



Visualization and the Improvement of Anodized Parts Using JMP

Presented by the North Haven Group, LLC

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Talk Outline

- Introduction
- Visualizing Historical Data
- Designing the Experiment
- Analyzing the Results
- Optimizing an Anodize Process
- Simulation at Optimal Settings
- The Improved Process
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Introduction

Six Sigma projects for manufacturing applications often involve two related, yet distinct, goals.

- **Quality improvement:** Finding the root cause(s) of the quality problems, and based upon this knowledge, either eliminate the problem altogether or reduce its severity and impact.
- **Optimization of a product or process:** For example, reducing manufacturing cycle time or raw material consumption, even though there is no inherent quality problem.

In this case study, a team is tasked with both objectives.

Introduction

- **Components Inc.** is a manufacturer of aluminum components for high-end audio equipment.
- The aluminum components are anodized for corrosion and wear protection, and the anodized surface is dyed to produce a visually smooth, rich black surface to match the color scheme of the audio equipment assembled and sold by Components Inc.'s customer.
- Given the premium price of the final product, buyers are very sensitive to workmanship and aesthetics, as well as performance.
- Discoloration of the dyed components is a chronic problem.

Introduction

A **defect** occurs when the anodized parts have a purple or smutty black surface appearance.

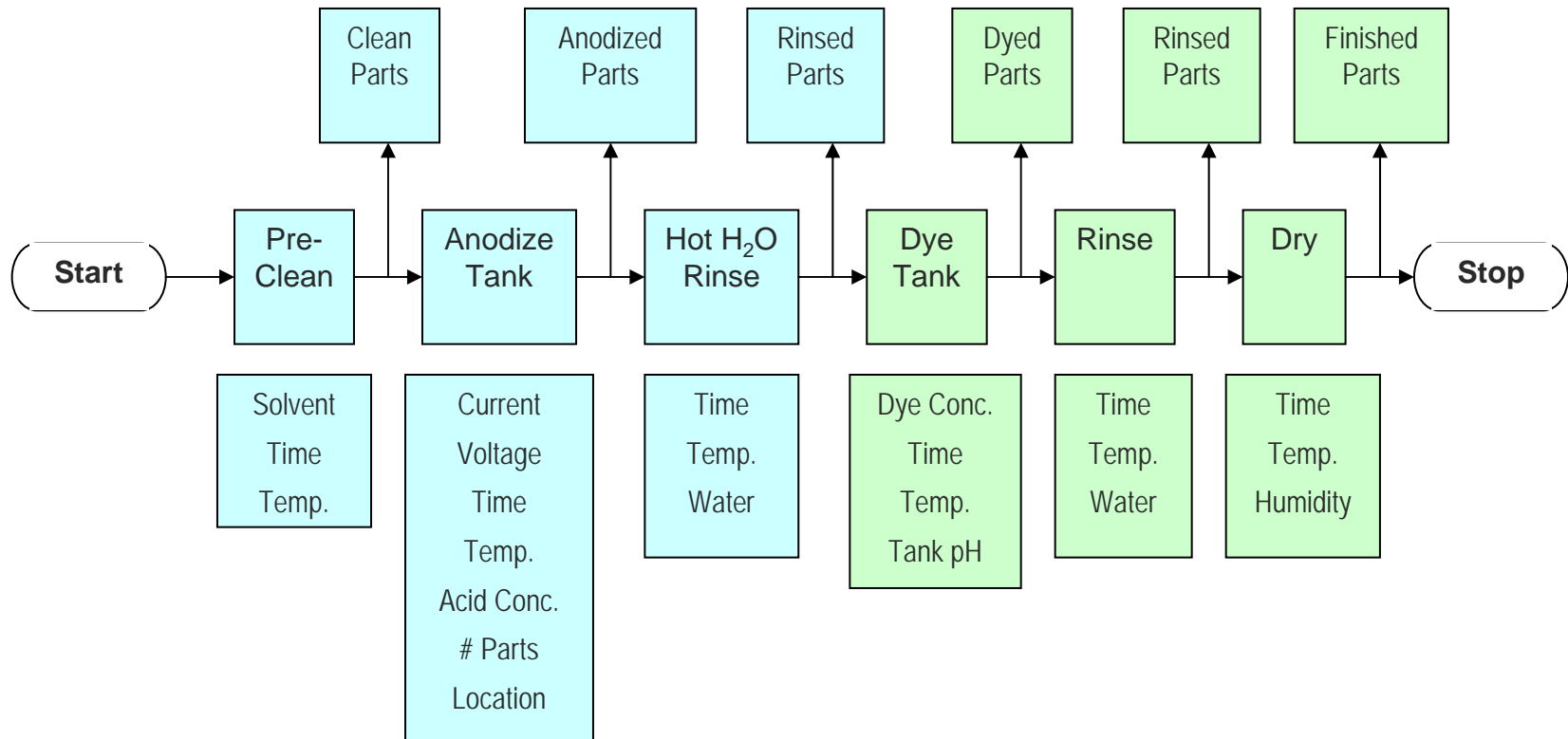
- The **purple** color varies from a very light to a deep purple, and is considered unacceptable.
- The **smutty black** appearance, which gives the impression that the finish is smudged, is also unacceptable, since the colored anodized surface must be blemish free.

An acceptable surface has a rich, black, blemish free (no smut) appearance.

Current process yields are at best 40%, but are much less in most cases.

Introduction

The team starts by developing a process map for anodize and dyeing.



Introduction

- The anodize process has two primary stages: **anodize (A)** and **dye (D)**.
- Using the process map as a guide, the team **brainstorms** process factors most likely causing discoloration of the parts.
- The **five process factors** selected for further study are:
 - Bath Temp (A),
 - Anodize Time (A),
 - Acid Concentration (A),
 - Dye tank concentration (D), and
 - Dye tank pH (D).

Introduction

The team identifies measures of quality (responses) for the parts.

- The four primary responses are all continuous measures:
 - **Anodize Thickness**,
 - **L*** (lightness of the color),
 - **a*** (redness/greenness of the color), and
 - **b*** (yellowness/blueness of the color).
- L*, a*, b* are traditional measures of color. Each color can be uniquely identified in a three dimensional coordinate system defined by these measures.
- A **nominal scale rating of color** is also given to each part.

