



# Data Analytics and Monitoring of the Tennessee Eastman Process

CHE 599 Process Data Analytics and Machine Learning

Instructor: Dr. S. Joe Qin, Spring 2017  
**Group 1**

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# Outline

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  - Fault detection
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  - PCA for Process Data
  - Fault detection
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  - LDA modeling on IDV (1) IDV(8) IDV(13) IDV(14)
- **Task 4**
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# Introduction

- In this project, we build PCA model on normal quality and process data.
- Then calculate  $T^2$  and Q control limit which are used as fault detection control limits to partition potential disturbances from the distorted data sets.
- After grouping the observations based on the PCA results, LDA is used to separate one from the other, the classification outcome needs be assessed.
- Further, using the CCCA to monitor the input and output of process with disturbances.

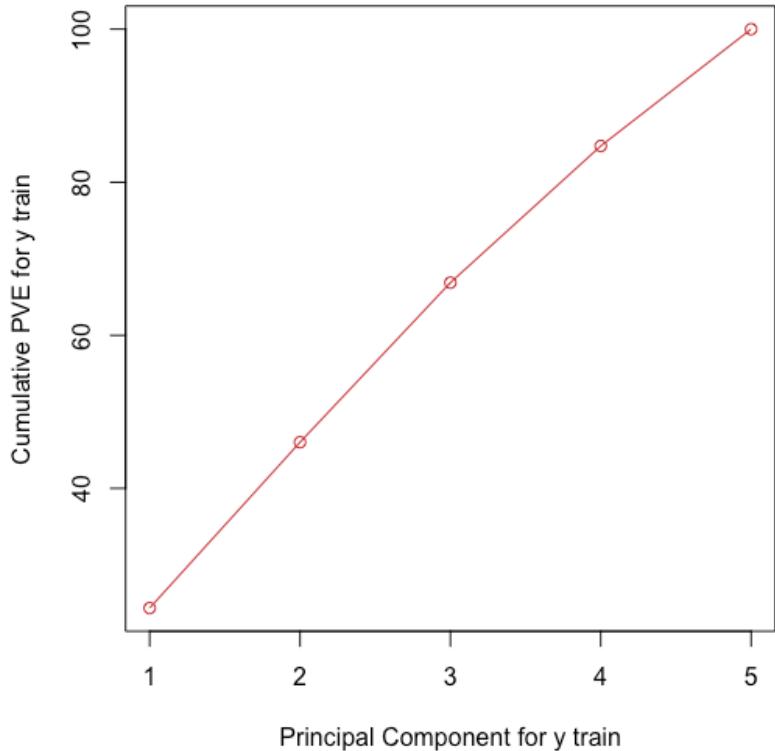


# Methodology

- PCA, LDA and CCCA are employed in R and MATLAB to modeling on both the quality and process datasets of the Tennessee Eastman Process.
- Plots are drawn to demonstrate the modeling results and analyses are presented.
- In LDA, results are used to decide which observation belongs to normal region or the other way around. Different combinations of variables are implemented to evaluate the appropriateness of LDA in our cases.



# PCA for Quality Data



**Choose 5 PCs**

Product D analysis (stream 11)  
Product E analysis (stream 11)  
Product F analysis (stream 11)  
Product G analysis (stream 11)  
Product H analysis (stream 11)

XMEAS(37)  
XMEAS(38)  
XMEAS(39)  
XMEAS(40)  
XMEAS(41)

**No SPE limit**  
 **$T^2$  control limit = 11.07**

Fig 1. variance explained by components for IDV (0)



# Fault Detection

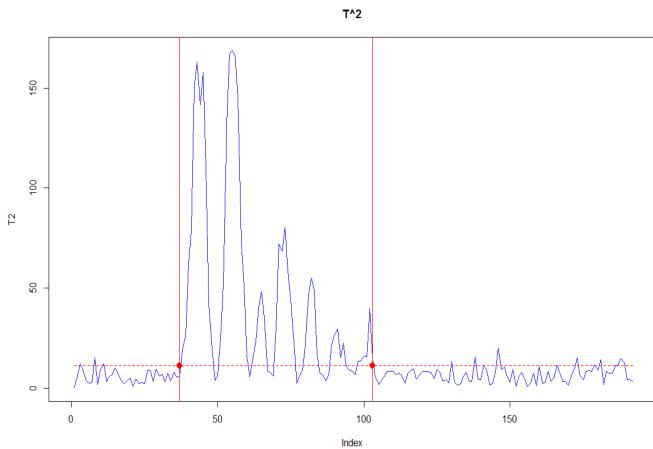


Fig.2. PCA-based monitoring result for IDV (1)

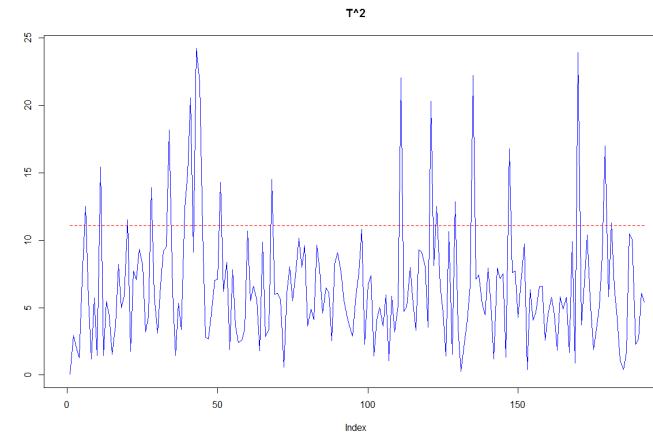


Fig.3. PCA-based monitoring result for IDV (3)

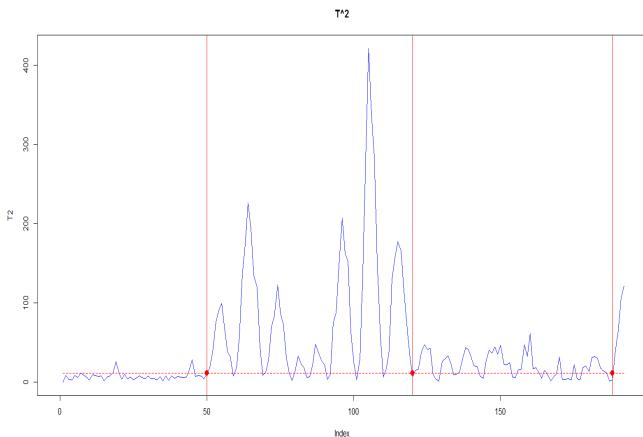


Fig.4. PCA-based monitoring result for IDV (8)

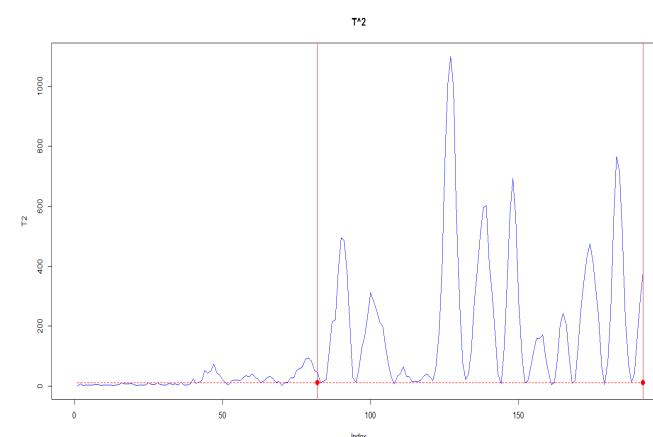


Fig.5. PCA-based monitoring result for IDV (13)



# Fault Detection

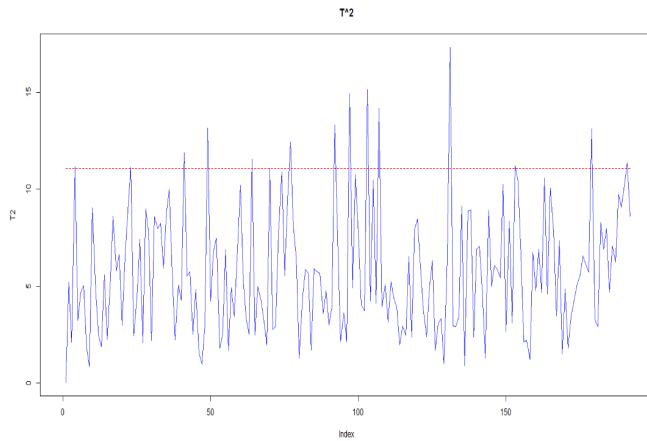


Fig.6. PCA-based monitoring result for IDV (14)



# Compare the classification

Table 1. Comparison table

AGREE

Test	% of Samples Beyond T <sup>2</sup> limit	Number of Samples Beyond T <sup>2</sup> limit	Total Number of Samples	Classification in paper
IDV (1)	34.375	66		Quality-Relevant
IDV (3)	10.938	21		Quality-Irrelevant
IDV (8)	71.875	138		Quality-Relevant
IDV (13)	57.291	110		Quality-Relevant
IDV (14)	7.8125	15		Quality-Irrelevant
			192	

<15%  
Quality-Irrelevant



# PCA for Process Data Monitoring

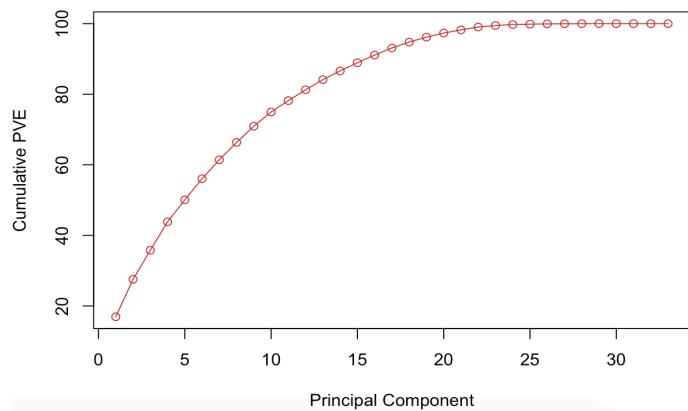
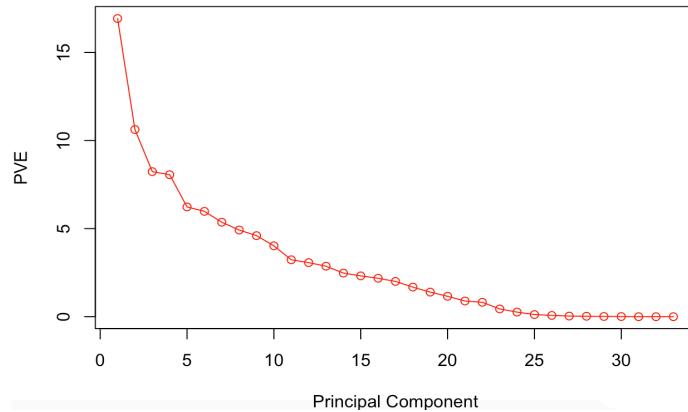


