Statistical Consulting at Draper Laboratory

A Project Report
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in
Applied Statistics

Submitted By:

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Abstract

This Master's capstone was conducted in conjunction with Draper Laboratory, a non-profit research and development organization in Cambridge, Massachusetts. During a three month period, the author worked for the Microfabrication Department, assisting with projects related to statistics and quality control. The author gained real-world experience in data collection and analysis, and learned a new statistical software. Statistical methods covered in this report include regression analysis, control charts and capability, Gage R & R studies, and basic exploratory data analysis.

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Introduction

This Master's capstone was conducted in conjunction with Draper Laboratory, a non-profit research and development organization in Cambridge, Massachusetts. During a three month period, I worked for the Microfabrication Department at Draper, assisting with projects related to statistics and quality control. This report summarizes five major statistical studies that I completed.

The first project dealt with an etch process - small holes, referred to as cavities, were etched into a glass wafer. Cavity diameters were recorded, as well as values for other parameters that were adjusted from wafer to wafer. For example, the length of time wafers spent in the etching bath varied. The goal was to see which variables potentially affected cavity diameter size, and to see if there were interesting relationships among variables. I fit general linear models to the data, with cavity diameter as the response and the other parameters as predictor variables. The final model, even though it included all significant variables, did not fit well and can be improved upon.

In the second project, I examined process variables pertaining to a tool in the Microfabrication Laboratory. Control charts and capability ratios had been previously created for these variables. However, the charts and ratios used were incorrect because the assumption of normality was violated. I corrected the charts by first transforming the data to obtain normality, and then created new charts with the transformed data. I also found updated capability ratios and examined autocorrelation plots.

The third project looked at the shear strength of tiny bumps on a wafer's surface. Engineers wanted to maximize shear strength, as well as see if strength was greatest at the center of a wafer. I fit general linear models for two sets of data, to see which wafers and locations produced the highest average shear strength. I also used Tukey's Method to examine pairwise comparisons.

The fourth project was entirely devoted to Gage R & R studies. I reviewed data and results from Gage R & R studies completed in May of 2013. I used Minitab to validate the results, as well as to analyze the data using a different method than previously used. I also conducted and analyzed new Gage R & R studies for three measuring tools in the Microfabrication Laboratory.

Finally, I created PowerPoint presentations that explain how to use Minitab to perform data analysis. Specially, I picked statistical topics I thought were most useful and applicable in the department, and then showed how to execute them in Minitab. Other Draper employees can refer to the presentations in the future. The hope is that employees will utilize Minitab more often for analysis.

Each chapter of this report focuses on one of the five projects. The chapters include a brief introduction with background information, goals of the statistical analysis, a description of the data, and statistical methods used to analyze the data. The chapters also include conclusions, comments, and recommendations.

Minitab was the primary statistical software used to perform the data analysis.

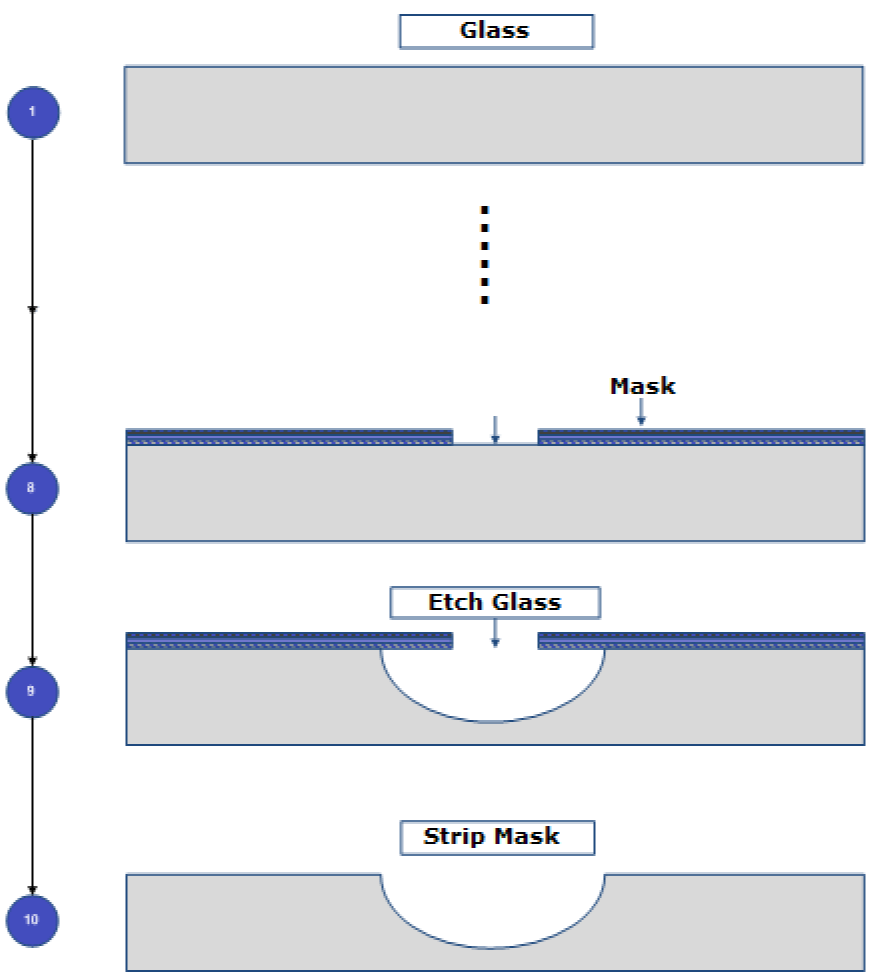
Chapter 1: Etch Process

Introduction

The first analysis I completed dealt with an etch process. First, a mask is placed on top of a glass wafer. This mask, by the end of placement, has circular holes in it. The wafer (with the mask) is put inside a heated chemical bath of hydrofluoric acid. This is where etching took place. The etch process is believed to be isotropic, meaning material was removed in all directions at an equal rate. After a few hours, a hemispherical cavity forms in the glass at the sites where there was an opening in the mask. Figure 1 displays the aforementioned process (the steps describing the placement of the mask are not included).

Various parameters, such as etch time, were adjusted throughout the project. Engineers hoped to achieve nearly perfect holes of a specific size.

Figure 1: Etch Process



Goals

The main goal for this study was to perform exploratory data analysis. I was asked to see what certain variables potentially affected cavity diameter size, and to see if there were interesting trends and correlations among variables.

Data/Variables

There were 53 wafers included in the dataset. For most wafers, the same mask diameter size was used across the whole wafer. A few wafers had varying mask diameter sizes. The number of holes measured on each wafer varied.

Response (Y)
Cavity Diameter: size of hole, in µm

Additional Variables/Possible Predictors (X1, X2, etc.)
Wafer: identifier of the wafer
Row, Column: Row and column of a cavity on the wafer
Cavity Center X, Cavity Center Y, Mask Center X, Mask Center Y: X and Y coordinates, in µm
Mask Diameter: Actual size of the mask hole, in µm
Nominal Mask Diameter: The target mask hole diameter, in µm
Mask Diameter Error: Difference between the actual and target mask hole diameter
Etch Time: Total time wafer spent in the chemical bath, in hours
Horizontal Undercut: Length of the "overhang" shown in step 9 of Figure 1, in µm
H rate (µm/hr): Horizontal etch rate, equal to Horizontal Undercut / Etch Time
HF concentration: Hydrofluoric acid % in the etching chemical bath

Off Centering X, Off Centering Y: Difference between Cavity Center and Mask Center coordinates, in µm
Off Centering D: Euclidean distance, in µm
Off Centering Angle: Measured in degrees

There were other variables in the data that I decided to exclude from my analysis, for various reasons. Some wafers contained information pertaining to cavity radius, cavity area, and cavity perimeter. These particular variables are directly related to cavity diameter, so, I could essentially use any of them as the response variable. However, cavity diameter was measured for every wafer, whereas the other variables were not. Therefore, it seemed reasonable to choose cavity diameter as the response.

"Judgment" variables were also recorded- these kept track of defects at each cavity location. The location was deemed either "GOOD" ("n" for some wafers) or "BAD" ("y"). As was the case with cavity radius, area, etc., not all judgment variables were listed for every wafer- in fact, very few wafers contained values for all judgment variables. In addition, I looked at a correlation matrix across all possible variables. I found the judgment variables to be significantly uncorrelated with any of the other variables, and thus, I decided to exclude them in the subsequent analysis.

Statistical Analysis

I first looked at the distribution of the response variable, cavity diameter. Many analyses assume (or require) that the response is normally distributed, so I wanted to check for that. The Anderson-Darling Normality Test, as well as Figures 2 and 3 below indicate that cavity diameter is not normally distributed, and is skewed to the left.

Figure 2: Distribution of Cavity Diameter

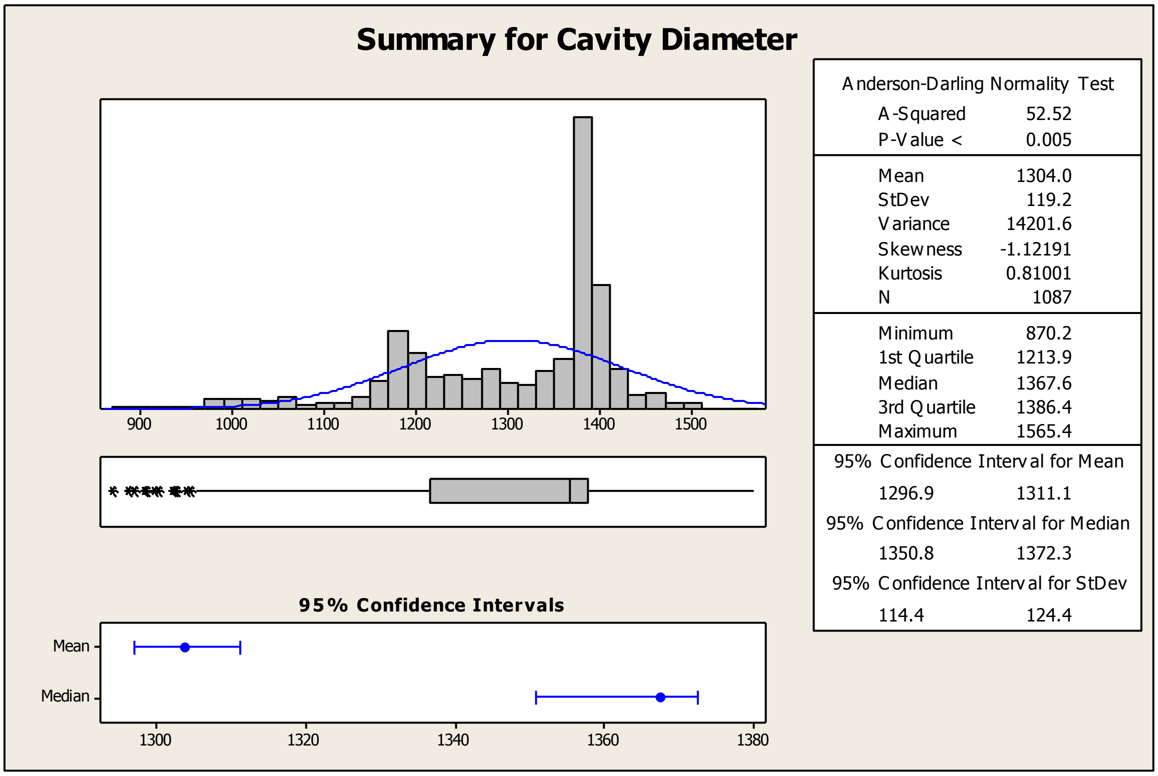
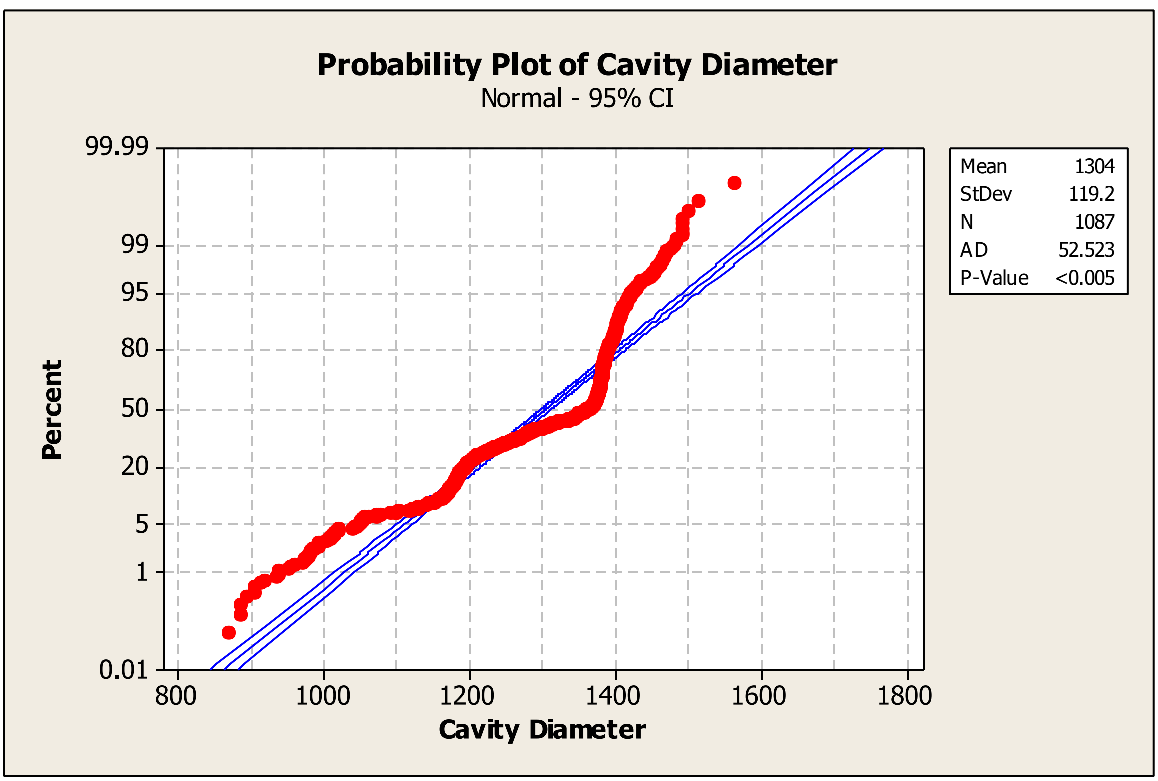


Figure 3: Normal Quantile Plot of Cavity Diameter



To try and achieve normality, I proceeded to use a Box-Cox transformation, which raises the variable to a power. Using Minitab, I was able to find an "optimal" power. However, even after transformation, the response was still not normally distributed. Because of this, I had to be cautious with any interpretations I made from my analysis. The normality assumption was violated, so the validity of certain results are questionable.

After looking at the response variable, I proceeded to examine the other variables as well. I looked at a correlation matrix and found strong evidence that cavity diameter was correlated with etch time and mask diameter. I also saw evidence of multicolinearity (correlation among "predictor" variables). In several cases, this multicolinearity made sense. For example, H-rate was correlated with Horizontal Undercut, but this is expected, since H-rate = Horizontal Undercut / Etch Time.

However, I needed to take multicolinearity into consideration later on in my analysis, when I fit models to the data. Multicolinearity doesn't inhibit inference about the mean response, but it does result in large standard errors of the least squares estimates (model coefficients). It can also affect interpretations of the model coefficients. For a particular predictor variable, the model coefficient is the change in mean response when the predictor variable increases by 1 unit, given the other variables remain fixed. If multicolinearity exists, the "fixed" assumption does not hold.

After my initial "first look", I decided to next try and fit a model to the data. If the model fit well, it could potentially be used as a reference in future work. One could attempt to hit a target cavity diameter, as long as the values chosen for the predictor variables were within the scope of the model (to avoid extrapolation). Fitting a model to the data would also reveal the significant predictors of cavity diameter, which may be useful information.

I first attempted to fit a general linear model (specifically, a multiple linear regression model) to the data.

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon}$$

where,

$\boldsymbol{Y} = (Y_1, Y_2, \dots Y_n)'$ is the response vector

$\boldsymbol{X} = \begin{pmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1p} \\ 1 & X_{21} & X_{22} & & X_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{n1} & X_{n2} & \cdots & X_{np} \end{pmatrix}$ is a matrix containing observations for the p predictor variables

$\boldsymbol{\beta} = (\beta_0, \beta_1, \dots \beta_p)'$ is a vector of model coefficients

$\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \dots \varepsilon_n)'$ is a vector of error (noise) terms

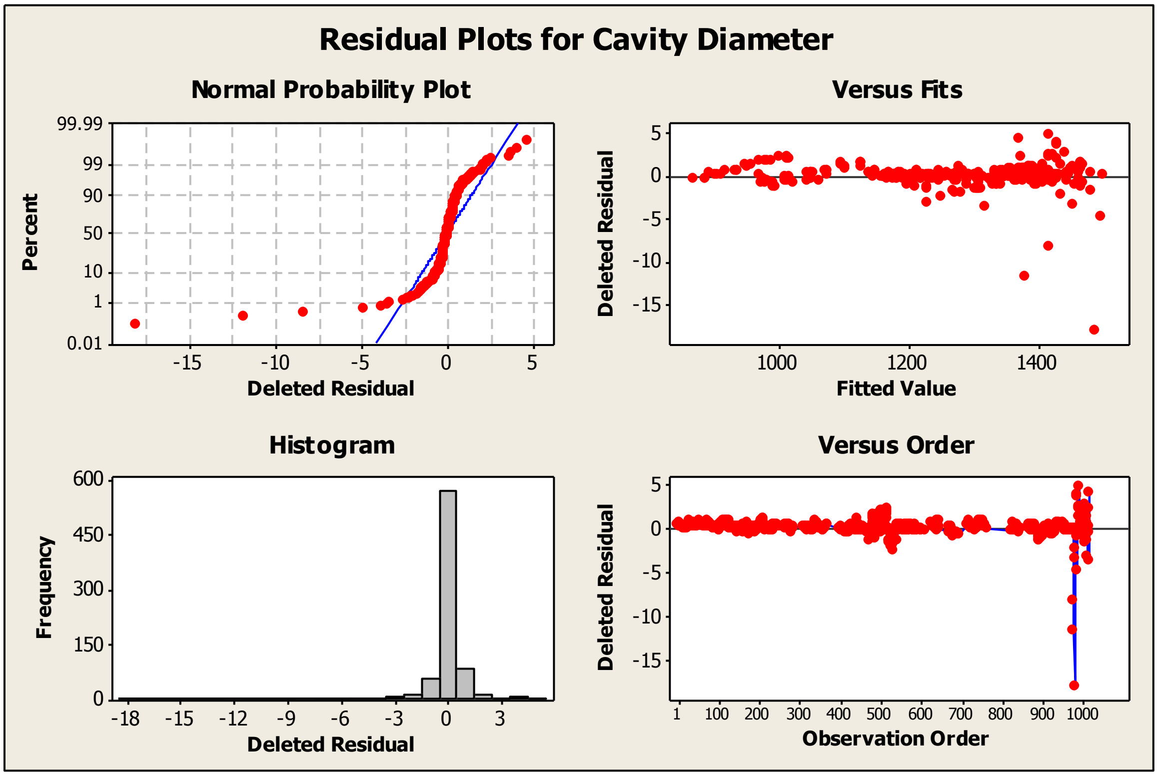
As mentioned before, the first assumption (of normality) is violated, so some results from any general linear model (GLM) are questionable.

For my first model, I chose to try cavity diameter versus all other variables, just to have a base. The results are shown in Figures 4 and 5. Although the R-square value is equal to 1, other things indicate that the model is not a good fit. The residuals do not follow a normal distribution, and there are very large VIF values, which indicate multicolinearity. In addition, coefficients for two variables could not be estimated. Minitab has the option of performing a Box-Cox Transformation when fitting a model. As Figure 4 shows, the optimal power is equal to 1 (the transformed data is equal to itself). Finally, the lack of fit test indicates that the proposed model does not fit well.

Figure 4: General Linear Model 1: Cavity Diameter vs. all other variables

```
* NOTE * Mask Diameter Error cannot be estimated and has been removed.
* NOTE * Off-Centering X (µm) cannot be estimated and has been removed.

Box-Cox transformation of the response with rounded lambda = 1
The 95% CI for lambda is (0.981252, 1.00425)

Regression Equation
Cavity Diameter  =  -1.86075 + 0.0235592 Row - 0.00281124 Column - 0.0030847
                    Cavity Center X + 416.024 Cavity Center Y + 0.0032698 Mask
                    Center X - 416.023 Mask Center Y + 0.925688 Mask Diameter +
                    2.2503 Etch Time + 0.0572378 Nominal Mask Dia. + 1.97875
                    Horizontal Undercut (H) + 0.112426 H rate (µm/hr) + 416.026
                    Off-Centering Y (µm) - 0.00238093 Off-Centering D (µm) +
                    3.32185e-005 Off-Centering Angle  (°)

741 cases used, 346 cases contain missing values


Coefficients
Term                            Coef  SE Coef        T      P          VIF
Constant                      -1.861    2.070   -0.899  0.369
Row                            0.024    0.007    3.475  0.001  1.14341E+00
Column                        -0.003    0.008   -0.357  0.721  1.05985E+00
Cavity Center X               -0.003    0.003   -1.135  0.257  3.22501E+01
Cavity Center Y              416.024  561.646    0.741  0.459  7.25283E+11
Mask Center X                  0.003    0.003    1.156  0.248  3.26123E+01
Mask Center Y               -416.023  561.646   -0.741  0.459  6.90839E+11
Mask Diameter                  0.926    0.009  105.396  0.000  3.02144E+02
Etch Time                      2.250    0.247    9.107  0.000  6.14460E+01
Nominal Mask Dia.              0.057    0.009    6.381  0.000  3.09290E+02
Horizontal Undercut (H)        1.979    0.004  519.883  0.000  3.89999E+01
H rate (µm/hr)                 0.112    0.024    4.715  0.000  8.12913E+01
Off-Centering Y (µm)         416.026  561.646    0.741  0.459  6.36018E+10
Off-Centering D (µm)          -0.002    0.002   -0.980  0.327  1.46000E+00
Off-Centering Angle  (°)       0.000    0.000    0.087  0.931  1.45117E+00


Summary of Model
S = 0.886933     R-Sq = 100.00%        R-Sq(adj) = 100.00%
PRESS = 634.601  R-Sq(pred) =  99.99%


Analysis of Variance
Source                       DF    Seq SS    Adj SS  Adj MS        F         P
Regression                   14  11929564  11929564  852112  1083215  0.000000
  Row                         1    156606         9       9       12  0.000541
  Column                      1     51306         0       0        0  0.721473
  Cavity Center X             1    457854         1       1        1  0.256858
  Cavity Center Y             1     47604         0       0        1  0.459102
  Mask Center X               1    513477         1       1        1  0.248146
  Mask Center Y               1     28711         0       0        1  0.459102
  Mask Diameter               1   3159534      8738    8738    11108  0.000000
  Etch Time                   1    559375        65      65       83  0.000000
  Nominal Mask Dia.           1    126829        32      32       41  0.000000
  Horizontal Undercut (H)     1   6828250    212614  212614   270278  0.000000
  H rate (µm/hr)              1        18        17      17       22  0.000003
  Off-Centering Y (µm)        1         0         0       0        1  0.459100
  Off-Centering D (µm)        1         1         1       1        1  0.327492
  Off-Centering Angle  (°)    1         0         0       0        0  0.930610
Error                       726       571       571       1
  Lack-of-Fit               676       571       571       1        *         *
  Pure Error                 50         0         0       0
Total                       740  11930135
```

Figure 5: Residual Plots from General Linear Model 1



Next, I decided to try stepwise regression in Minitab, which utilizes forward and backward elimination simultaneously (for choosing the vital/significant predictor variables.) Variables were added to the model if its corresponding F-statistic was greater than or equal to 4, and removed if the F-statistic dropped below 4. F-statistics greater than or equal to 4 means the p-value will be very significant (close to 0). Figure 6 displays the results from the stepwise regression.