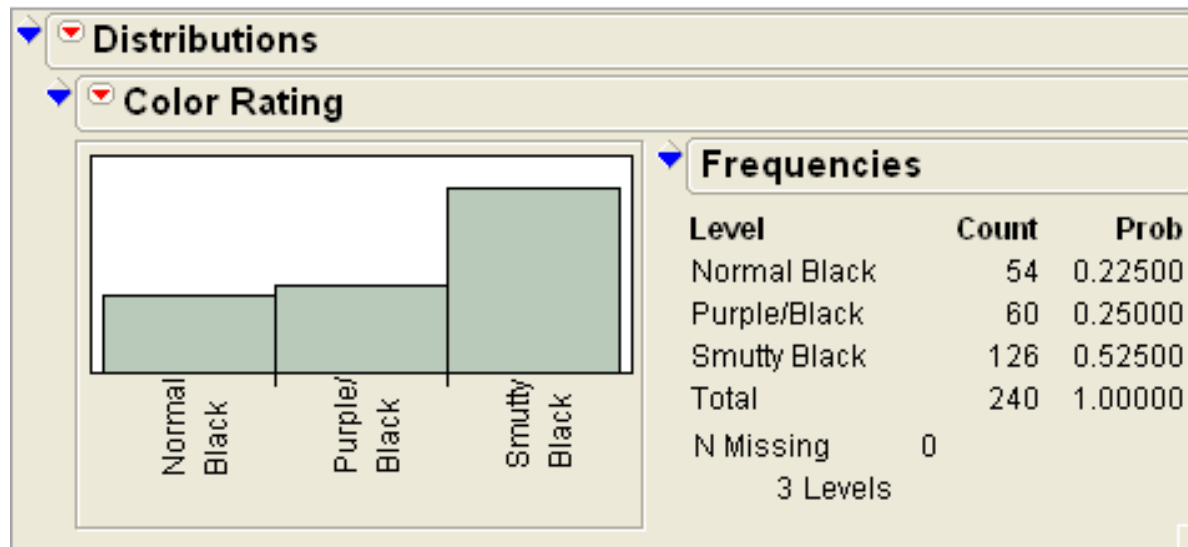
Visualizing Historical Data

The team gathers data on **240 production parts** to establish a baseline.

- The L^* , a^* , and b^* color responses are measured with a spectrophotometer.
- The parts are also graded visually for acceptability of color using one of three color categories:
 - Purple/Black,
 - Normal Black, and
 - Smutty Black.
- Recall that only **Normal Black** product is acceptable to the customer.

Visualizing Historical Data

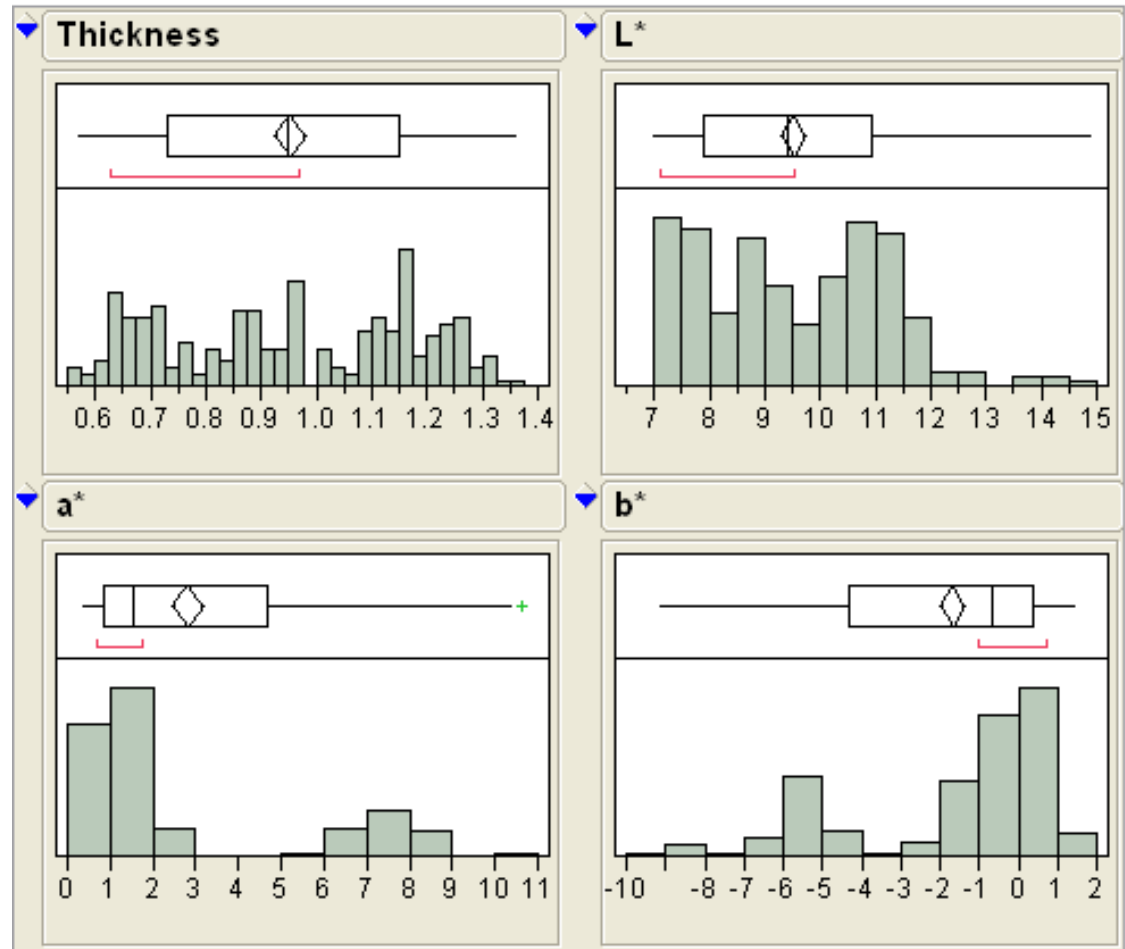
- The distribution of **Color Rating** shows the percentage of good parts, Normal Black, to be only 22.5.
- The proportion of Smutty Black parts is about twice the proportion of Purple/Black parts.



Visualizing Historical Data

These are the distributions for **Thickness**, **L***, **a***, and **b***.

Unfortunately, there are no targets or specifications defining which values are required to make good parts.



