Solving a Costly and Persistent Quality Problem
with Visual Six Sigma

ASQ Granite State Section
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Presented by the North Haven Group

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Talk Outline

- The Visual Six Sigma Book
- Visual Six Sigma
- Visual Six Sigma Roadmap
- The JMP Statistical Software
- Case Study: Improving a Polymer Manufacturing Process
- Case Study: Framing the Problem
- Case Study: Uncover Relationships
- Case Study: Model Relationships
- Case Study: Revise Knowledge
- Case Study: Utilize Knowledge
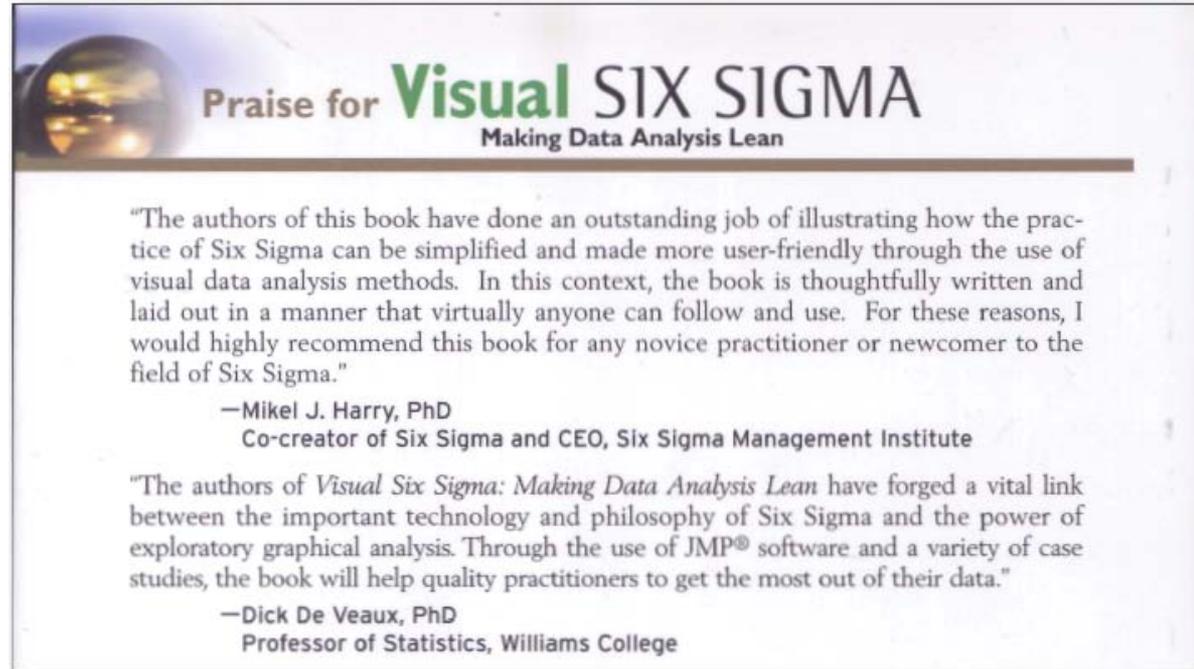- Summary

The Visual Six Sigma Book

Visual SIX SIGMA

Making Data Analysis Lean

Ian Cox   Marie A. Gaudard   Philip J. Ramsey
Mia L. Stephens   Leo T. Wright

Praise for Visual SIX SIGMA
Making Data Analysis Lean

"The authors of this book have done an outstanding job of illustrating how the practice of Six Sigma can be simplified and made more user-friendly through the use of visual data analysis methods. In this context, the book is thoughtfully written and laid out in a manner that virtually anyone can follow and use. For these reasons, I would highly recommend this book for any novice practitioner or newcomer to the field of Six Sigma."

—Mikel J. Harry, PhD
Co-creator of Six Sigma and CEO, Six Sigma Management Institute

"The authors of *Visual Six Sigma: Making Data Analysis Lean* have forged a vital link between the important technology and philosophy of Six Sigma and the power of exploratory graphical analysis. Through the use of JMP® software and a variety of case studies, the book will help quality practitioners to get the most out of their data."

—Dick De Veaux, PhD
Professor of Statistics, Williams College

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An eBook version is available from Amazon.com.

The Visual Six Sigma Book

The book is based upon six comprehensive case studies with a chapter for each study:

Chapter 4   **Reducing Hospital Late Charge Incidents**

Chapter 5   **Transforming Pricing Management in a Chemical Supplier**

Chapter 6   **Improving the Quality of Anodized Parts**

Chapter 7   **Informing Pharmaceutical Sales and Marketing**

Chapter 8   **Improving a Polymer Manufacturing Process**

Chapter 9   **Classification of Breast Cancer Cells**

Data sets are available for download, so that the reader can work through the case studies while reading the text.

Visual Six Sigma

In conjunction with the development of powerful computers and software was the beginning of the data explosion.

When Six Sigma was first deployed, the problems tackled were often narrow in scope and limited data existed. In fact, teams typically had to initiate data collection plans to have any data at all.

Fast forward to 2011 where large data bases abound, even in small companies, partly due to the ability to collect large amounts of data in an automated or semi-automated manner.

We have gone from complaining about the lack of data to puzzling over what to do with too much data.

Today analysts struggle to deal with petabytes (2^{50} bytes) and now zettabytes (2^{70} bytes) of data collected on millions of variables.

Traditional statistical tools were never meant to deal with such large amounts of data and variables. Visualization now becomes ever more important to statistical analyses.

Visual Six Sigma

Visual Six Sigma Strategies

Visual Six Sigma exploits the following three key strategies to support the goal of managing variation in relation to performance requirements (the fundamental goal of Six Sigma):

1. Using dynamic visualization to literally see the sources of variation in your data.

2. Using exploratory data analysis (**EDA**) techniques to identify key drivers and models, especially for situations with many variables.

3. Using confirmatory statistical methods (**CDA**) only when the conclusions are not obvious. This leans out the data analysis effort.

Visual Six Sigma Roadmap

In defining the **Visual Six Sigma Roadmap** we use the usual convention in Six Sigma that a process output is represented by a "Y" and a process input is represented by an "X". The Xs are the sources of variation in Ys.

Frame Problem. Identify the specific failure to produce what is required. Identify your general strategy for improvement, estimate the time and resources needed, and calculate the likely benefit if you succeed. Identify the Y or Ys of interest.

Collect Data. Identify potential Xs using techniques such as brainstorming, process maps, data mining, failure modes and effects analysis (FMEA), and subject matter knowledge. Passively or actively collect data that relate these Xs to the Ys of interest. Baseline the current process and determine measurement system capability.

Visual Six Sigma Roadmap

Uncover Relationships. Validate the data to understand their strengths, weaknesses, and relevance to your problem. Use exploratory tools and your understanding of the data, generate hypotheses and explore whether and how the Xs relate to the Ys.

Model Relationships (optional). Build models relating the Xs to the Ys. Determine statistically which Xs explain variation in the Ys.

Revise Knowledge. Optimize settings of the Xs to give the best values for the Ys. Explore the distribution of Ys as the Xs are allowed to vary a little. Collect new data to verify that the improvement is real.

Utilize Knowledge. Implement the improvement and monitor the Ys to see that the improvement is maintained.

Visual Six Sigma Roadmap

The Visual Six Sigma roadmap relates to the traditional DMAIC process in the following manner:

The **Frame the Problem** and **Collect Data** steps correspond to the **Define** and **Measure** phases of DMAIC. However, considerable data mining and clean-up may occur in these first two steps of the Visual Six Sigma Roadmap.

The **Uncover Relationships** step loosely corresponds to the **Analyze** phase of DMAIC. However, the initial emphasis is on data exploration and visualization not hypothesis testing.

If the results permit, then the **Model Relationships** step is skipped and one goes directly to the **Revise Knowledge** step. If results are unsatisfactory, then one may have to return to the Collect Data step.

The **Model Relationships** step is a bridge between the Analyze and Improve phases of DMAIC. It may not be necessary in many cases.

Visual Six Sigma Roadmap

The **Revise Knowledge** step corresponds to the **Improve** phase of DMAIC.

Finally, the **Utilize Knowledge** step corresponds to the latter stages of **Improve** and then the **Control** phases of DMAIC.

The roadmap can be visualized as follows:
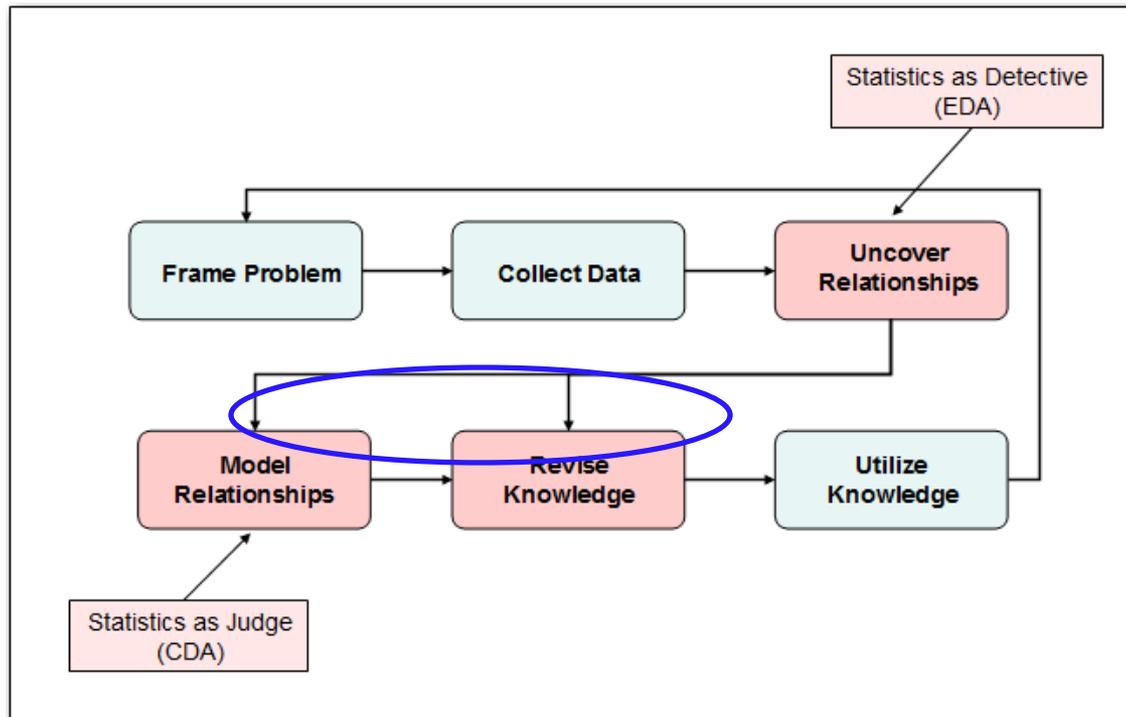
Visual Six Sigma Roadmap