After determining the significant variables in stepwise regression, I fit another general linear model. The results are shown in Figures 7 and 8. Unfortunately, the model did not fit well. The residuals were still not normally distributed and VIF's were still very high. However, all of the predictor variables had significant p-values, as expected, and the R-square value was still high.

The R-square value was almost equal to 1 after adding two variables via stepwise regression. At the time of the analysis, I was still learning about the etch process. I didn't want to exclude a variable that may important or of interest to the engineers. This was why I kept all the significant variables in the second general linear model.

Figure 6: Stepwise Regression with both Forward and Backward Elimination

```
Stepwise Regression: Cavity Diameter versus ALL

  F-to-Enter: 4  F-to-Remove: 4

Response is Cavity Diameter on 16 predictors, with N = 741

Step                            1        2        3        4        5        6
Constant                  727.575    7.244    7.540    7.431   -1.191   -1.012

Horizontal Undercut (H)   2.05230  2.00198  1.99729  1.99687  1.97932  1.97948
T-Value                     46.79  2122.41  3067.05  3076.55   520.85   525.48
P-Value                     0.000    0.000    0.000    0.000    0.000    0.000

Mask Diameter                      0.98908  0.98082  0.94172  0.93346  0.92874
T-Value                            1264.80  1657.38   110.10   108.34   107.59
P-Value                              0.000    0.000    0.000    0.000    0.000

Etch Time                                     1.141    1.114    2.260    2.239
T-Value                                       30.09    29.43     9.13     9.13
P-Value                                       0.000    0.000    0.000    0.000

Nominal Mask Dia.                                    0.0398   0.0496   0.0540
T-Value                                                4.58     5.63     6.13
P-Value                                               0.000    0.000    0.000

H rate (µm/hr)                                                 0.112    0.111
T-Value                                                         4.68     4.69
P-Value                                                        0.000    0.000

Row                                                                    0.0247
T-Value                                                                  3.76
P-Value                                                                 0.000

S                            63.8     1.37    0.919    0.907    0.894    0.887
R-Sq                        74.77    99.99    99.99    99.99   100.00   100.00
R-Sq(adj)                  74.73    99.99    99.99    99.99   100.00   100.00
```

Figure 7: Residual Plots from General Linear Model 2

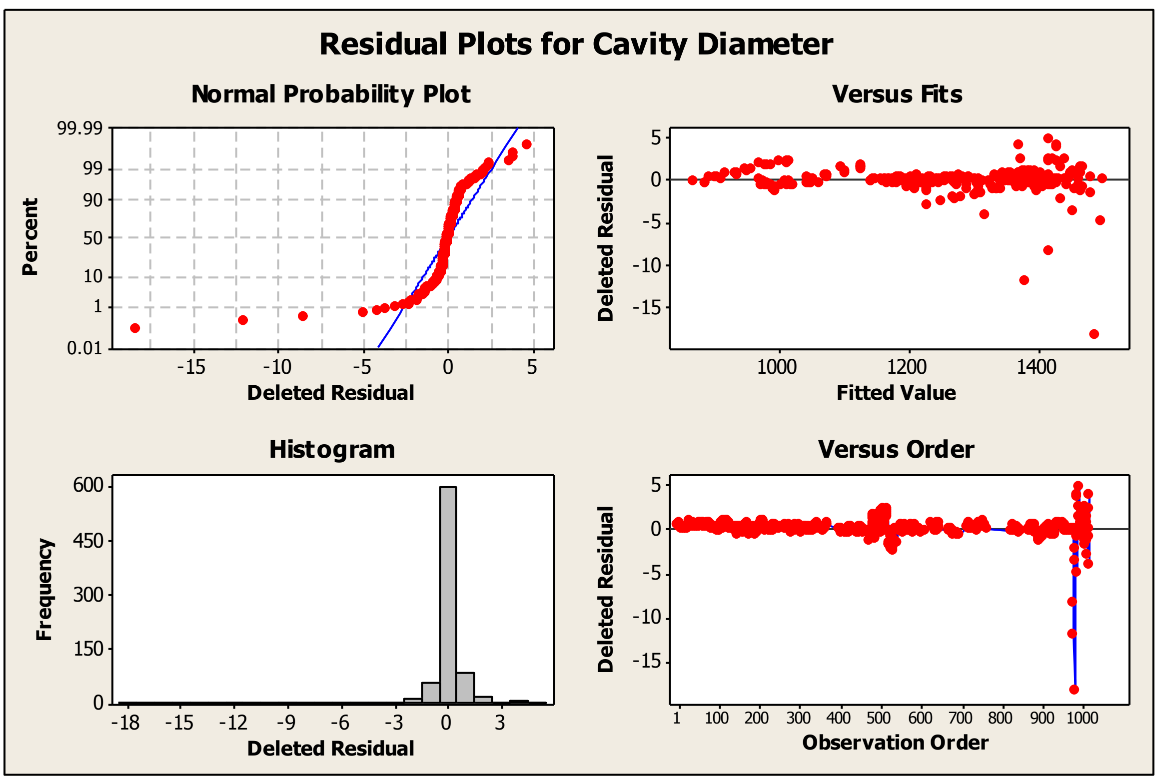


Figure 8: General Linear Model 2: Cavity Diameter vs. Horizontal Undercut, Mask Diameter, Etch Time, Nominal Mask Diameter, H rate, Row

```
General Regression Analysis: Cavity Diameter versus Horizontal Undercut,
Mask Diameter, Etch Time, Nominal Mask Diameter, H rate, Row

Box-Cox transformation of the response with rounded lambda = 1
The 95% CI for lambda is (0.980835, 1.00183)

Regression Equation
Cavity Diameter  =  -0.974987 + 1.97959 Horizontal Undercut (H) + 0.929582 Mask
                    Diameter + 2.23429 Etch Time + 0.0531667 Nominal Mask Dia.
                    + 0.110478 H rate (µm/hr) + 0.0241636 Row

767 cases used, 320 cases contain missing values

Coefficients
Term                          Coef   SE Coef        T      P      VIF
Constant                  -0.97499   1.83877   -0.530  0.596
Horizontal Undercut (H)    1.97959   0.00370  534.786  0.000   38.618
Mask Diameter              0.92958   0.00841  110.535  0.000  286.765
Etch Time                  2.23429   0.24123    9.262  0.000   60.858
Nominal Mask Dia.          0.05317   0.00859    6.192  0.000  293.407
H rate (µm/hr)             0.11048   0.02329    4.743  0.000   80.257
Row                        0.02416   0.00636    3.797  0.000    1.079


Summary of Model
S = 0.871969     R-Sq = 100.00%        R-Sq(adj) = 100.00%
PRESS = 620.498  R-Sq(pred) =  99.99%


Analysis of Variance
Source                      DF    Seq SS    Adj SS   Adj MS        F          P
Regression                   6  12056635  12056635  2009439  2642853  0.0000000
  Horizontal Undercut (H)    1   9045751    217451   217451   285996  0.0000000
  Mask Diameter              1   3010071      9290     9290    12218  0.0000000
  Etch Time                  1       768        65       65       86  0.0000000
  Nominal Mask Dia.          1        17        29       29       38  0.0000000
  H rate (µm/hr)             1        17        17       17       22  0.0000025
  Row                        1        11        11       11       14  0.0001581
Error                      760       578       578        1
  Lack-of-Fit              707       578       578        1        *          *
  Pure Error                53         0         0        0
Total                      766  12057213
```

Nominal mask diameter and mask diameter are two variables in GLM2. They contain the same information, so I decided to remove one of them from the model (I kept nominal mask diameter). Also, horizontal undercut, etch time, and H rate were all in the model. Recall, H rate = Horizontal Undercut / Etch Time. I decided to also remove H-rate, to see if that alleviated the multicolinearity issues. At this time in my analysis, I was provided with information regarding HF concentration. It was believed that this would be an important variable, so I included it in the model. The results can be found in Figures 9 and 10.

The results for GLM3 are much better than GLM1 and GLM2. The predictor variables are significant, VIF values are all less than 10 (indicates low multicolinearity) and the R-Squared value is close to 1 as well. The residuals are slightly closer to being normally distributed, however they are still not (skewed to the left).

However, the lack of fit test indicates the proposed model is not a good fit. I was told that the relationship between etch time and cavity diameter is not linear, so the results from the lack of fit test seem to make sense. Therefore, a different model is needed, such as a GLM with higher order terms, a generalized linear model (GLMM) with higher order terms, or a nonlinear model.

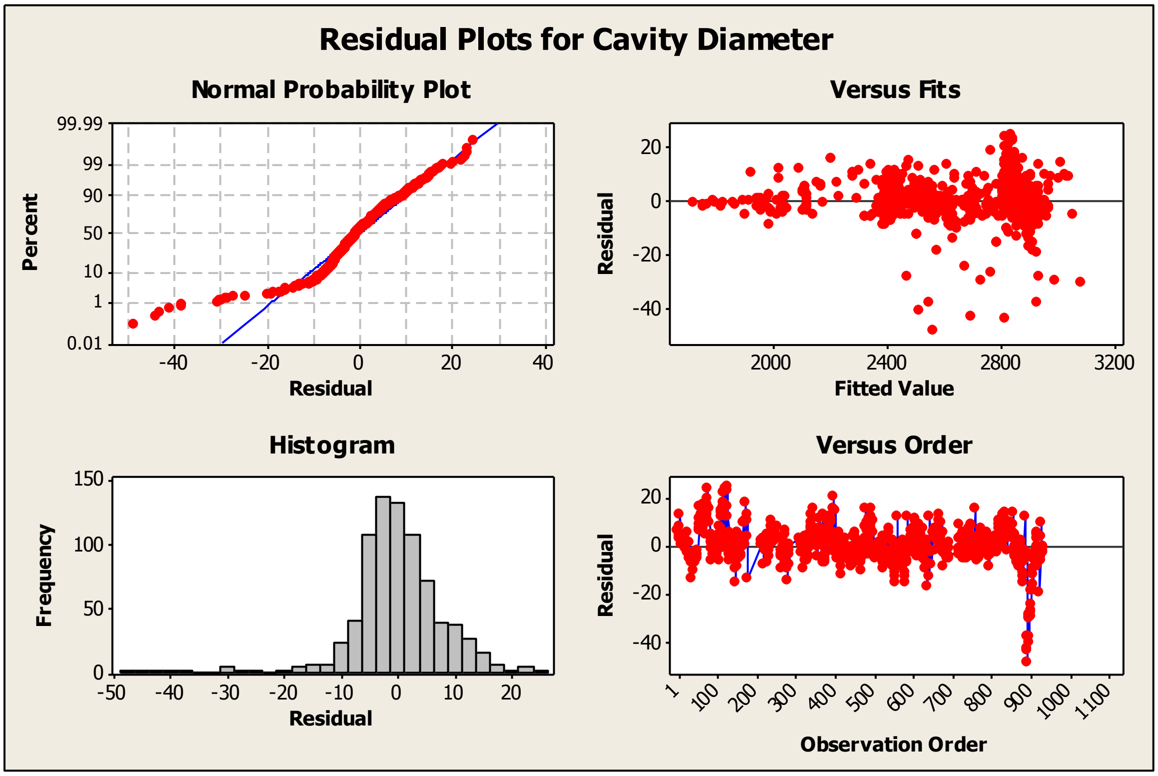
It’s interesting to note that both HF concentration and etch time have negative coefficients and the corresponding confidence intervals, not shown, do not contain 0. This would mean that, if all other variables are held constant (which is possible), the average cavity diameter would decrease when either of these variables increases. This is not expected, at least to me – it makes more sense that the etched holes would become larger the longer the wafer sat in the chemical bath or the stronger the concentration of HF. Since the lack of fit test indicates a linear model is not the correct choice, it’s possible these coefficients are incorrect.

Figure 9: General Linear Model 3: Cavity Diameter vs. Horizontal Undercut, Etch Time, Nominal Mask Diameter, Row, and HF Concentration

General Regression Analysis: Cavity Diameter versus Horizontal Undercut, Etch Time, Nominal Mask Diameter, Row and HF concentration

```
Box-Cox transformation of the response with rounded lambda = 1.10057
The 95% CI for lambda is (1.06207, 1.14007)

Regression Equation
Cavity Diameter^1.10057  =  -117.627 + 4.47578 Horizontal Undercut (H) -
                            0.664945 Etch   Time + 0.290279 Row + 2.17203
                            Nominal Mask Dia. - 14.9239 HF Concentration (%)

783 cases used, 330 cases contain missing values

Coefficients
Term                          Coef  SE Coef        T      P      VIF
Constant                  -117.627  9.09602  -12.932  0.000
Horizontal Undercut (H)      4.476  0.00540  829.347  0.000  1.01932
Etch   Time                 -0.665  0.15945   -4.170  0.000  4.35114
Row                          0.290  0.05994    4.843  0.000  1.10793
Nominal Mask Dia.            2.172  0.00708  306.604  0.000  1.70244
HF Concentration (%)       -14.924  1.09390  -13.643  0.000  5.45408


Summary of Model
S = 8.05776      R-Sq = 99.91%        R-Sq(adj) = 99.91%
PRESS = 51007.3  R-Sq(pred) = 99.91%


Analysis of Variance
Source                      DF    Seq SS    Adj SS    Adj MS       F           P
Regression                   5  58679480  58679480  11735896  180754  0.0000000
  Horizontal Undercut (H)    1  47477089  44658111  44658111  687816  0.0000000
  Etch   Time                1   1114021      1129      1129      17  0.0000338
  Row                        1    408924      1523      1523      23  0.0000015
  Nominal Mask Dia.          1   9667362   6103568   6103568   94006  0.0000000
  HF Concentration (%)       1     12085     12085     12085     186  0.0000000
Error                      777     50449     50449        65
  Lack-of-Fit              722     50443     50443        70     738  0.0000000
  Pure Error                55         5         5         0
Total                      782  58729929
```

Figure 10: Residual Plots from General Linear Model 3



Comments/Recommendations

As shown previously, cavity diameter appears bi-modal. One possible reason for this is that engineers were targeting different size holes. The etching of the wafers was just the first step of a much more involved project, and certain size holes were needed. Another reason could be that not every hole on every wafer was measured. Select holes were measured, so a true random sample was not taken.

I would suggest looking further into the bimodality of cavity diameter, and seeing if wafers can be grouped. Correlation within wafers was something I did not have a chance to look at, but is something that should be examined.

Chapter 2: Denton

Introduction

After a layer of dielectric material is placed on a wafer, the wafer then goes through a series of other production steps, which include receiving layers of metal and conductive material. In the Microfabrication Laboratory at Draper, the equipment responsible for these steps, such as receiving metal, is the Denton.

Another employee at Draper had created control charts for variables pertaining to the Denton. For example, each time the Denton performed etching, the etch rate was recorded. Individual and moving range charts were created for the data. Capability ratios were calculated for the variables as well. The charts and ratios are updated as new data is collected, and are used to make sure the Denton processes are in control and meeting specifications.

For several of the variables, the data was not normally distributed. This meant that the corresponding control charts and capability ratios were potentially incorrect. Shewhart's I-MR charts and certain capability ratios assume that the data follow a normal distribution.

Goals

I decided to correct the control charts and capability ratios for the cases where the data was not normally distributed. I used data transformations to obtain normality, and then found new charts and ratios. The updated information would hopefully provide better insight as to whether or not the process was in control and meeting specifications. By comparing the "before" and "after" charts, one could see if the results from prior to the transformation were incorrect as well.

I was also prepared to propose and set up alternate charts to use if transformations did not work, or if I thought another chart was more appropriate. Certain charts, such as EWMA charts, are robust for non-normality, and are used to detect small shifts. However, for every variable that was non-normal, the transformation worked, and I obtained normality. The I-MR chart also was the most appropriate, because in each case, individual measurements were taken, as opposed to samples.

Statistical Analysis

Figure 11 displays the original analysis for Etch Rate (DERC). There are two primary processes (known as recipes) for which Etch Rate is recorded. These recipes have code names – they are Ajowan and Ginger.

I utilized Minitab's "Individual Distribution Identification" tool in order to see if I could transform the data to obtain normality. This tool also tests whether the data follows one of the common, non-normal distributions as well. If the data followed one of the common non-normal distributions, Minitab would have allowed me to create control charts and perform capability analysis based on that distribution.

Based on all the probability plots drawn (more than what is shown in Figure 12), a Box-Cox transformation to obtain normality was the best choice. "AD" stands for Anderson – Darling, which tests whether the sample data was drawn from a given probability distribution. One does not reject the null hypothesis, which states that the data follows the given distribution, when the p-value is greater than 0.05.

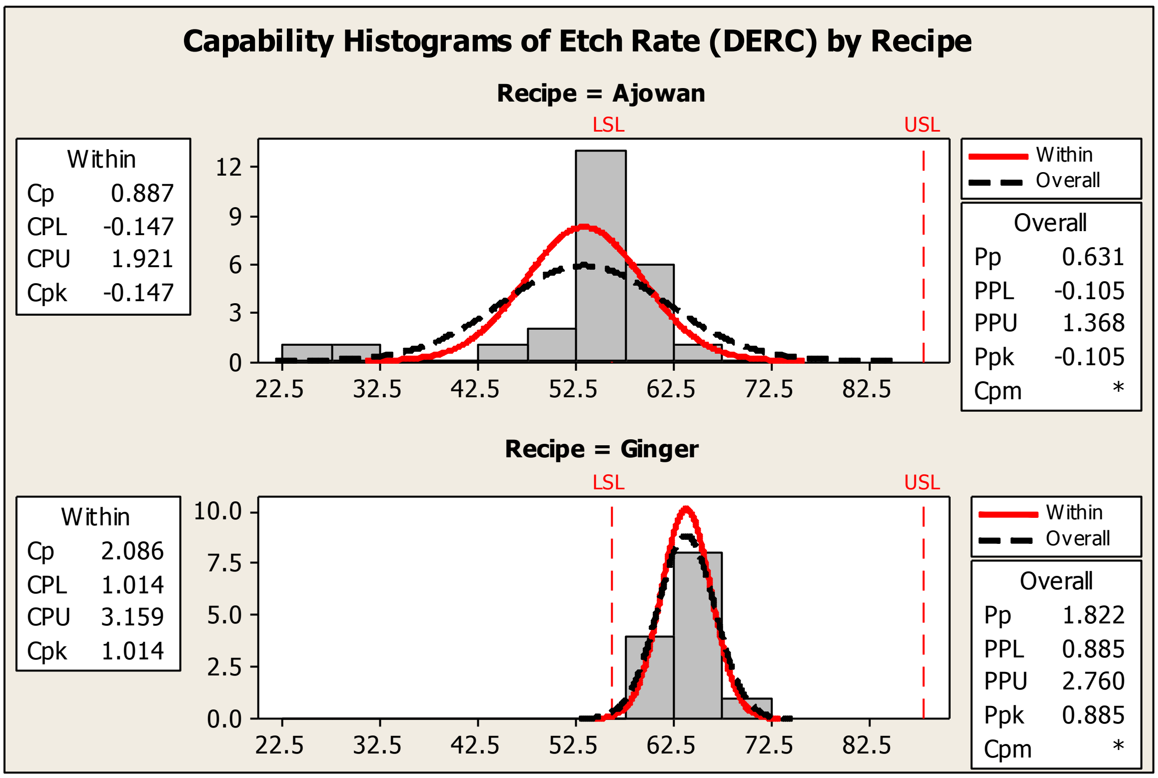
Box-Cox transformations attempt to obtain normality by raising all the data to a power. For example, one transformation may be:

$$y_i = {x_i}^2 \quad i = 1 \dots n$$

Here, x_i is the original data point and y_i is the transformed data. One requirement is that $x_i > 0$ for all i.

Figures 13 and 14 display the new analysis for Etch Rate (DERC), using the transformed data, which was obtained by raising the data to the power 3. The process appears to be out of control. Observation 25 goes outside the 3σ limits. Also, there appears to be an upward trend starting around observation 27. The Ginger recipe is within the specification limits, but is off center. Ajowan is not meeting specifications. The capability ratios from "after" are larger than "before", but provide essentially the same interpretation.

