Designing Robust Products

Kevin Gallagher, Ph.D.

PPG Industries

Fall 2020

PPG is a global maker of

paints, coatings and specialty materials

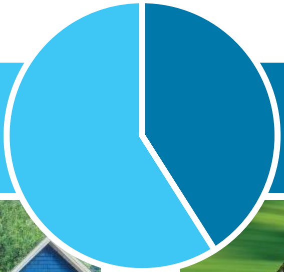
Founded in 1883

Headquarters in Pittsburgh, PA

Operations in 70+ countries

#209 on the Fortune 500

Two product segments drive our $15.1B business*



Performance Coatings: 59%

Aerospace

Architectural Coatings**

Automotive Refinish Coatings

Protective and Marine Coatings

Industrial Coatings: 41%

Automotive OEM Coatings

Industrial Coatings

Packaging Coatings

Specialty Coatings and Materials

* 2019 revenue ** Includes Architectural Coatings (Americas and Asia Pacific) and Architectural Coatings (Europe, Middle East and Africa)

PPG Coatings Innovation Center

Allison Park, PA

- 250+ researchers
- synthesis chemists, formulators, analytical chemists, engineers
- 600+ patents in past 10 years

Ford 2016 Excellence Award

R&D 100
54 Years of Invention

Automotive News PACE AWARD
EY Building a better working world
TRC Transportation Research Center Inc.

GREEN CHEMISTRY
A U.S. EPA Program

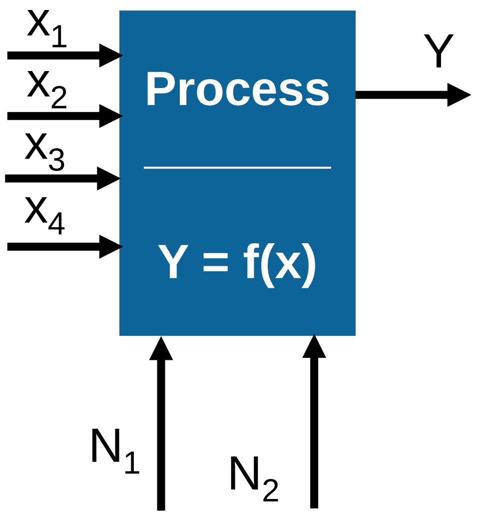
Fiat Sustainability Award

PPG is a coatings industry benchmark for innovation

What do we mean by a robust product?

A robust product delivers consistent results!

The strategy of robust design is to purposefully set Control factors (x) to desensitize the product or process to Noise factors (N).



Y = key performance properties for which consistent results are important

X = Control factors: Set by those designing the product or process

N = Noise factors: Potentially affect Y but are not controlled

- Variations in the manufacturing process - in-house, customer process
- Environmental factors

Process Map – Automotive Coating Development

Design

X – Material Types
X – Material Levels
X – Processing Conditions

Manufacture

N – Charge Weights
N – Raw Material Variation

Apply

N – Thickness
N – Booth Temp/Humidity
N – Applicator settings

Y – Showroom Appearance
Y - Color

Use

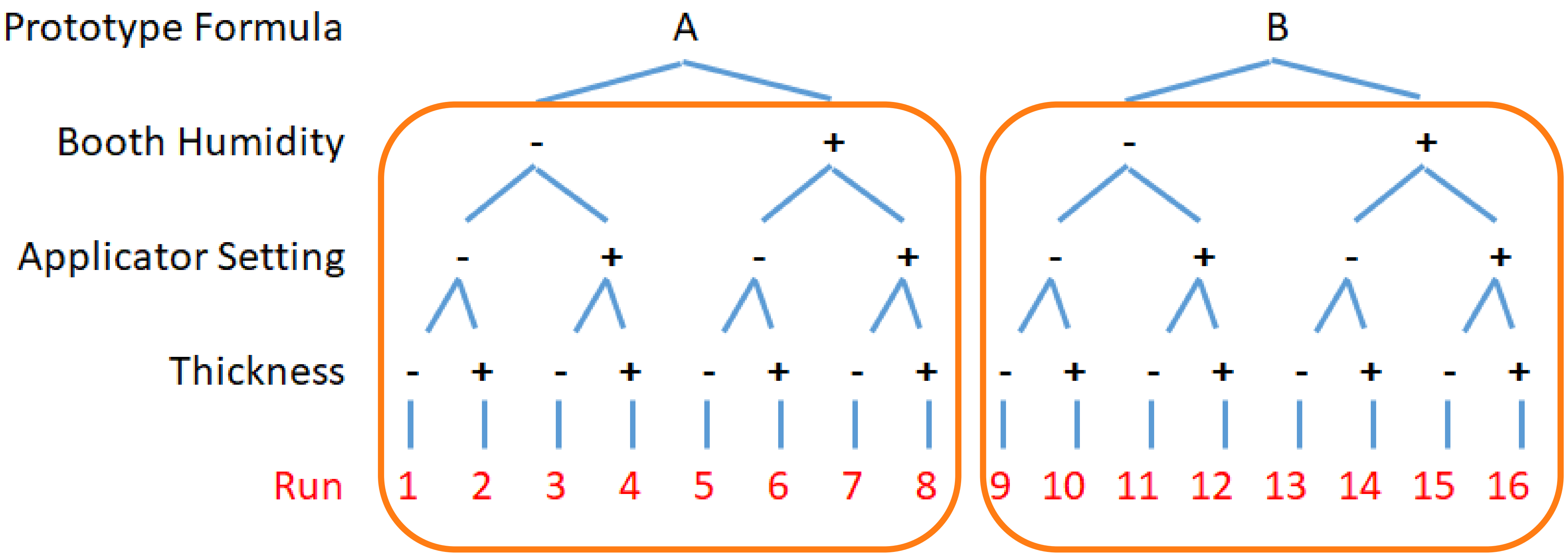
N – Sunlight Exposure
N – Car Washing
N – Stone Impact

