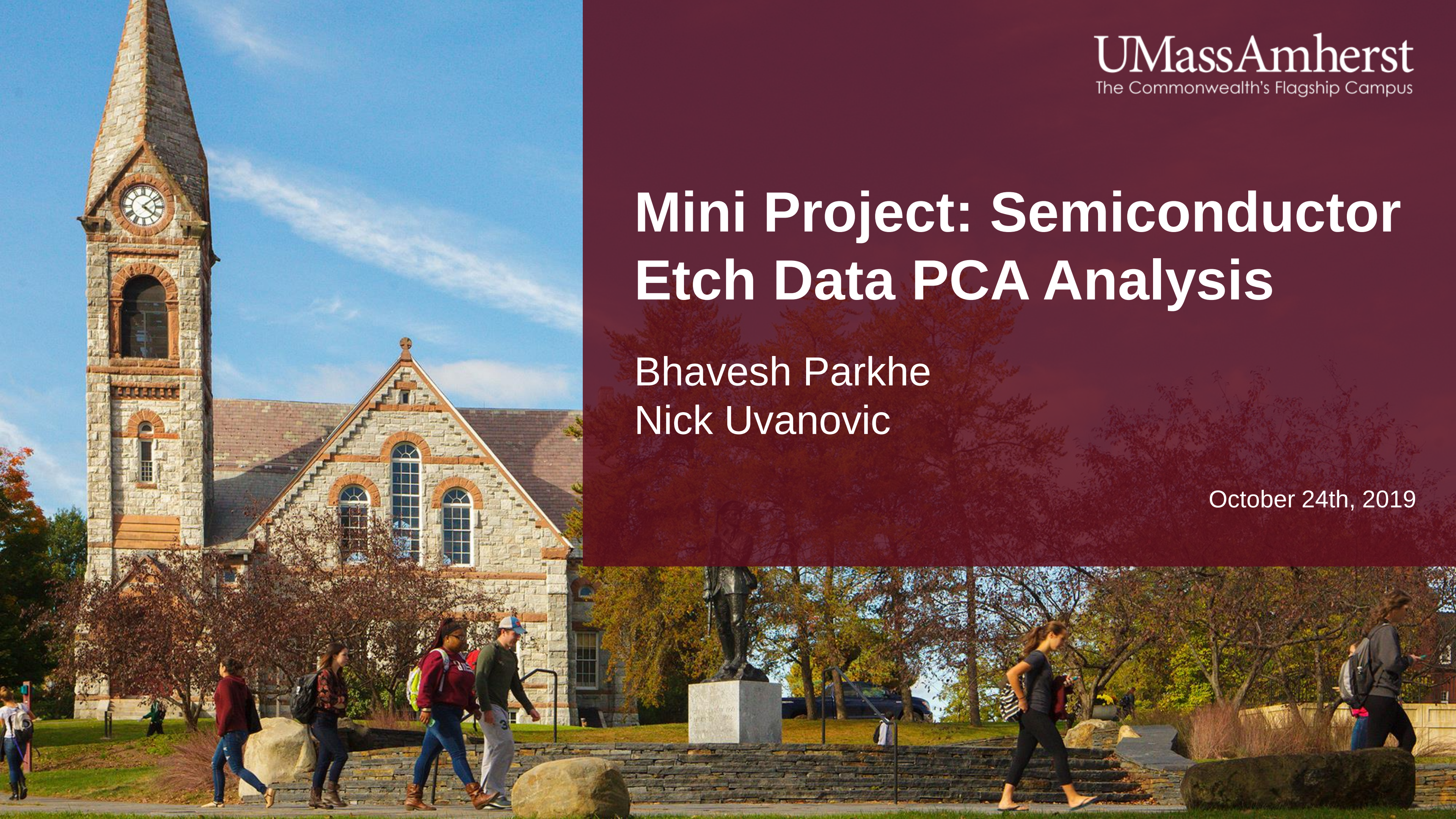

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Mini Project: Semiconductor Etch Data PCA Analysis

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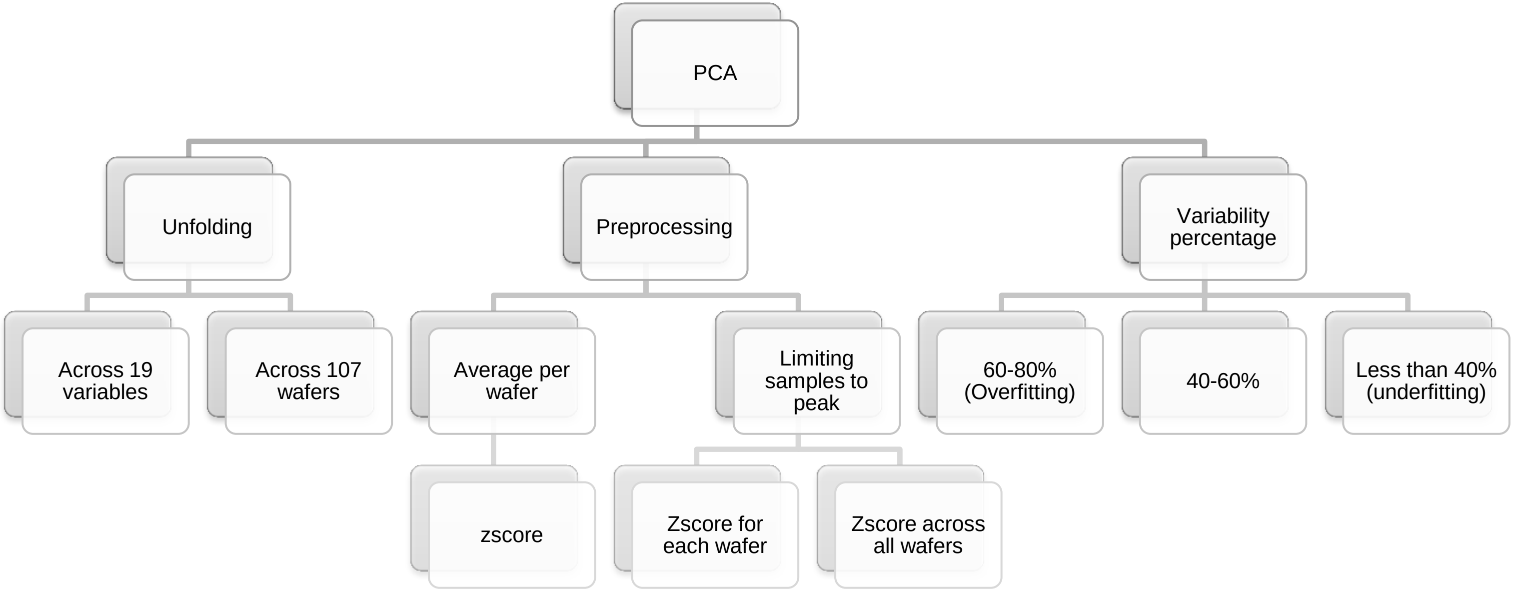
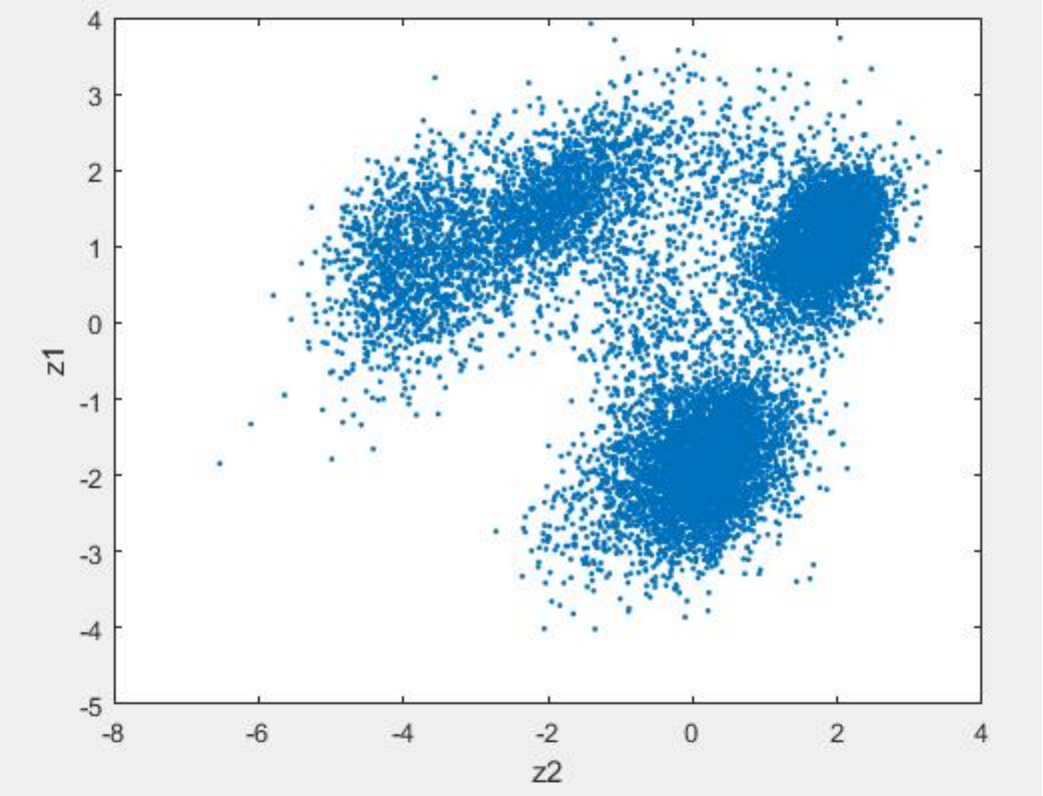
October 24th, 2019

