

# **Data Mining Study of Surface Roughness**



### Introduction

- Surface roughness measurement is the most critical indicator of defect performance in semiconductor and display industry fabrication as roughness adversely degrades device electrical characteristics and impacts lifespan.
- This project aims to create JMP Analytics package. capable to detect the Normality Violation Modes associated with Surface Roughness Measurement Metric for Root Cause Analysis and Process Tuning.

### Methodology

Project was deployed as shown below:

- Data simulation: JMP Random Simulation was used to create Simulated Roughness Z profile data into six Normality Violation Modes
- **13 variables calculation**: 5 Surface Roughness Variables and 8 Distribution Descriptive Statistics were calculated
- Clustering methods analysis: Different clustering methods were compared to see if they're powerful to differentiate 6 distributions into Light Tail Cluster and Discrete Points, and to group 13 variables into Peak Sensitive Cluster, Asymmetric Sensitive Cluster and Light Tail cluster.
- **JMP Workflow builder**: workflow was built to save time and enable more effective collaboration on projects while reducing variation and errors

Normal		Uniform		Heavy Tail -		-Right Skewed		Bimodal		Outliers (3%)		
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
	0.00	1.00	-0.00	1.00	-0.00	1.00	0.00	1.00	-0.00	1.00	0.00	1.00

#### Results





#### 2<sup>nd</sup> Hypothesis (13 variables)



## **Conclusions**

Different clustering methods were compared to evaluate surface roughness.  $\checkmark$ 

RSquare with

Next Closest 0.459

0.46

0.373

0.282

0.288

0.366

0.047

0.054

0.26

0.309

0.33

0.536

0.982

0.978

0.958

0.857

0.846

0.983

0.949

0.857

0.844

0.986

0.985

0.97

0.032

0.033

0.035

0.058

0.201

0.243

0.055

0.151

0.211

0.02

0.022

0.064

JMP Surface Roughness clustering workflow was built to detect process failure mode and shorten ✓ troubleshooting time, and to promote data mining application in Applied Materials.

### **References & Acknowledgements**

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# **Data Collection and Hypothesis**



## 1. Data collection

- JMP Random Simulation platform was used to create Simulated Roughness Z profile data into six Normality Violation Modes.
- Five Surface Roughness Variables and eight Distribution Descriptive Statistics are calculated.

No	rmal	Uni	form	Heav	Heavy Tail -Right Skewed Bimodal Ou		-Right Skewed Bimodal		Outlie	rs (3%)	
Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
0.00	1.00	-0.00	1.00	-0.00	1.00	0.00	1.00	-0.00	1.00	0.00	1.00

# 2. Two Surface Roughness Hypothesis

- 1<sup>st</sup> Hypothesis (6 Distributions)
- Light Tail Cluster: Uniform and Bimodal
- Discrete Points: Heavy Tail, Right Skewed, Outliers



### Clustering History

Number of				
Clusters	Distance	Leader	Joiner	
5	0.574490659	Uniform	Bimodal	
4	2.094844123	Normal	Uniform	
3	3.726189839	Normal	Heavy Tail	
2	4.205819552	Normal	<b>Right Skew</b>	ed
1	5.358001471	Normal	Outliers (39	%)

2<sup>nd</sup> Hypothesis (5 Roughness and 8 Descriptive Statistics)

 1<sup>st</sup> Cluster (Peak Sensitive), 2<sup>nd</sup> Cluster (Asymmetry), 3<sup>rd</sup> Cluster (Light Tail)

Proportion of variation explained by clustering: 0.937 Cluster Members

Cluster	Members	RSquare with Own Cluster	RSquare with Next Closest	1-RSquare Ratio			
1	Kurtosis	0.983	0.459	0.032			
1	Rk	0.982	0.46	0.033			
1	Rz	0.978	0.373	0.035			
1	Robust Std Dev	0.958	0.282	0.058			
1	Rp	0.857	0.288	0.201			
1	Rv	0.846	0.366	0.243			
2	Skewness	0.983	0.047	0.018			
2	5% Trimmed	0.949	0.079	0.055			
2	Median	0.857	0.054	0.151			
2	Robust Mean	0.844	0.26	0.211			
3	IQR	0.986	0.309	0.02			
3	MAD	0.985	0.33	0.022			
3	Ra	0.97	0.536	0.064			