Visualizing Historical Data

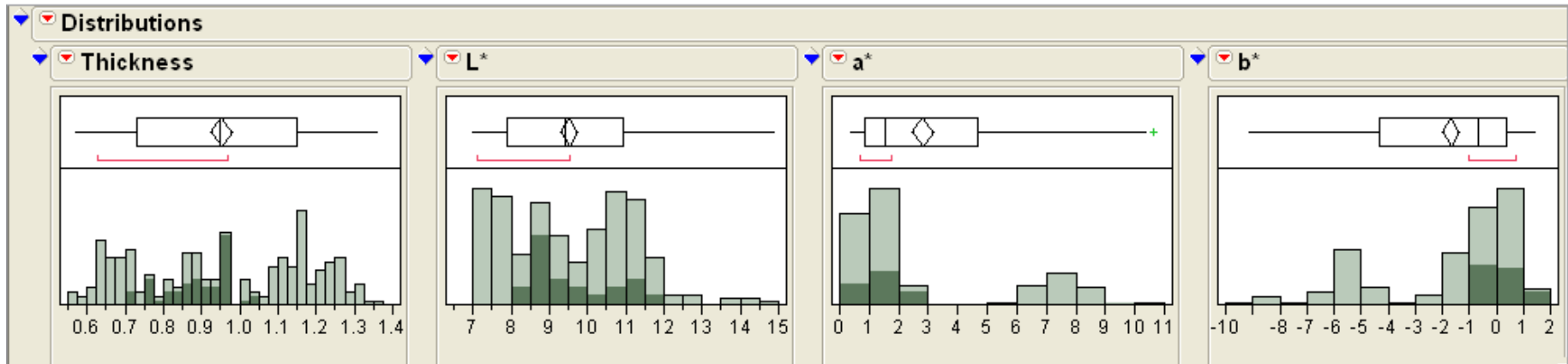
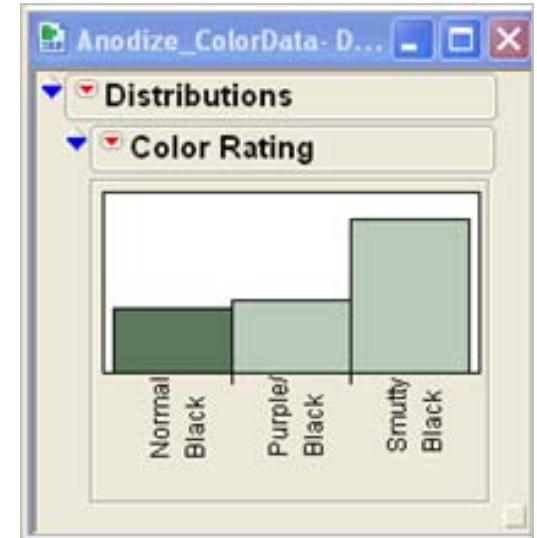
The team would really like to see the values of **Thickness, L*, a*, and b*** stratified by the three categories of **Color Rating**.

- There are many ways to do this in JMP.
- They decide to use the simple approach of clicking on the bars in the bar graph for Color Rating.

When one clicks on the bar for Normal Black, the 54 rows corresponding to Normal Black parts are selected in the data table, and JMP shades all open histograms to represent these 54 points.

Visualizing Historical Data

The shaded areas of the histograms reveal that only certain values of the four responses correspond to good parts (Normal Black).



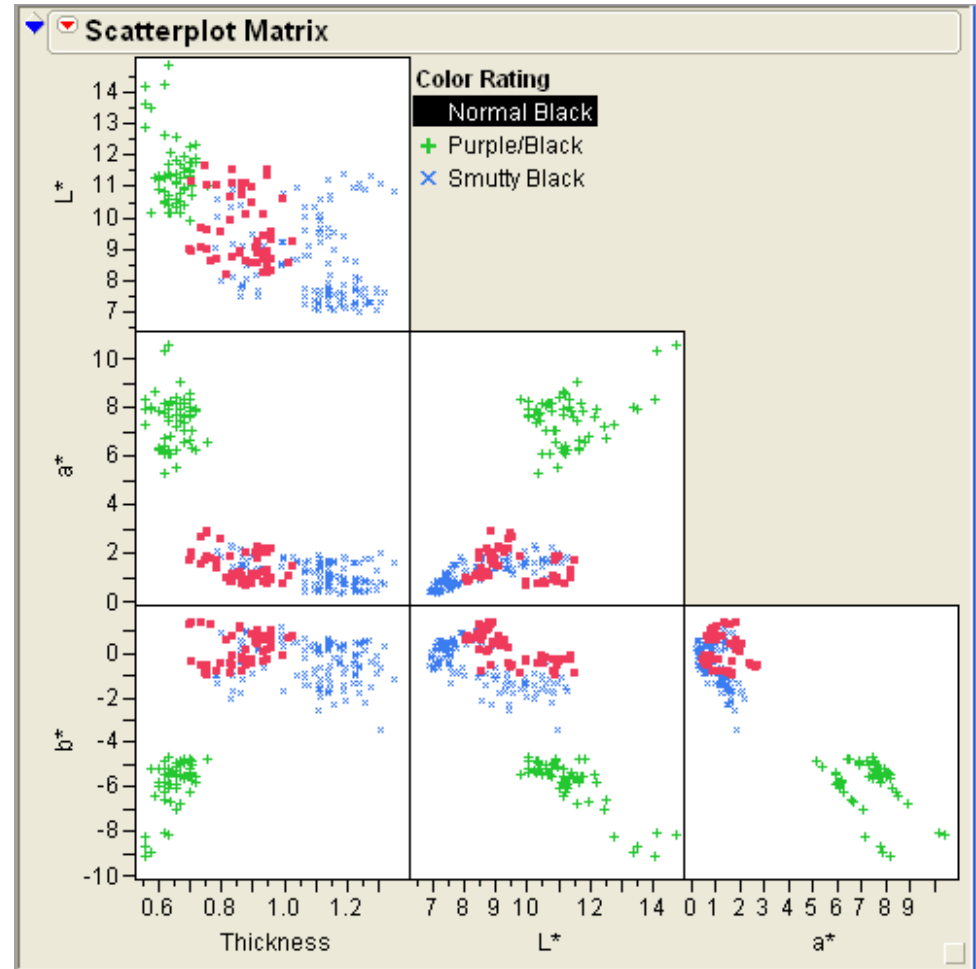
Visualizing Historical Data

The team also uses a **Scatterplot Matrix** in JMP to help better understand the relationship between the color ratings and the four responses.

- The regions that define each Color Rating are even more striking than when viewed in the histograms.
- Note, for example, that Purple/Black (the green +’s) parts occur in different regions than do Normal Black and Smutty Black (the blue X’s).
- On the other hand, some regions seem associated with both Normal Black and Smutty Black parts.

Visualizing Historical Data

Scatterplot Matrix for the four responses stratified by Color Rating.



