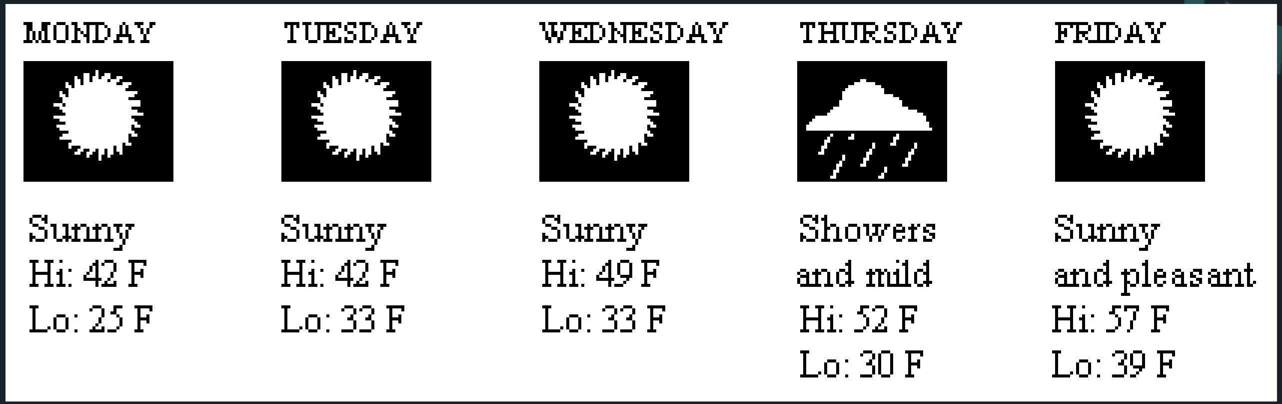
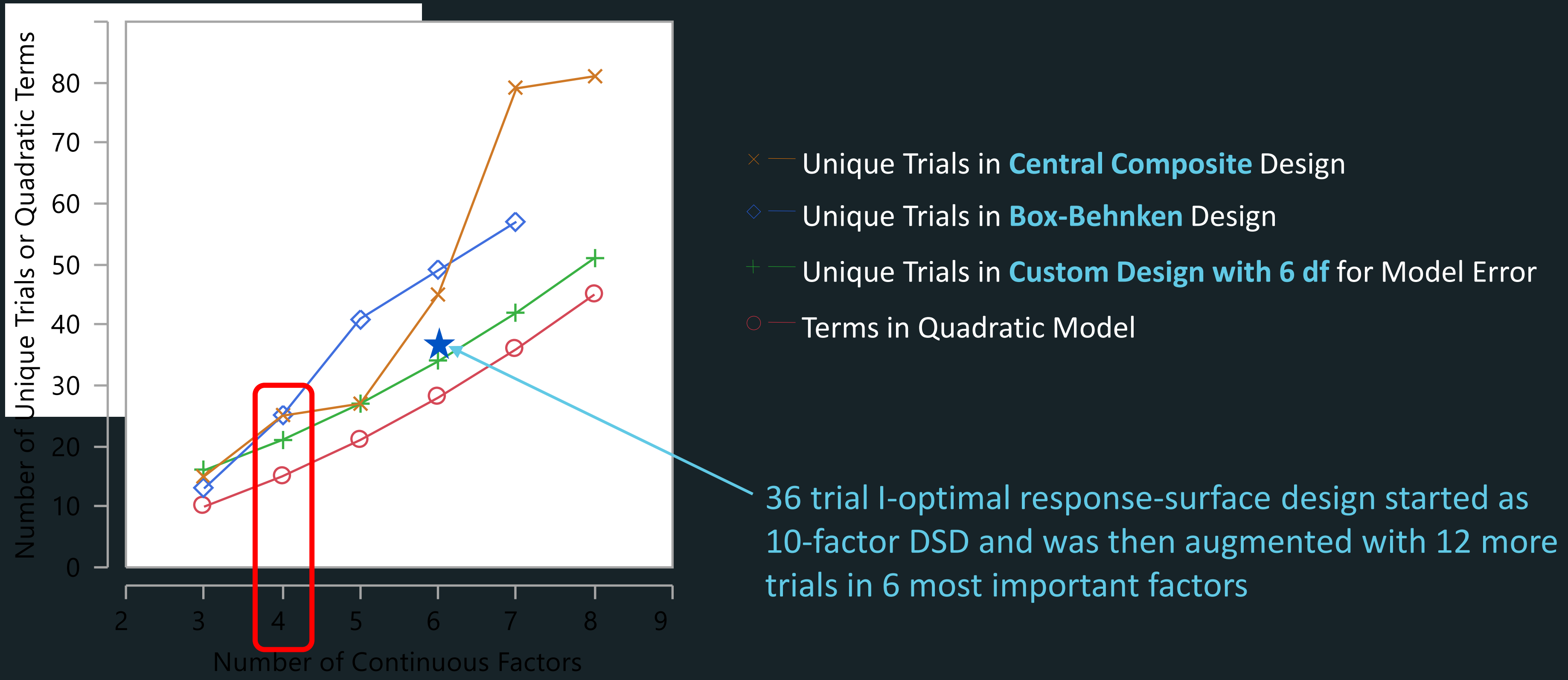
Blocking Factor like “Day” or “Batch”



- A design run over 5 days that is sensitive to humidity might SHIFT on Thursday
  - But what if because of the rain the tester from days 1, 2, 3 & 5 didn’t make it to work?
  - What if that day the power went out briefly? Or all-hands meeting “paused” the work? Or…?
- The block variable doesn’t tell you the cause of the effect - just that a shift has been detected among blocks.
- Hoping block variable has no effect. If it does, then how can we reliably predict other blocks? If significant, it probably means we are missing a factor.
- The only way to be sure that no “unknown” factor has crept into the experiment, is to test for it - and “blocking” your design is an inexpensive insurance policy to buy.
- Block variable is a categorical factor having only 1-way effects (no interactions)

Number of Unique Trials for 3 Response-Surface Designs and Number of Quadratic Model Terms vs. Number of Continuous Factors