The following are basic steps that occur in three of the steps:

Visual Six Sigma Roadmap - What We Do
Uncover Relationships
Dynamically visualize the variables one at a time
Dynamically visualize the variables two at a time
Dynamically visualize the variables more than two at a time
Visually determine the Hot Xs that affect variation in the Ys
Model Relationships
For each Y, identify the Hot Xs to include in the signal function
Model Y as a function of the Hot Xs; check the noise function
If needed, revise the model
If required, return to the Collect Data step and use DOE
Revise Knowledge
Identify the best Hot X settings
Visualize the effect on the Ys should these Hot X settings vary
Verify improvement using a pilot study or confirmation trials

The JMP Statistical Software

The Visual Six Sigma book is built around analyses performed using the JMP® statistical software from the SAS Institute.

All the JMP data sets used in the book are available for download at a Website referenced in the book.

Why JMP? At present JMP is unique among statistical software packages in that it has fully dynamic and integrated visualization built into its architecture and statistical modeling is straightforward.

All graphics and data tables opened in JMP are dynamically linked, which is critical to data mining and visualization. This is essential to the **Uncover Relationships** phase of Visual Six Sigma.

JMP also provides powerful analytic techniques for confirmatory data analysis. All graphics and analyses are fully integrated.

Note: **I have absolutely no financial interest in sales of JMP**.

Improving a Polymer Manufacturing Process

Case Study: For the past 25 years, MoldMat Ltd. has supplied the plastic used by one of its major customers in Italy in making white garden furniture. Over the years, mysterious crises intermittently occur during which the flowability of the plastic leads to low yields for both MoldMat and its Italian customer. The crises tend to occur about 2 or 3 times per year with acceptable product yields in between the crisis periods. To date, numerous efforts to find the root causes of these crises have failed. Historically, many surefire fixes, that ultimately fail, have been implemented by different teams. Generally, the problem seems to go away on its own after a few weeks (although teams always believe it is a result of their fix) only to reappear later on. After the most recent crisis, a new team is formed, led by an engineer who is a black belt with training in Visual Six Sigma.

Improving a Polymer Manufacturing Process

Case Study: Below is a schematic of the MoldMat polymer manufacturing process – this is a continuous batch process.
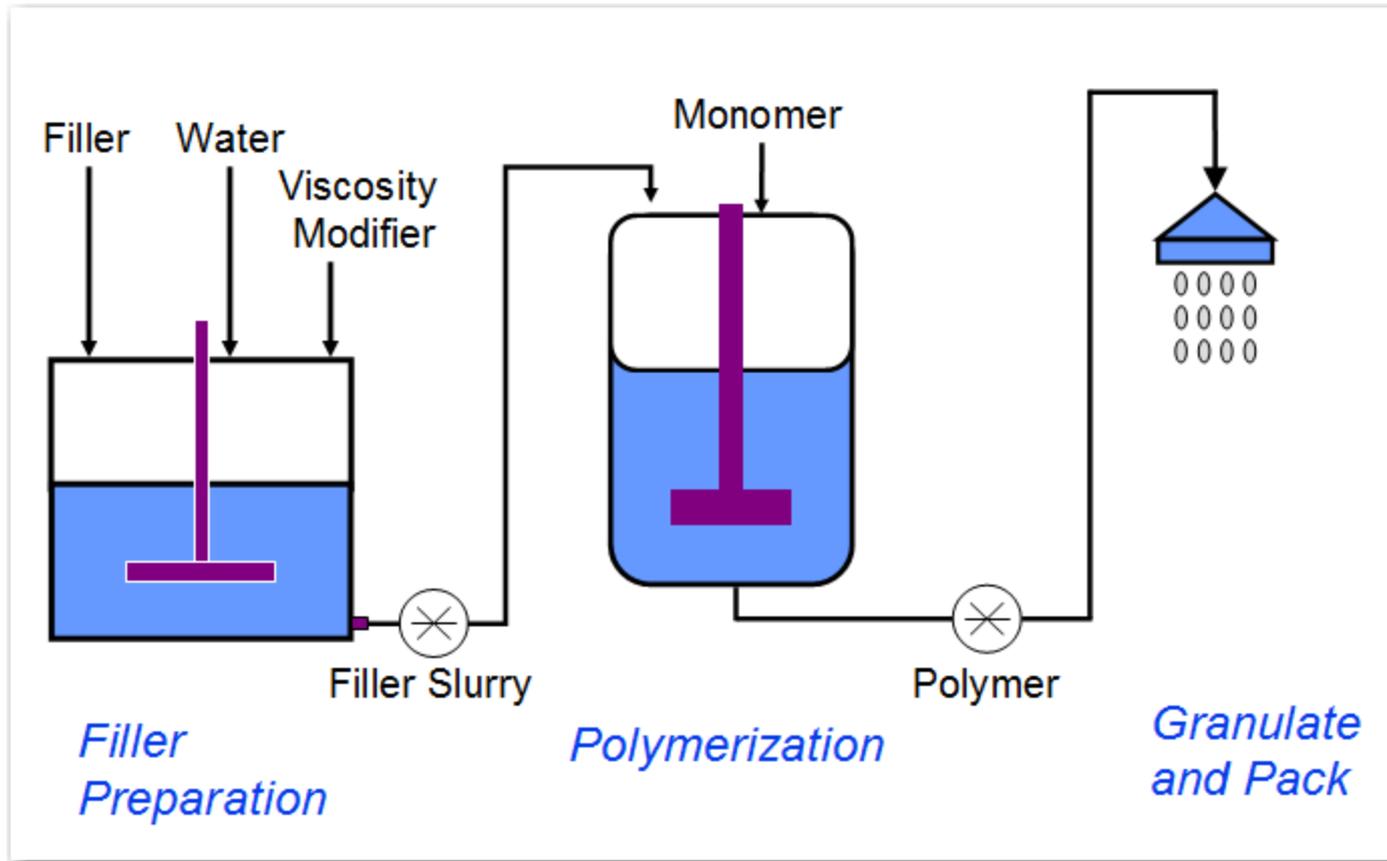
Improving a Polymer Manufacturing Process

Case Study: The manufacturing process is driven by three critical to quality (CTQ) characteristics that are monitored or measured in process and batch adjustments can often be made if necessary.

The three CTQ's are:

- **Whiteness** of plastic color measured by a colorimeter;

- **Melt flow index** (MFI), this is a surrogate measurement for how well the plastic will flow during the molding operation;

- **Yield**, the amount of good polymer produced.

The filler content is an inert white powder that provides the correct color of the polymer and is an important process factor.

However, filler content also affects flowability, so content must be in a proper range to achieve desired color with acceptable flowability.

Framing the Problem

The team first puts together a project charter agreed upon by the team and by the management sponsor of the project.

| Project Title	Improve White Polymer Process Yield
Business Case	The manufacture of white polymer results in periodic flowability crises at a large Italian customer's molding plant. The molding plant sells suspect polymer at scrap prices. These crises have been going on for years and, although the crises resolve temporarily, they continue to recur, causing significant disruption and great financial loss for both MoldMat and its customer. Demand for white furniture keeps increasing, and the molding plant in Italy can't afford to be down due to lack of acceptable white polymer. The molding plant has to turn orders away in crisis periods, causing a significant loss in revenue and great dissatisfaction.
Problem/Opportunity Statement	It is estimated that, due to the crisis periods, the polymer plant suffers a yield loss of about £700,000 per year in scrap material. There is the opportunity to recover at least £700,000 annually in what would otherwise be scrap. Also, a significant margin loss is generated by the molding plant, which has to turn orders away in crisis periods. If the problem could be fixed, the accounting department estimates that the company would realize an additional £2,000,000 of revenue annually.
Project Goal Statement and KPI (Key Performance Indicator)	Increase the average yield of white polymer from 88 percent to 95 percent or higher by December 31, 2007 (four months). Daily yield will be plotted using an individual measurement control chart.
Project Scope	The polymer plant's part of the process.

Project Team	Sponsor: Edward Constant
	Black belt and polymer process engineer: Carl Linton
	Team members:
	  Henry Doyle, the polymer plant quality manager
	  Bill Wright, a polymer chemist from a technical support group
	  Roberto Valentino, a process engineer from the Italian molding plant

Framing the Problem

To capture all of the process inputs (X's) and outputs (Y's), the team constructed a **SIPOC** map (or model). A **S**uppliers **I**nputs **P**rocess **O**utputs **C**ustomers, although simple in nature, is very useful in identifying all important variables in the manufacturing system.