## **3. Select appropriate JMP Data Mining Platforms**



Data Mining Tasks	JMP Tool Menu	JMP Platform		
		Hierarchical Clustering		
Clustering (Unsupervised)	Applyzo >> Clustoring	K-Means Cluster		
	Analyze >> Clustering	Normal Mixtures		
		Cluster Variables		
	Analyze >> Multivariate	Multivariate		
Multivariate Statistics	Methods	Principal Components		
Quality and Process	Analyze >> Quality and Process	Model Driven Multivariate Contro Chart		



# 1<sup>st</sup> Hypothesis (6 Distributions)



# 1. K-means Cluster



» Different Cluster Numbers may impact the K-Means Clustering Patterns based on the first two Principal Components (questionable)

# 2. Hierarchical Cluster



#### Complete (Maximum)



» Different Clustering Method may impact the Hierarchical Clustering History among six distributions »4 K-means Clusters method has shown closer results with Hierarchical Clustering

## **3.** Principal Component Analysis, Relative Score Contribution Plot, T-Square Contribution Heat Map





- » PCA and Heat map has good detection power to differentiate 6 distributions.
- »Relative Score Plot has the best detection power
- »Heat Map can provide a better visualization capability, compared with other clustering tools



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# 2<sup>nd</sup> Hypothesis (13 Variables)



## 1. Cluster Variables vs. Multivariate Correlation



» Clustering Variables method has split 13 variables into 3 clusters, all > 0.8 of R-Square with own cluster

» Within each cluster, there are extremely strong correlations between Multivariate Correlation and Cluster Variables

## 2. Principal Component Analysis



» all three Loading Plots across the first three Principal Component Pairs show extremely strong correlations between PCA and Cluster Variables

### 3. Multivariate Model Driven Score Plot



» Score Plot has the same pattern as PCA Loading Plot since both are based on Principal Component Model







## 1. Summary

#### 1<sup>st</sup> Hypothesis (6 Distributions)

- Light Tail Cluster: Uniform and Bimodal
- Discrete Points: Heavy Tail, Right Skewed, Outliers

#### 2<sup>nd</sup> Hypothesis (5 Roughness, 8 Descriptive Statistics)

- 1<sup>st</sup> Cluster (Peak Sensitive)
- 2<sup>nd</sup> Cluster (Asymmetry)
- 3<sup>rd</sup> Cluster (Light Tail)

Data Mining Tasks	JMP Platform	Criteria	Hypothesis #1	Hypothesis #2
	Hierarchical Clustering	Clustering History	Fair	Good
Clustering (Unsupervised)	K-Means Cluster	Cluster Group ID	Fair	
Clustering (Onsupervised)	Normal Mixtures	Cluster Group ID	Poor	
	Cluster Variables	Cluster Members		Good
Multivariate Statistics	Multivariate	Correlations		Good
WUILIVALIALE STATISTICS	Principal Component Analysis	Loading Plot	Good	Good
Quality and Process	Model Driven Multivariate	Contributin Plot	Poor	
Quality and Process	Control Chart	Score Plot		Good
		Heat Map	Good	
		<b>Relative Contribution Plot</b>	Good	

- Data Mining techniques is more powerful to achieve the 2<sup>nd</sup> Hypothesis than the 1<sup>st</sup> Hypothesis
- Next Step: Establish Database (Roughness, Raw Z-Profile, Roughness Metric, Process Tuning)

## 2. JMP Workflow Builder

#### **Execute Function**

• able to skip the mess and frustration and get straight to experimentation and discovery

▼Workflow Builder	
S Execute the workflow	
Filter	◄ م
Import Excel file: New Microsoft Excel Worksheet.xlsx	
⊿ 1st Hypothesis (5/0)	
Hierachical Cluster (2/0)	
Hierarchical Cluster by Ward	
Hierarchical Cluster by Complete	
K Means Cluster	
Normal Mixtures	
2rd Hypothesis (6/0)	
Cluster Variables	
Multivariate	
Multivariate - Cluster 1	
Multivariate - Cluster 2	
Multivariate - Cluster 3	
Model Driven Multivariate Control Chart, Heat Map and Relative Score Plot	
Principle Components Analysis (3/0)	
Principal Components Analysis - Component 1 vs. Component 2	
Principal Components Analysis - Component 1 vs. Component 3	
Principal Components Analysis - Component 2 vs. Component 3	

- JMP Workflow Builder can save time and enable more effective collaboration on projects while reducing variation and errors, especially for JMP beginners
- Workflow can promote JMP Data Mining project applicable across Applied Materials