Task 1 : Control Monitoring

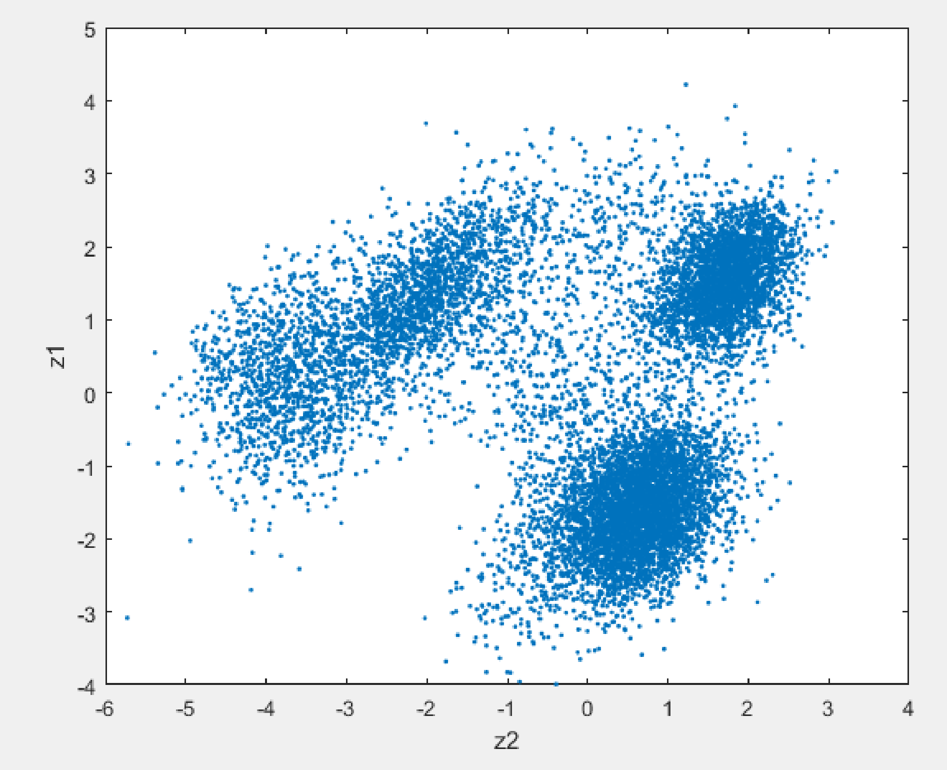
- Unfolding
- Preprocessing
- Decomposition
- Calculating T-square and determining control limits


PCA
Unfolding
Preprocessing
Variability percentage
Across 19 variables
Across 107 wafers
Average per wafer
Limiting samples to peak
60-80% (Overfitting)
40-60%
Less than 40% (underfitting)
zscore
Zscore for each wafer
Zscore across all wafers

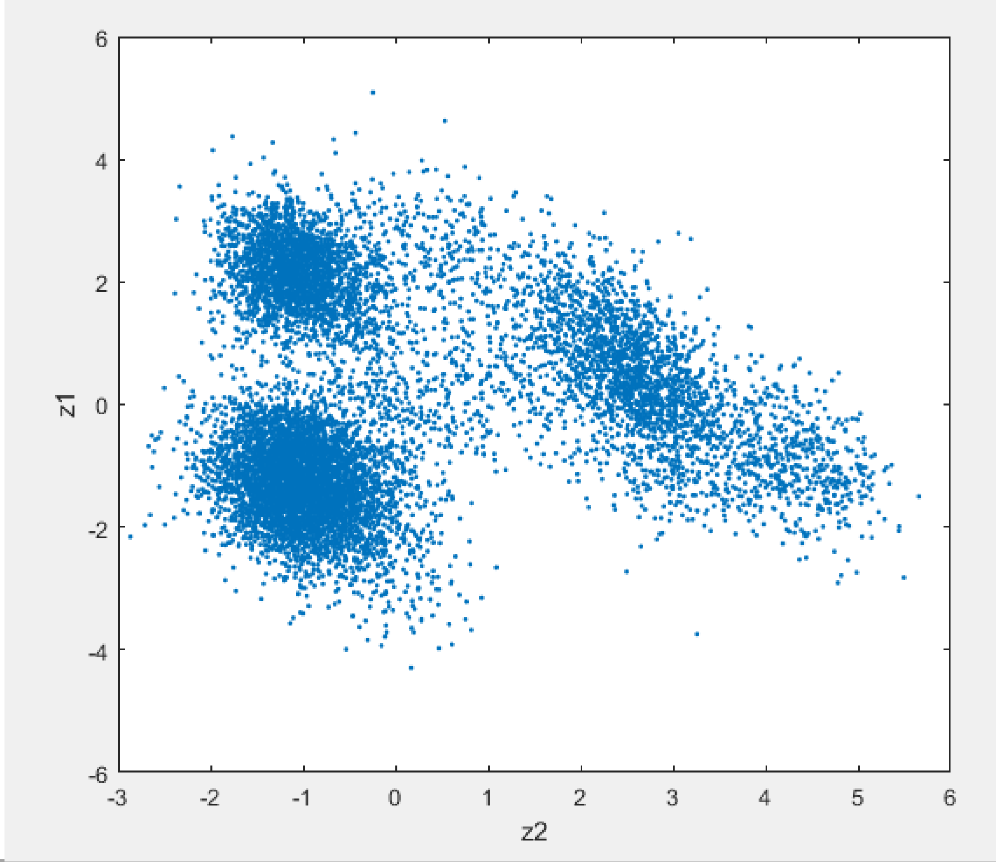
n = all, var = 32%, unfolded variables together



