# Dynamic JMP Dashboard for optimizing tool maintenance in Semiconductor Processes

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# Abstract

**Title:**
**Dynamic JMP Dashboard for optimizing tool maintenance in Semiconductor Processes**
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In the semiconductor industry, because of ongoing customer demand for lower cost devices, tool log data analysis is important for efficient tool usage. Deploying Tech Enabled services with JMP® (SAS institute) visualization tools allow us to become more efficient in responding to maintenance events. Analyzing the process runs using JMP distribution, histogram, and boxplot options helps to focus on the problem areas and reduce the maintenance duration. Wilcoxon non-parametric test is applied to perform hypothesis study on the tool down duration to check variation with respect to target and to determine the confidence interval for maintenance events. JMP quality and control Pareto plot and Ishikawa cause and effect diagram is implemented for root cause analysis and action plans. Dynamic JMP dashboard displaying box plot along with the above performance tests facilitated for better planning of maintenance activities and assigning priority. Dependency of PM success and failure on PM types were reported by quick visualization from JMP Dashboard.

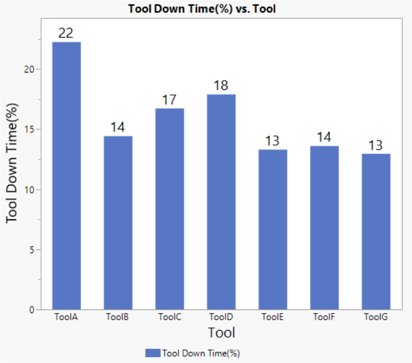
# Dynamic JMP Dashboard for optimizing tool maintenance in Semiconductor Processes

## Introduction

- In the semiconductor industry, deploying tech enabled services enable efficient tool usage. Accordingly, minimizing tool down time is a high value problem.
- Optimizing the Preventive Maintenance(PM) duration on tool is a key driver for enhanced tool performance
- Better PM Services = Better Yield = Higher customer satisfaction
- JMP® (SAS institute) visualization tools is one of the reliable platforms for statistical exploration.
- Dynamic JMP dashboard displaying performance tests can facilitate better planning of PM activities.

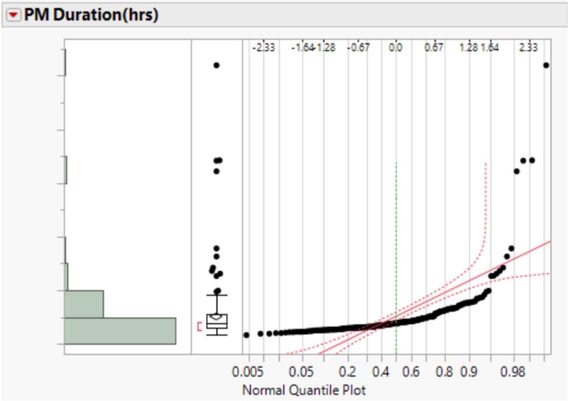
## Methods & Objectives

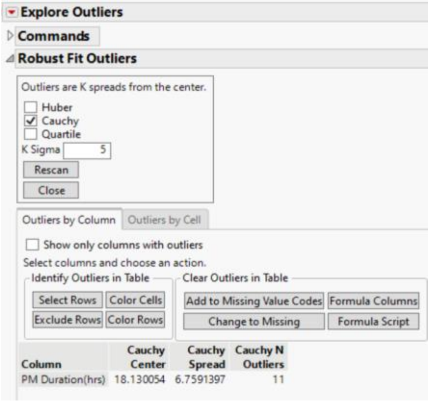
- Objective is to identify the improvement opportunities in Production Down Time during different types of PMs
- To prioritize the tools for optimizing PM procedures, down time for different tools are studied from the log data using JMP graph builder
- Next, the distribution models are fitted to identify the deviation from normality.
- Non-parametric ANOVA approach is applied to perform hypothesis study to check variation among four PM events.
- A quick and interactive dashboard is developed for analyzing tool down time with PM performance