Suppliers	Inputs	Process	Outputs	Customers
Umboga A Kuanga A Kuanga B	Filler	Prepare Slurry	Filler Slurry	Polymerization
North West Water Authority	Water			
Slurry Preparation	Filler Slurry	Make Polymer	Polymer	Granulation
Monomers Inc.	Monomer			
Granulation	Polymer	Granulate	Granules	Packing
Packing	Granules	Pack	Bags	Molding Plant

Framing the Problem

The team put together a detailed process map used in identifying potential critical process inputs (X's) and help everyone on the team to understand the general manufacturing process.
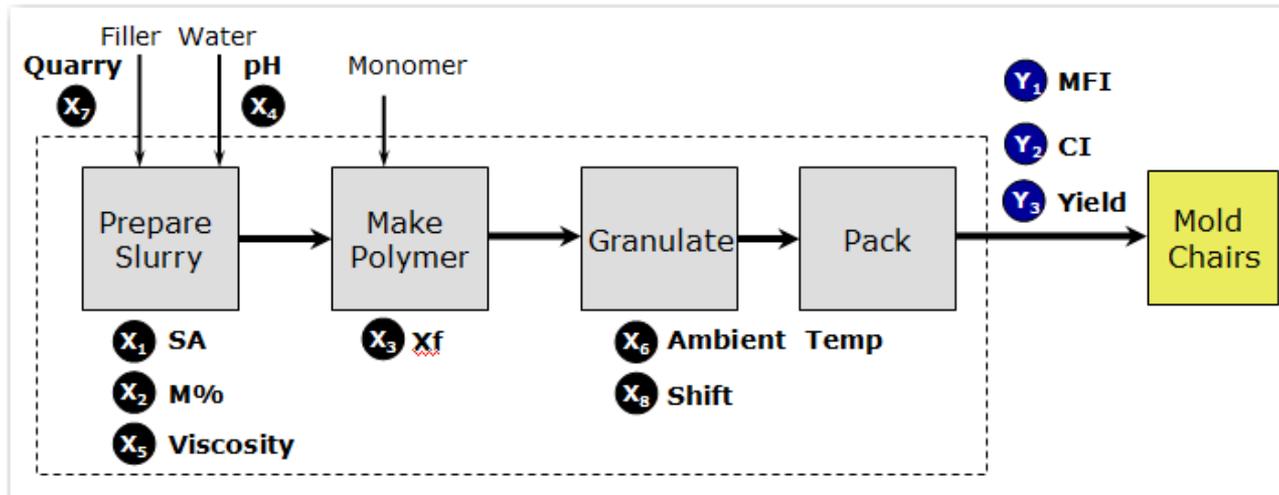
The key performance indicator or **KPI** for the process is daily yield (Y_3) computed as weight of good polymer produced divided by the weight of total polymer produced. The target for yield is 95% and good polymer is that which can be successfully used for molding.
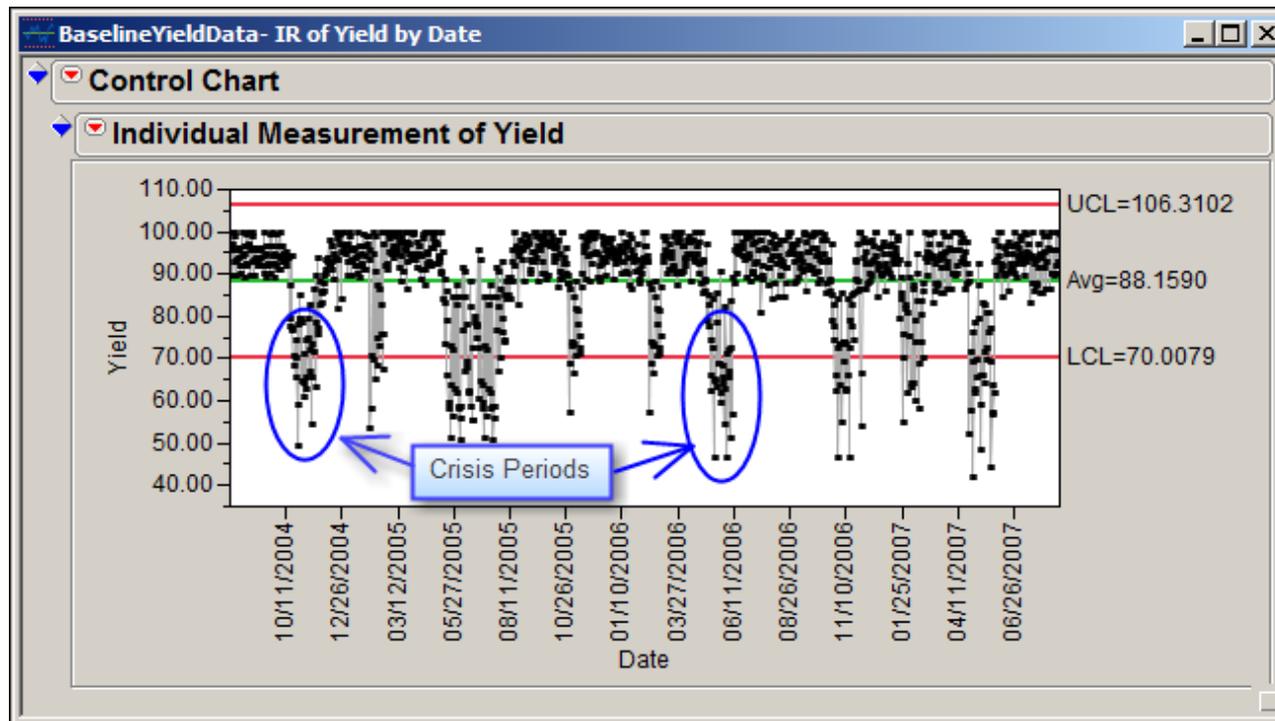
Framing the Problem

Below are definitions of the various X's and Y's. We refer back to these later.

| Variable Type	Name	Description
ID	Batch Number	Identifying number for slurry batch
Ys	MFI	Melt flow index of the polymer
	CI	Color index of the polymer
	Yield	Weight of good polymer as determined by the molding plant, divided by weight of total polymer produced
Xs	SA	Amps for slurry tank stirrer
	M%	Viscosity modifier percent measured in the filler slurry tank
	Xf	Percent of filler in the polymer
	pH	pH of the slurry
	Viscosity	Viscosity of the slurry
	Ambient Temp	Ambient temperature in the slurry tank area
	Quarry	Quarry of origin for filler
	Shift	Shift during which batch was processed

Framing the Problem

Fortunately for the team a considerable mount of historical data on yield is available and can be used to baseline the current process performance. Notice that overall yield is around 88.2% with many very low yield values during crisis periods. The data are in the file **BaselineYieldData.JMP.**

Framing the Problem

In non-crisis periods the lowest yields seems to be about 85%. Using a tool in JMP called the Data Filter, the team excludes all of the yields below 85% and regenerates the control chart. Notice that average yield for non-crisis periods is around 95% and this becomes the KPI target for improvement.
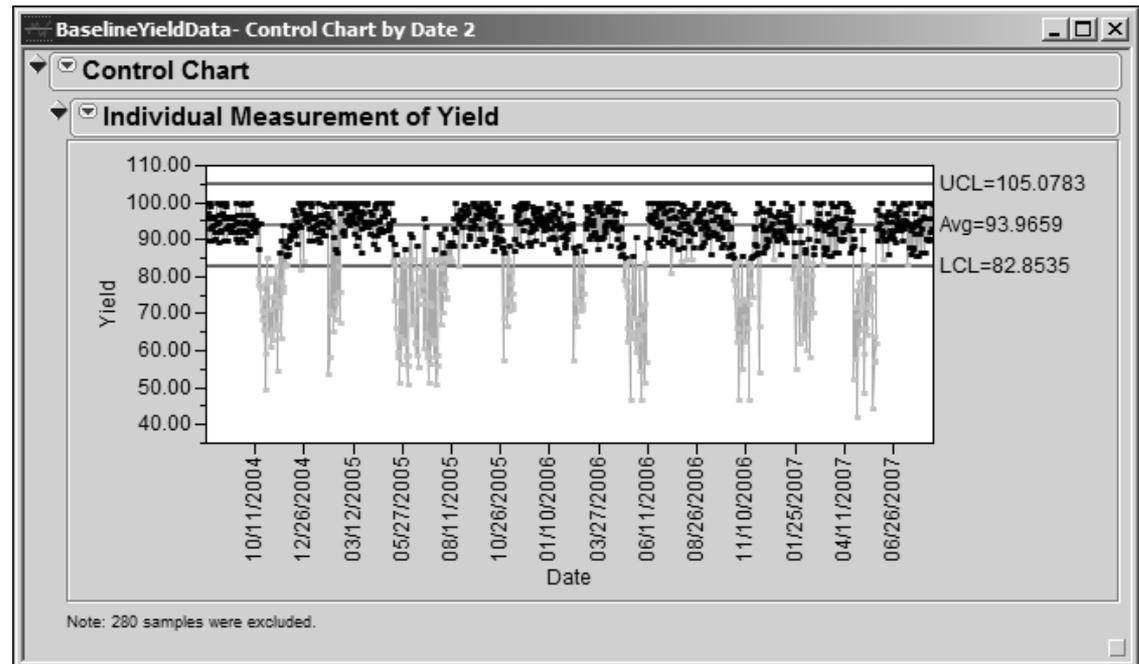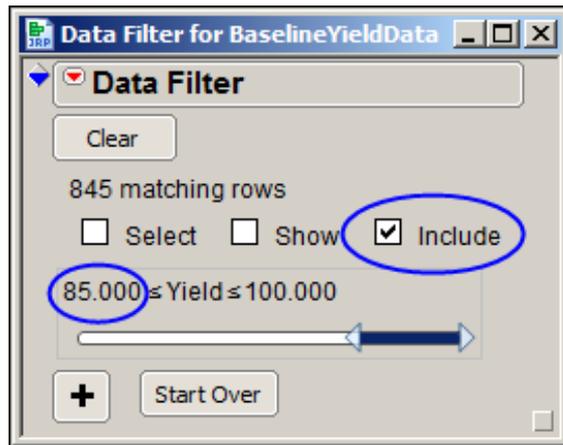
Framing the Problem

In consultation with the customer, the team also narrowed down the focus on CTQ's and collected technical information. This can be displayed in a CTQ tree (or decision tree). The customer has two critical parameters melt flow index (MFI) and color index (CI).