Figure 11: Etch Rate (DERC) Original Analysis



Original LSL = 56 USL = 88

Figure 12: Individual Distribution Identification for Etch Rate (DERC)

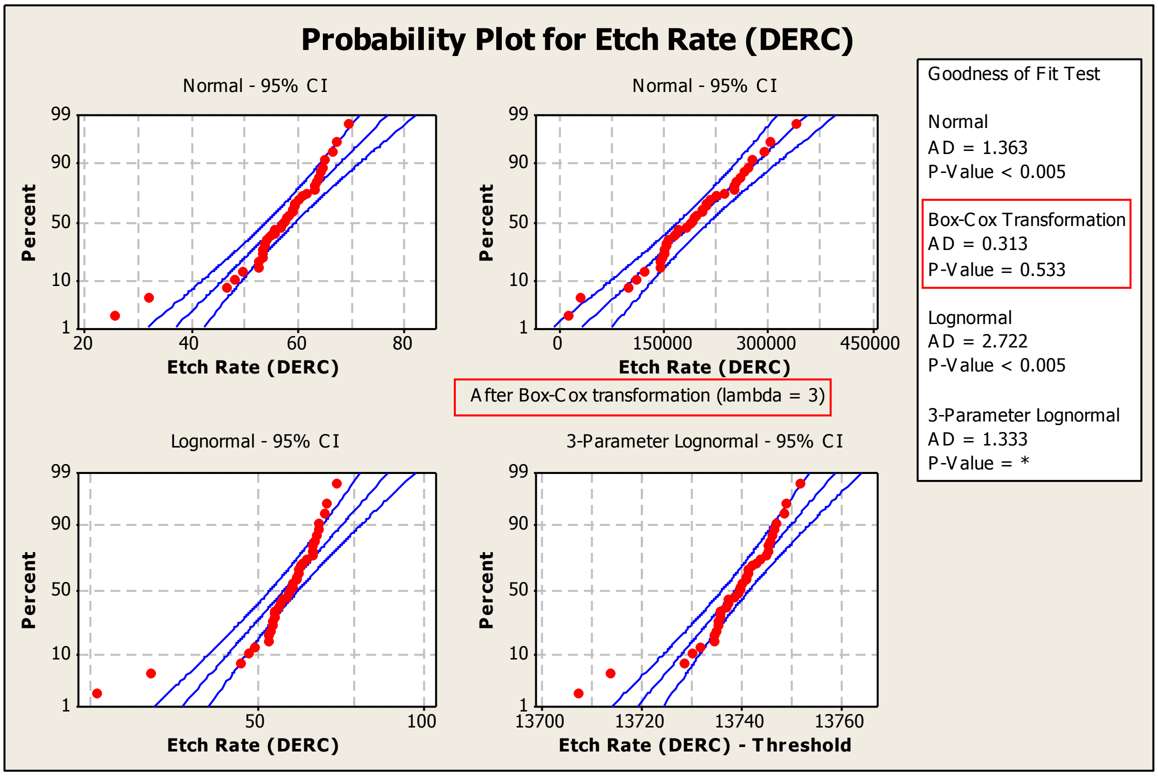


Figure 13: Etch Rate (DERC) Updated Analysis

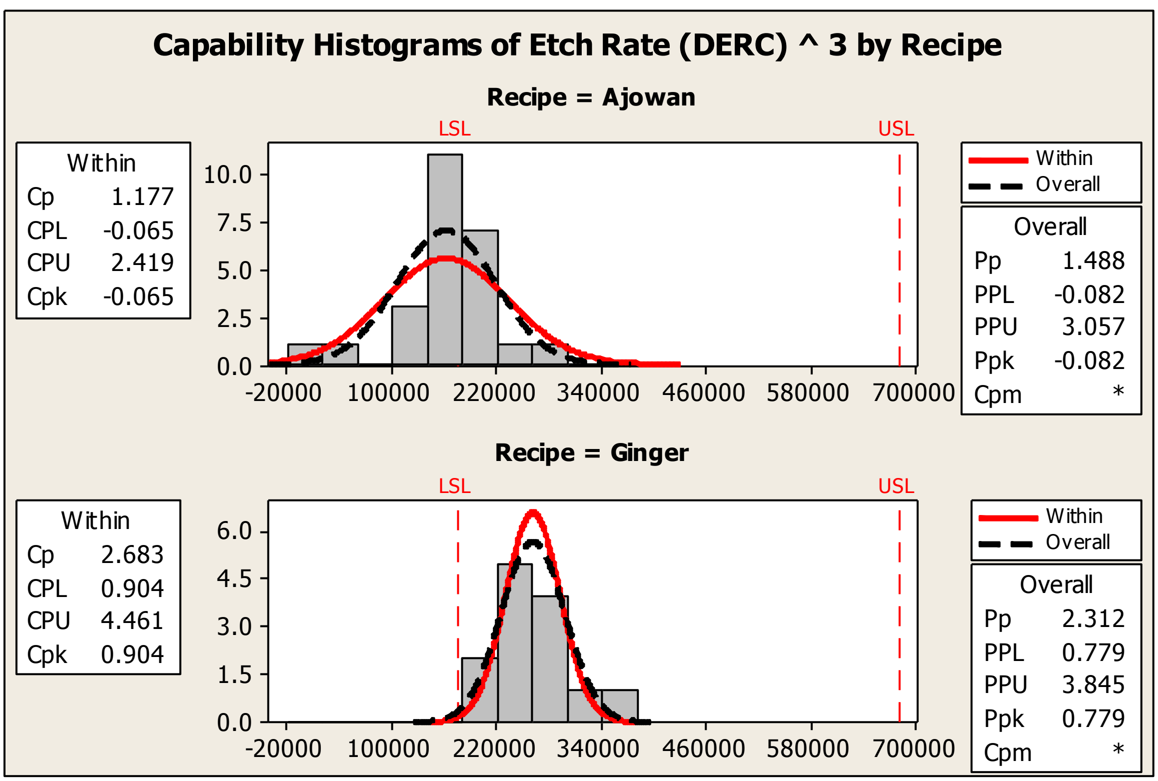
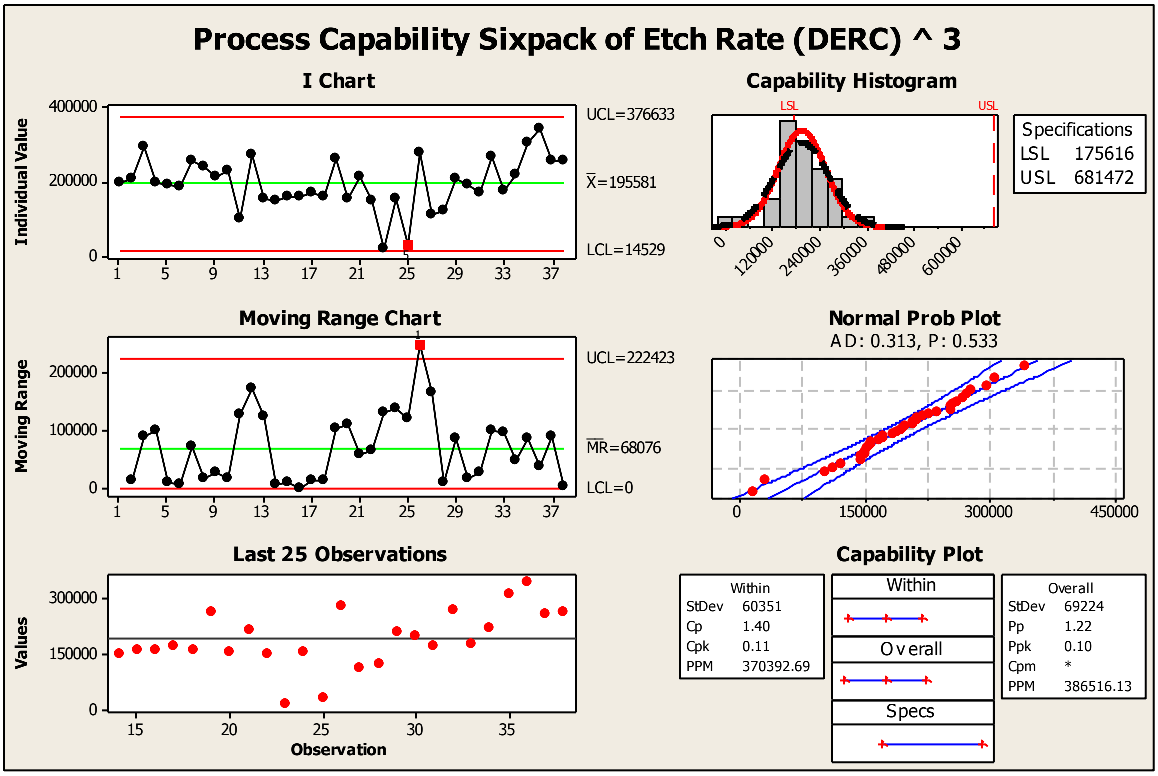


Figure 14: Etch Rate (DERC) Updated Analysis Continued



Updated LSL = 56^3 = 175616 USL = 88^3 = 681472

I used the same approach (Individual Distribution Identification tool) for the other variables that were not normally distributed as well. These variables are Cu Stress 90 (MPa), Leak Rate (CH), Average Sheet Rho (Ti), and Etch Rate Coupon. Etch Rate Coupon did not have an original analysis, but specification limits were provided to me, so I was able to complete my own analysis.

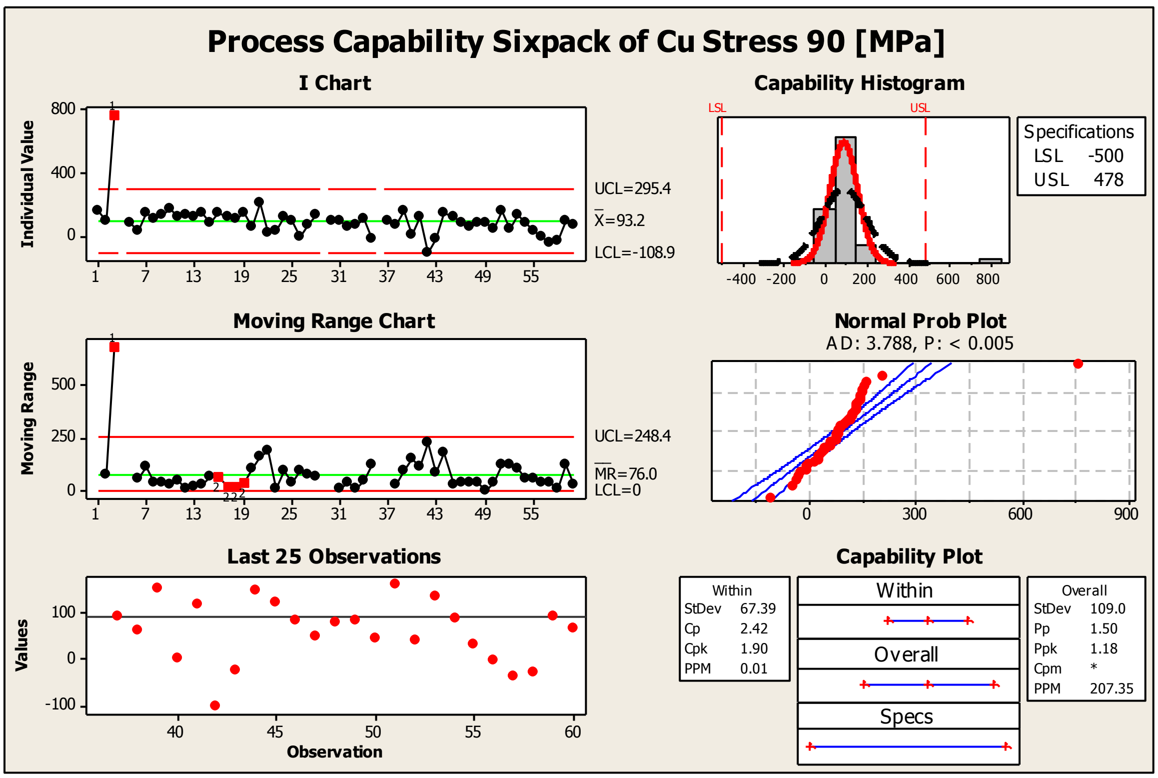
The results are shown in Figures 15 through 26. The Leak Rate (CH) data obtained normality through a Box Cox transformation. Cu Stress 90 (MPa), Average Sheet Rho (Ti), and Etch Rate Coupon, on the other hand, obtained normality via another type of transformation: Johnson Transformation.

Johnson Transformations do not require that your original data be positive (Cheshire, 2012). These transformations try to obtain normality by selecting one of three types of functions. The function types are known as families and are shown in Table 1 (Cheshire, 2012). Again, x_i is the original data, y_i is the transformed data, and $\gamma, \eta, \varepsilon,$ and λ are parameters. These transformations are monotone, which means that relationships among variables and data points are preserved.

Table 1: Johnson Transformations

Johnson Family	Transformation Function
SB	$y_i = \gamma + \eta \ln\left(\dfrac{x_i - \varepsilon}{\lambda + \varepsilon - x_i}\right)$
SL	$y_i = \gamma + \eta \ln(x_i - \varepsilon)$
SU	$y_i = \gamma + \eta \,\mathrm{Sinh}^{-1}\left(\dfrac{x_i - \varepsilon}{\lambda}\right)$ where $\mathrm{Sinh}^{-1}(x) = \ln\left(x + \sqrt{1 + x^2}\right)$

Figure 15: Cu Stress 90 (MPa) Original Analysis



Original LSL = -500 USL = 478

Figure 16: Cu Stress 90 (MPa) Johnson Transformation

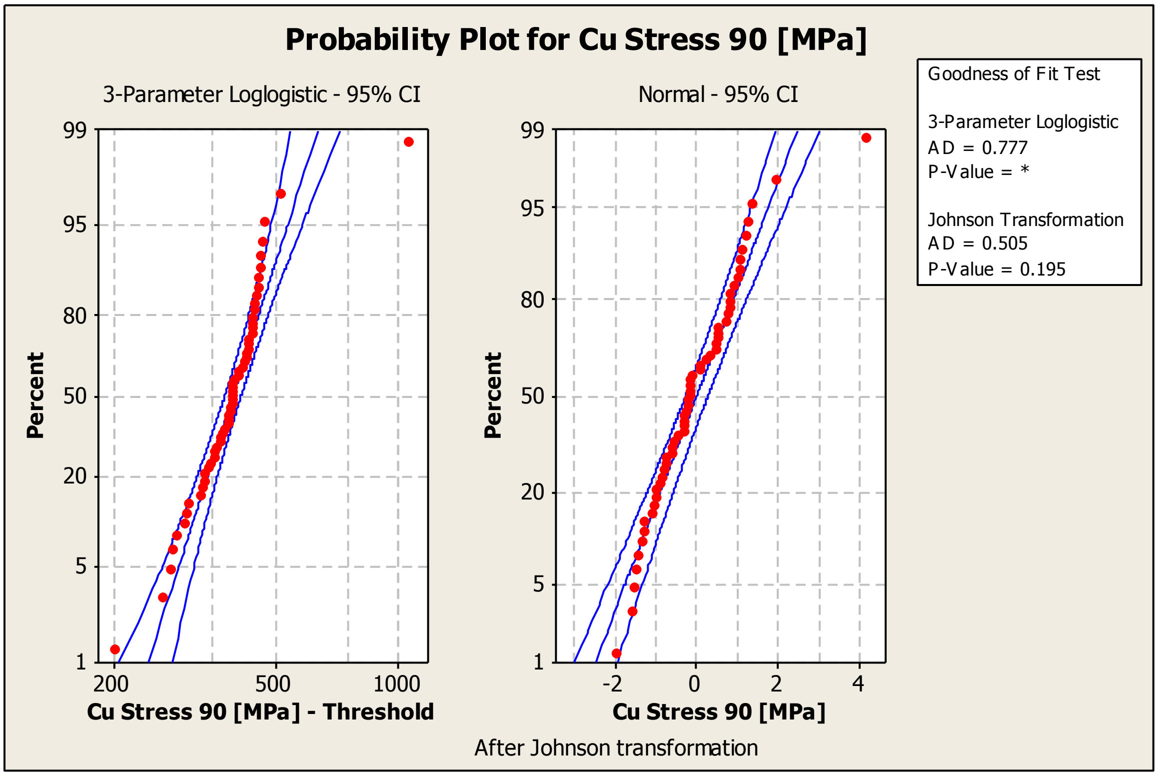
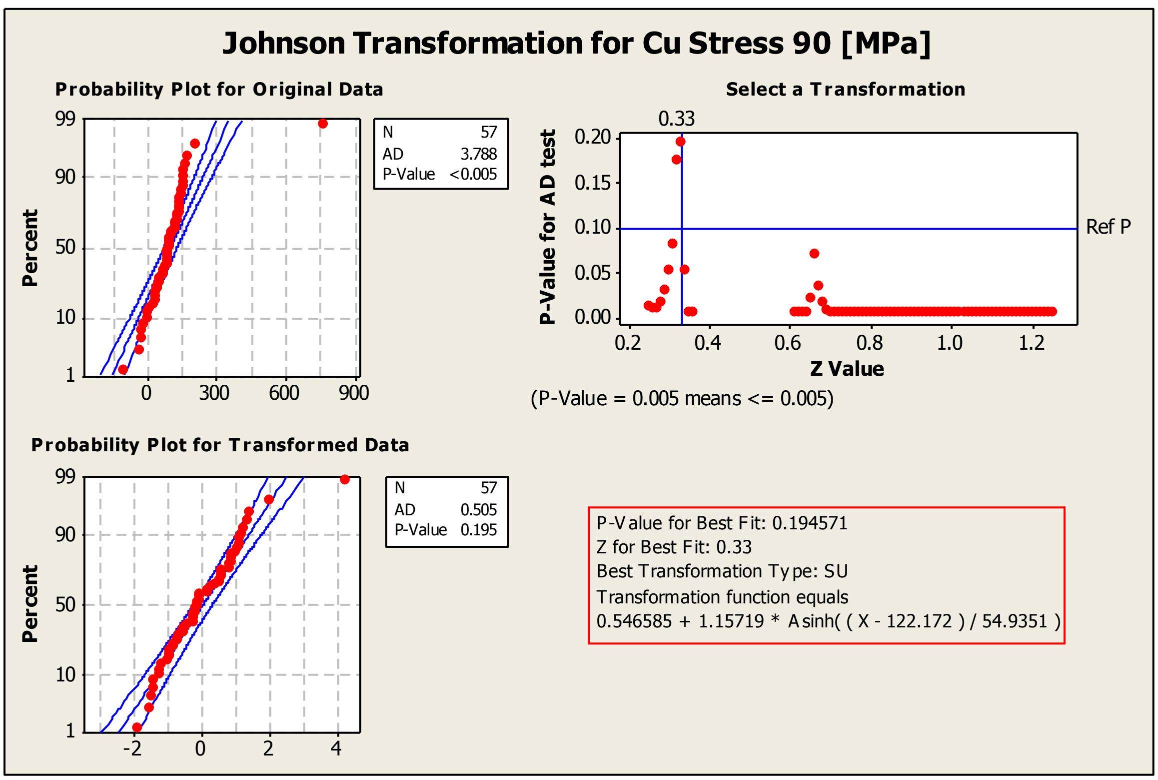
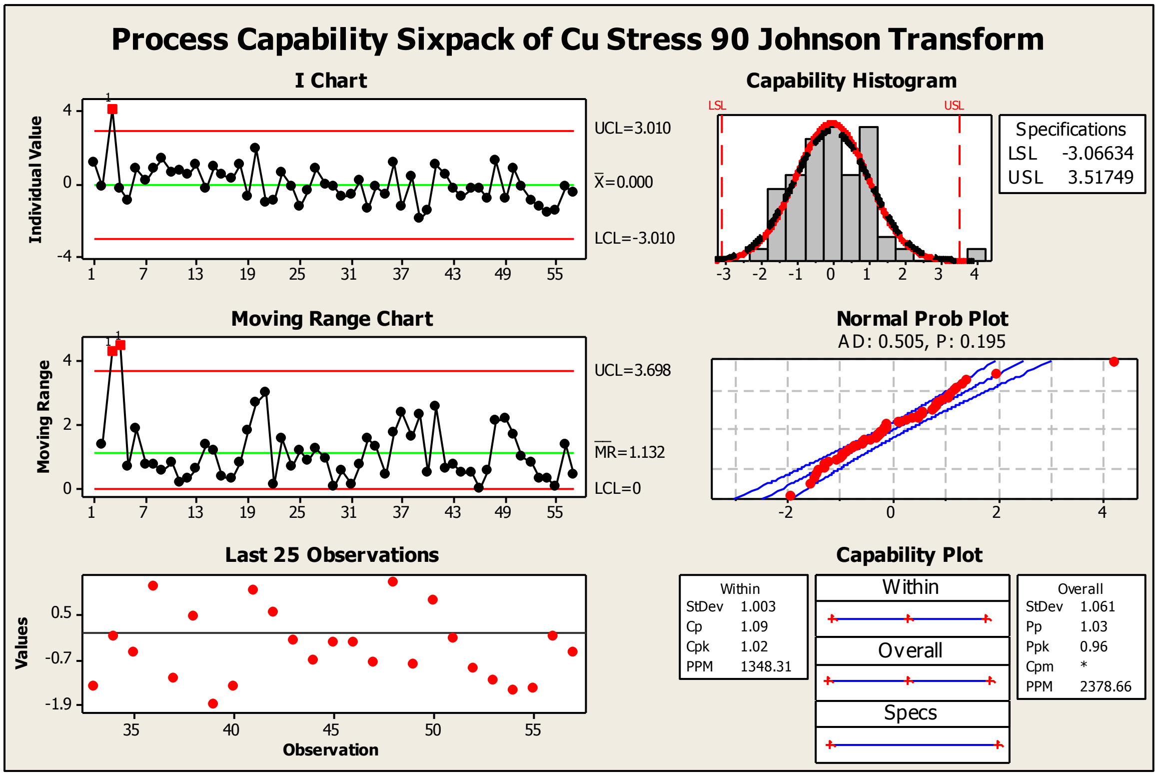


Figure 17: Cu Stress 90 (MPa) Johnson Transformation Continued



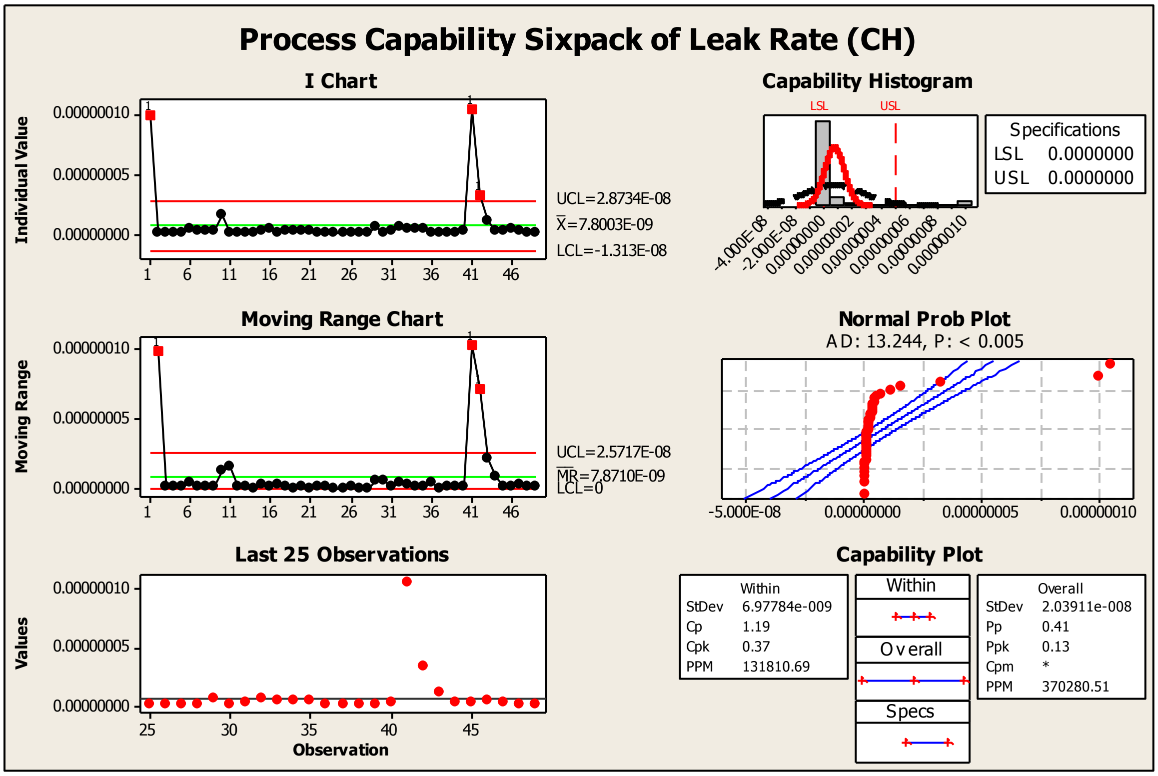
In the updated analysis for Cu Stress 90 (MPa) (Figure 18), observation 3 is outside the control limits. If assignable cause can be found for this point, it can be removed, and the limits can be recalculated. When this is done, the process appears to be in control. The process is meeting specification limits (besides observation 3), and based on Cpk, the process yield is about 99.73%. The Cp and Cpk ratios are much lower in the updated analysis compared with the original.