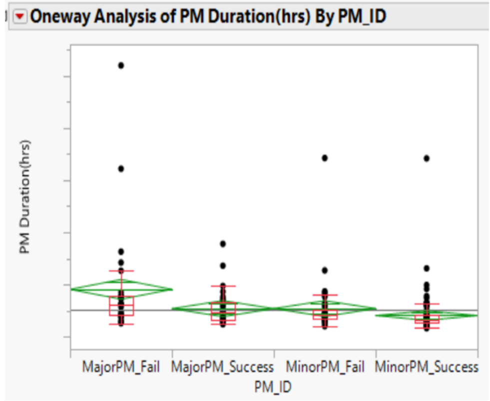


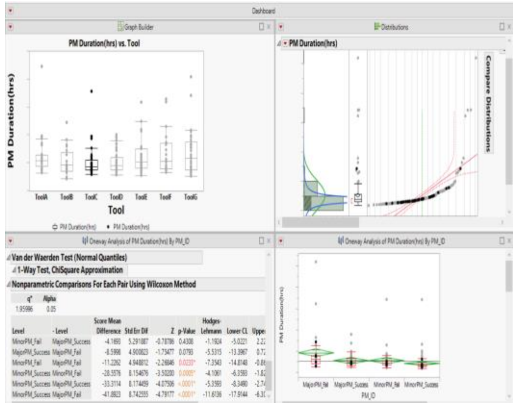

## Results

*Click graphs to enlarge*



## Conclusions

- First-time PM success has high impact on Minor PMs
- First-time PM success has negligible impact on Major PMs
  - Median PM duration of First-time PM Success & Fail are equivalent
- Next step is Tool wise analysis to identify the scope of improvement



## References & Acknowledgements

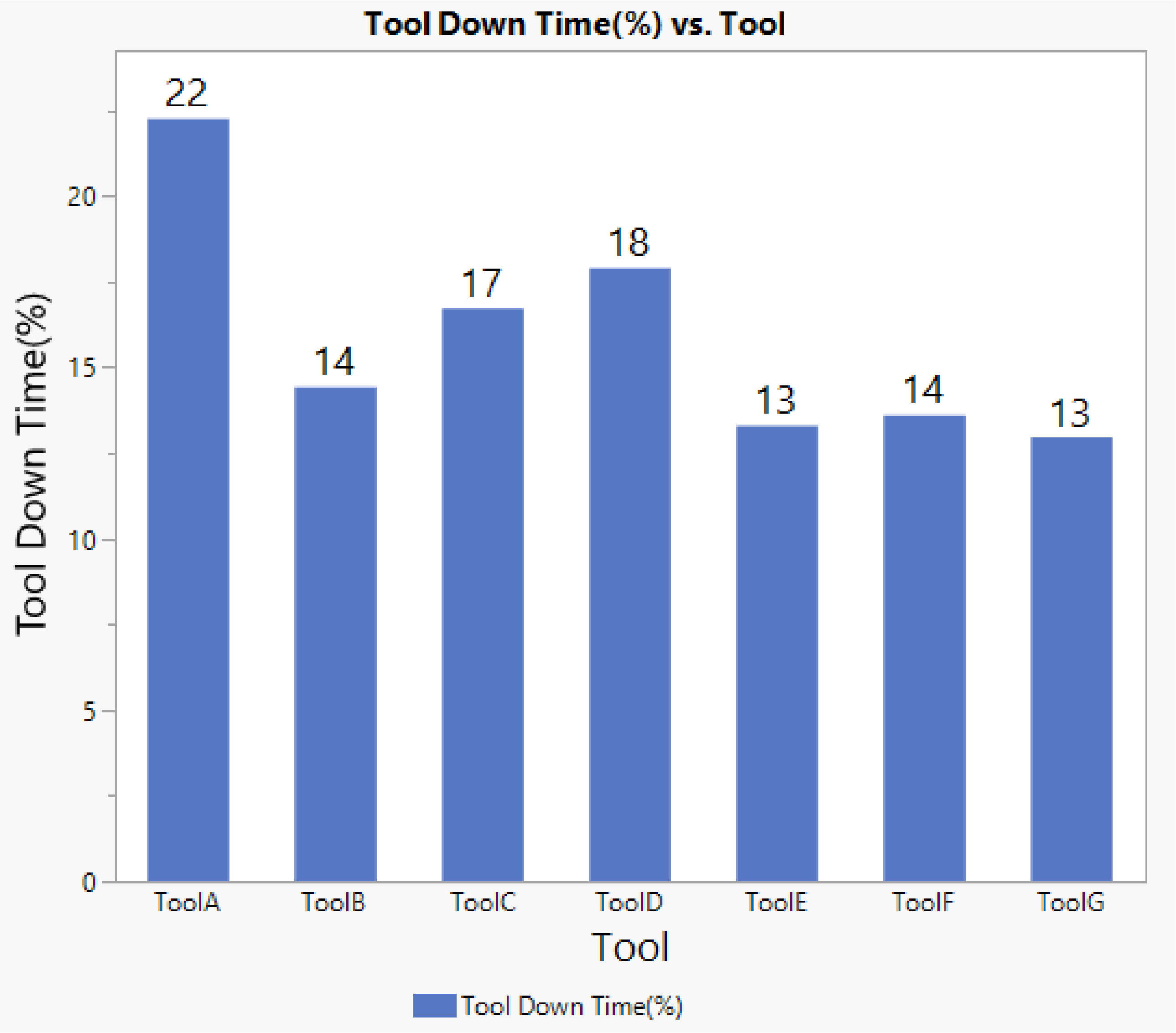
Thanks to the below people for helping and supporting the study:
- Charles C Chen
- Chandrasekhar Roy, Vikas Jangra, Sidda Reddy Kurakula