Fig 2.1. variance explained by components

PC	PC17	PC18	PC19	PC20
CUMPVE	93.1	94.77	96.17	97.32

**Choose 19 PCs**

**SPE limit=2.84**

**T2 limit=30.14**



# Fault Detection

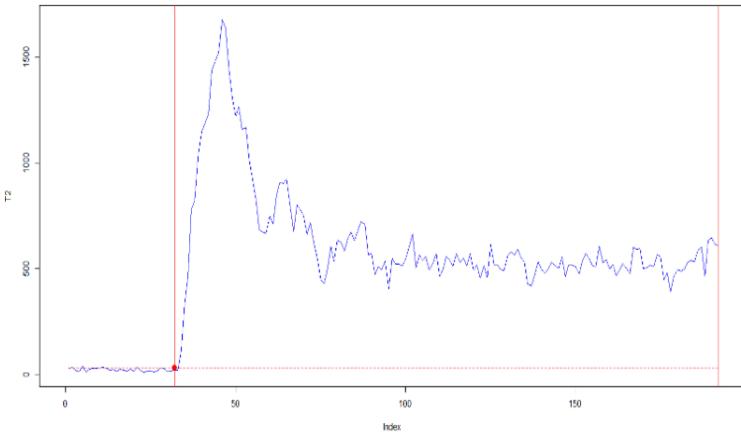


Fig.7. PCA – based process modeling result for IDV(1)

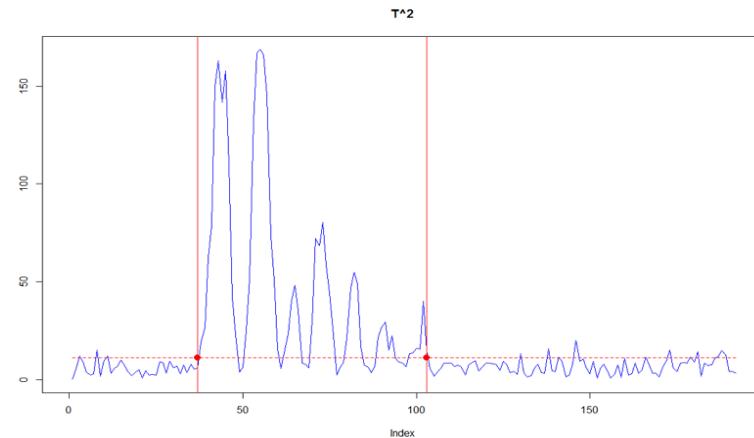


Fig.8. PCA – based quality monitoring result for IDV(1)

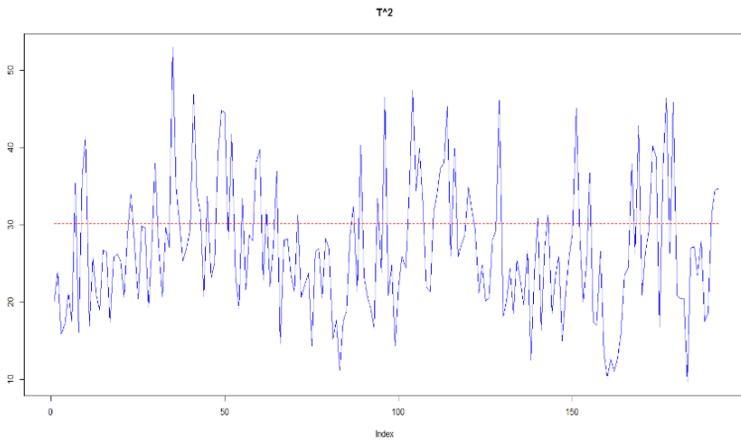


Fig.9. PCA – based process modeling result for IDV(3)

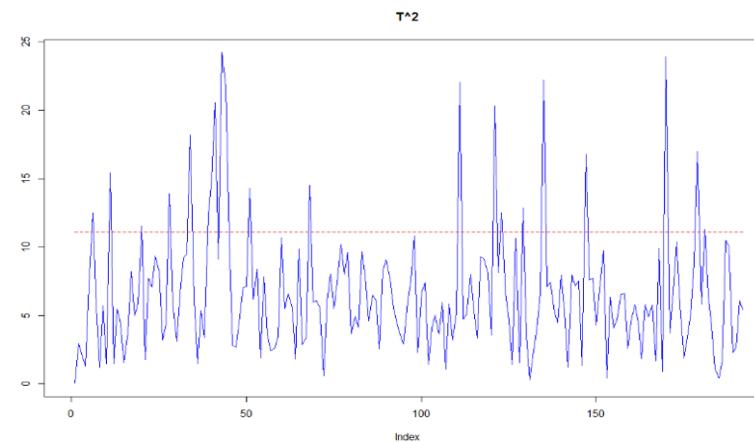


Fig.10. PCA – based quality monitoring result for IDV(3)



# Fault Detection

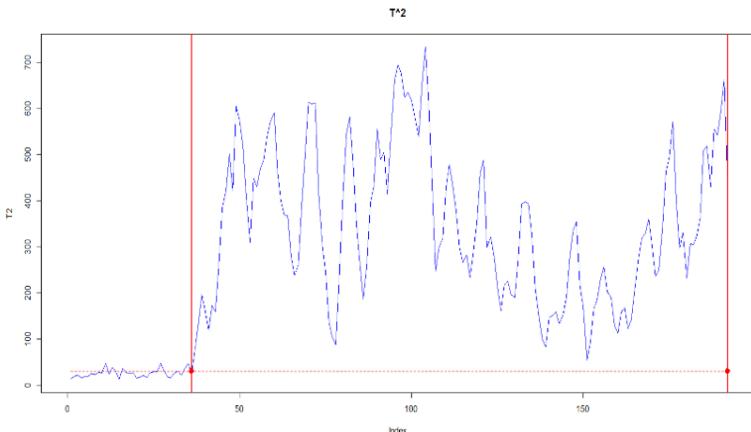


Fig.11. PCA – based process modeling result for IDV(8)

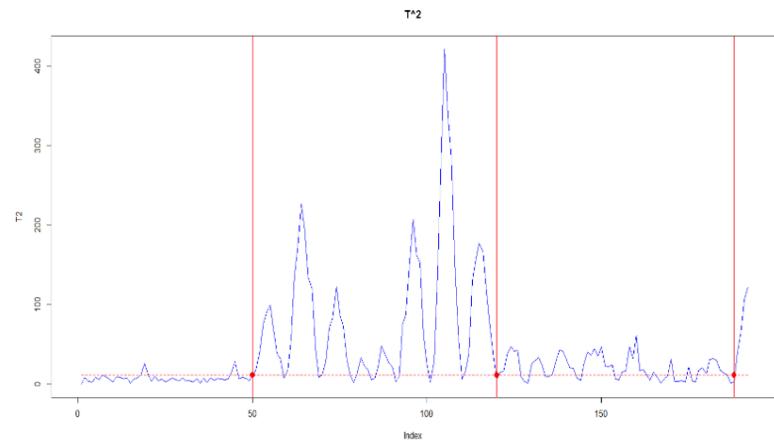


Fig.12. PCA – based quality monitoring result for IDV(8)

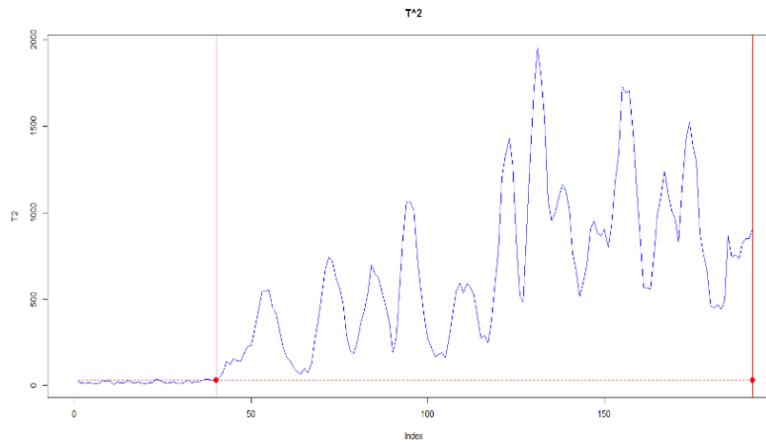


Fig.13. PCA – based process modeling result for IDV(13)

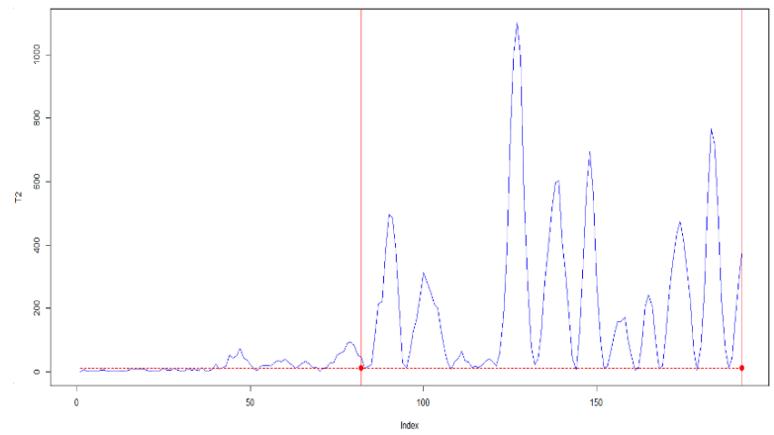


Fig.14. PCA – based quality monitoring result for IDV(13)