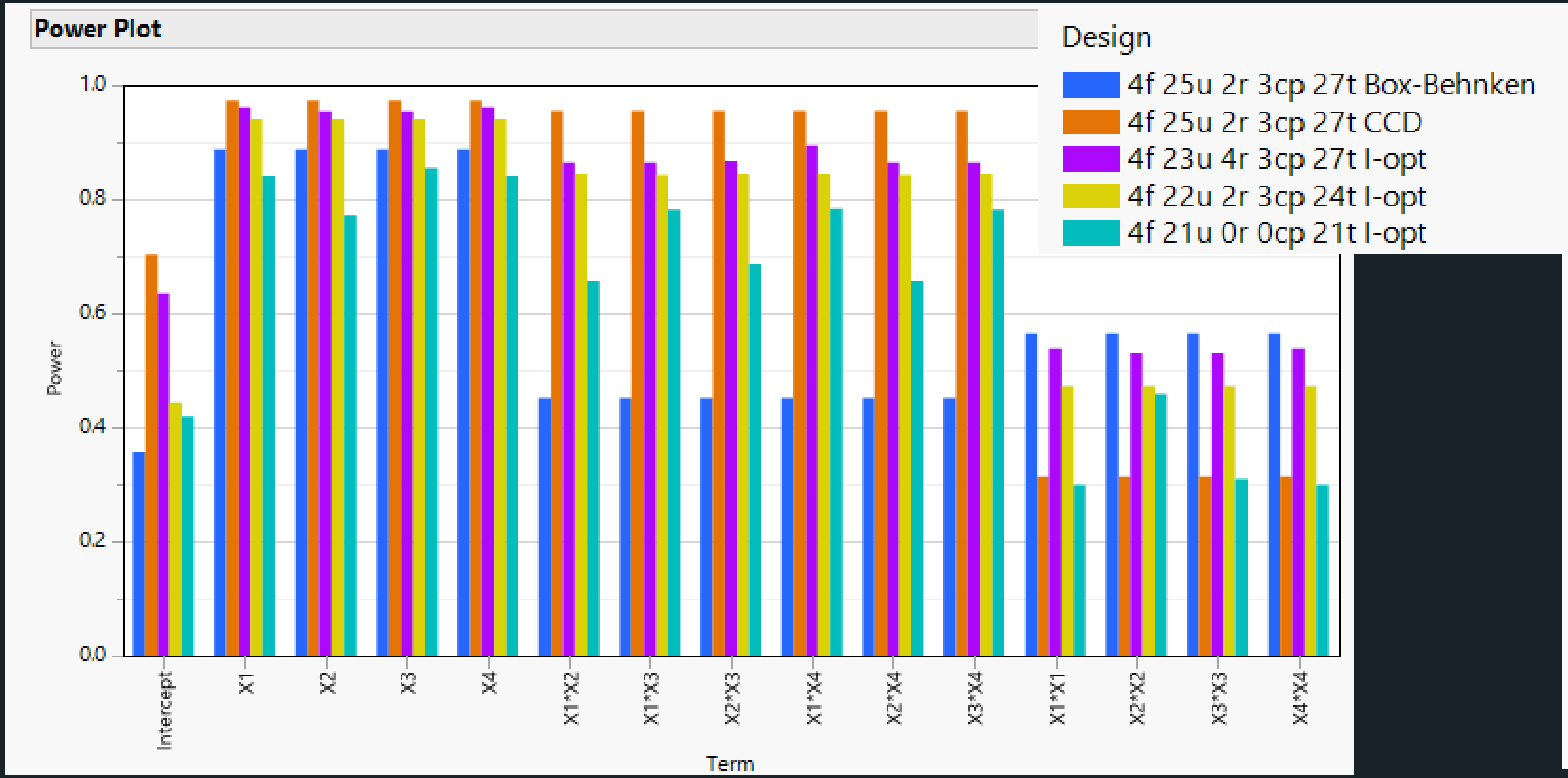


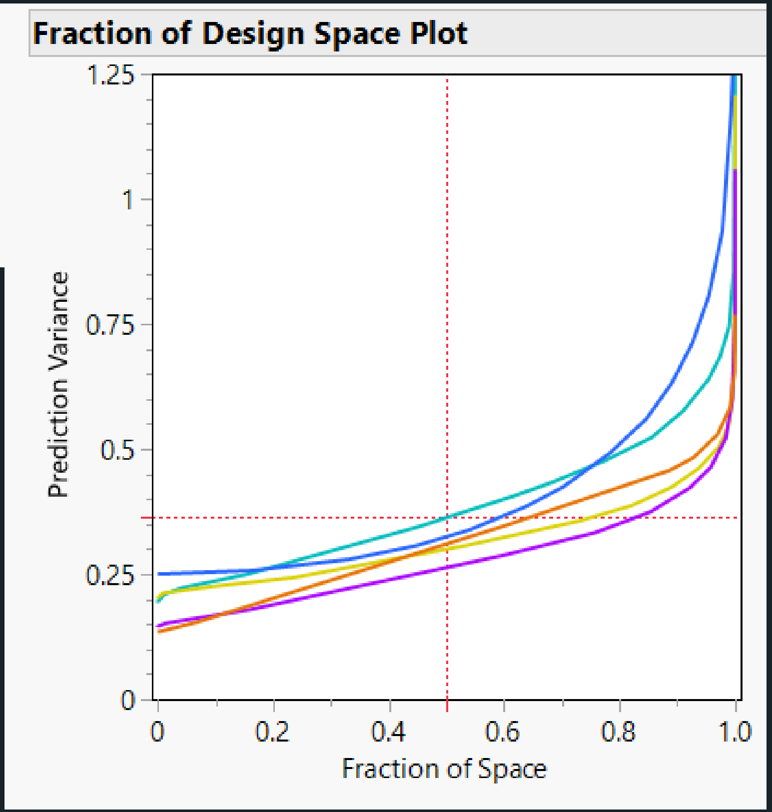
If generally running 3, 4 or 5-factor fractional-factorial designs…

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

Power & Fraction of Design Space Plots

COMPARISON FOR SAME SIZED, 27-TRIAL 4-FACTOR DESIGNS: BOX-BEHNKEN, CENTRAL COMPOSITE, I-OPTIMAL, AND SMALLER 24-TRIAL & 21-TRIAL I-OPTIMAL DESIGNS





BB best for Quadratics
CC best for Main Effects & Interactions
IO-27 strong second for ALL
IO-24 nearly as good

BB highest Prediction Variance
CC lower and flatter than BB
IO-27 lowest & flattest Prediction Variance
IO-24 nearly as good

Recording

https://community.jmp.com/t5/JMP-On-Air/Can-You-Stop-Using-Classic-RSM-Designs-Cold-Turkey-or-Take-Two-I/ta-p/263202

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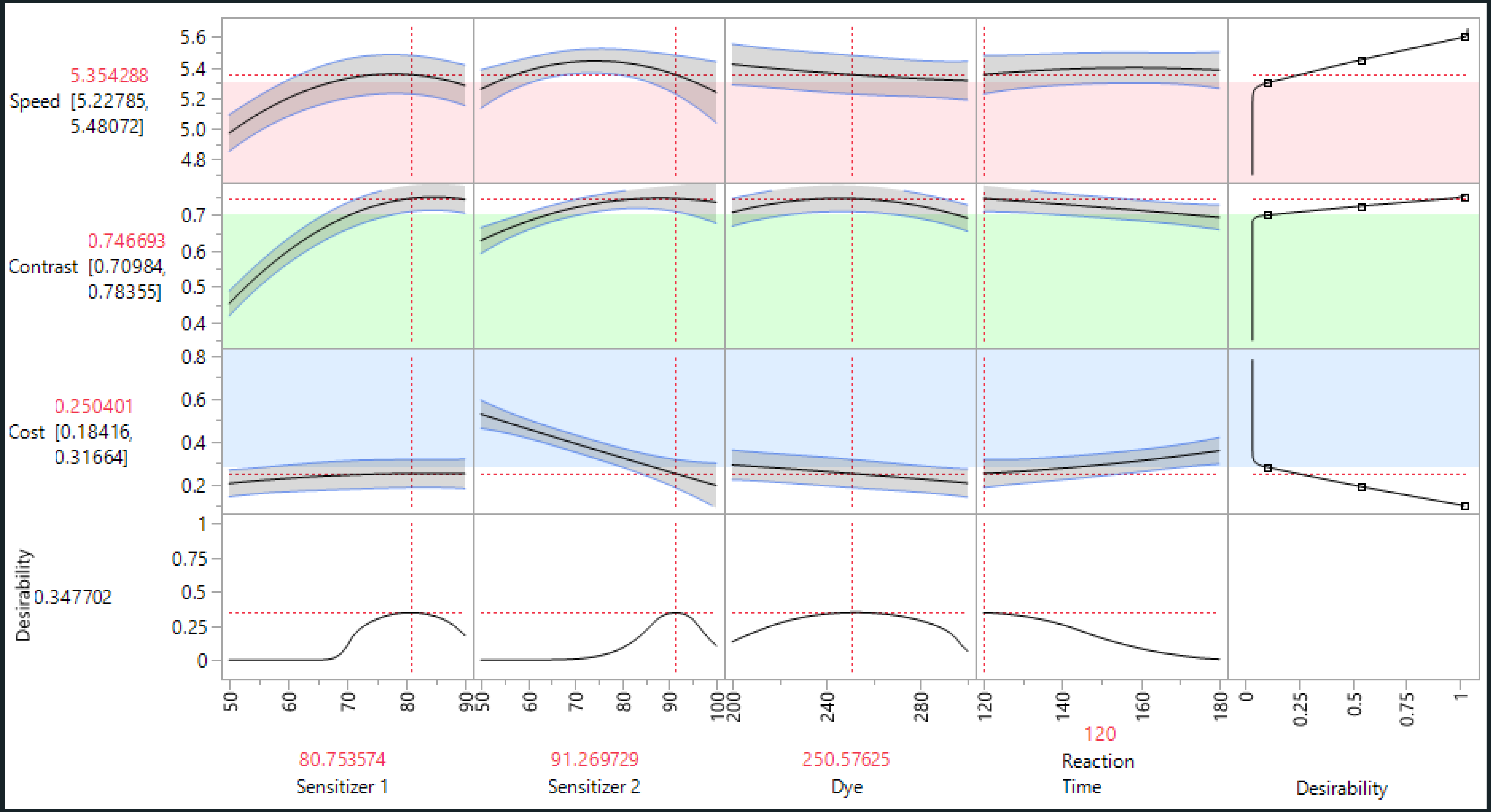
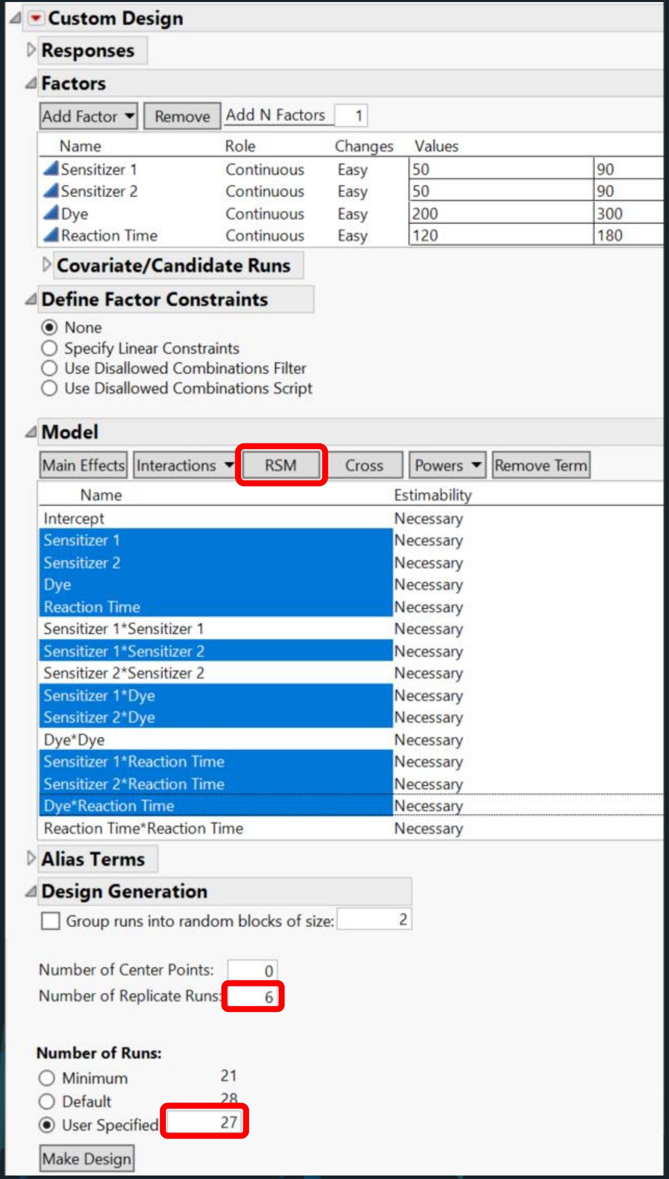
Four Continuous Factor RSM Design