Y – Gloss/Color Fade
Y – Adhesion Loss / Delamination
Y - Corrosion

Example 1 – Robustness

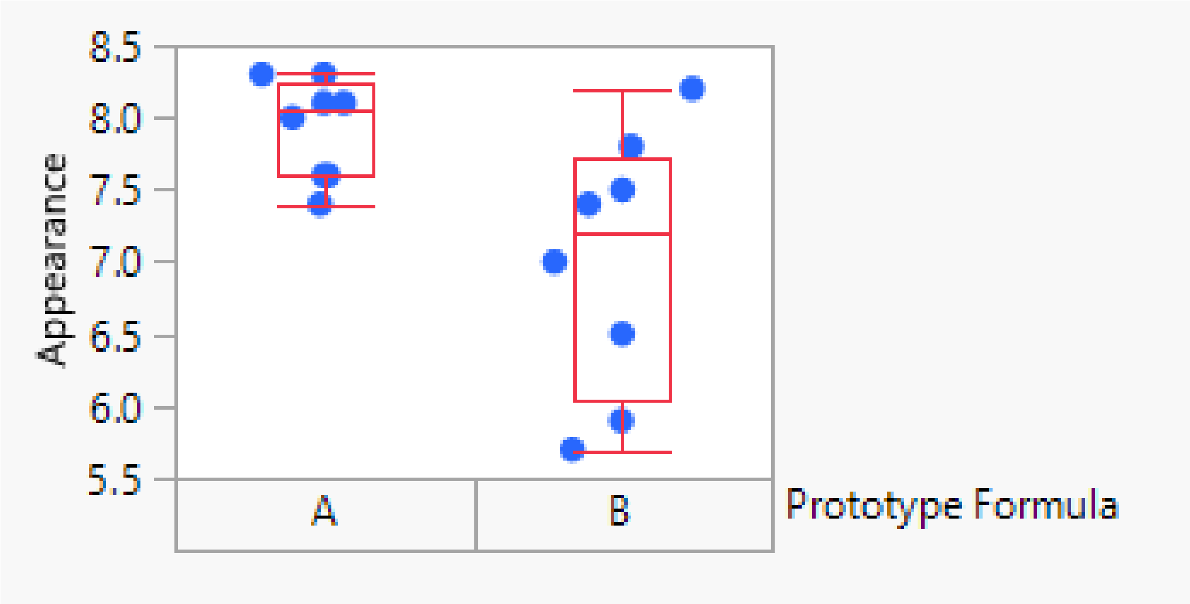
The influence of several processing variables likely to vary during coating application at our customers were studied for two prototype paint formulations.

Which prototype formula appears to be the most robust for appearance over the range of tested processing conditions?



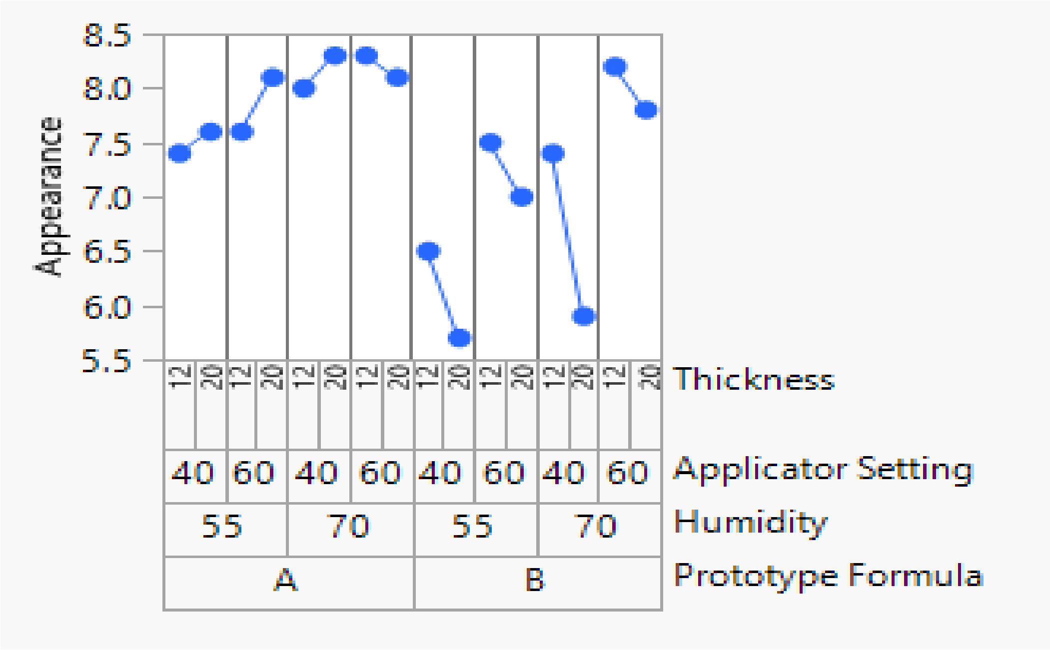
Example 1 - Robustness

Box Plot



Nice visualization of robustness

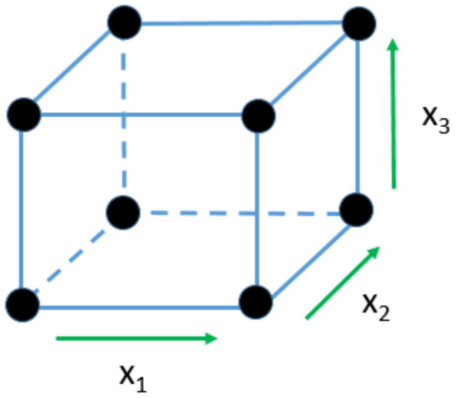
Variability chart



Dig deeper to find reason for variability

Design of Experiment (DOE)

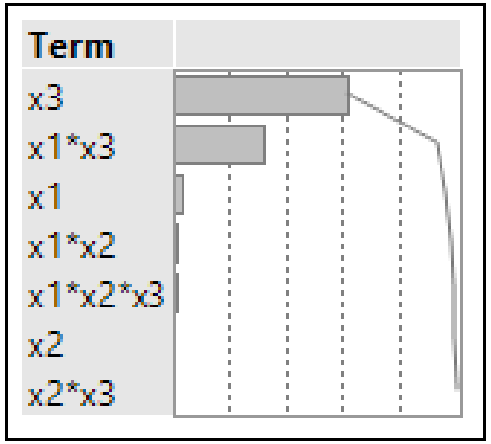
1) Plan

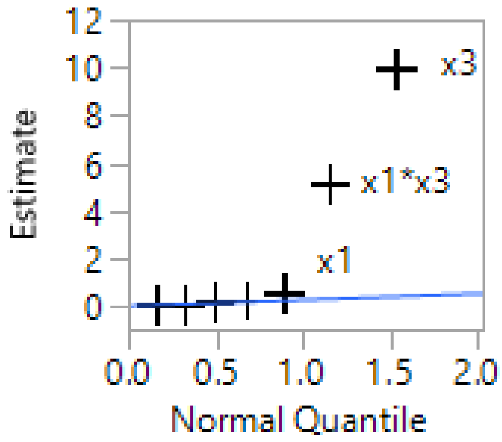


2) Model

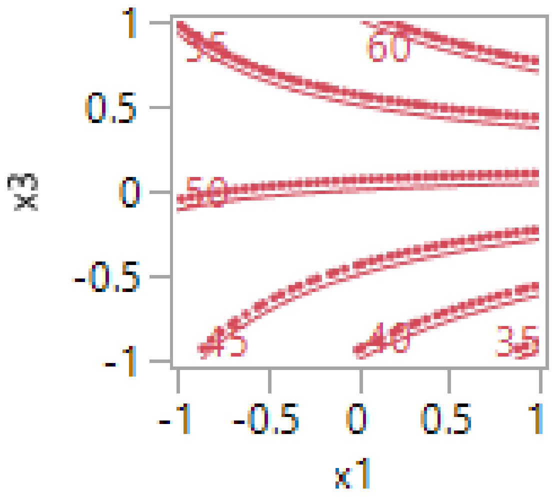
$$Y = b_o + b_1x_1 + b_2x_2 + b_3x_3$$
$$+ b_{12}x_1x_2 + b_{13}x_1x_3 + b_{23}x_2x_3$$
$$+ b_{123}x_1x_2x_3$$