# Fault Detection

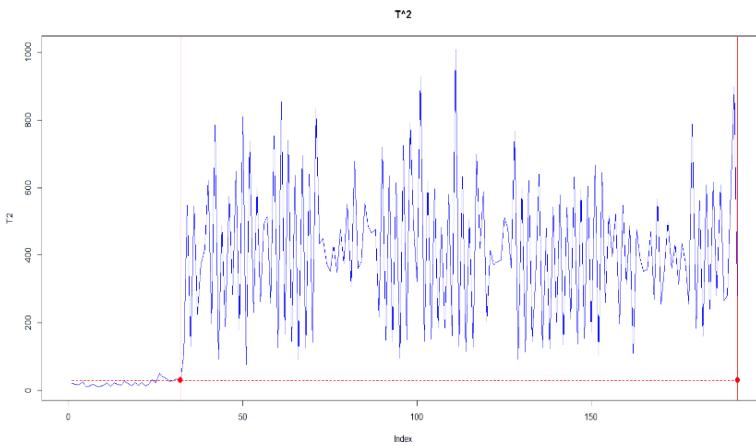


Fig.15. PCA – based process modeling result for IDV(14)

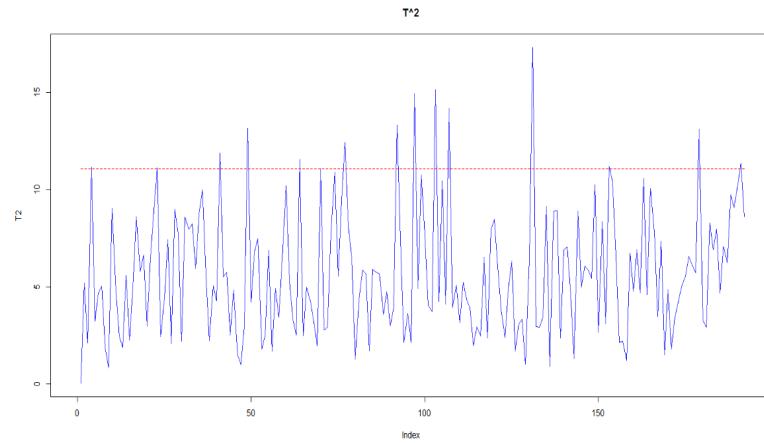


Fig.16. PCA – based quality monitoring result for IDV(14)



# Fault Detection

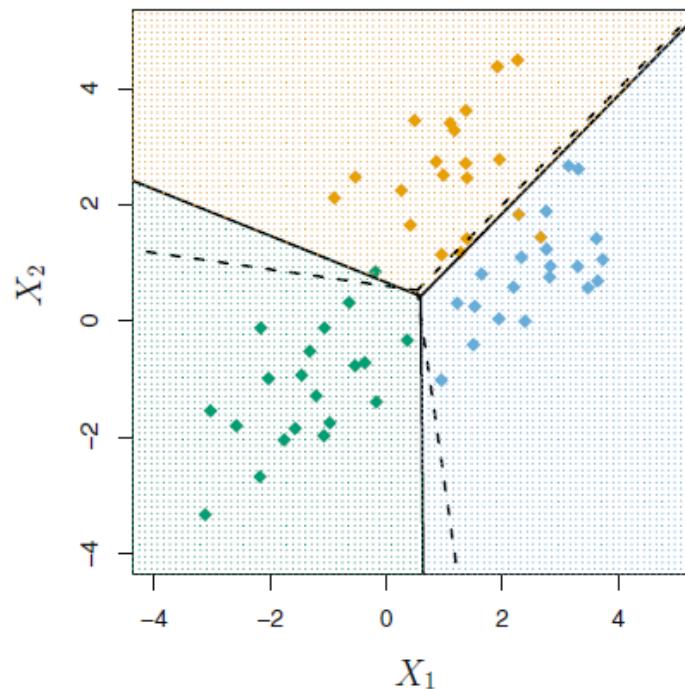
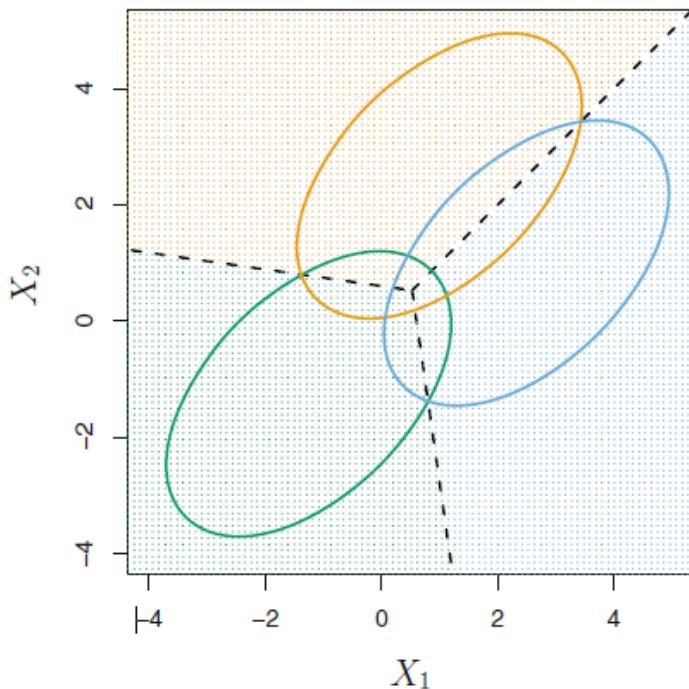
Table 2. False Alarming and Miss Detecting Rates

Disturbances	FAR	MDR
IDV (1)	75%	0.00%
IDV (3)	/	/
IDV (8)	70%	0.00%
IDV (13)	51%	0.00%
IDV (14)	83%	0.00%



# LDA

the *discriminant functions*  $\delta_k(x)$  are linear functions of  $x$





# LDA

*a stacked histogram for quality monitoring*

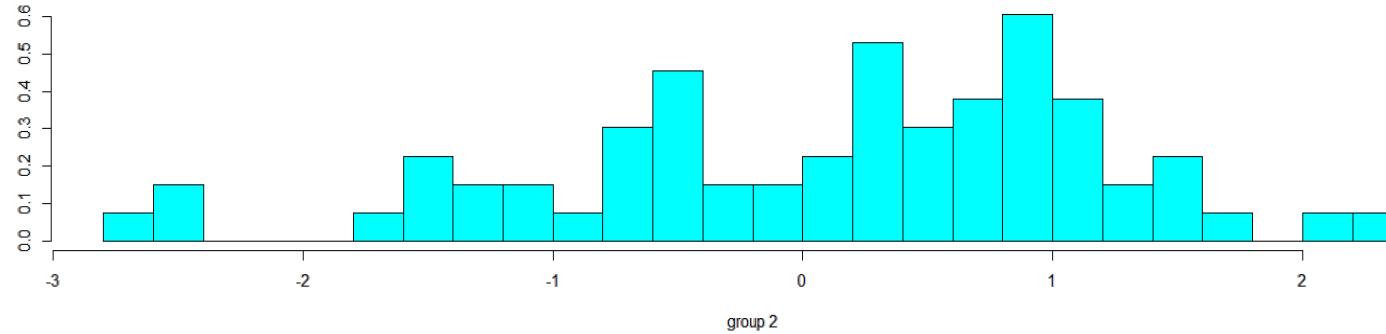
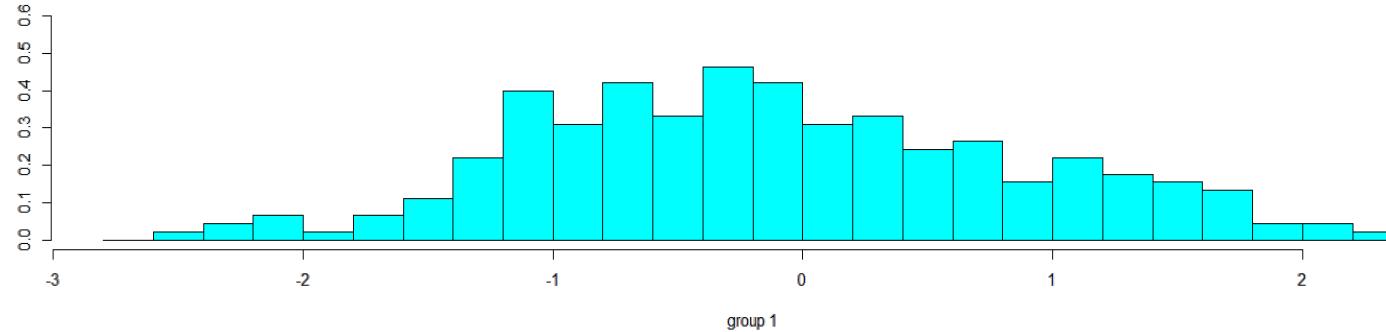


Fig.17. LDA- based classification result for IDV (1)



# LDA

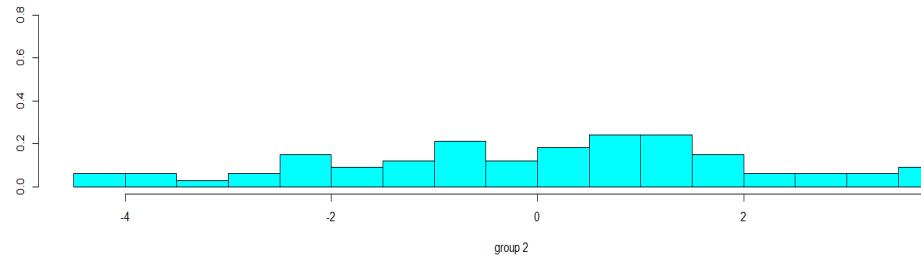
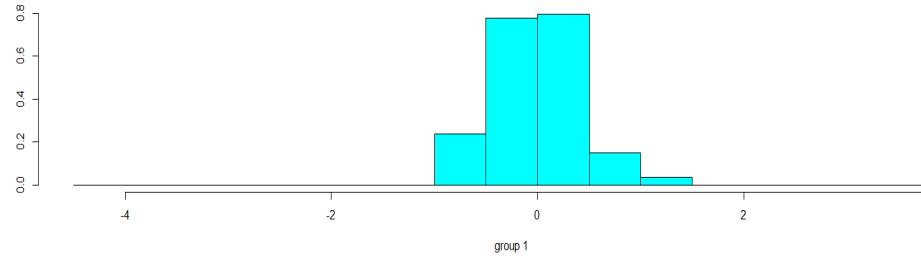