MFI must be in a range of 192 to 198 with a target of 195. The CI only need exceed 80 (out of 100).
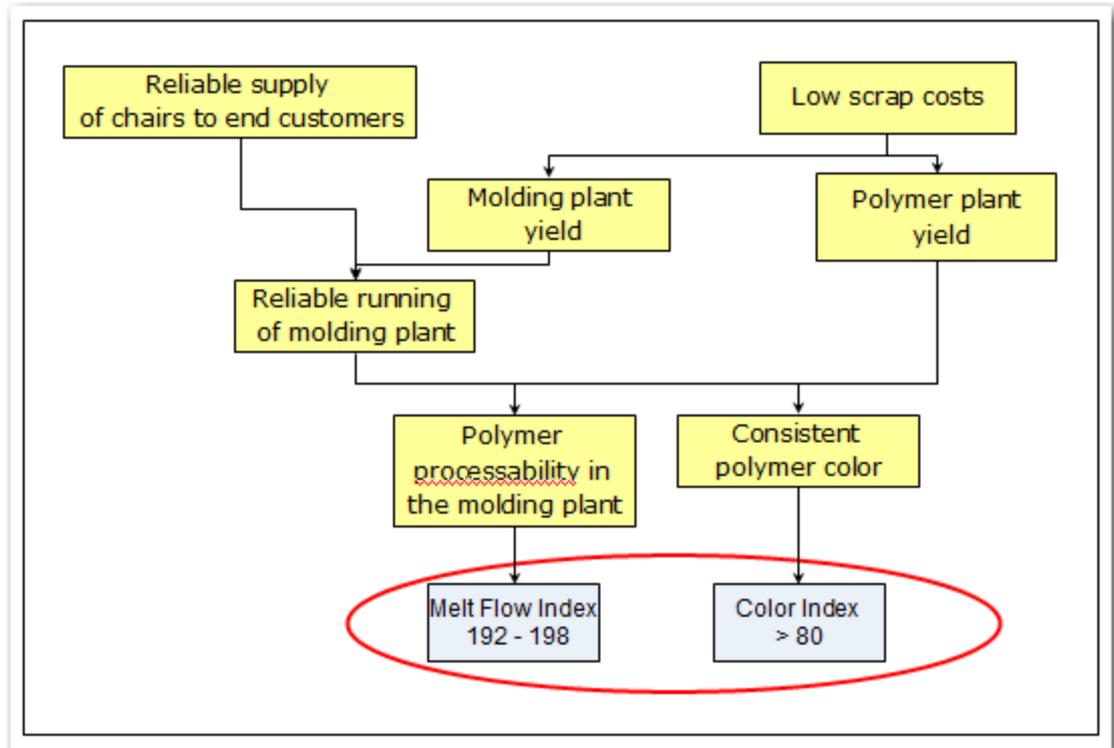
Uncover Relationships

The team was fortunate to find out that a previous crisis team had compiled about six weeks worth of historical data on the process inputs and outputs.

The data covered about 127 production batches.

The data was available and the team Blackbelt combined the data into a large data set for further analysis.

File **CrisisTeamData.JMP** contains the historical data.

This precluded the need for the Data Collection step at this point in the project and they moved on to the Uncover Relationships step.

Generally, it is best to start the analysis of the data by looking at "one variable at a time" to look at the shapes of the distributions, spot potential outliers, anomalous conditions, etc.

Uncover Relationships

Below is a partial view of the individual variable analysis done in the Distribution platform in JMP. The 14 lowest Yield values are highlighted in that report and interactively those points are highlighted in the other reports. The low yield batches tended have lower SA values, but not much relationship to CI and MFI, which is puzzling. Given the importance of CI and MFI as CTQ's there should be a relationship to Yield.
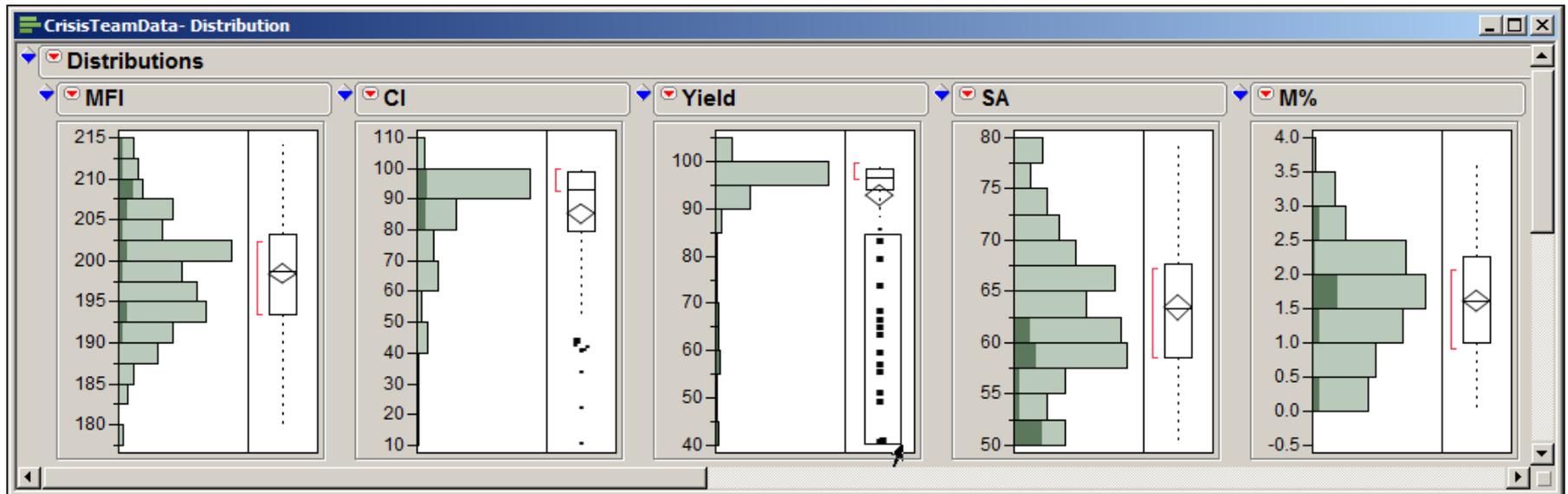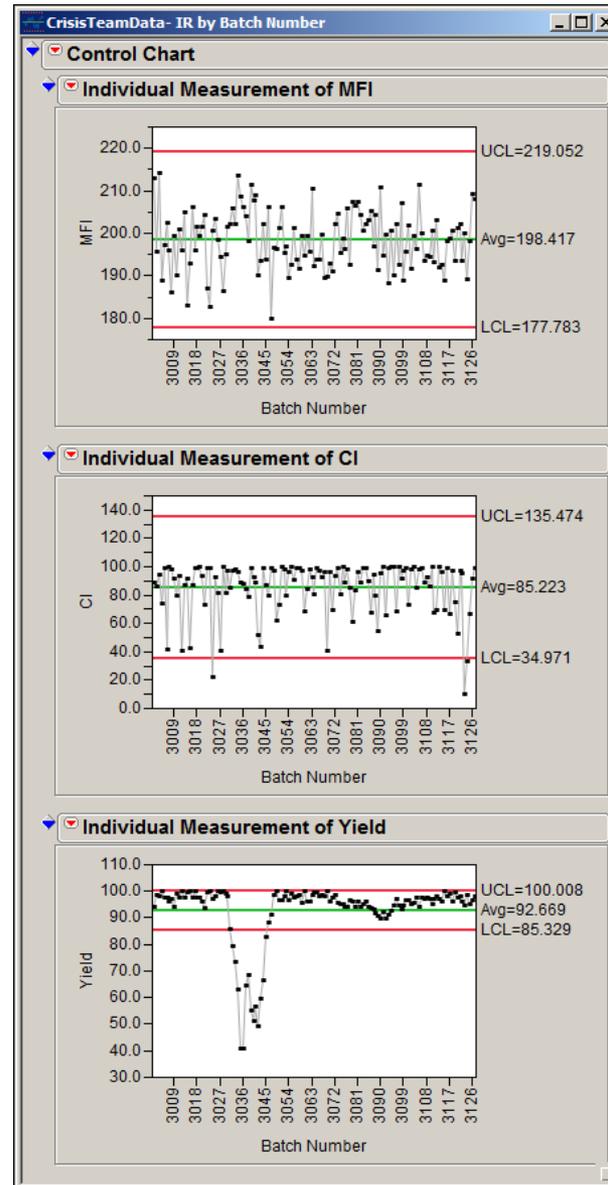
Uncover Relationships

Digging deeper the time creates control charts of the three CTQ's to see if some relationship can be uncovered over time. Again, no clear relationship seems to exist between Yield, MFI, and CI.

Overall, MFI and CI seem stable over time despite the clear crisis period in yield.

Also, the upper spec. for MFI is 198, yet the process is averaging around 198, so many of the batches appear to be out of spec.

Uncover Relationships

The team quickly suspects that poor measurement system capability might be a potential reason for the inability to see relationships between MFI, CI, and Yield.

It was found that thorough measurement systems analyses (**MSA**) had been performed on most of the X's and Y's, but no record existed of an MSA on MFI or Xf.

Recall, Xf measures the amount of filler in the polymer and is directly related to color, viscosity, and somewhat to MFI.

The team decides that it is unwise to proceed with further data analysis until the capability of MFI and Xf are assessed and if need be improved.

Note, a simple form of MSA is a traditional Gage R&R study, however a full MSA may be significantly more complicated.

Uncover Relationships

The MFI is measured using a commonly available type of instrument and the reported measures are average melted polymer flow in grams normalized to 10 minutes.

Four such instruments are used in the MoldMat lab.

The MSA included all four instruments, three operators, and three randomly chosen batches of polymer.

Each combination was repeated twice for a total of 72 measurements in the study.