Figure 18: Cu Stress 90 (MPa) Updated Analysis



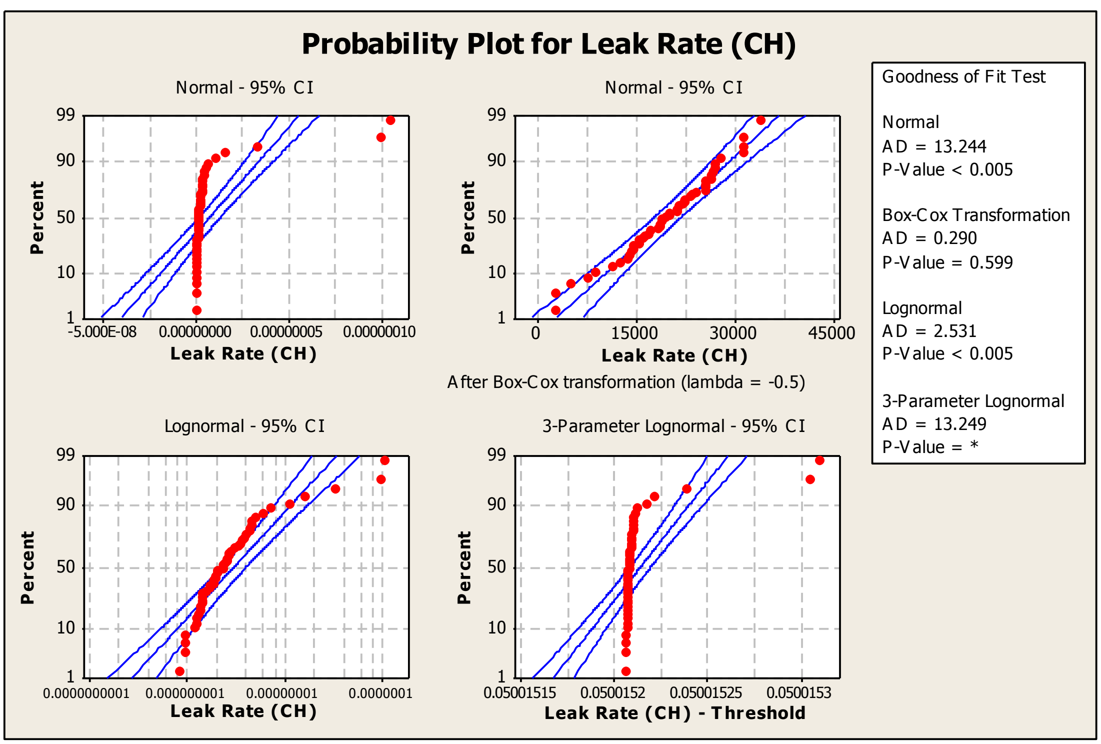
Updated LSL = -3.06634 USL = 3.51749

Figure 19: Leak Rate (CH) Original Analysis



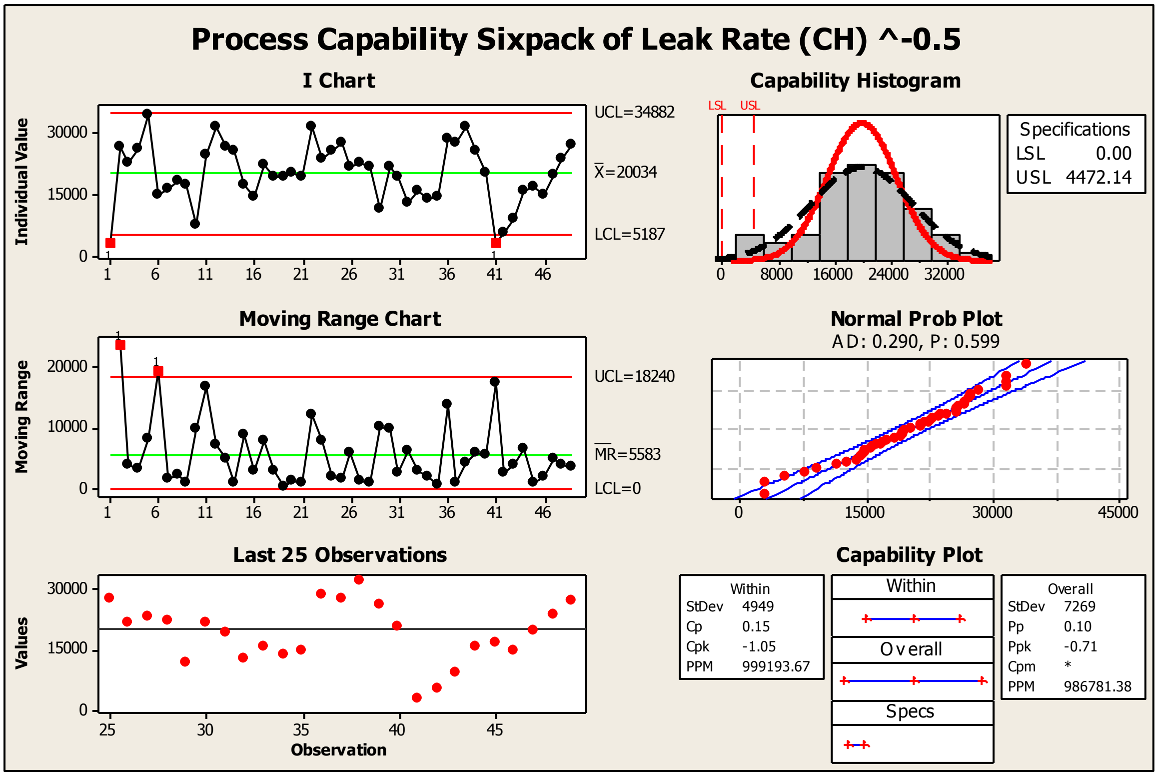
Original LSL = 0 USL = 5e-8

Figure 20: Leak Rate (CH) Box – Cox Transformation



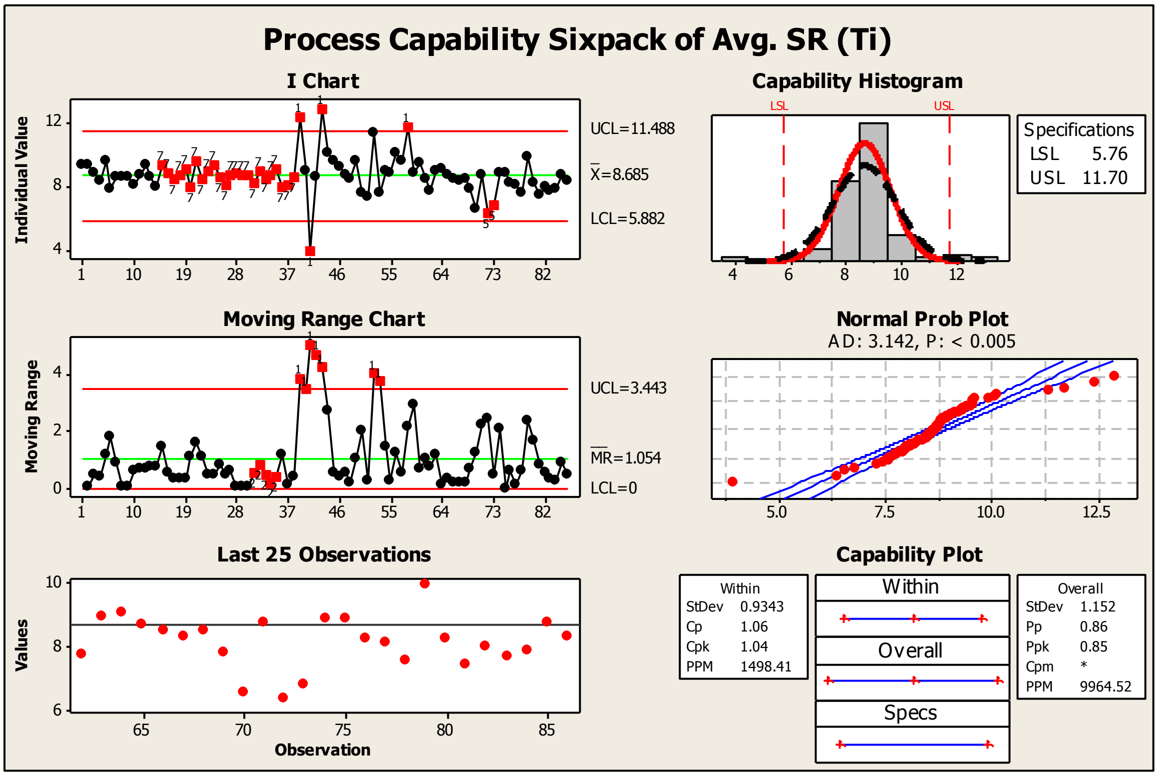
The updated analysis for Leak Rate (CH) is shown in Figure 21. There are two out of control points (on both the individuals and moving range chart), and an upward trend starting at observation 41. The process appears to be out of control. The process is also not meeting specifications, indicated by the low Cp value.

Figure 21: Leak Rate (CH) Updated Analysis



Updated LSL = 0 USL = 4472.136

Figure 22: Average Sheet Rho (Ti) Original Analysis



Original LSL = 5.76 USL = 11.7

Figure 23: Average Sheet Rho (Ti) Johnson Transformation

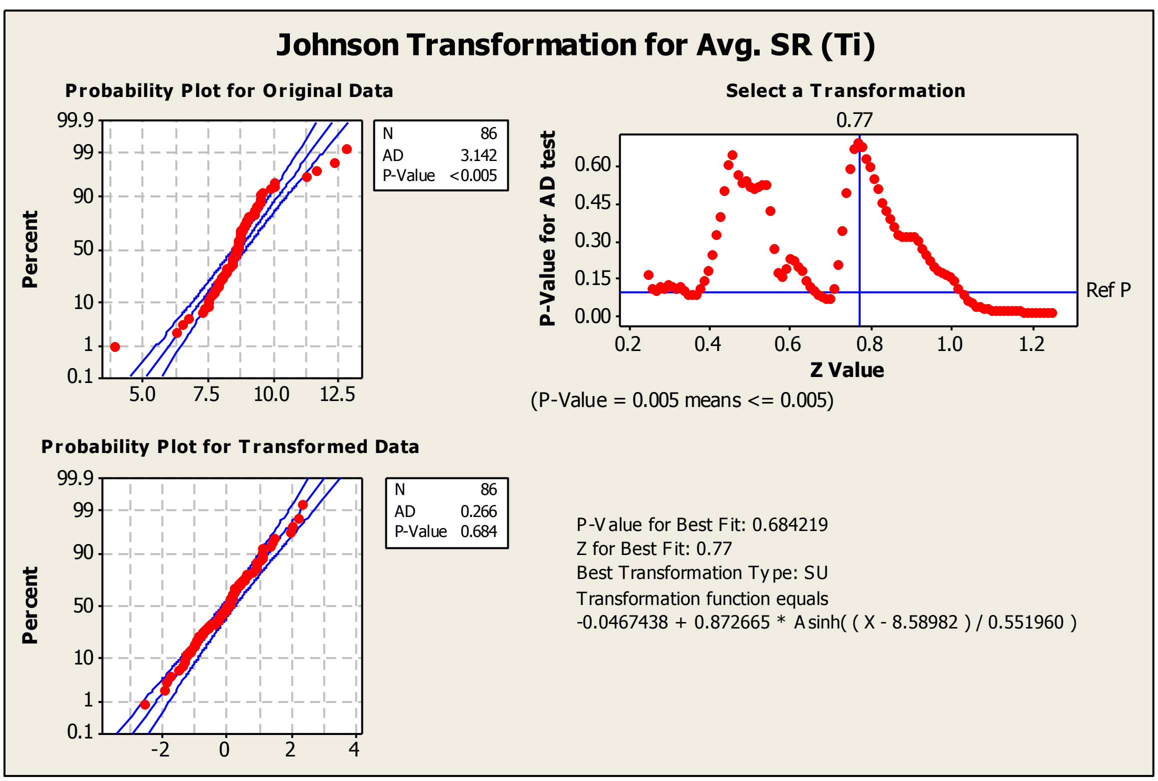
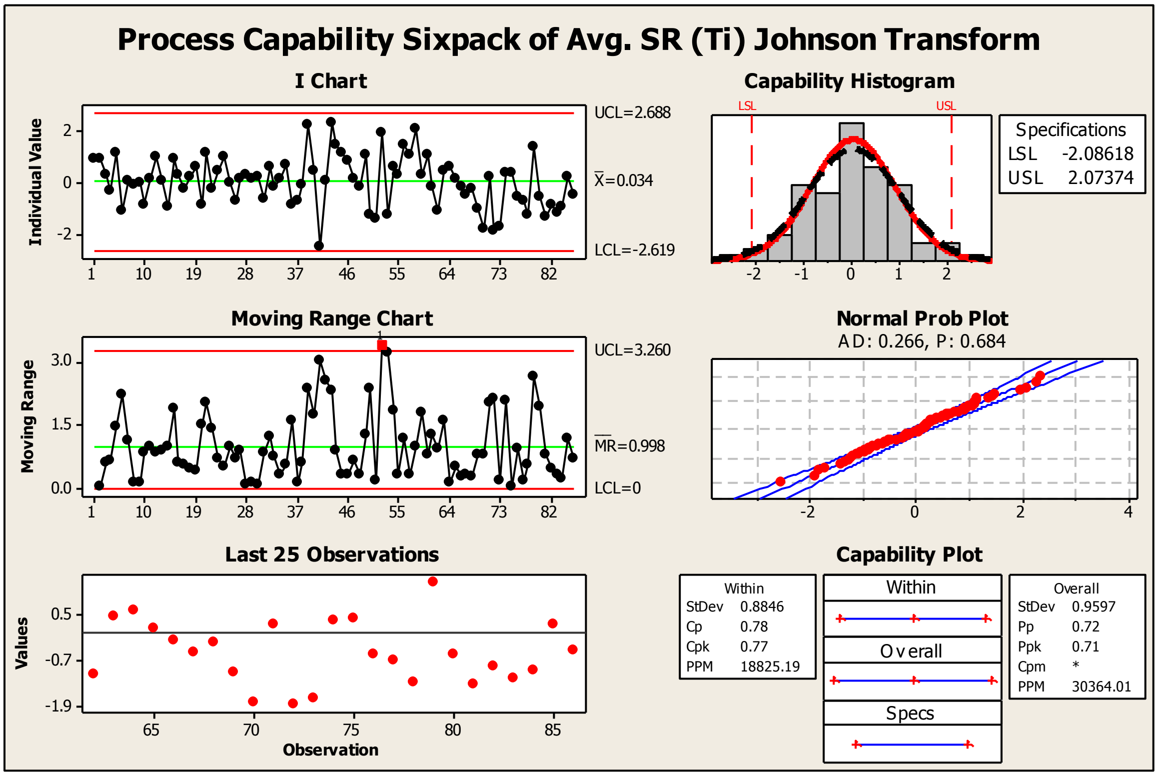


Figure 24 shows the updated analysis for Average Sheet Rho (Ti). If assignable cause can be found for the one out of control point on the MR chart, then the process is in control. The process has a yield of about 96%.

Figure 24: Average Sheet Rho (Ti) Updated Analysis



Updated LSL = -2.08618 USL = 2.07374

Figure 25: Etch Rate Coupon Johnson Transformation

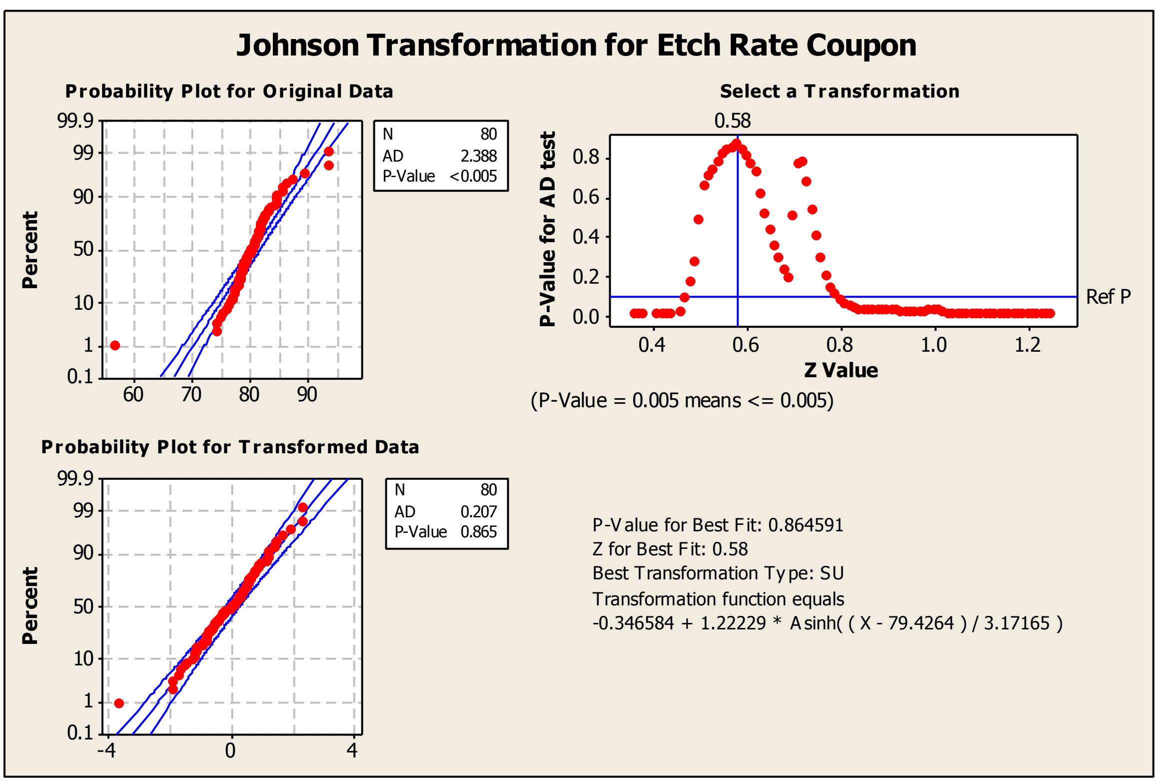
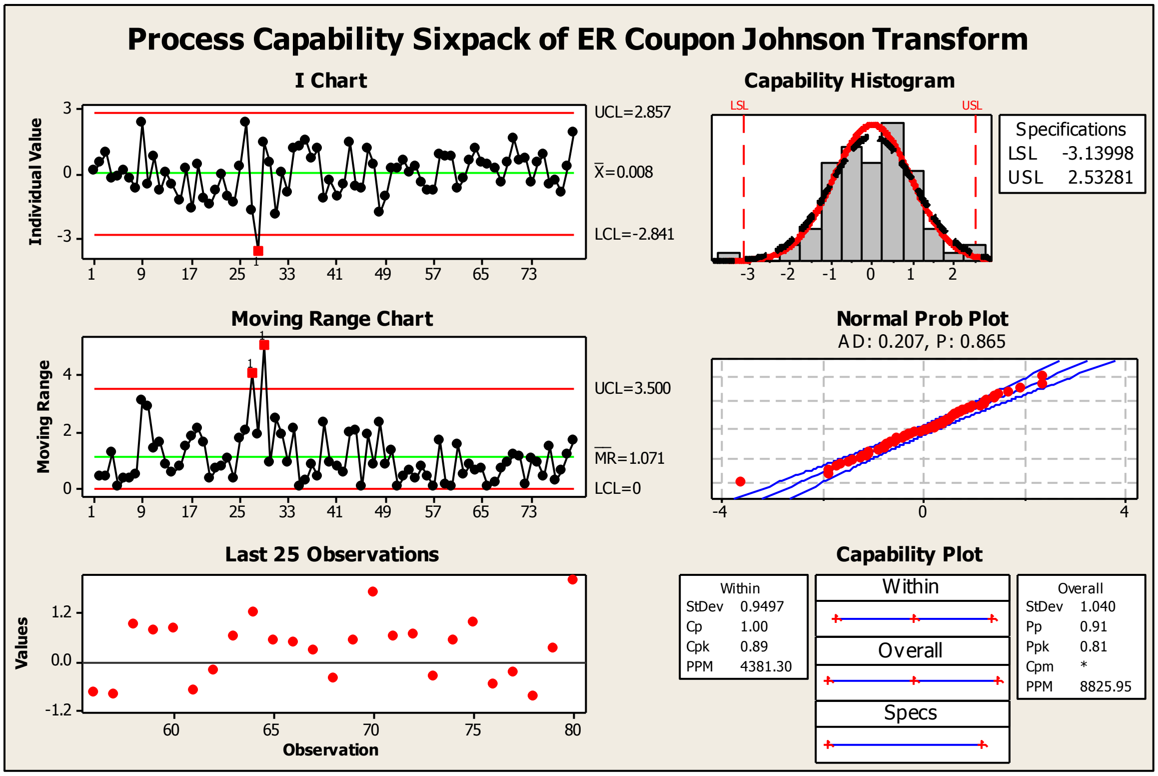


Figure 26 displays the analysis for Etch Rate Coupon. The process yield is about 99.73%. There are a couple of out of control points (one on the individuals chart, two on the MR chart). The variation between observations seems to decrease starting around observation 49 on the MR chart (many points below the centerline). It's possible this phenomenon could be explained by some assignable cause (such as replacement of new machine parts, etc.). If so, then the process would be in control from observation 49 onward.

Figure 26: Etch Rate Coupon Analysis



Original:	LSL = 64	USL = 96
Updated:	LSL = -3.13998	USL = 2.53281

Comments

One of my supervisors pointed out that in the original control chart for Leak Rate (CH), there are three points that are clearly out of control. In the updated charts, two points are still out of control, but a third point is within the control limits (it is on the edge of being out of control, however). This same supervisor said that the original chart is more useful for him, as it clearly displays the out of control points. He would be more likely to take action after seeing the original chart than after seeing my updated one. He said that in some cases, he is not concerned with false positives.

I suggested that in the future, both charts (original and updated using transformed data) could be considered simultaneously. Although the original charts may give false positives, it's also possible that they give false negatives. Also, some employees may have difficulty interpreting the updated charts, so being able to look at the original chart may prove to be helpful.

Another option is to take an updated control chart, and transform it back into original units. The individual data points will be exactly the same as the original, un-transformed data. The only difference is that there will be new control limits, which reflect the data's distribution. Figures 15 and 16 show this for Etch Rate (DERC) and Leak Rate (CH). Table 2 compares the original and new control limits.