Fig.18. stacked histogram of V2 verse V3 for IDV (1)

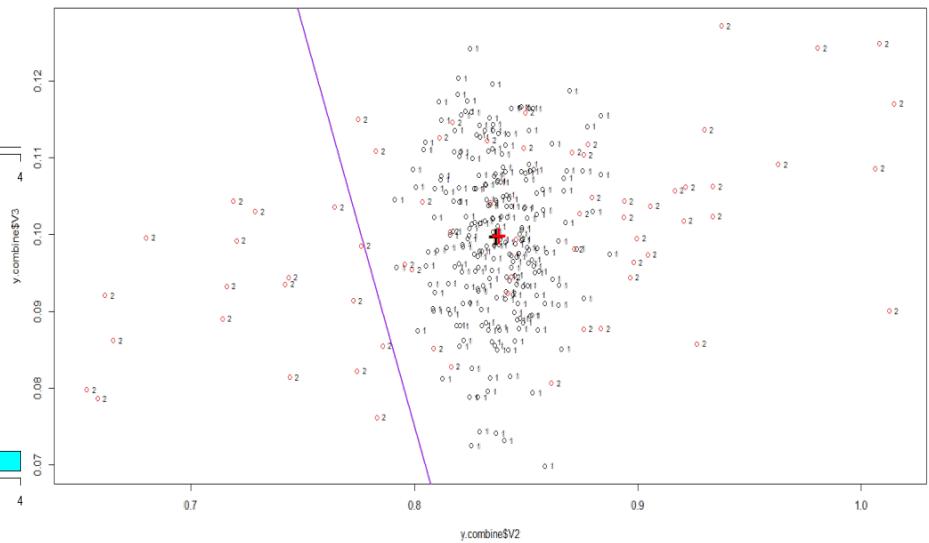


Fig.19. scatterplot of V2 verse V3 for IDV(1)



# LDA

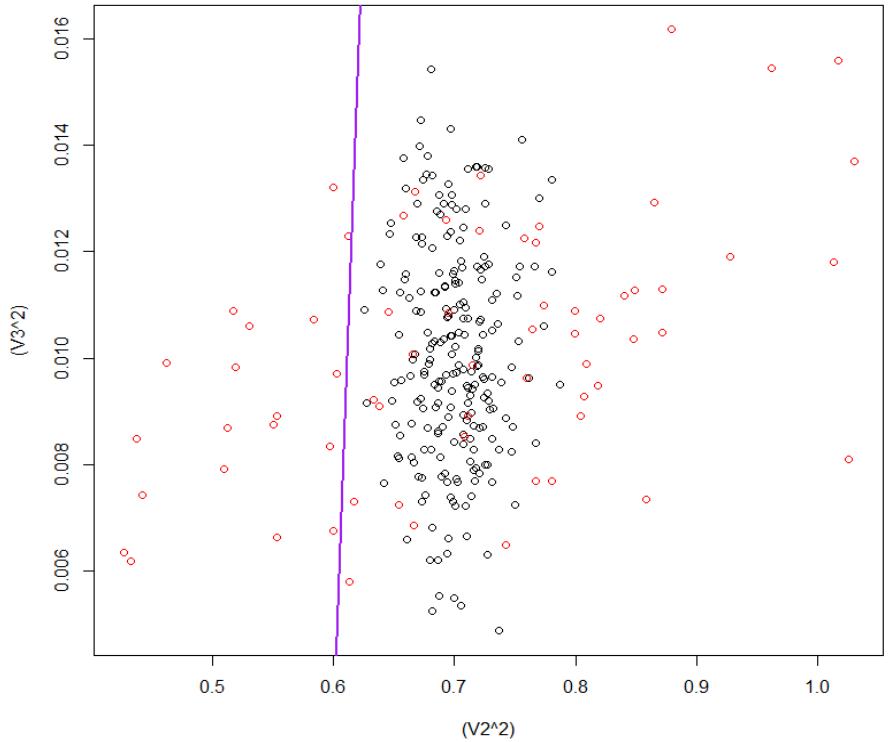
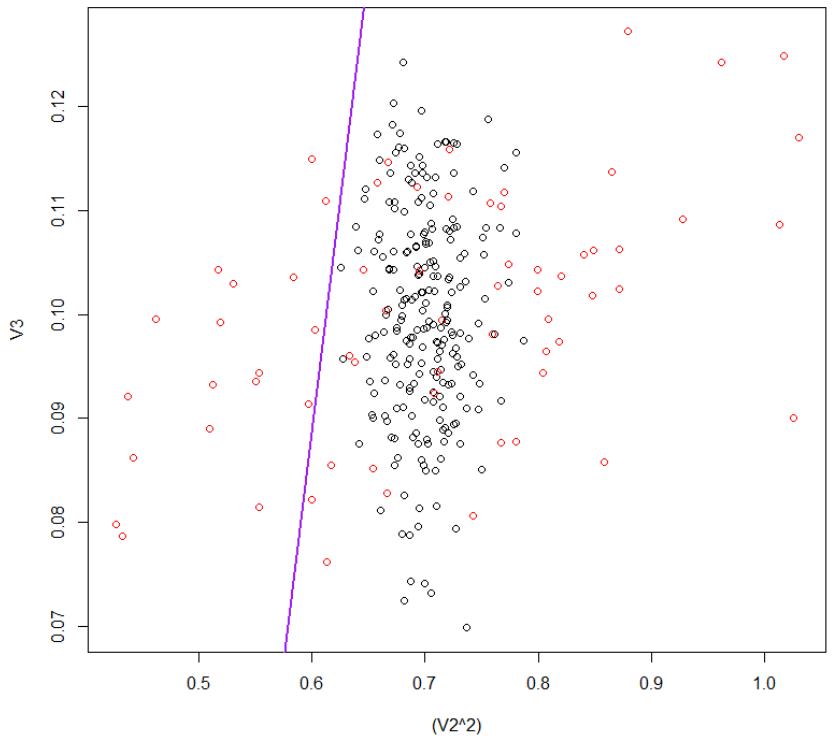


Fig.20. scatterplots for using quadratic terms in LDA



# LDA

## *Processing monitoring result*

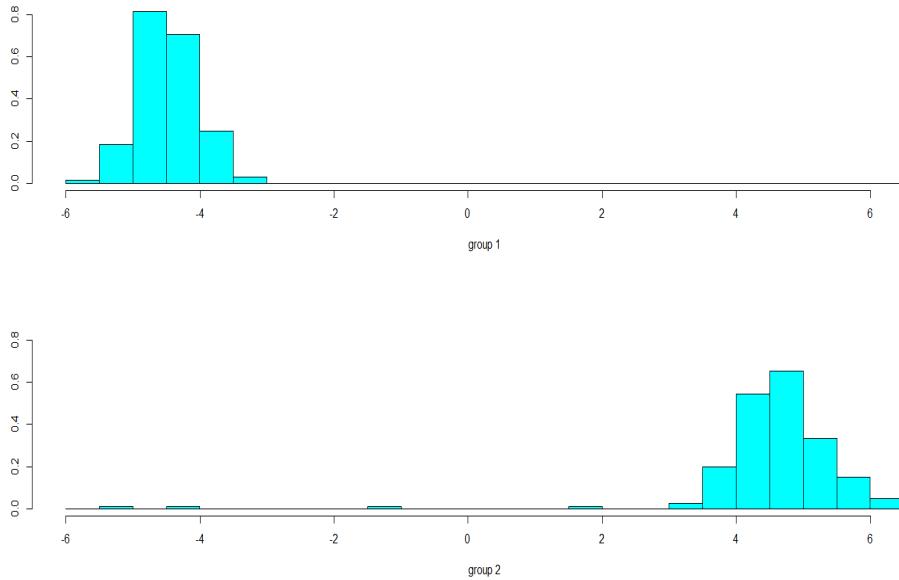


Fig.21. LDA- based process modeling result for IDV (1)

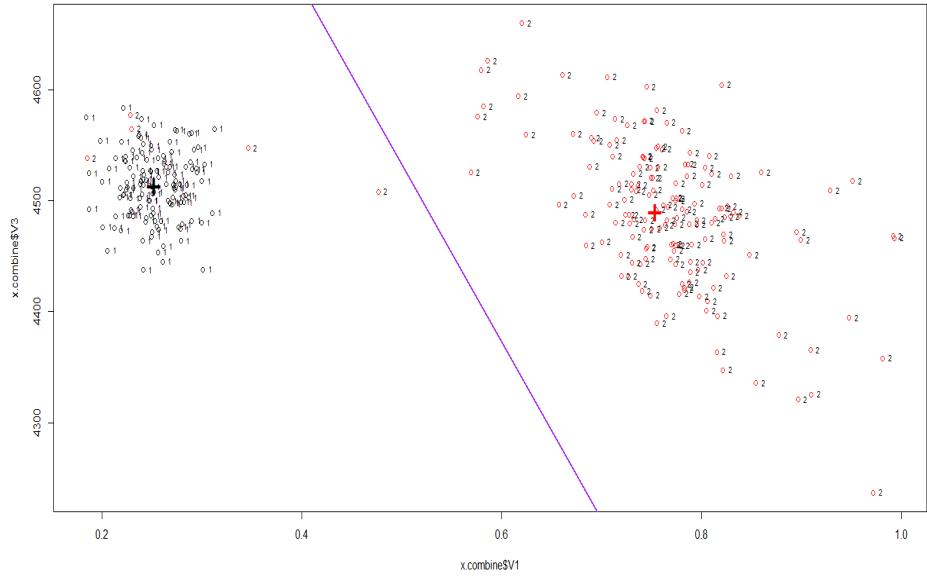


Fig.22. LDA scatterplot of V1 verse V3 for IDV(1)