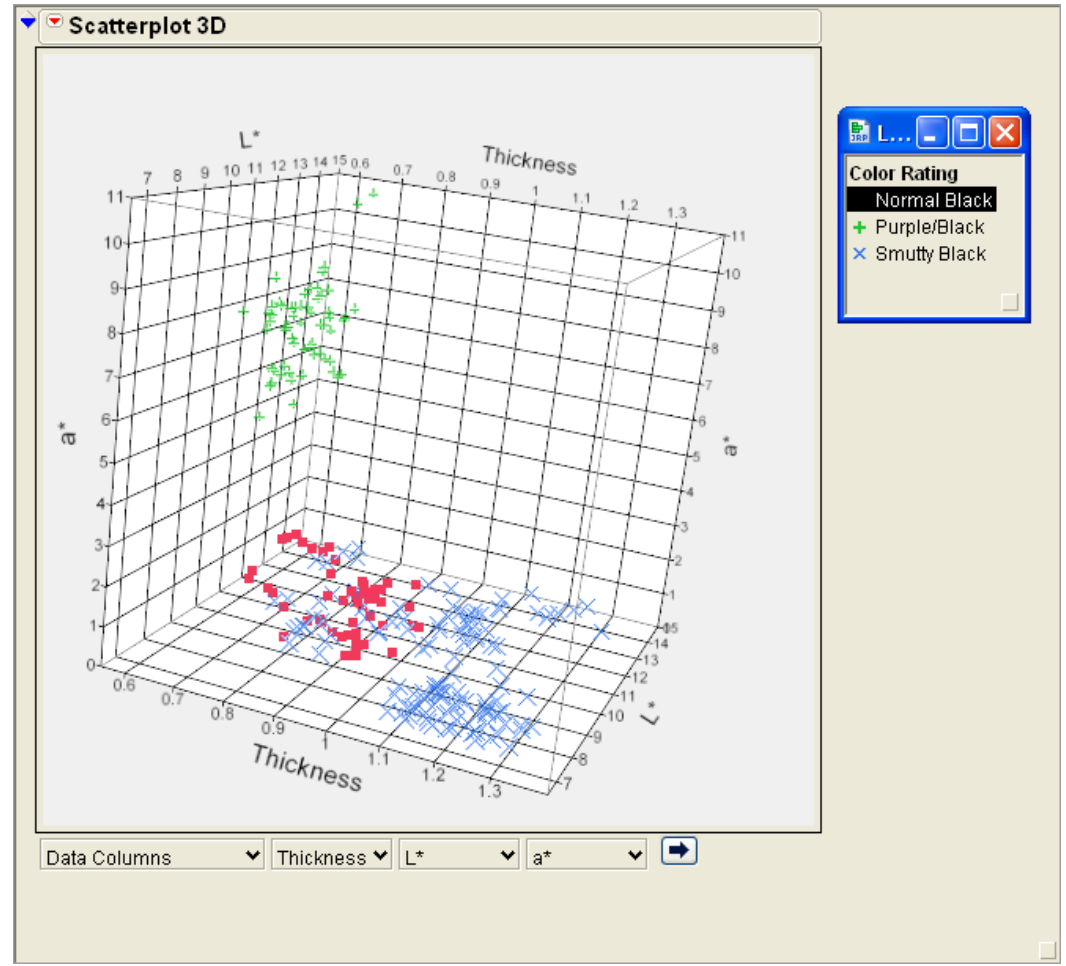
Visualizing Historical Data

Finally, to more accurately define the region of the continuous measurements where parts are mostly Normal Black, the team uses a **3D Scatterplot** in JMP.

- These regions become even more striking when viewed in three dimensions.
- In the 3D plot we have Thickness, L^* , and a^* on the three axes, with points corresponding to Normal Black highlighted using the distribution plot of Color Rating.
- Using the drop down lists at the bottom of the graph, one can generate three-dimensional plots of all possible combinations of the four response measures.

Visualizing Historical Data

3D Scatterplot with points highlighted for Normal Black.



Visualizing Historical Data

From the visual analysis, the engineers set the following **targets and specifications** for the four responses:

- **Anodize Thickness:** 0.9 ± 0.2 microns
- **L*:** 10 ± 2
- **a*:** 2 ± 2
- **b*:** 0 ± 2

The team next focuses on **designing an experiment** to determine if **relationships** exist between these four responses and the five process variables identified earlier.

Designing the Experiment

The team faces a number of difficult **challenges**:

- The experiment must be **performed on production equipment**, and only enough equipment time is available to perform at **most 10 or 12 experimental trials**.
- Engineers are convinced that **two factor interactions are likely to occur**, so a design capable of resolving these interactions is required.
- Fortunately, it is believed that interactions can not occur between variables in the anodize and the dye stages.

This means that **six potential two factor interactions can be discounted**.

Designing the Experiment

A 2^{5-2} fractional factorial design only requires 8 runs.

- However, the design is resolution III - main effects and two factor interactions are aliased.

Since the team can run 12 trials, and only needs to estimate certain interactions, they decide to make use of the flexible **Custom Design** platform in JMP.

- In Custom Design, one can specify the effects to be estimated and the maximum allowable number of trials.
- JMP then searches for an optimal design meeting the specified requirements (constraints on factor settings and split plot constraints can also be added).

Designing the Experiment

Responses, Factors, and the Model are specified in the Custom Design window.

DOE - Custom Design

Custom Design

Responses

Add Response Remove Number of Responses...

Response Name	Goal	Lower Limit	Upper Limit	Importance
Thickness	Match Target	0.7	1.1	1
L*	Match Target	8	12	1
a*	Match Target	0	4	1
b*	Match Target	-2	2	1

Factors

Add Factor Remove Add N Factors 1

Name	Role	Changes	Values
Anodize Temp	Continuous	Easy	60 90
Anodize Time	Continuous	Easy	20 40
Acid Conc	Continuous	Easy	170 205
Dye pH	Continuous	Easy	5 6.5
Dye Conc	Continuous	Easy	10 15

Define Factor Constraints

Model

Main Effects Interactions RSM Cross Powers Remove Term

Name	Estimability
Intercept	Necessary
Anodize Temp	Necessary
Anodize Time	Necessary
Acid Conc	Necessary
Dye pH	Necessary
Dye Conc	Necessary
Anodize Temp*Anodize Time	Necessary
Anodize Temp*Acid Conc	Necessary
Anodize Time*Acid Conc	Necessary
Dye pH*Dye Conc	Necessary

Designing the Experiment

The team specifies a **10 run design**.

JMP creates a D Optimal design.

The team adds **two center points** for lack of fit testing.

Design Generation

Group runs into random blocks of size:

Number of Runs:

Minimum 10

Default 16

User Specified

Design

Run	Anodize Temp	Anodize Time	Acid Conc	Dye pH	Dye Conc
1	90	40	205	6.5	15
2	60	20	170	5	10
3	60	40	170	6.5	15
4	60	40	205	5	15
5	90	20	170	6.5	10
6	90	20	205	5	10
7	90	40	170	5	15
8	90	40	170	5	10
9	90	20	170	6.5	15
10	60	20	205	6.5	10

Output Options

Run Order:

Make JMP Table from design plus

Number of Center Points:

Number of Replicates:

Designing the Experiment

Below is the JMP data table for the design.