We omit most of the details of the MSA design, however the results are contained in the file **MSA_MFI_Initial.JMP**.
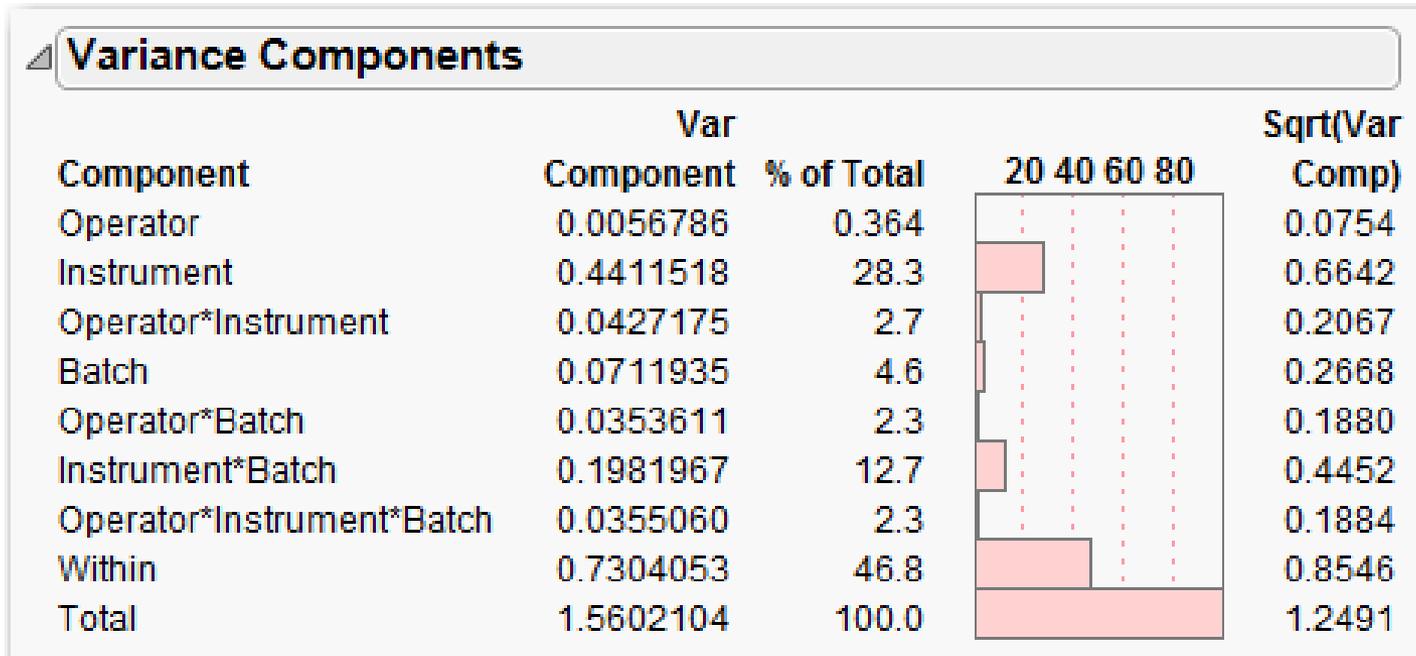
Uncover Relationships

Using the Variability Chart platform in JMP one can visually see that a great deal of variation exists in the MFI measurement process. In some cases, the repeated MFI reading on the same batch and instrument by the same operator varies more than 4 units. Given MFI measurements are a key driver in batch manufacturing, this is "bad news" for manufacturing and for the customer.
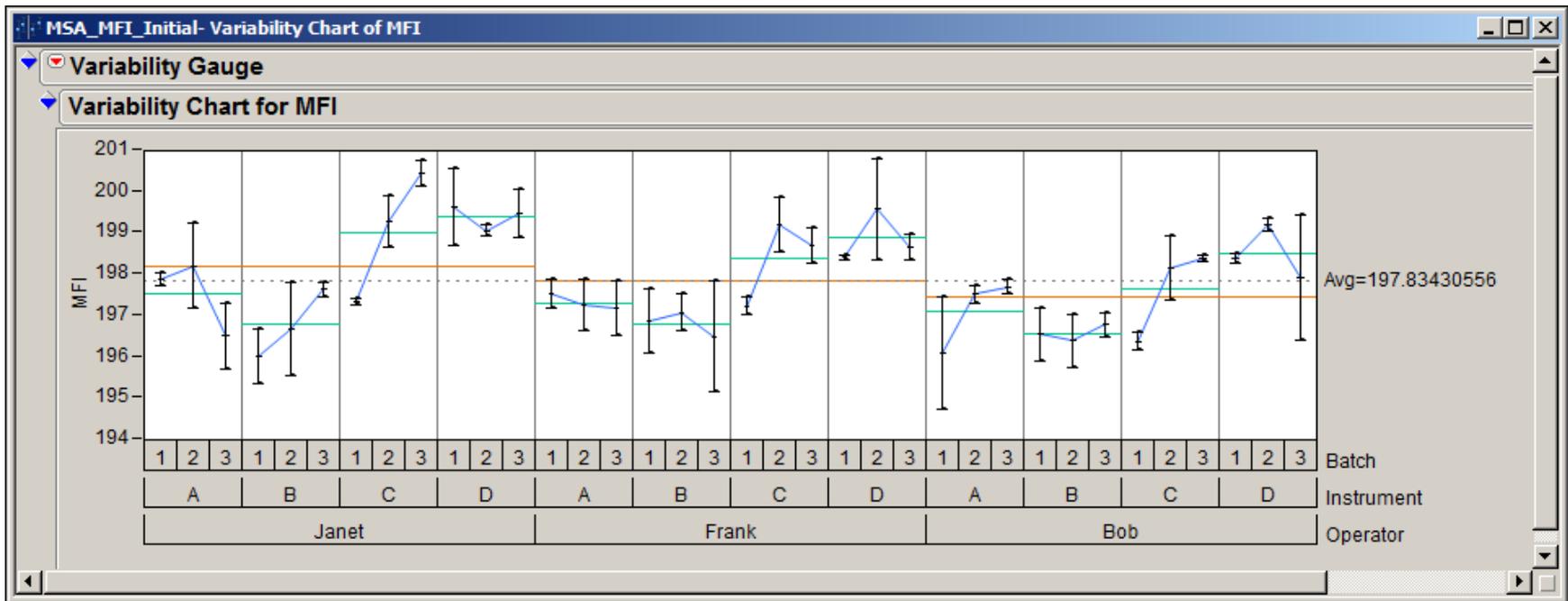
Uncover Relationships

One way to assess the portion of total variation attributable to each of the sources is through variance components analysis. Below is the variance component result from JMP. Note that 47% of the variation is from the failure to repeat MFI measurements, while 28% is due to instrument to instrument differences. Clearly, the MFI measurement system is incapable for a spec of 192 to 198.

Variance Components

Component	Var Component	% of Total	20 40 60 80	Sqrt(Var Comp)
Operator	0.0056786	0.364		0.0754
Instrument	0.4411518	28.3		0.6642
Operator*Instrument	0.0427175	2.7		0.2067
Batch	0.0711935	4.6		0.2668
Operator*Batch	0.0353611	2.3		0.1880
Instrument*Batch	0.1981967	12.7		0.4452
Operator*Instrument*Batch	0.0355060	2.3		0.1884
Within	0.7304053	46.8		0.8546
Total	1.5602104	100.0		1.2491

Uncover Relationships

We can also provide a traditional Gage R&R report. The Precision to Tolerance ratio is 1.22 where a maximum of 0.3 is considered capable this reinforces the lack of capability in MFI measurements.

Gauge R&R

Measurement Source		Variation (6*StdDev)	% of Tolerance		which is 6*sqrt of
Repeatability	(EV)	5.1278252	85.46	Equipment Variation	V(Within)
Reproducibility	(AV)	5.2258989	87.10	Appraiser Variation	V(Total)-V(Batch)-V(Within)
Operator		0.4521374	7.54		V(Operator)
Instrument		3.9851557	66.42		V(Instrument)
Operator*Instrument		1.2400928	20.67		V(Operator*Instrument)
Operator*Batch		1.1282729	18.80		V(Operator*Batch)
Instrument*Batch		2.6711571	44.52		V(Instrument*Batch)
Operator*Instrument*Batch		1.1305820	18.84		V(Operator*Instrument*Batch)
Gauge R&R	(RR)	7.3215170	122.03	Measurement Variation	V(Total)-V(Batch)
Part Variation	(PV)	1.6009261	26.68	Part Variation	V(Batch)
Total Variation	(TV)	7.4945030	124.91	Total Variation	V(Total)

6	k
97.6918	% Gauge R&R = 100*(RR/TV)
4.5733	Precision to Part Variation = RR/PV
0	Number of Distinct Categories = 1.41(PV/RR)
6	Tolerance = USL-LSL
1.22025	Precision/Tolerance Ratio = RR/(USL-LSL)

Uncover Relationships

Similarly an MSA was performed for the Xf measurements. This is a common type of test referred to as an "ash test."

The Xf MSA similarly revealed an incapable measurement system and since Xf measurements are used to control the amount of filler in the polymer this is further "bad news" for manufacturing and the customer.

We skip substantial detail, however significant sources of variation were uncovered in both measurement systems and fixes put in place by the team, causing a considerable delay in the project.

After improvements to the two measurements systems, both were found to be capable by additional MSAs.

Despite the delay, it would have been pointless to continue the project until capable MFI and Xf measurements were available.

Uncover Relationships

Since two important measurement systems were incapable when the historical data was collected, the team had to backtrack to the **Collect Data** step and collect new process data.

A total of five weeks of new process data were collected and at that point the team returned to the Uncover Relationships step.

The new data are in the file **VSSTeamData.JMP**.

Since, we have new and higher quality data it is useful to go back and examine the control charts for MFI, CI, Yield to see if we can detect any patterns in the relationships.

Uncover Relationships

Notice in the Yield chart that four batches clearly represent a crisis level of performance.

This time in the MFI chart we can clearly see that the four low yield batches are associated with very high MFI levels.