n = 90, var = 31.82%, unfolded variables together



n = 5-75, var = 32%, unfolded variables together



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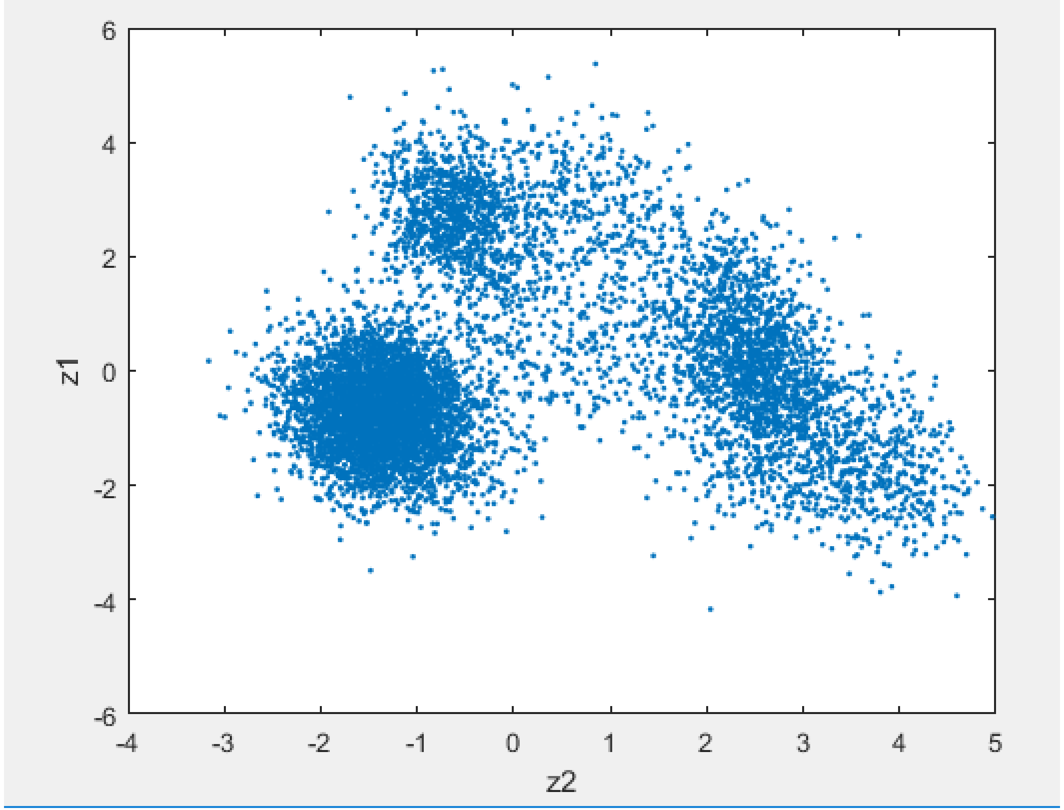
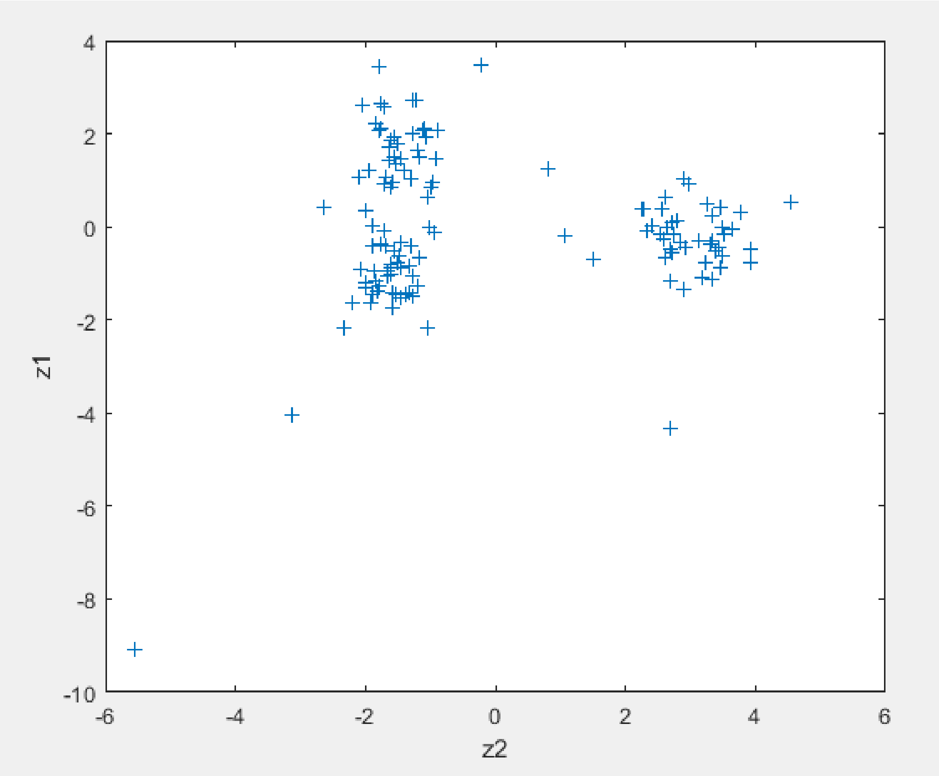
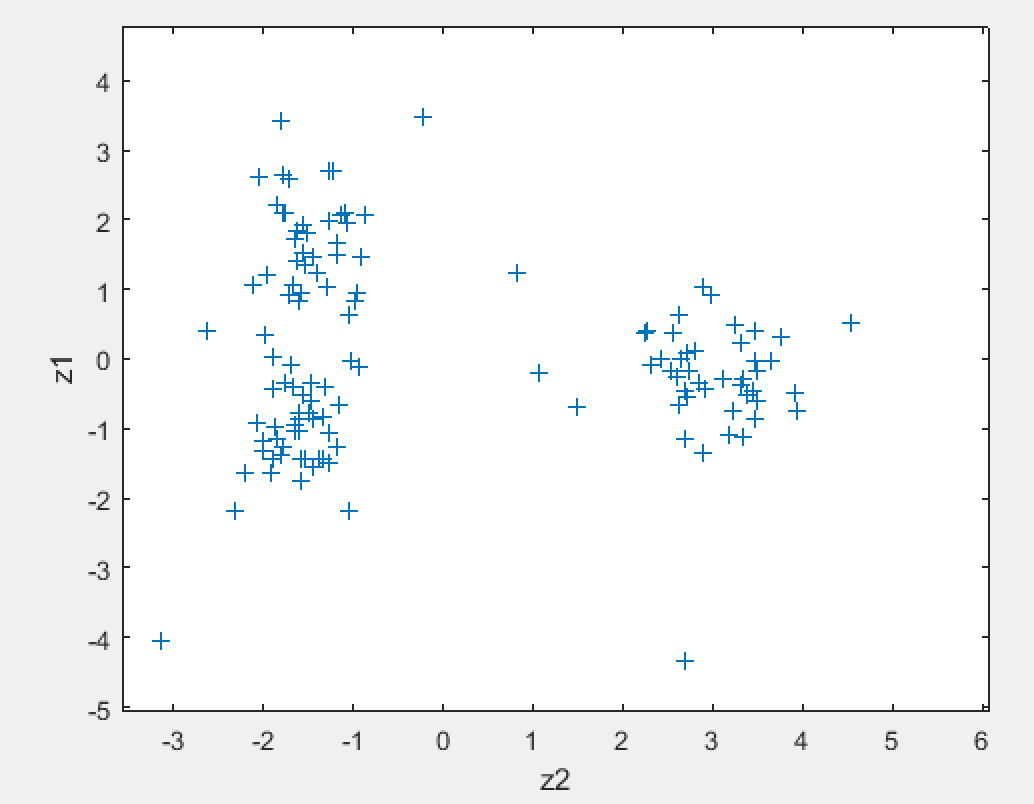
n = 10-75, var = 32%, unfolded variables together