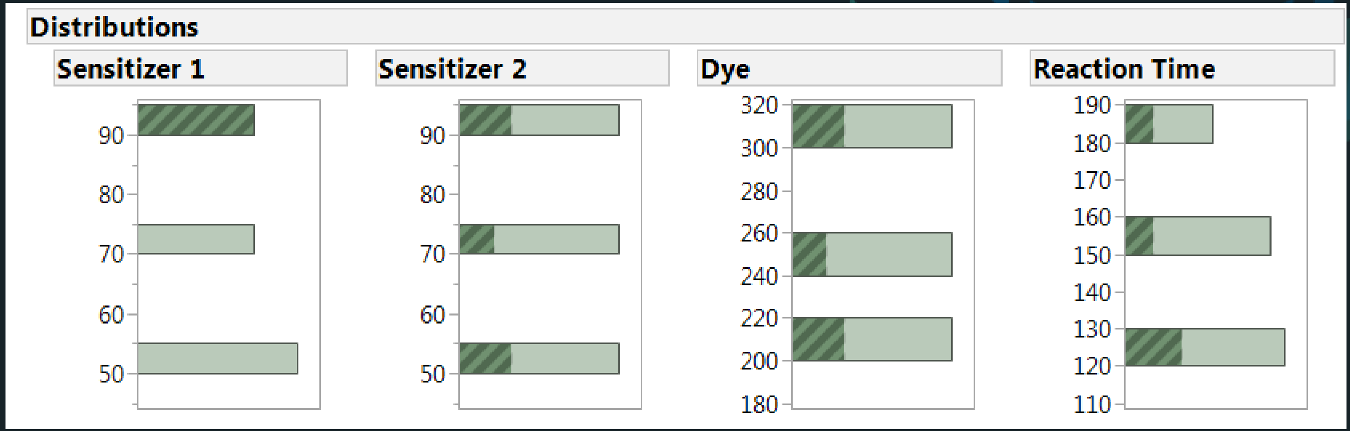
MAKE THE DOE FOR THIS ANALYSIS

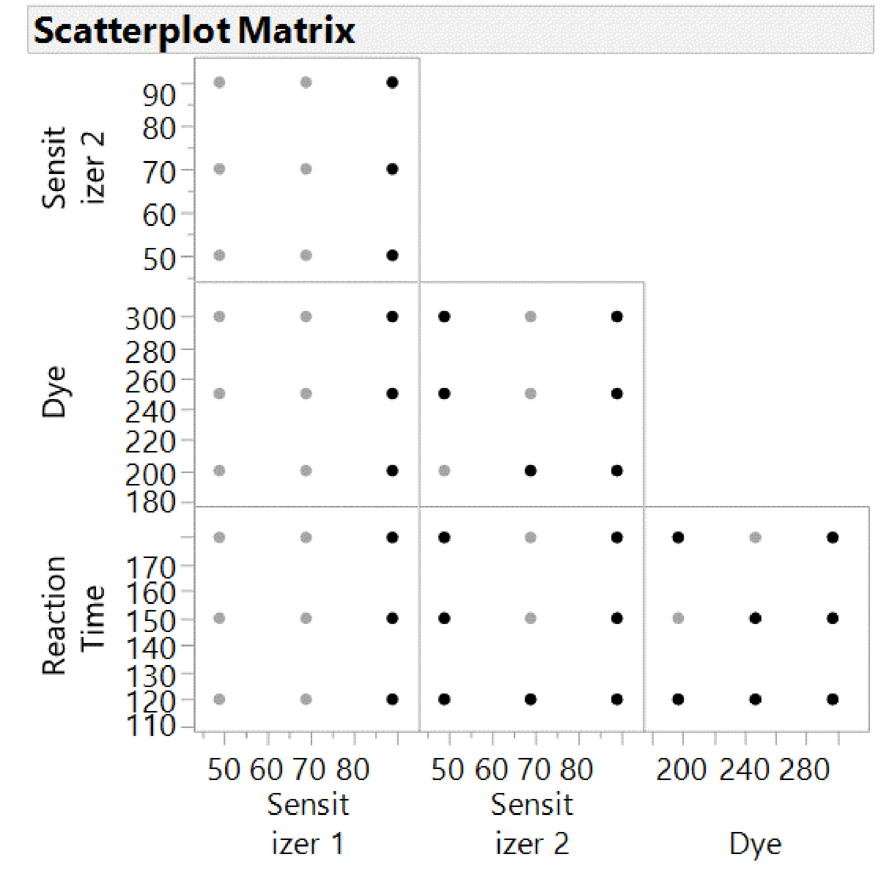


Custom DOE Dialog, Design, Distribution of Design Trials, & Projections of Designs Trials in 2-D



	Sensitizer 1	Sensitizer 2	Dye	Reaction Time	Speed	Contrast	Cost
1	50	50	250	120	5.36	0.616	0.198
2	50	50	200	180	5.39	0.537	0.175
3	90	70	200	120	5.31	0.623	0.447
4	50	90	200	150	5.13	0.431	0.177
5	70	70	250	180	5.37	0.643	0.445
6	50	90	300	120	4.79	0.375	0.231
7	90	90	200	180	5.45	0.626	0.471
8	90	50	250	150	5.00	0.470	0.670
9	50	50	300	150	5.22	0.478	0.283
10	70	90	200	120	5.41	0.668	0.226
11	90	90	250	120	5.33	0.734	0.310
12	50	50	250	120	5.32	0.574	0.257
13	70	50	200	150	5.49	0.596	0.456
14	50	70	250	180	5.22	0.558	0.166
15	70	70	250	150	5.57	0.689	0.390
16	90	90	300	150	5.26	0.653	0.226
17	70	70	250	150	5.47	0.688	0.356
18	70	70	300	120	5.42	0.657	0.337
19	50	70	200	120	5.43	0.518	0.222
20	50	50	300	150	5.15	0.505	0.287
21	90	70	200	120	5.33	0.661	0.457
22	50	90	300	120	4.97	0.411	0.191
23	90	50	300	120	5.09	0.492	0.588
24	90	50	300	180	5.03	0.358	0.733
25	70	70	250	150	5.59	0.707	0.318
26	70	90	300	180	5.25	0.605	0.290
27	50	90	200	150	5.24	0.476	0.177