Figure 27: Original Data with New Control Limits

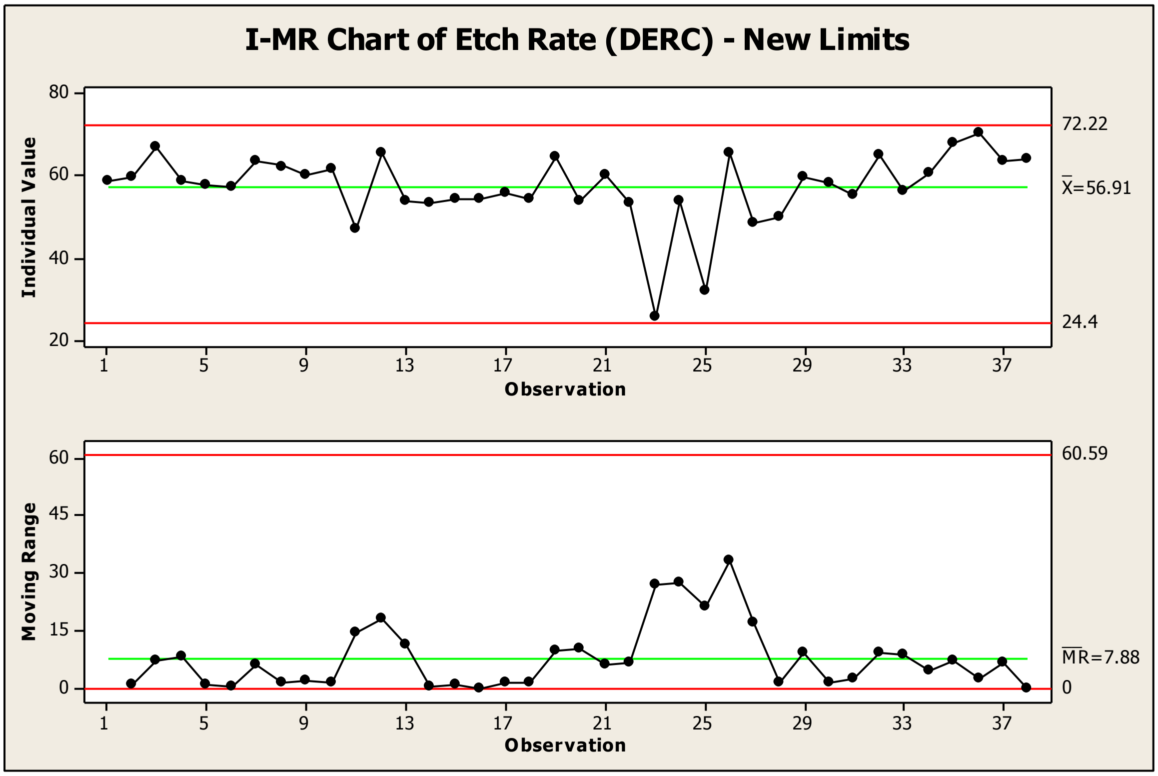


Figure 28: Original Data with New Control Limits

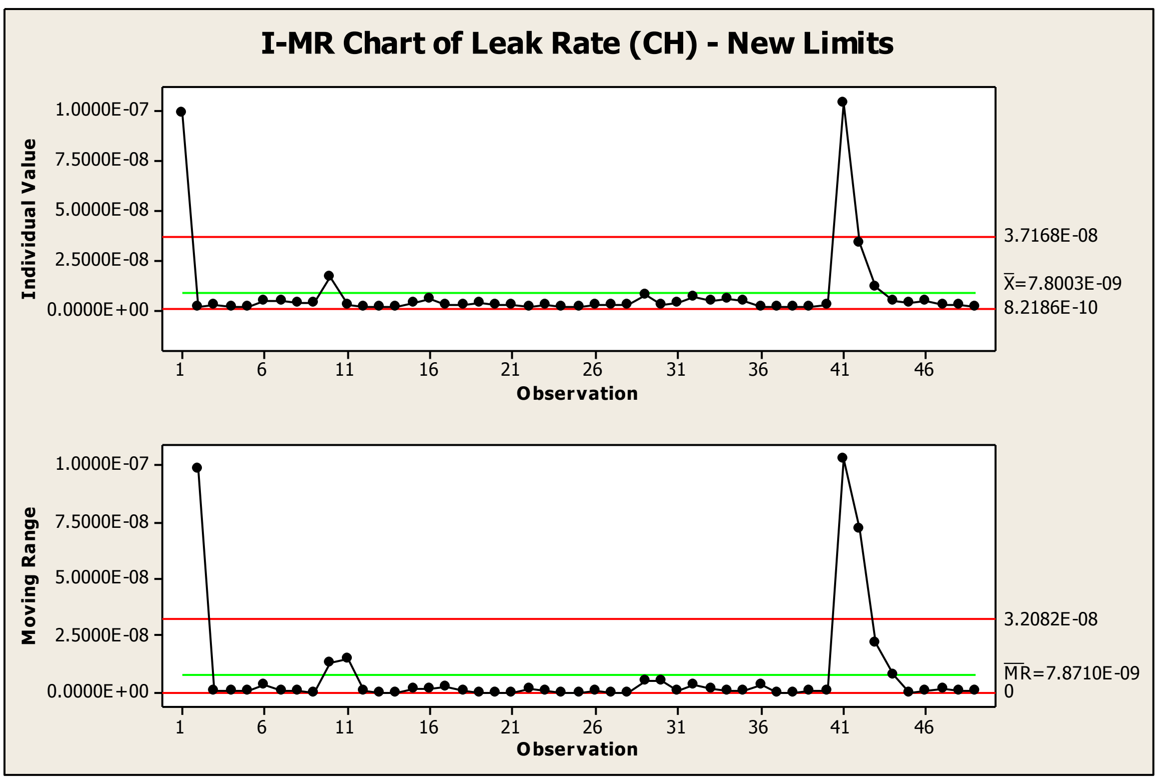


Table 2: Comparison of Original and New Control Limits

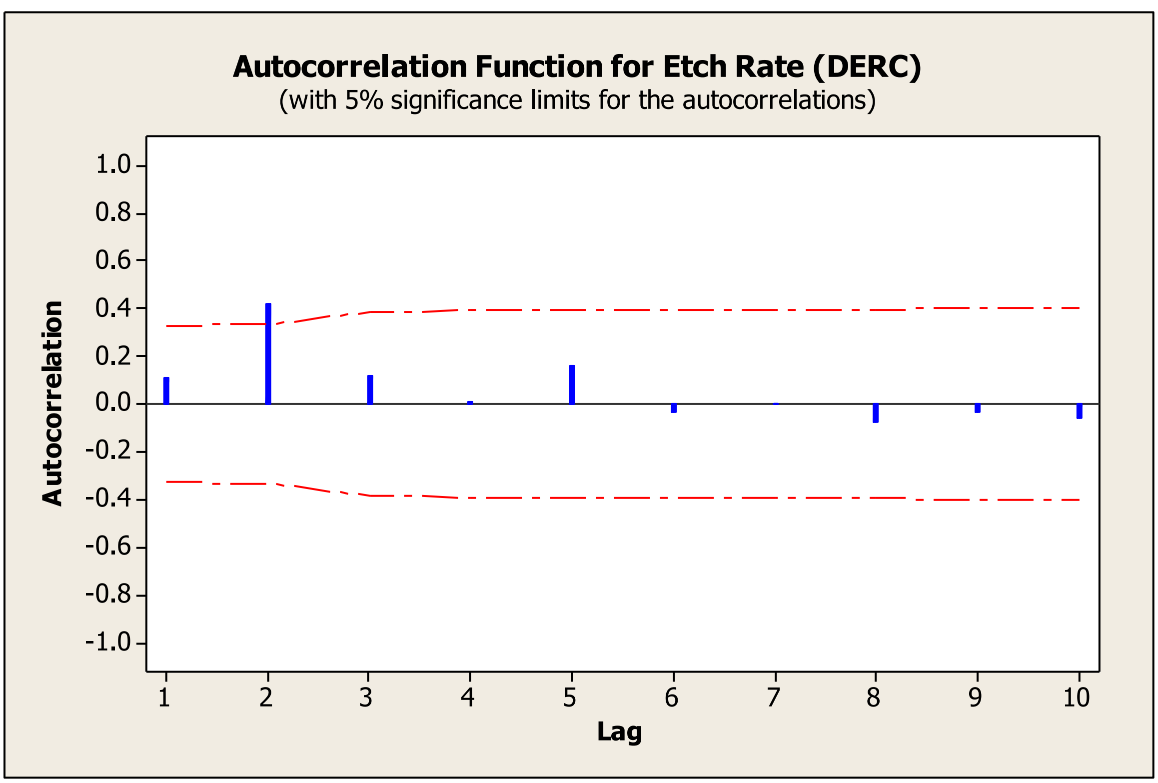
Etch Rate (Derc)	Original Individual	New Individual	Original Moving Range	New Moving Range
LCL	35.95	24.40	0	0
UCL	77.86	72.22	25.74	60.59

Leak Rate (CH)	Original Individual	New Individual	Original Moving Range	New Moving Range
LCL	- 1.3130E-08	8.2186E-10	0	0
UCL	2.8734E-08	3.7168E-08	2.5717E-08	3.2082E-08

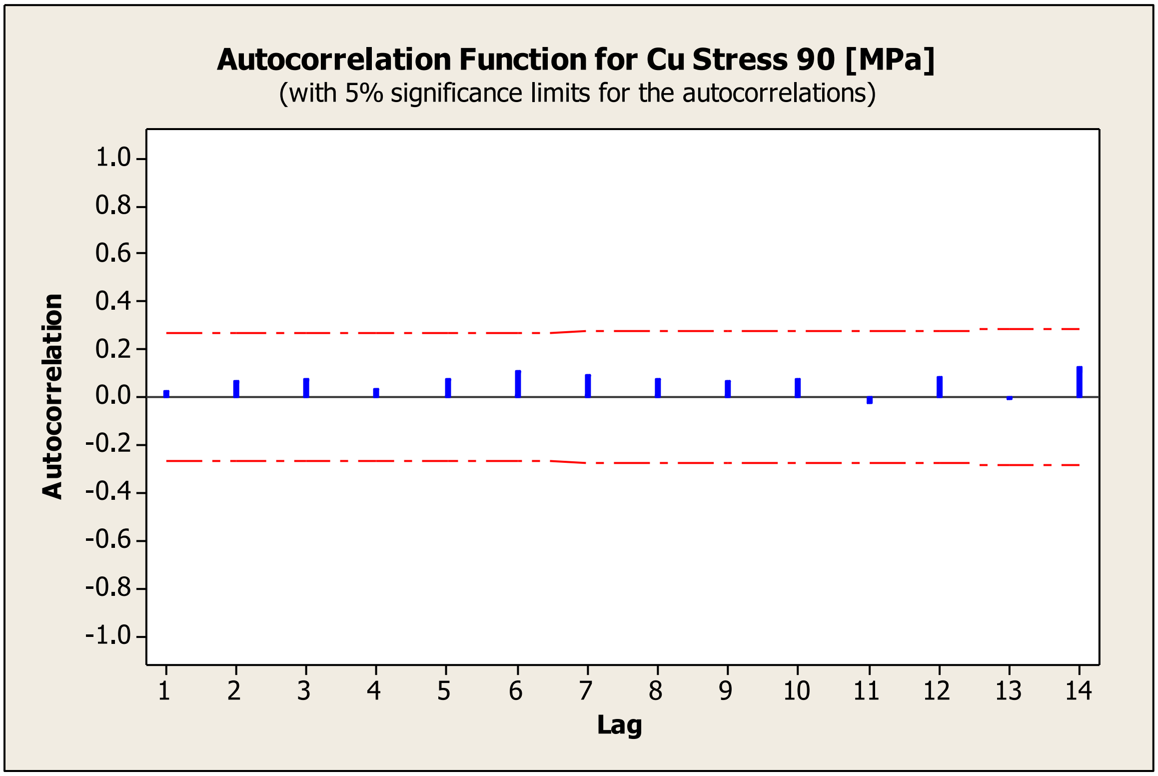
Finally, I checked the data for autocorrelation. The results are shown in Figure 29. There appears to be significant correlation for observations two time units apart for Etch Rate (Derc) and for Average Sheet Rho (Ti). Also, there is significant correlation for observations two time units and nineteen units apart for Etch Rate Coupon. The 4 significant estimates out of all 78 is not out of line with the expected number of significant sample autocorrelations when there is no process autocorrelation.

Figure 29: Autocorrelation Plots

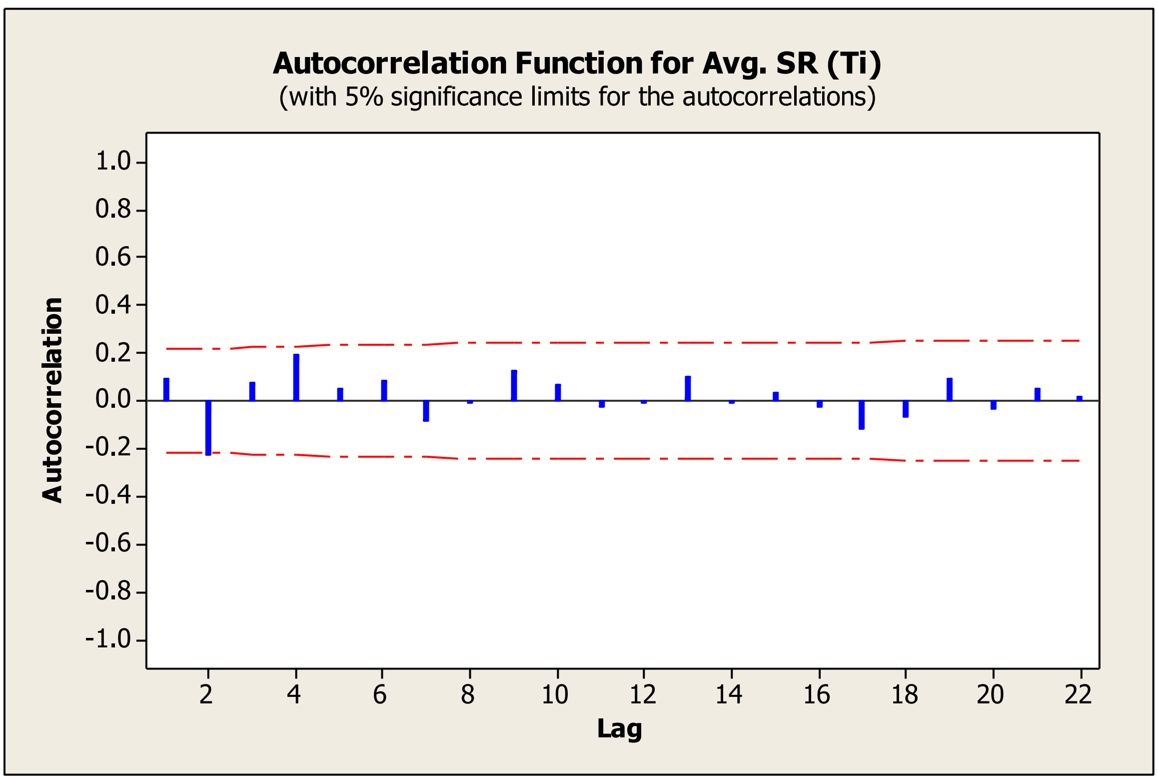
a.) Etch Rate (DERC)



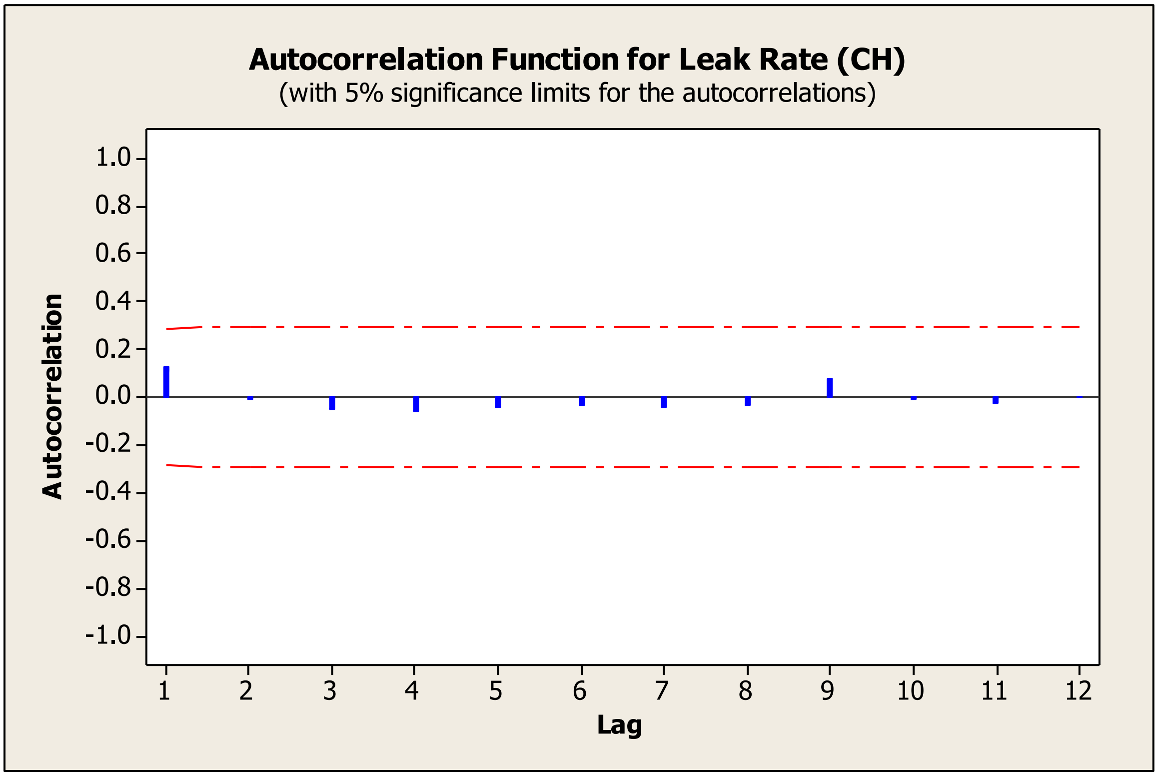
b.) Cu Stress 90 (MPa)



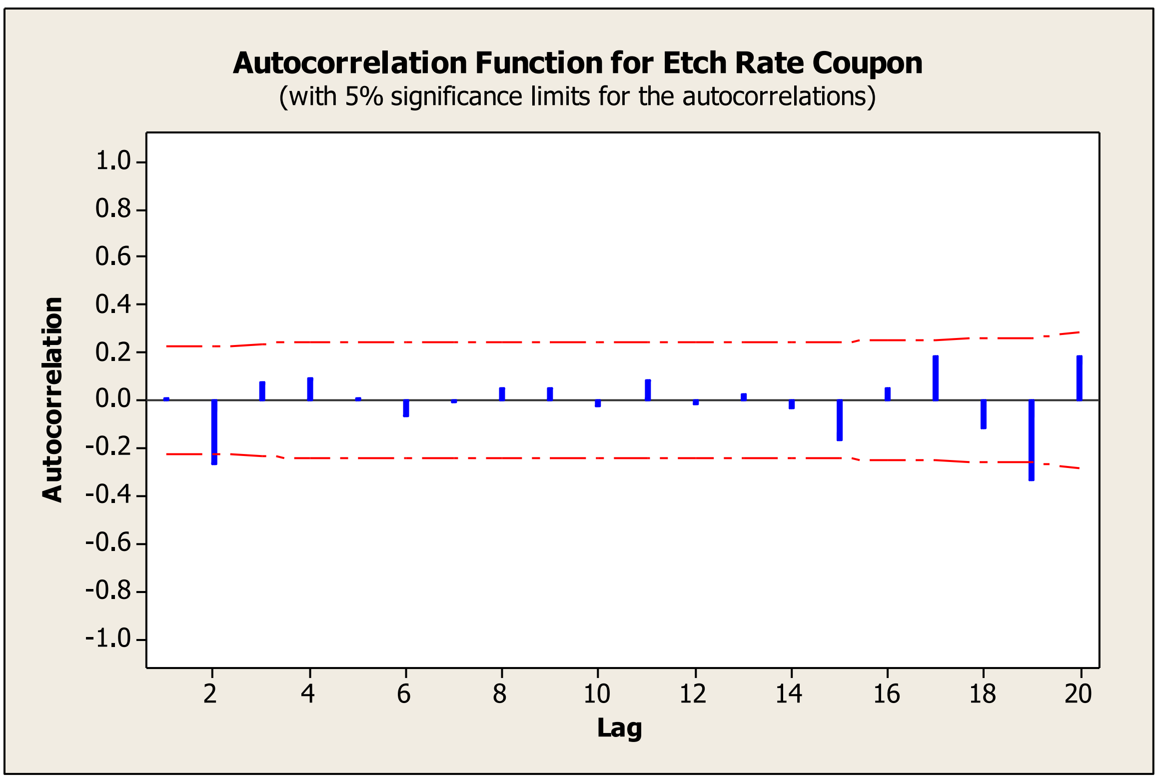
c.) Average Sheet Rho (Ti)



d.) Leak Rate (CH)



e.) Etch Rate Coupon



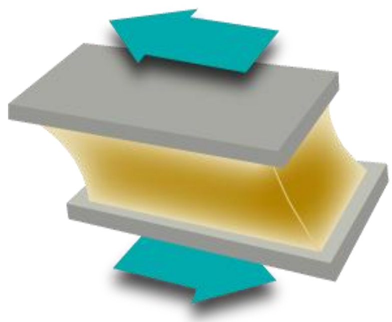
Chapter 3: COIST Wafers

Part 1

Introduction

A collection of wafers, identified as COIST wafers, have tiny bumps on their surfaces. The shear strength, that is, “the maximum shear stress which a material can withstand without rupture” was tested for these bumps (Corrosionpedia, 2014).

Figure 30: Shear Strength



http://www.masterbond.com/sites/default/files/lpimages/physical-strength_properties-shear.png

The COIST wafers had been produced using different methods/processes. This meant it was likely that the shear strength of the bumps varied across the set of wafers. It was also hypothesized that the shear strength varied within wafers, and that the bumps with the strongest shear strength were located at the center of the wafer.

Goals

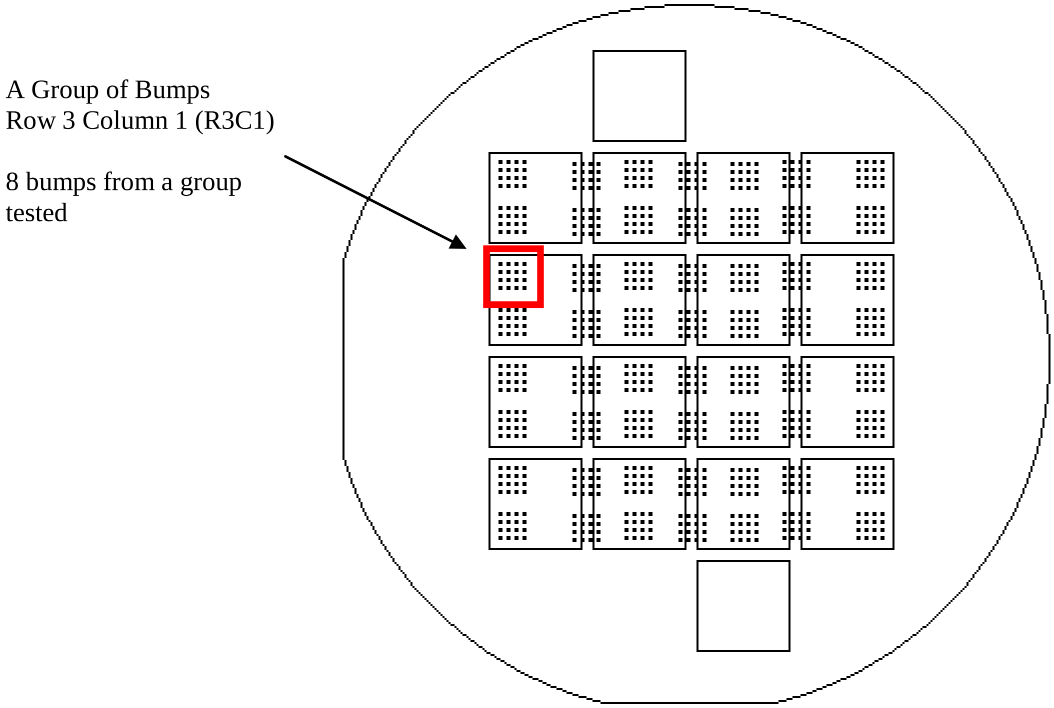
The first goal of this analysis was to determine if shear strength varied across wafers. Ultimately, engineers were interested in finding out which specific process yielded the largest shear strengths. The second goal of the analysis was to see how much shear strength varied within a wafer.