n = 80, var = 40%, unfolded average of each wafer



n = 70, var = 40%, unfolded average of each wafer



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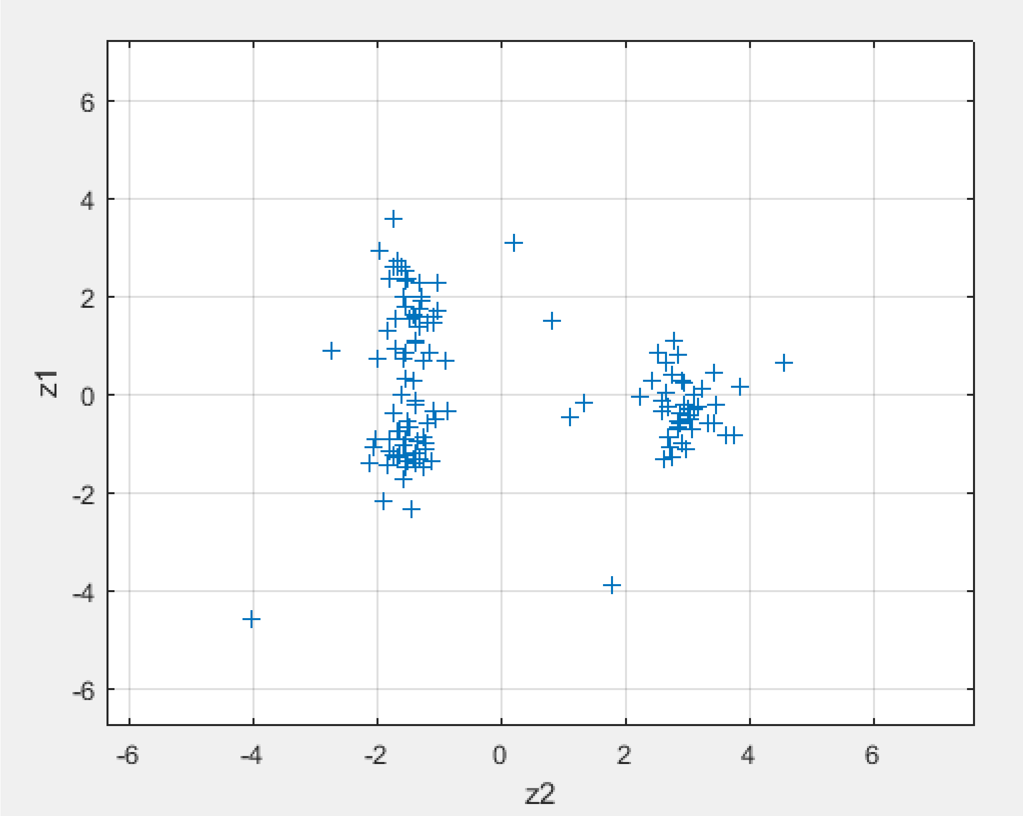
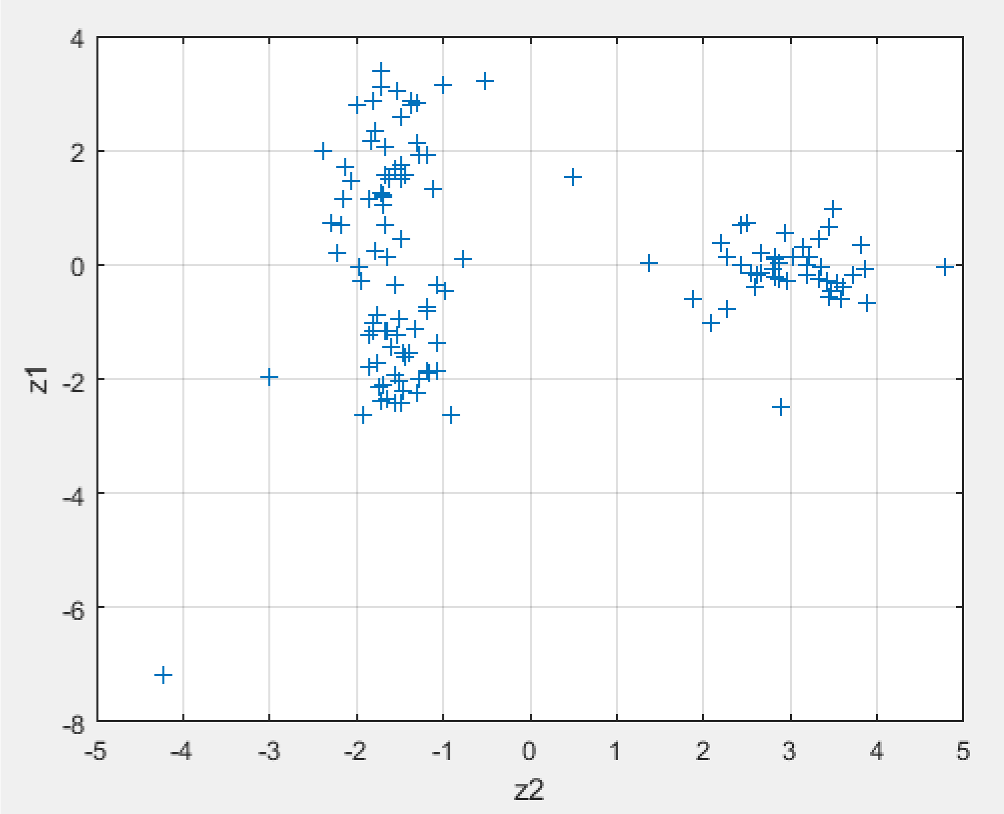
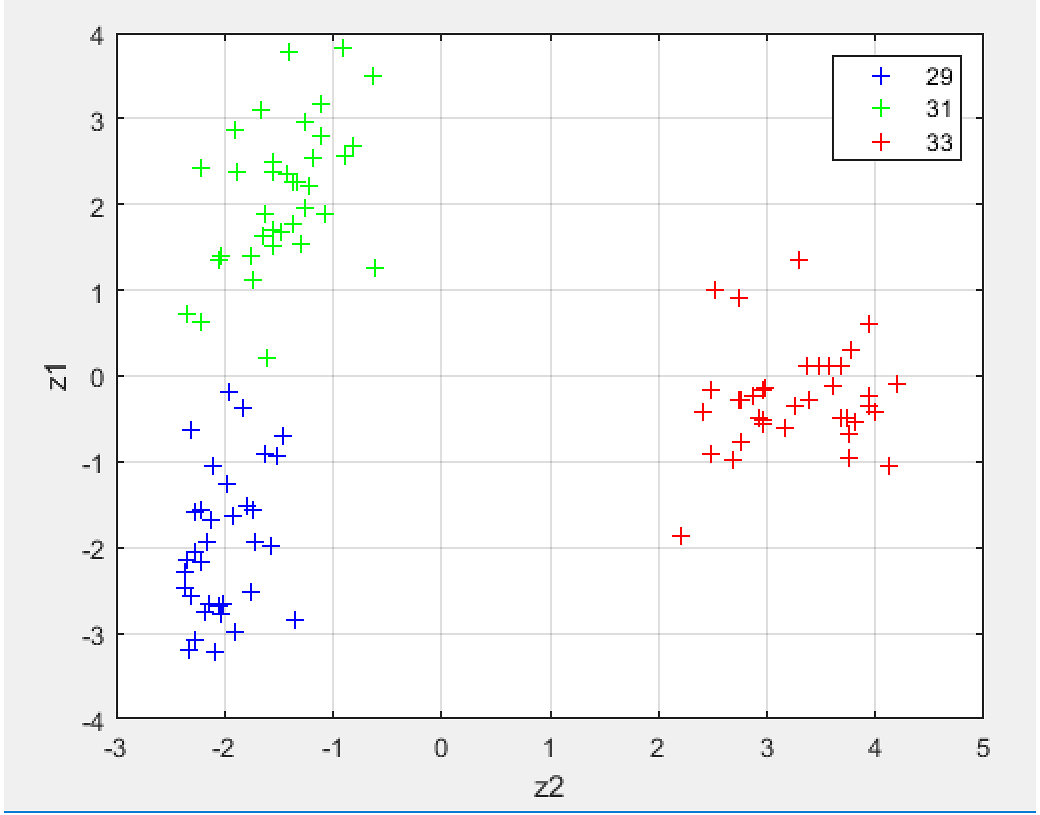
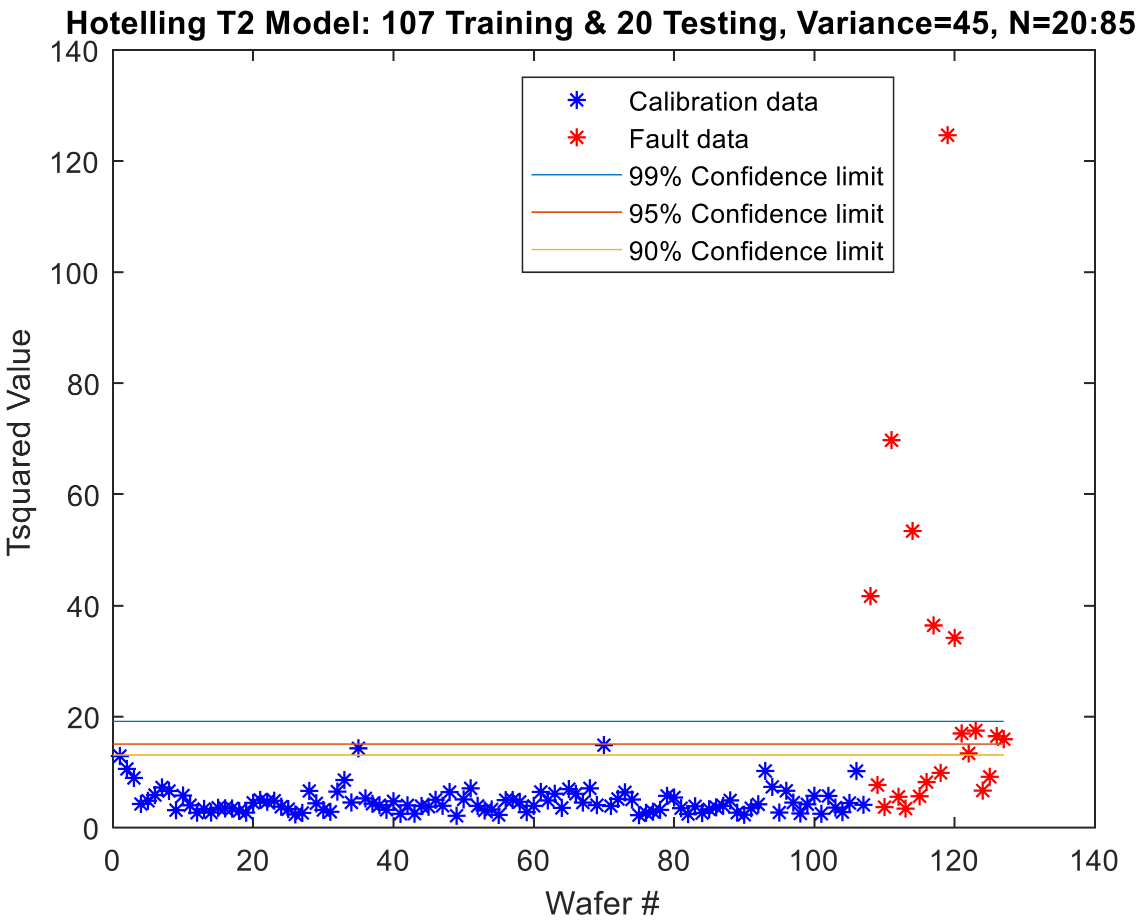
n = 60, var = 40%, unfolded average of each wafer



n = 20-90, var = 40%, unfolded average of each wafer




29
31
33
z1
z2
4
3
2
1
0
-1
-2
-3
-4
-3
-2
-1
0
1
2
3
4
5


Hotelling T2 Model: 107 Training & 20 Testing, Variance=45, N=20:85
Calibration data
Fault data
99% Confidence limit
95% Confidence limit
90% Confidence limit
Tsquared Value
Wafer #
0
20
40
60
80
100
120
140