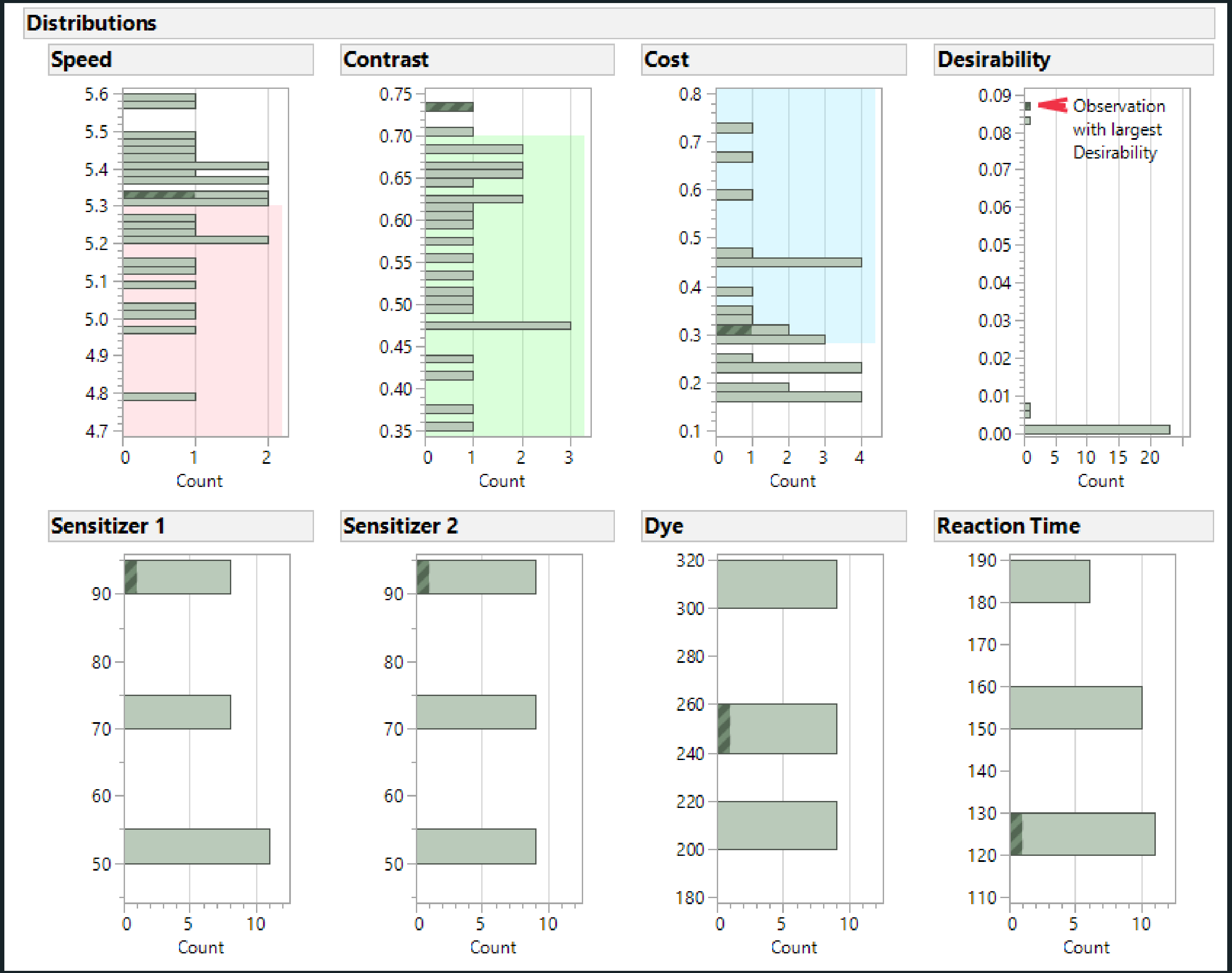




JMP STATISTICAL DISCOVERY

Distributions of Responses and Factors

CAN FIND OBSERVATION WITH HIGHEST DESIRABILITY

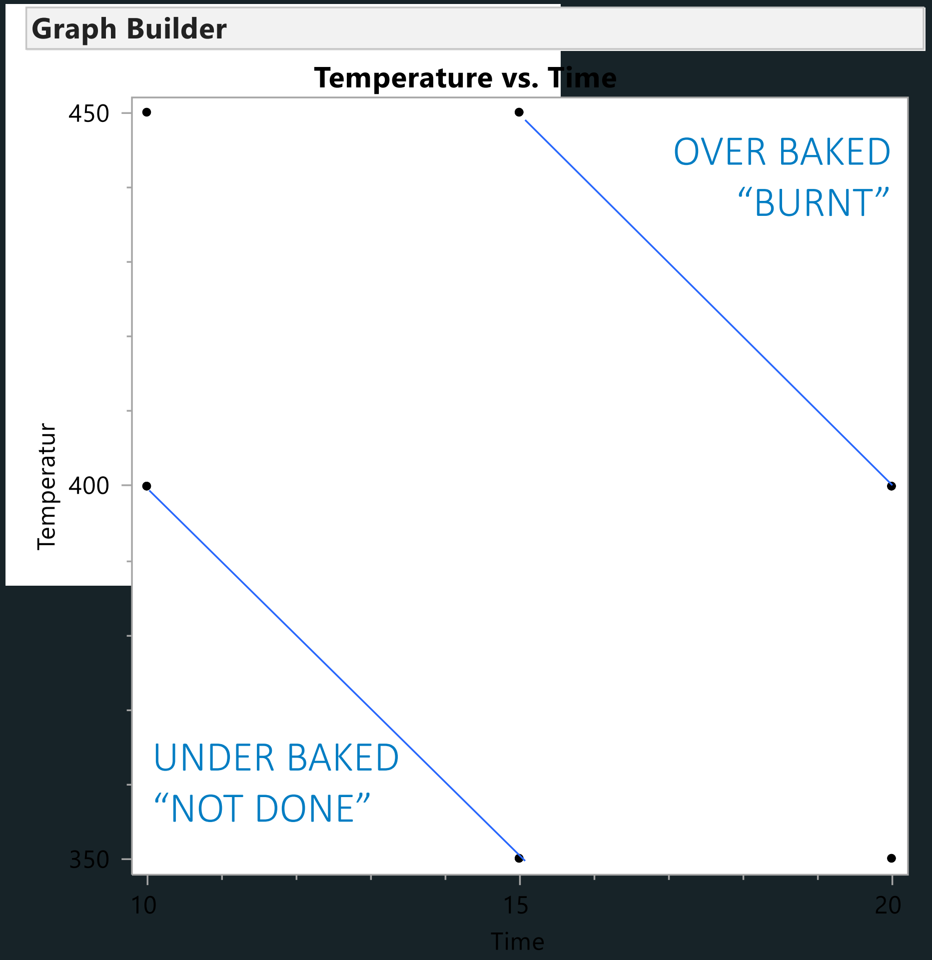


jmp STATISTICAL DISCOVERY

4 Factors, 3 Types, 1 Hard-to-Change, Plus 2 constraints

CREATE DOE FOR A REAL-WORLD PIZZA PROCESS

Continuous	• **Time**: 10 20 (easy)
Continuous	• **Temp**: 350 450 (hard)
Discrete Numeric with 4 levels	• **Pizza Size**: 9, 12, 14, & 16 (easy)
Categorical with 3 levels	• **Pizza Type**: (easy) – Cheese – Meats – Veggies



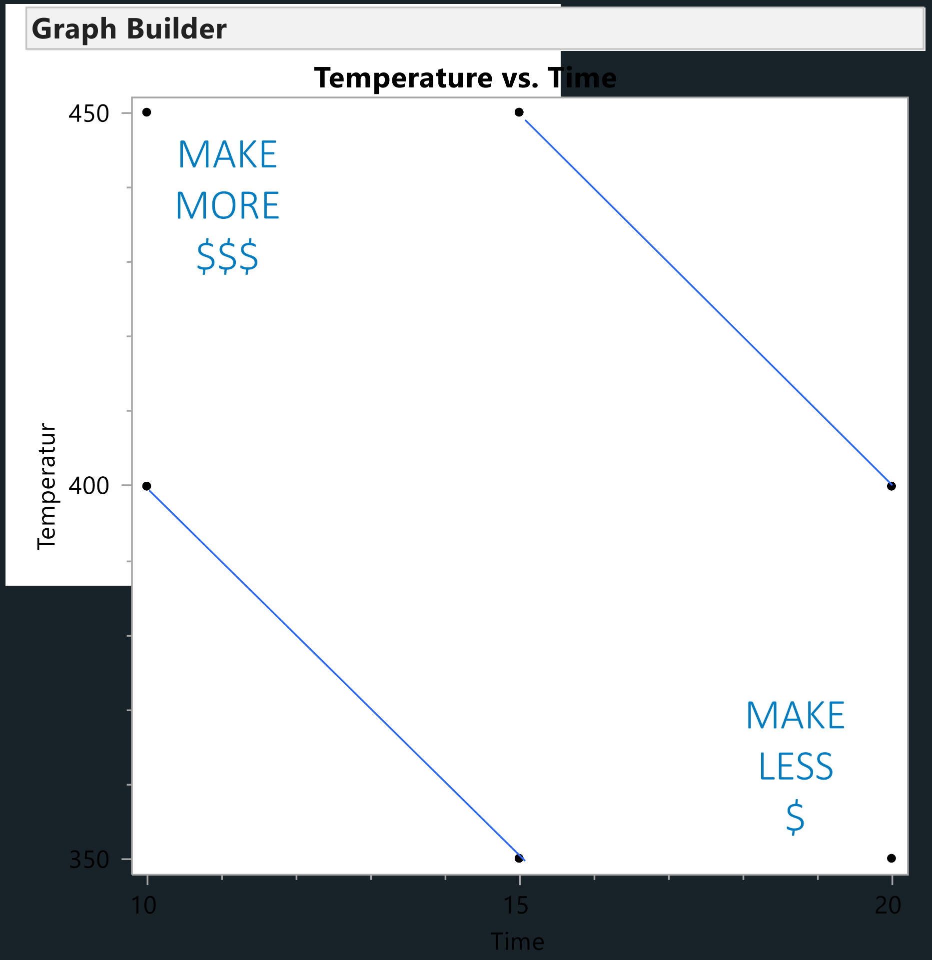
Hi + Hi = “Burnt”

Lo + Lo = “Not Done”