References:

1. Statistical Thinking for Industrial Problem Solving (STIPS) Course
https://www.jmp.com/en_in/online-statistics-course.html

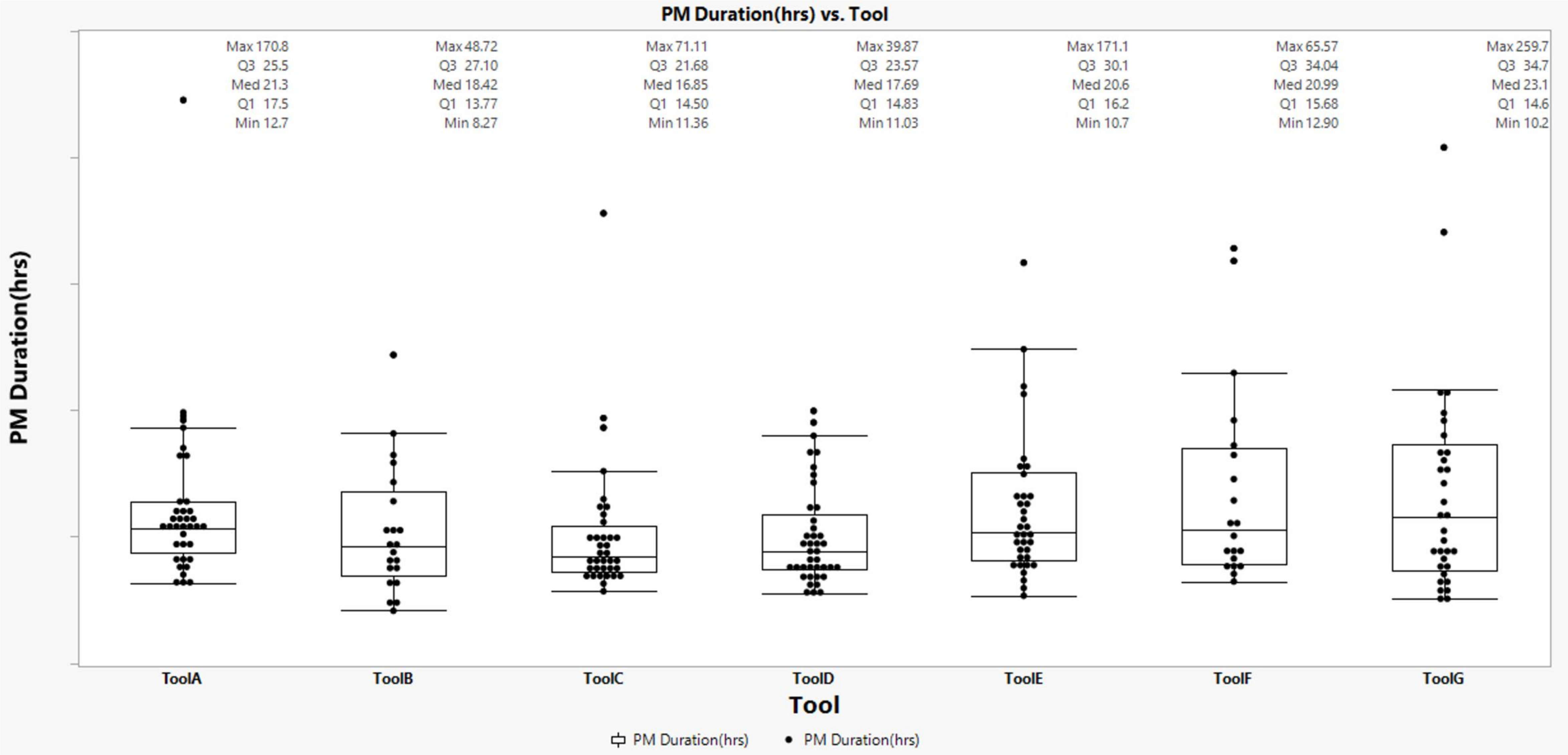
APPLIED MATERIALS