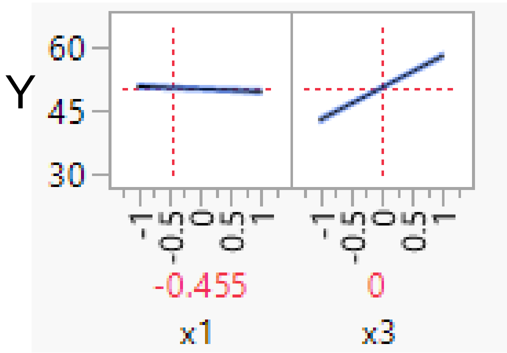
3) Find “active” factor effects





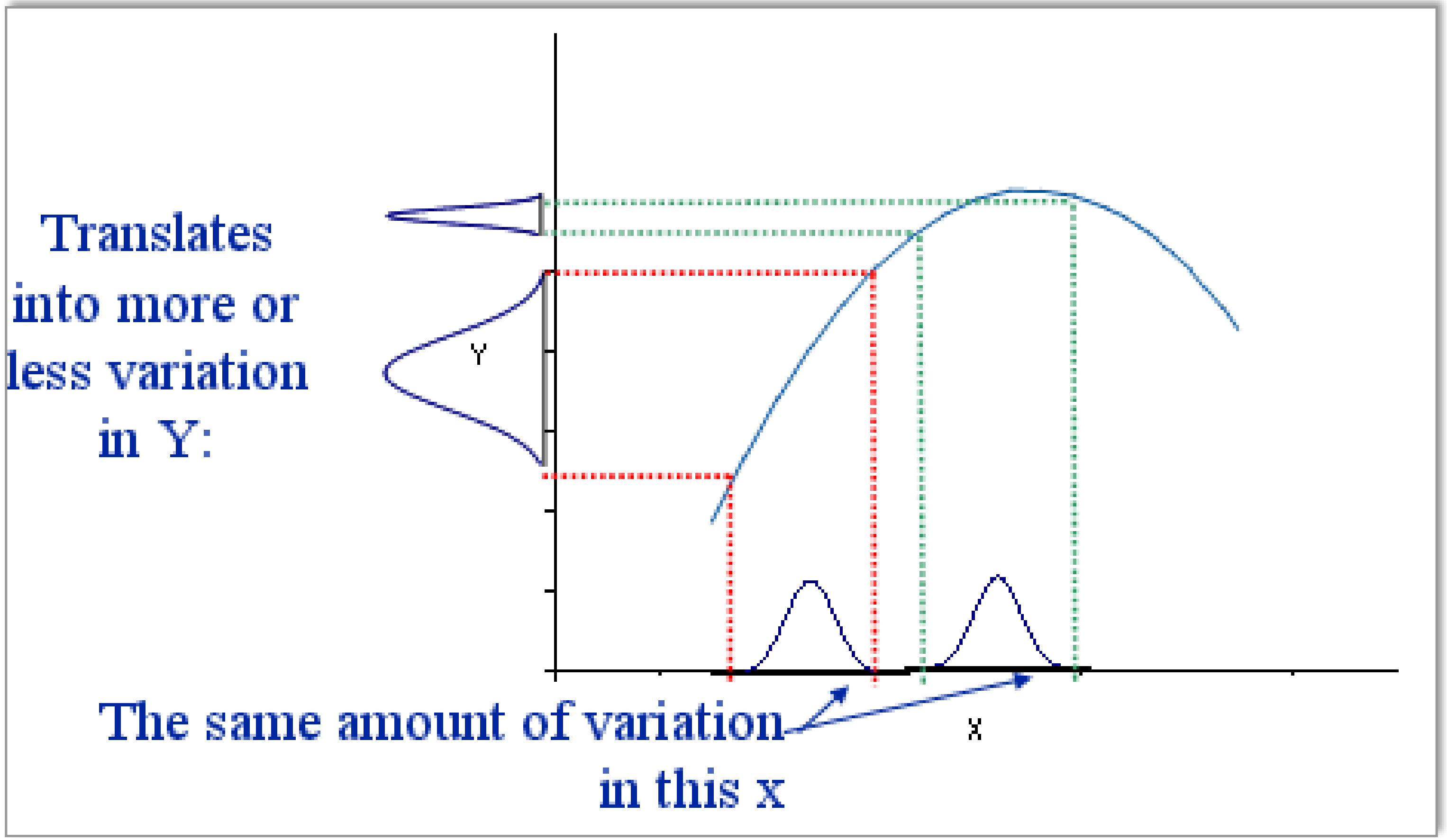
4) Make Predictions





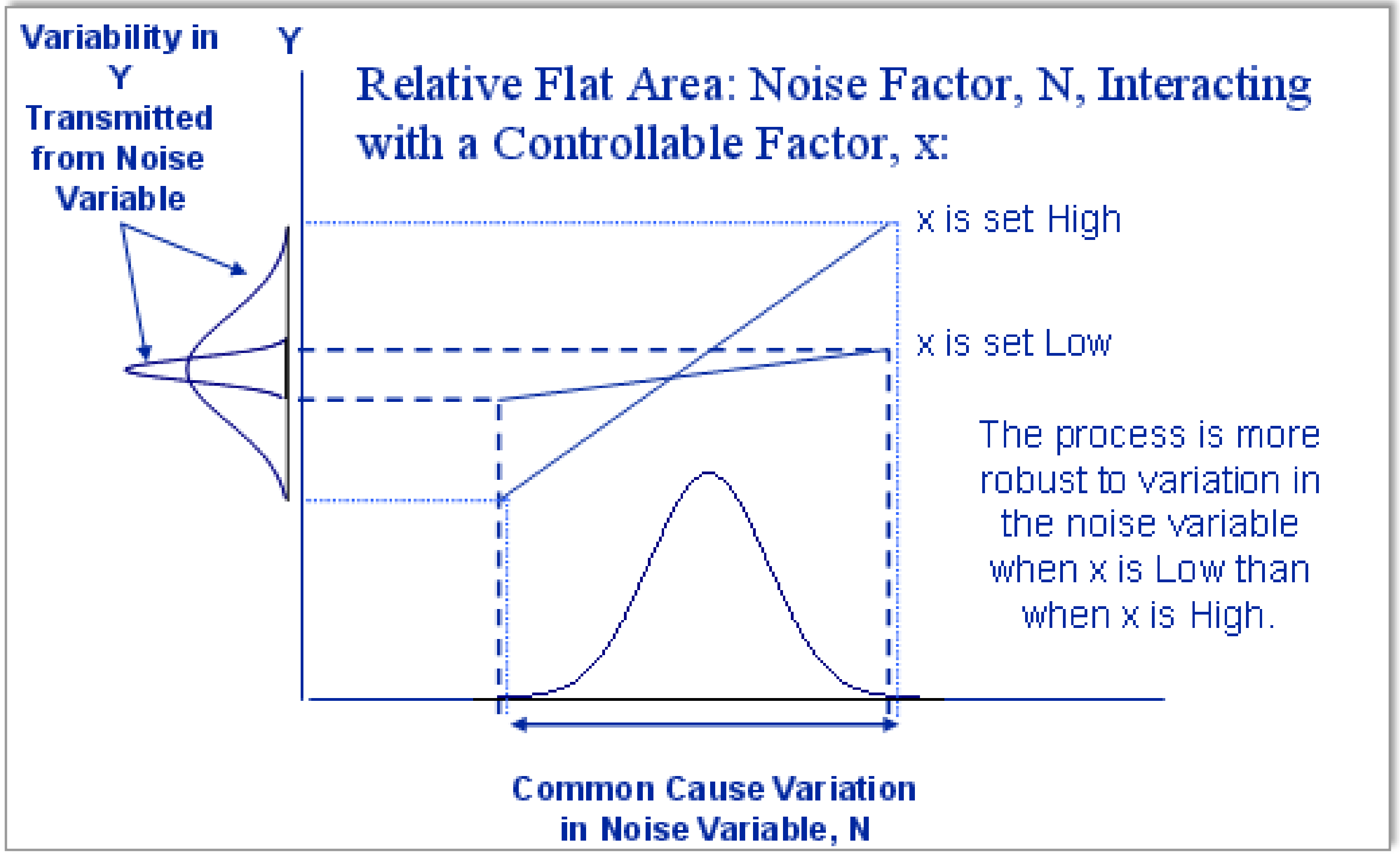
Finding Robust Settings

- Flat spots in the response surface are of interest because this is where the response is least sensitive to variation in x’s or N’s:



Finding Robust Settings

- Flat spots can also be present from the interaction between two variables:

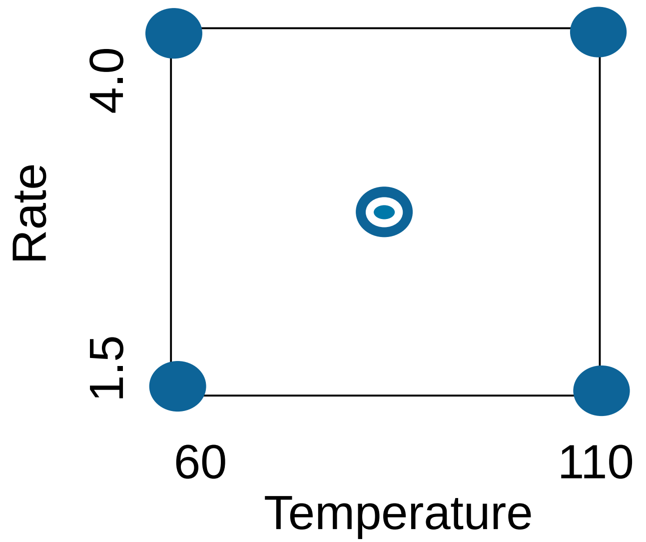


Example 2

Background

A chemist's project focused on finding the variables that are contributing to unacceptable variation in the yellowness (b*) of a product.

- A series of experiments were conducted to identify important factors influencing yellowness.
- The two most influential were:
  - Reaction Temperature (Temp)
  - Rate of Addition (Rate)
- Specification range for b* is 2.0 ± 1.



2^2 Full Factorial with 3 center points