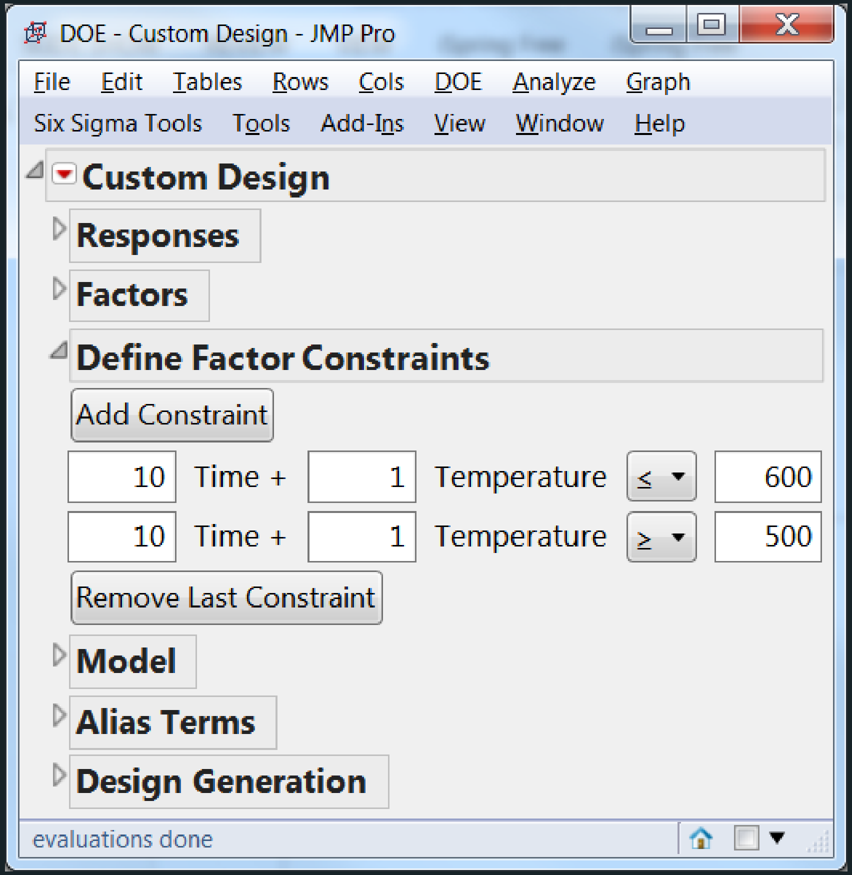
jmp STATISTICAL DISCOVERY

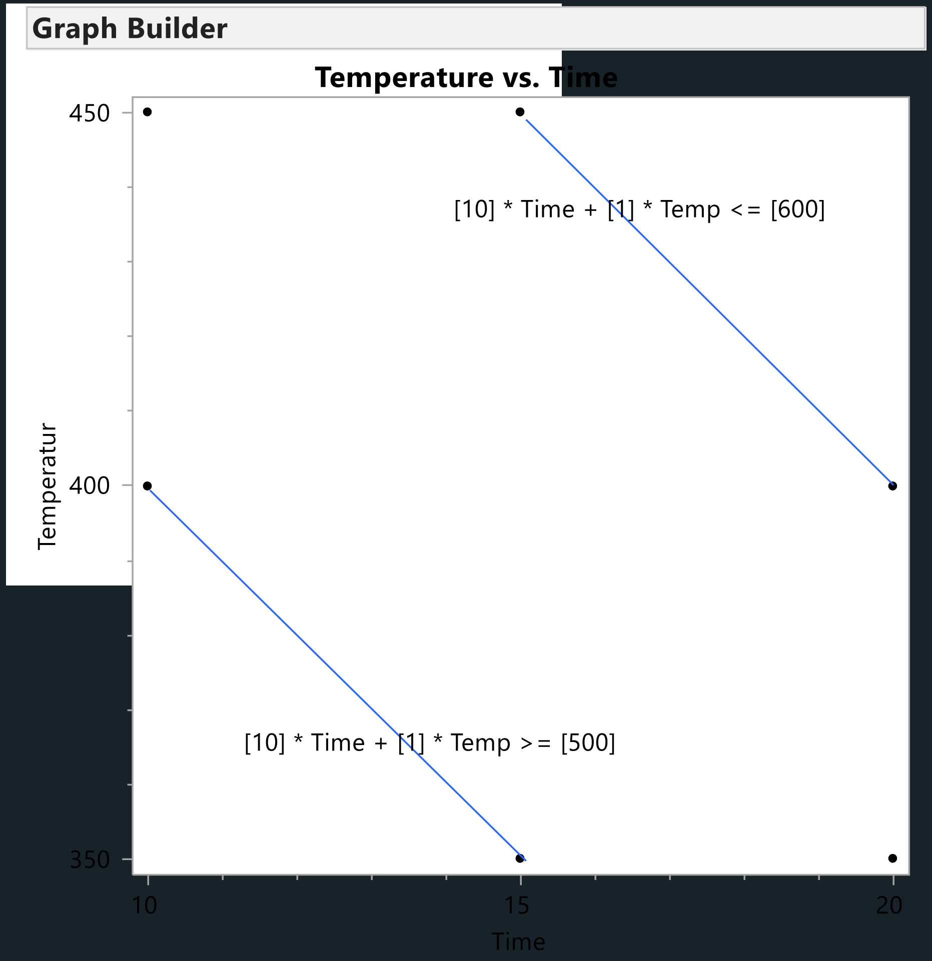
Time and Temperature Constraints

- Shorter times means more pizzas produced per hour
- Make most of your money in a few hours each evening
- *"No pizza shall take more than 7 minutes!"* – Mgmt.



Time and Temperature Constraints
Uncoded = Raw Units

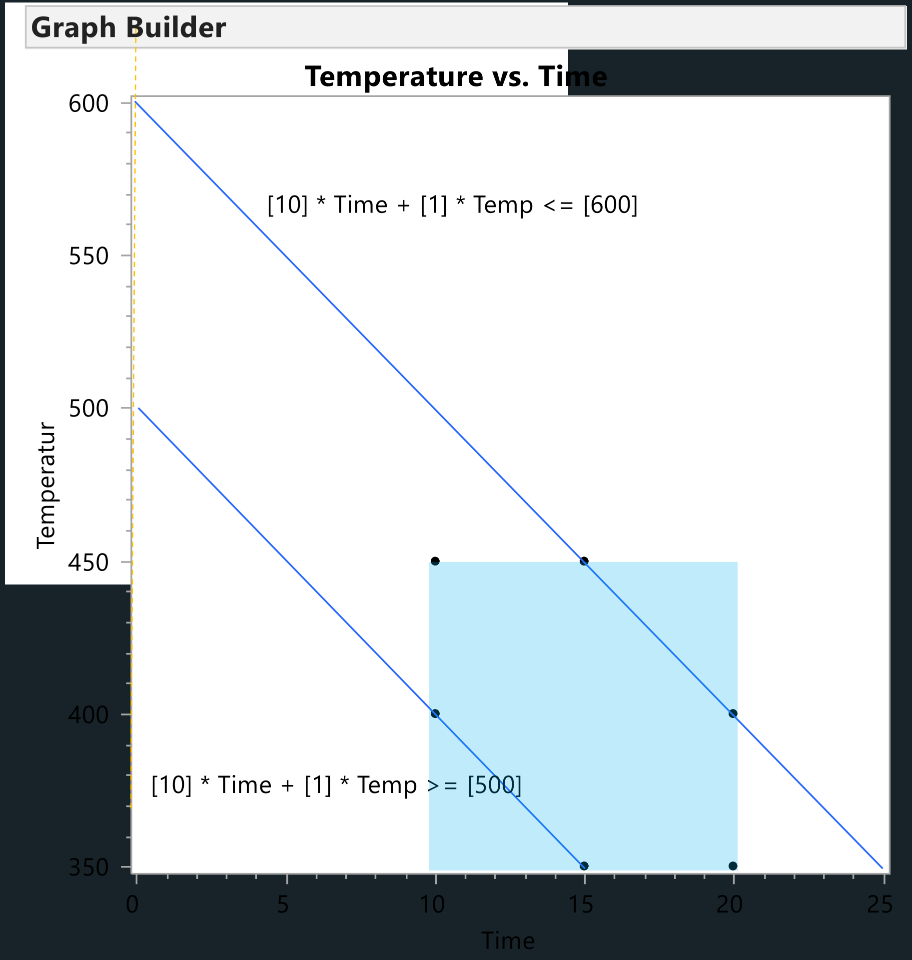


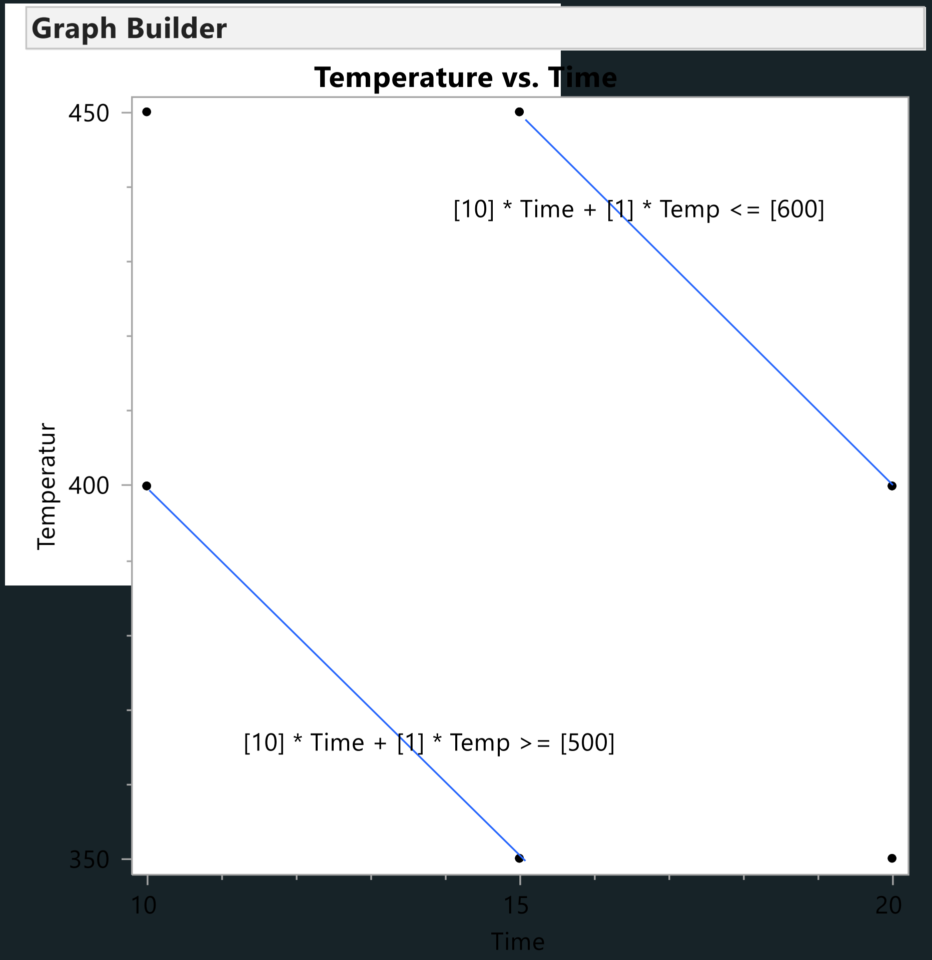


Time and Temperature Constraints Uncoded = Raw Units

RECALL EQUATION OF A STRAIGHT LINE?