Data/Variables

Wafers	COIST - 153
	COIST - 156
	COIST - 157
	COIST - 158
	COIST - 159
	COIST - 160
	COIST - 162

The wafers were the same size (100mm) and each wafer contained the same number of bumps. Bumps were organized in groups, and these groups were aligned in rows and columns. Figure 31 gives a rough picture of a COIST wafer. Eleven groups were selected by engineers (not random) and the total force at failure was measured for 8 randomly selected bumps in each group. Then, the shear strength was calculated. This was done for each of the seven wafers.

Figure 31: A COIST Wafer



Note: This is not an exact representation of a COIST wafer. There are more groups of bumps, as well as more bumps within a group than what is shown above.

Response (Y)

Shear Normalized: This is the "shear strength" I refer to throughout the rest of the analysis.

$$Shear\ Normalized = \frac{1000 * Shear\ Raw\ Data}{Force - Resisting\ Area}$$

Additional Variables/Possible Predictors (X1, X2, etc.)

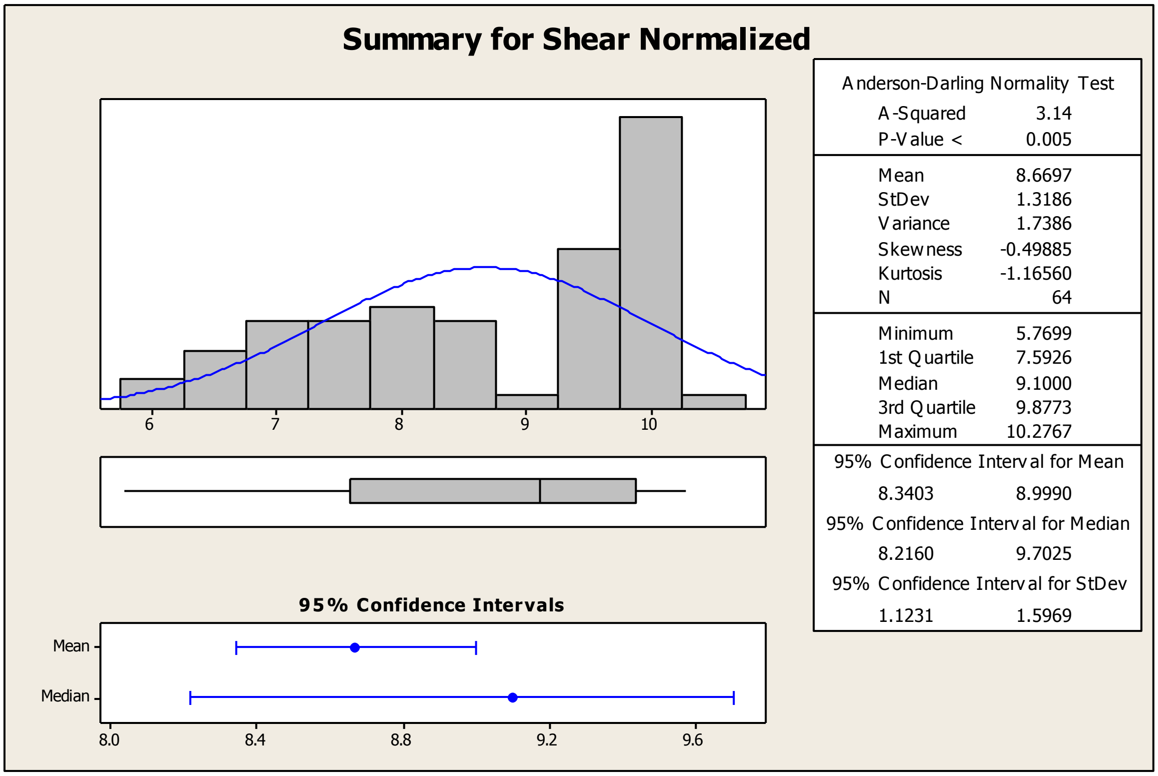
Location: Row # and column # of a group of bumps
Shear Raw Data: Total Force at Failure
Force – Resisting Area: Size of the bump

Statistical Analysis

I first looked at the distribution of all wafers together variable (see Figure 32). It did not follow a normal distribution and was skewed to the left. It did not follow one of the common non-normal distributions either. I tried obtaining normality using a transformation, but neither a Box – Cox transformation nor a Johnson Transformation were successful. This seems to makes sense: the distribution is possibly bi-modal, and monotone transformations (like Box – Cox or Johnson) would not fix bi-modality.

The reason for bimodality is unknown. I examined data for individual wafers, and almost all wafers contributed to the left tail of the distribution, as opposed to one or two wafers. I didn't see any common characteristics between points within each peak. The shearing process requires an engineer to properly align the tool to each bump. It's possible the bimodality is a result of poor alignment. It's also possible multiple engineers sheared the same wafer.

Figure 32: Distribution of Shear Strength



I proceeded with my analysis, despite the lack of normality. I just needed to be careful with interpretations of some of the results.

I decided to fit a general linear model to the data. I used wafer and location as categorical predictor variables and shear normalized (shear strength) as the response. The results are shown in Figures 33 and 34. Due to lack of time, interactions were not examined, but should be considered in future analyses.

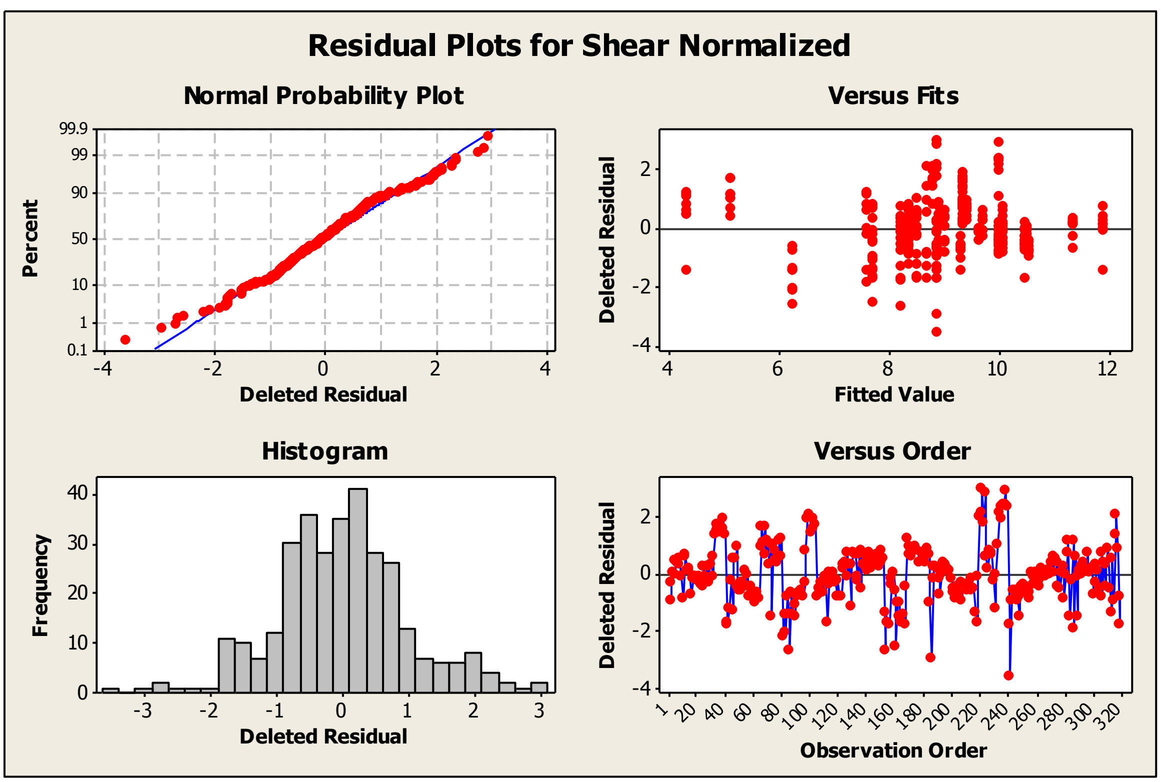
The "constant" coefficient is the overall shear strength for COIST – 162 at location R9C7 (Row 9 Column 7). The "wafer" and "location" coefficients are the change in average shear strength when referring to a particular wafer and location. For example, the average shear strength for any location on COIST – 153 is 0.85265 units larger than COIST – 162 at location R9C7. The average shear strength will increase by an additional 1.11544 if referring to location R14C6 on COIST – 153.

The model appears to be a relatively good fit. The residuals roughly follow a normal distribution, minus a few outliers. There doesn't seem to be any pattern in the Residual versus Fitted Value plot. All but one p-value are significant, indicating a difference in average shear strength between wafers and between locations. The R-square value is 78.76%, which is relatively good.

Figure 33: General Linear Model

```
General Regression Analysis: Shear Normalized versus Wafer, Location

Coefficients
Term              Coef   SE Coef          T      P           95% CI
Constant       8.85412  0.119070    74.3607  0.000  ( 8.61981,   9.08843)
Wafer
  COIST - 153  0.85265  0.259265     3.2887  0.001  ( 0.34246,   1.36284)
  COIST - 156  0.50091  0.094429     5.3046  0.000  ( 0.31509,   0.68673)
  COIST - 157 -0.16204  0.103852    -1.5603  0.120  (-0.36640,   0.04233)
  COIST - 158  0.95716  0.132289     7.2353  0.000  ( 0.69683,   1.21748)
  COIST - 159 -3.24216  0.163262   -19.8587  0.000  (-3.56343,  -2.92089)
  COIST - 160  0.97036  0.140213     6.9206  0.000  ( 0.69444,   1.24627)

Location
  R14C5       -1.30918  0.261960    -4.9976  0.000  (-1.82467,  -0.79369)
  R14C6        1.11544  0.327157     3.4095  0.001  ( 0.47165,   1.75922)
  R14C7       -0.99467  0.153040    -6.4994  0.000  (-1.29583,  -0.69352)
  R1C5        -0.68851  0.302975    -2.2725  0.024  (-1.28471,  -0.09231)
  R2C5        -0.47885  0.174638    -2.7419  0.006  (-0.82251,  -0.13519)
  R4C6         2.22013  0.302975     7.3278  0.000  ( 1.62392,   2.81633)
  R7C2        -0.79434  0.302975    -2.6218  0.009  (-1.39054,  -0.19814)
  R7C6         0.65748  0.174638     3.7648  0.000  ( 0.31382,   1.00114)
  R8C6         1.64763  0.302975     5.4382  0.000  ( 1.05143,   2.24383)
  R9C10       -2.10150  0.302975    -6.9362  0.000  (-2.69771,  -1.50530)

Summary of Model
S = 0.775680     R-Sq = 78.76%          R-Sq(adj) = 77.64%
PRESS = 200.697  R-Sq(pred) = 76.62%

Analysis of Variance
Source           DF   Seq SS   Adj SS   Adj MS         F  P
Regression       16  675.936  675.936  42.2460   70.2135  0
  Wafer           6  413.996  302.308  50.3846   83.7400  0
  Location       10  261.940  261.940  26.1940   43.5348  0
Error           303  182.309  182.309   0.6017
Total           319  858.244
```

Figure 34: General Linear Model continued



I next used Tukey's Method (for simultaneous confidence intervals) to group locations by average shear strength. Locations that do not share a letter are significantly different. The results are shown in Figure 35. I also grouped wafers using Tukey's Method as well (Figure 36).

Figure 35: Tukey Method - Pairwise Comparisons among Levels of Location

Location	Mean	Grouping				
R4C6	11.927	A				
R8C6	11.354	A	B			
R14C6	10.093	A	B	C		
R9C7	9.970		B	C		
R7C6	9.510			C		
R1C5	9.018			C	D	
R7C2	8.912			C	D	
R2C5	8.374				D	
R14C7	8.286				D	
R9C10	7.605				D	E
R14C5	6.409					E

```
Tukey 95% Simultaneous Confidence Intervals
Individual confidence level = 99.86%
```

Figure 36: Tukey Method - Pairwise Comparisons among Levels of Wafer

Wafer	Mean	Grouping		
COIST - 158	9.789	A		
COIST - 160	9.723	A		
COIST - 153	9.588	A		
COIST - 162	9.482	A		
COIST - 156	9.265	A		
COIST - 157	8.670		B	
COIST - 159	5.235			C

```
Tukey 95% Simultaneous Confidence Intervals
Individual confidence level = 99.66%
```

Conclusions

Based on the above analysis, COIST – 158 and COIST – 160 had the greatest average shear strength compared to the other wafers in the analysis. However, only two other wafers are significantly different from COIST – 158 and COIST – 160.

Location R4C6 (Row 4 Column 6) had the greatest shear strength out of all the locations. It seems, at first, that bumps at the center of the wafer have the strongest shear strength. Looking closer at the Tukey groupings and considering the rest the model, this isn't necessarily the case. Location R14C6 is not significantly different from R8C6 and R4C6. R14C6 is located at the edge of the wafer, while the other two are near the center. Also, R7C6 and R8C6 are right next to each other at the center of the wafer, but they are significantly different based on Tukey. See Figure 37.

The general linear model suggests that COIST – 160 at location R4C6 will lead to the greatest shear strength.

Figure 37: Wafer Map with Average Shear Strength

1	2	3	4	5	6	7	8	9	10	
				9.018						1
				8.374						2
										3
					11.927					4
										5
										6
	8.912				9.510					7
					11.354					8
						9.970			7.605	9
										10
										11
										12
										13
				6.409	10.093	8.286				14

Part 2

Introduction

In the first analysis, all wafers had the same number of bumps and the same locations were measured on each. I was also given data for wafers where this wasn't the case. Wafers had different numbers of bumps on them and a different sample size was taken for each wafer. The same locations weren't measured on every wafer. All wafers were the same size however, so, the ID for a location on one wafer corresponded to the same location on another wafer.

Goals

The goals of this analysis were to see which wafers and locations yielded the largest shear strength, and to examine how shear strength varied across a wafer.

Statistical Analysis

An ANOVA table (see Figure 38) shows that both wafer and location are significant. More variation occurs between wafers rather than within wafers. Only 56.35% of the variation is explained by those two factors, however.

Figure 38: ANOVA table

```
General Linear Model: Shear Normalized versus Wafer, Location

Factor    Type   Levels  Values
Wafer     fixed      11  COIST - 019, COIST - 123, COIST - 130, COIST - 134,
                         COIST - 137, COIST - 138, COIST - 139, COIST - 140,
                         COIST - 141, COIST - 142, COIST - 143
Location  fixed      19  1A, 1G, 2A, 2B, 2D, 2G, 4C, 4D, 5D, 5E, 6C, 6E, 6F,
                         7F, 7G, 7H, 8A, 8F, 8G

Analysis of Variance for Shear Normalized, using Adjusted SS for Tests

Source      DF    Seq SS    Adj SS   Adj MS       F      P
Wafer       10  1332.563  1303.325  130.333  118.47  0.000
Location    18   239.515   239.515   13.306   12.10  0.000
Error     1107  1217.823  1217.823    1.100
Total     1135  2789.901


S = 1.04886   R-Sq = 56.35%   R-Sq(adj) = 55.24%
```

Figure 39 and Figure 40 show the Tukey groups by location and by wafer. When referring to location, the rows are identified by a number (Row 1, 2, etc.) and the columns are identified by a letter (Column A, B, etc.). Location 1A is row 1 column 1. Groups that do not share a letter are significantly different.

Figure 39: Tukey Method - Pairwise Comparisons among Levels of Location

Location	N	Mean	StDev	Grouping (Tukey)			
7H	8	12.866	0.815	A			
4C	8	12.816	0.426	A			
7F	8	12.678	0.747	A			
1A	8	12.227	0.989	A	B		
6F	8	12.049	0.757	A	B		
8F	16	11.697	1.118	A	B		
2B	38	11.341	1.209	A	B		
7G	23	11.291	0.563	A	B	C	
5E	16	11.275	0.673	A	B	C	
8A	24	11.202	1.652	A	B	C	
2G	15	11.195	0.727	A	B	C	
6E	232	11.116	1.554	A	B	C	
8G	207	11.081	1.843	A	B	C	
5D	24	11.038	0.644	A	B	C	
2A	216	10.699	1.716		B	C	
4D	253	10.641	1.305		B	C	
6C	16	10.058	0.759		B	C	D
2D	8	9.244	0.225			C	D
1G	8	8.225	0.839				D

Tukey 95% Simultaneous Confidence Intervals
Individual confidence level = 99.95%

Figure 40: Tukey Method - Pairwise Comparisons among Levels of Wafer

Wafer	N	Mean	Grouping (Tukey)						
COIST - 134	128	12.248	A						
COIST - 019	88	12.030	A	B					
COIST - 142	164	11.614		B	C				
COIST - 143	180	11.294			C	D			
COIST - 139	128	10.907				D	E		
COIST - 138	32	10.750				D	E	F	
COIST - 140	128	10.658					E	F	
COIST - 123	127	10.601					E	F	
COIST - 141	32	10.160						F	
COIST - 137	32	10.067						F	
COIST - 130	97	7.994							G

Tukey 95% Simultaneous Confidence Intervals
Individual confidence level = 99.87%

Some locations only have 8 observations – these observations were all taken from only one wafer.
7H: COIST – 142   4C: COIST – 019   7F: COIST – 143   1A: COIST – 142
6F: COIST – 143   2D: COIST – 141   1G: COIST – 019

COIST – 019 had one of the largest overall average shear strengths. But, location 1G was measured only on this wafer, and it was the location with the lowest average shear strength. This location was not as low as the entire COIST – 130 wafer however, which was consistently lower at each location compared with the other wafers. COIST – 134 consistently had higher shear strengths at each location. Other wafers, such as COIST – 142 and COIST – 143, had higher variation between locations.

Locations at the center of the wafer do have large shear strengths, but there are also some equivalently high strengths near the edges (See Figure 41).

Figure 41: Wafer Map with Average Shear Strength

12.227						8.225	
10.699	11.341		9.244			11.195	
		12.816	10.641				
			11.038	11.275			
		10.058		11.116	12.049		
					12.678	11.291	12.866
11.202					11.697	11.081	

Chapter 4: Gage R & R Studies

Part 1: Review of Past Studies

Introduction

In May of 2013, Gage R & R studies were conducted for three pieces of measuring equipment-

- Filmetrics F20
- Filmetrics F40
- Woollam

Specifically, these tools measure the thickness of a thin film on a wafer.

Past Procedure

For each of the measurement tools above, three Gage R & R studies were conducted:

1. Three operators measured 5 silicon wafers (parts) containing 0.5 microns of silicon dioxide. Each part was measured three times.
2. Three operators measured 5 silicon wafers (parts) containing 1.0 microns of silicon dioxide. Each part was measured three times.
3. Three operators measured 5 silicon wafers (parts) containing 2.0 microns of silicon dioxide. Each part was measured three times.

Parts were measured in a random order, and not consecutively. In other words, an operator measured each part once, in a random order. The parts were measured a second time, again in random order. Finally, the parts, in a random order, were measured a third time.

The Xbar – R method was used to analyze the data collected. The Xbar – R method is limited, however, because it does not include an operator – part interaction term. In some cases, this interaction is significant, and should be taken into account. In addition, as shown in Figure 42, the Xbar – R method can produce negative variance components. Other methods for analyzing Gage R & R studies avoid such issues. Restricted maximum likelihood, for example, does not produce negative components.

Minitab has two options for analyzing a Gage R & R study: the ANOVA method and the Xbar – R method. The ANOVA method fits a general linear model to calculate the variance components. It also includes the operator – part interaction term in the variance components model, if it's deemed significant. If the interaction term is not significant, Minitab will fit a reduced model to calculate variance components.

Occasionally, one or more of the estimated variance components could be less than zero when the operator – part interaction term is insignificant (Minitab, 2014). "If a variance component is negative, then Gage R&R will report it as zero" (Minitab, 2014).

Figure 42: Gage R & R Study using Xbar – R method

MEMS Filmetrics F20 --- 0.5µm SiO2 on Si

Process:	Thin Film Measurement	Metrology Tool:	MEMS Filmetrics	Product Code Name:	Gauge Study Box 1
Parameter:	SiO2 on Si	Tool Make/Model:	F20	Measurement Units:	Å
Specification +/-:		Measurement Range:			

	Gunnar Operator A				Cheryl Operator B				Jeff Operator C				Part Average
Sample	Trial #1	Trial #2	Trial #3	Range	Trial #1	Trial #2	Trial #3	Range	Trial #1	Trial #2	Trial #3	Range	
1	5255.0	5245.8	5252.1	**9.2**	5257.7	5244.7	5257.8	**13.1**	5244.0	5229.1	5247.2	**18.1**	5248.2
2	5226.7	5197.2	5253.4	**56.2**	5218.5	5204.5	5223.5	**19.0**	5223.8	5196.7	5200.9	**27.1**	5216.1
3	5211.1	5190.1	5209.7	**21.0**	5210.3	5183.4	5215.5	**32.1**	5211.7	5183.4	5188.3	**28.3**	5200.4
4	5140.4	5144.5	5196.7	**56.3**	5193.9	5189.0	5223.5	**34.5**	5209.1	5168.8	5186.6	**40.3**	5183.6
5	5221.4	5223.2	5216.3	**6.9**	5229.0	5215.4	5232.1	**16.7**	5235.1	5199.6	5216.7	**35.5**	5221.0
Totals	**26054.6**	**26000.8**	**26128.2**		**26109.4**	**26037.0**	**26152.4**		**26123.7**	**25977.6**	**26039.7**		

Average Range Op A	29.9	Average Range Op B	23.1	Average Range Op C	29.9	Part Average Range	64.5

Average Test-Retest Range	27.6
Test for Control/Upper Range Limit	71.3
Repeatability (test-retest metric)	264.0
Reproducibility (Operator variance metric	-4.7
Product variance metric	723.3
Total Variance	982.5
Repeatability Proportion	0.27
Reproducibility Proportion	0.00
Product Variation Proportion	0.74
Total Variance Proportions	1.0
Probable error	11.0

259.2 R&R (Repeatability and Reproducibility)

Classification **2**

Classification
Class 1 - captures >90% of product signal -
Use for Process Monitoring (i.e. SPC) or Production
Class 2 - captures 70-90% of product signal -
Good for Production use, limited use for Process Monitoring
Class 3 - captures 45-70% of the product signal -
Review tolerance and criticality for Production use
Class 4 - captures <45% of the product signal -
Review tolerance and criticality for Production use

This is the median error of the measurements, which limits the resolving ability of the measurement.

Goals

I decided to re-analyze the Gage R & R study data from May 2013 using Minitab. I ran the data through both the Xbar – R and ANOVA methods. First, I used the Xbar – R method to see if I could duplicate the same results as the original. Then, I used the ANOVA method to see if the interaction term was significant, and if the results were much different than the Xbar – R method.