Example 2

Temp	Rate	b*
110	1.5	5.90
85	2.75	2.54
110	4	2.57
60	4	1.81
85	2.75	2.80
60	1.5	1.12
85	2.75	2.95

Summary of Fit

RSquare	0.9927
RSquare Adj	0.985401
Root Mean Square Error	0.181607
Mean of Response	2.812857
Observations (or Sum Wgts)	7

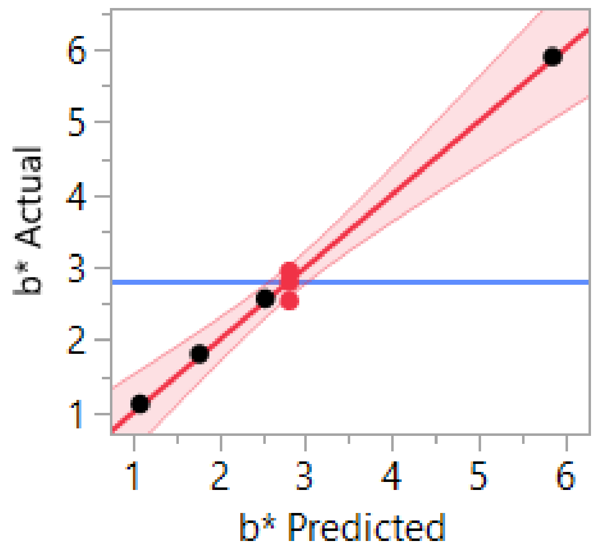
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	13.455400	4.48513	135.9916
Error	3	0.098943	0.03298	**Prob > F**
C. Total	6	13.554343		0.0011*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.444143	0.374077	-1.19	0.3206
Temp	0.0554	0.003632	15.25	0.0006*
Rate	-0.528	0.072643	-7.27	0.0054*
(Temp-85)*(Rate-2.75)	-0.03216	0.002906	-11.07	0.0016*

Actual by Predicted Plot



$$b^* = -0.444 + 0.055(Temp) - 0.528(Rate) - 0.032(Temp-85)(Rate-2.75)$$

Example 2

With just 2 independent variables, we can use the contour profiler to visualize how b* varies over the space covered by our experimental design.