# Tool Down %



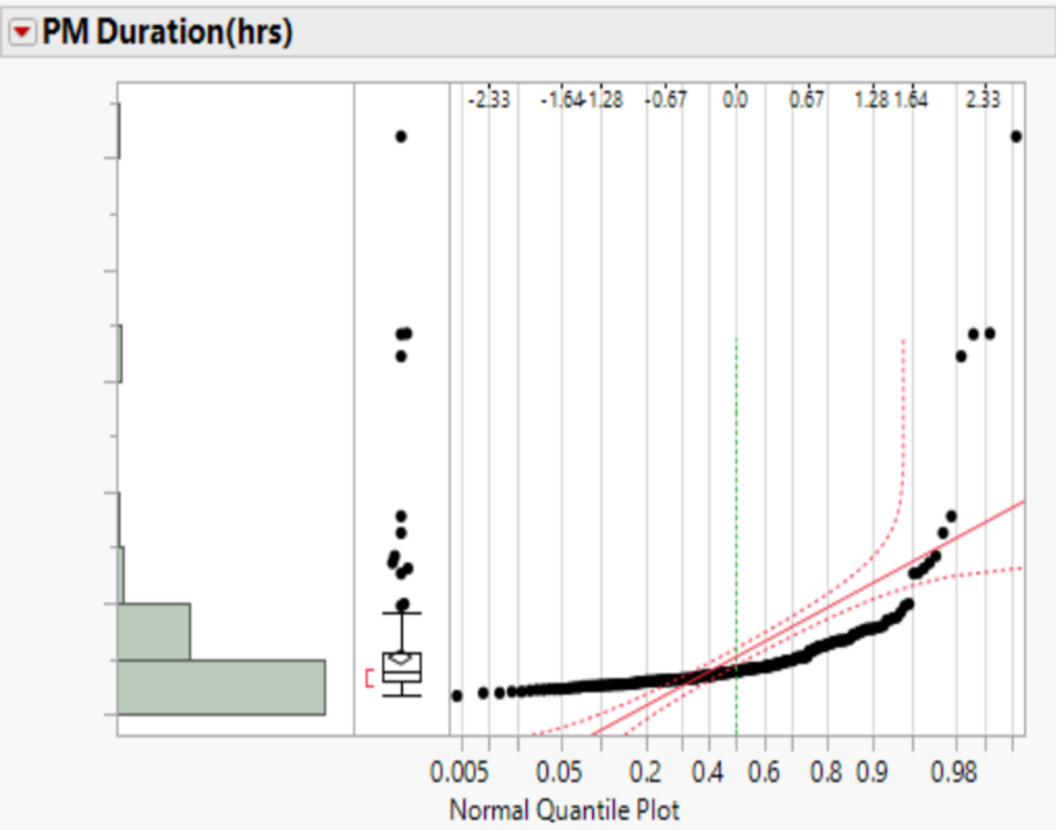

ToolA has highest Tool Down % - Top priority tool for improvement

# Box plot




ToolE has a greater number of data points on the upper side; needs process control