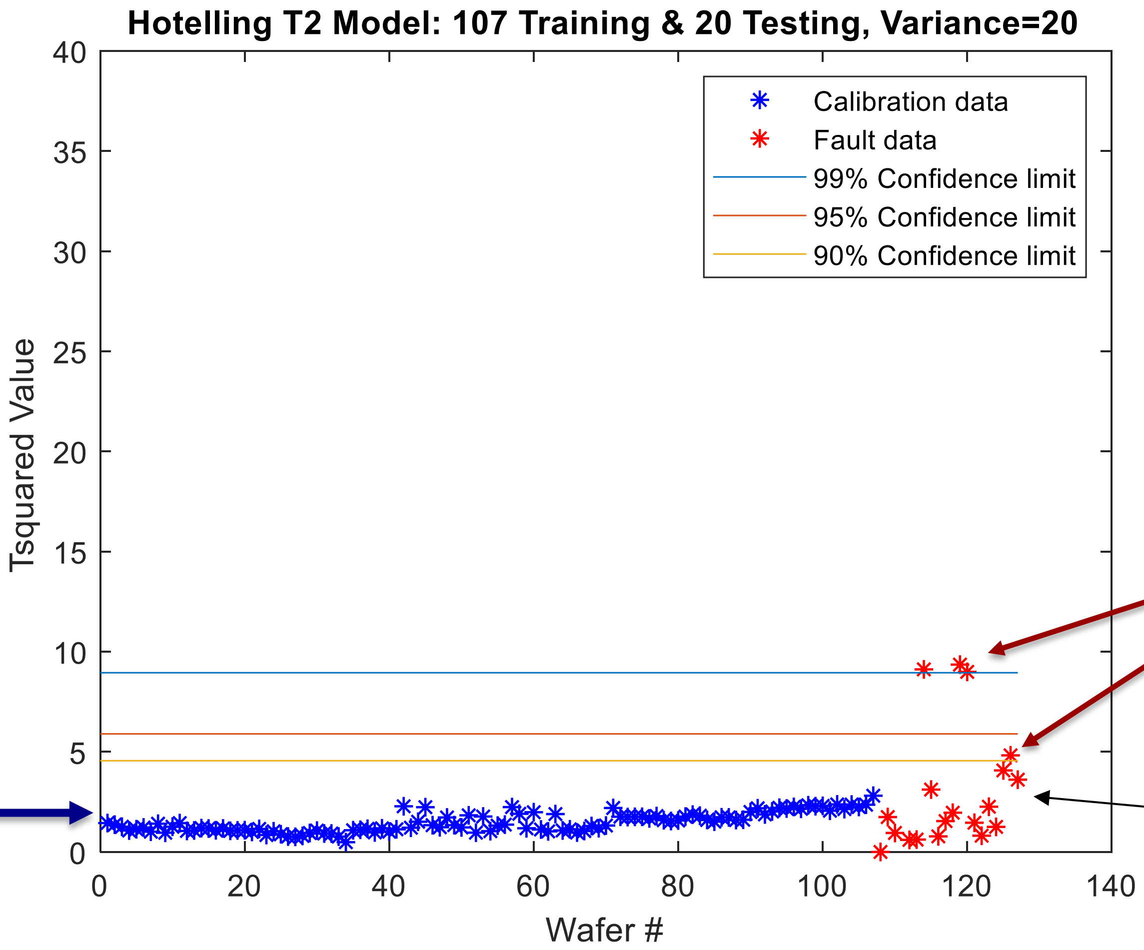
Task 2a: Error Analysis

- Use of T^2 for fault detection
- T^2 measure of the distance from the multivariate mean to the projection of the operating point onto the plane defined by the PCAs
- A T^2 fault indicates the process has outside the normal range of operation but in the direction of variation common in the process
- Calculated for Local & Global model

		Condition (as determined by "Gold standard")		
		Condition positive	Condition negative	
Test outcome	Test outcome positive	**True positive**	**False positive** (Type I error)	Precision = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Test outcome positive}}$
	Test outcome negative	**False negative** (Type II error)	**True negative**	Negative predictive value = $\frac{\Sigma \text{ True negative}}{\Sigma \text{ Test outcome negative}}$
		Sensitivity = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$	Specificity = $\frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$	Accuracy