$$y = mx + b$$





Slope = m = rise/run = -150/15; m = -10

Intercept = b = y when x = zero; b = 600

Intercept = b = y when x = zero; b = 500

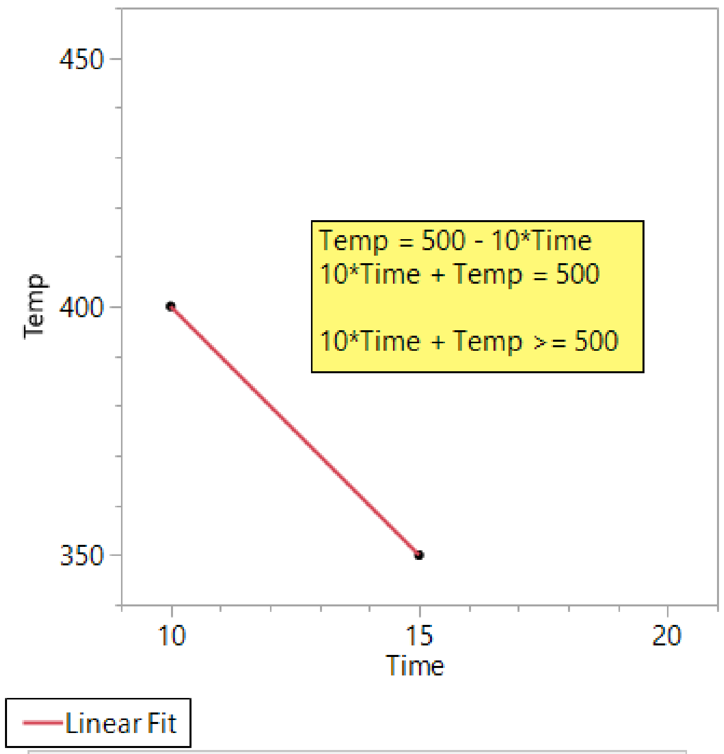
Time and Temperature Constraints
Uncoded = Raw Units

	Time	Temp	Constraint Location
1	15	450	Upper
2	20	400	Upper
3	15	350	Lower
4	10	400	Lower

HAVE JMP SOLVE

$y = mx + b$

Bivariate Fit of Temp By Time Constraint Location=Lower



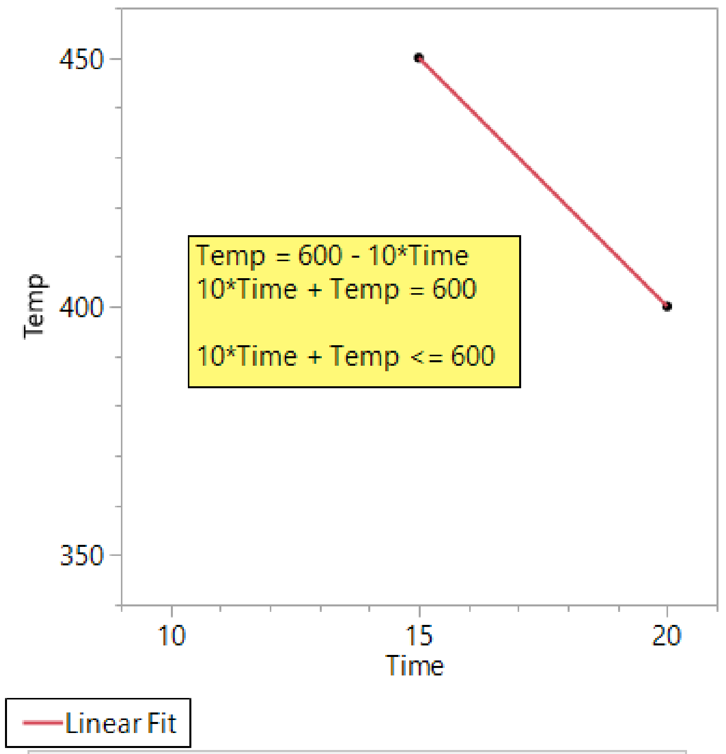
Linear Fit

Temp = 500 - 10*Time

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	500	.	.	.
Time	-10	.	.	.

Bivariate Fit of Temp By Time Constraint Location=Upper



Linear Fit

Temp = 600 - 10*Time

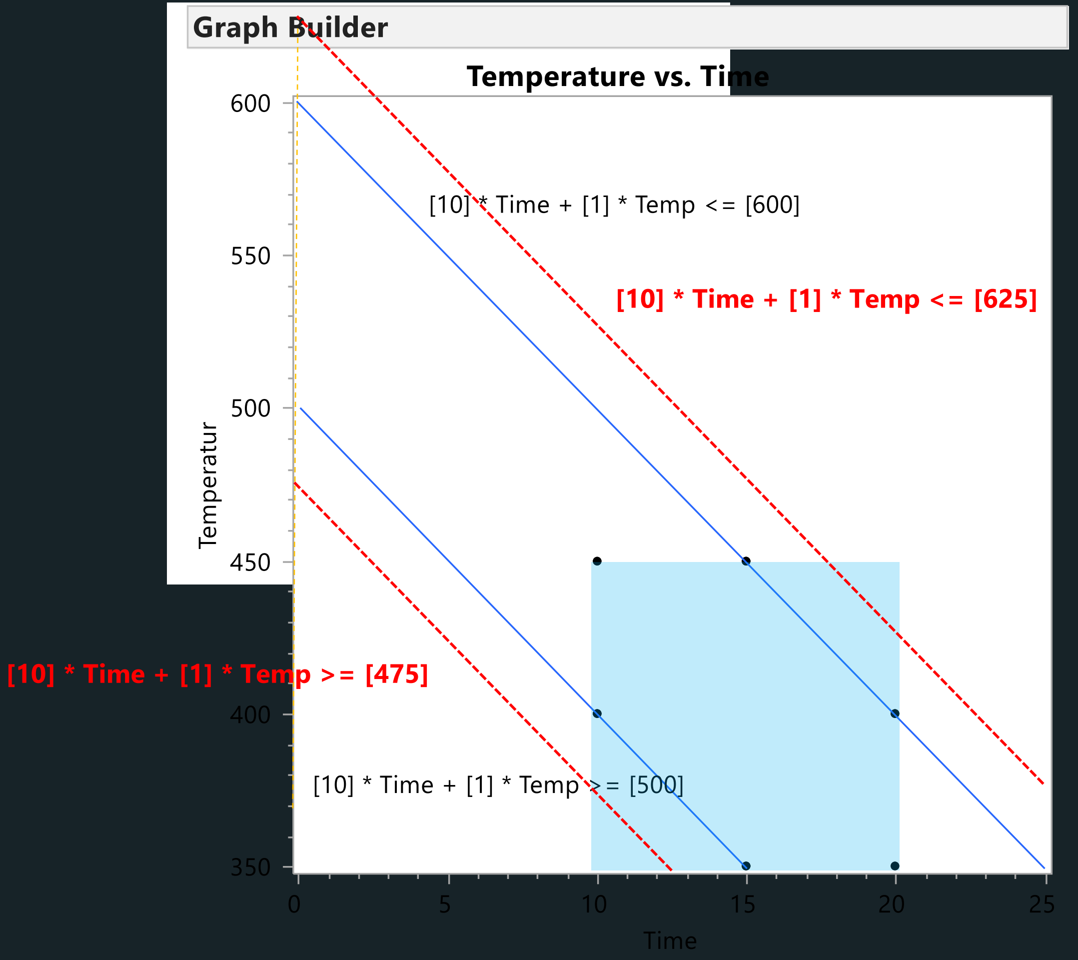
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	600	.	.	.
Time	-10	.	.	.

STATISTICAL DISCOVERY

Time and Temperature Constraints Uncoded
“Broadened” Design

WHAT IF CONSTRAINTS NARROWED DESIGN REGION TO A THIN DIAGONAL SLICE IN TIME & TEMP? THEY WOULD THEN BE HIGHLY CORRELATED.



Slope = m = rise/run = -150/15; m = -10

Intercept = b = y when x = zero; b = 625

Intercept = b = y when x = zero; b = 475

y = mx + b

Temp = m*Time + b

[1]*Temp = [-10]*Time + [625]

[10]*Time + [1]*Temp = [625]

[10]*Time + [1]*Temp <= [625]

y = mx + b

Temp = m*Time + b

[1]*Temp = [-10]*Time + [475]

[10]*Time + [1]*Temp = [475]

[10]*Time + [1]*Temp >= [475]

4 Factors, 3 Types, 1 Hard-to-Change, Plus 2 constraints

GO TO JMP AND CREATE DOE FOR THIS REAL-WORLD PIZZA PROCESS

Factors

Add Factor | Remove | Add N Factors 1

Name	Role	Changes	Values			
Time	Continuous	Easy	10	20		
Temperature	Continuous	Hard	350	450		
Pizza Size	Discrete Numeric	Easy	9	12	14	16
Pizza Type	Categorical	Easy	Cheese	Veggies	Meats	

Define Factor Constraints

- None
- Specify Linear Constraints (selected)
- Use Disallowed Combinations Filter
- Use Disallowed Combinations Script

Linear Constraints

Add

10 Time + 1 Temperature ≤ 625

10 Time + 1 Temperature ≥ 475

Remove Last Constraint

Check Constraints

Model

Main Effects | Interactions | RSM | Cross | Powers | Remove Term

Name	Estimability
Intercept	Necessary
Time	Necessary
Temperature	Necessary
Pizza Size	Necessary
Pizza Size*Pizza Size	If Possible
Pizza Size*Pizza Size*Pizza Size	If Possible
Pizza Type	Necessary
Time*Time	Necessary
Time*Temperature	Necessary
Temperature*Temperature	Necessary
Time*Pizza Size	Necessary

Design Generation

Number of Whole Plots 6

Number of Runs:

- Minimum 17
- Default 24 (selected)
- User Specified 24

Make Design

6/2 Cols

24/12

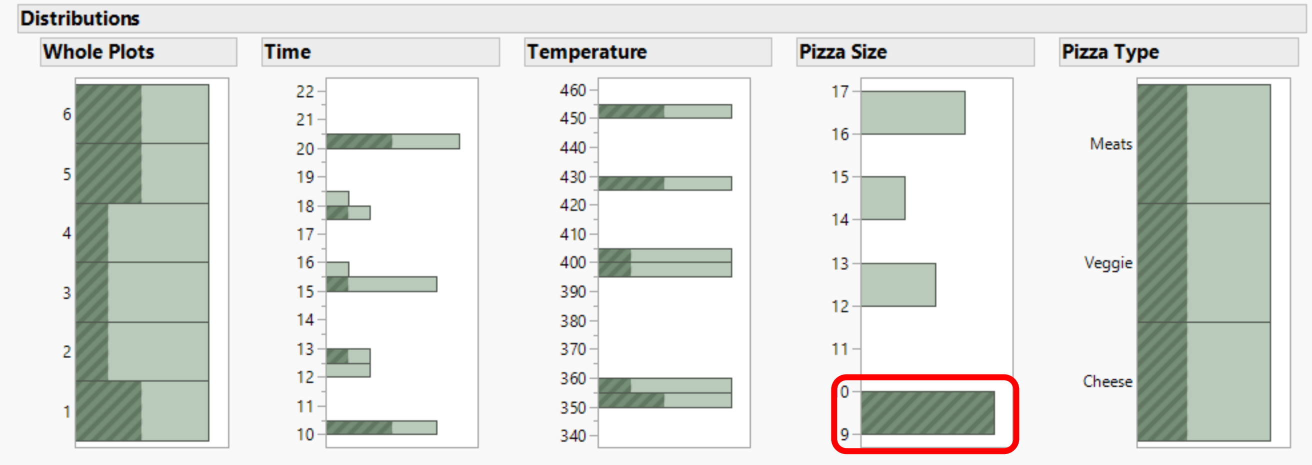
	Whole Plots	Time	Temperature	Pizza Size	Pizza Type
1	1	10	450	14	Veggie
2	1	17.5	450	9	Meats
3	1	10	450	9	Cheese
4	1	17.5	450	16	Cheese
5	2	15	397.5	14	Cheese
6	2	10	397.5	16	Cheese
7	2	10	397.5	9	Veggie
8	2	15	397.5	12	Meats
9	3	12	355	16	Veggie
10	3	20	355	16	Cheese
11	3	15.2	355	12	Meats
12	3	20	355	9	Veggie
13	4	20	400	14	Meats
14	4	18	400	16	Veggie
15	4	15	400	12	Cheese
16	4	10	400	9	Meats
17	5	15	425	9	Veggie
18	5	12	425	16	Meats
19	5	20	425	9	Cheese
20	5	20	425	12	Veggie
21	6	12.5	350	16	Meats
22	6	12.5	350	9	Cheese
23	6	20	350	9	Meats
24	6	15.5	350	12	Veggie

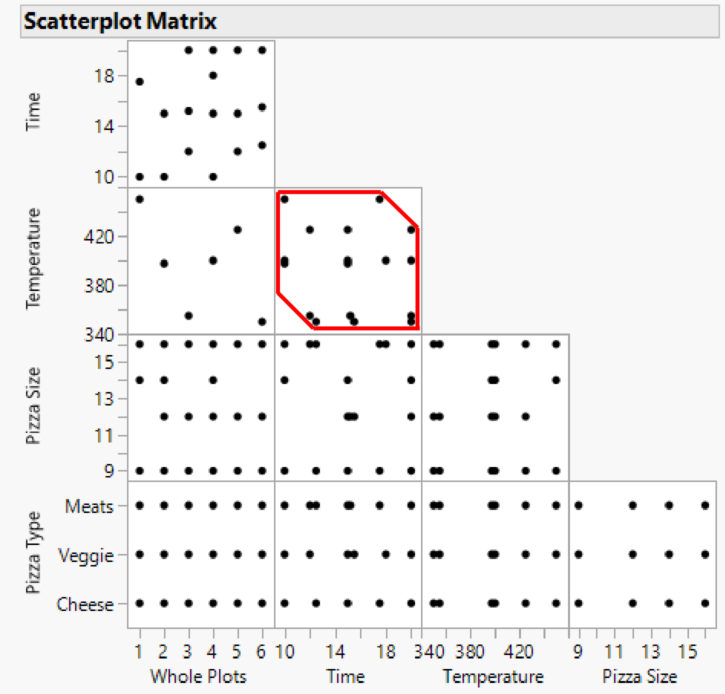
Visualize Design Balance

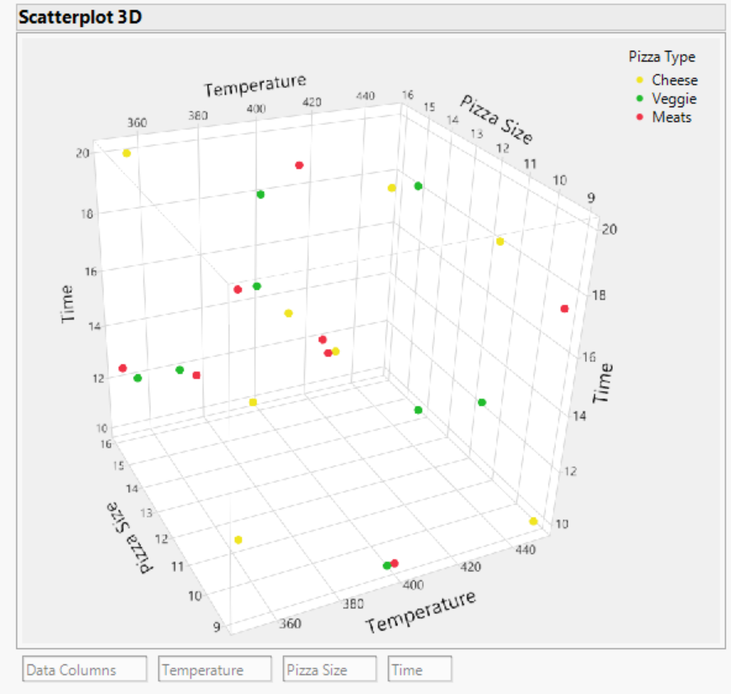
DISTRIBUTION OF DESIGN TRIALS & PROJECTIONS OF DESIGNS TRIALS IN 2-D & 3-D

6/2 Cols, 24/12

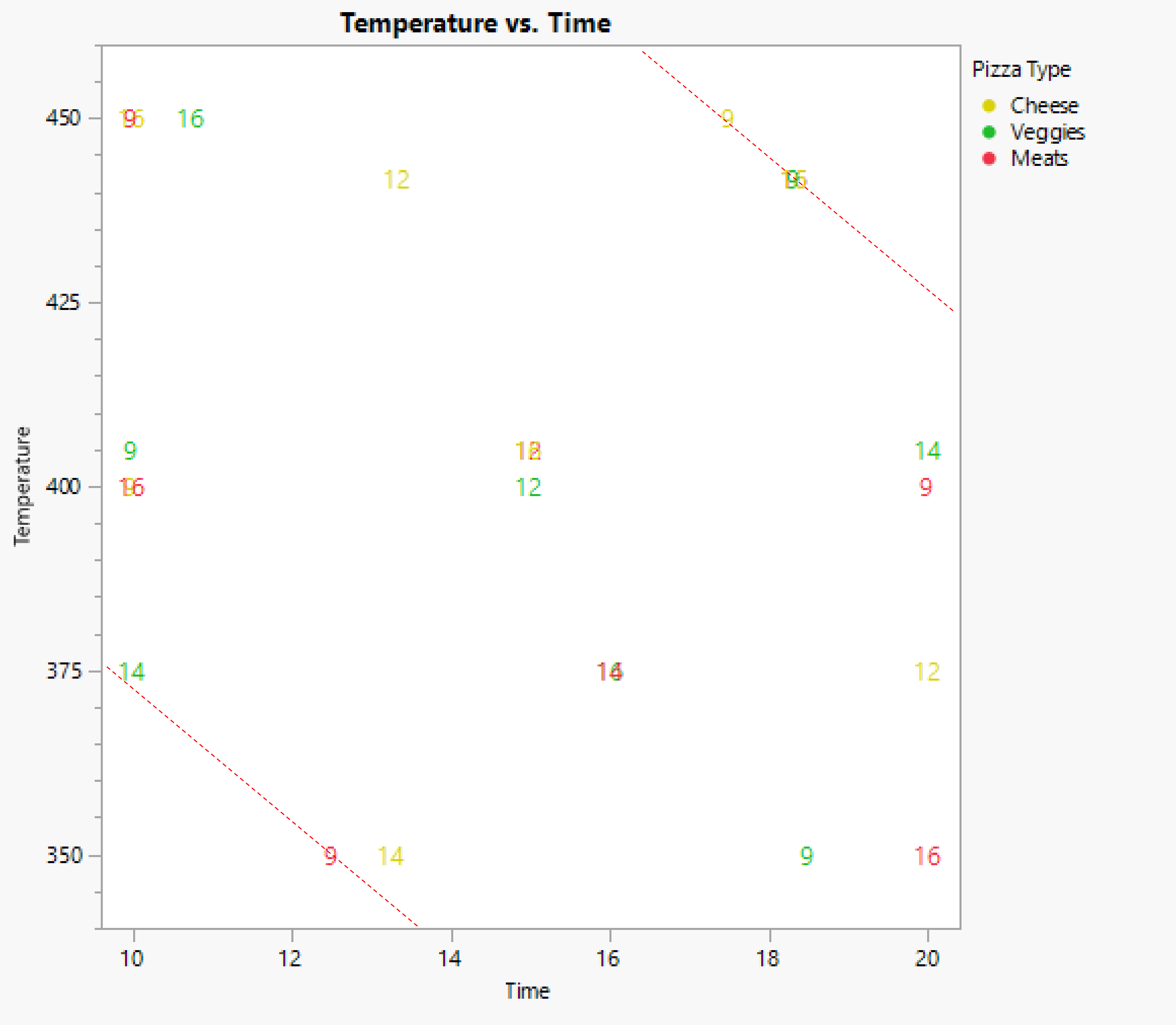
	Whole Plots	Time	Temperature	Pizza Size	Pizza Type
1	1	10	450	14	Veggie
2	1	17.5	450	9	Meats
3	1	10	450	9	Cheese
4	1	17.5	450	16	Cheese
5	2	15	397.5	14	Cheese
6	2	10	397.5	16	Cheese
7	2	10	397.5	9	Veggie
8	2	15	397.5	12	Meats
9	3	12	355	16	Veggie
10	3	20	355	16	Cheese
11	3	15.2	355	12	Meats
12	3	20	355	9	Veggie
13	4	20	400	14	Meats
14	4	18	400	16	Veggie
15	4	15	400	12	Cheese
16	4	10	400	9	Meats
17	5	15	425	9	Veggie
18	5	12	425	16	Meats
19	5	20	425	9	Cheese
20	5	20	425	12	Veggie
21	6	12.5	350	16	Meats
22	6	12.5	350	9	Cheese
23	6	20	350	9	Meats
24	6	15.5	350	12	Veggie