# Distribution Model fitting




**Summary Statistics**

| | |
|---|---|
| Mean | 25.874778 |
| Std Dev | 25.97823 |
| Skewness | 5.6878925 |
| Kurtosis | 39.984869 |
| Autocorrelation | -0.00345 |
| Median | 19.351259 |
| Interquartile Range | 12.688298 |
| Robust Mean | 22.151823 |

**Fitted Normal Distribution**

| Parameter | | Estimate | Std Error | Lower 95% | Upper 95% |
|---|---|---|---|---|---|
| Location | μ | 25.874778 | 1.7357435 | 22.454219 | 29.295336 |
| Dispersion | σ | 25.97823 | 1.2314862 | 23.774706 | 28.635456 |

| Measures | |
|---|---|
| -2*LogLikelihood | 2093.9364 |
| AICc | 2097.9907 |
| BIC | 2104.7597 |

**Goodness-of-Fit Test**

| | W | Prob<W |
|---|---|---|
| Shapiro-Wilk | 0.4497015 | <.0001* |

| | $A^2$ | Simulated p-Value |
|---|---|---|
| Anderson-Darling | 32.620314 | <.0001* |

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

**Fitted Cauchy Distribution**

| Parameter | | Estimate | Std Error | Lower 95% | Upper 95% |
|---|---|---|---|---|---|
| Location | μ | 18.130101 | 0.4700431 | 17.231911 | 19.079091 |
| Scale | σ | 4.5061286 | 0.4085019 | 3.772644 | 5.3838418 |

| Measures | |
|---|---|
| -2*LogLikelihood | 1731.5138 |
| AICc | 1735.5681 |
| BIC | 1742.3371 |