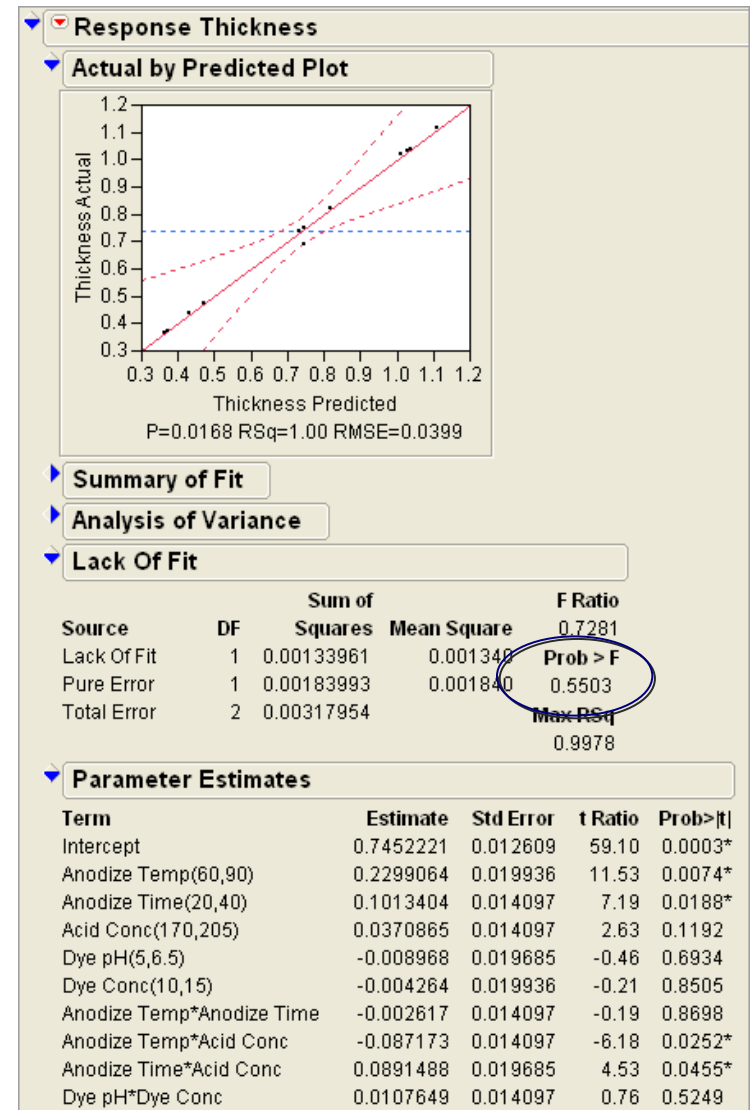
Measurements of the four responses for each trial of the experiment have been recorded.

Anodize_CustomDesign_Results											
Anodize_CustomDesign		Anodize Temp	Anodize Time	Acid Conc	Dye pH	Dye Conc	Thickness	L ^a	a ^a	b ^a	
Design	Custom Design	1	60	20	205	5	10	0.48	12.26	4.21	-1.75
Criterion	D Optimal	2	90	20	205	5	15	0.74	9.32	2.06	-2.11
Screening		3	60	40	170	5	10	0.44	14.53	3.16	-3.43
Model		4	90	20	170	5	10	1.04	1.11	0.55	-1.19
Columns (9/0)		5	75	30	187.5	5.75	12.5	0.69	10.85	2.73	-2.85
Anodize Temp *		6	90	40	170	5	15	1.03	7.66	0.82	-3.10
Anodize Time *		7	60	40	205	6.5	10	0.82	11.46	4.58	-0.67
Acid Conc *		8	90	20	170	6.5	15	1.02	8.11	4.40	-4.95
Dye pH *		9	75	30	187.5	5.75	12.5	0.75	11.02	3.36	-2.80
Dye Conc *		10	60	20	170	5	15	0.37	17.18	7.31	-7.95
Thickness *		11	90	40	205	6.5	15	1.12	7.33	0.90	-1.00
L ^a *		12	60	20	170	6.5	10	0.37	14.59	8.14	-5.25
a ^a *											
b ^a *											

Analyzing the Results

To identify significant factors and interactions, the team uses the **Fit Model** platform for each response, starting with **Thickness**.

- Notice that the lack of fit test (based on center points) is not significant.
- Also, some of the model terms appear not to be significant and can be dropped from the model.



Analyzing the Results

Below is the reduced model for Thickness.

- Notice that only factors in the anodize step are significant for Thickness.
- A couple of the two factor interactions appear very significant.

Parameter Estimates				
Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	0.7470616	0.008761	85.27	<.0001*
Anodize Temp(60,90)	0.2292941	0.009439	24.29	<.0001*
Anodize Time(20,40)	0.099041	0.009654	10.26	<.0001*
Acid Conc(170,205)	0.0347871	0.009654	3.60	0.0113*
Anodize Temp*Acid Conc	-0.090825	0.009439	-9.62	<.0001*
Anodize Time*Acid Conc	0.0824806	0.009654	8.54	0.0001*

Analyzing the Results

The team fits reduced models for all four responses.

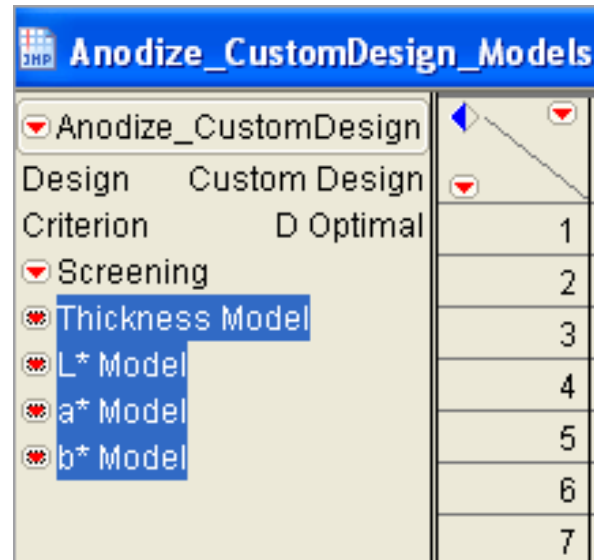
- For each model, the **Prediction Formula** is saved from the Fit Model report window to the data table.
- These saved prediction formulas will be used later for optimization.

Pred Formula Thickness	Pred Formula L ^a	Pred Formula a ^a	Pred Formula b ^a
0.46185799	12.6136238	4.09210075	-1.7679875
0.73879628	9.07727021	1.84693015	-2.1085865
0.40871593	14.4923762	2.94475155	-3.4309557
1.01583308	1.10512703	0.70226098	-1.1851063
0.74706162	10.7119499	3.40643562	-2.7921295
1.04895393	7.81398185	0.69958095	-3.1167411
0.82490117	11.2154617	4.58464445	-0.6755185
1.01583308	8.06269157	4.24941634	-4.9534573
0.74706162	10.7119499	3.40643562	-2.7921295
0.37559509	17.1833542	7.46317005	-7.9528036
1.10183947	7.67910809	0.87566701	-1.0161175
0.37559509	14.7410859	7.95839378	-5.267672

Analyzing the Results

It is a good practice to **save the script** that is executed to fit each model.

This allows a user to recreate an analysis simply by clicking on the script button.