# LDA

## *Processing monitoring result*

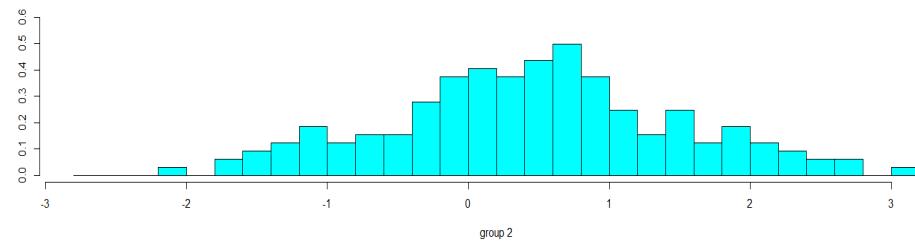
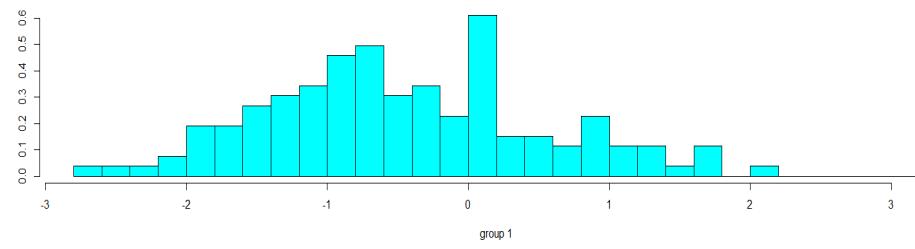


Fig.23. stacked histogram for IDV(14)

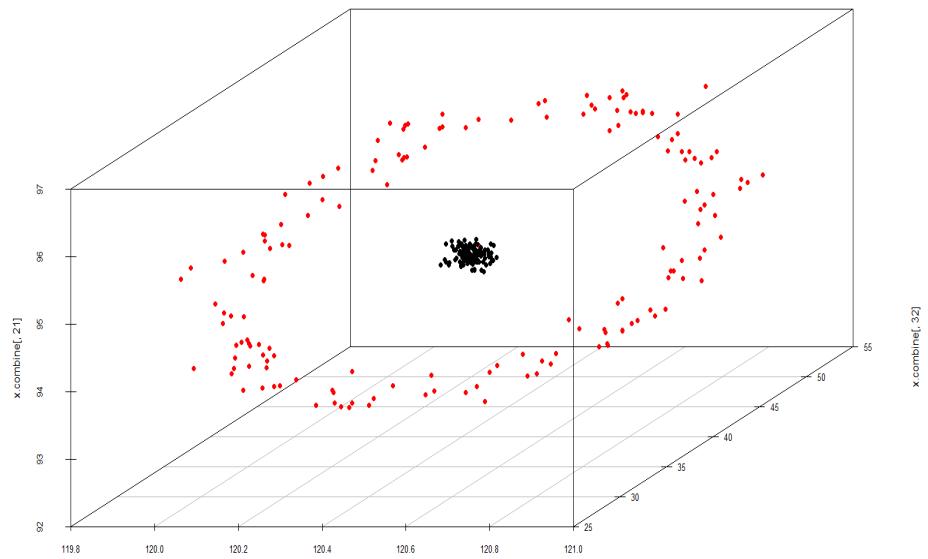


Fig.24. 3-D scatterplot in direction (V21, V9, V32) for IDV (14)



# Concurrent CCA Monitoring

*IDV (1): Step Change in A/C feed Ratio and B Composition Constant*

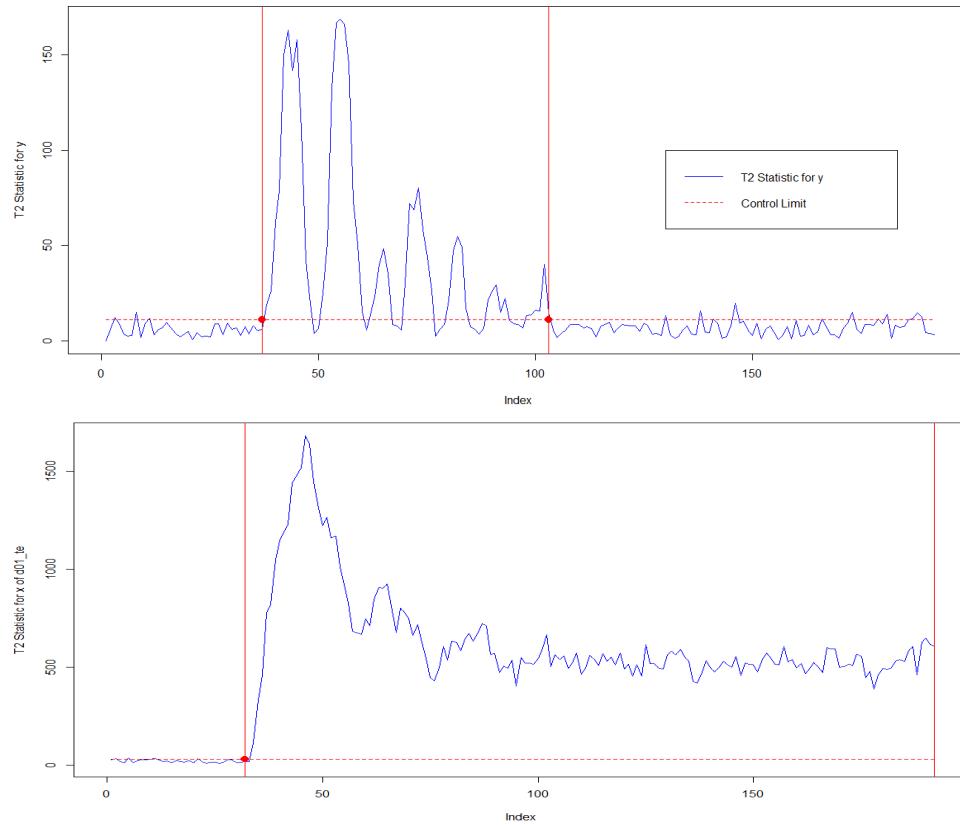


Fig.25. PCA Modeling for IDV(1)

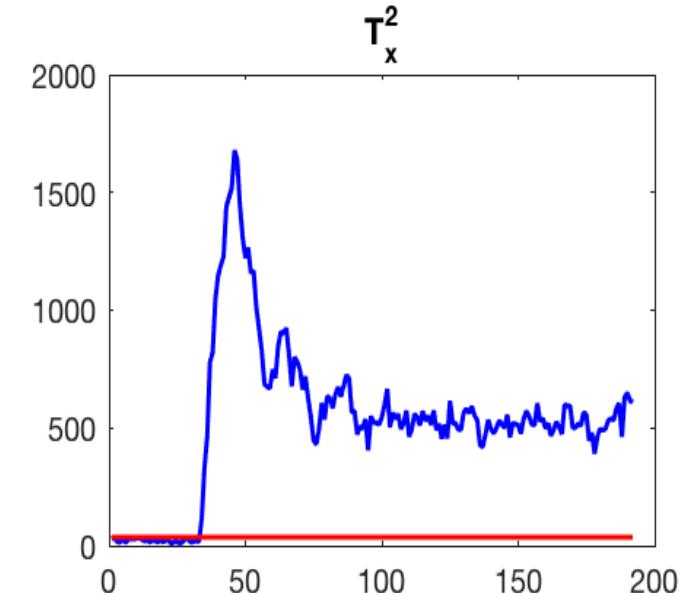


Fig.26.  $T_x^2$  plot for IDV(1)



# Concurrent CCA Monitoring

*IDV(1): Step Change in A/C Ratio and B Composition Constant*

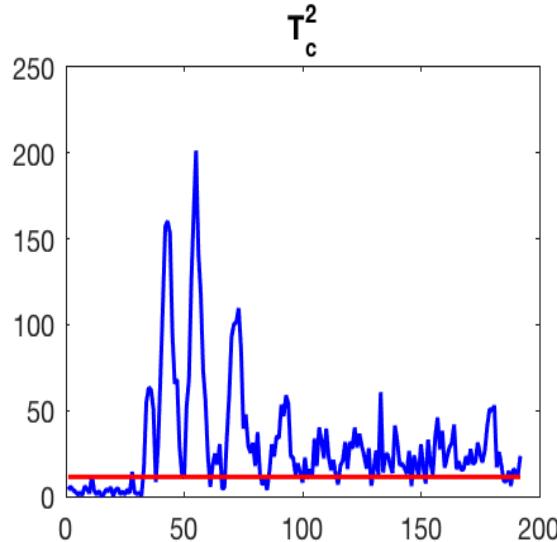


Fig.27.  $T_c^2$  plot for IDV(1)

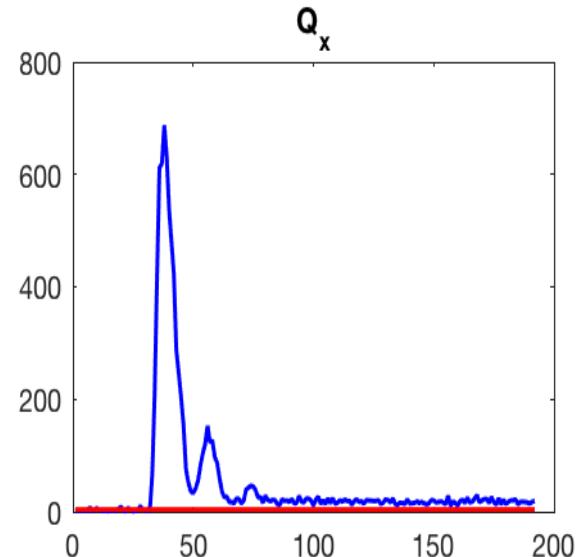


Fig.28.  $Q_x^2$  plot for IDV(1)