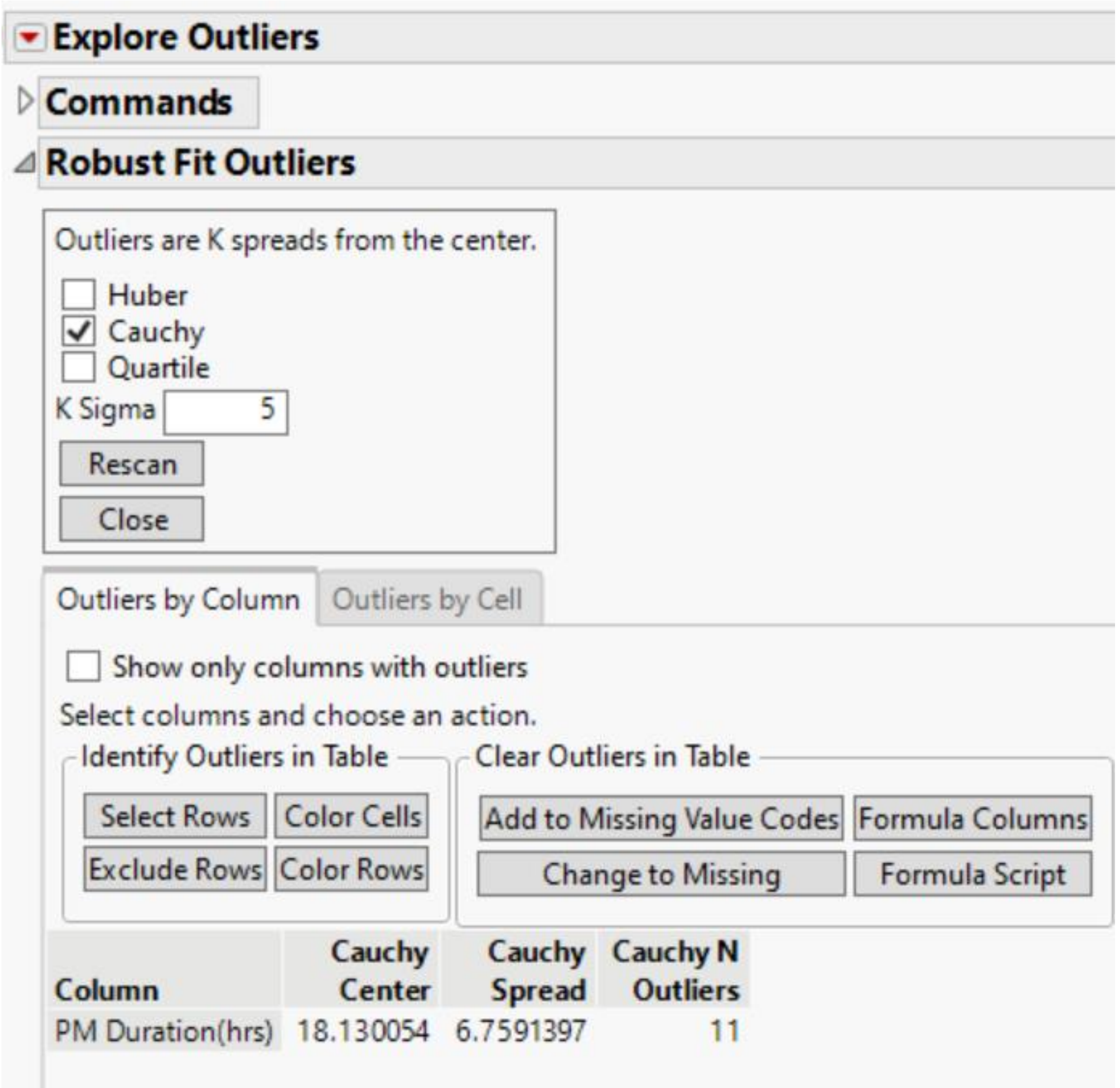
**Goodness-of-Fit Test**

| | $A^2$ | Simulated p-Value |
|---|---|---|
| Anderson-Darling | 11.483636 | 0.0920 |

Note: Ho = The data is from the Cauchy distribution. Small p-values reject Ho.

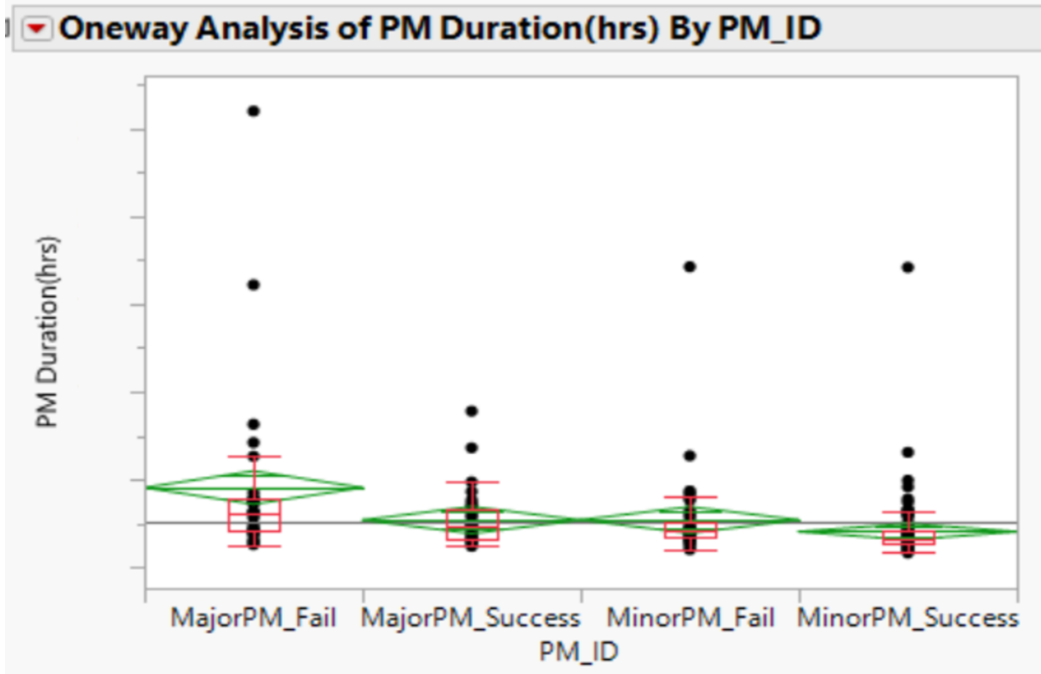
As dataset is right skewed, Cauchy is the best fit