Optimizing an Anodize Process

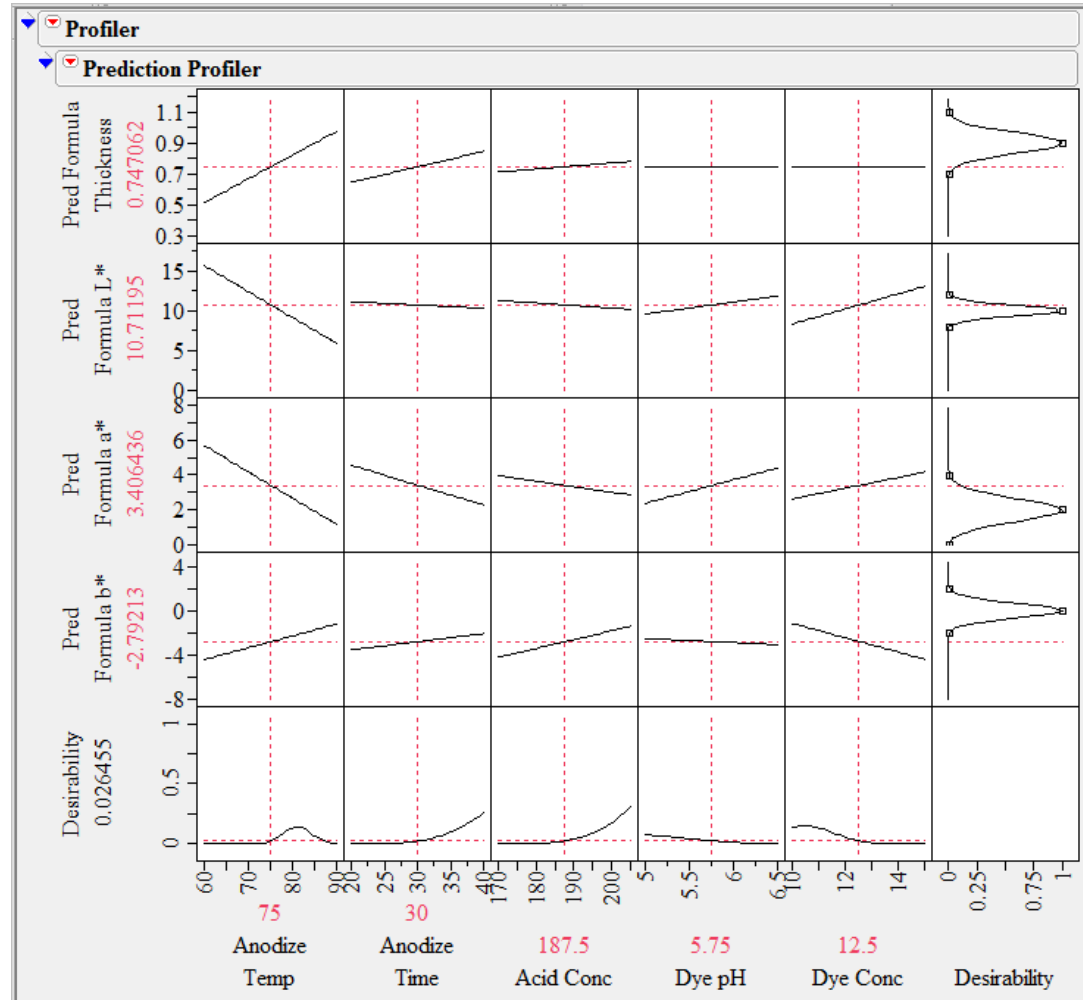
Having fit four separate models representing the relationships between the four responses and the five process variables, the team next attempts to **optimize the process**.

- The **objective is to find settings of the five factors, based on the four fitted models, that simultaneously result in desirable levels of the four responses.**
- To do this, we access the **Profiler** in JMP, which is located under the Graph menu.
- The Profiler provides a dynamic visualization of the fitted models, and **includes a mechanism for optimization** based on the popular Desirability criterion.

Optimizing an Anodize Process

This is the **Profiler** report window.

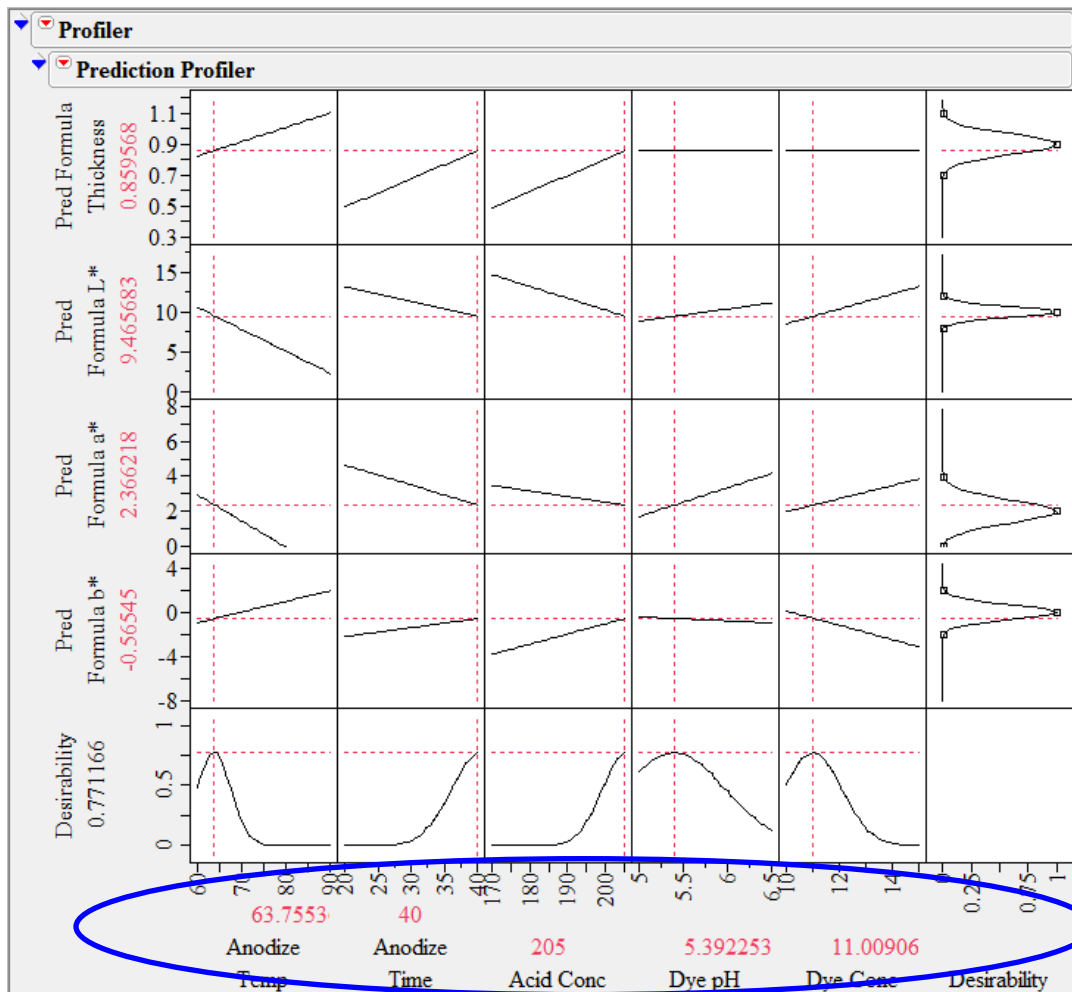
- The last column to the right displays the desirability profiles for each response.
- The response goal, for each response, is to match the targets set earlier.