The original analysis classified each tool on a scale from 1 to 4. This classification was based on the percentage of part-to-part variation (labeled as product variation percent in these studies). See Table 3. I also classified the tools based on the part-to-part variation from Minitab's output from the Xbar – R and ANOVA methods.

Table 3: Classification of Measurement Tools (based on Part-to-Part variation)

Classification
Class 1 - captures >90% of product signal -
Use for Process Monitoring (i.e. SPC) or Production
Class 2 - captures 70-90% of product signal -
Good for Production use, limited use for Process Monitoring
Class 3 - captures 45-70% of the product signal -
Review tolerance and criticality for Production use
Class 4 - captures <45% of the product signal -
Review tolerance and criticality for Production use

Statistical Analysis

Minitab's Xbar – R method produced similar results as the original method used. However, the results were not identical. Minitab's Xbar – R method does not output negative variation - it sets negative variation equal to zero. This explains the slight differences in results. The method produced the same classification as the original method (see Table 4).

Table 4: Classification Comparison

Tool	Sample Type	Original Product Variation %	Original Xbar – R Classification	ANOVA Product Variation %	ANOVA Classification	Xbar – R Product Variation %	Minitab's Xbar – R Classification
Filmetrics F20	0.5um SiO2 on Si	74%	2	64.61%	3	71.21%	2
	1.0um SiO2 on Si	2%	4	0%	4	5.66%	4
	2.0um SiO2 on Si	2%	4	0%	4	6.25%	4
Filmetrics F40	0.5um SiO2 on Si	93%	1	93.76%	1	94.58%	1
	1.0um SiO2 on Si	30%	4	18.76%	4	27.70%	4
	2.0um SiO2 on Si	78%	2	77.97%	2	78.58%	2
Woolam SE	0.5um SiO2 on Si	100%	1	99.25%	1	99.45%	1
	1.0um SiO2 on Si	93%	1	87.99%	2	91.83%	1
	2.0um SiO2 on Si	87%	2	88.63%	2	88.90%	2

In eight of the nine Gage R & R studies, the operator – part interaction was not significant, according to the ANOVA method. All p-values were greater than 0.25. Figure 43 shows the Minitab output for one of the studies. The only case where the interaction term was significant was for the Woollam, measuring 0.5 microns of SiO2.

The ANOVA method classified three of the studies differently than the original method. Those studies are highlighted in yellow in Table 2 above. For these studies, the operator – part interaction term was not significant, and thus not included in the variance components model. The differences in classification, therefore, might be due to the fact that the Xbar – R method uses the range to estimate variation, whereas the ANOVA method uses sums of squares.

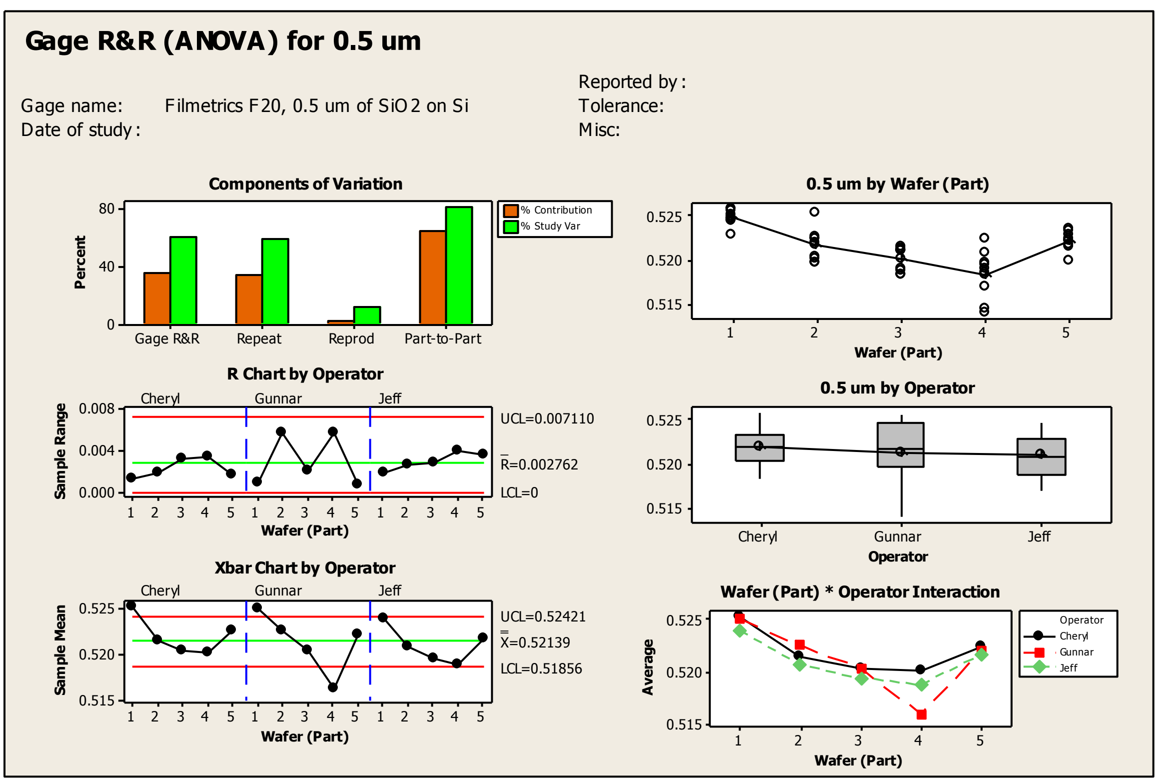
In the case where the interaction term was significant (Woollam, 0.5 microns of SiO2), the classification was the same across all three methods.

The classifications for the Woollam studies were similar – the tool is good to use for production use, as well as statistical process control. The Filmetrics F20, on the other hand, is an inconsistent measuring tool.

The classifications for the Filmetrics F40 studies were very different. The tool performed inconsistently for 1.0 microns of silicon dioxide, but was good for 0.5 microns and 2.0 microns.

Figure 43: ANOVA Method Results – Filmetrics F20, 0.5 microns of SiO2 on Si

```
Gage R&R Study - ANOVA Method
Gage name:        Filmetrics F20, 0.5 um SiO2 on Si

Two-Way ANOVA Table With Interaction
Source                     DF         SS         MS        F      P
Wafer (Part)                4  0.0002096  0.0000524  14.5051  0.001
Operator                    2  0.0000089  0.0000044   1.2301  0.342
Wafer (Part) * Operator     8  0.0000289  0.0000036   1.3266  0.269
Repeatability              30  0.0000817  0.0000027
Total                      44  0.0003290

Alpha to remove interaction term = 0.25

Two-Way ANOVA Table Without Interaction
Source          DF         SS         MS        F      P
Wafer (Part)     4  0.0002096  0.0000524  18.0043  0.000
Operator         2  0.0000089  0.0000044   1.5268  0.230
Repeatability   38  0.0001106  0.0000029
Total           44  0.0003290

Gage R&R
                                %Contribution
Source              VarComp    (of VarComp)
Total Gage R&R    0.0000030           35.39
  Repeatability   0.0000029           34.19
  Reproducibility 0.0000001            1.20
    Operator      0.0000001            1.20
Part-To-Part      0.0000055           64.61
Total Variation   0.0000085          100.00

Process tolerance = 0.2
                                 Study Var  %Study Var  %Tolerance
Source              StdDev (SD)  (6 * SD)       (%SV)  (SV/Toler)
Total Gage R&R        0.0017355  0.0104133      59.49        5.21
  Repeatability       0.0017058  0.0102351      58.48        5.12
  Reproducibility     0.0003197  0.0019182      10.96        0.96
    Operator          0.0003197  0.0019182      10.96        0.96
Part-To-Part          0.0023448  0.0140685      80.38        7.03
Total Variation       0.0029172  0.0175031     100.00        8.75

Number of Distinct Categories = 1
```



Comments/Suggestions

I would suggest repeating the Filmetrics F40 Gage R & R studies – specifically, the 1.0 microns of SiO_2. It would be interesting to see if the low classification (compared to the other two) was an anomaly.

Minitab's ANOVA method can output a value known as %Tolerance. The %Tolerance compares the estimates of variation with the allowable spread of variation. The ANOVA method also outputs the range of values contained within 6 standard deviations (of the sample). One of my supervisors noted that these two pieces of information are more important to him than the actual Gage R & R variation percent (%Contribution of VarComp). The Gage R & R variation component is good when the goal is process improvement (Minitab, 2010). If the main interest is in how well the tool measures parts relative to specification limits, then %Tolerance is better to use (Minitab, 2010).

Typically, in the Microfabrication Department at Draper, parts are allowed to vary as such:

$$\text{Target } \pm 20\%$$

So, for a target of 1 micron, the lower specification limit would be 0.8 microns, and the upper specification limit would be 1.2 microns.

In all of the Gage R & R studies, the samples were well within the specification limits. Looking at Figure 2, the Gage R & R contribution to total variation is 35.39%. This value indicates the tool is unacceptable, with regards to process improvement. Greater than 30% is considered unacceptable, 10-30% is acceptable depending on the situation, and less than 10% is acceptable (Minitab, 2010). However, the %Tolerance is 5.21%, which says the tool is acceptable with regards to the specifications.

Part 2: New Studies

Goals

I was asked to conduct Gage R & R studies for other measurement tools in the Microfabrication Laboratory. The goal was to see if these other tools take consistent measurements, or if the measurement system variation is unacceptable. Process tolerance was considered when determining whether a tool was acceptable or unacceptable. In the case of these specific studies, if %Tolerance < 30%, the tool was classified as acceptable.

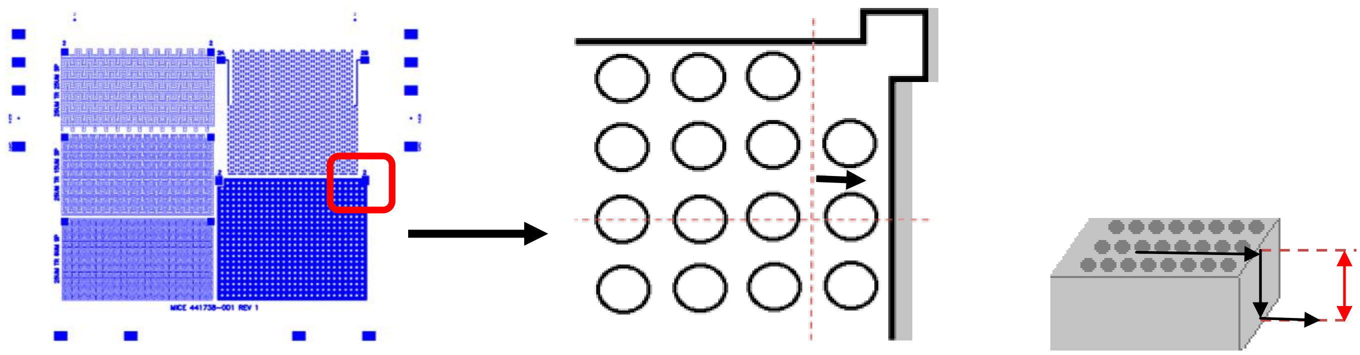
Tencor

The Tencor is a profilometer, a tool used to scan a wafer's surface. A stylus moves along the surface of the wafer. Any ups or downs the stylus makes (because of features on the wafer) are recorded. At the end of the scan, one can see the roughness of the surface, as well as the height and width of certain features. See Figure 44c. The black arrows show the movement of the stylus, and the red arrows indicate the step height.

For the Tencor, two separate Gage R & R studies were conducted. The first study measured the height of a surface feature that was 2 microns high. The second study measured the height of a 5 micron feature. The studies were conducted as such:

> Three operators measured 10 identical parts on a wafer. Each part was measured three times, not consecutively. Parts were measured once, in a random order, then a second time (random order) and a third time (random order).

Figure 44: Tencor Step Height



a.) One Module on a Wafer   b.) Top View (of area in the red box in part a.)   c.) Side View

Note: Not drawn to scale.
The black arrows in c.) "Side View" show how the stylus moves along the surface.
The red arrows indicate the step height.

The ANOVA method was used to analyze the data, and the results of the two studies are shown below in Figures 45 and 46.

Figure 45: Gage R & R Study - 2.0 um Feature

```
Gage R&R Study - ANOVA Method
Gage R&R for Height

Gage name:         Tencor 2 micron Feature
Tolerance:         2+- 20%
Misc:              LSL = 1.6   USL = 2.4   Target = 2


Two-Way ANOVA Table With Interaction
Source             DF         SS          MS         F      P
Part                9  0.0521317  0.0057924  16.0065  0.000
Operator            2  0.0077194  0.0038597  10.6657  0.001
Part * Operator    18  0.0065138  0.0003619   3.3638  0.000
Repeatability      60  0.0064549  0.0001076
Total              89  0.0728198

Alpha to remove interaction term = 0.25

Gage R&R
                                %Contribution
Source               VarComp    (of VarComp)
Total Gage R&R     0.0003089           33.86
  Repeatability    0.0001076           11.79
  Reproducibility  0.0002014           22.07
    Operator       0.0001166           12.78
    Operator*Part  0.0000848            9.29
Part-To-Part       0.0006034           66.14
Total Variation    0.0009123          100.00

Process tolerance = 0.8
                                  Study Var  %Study Var  %Tolerance
Source             StdDev (SD)   (6 * SD)       (%SV)  (SV/Toler)
Total Gage R&R       0.0175767   0.105460       58.19       13.18
  Repeatability      0.0103721   0.062233       34.34        7.78
  Reproducibility    0.0141901   0.085141       46.98       10.64
    Operator         0.0107978   0.064787       35.75        8.10
    Operator*Part    0.0092068   0.055241       30.48        6.91
Part-To-Part         0.0245641   0.147384       81.32       18.42
Total Variation      0.0302049   0.181229      100.00       22.65

Number of Distinct Categories = 1
```

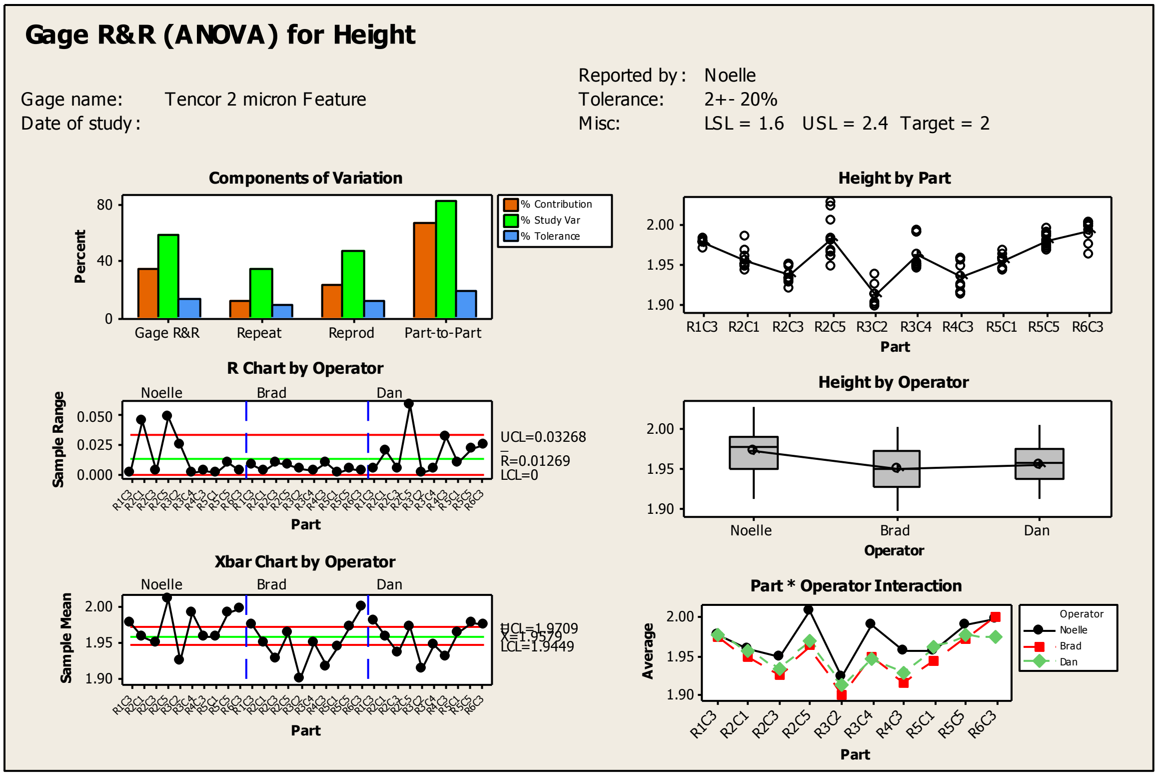
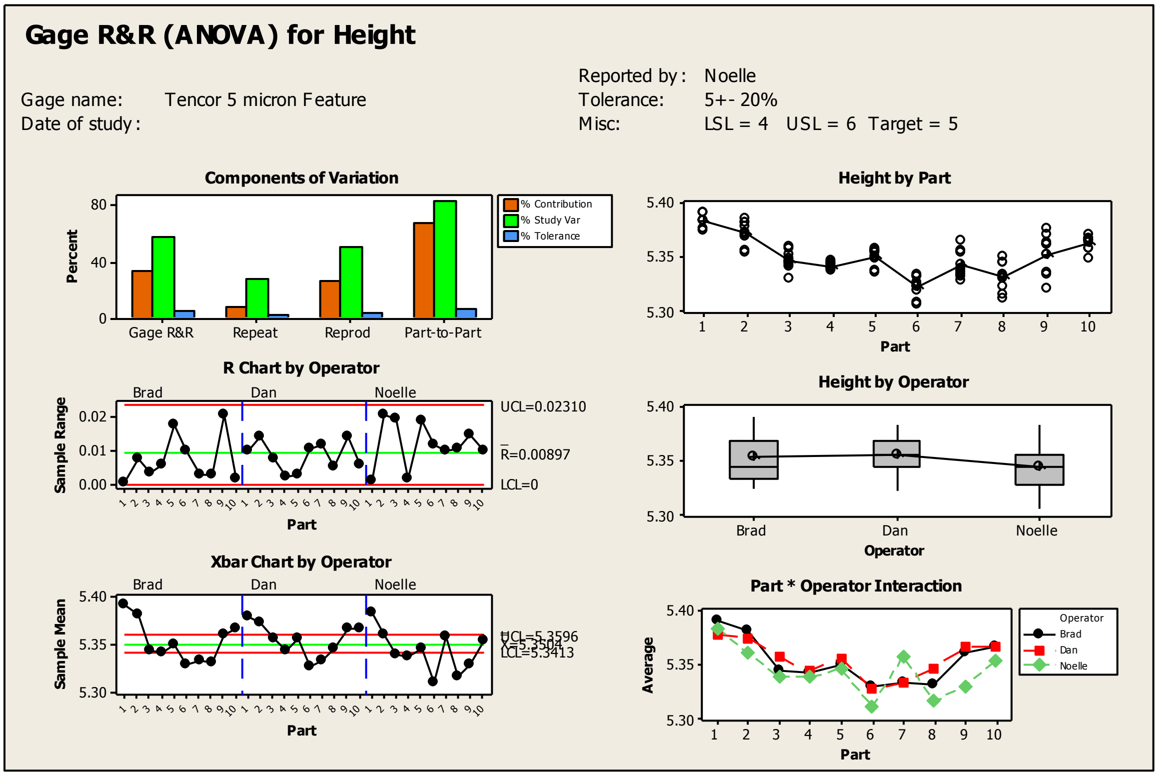


Figure 46: Gage R & R Study - 5.0 um Feature

```
Gage R&R Study - ANOVA Method
Gage R&R for Height

Gage name:        Tencor 5 micron Feature
Tolerance:        5+- 20%
Misc:             LSL = 4    USL = 6   Target = 5

Two-Way ANOVA Table With Interaction
Source            DF         SS          MS        F      P
Part               9  0.0273925   0.0030436  10.3271  0.000
Operator           2  0.0021741   0.0010870   3.6884  0.045
Part * Operator   18  0.0053050   0.0002947   8.8514  0.000
Repeatability     60  0.0019978   0.0000333
Total             89  0.0368693

Alpha to remove interaction term = 0.25

Gage R&R
                                  %Contribution
Source               VarComp      (of VarComp)
Total Gage R&R     0.0001468             32.47
  Repeatability    0.0000333              7.36
  Reproducibility  0.0001136             25.11
    Operator       0.0000264              5.84
    Operator*Part  0.0000871             19.27
Part-To-Part       0.0003054             67.53
Total Variation    0.0004523            100.00

Process tolerance = 2
                                    Study Var  %Study Var  %Tolerance
Source             StdDev (SD)     (6 * SD)        (%SV)   (SV/Toler)
Total Gage R&R       0.0121181     0.072709        56.98         3.64
  Repeatability      0.0057703     0.034622        27.13         1.73
  Reproducibility    0.0106561     0.063937        50.11         3.20
    Operator         0.0051391     0.030835        24.16         1.54
    Operator*Part    0.0093350     0.056010        43.89         2.80
Part-To-Part         0.0174766     0.104860        82.18         5.24
Total Variation      0.0212669     0.127601       100.00         6.38

Number of Distinct Categories = 2
```



In both cases, the operator – part interaction was significant and thus included in the model.

For the first study (2.0 micron feature), the %Tolerance was 13.18%. Based on this, the measurement tool is acceptable. For the second study (5 microns) the %Tolerance was 3.64%, indicating that the tool is acceptable.

The Repeatability measure is larger in the first study than in the second. At the time, two of the operators were newer users of the Tencor. It's possible that some of the variation is due to unfamiliarity with the tool. The Reproducibility measure is larger in the second study than in the first. The particular parts measured in the second study were difficult to locate on the wafer. It's possible that the operators accidentally measured different parts from one another. If the study was aimed toward process improvement, the Gage R & R variance component would be considered unacceptable (>30%) in both cases.

Considering both studies, I believe the Tencor takes acceptable measurements with respect to the specification limits.