The CI values for the four low yield batches appear acceptable, so the problem appears to be related to MFI and not color.
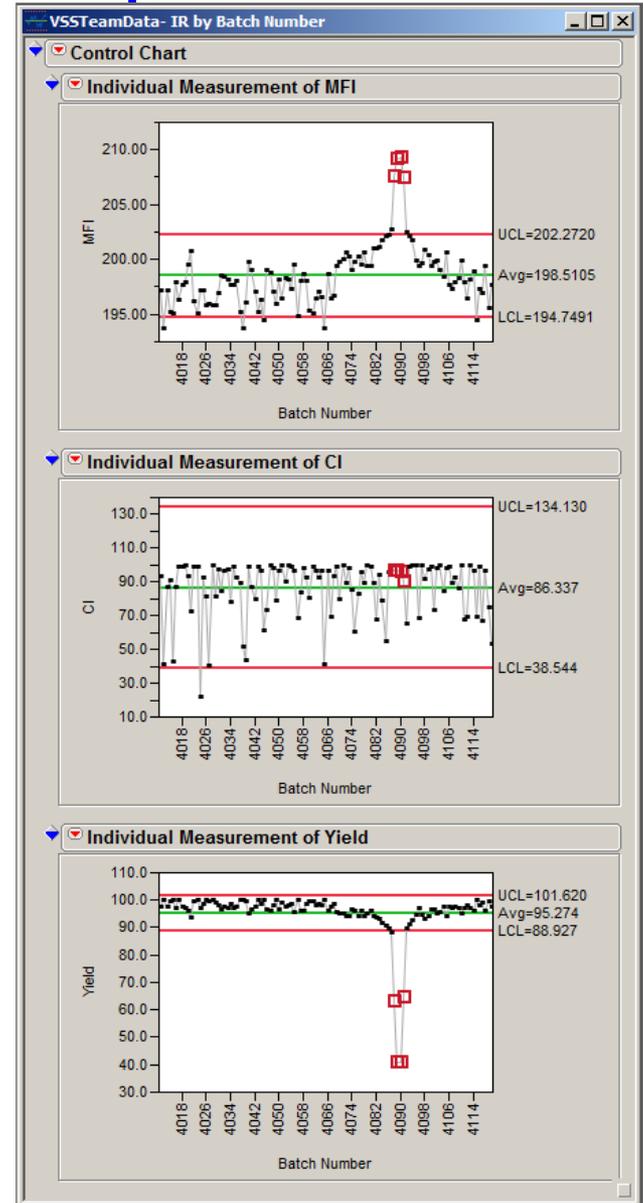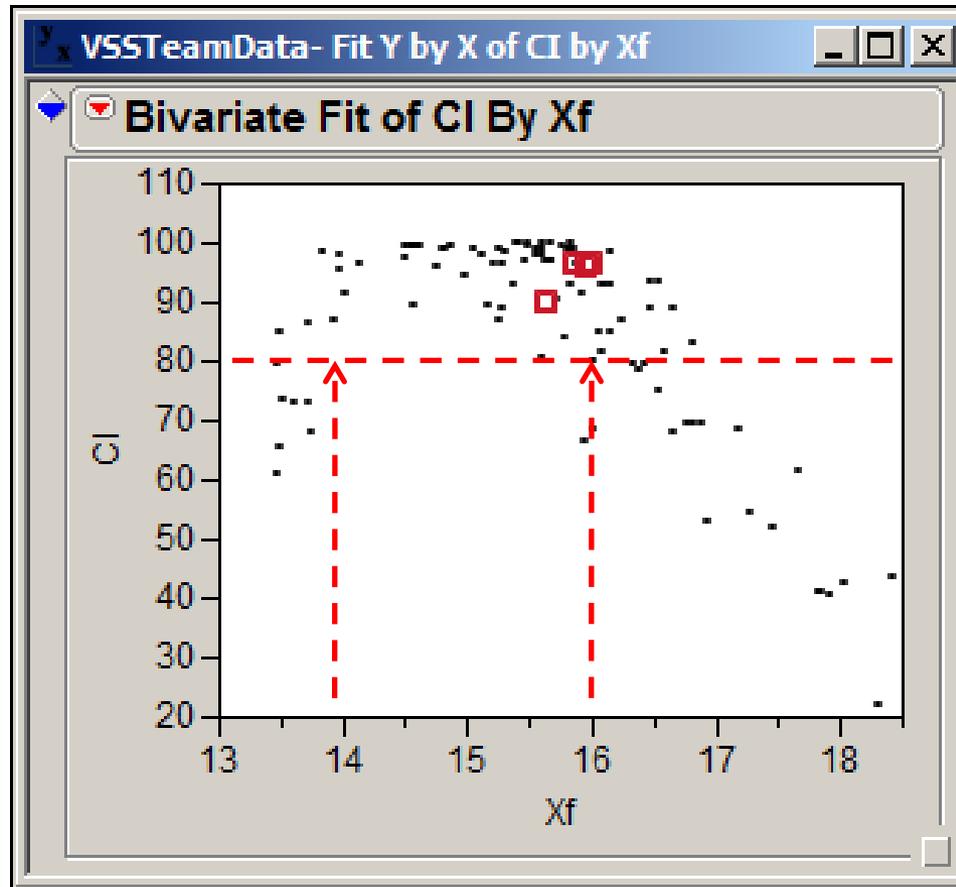
Uncover Relationships

In order to better understand the relationships between Yield, MFI, CI, and Xf we use a series of scatter plots for the Fit Y by X platform in JMP.

From the Yield by MFI plot it appears that the upper MFI spec of 198 may be too high and should be closer to 194 or 195.
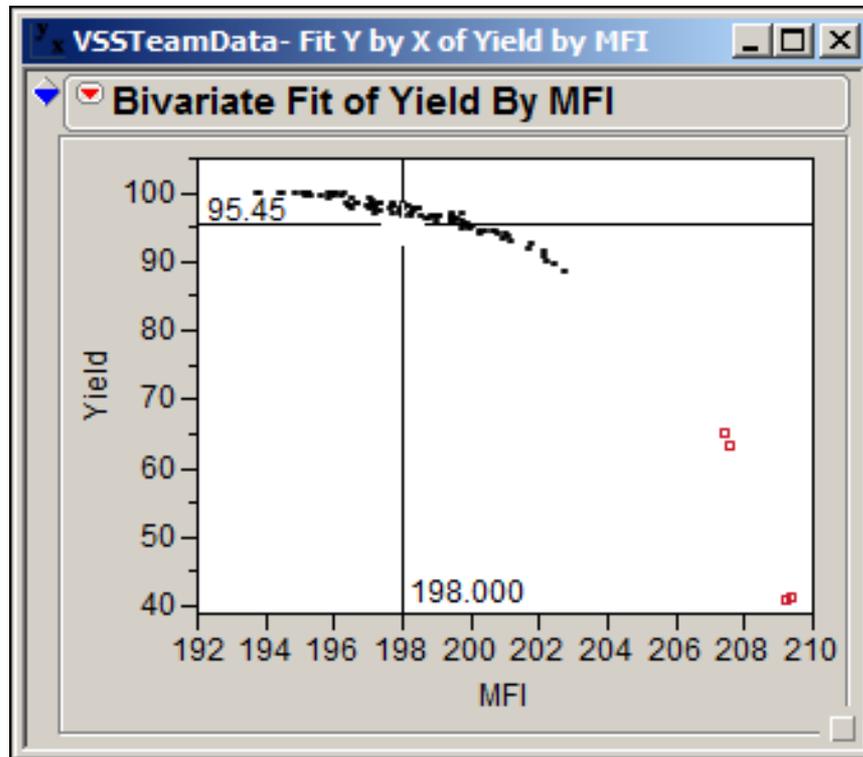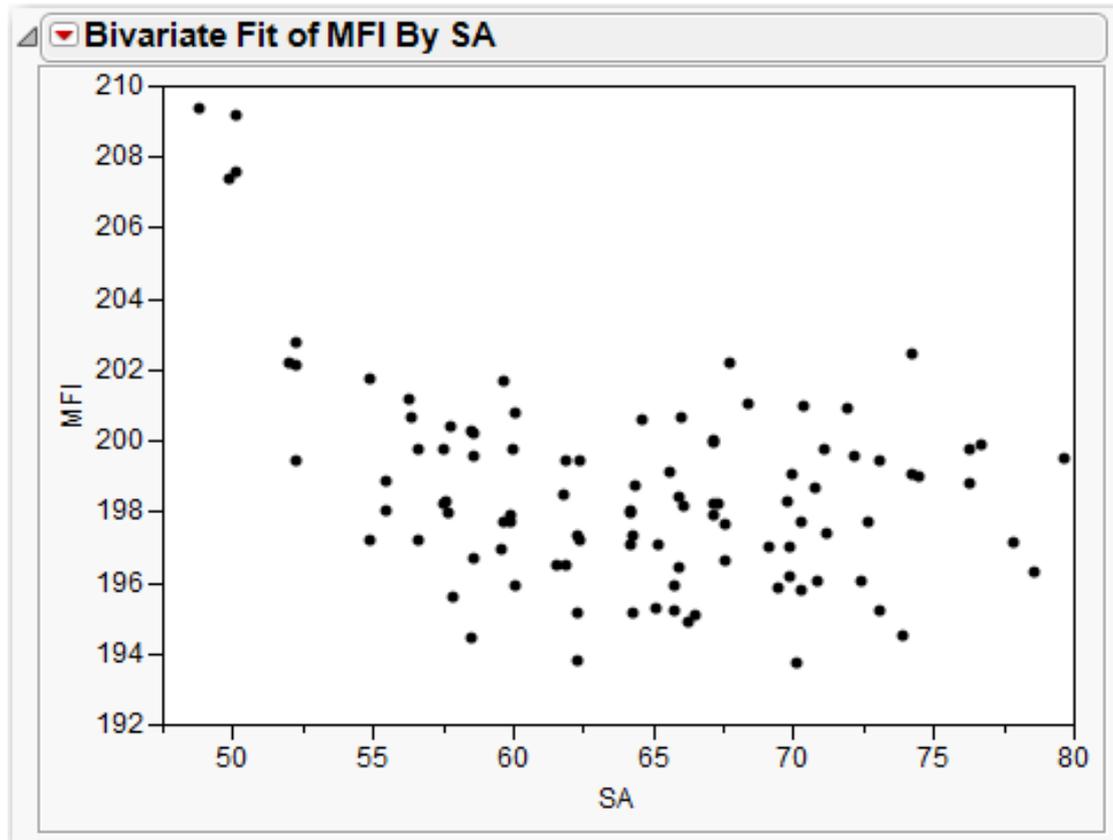
Uncover Relationships

A Fit Y by X plot of CI by Xf also revealed an interesting relationship. It appears that Xf needs to be kept in an operating range in order to achieve acceptable CI.