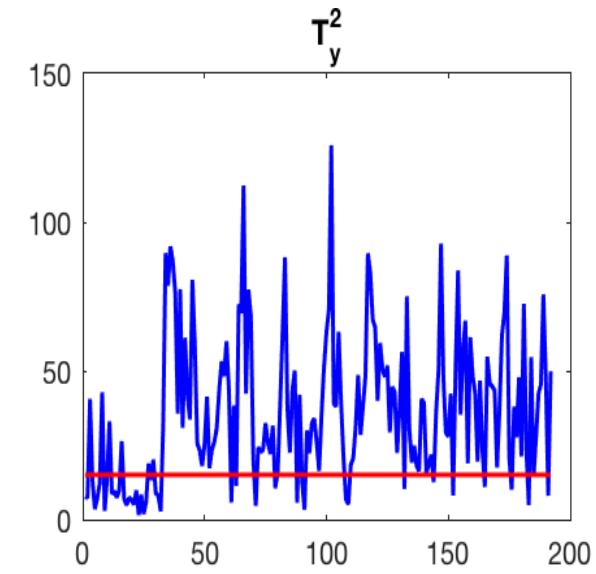


Fig.29.  $T_y^2$  plot for IDV(1)



# Concurrent CCA Monitoring

*IDV (3): Step Change in D Feed Temperature*

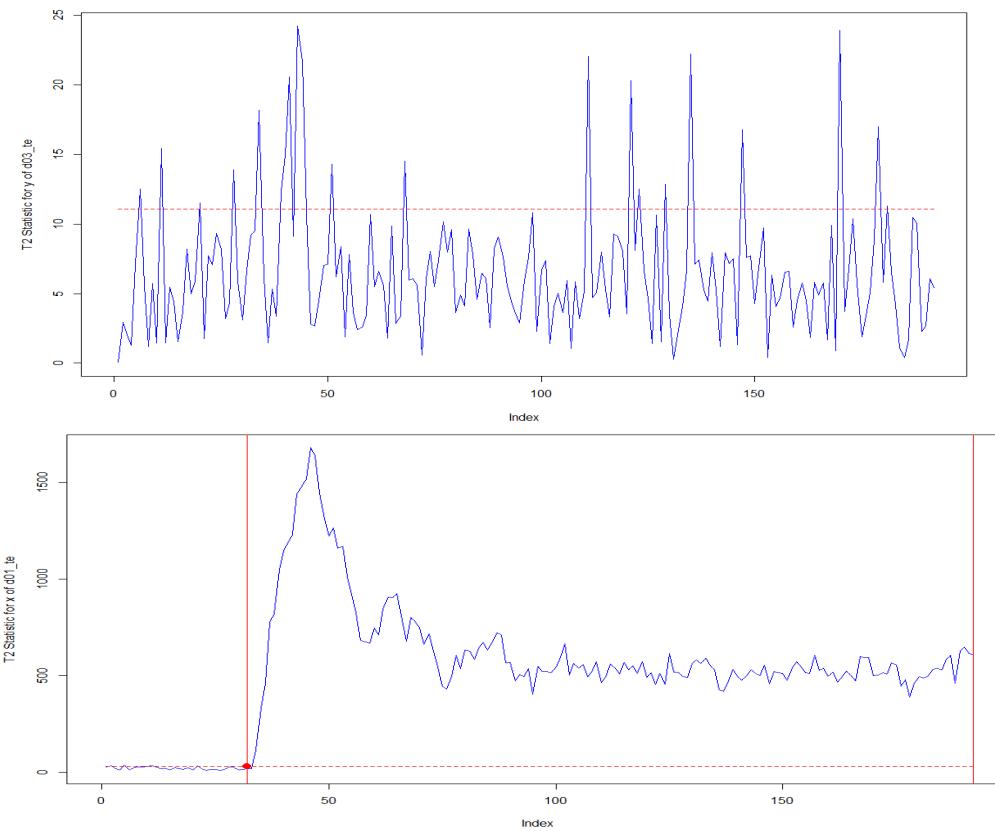


Fig.30. PCA Modeling for IDV(3)

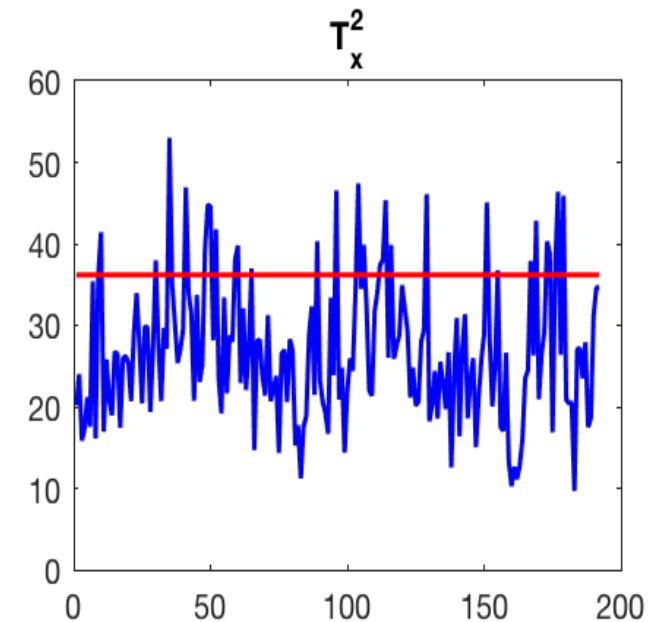


Fig.31. T<sub>x</sub><sup>2</sup> plot for IDV(3)



# Concurrent CCA Monitoring

*IDV (3): Step Change in D Feed Temperature*

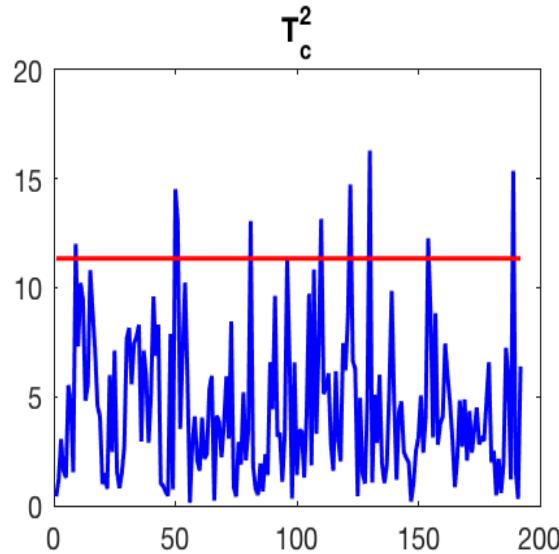


Fig.32.  $T_c^2$  plot for IDV(3)

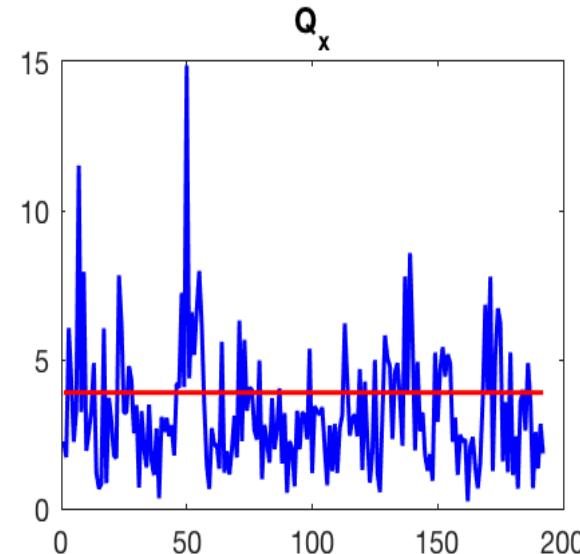


Fig.33.  $Q_x^2$  plot for IDV(3)

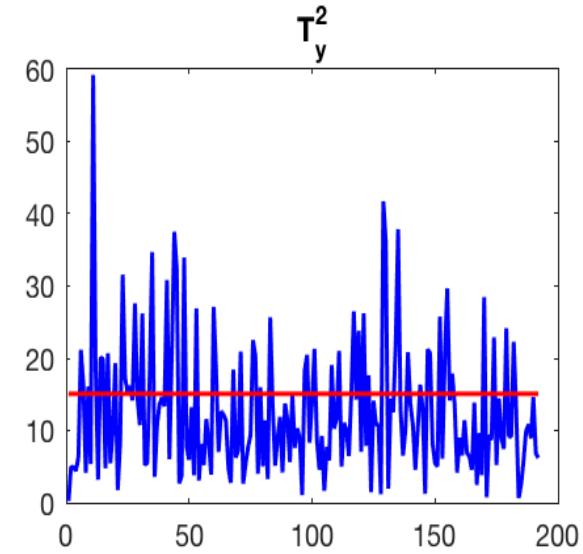


Fig.34.  $T_y^2$  plot for IDV(3)



# Concurrent CCA Monitoring

*IDV (8): Random Variation in A,B,C Feed Composition*

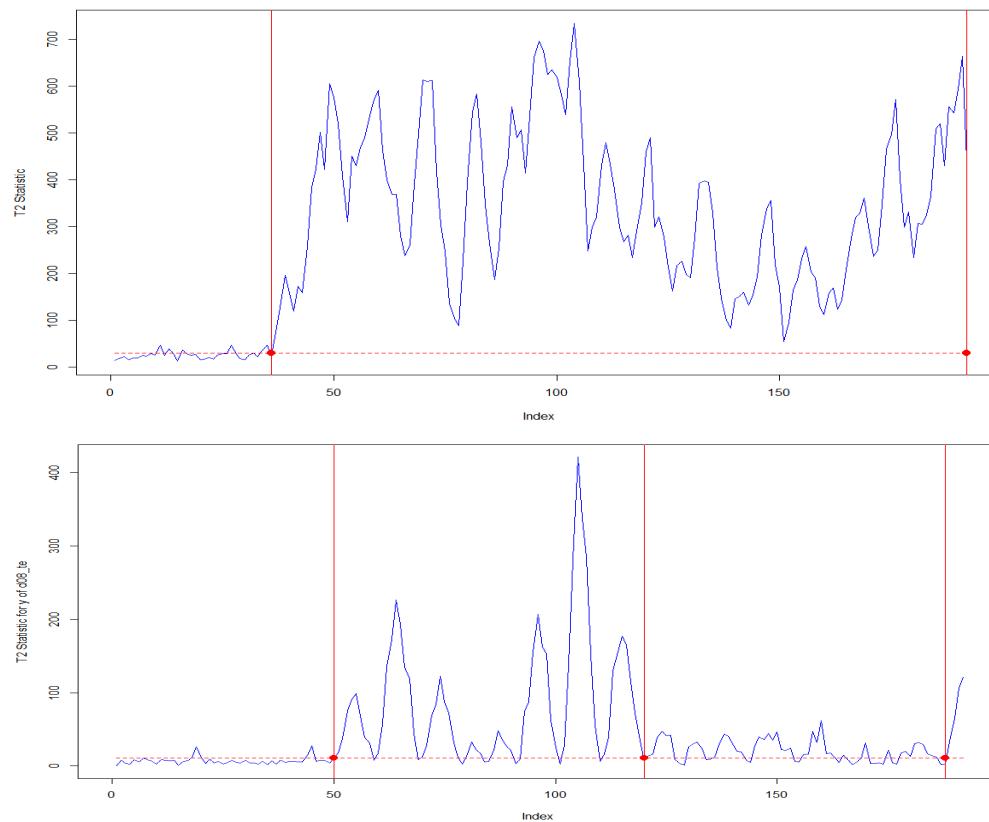


Fig.35. PCA Modeling for IDV(8)