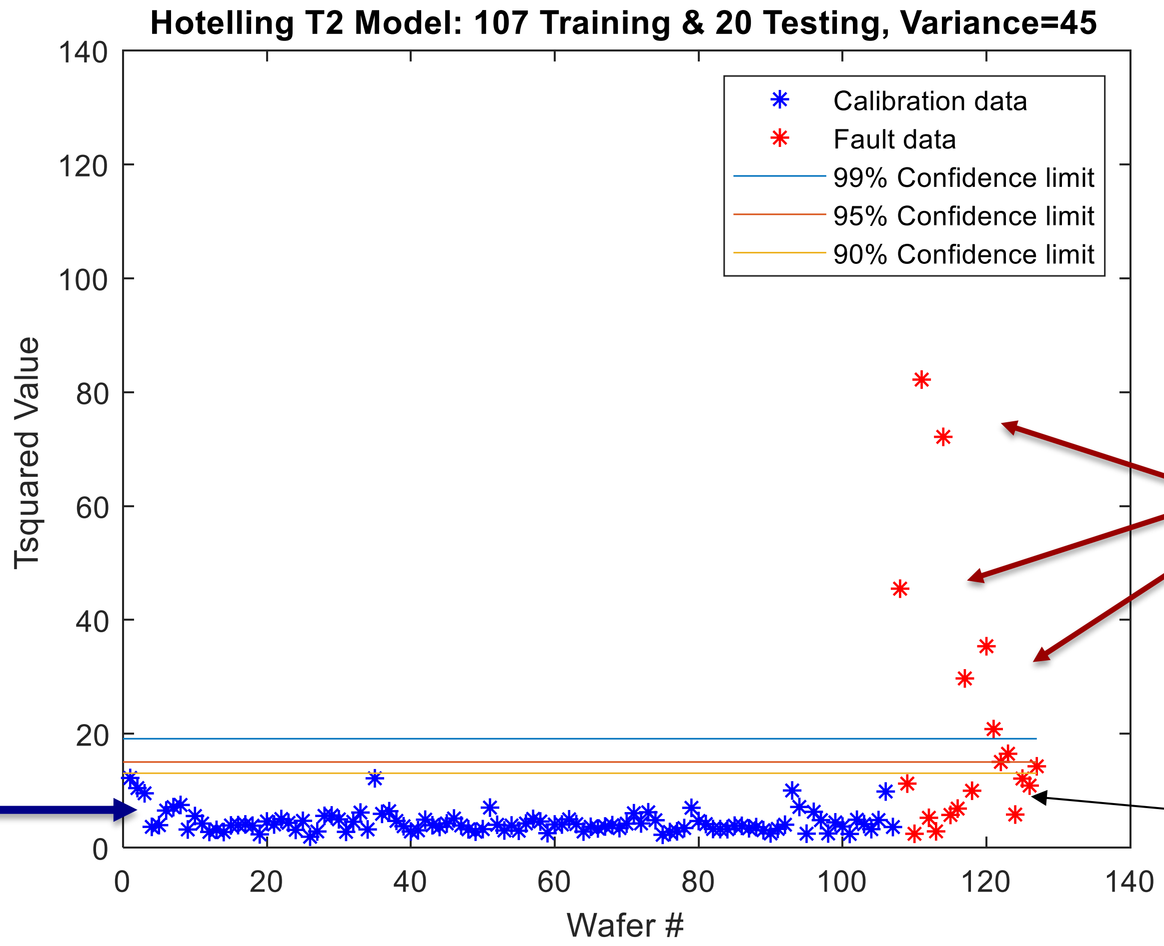
FN=0
95%
Type II

TP



TN=3
95%

FP = 17
95%

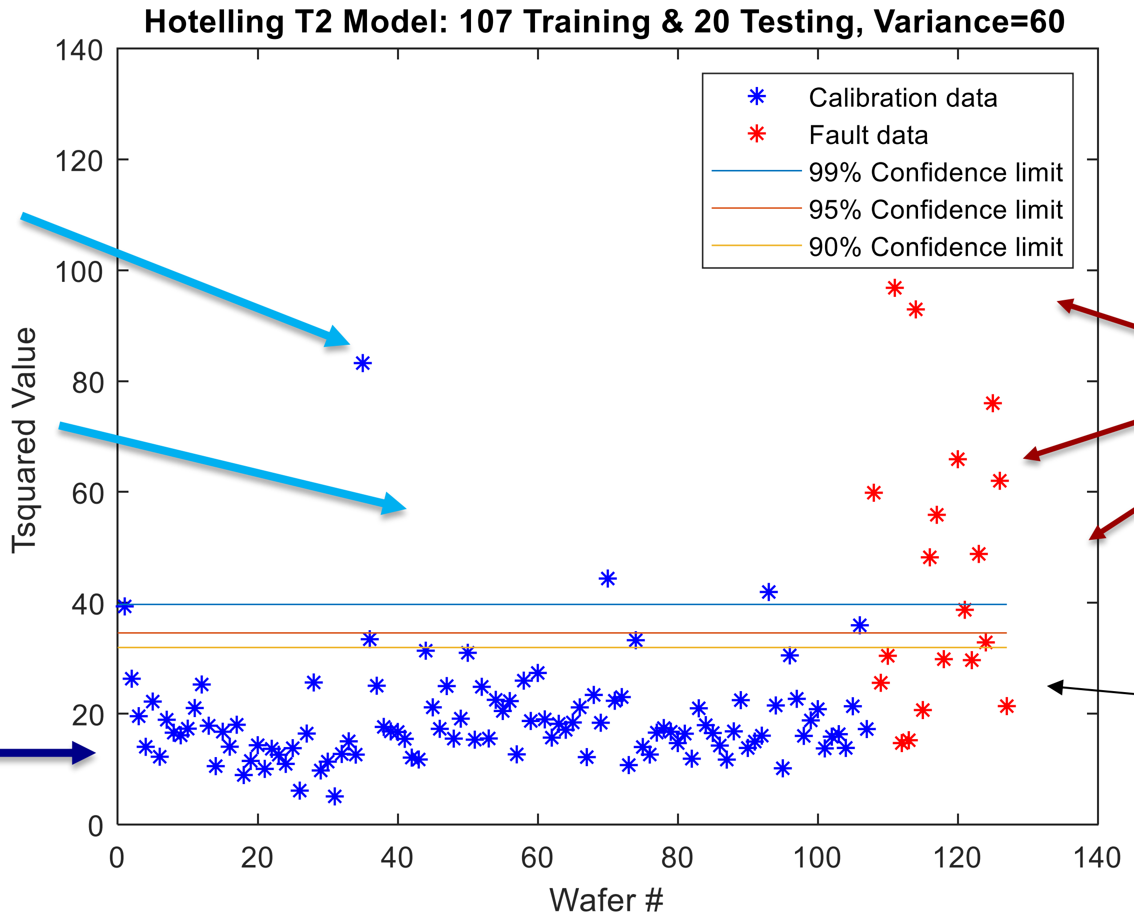


FN=0
95%
Type II

TN = 7
95%

TP

FP = 13
95%
Type I



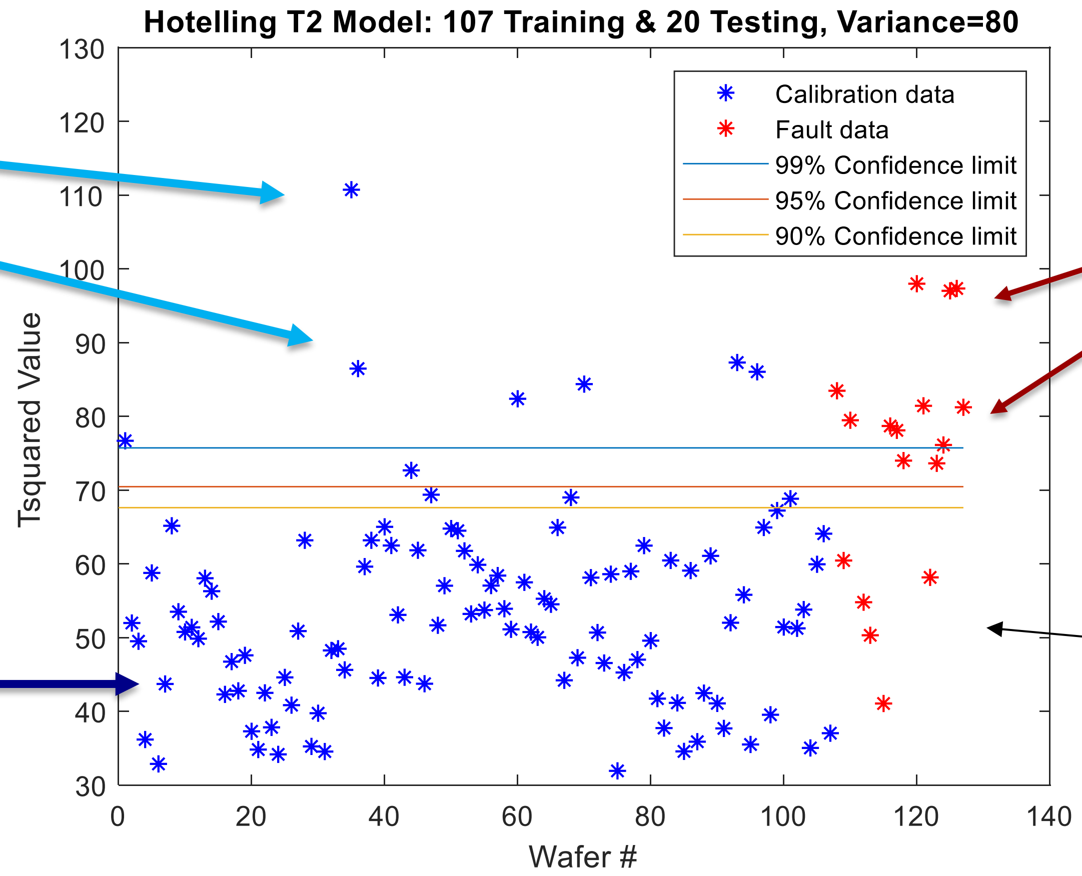
FN=4
95%
Type II

TN =10
95%

TP

FP = 10
95%
Type I

FN=8
95%
Type II



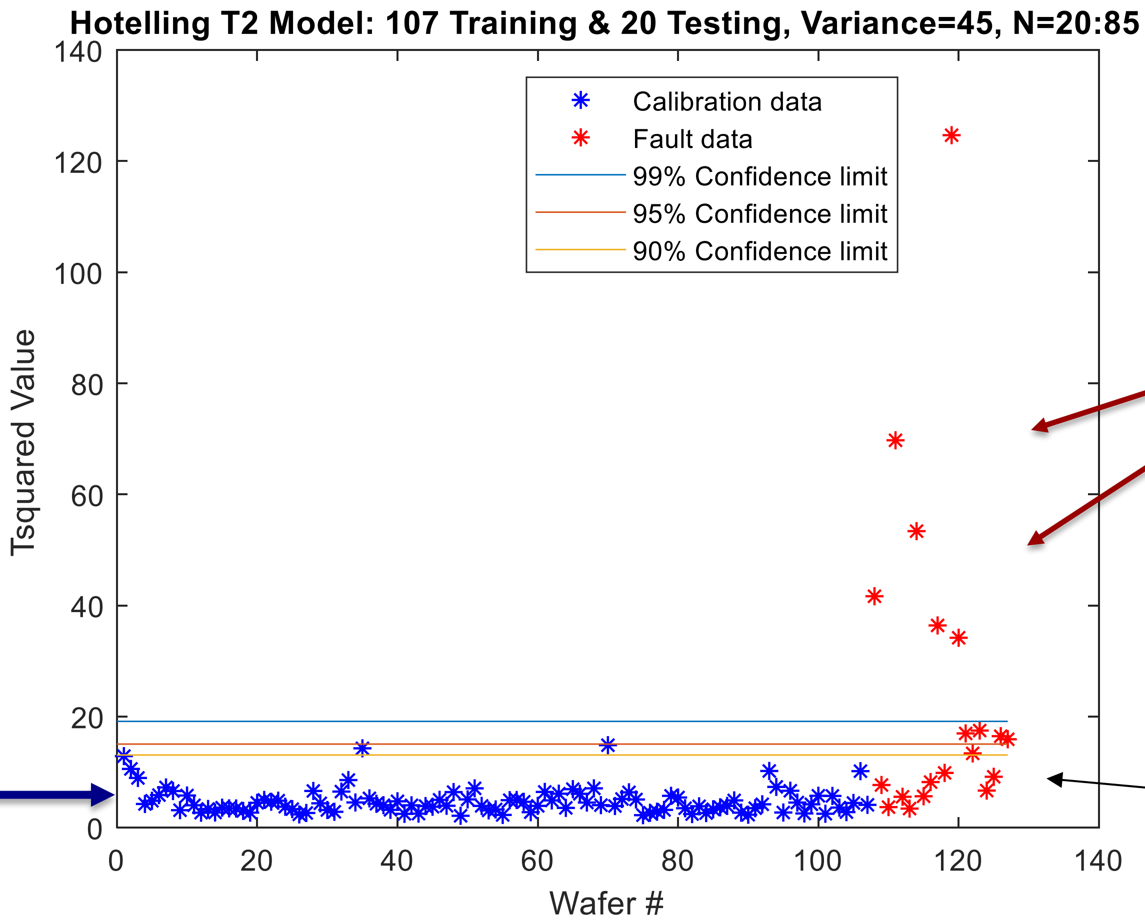
TN =15
95%

TP

FP = 5
95%
Type I

FN=0
95%
Type II

TP



TN =10
95%

FP =10
95%
Type I

Task 2b: **Performance measures**

- Experimental calculation
- Cross-validation

Experimental calculation in classification of two classes

The confusion matrix is also called the contingency table.

		predicted	
		negative	positive
actual examples	negative	a TN - True Negative correct rejections	b FP - False Positive false alarms type I error
	positive	c FN - False Negative misses, type II error overlooked danger	d TP - True Positive hits

R. Kohavi, F. Provost: Glossary of terms, Machine Learning, Vol. 30, No. 2/3, 1998, pp. 271-274.

Performance measures calculated from the confusion matrix entries:

- Accuracy $= (a+d)/(a+b+c+d) = (TN + TP)/total$
- **True positive rate**, recall, sensitivity $= d/(c+d) = TP/\textit{actual positive}$
- Specificity, true negative rate $= a/(a+b) = TN/\textit{actual negative}$
- Precision, predicted positive value $= d/(b+d) = TP/\textit{predicted positive}$
- **False positive rate**, false alarm $= b/(a+b) = FP/\textit{actual negative} = 1 - \textit{specificity}$