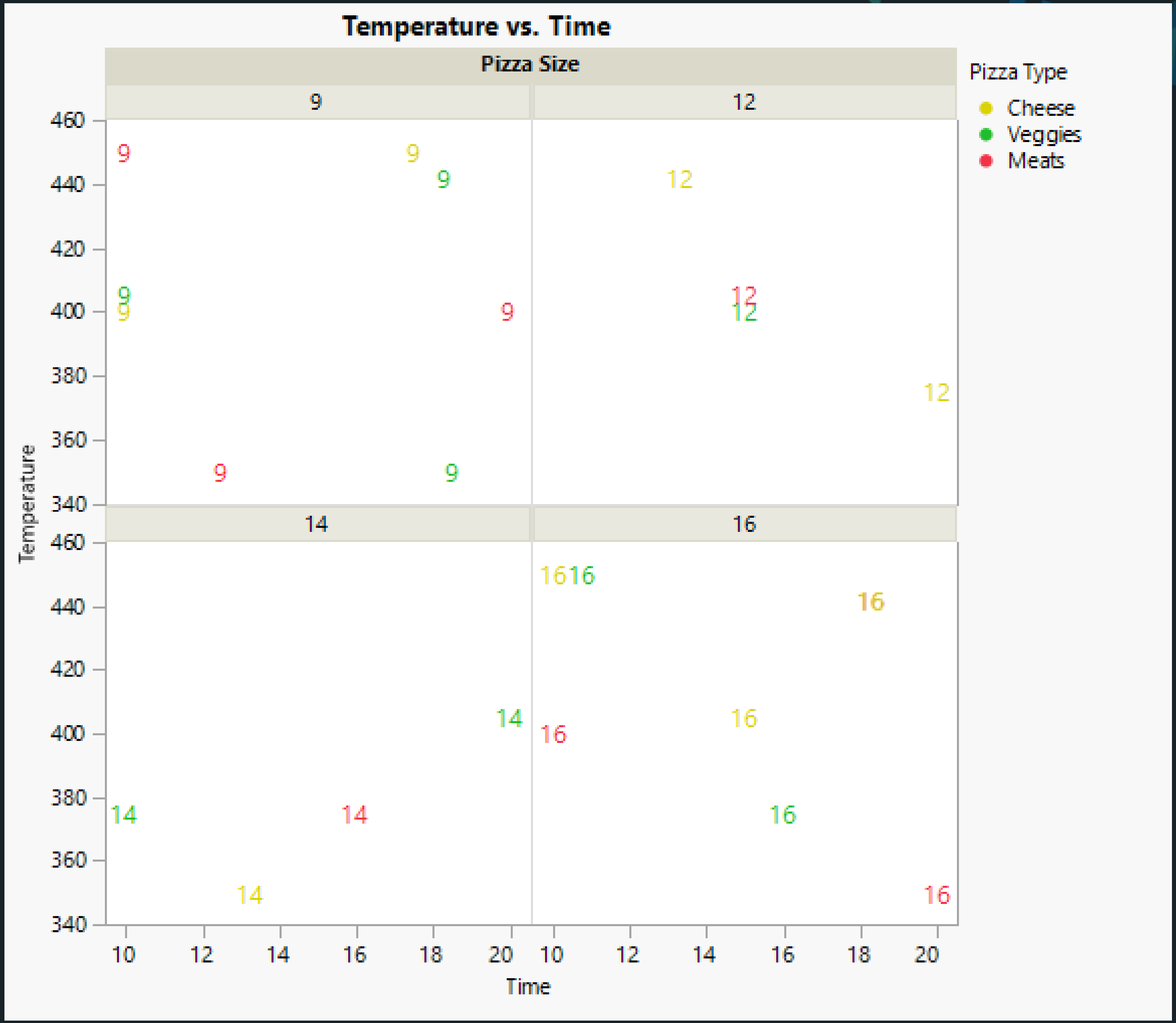




Final Design Showing Constrained Regions

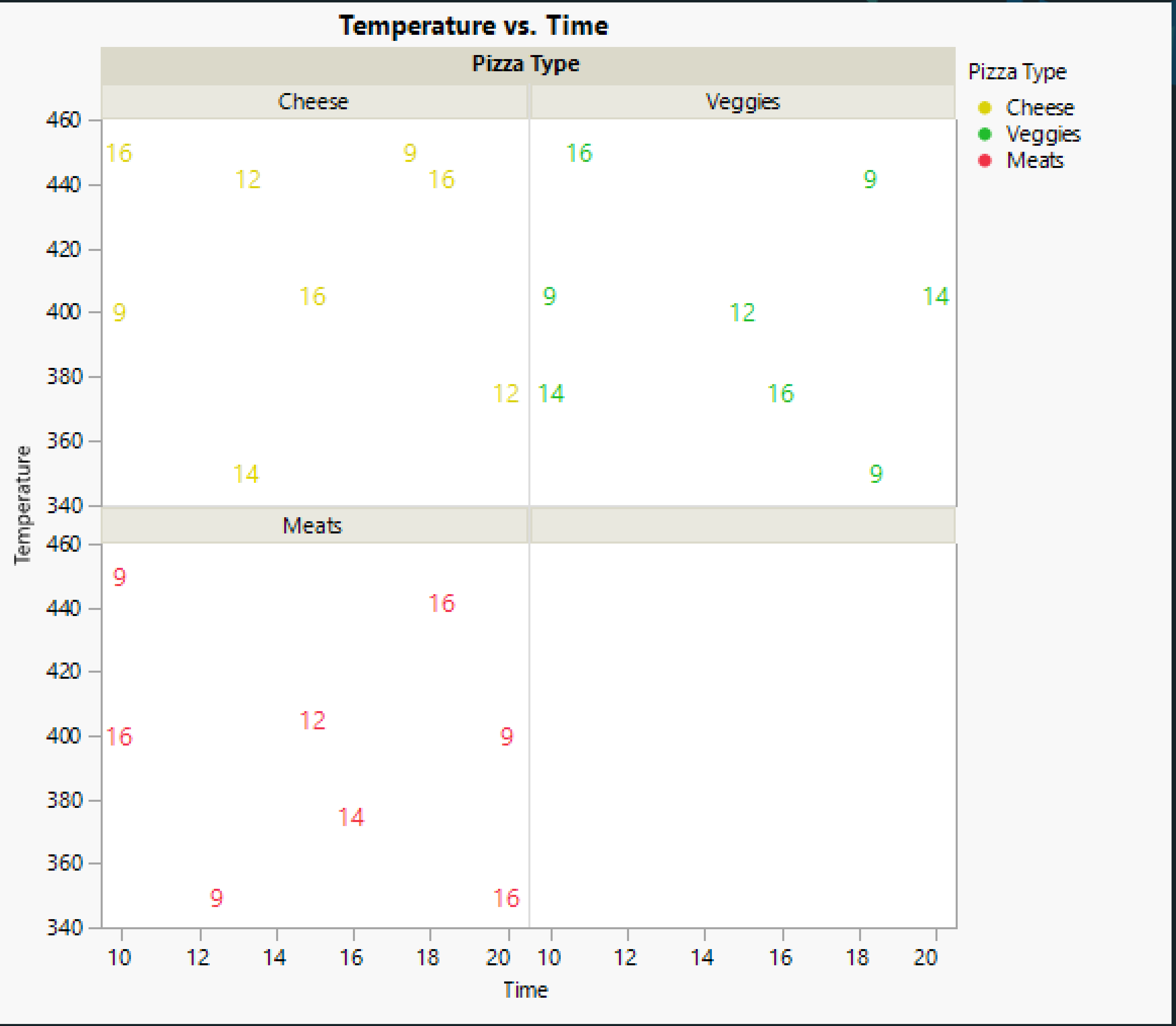


Final Design Showing Constrained Regions



JMP STATISTICAL DISCOVERY

Final Design Showing Constrained Regions



Agenda

30-MINUTE PRESENTATION & 15-MINUTE Q & A

- Multiple Response Optimization

  Trade-Space Analysis – Why we do Design of Experiments (DOE)

- Six step framework for creating a successful DOE
  & important questions to consider

- Real-World Experimental Issues – Custom DOE is all about

  Making Designs Fit the Problem –
  NOT Making Problems Fit the Designs!

- Two Example Designs – 1st Quick (slide), 2nd Detailed (run JMP)

  1. Four continuous factors, three responses, and 2nd order RSM model
  2. Continuous, discrete numeric, categorical, and hard-to-change factors, plus added constraints, and 2nd order RSM model

jmp STATISTICAL DISCOVERY