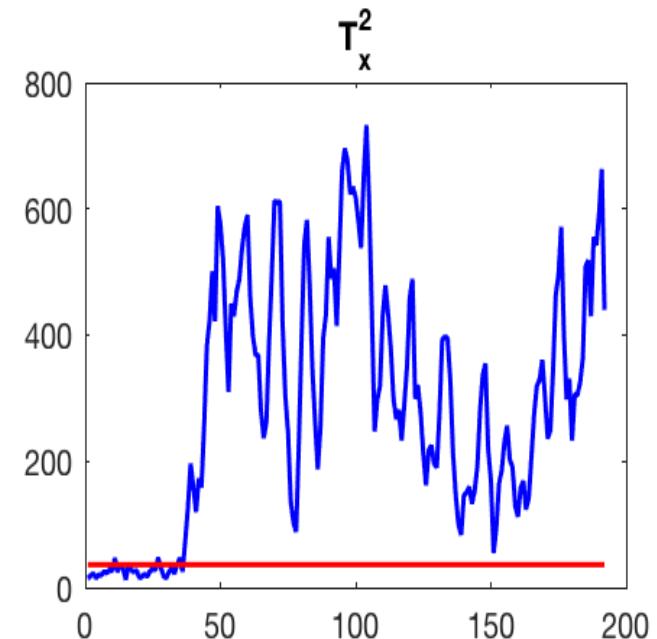


Fig.36.  $T_x^2$  plot for IDV(8)



# Concurrent CCA Monitoring

*IDV (8): Random Variation in A,B,C Feed Composition*

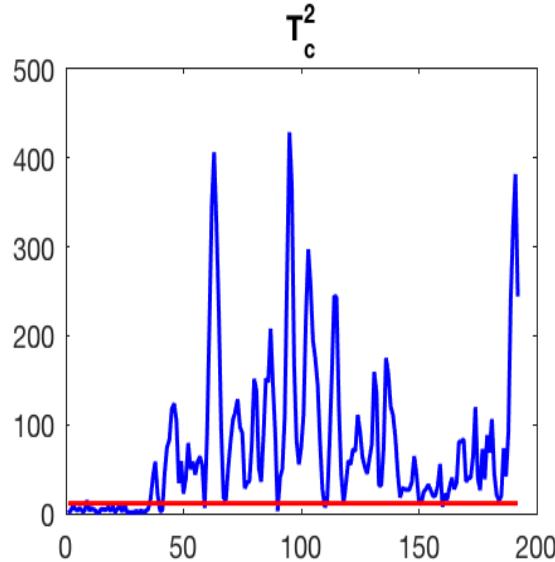


Fig.37.  $T_c^2$  plot for IDV(8)

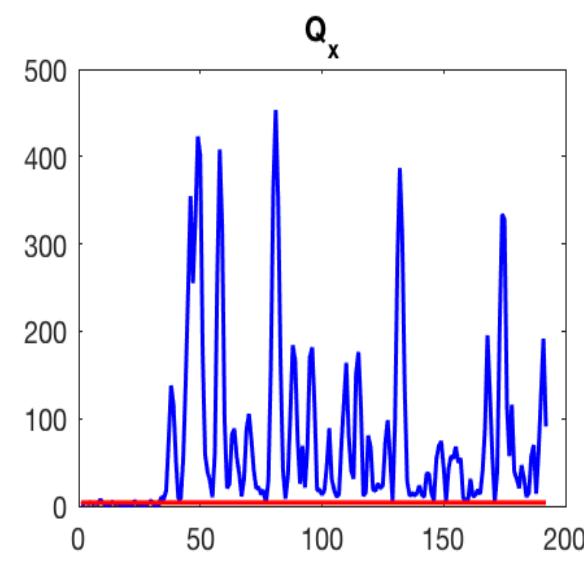


Fig.38.  $Q_x^2$  plot for IDV(8)

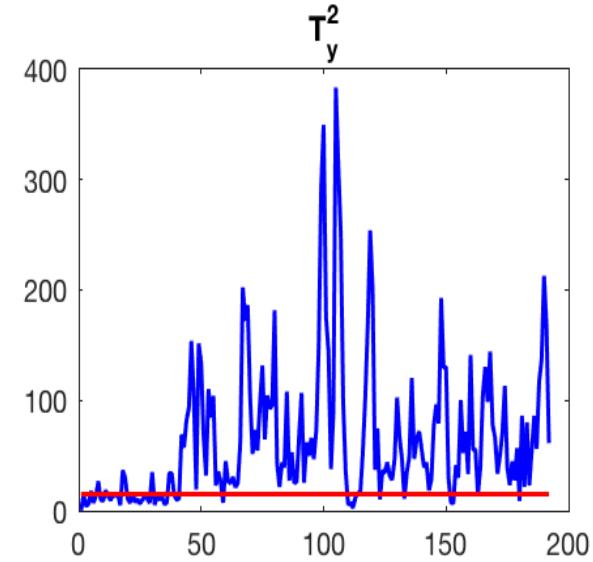


Fig.39.  $T_y^2$  plot for IDV(8)



# Concurrent CCA Monitoring

*IDV(13): Slow Drift in Reaction Kinetics*

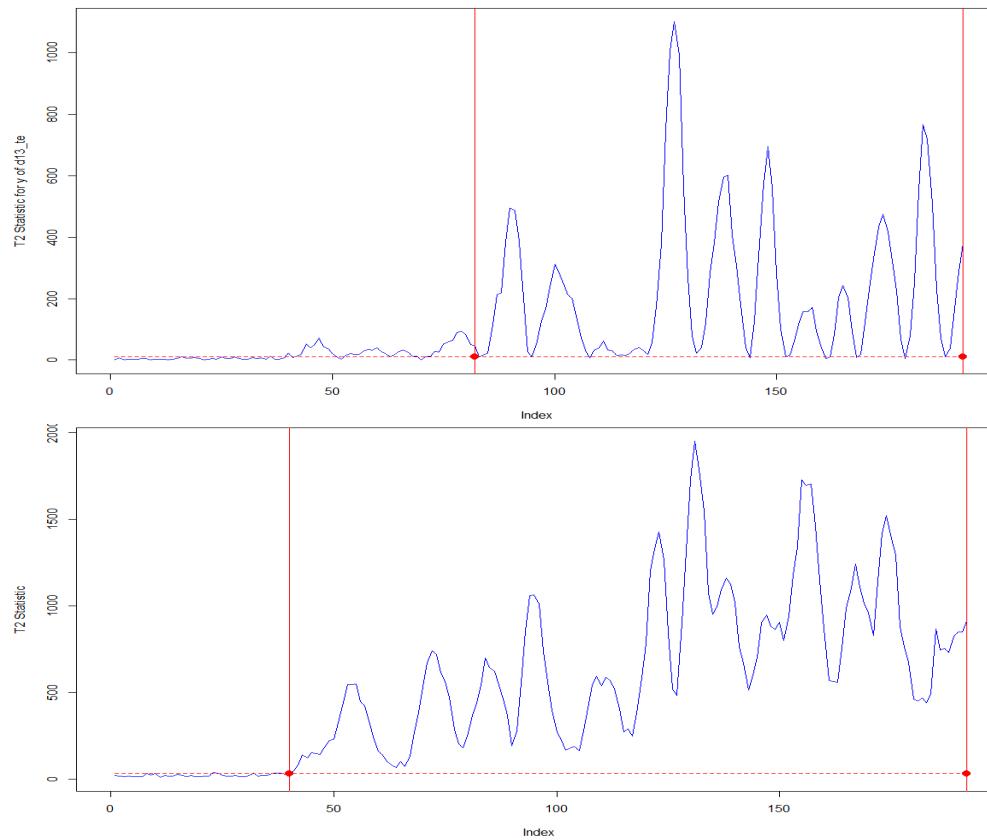


Fig.40. PCA Modeling for IDV(13)

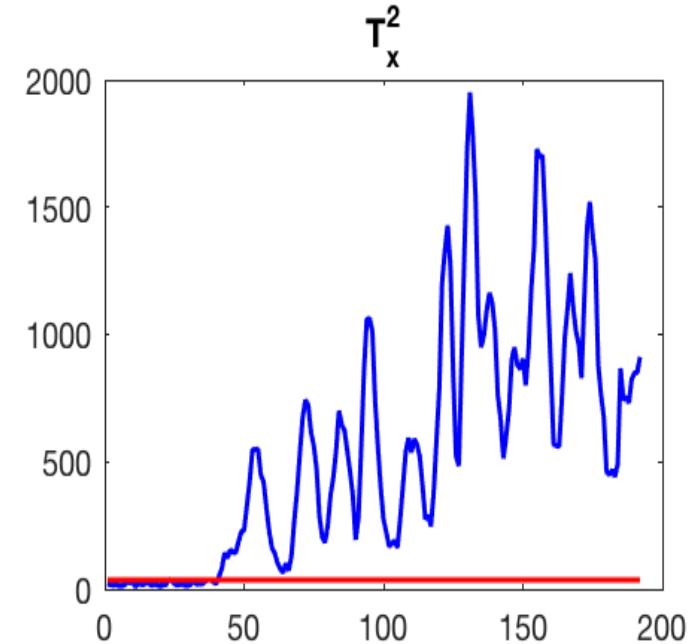


Fig.41.  $T_x^2$  plot for IDV(13)