- False negative rate $= c/(c+d) = FN/\textit{actual positive}$

a=10	b=0
c= 10	d=107

Accuracy = 92.13%
Error rate = 7.87%
True positive rate = 84.25%
True negative rate = 1000%
False alarm = 0%
Precision = 84.25%

K-Fold cross validation with K=5
Error rate = 28.57%

As predicted, experimental techniques are over optimistic about the accuracy of the process and is not a correct gauge for the health of process

Task 3 : Analysis of PCA results

- Comparison with the techniques in the paper
- Comparison of results
- Scope for improvement of PCA model
- Comparison with other algorithms

Table 5. Faults detected for each combination of sensor, method and timescale

		TLD	PARAFAC	MPCA	PCA/mean
Global	Machine	11	12	10	10
	RFM	7	6	11	9
	OES	9	6	6	5
Local	Machine	14	17	11	16
	RFM	12	14	14	12
	OES	12	11	6	13
Mean		10·8	11·0	9·7	10·8

Conclusions

- MPCA method gave almost similar fault detection characteristics for our global model
- Global models fared better than local for each of the observations given the computational complexity involved
- RFM data would help in getting accurate sections of the data
- Controlling false negative rate, we can get higher fault detection using MPCA while compromising with the manufacturer's loss
- PARAFAC and TLD are better means for getting a better estimation from global fault data

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