Uncover Relationships

A plot of MFI by SA also reveals that low SA settings may contribute to high MFI and most likely we need at least a lower limit for SA.

Uncover Relationships

With the new capable data the team has found relationships between yield and MFI.

In addition, it is clear that both MFI and CI are affected by settings of at least some of the process variables.

However, it is difficult to find proper control points for the process factors based solely on one and two dimensional visualizations.

Most likely more complicated relationships exist among the input variables and the output variables than we can capture visually.

At this point, it appears that the team needs to move on to the **Model Relationships** step in order to understand how the input factors control MFI and CI (and thereby control Yield).

The model then becomes a basis for setting desirable processing conditions to assure high Yield.

Model Relationships

Ideally the team would like to run designed experiments to better understand causal relationships between the input variables and the outputs MFI and CI.

Unfortunately, they are unable to secure production equipment time to run experiments due to an excessive production backlog attributable to the latest crisis.

However, given they do have a valid dataset it may be possible to generate useful process models from their observational data.

Before proceeding to model development, the four low yield batches were excluded from the data, since they appear to be outliers with the respect to the remainder of the data.

We want to find operating settings that deliver good polymer not bad.

Model Relationships

Given the number of input factors and possible nonlinear relationships the modeling task is a difficult one.

A new platform in JMP called "Screening", can be useful, especially for those not thoroughly versed in statistical modeling.

Screening automatically looks a lot of potential models and tries to select the best one for the user.

The team decided to try the Screening platform in JMP to see if a significant model could be found relating MFI and CI to the input variables.

Model Relationships

We omit considerable detail, but the final model relating MFI to the process variables contained the following significant terms.

The model represents the relationship of MFI to the input variables or X's that are considered "hot" for that variable.

Shortly we will see that we can use the model to optimize the process to produce batches with acceptable MFI.

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
M%	1	1	209.11435	719.6548	<.0001*
Xf	1	1	69.17430	238.0593	<.0001*
SA	1	1	0.90577	3.1171	0.0807
SA*SA	1	1	46.72285	160.7940	<.0001*
SA*SA*SA	1	1	17.49764	60.2171	<.0001*
Quarry	2	2	0.76733	1.3204	0.2718
SA*Quarry	2	2	1.36411	2.3473	0.1011

Model Relationships

A similar process was followed for CI and below is the best process model found that related CI to process factors, again the model contains the "hot" X's for CI.

Notice that Xf is by far the most important factor to control in order to maintain an acceptable CI level.

However, Xf and SA, affect both MFI and CI, so it may be difficult to find a "best" setting for these two X's that will simultaneously achieve a desirable level of MFI and CI.

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Xf	1	1	3719.601	67.8368	<.0001*
Xf*Xf	1	1	15267.977	278.4520	<.0001*
Xf*Xf*Xf	1	1	728.759	13.2909	0.0004*
SA	1	1	129.958	2.3701	0.1268

Revise Knowledge

The remaining process variables not included in either model are assumed not to have a significant affect on MFI or CI and can be set a convenient levels in their current process range.

The two models amount to prediction formulas or equations that predict the MFI and CI levels for any given settings of the process factors included in the model.

We can now use these models in JMP to perform an optimization and capability analysis on the process.

Again, we skip some detail, however the Profiler in JMP contains a powerful optimization routine that also performs capability analysis.

Revise Knowledge

Below is the results of the optimization using the popular criterion called Desirability. At the bottom of the report are the settings for the process factors to achieve desirable levels of MFI and CI.
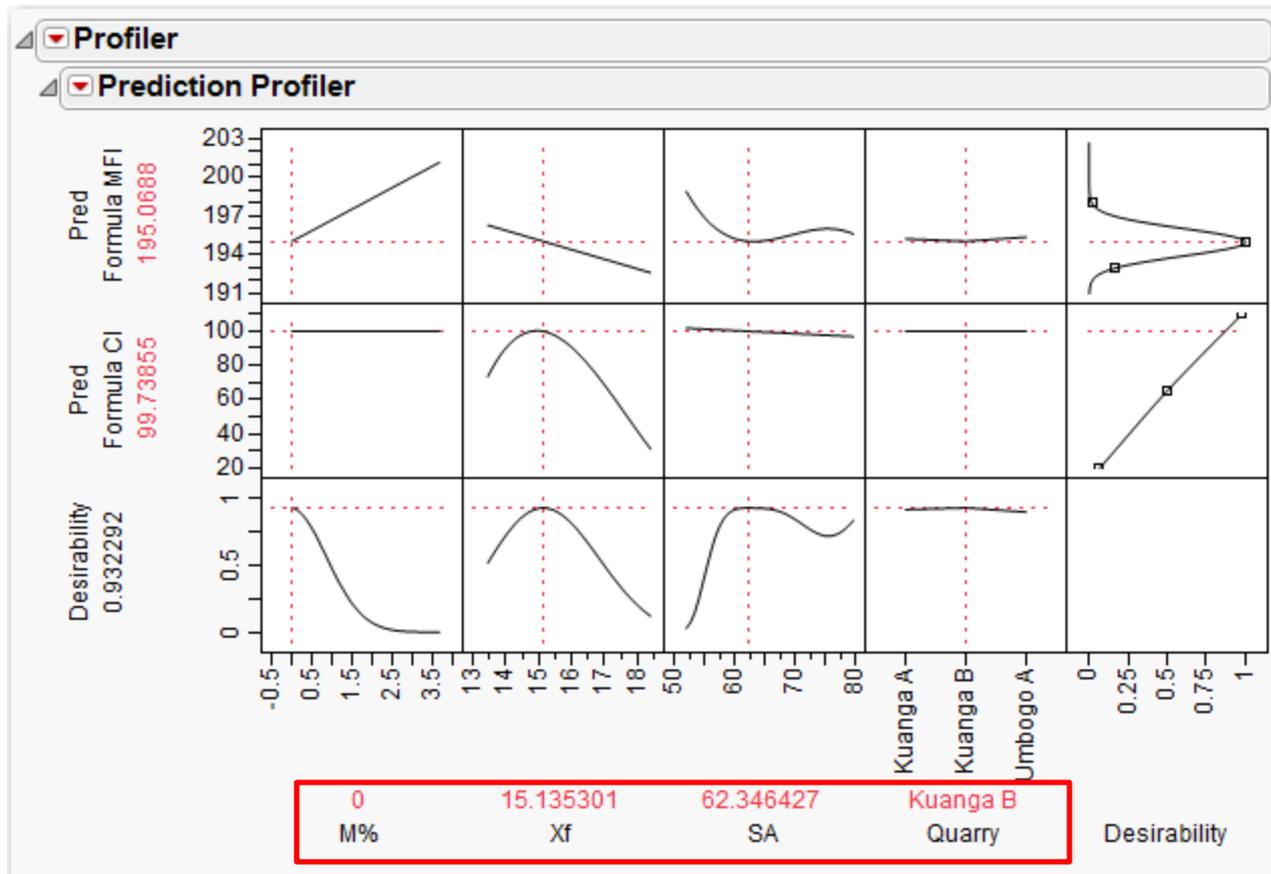
Revise Knowledge

In manufacturing the team has observed that neither Xf nor SA are tightly controlled and they would like to know the impact on capability due to variation in Xf and SA.

The Profiler in JMP has a "Simulator" which allows one to vary the inputs to the process models and evaluate the overall impact on the process capability.

The team, using the process data that they have collected, have a good estimate of the variation in Xf and SA.

We express the variation as a standard deviation (a common measure of variation).

For Xf we have the standard deviation = 0.4 and for SA the standard deviation is 1.9. We will use these as inputs to the Simulator and assess the resultant process capability.

Revise Knowledge

Notice that the defect rate for MFI is very low, but for CI it is too high, meaning in practice a problem with low CI may well occur.
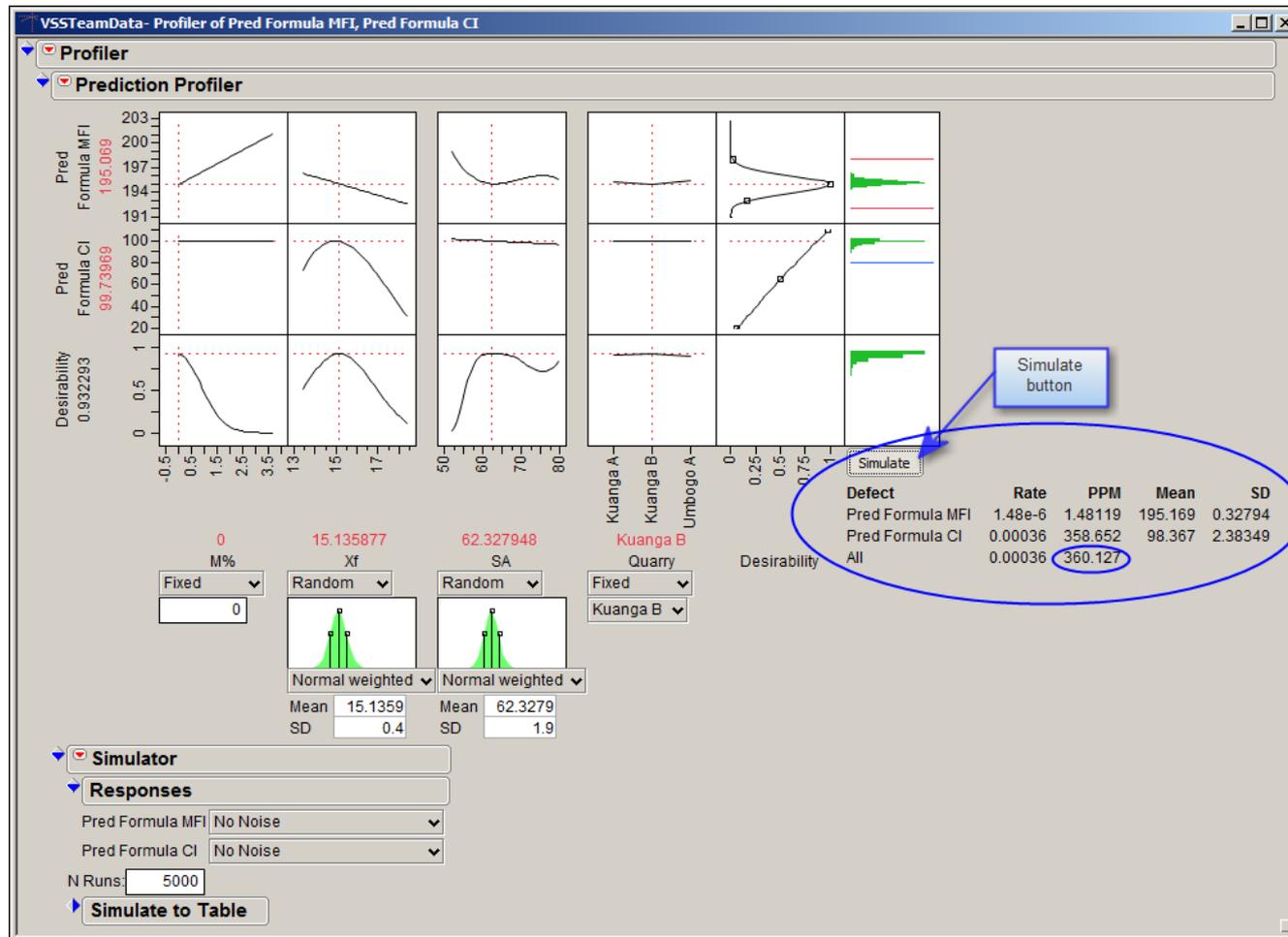
Revise Knowledge