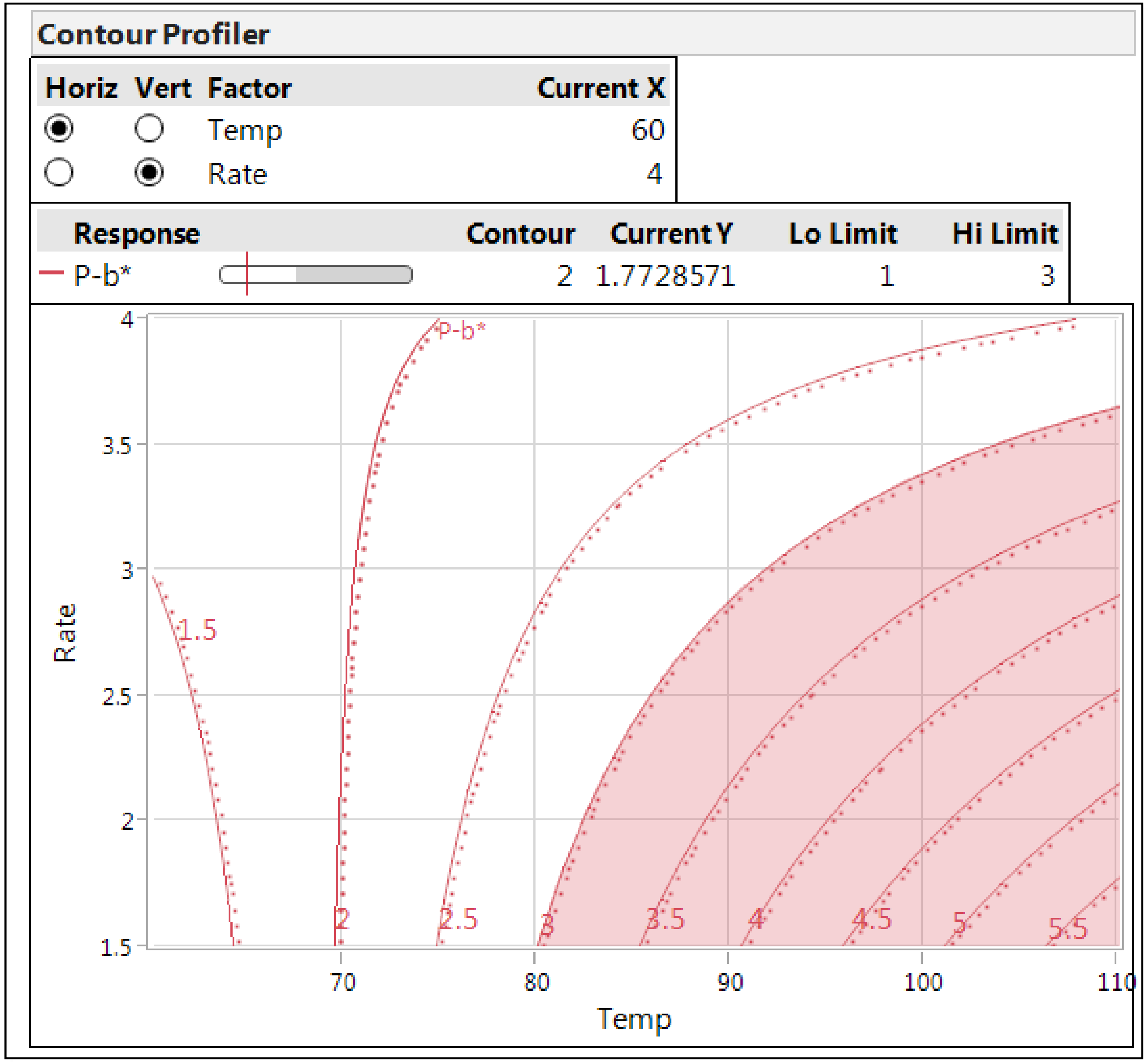
The shaded region is outside the specified target range of 1 to 3.

We would expect to produce in-spec product if we keep the Temp and Rate within the ranges:

60 < Temp < 80

&

1.5 < Rate < 4.0

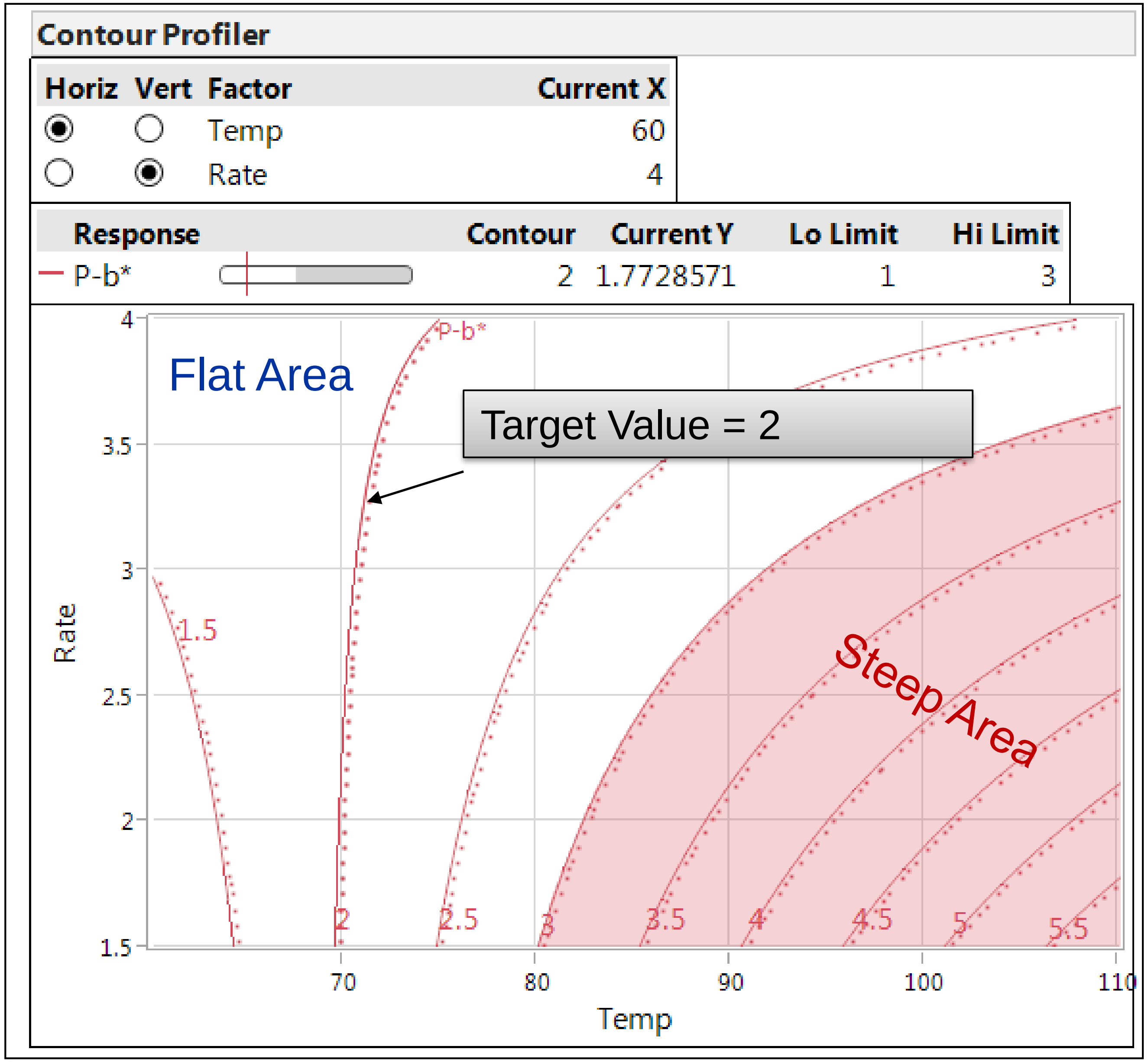


Example 2

But look at the contour line for the target value of 2.

Note that the lines for b* = 1.5 and b* = 2.5 are closer to the target line for b* = 2.0 at low Rates than at high Rates.

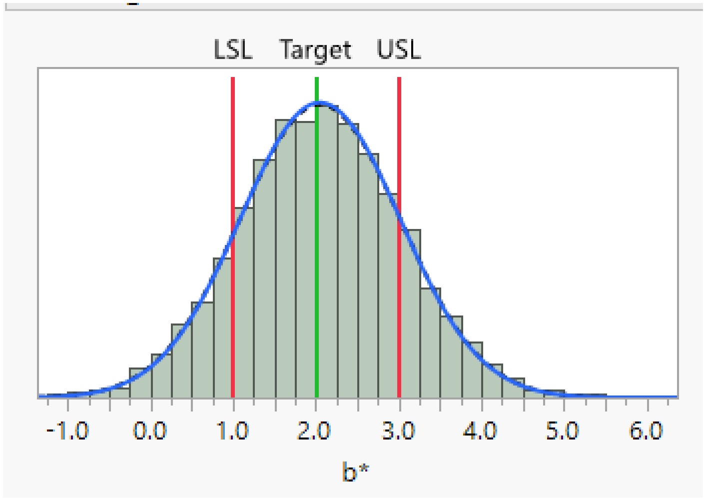
This indicates that b* is more sensitive to variation in Temperature at low Rates than at High Rates.



Predicting Capability

If we know Y=f(x), we can estimate the process capability using Monte Carlo simulation.

Process capability is a measure of how reliably a process is able to produce products that meet the requirements of the customer (specifications).



Process Summary

LSL	1
Target	2
USL	3
N	5000
Sample Mean	2.052451
Within Sigma	0.96302
Overall Sigma	0.969425
Stability Index	1.006651

Within sigma estimated by average moving range.

Within Sigma Capability

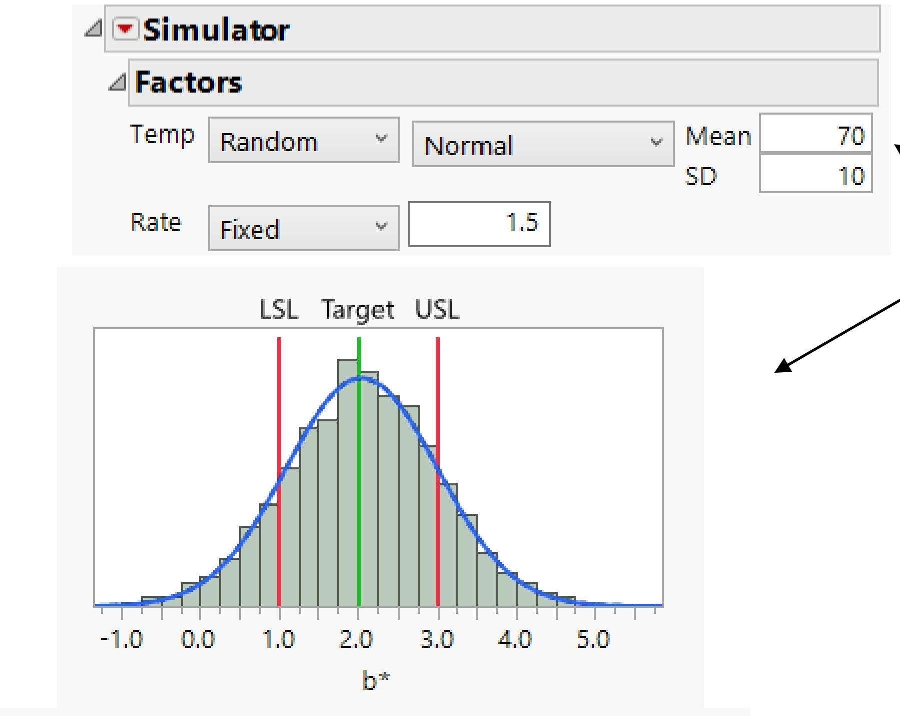
Index	Estimate	Lower 95%	Upper 95%
Cpk	0.328	0.316	0.340
Cpl	0.364	0.351	0.377
Cpu	0.328	0.316	0.340
Cp	0.346	0.338	0.355
Cpm	0.346	0.339	0.352

Nonconformance

Portion	Observed %	Expected Within %	Expected Overall %
Below LSL	13.7400	13.7227	13.8818
Above USL	16.5800	16.2574	16.4177
Total Outside	30.3200	29.9800	30.2996

Predicting Capability

We can simulate variation in Temperature in the Flat Area (high Rate) and seeing how much variation we get in b* compared to the variation we get in b* in the “Steep Area” (low Rate):