# Outliers and Dashboard




11 Outlier points found for root cause analysis

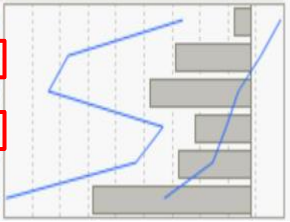
# Non-parametric test




**Nonparametric Comparisons For Each Pair Using Wilcoxon Method**

| q* | Alpha |
|---|---|
| 1.95996 | 0.05 |

| Level | - Level | Score Mean Difference | Std Err Dif | Z | p-Value | Hodges-Lehmann | Lower CL | Upper CL | Difference Plot |
|---|---|---|---|---|---|---|---|---|---|
| MinorPM_Fail | MajorPM_Success | -4.1693 | 5.291887 | -0.78786 | 0.4308 | -1.1924 | -5.0221 | 2.22141 | |
| MajorPM_Success | MajorPM_Fail | -8.5998 | 4.900823 | -1.75477 | 0.0793 | -5.5315 | -13.3967 | 0.72632 | |
| MinorPM_Fail | MajorPM_Fail | -11.2262 | 4.948812 | -2.26846 | 0.0233* | -7.3543 | -14.8148 | -0.86843 | |
| MinorPM_Success | MinorPM_Fail | -28.5576 | 8.154676 | -3.50200 | 0.0005* | -4.1061 | -6.3593 | -1.82411 | |
| MinorPM_Success | MajorPM_Success | -33.3114 | 8.174459 | -4.07506 | <.0001* | -5.3593 | -8.3490 | -2.74757 | |
| MinorPM_Success | MajorPM_Fail | -41.8923 | 8.742555 | -4.79177 | <.0001* | -11.6136 | -17.9144 | -6.30475 | |



**Wilcoxon / Kruskal-Wallis Tests (Rank Sums)**

| Level | Count | Score Sum | Expected Score | Score Mean | (Mean-Mean0)/Std0 |
|---|---|---|---|---|---|
| MajorPM_Fail | 27 | 4278.00 | 3037.50 | 158.444 | 3.927 |
| MajorPM_Success | 41 | 5564.00 | 4612.50 | 135.707 | 2.535 |
| MinorPM_Fail | 42 | 5330.00 | 4725.00 | 126.905 | 1.597 |
| MinorPM_Success | 114 | 10028.0 | 12825.0 | 87.965 | -5.767 |

**Kruskal-Wallis Test, ChiSquare Approximation**

| ChiSquare | DF | Prob>ChiSq |
|---|---|---|
| 37.2418 | 3 | <.0001* |

**Median Test (Number of Points Above Median)**

| Level | Count | Score Sum | Expected Score | Score Mean | (Mean-Mean0)/Std0 |
|---|---|---|---|---|---|
| MajorPM_Fail | 27 | 22.000 | 13.500 | 0.814815 | 3.481 |
| MajorPM_Success | 41 | 27.000 | 20.500 | 0.658537 | 2.241 |
| MinorPM_Fail | 42 | 26.000 | 21.000 | 0.619048 | 1.708 |
| MinorPM_Success | 114 | 37.000 | 57.000 | 0.324561 | -5.334 |