Optimizing an Anodize Process

These are the **optimization results.**

- JMP provides settings for each process factor that achieve the most desirable levels for the four responses.



Optimizing an Anodize Process

The team now has recommended settings for the five process factors, and is being pressed to act.

- However, before implementing these process settings, it is important to **perform confirmatory** trials to see if the predicted results will be achieved.
- The suggested optimized settings are far from the current process settings, so some engineers are skeptical of the experimental results.
- Two confirmatory runs are performed at the suggested settings. Both runs have 100% yields, which have never been accomplished historically.

Optimizing an Anodize Process

Although the trials were successful, the team is not fully satisfied.

They recognize that some of the process factors are not currently well controlled, and that this will result in variation in the responses.

They decide they need to better understand the relationship between the process factors and the responses.

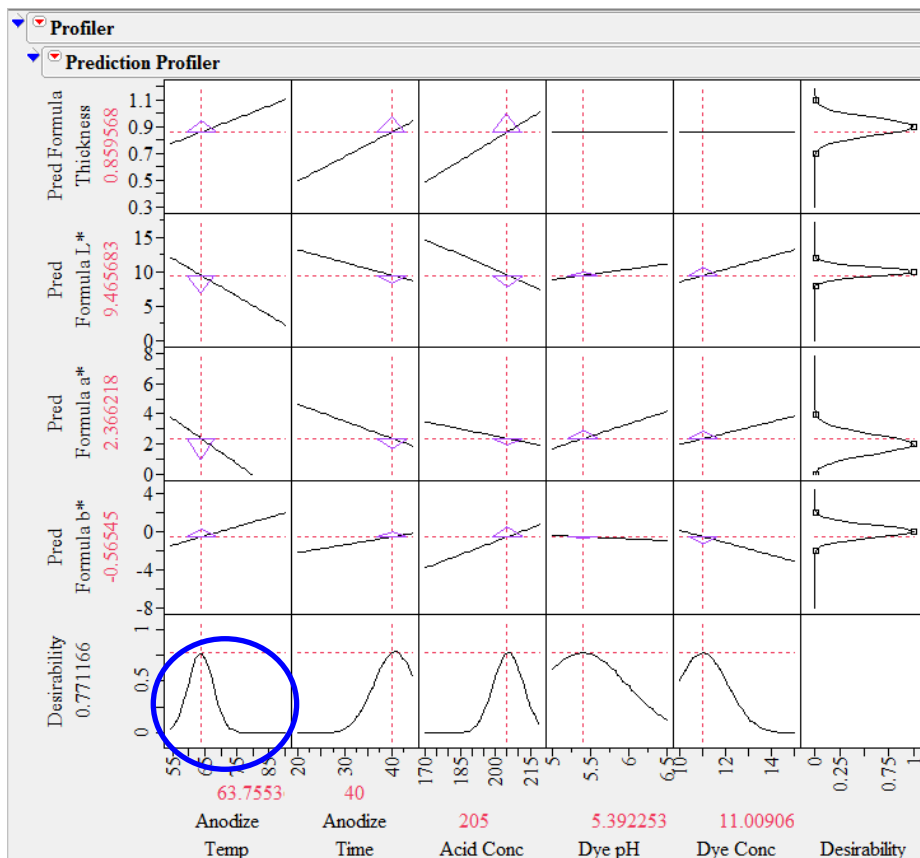
In particular, they are interested in **understanding the sensitivity** of the responses to variation in the process factors and in **predicting process capability** at the recommended settings.

Optimizing an Anodize Process

- Sensitivity of the responses to variation in the process factors, at the optimized settings, can be assessed in two ways:
 - **Desirability traces, and**
 - **Sensitivity indicators.**
- **Desirability Traces** are the traces shown in the bottom row of the Prediction Profiler output.
- **Sensitivity Indicators** are triangles plotted at the factor level settings on the response traces, representing the degree of change in the response surface in the direction of that factor.

Optimizing an Anodize Process

- Notice that the desirability trace for Anodize Temp is sharply peaked.
- This indicates that variation in Anodize Temp will cause significant variation in the desirability of the four responses.
- *The team realizes that temperature is not well controlled in the current process.*



Optimizing an Anodize Process

The Prediction Profiler also provides **Sensitivity Indicators** for each of the responses.

- The indicators appear as triangles on the Prediction Profiler output.
- The height of the triangle indicates relative sensitivity of that response to variation in the associated process factor.
- The up or down orientation of the triangle indicates the direction of movement in that response as the factor level increases.
- On the previous slide, notice the substantial sensitivity of each response to Anodize Temp.

Simulation at Optimal Settings

At this point, the team is interested in the impact of variation in the process factors on the responses.

The Profiler contains a **Simulator** function that can be used to assess capability.

From prior process data, the team has estimates of the standard deviations for four of the process factors.

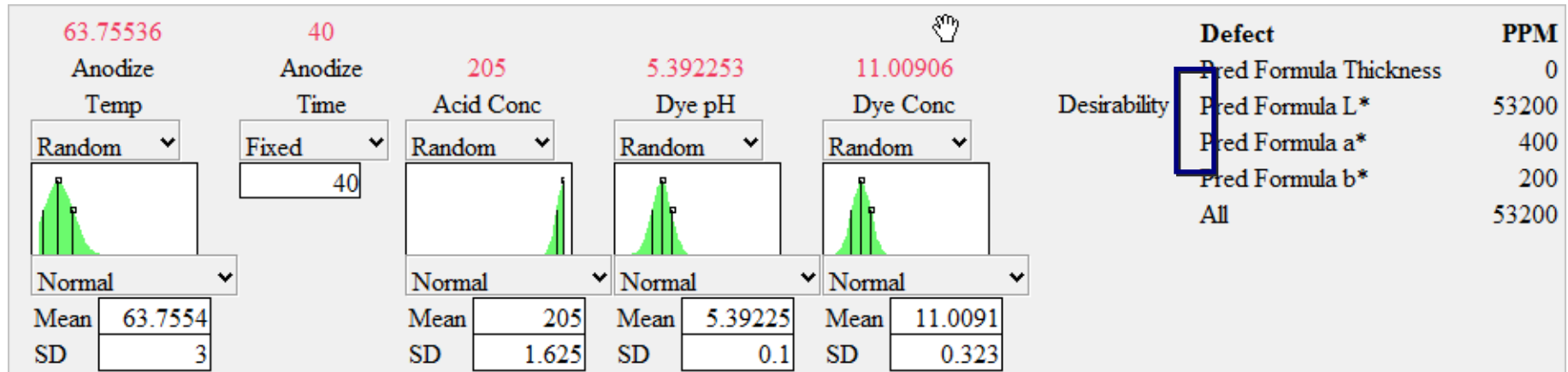
- Anodize time is easily controlled and is considered a fixed effect.
- The other four factors are known to vary.
Anodize Temperature, in particular, is not well controlled.