Since CI is very sensitive to Xf, it should be possible to improve CI performance simply by instituting tighter process controls on Xf.

Although the results look promising, it is important perform confirmation production runs at the optimized settings to determine if the models are indeed properly predicting performance.

Below are the results of five confirmation runs and the team is quite pleased.
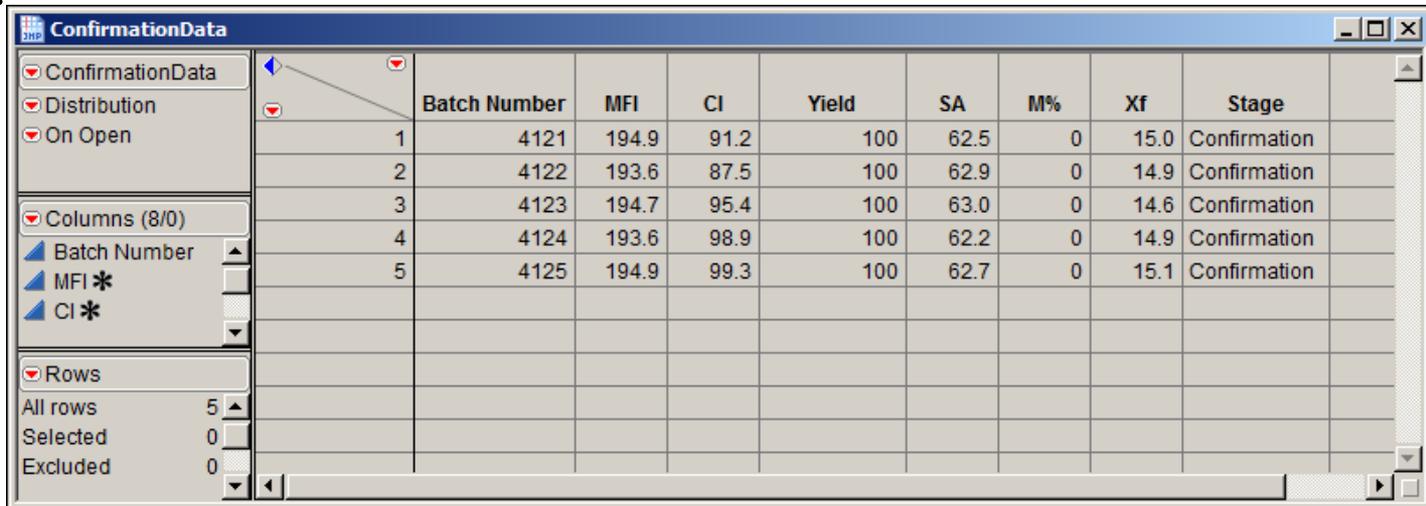
	Batch Number	MFI	CI	Yield	SA	M%	Xf	Stage
1	4121	194.9	91.2	100	62.5	0	15.0	Confirmation
2	4122	193.6	87.5	100	62.9	0	14.9	Confirmation
3	4123	194.7	95.4	100	63.0	0	14.6	Confirmation
4	4124	193.6	98.9	100	62.2	0	14.9	Confirmation
5	4125	194.9	99.3	100	62.7	0	15.1	Confirmation

ConfirmationData — ConfirmationData / Distribution / On Open

Columns (8/0): Batch Number, MFI ✱, CI ✱

Rows: All rows 5, Selected 0, Excluded 0

Utilize Knowledge

Given the promising confirmation results the team moves on to the Utilize Knowledge step where the new process will be implemented and monitored.

As an aside, based upon the results presented by the team the sponsor agreed to invest in a new controller for SA and institute better control over filler to maintain tighter Xf control.

Although, the results look promising, the team must monitor the new process for sometime to ensure that the predicted capability or gains are sustainable.

The results for the next 79 batches after the changes are implemented is contained in the file **VSSTeamFinalData.JMP**.

Utilize Knowledge

We use "phase control charts" to compare the performance in yield across the three phases of the data: original, confirmation, and control.
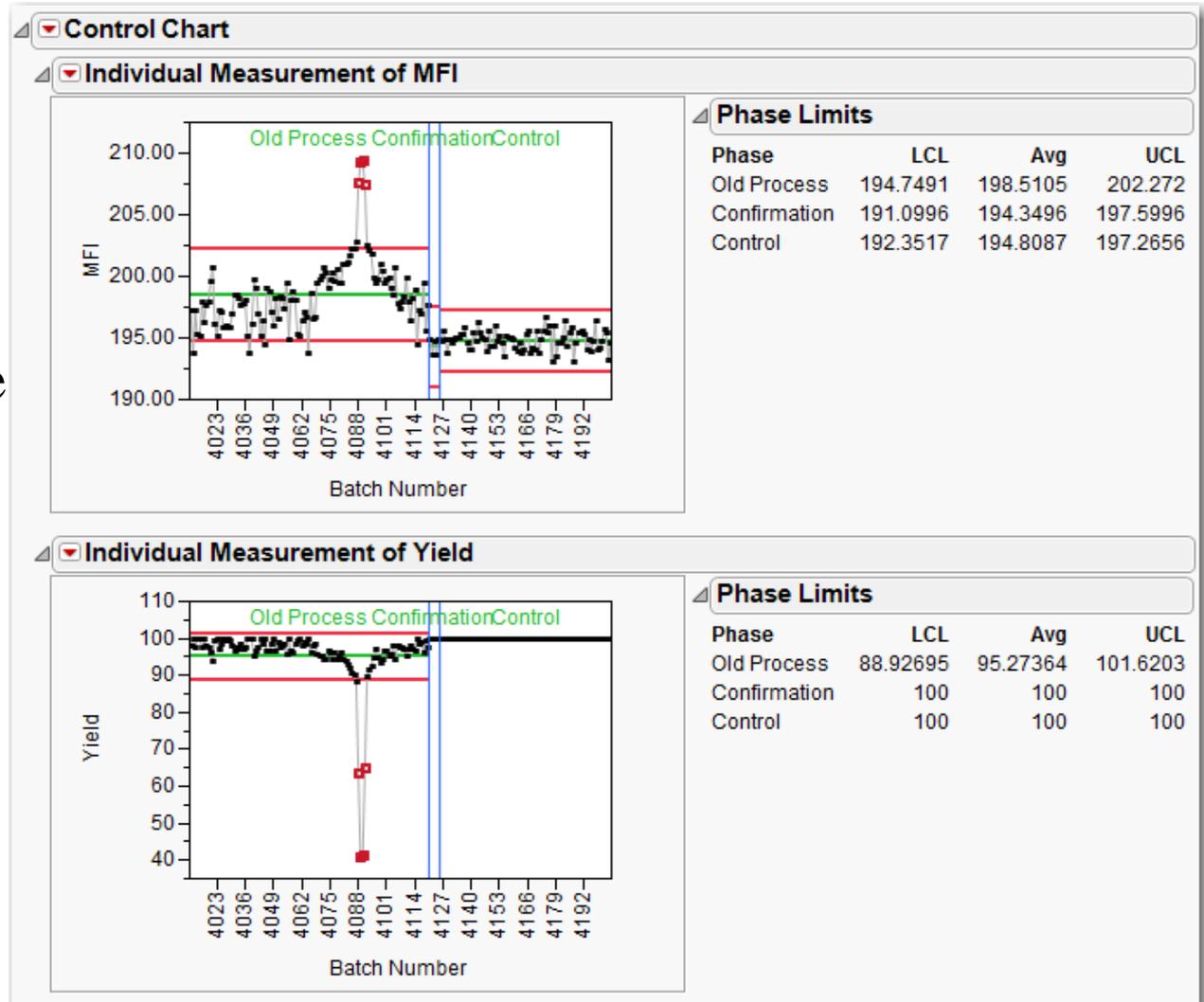
Summary

It has been over 2 years since the changes were implemented and not a single batch of polymer has been rejected by the molding plant.

The total addition to margin for the polymer plant is about £2,100,000.

Some key lessons from the project:

- Never trust a measurement system until a proper MSA is performed.

- Without capable measurements it is impossible to get meaningful results from analyses of data – garbage in garbage out.

- Following the VSS roadmap results in a high level of process understanding gained in a straightforward manner.

- VSS methodology allows technical and business users to solve problems effectively in a timely manner.