**1-Way Test, ChiSquare Approximation**

| ChiSquare | DF | Prob>ChiSq |
|---|---|---|
| 31.1022 | 3 | <.0001* |

**Van der Waerden Test (Normal Quantiles)**

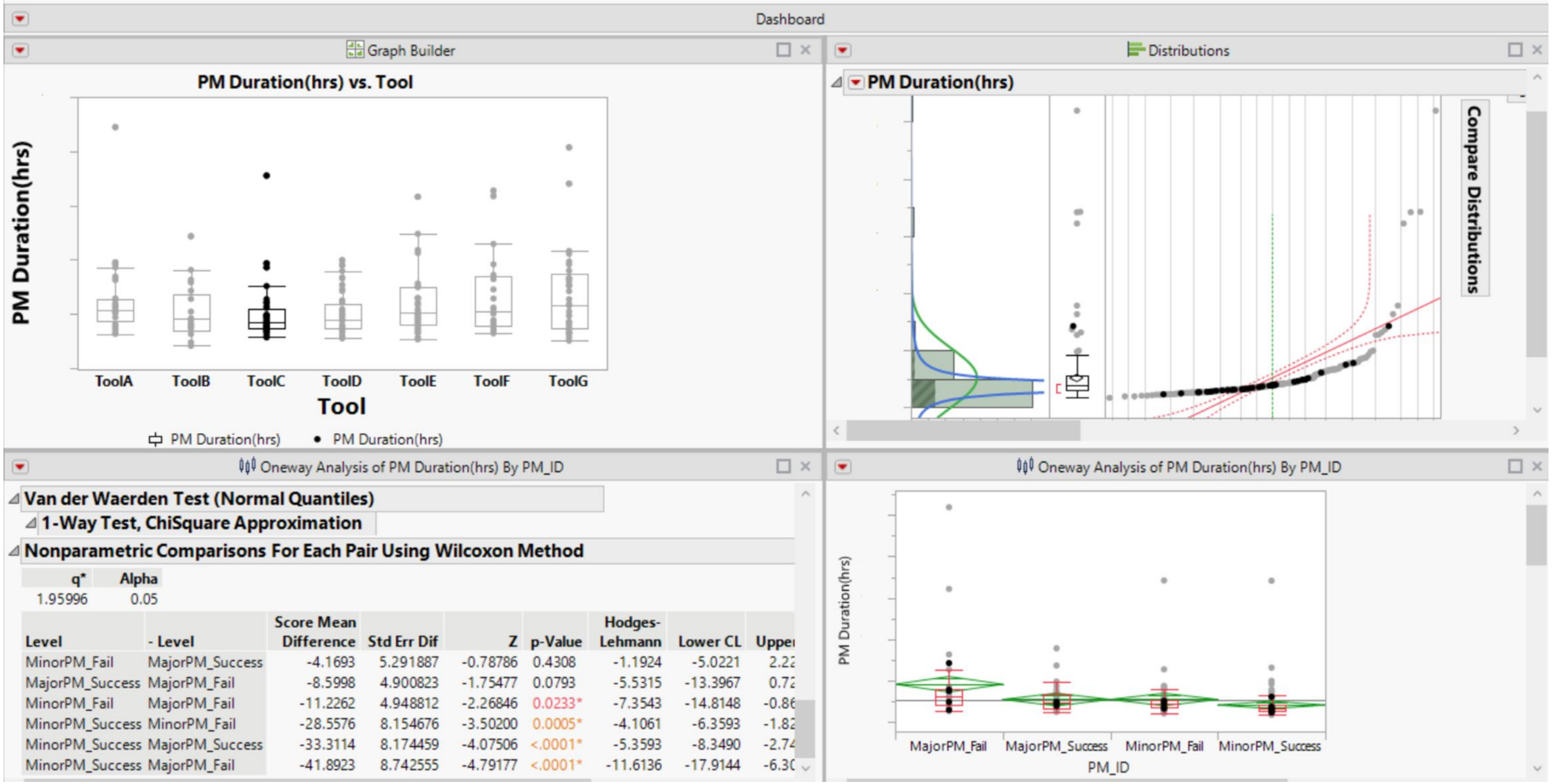
| Level | Count | Score Sum | Expected Score | Score Mean | (Mean-Mean0)/Std0 |
|---|---|---|---|---|---|
| MajorPM_Fail | 27 | 19.644 | 0.000 | 0.72757 | 4.107 |
| MajorPM_Success | 41 | 13.786 | 0.000 | 0.33625 | 2.427 |
| MinorPM_Fail | 42 | 8.565 | 0.000 | 0.20394 | 1.494 |
| MinorPM_Success | 114 | -41.996 | 0.000 | -0.36838 | -5.719 |

**1-Way Test, ChiSquare Approximation**

| ChiSquare | DF | Prob>ChiSq |
|---|---|---|
| 37.5238 | 3 | <.0001* |

- MinorPM_Success and MinorPM_Fail are significantly different based on p-value
- MajorPM Success and MajorPM_Fail are not significantly different based on p-value

# Dashboard




Quick reporting on dependency of PM success and failure on PM types

APPLIED MATERIALS®

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