Within Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Cpk	0.328	0.316	0.340

Temp = 70+/- 10,

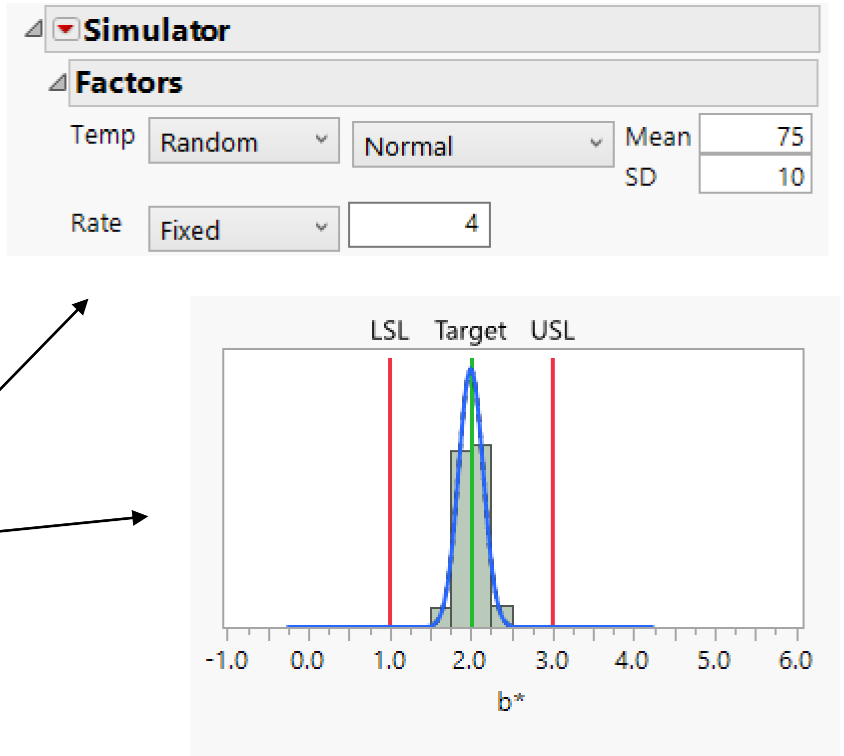
Rate = 1.5

(Steep Area)

Temp = 75+/- 10,

Rate = 4.0

(Flat Area)



Within Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Cpk	2.192	2.136	2.247

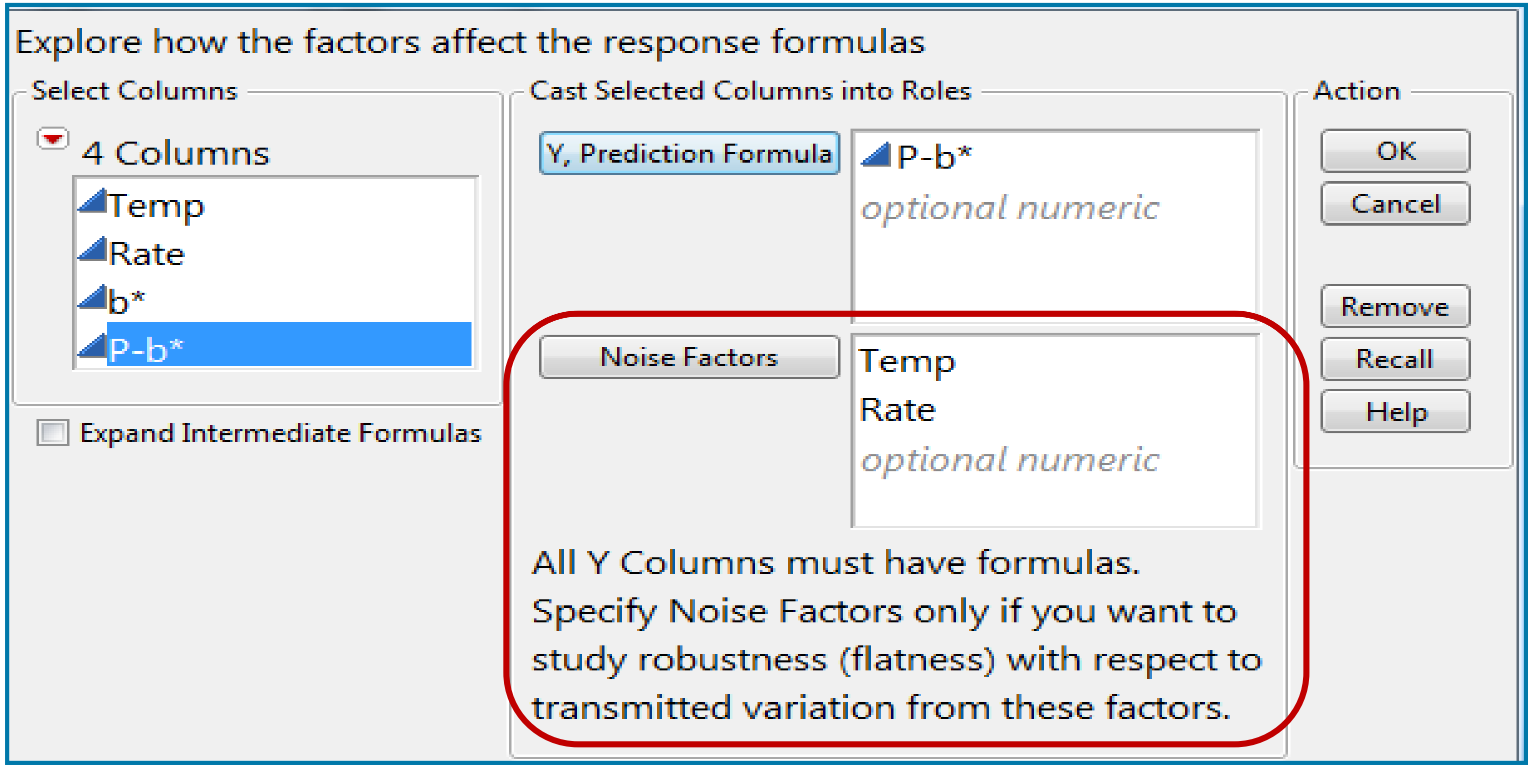
Same predicted mean,

Much different capability!

Finding the Flat Areas

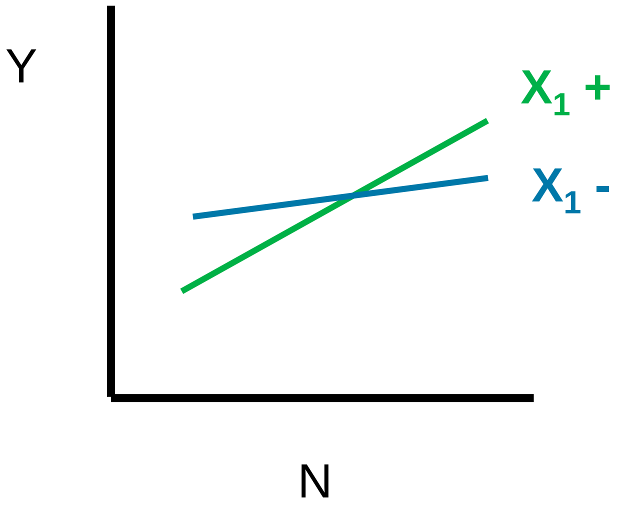
In this example, it is easy to see the “flat area” graphically because we only have 2 x’s to consider – but what if we have more than 2 factors?