Simulation at Optimal Settings

Some of the output from the simulation is shown below.

- Notice that predicted PPM levels are given on the far right.
- The team notices that the PPM level for L* is very high.

This indicates a potential process capability issue.

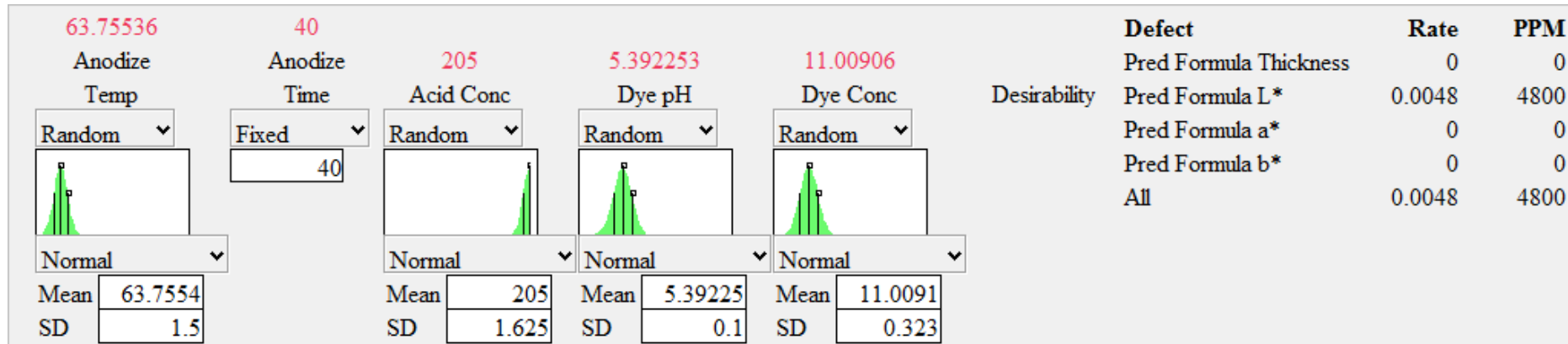


Simulation at Optimal Settings

- The predicted ppm indicates that, although the confirmatory runs produced positive results, overall capability may not be acceptable.
- Recall that all of the responses, particularly L^* , are very sensitive to Anodize Temperature.
- Since Anodize Temperature is not well controlled, the team believes that tighter control can lead to significant improvement.
- The team does a little research, and finds an affordable temperature control system for the anodize bath that they believe will greatly reduce variation.

Simulation at Optimal Settings

- To simulate the anticipated improvement from controlling Anodize Temperature, a new simulation is performed with the standard deviation reduced by 50%, from 1.5 from 3.0.
- The predicted PPM rate for L* is reduced from 53,200 to 4,800.

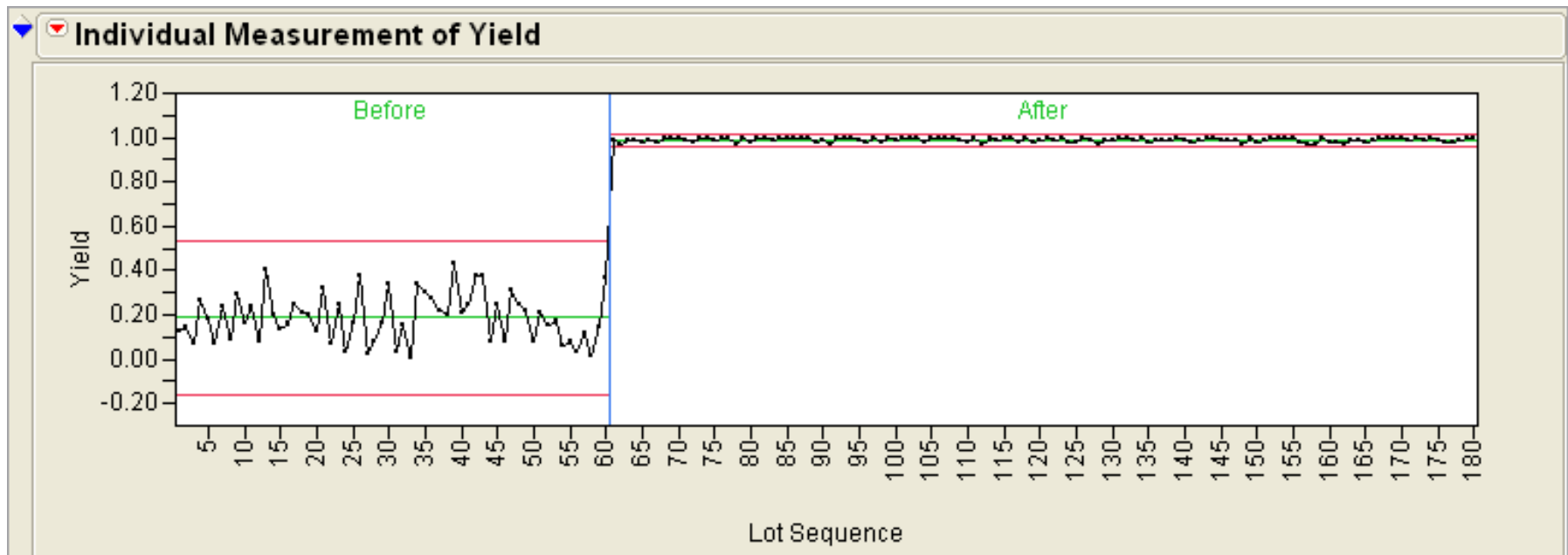


The Improved Process

- With the data in hand, the team convinces management to purchase the temperature control equipment.
- In addition, process controls are put in place for Acid Concentration, Dye Concentration, and Dye pH.
- Once the improvements are implemented, the team tracks the yield of the anodize process for approximately four months.
- The next slide shows an **Individuals control chart** for the process yield for the baseline period, and for the four months after the improvements were implemented.

The Improved Process

- The new process has a yield of approximately 99%!
- The customer is so delighted with the quality that they give the supplier increased business. Yeah, team!



Summary

- Using the JMP visualization and Custom Design capabilities, a team was able to successfully improve the performance of a low yield anodize process.
- **Visualization** techniques allowed the team to set specifications for the four quality characteristics.
- The **Custom Design** platform allowed the team to design an experiment in five process factors that estimated the effects of interest, subject to constraints on the number of runs.
- Using the **Profiler** and **Desirability**, the team found settings for the process factors that greatly improved yield.