Tencor P – 6

The Tencor P – 6 is another profilometer used to scan a wafer's surface. For this tool, only one Gage R & R study was performed. The height of a surface feature that was 2 microns high was measured. The study was conducted as such:

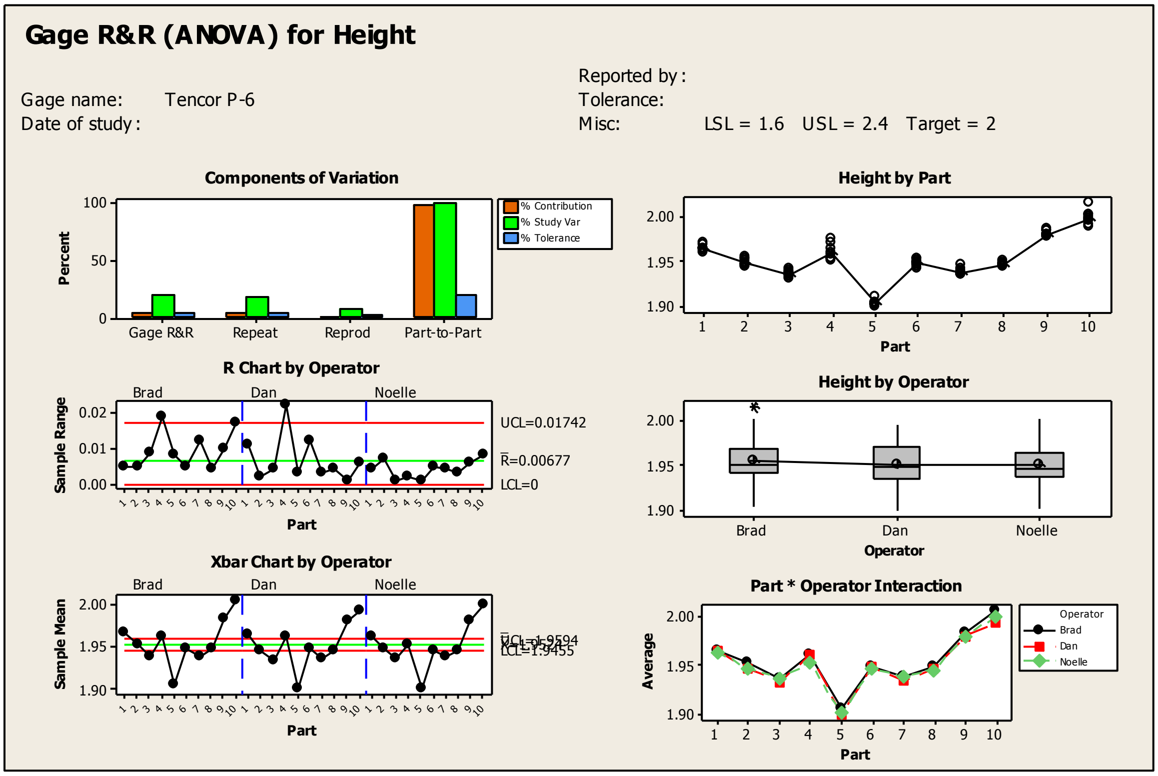
> Three operators measured 10 identical parts on a wafer. Each part was measured three times, not consecutively. Parts were measured once, in a random order, then a second time (random order) and a third time (random order).

The ANOVA method was used to analyze the data and the results of the study is shown below in Figure 47.

The tool is acceptable with respect to the specification limits, since the %Tolerance is less than 30%. The tool is also acceptable with respect to process improvement.

Figure 47: Gage R & R Study – 2.0 um Feature

```
Gage R&R Study - ANOVA Method
Gage R&R for Height

Gage name:       Tencor P-6
Misc:            LSL = 1.6   USL = 2.4   Target = 2

Two-Way ANOVA Table With Interaction
Source           DF         SS         MS        F      P
Part              9  0.0562044  0.0062449  321.822  0.000
Operator          2  0.0002798  0.0001399    7.210  0.005
Part * Operator  18  0.0003493  0.0000194    0.960  0.515
Repeatability    60  0.0012127  0.0000202
Total            89  0.0580462

Alpha to remove interaction term = 0.25

Two-Way ANOVA Table Without Interaction
Source         DF         SS         MS        F      P
Part            9  0.0562044  0.0062449  311.856  0.000
Operator        2  0.0002798  0.0001399    6.987  0.002
Repeatability  78  0.0015620  0.0000200
Total          89  0.0580462

Gage R&R
                              %Contribution
Source               VarComp   (of VarComp)
Total Gage R&R     0.0000240           3.36
  Repeatability    0.0000200           2.80
  Reproducibility  0.0000040           0.56
    Operator       0.0000040           0.56
Part-To-Part       0.0006917          96.64
Total Variation    0.0007157         100.00

Process tolerance = 0.8

                                Study Var  %Study Var  %Tolerance
Source             StdDev (SD)   (6 * SD)       (%SV)  (SV/Toler)
Total Gage R&R       0.0049012   0.029407       18.32        3.68
  Repeatability      0.0044749   0.026850       16.73        3.36
  Reproducibility    0.0019991   0.011994        7.47        1.50
    Operator         0.0019991   0.011994        7.47        1.50
Part-To-Part         0.0262994   0.157796       98.31       19.72
Total Variation      0.0267522   0.160513      100.00       20.06

Number of Distinct Categories = 7
```



Filmetrics F50

Filmetrics F50 measures the thickness of a thin film on a wafer. For this study, operators measured the thickness of a layer of silicon dioxide on a silicon wafer. More specifically,

> Three operators measured 5 silicon wafers (parts) containing 1000 Angstroms (0.1 micron) of silicon dioxide. Each part was measured three times, not consecutively. Parts were measured once, in a random order, then a second time (random order) and a third time (random order).

The results of the study are shown in Figure 48.

Specification limits were not provided for this study. I used Target ± 20%, in my analysis. Based on those limits, the tool is acceptable. If the tolerance was lowered to 20 Angstroms (LSL = 990, USL = 1010), the tool would be unacceptable, and would have a %Tolerance of 37.75.

Figure 48: Gage R & R Study – 1000 Angstroms of SiO_2 on Si

Gage R&R Study - ANOVA Method

Gage R&R for Thickness

Gage name: Filmetrics F50

Misc: LSL = 800 Target = 1000 USL = 1200

Two-Way ANOVA Table With Interaction

Source	DF	SS	MS	F	P
Part	4	65.022	16.2556	79.0811	0.000
Operator	2	11.911	5.9556	28.9730	0.000
Part * Operator	8	1.644	0.2056	0.1321	0.997
Repeatability	30	46.667	1.5556		
Total	44	125.244			

Alpha to remove interaction term = 0.25

Two-Way ANOVA Table Without Interaction

Source	DF	SS	MS	F	P
Part	4	65.022	16.2556	12.7861	0.000
Operator	2	11.911	5.9556	4.6845	0.015
Repeatability	38	48.311	1.2713		
Total	44	125.244			

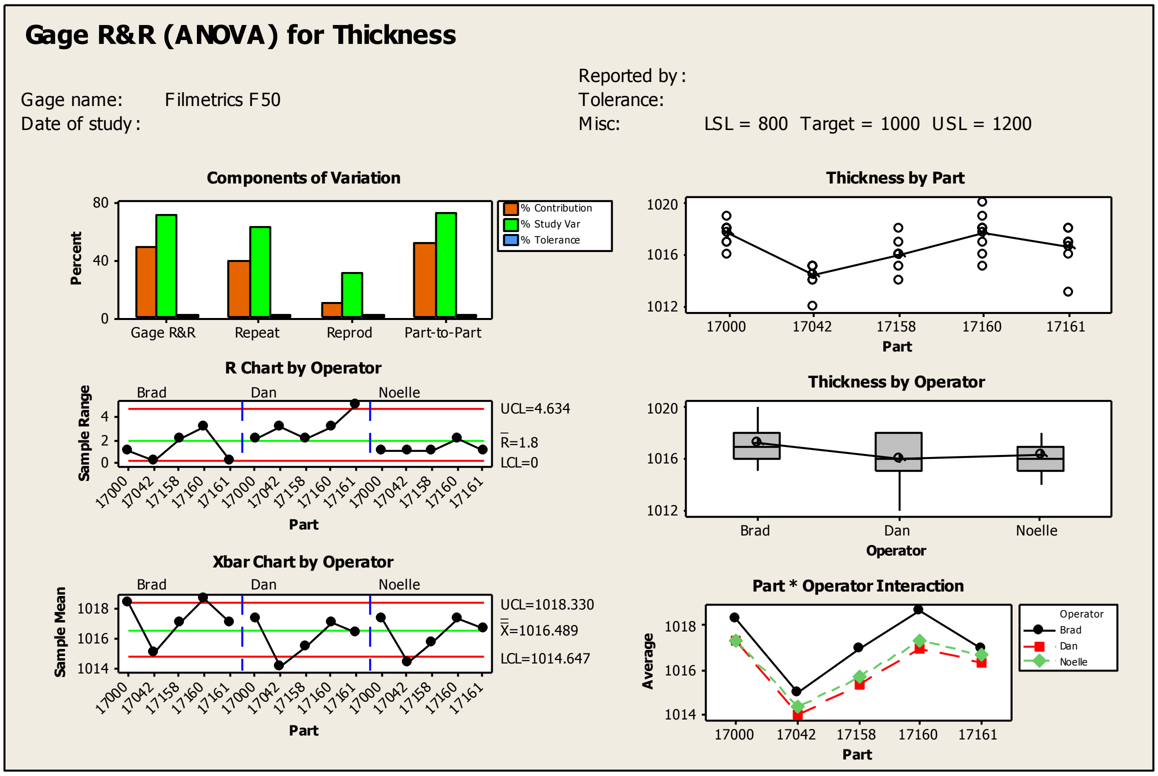
Gage R&R

Source	VarComp	%Contribution (of VarComp)
Total Gage R&R	1.58363	48.75
Repeatability	1.27135	39.14
Reproducibility	0.31228	9.61
Operator	0.31228	9.61
Part-To-Part	1.66491	51.25
Total Variation	3.24854	100.00

Process tolerance = 400

Source	StdDev (SD)	Study Var (6 * SD)	%Study Var (%SV)	%Tolerance (SV/Toler)
Total Gage R&R	1.25842	7.5505	69.82	1.89
Repeatability	1.12754	6.7652	62.56	1.69
Reproducibility	0.55882	3.3529	31.00	0.84
Operator	0.55882	3.3529	31.00	0.84
Part-To-Part	1.29031	7.7419	71.59	1.94
Total Variation	1.80237	10.8142	100.00	2.70

Number of Distinct Categories = 1



Summary

Tool	Status
Tencor	Acceptable
Tencor P – 6	Acceptable
Filmetrics F50	Acceptable (depending on tolerance)

Chapter 5: Minitab PowerPoint Presentations

Introduction

The Microfabrication Department at Draper (Cambridge location) primarily uses Excel and MATLAB to perform its data analysis. Draper has a license for Minitab, although many people are unfamiliar with the program. One of my supervisors asked me to learn Minitab and then create PowerPoint presentations about it. Specifically, he wanted me to pick statistical methods I thought would be most useful and applicable in the department, and then show how to execute them in Minitab. Other employees could later refer to the presentations to find out which specific statistical test to choose and how to carry it out. The goal is that employees will utilize Minitab more often for data analysis.

Data/Variables

I used a variety of data for these presentations. I used Draper's data (some collected by myself, some from others), data I found online, and data from my previous courses as WPI.

Presentations

I created four presentations about Minitab:

1. Introduction/Basics
    a. Minitab Environment
    b. Uploading Data to Minitab/Saving Projects
    c. Graphical Summary
    d. Normality Test
    e. Descriptive Statistics
    f. Confidence Intervals and Plots
    g. ANOVA tables
    h. Hypothesis Tests
    i. One-Way ANOVA
    j. Tukey Comparisons
    k. Standardizing Data

2. Quality Control
    a. Control Charts
        i. X Bar and R chart
        ii. X Bar and S chart
        iii. Individuals and MR chart
        iv. EWMA chart
        v. CUSUM chart
        vi. P, C, and U chart
        vii. T^2 chart
    b. Capability Analysis
        i. C_P, C_{PL}, C_{PU}, C_{PK}, C_{PM}

3. Gage R & R Studies
    a. ANOVA vs. Xbar – R methods
    b. Nested vs. Crossed

4. Design of Experiments
    a. Terminology
    b. Factorial Designs
        i. Full Factorial Design
        ii. General Full Factorial Design
        iii. Fractional Factorial Design
        iv. Screening Experiments
        v. Replication
        vi. Blocking
        vii. Interaction Plots
    c. Split Plot Designs
    d. Response Surface Designs
        i. Central Composite Design
        ii. Box Behnken Design
        iii. Contour/Surface Plots
        iv. Optimization

Figure 49 displays example pages of the presentation.

Figure 49: Example slides of Minitab Presentation

a.) Table for Determining What Control Chart to Use

TYPES OF CONTROL CHARTS

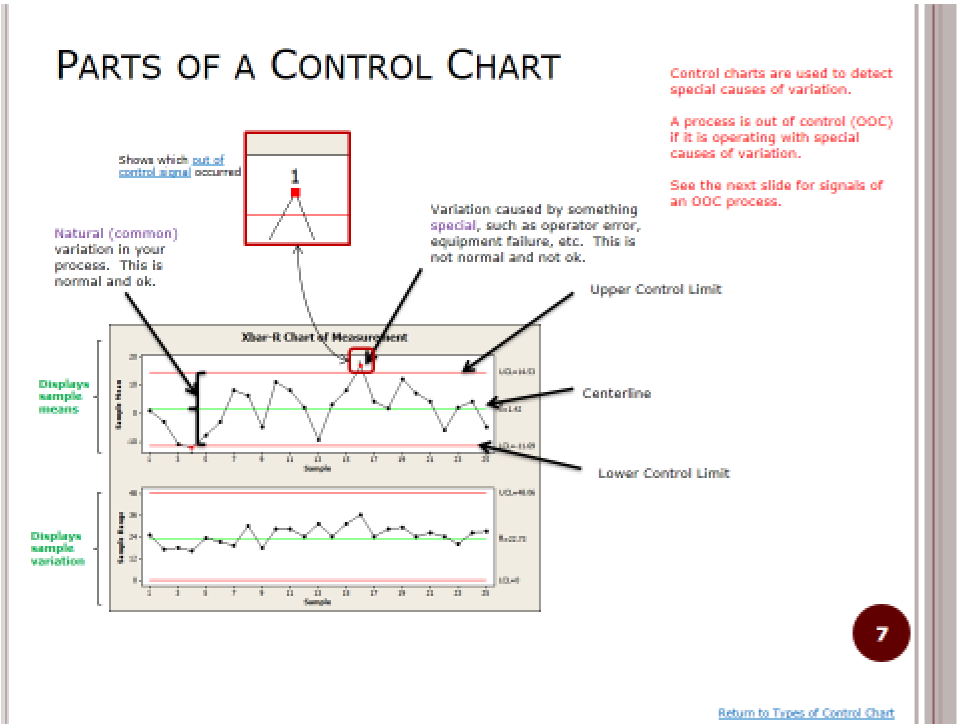
* Click on the links to jump to that page in the presentation. *

Chart	Use This Chart When... You have...	You have...	You want to find...
Xbar – R Chart	One Variable- Measurement Data	A sample at each time t. Samples can be different sizes	Out of control signals, **large process shifts** ($\geq 1.5\sigma$)
Xbar – S Chart	One Variable- Measurement Data	A sample at each time t. Samples can be different sizes.	Out of control signals, **large process shifts** ($\geq 1.5\sigma$)
I – MR Chart	One Variable- Measurement Data	Individual measures (sample size =1) at each time t	Out of control signals, **large process shifts** ($\geq 1.5\sigma$)
EWMA Chart	One Variable- Measurement Data	Either samples or individual measures at each time t	Out of control signals, **small process shifts** ($< 1.5\sigma$)
CUSUM Chart	One Variable- Measurement Data	Either samples or individual measures at each time t	Out of control signals, **small process shifts** ($< 1.5\sigma$)
P Chart	Attribute (Categorical) Data	A sample at each time t. Samples can be different sizes	The fraction of non-conforming units p, **large process shifts** ($\geq 1.5\sigma$)
C Chart	Attribute (Categorical) Data	Samples that are all the same size	The # of non-conformities in a sample, **large process shifts** ($\geq 1.5\sigma$)
U Chart	Attribute (Categorical) Data	Samples that differ in size	The # of non-conformities per unit in a sample, **large process shifts** ($\geq 1.5\sigma$)
T^2 Chart	Several Variables- Measurement Data	A sample at each time t, for each variable- considering variables jointly, rather than separately	Out of control signals, **large process shifts** ($\geq 1.5\sigma$),

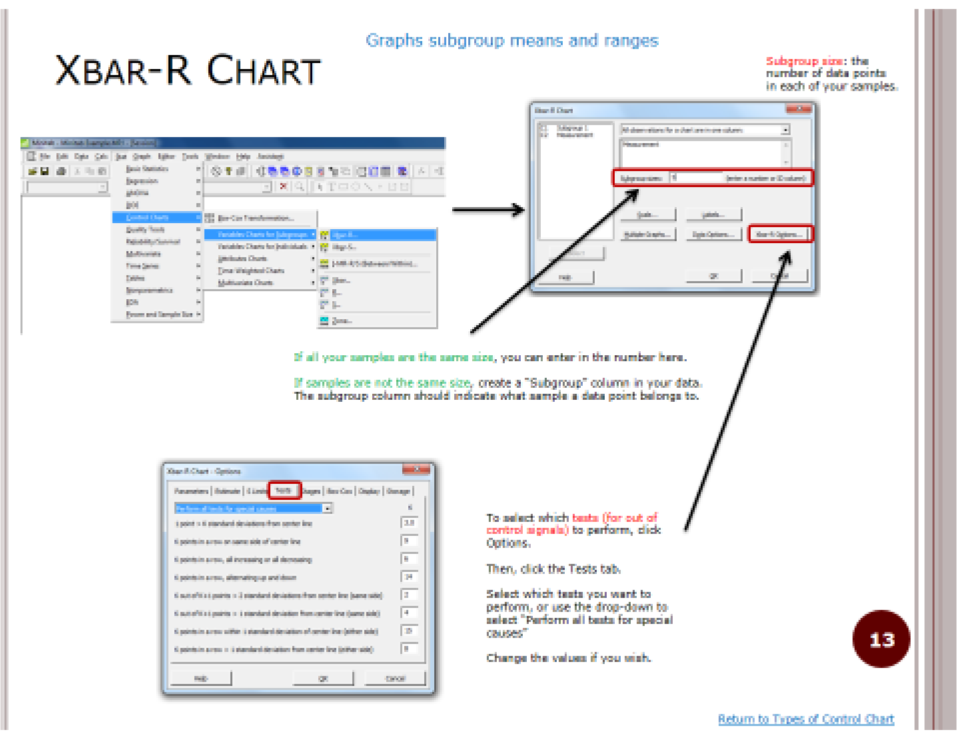
σ = standard deviation

5

b.) Parts of a Control Chart



c.) Example of How to Set Up an Xbar – R Chart



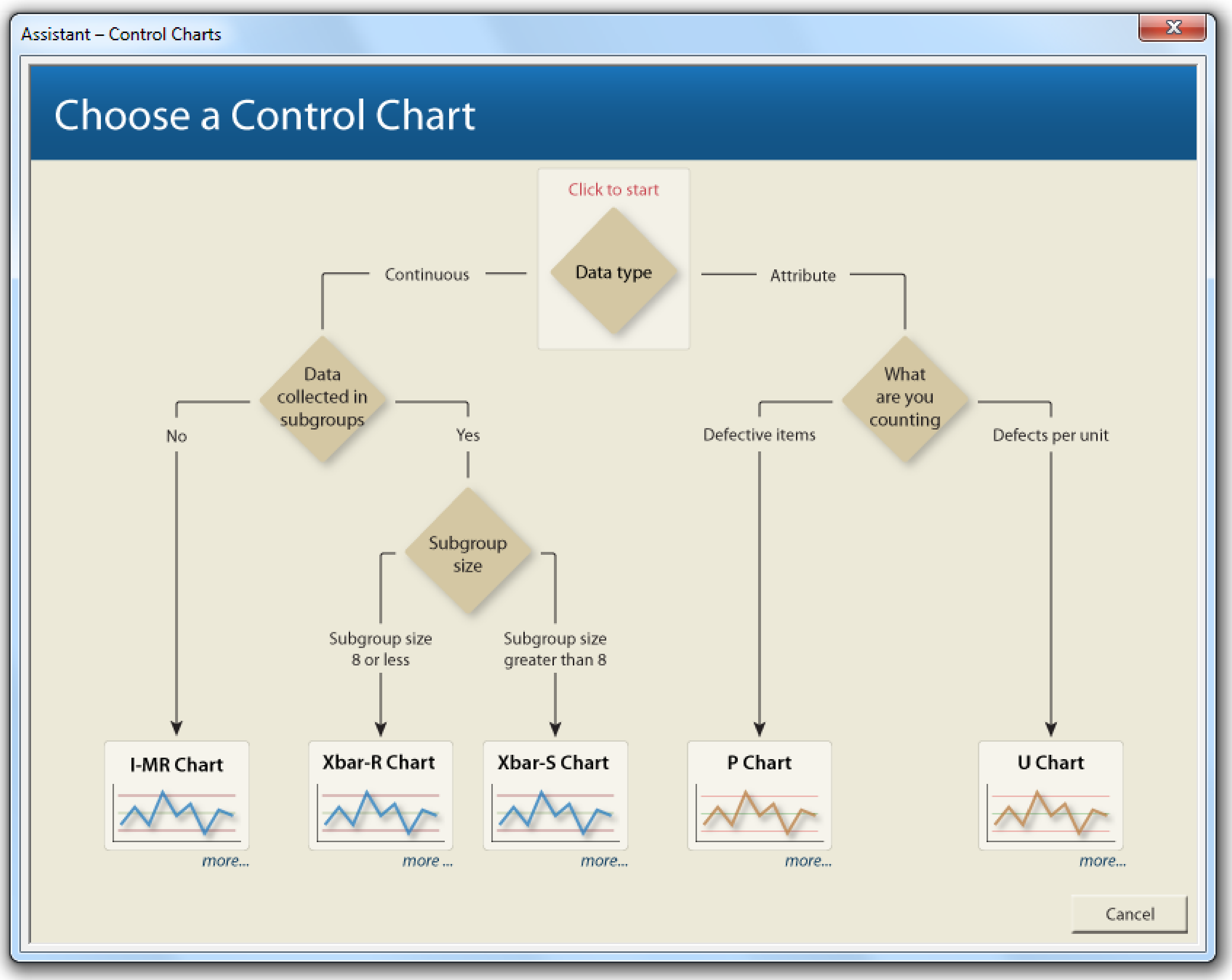
Conclusions/Critique

I found Minitab to be a very easy and straightforward program to learn. For those unfamiliar with statistics, Minitab's "Assistant" feature will be very helpful. Assistant has the user follow a flow chart of questions to help them figure out what particular statistical test to choose. Assistant will also output interpretations and warnings for the user. Figure 50 displays Assistants "flow chart" for control charts. However, take note that Assistant's flow charts often do not include all available options. Referring back to Figure 50, notice that EWMA, CUSUM, and C-charts are not listed in the flow chart, but they are available in the drop-down menu.

In addition, while creating these presentations and using Minitab on a regular basis, I noticed some limitations with the program. There are many features that Minitab lacks, which other programs, such as SAS, do have. For example, SAS has the ability to fit generalized linear models, which are used for non-normal data. Minitab, to my knowledge, does not have this feature.

Nevertheless, for the type of data that the Microfabrication Department deals with every day, I believe Minitab is a good program to use, and has almost all of the necessary features.

Figure 50: Minitab's Assistant feature



Concluding Remarks

Over the summer, I learned how to apply statistics to real world situations, as well as the importance of thinking as both a statistician and an engineer. I learned new statistical methods, such as the Johnson Transformation, as well as a new statistical program (Minitab). I discovered that in most cases, data does not follow a normal distribution, or even one of the common non-normal distributions. Transformations sometimes work, but in most cases, you must look deeper into the data to find the source of non-normality. Understanding how a process works and exactly where the data comes from can help with this as well. Minitab is limited with regards to analysis for non-normal data, so a more involved program, such as SAS or R will be required.

Throughout this Master's capstone, I was able to complete projects that dealt with the following: exploratory data analysis, quality control (control charts and capability analysis) and Gage R & R studies. I also created PowerPoint presentations that can be used to teach technicians and engineer may types of statistical analyses and how to perform them in Minitab.

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