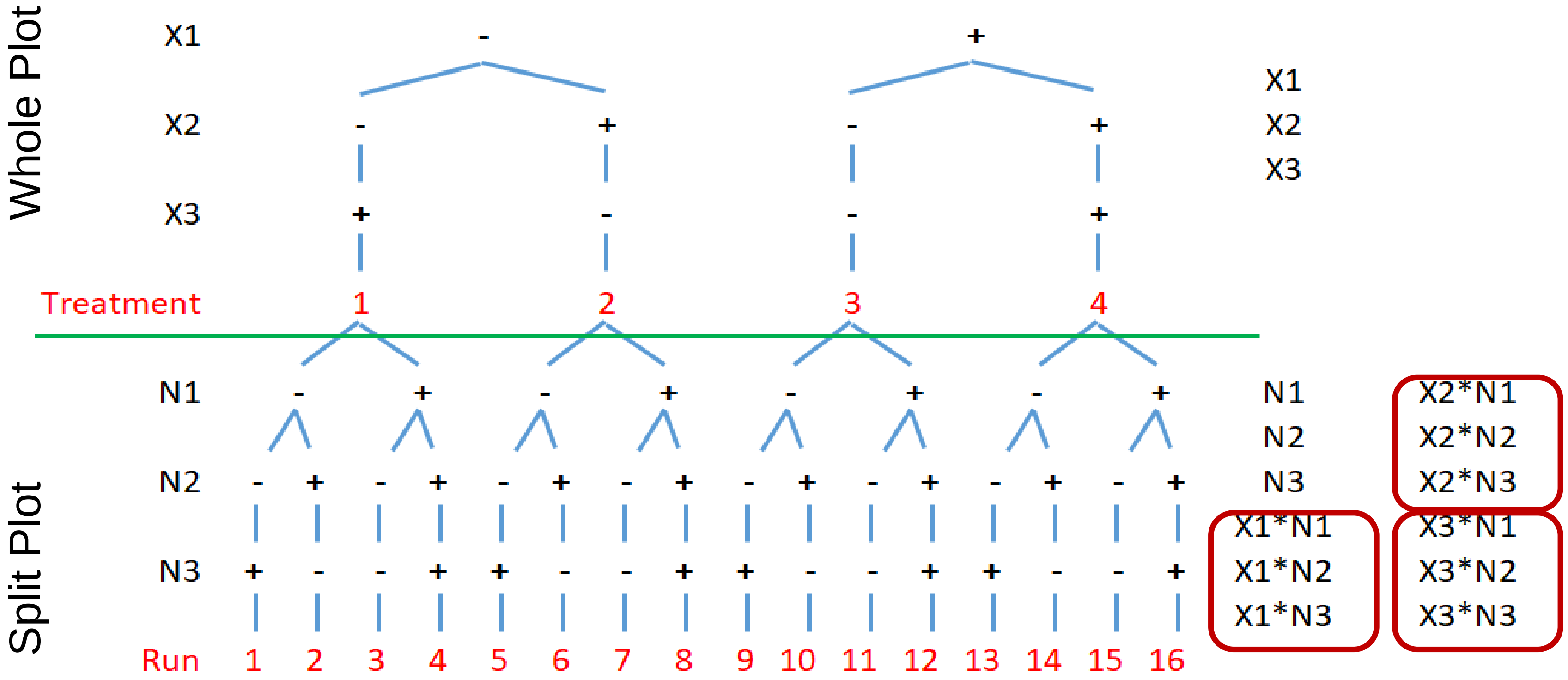
JMP has a feature to help identify the flat spots mathematically. We need only specify the process variable for which we want robust performance prediction as “Noise Variables” in the profiler set up:



Good DOEs for Robustness Studies

Use **Split Plot** designs to combine Control and Noise factors into the same experiment.



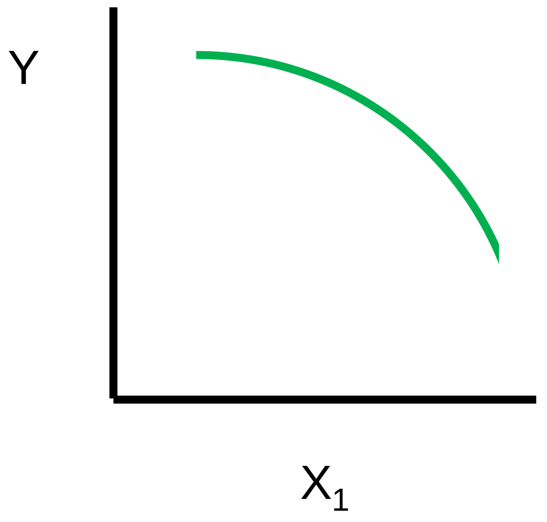


Good DOEs for Robustness Studies

Use **Definitive Screening Designs** to identify "curvature"

- Interactions
- Quadratic / squared terms

$$Y = b_o + b_1x_1 + b_{11}x_1^2$$



	A	B	C	D	E	F	G	H
1	0	1	1	1	1	1	1	1
2	0	-1	-1	-1	-1	-1	-1	-1
3	1	0	1	1	-1	1	-1	-1
4	-1	0	-1	-1	1	-1	1	1
5	1	-1	0	1	1	-1	1	-1
6	-1	1	0	-1	-1	1	-1	1
7	1	-1	-1	0	1	1	-1	1
8	-1	1	1	0	-1	-1	1	-1
9	1	1	-1	-1	0	1	1	-1
10	-1	-1	1	1	0	-1	-1	1
11	1	-1	1	-1	-1	0	1	1
12	-1	1	-1	1	1	0	-1	-1
13	1	1	-1	1	-1	-1	0	1
14	-1	-1	1	-1	1	1	0	-1
15	1	1	1	-1	1	-1	-1	0
16	-1	-1	-1	1	-1	1	1	0
17	0	0	0	0	0	0	0	0

fold over pairs

center point

How about you?

Take a minute and think about the products that your company delivers.

Y: What is one of your key performance properties?

N: Are there specific variables that may influence Y for which you have little or no control?

- In your process?
- In your customers process?
- During use by the end-user?

X: What factors can you control that could make Y less sensitive to the Noise variables?

Summary

- Box plots are a useful way to graphically illustrate the robustness of a product.
- If “curvature” exists, it may be possible to find a flat spot where the response variable is least sensitive to random variation in the factors.
- DOE is an effective way to uncover “curvature” (interactions, quadratic terms)
- With 2 factors, we can visualize the relative flat areas using contour plots.
- For more than two factors, JMP has a built in capability for finding these areas mathematically.
- Given a model for the data, we can predict the capability of the product or process through simulation.

We protect and beautify the world™