# Concurrent CCA Monitoring

*IDV(13): Slow Drift in Reaction Kinetics*

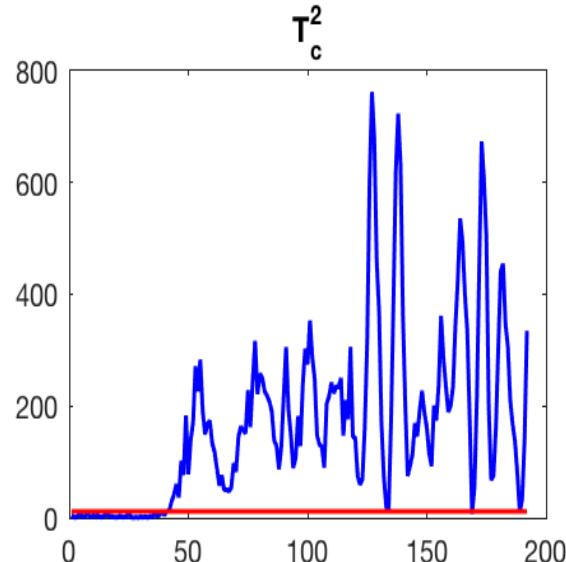


Fig.42.  $T_c^2$  plot for IDV(13)

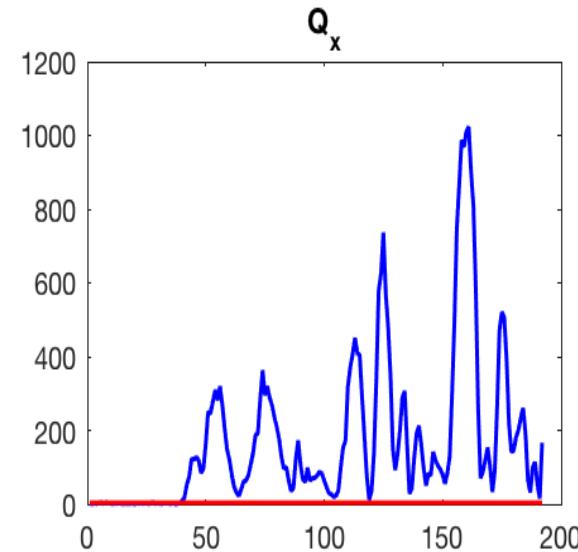


Fig.43.  $Q_x^2$  plot for IDV(13)

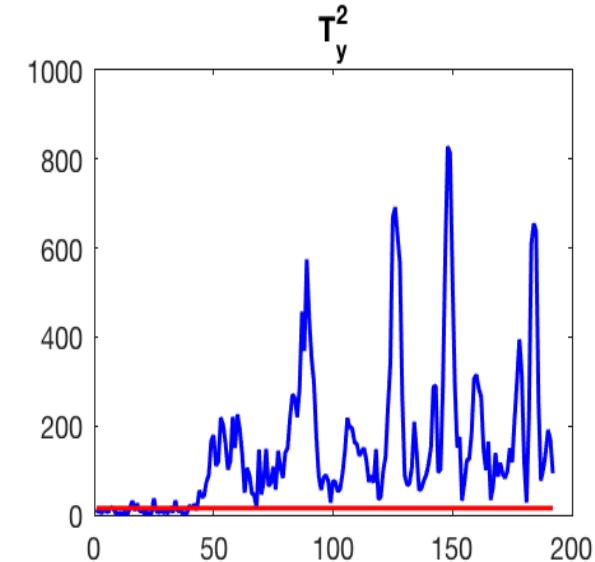


Fig.44.  $T_y^2$  plot for IDV(13)



# Concurrent CCA Monitoring

*IDV(14): Sticking in Reactor Cooling Water Valve*

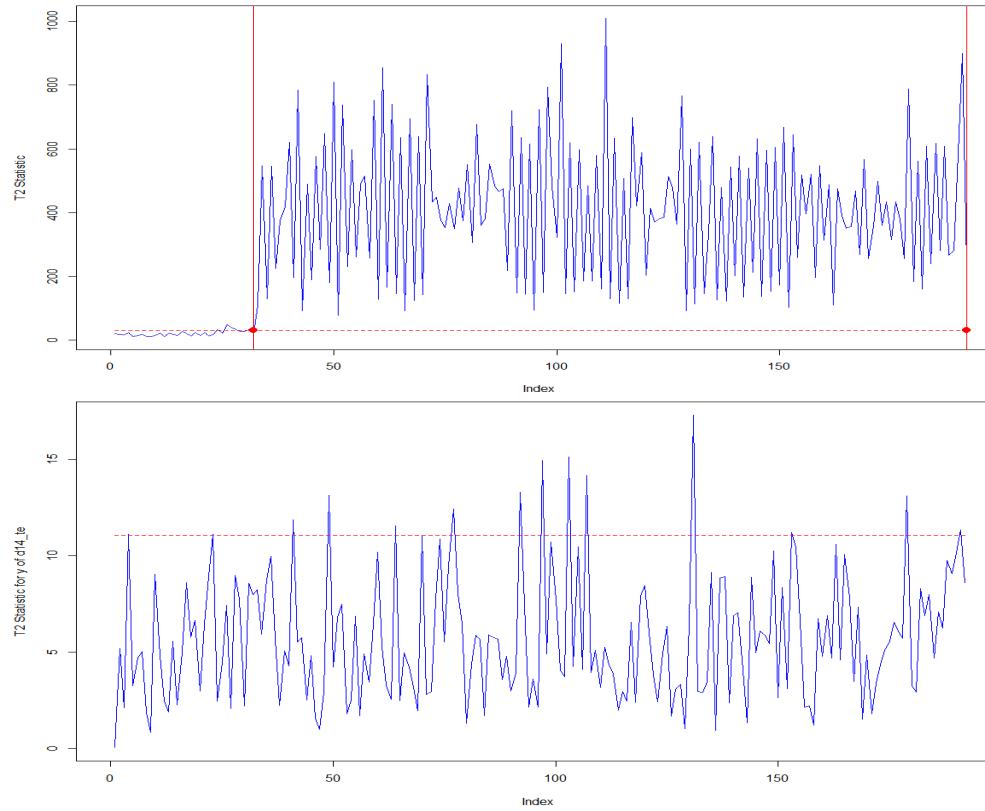


Fig.45. PCA Modeling for IDV(14)

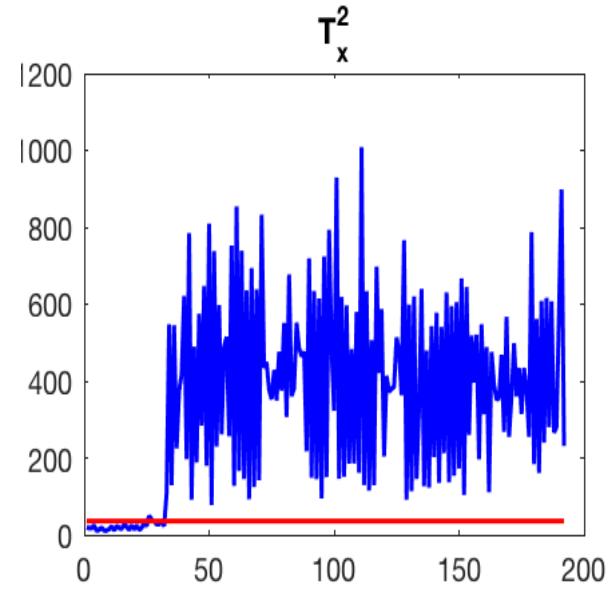


Fig.46. T<sub>x</sub><sup>2</sup> plot for IDV(14)



# Concurrent CCA Monitoring

*IDV (14): Sticking in Reactor Cooling Water Valve*

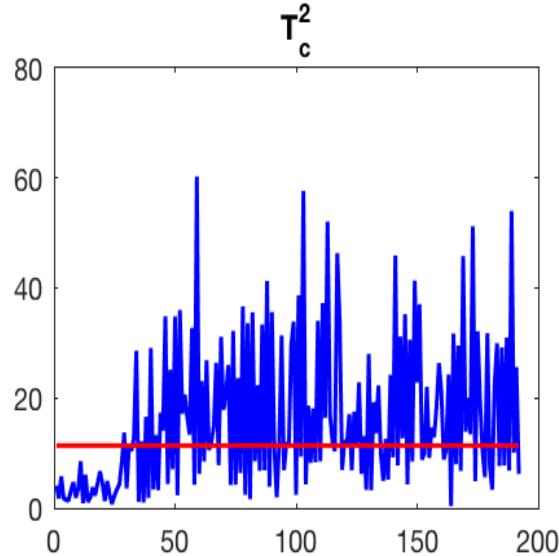


Fig.47.  $T_c^2$  plot for IDV(13)

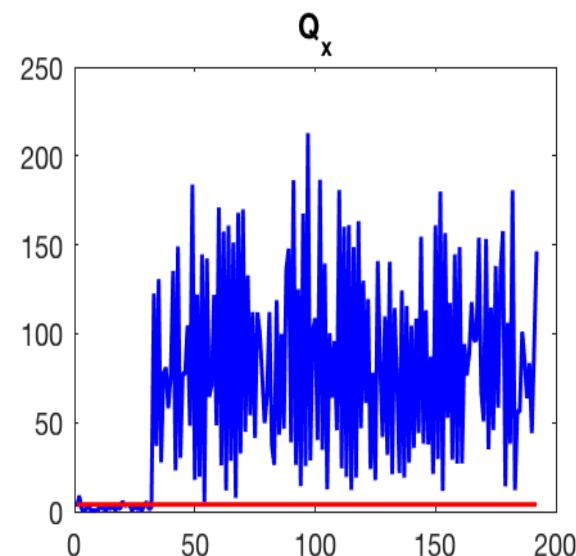


Fig.48.  $Q_x^2$  plot for IDV(13)

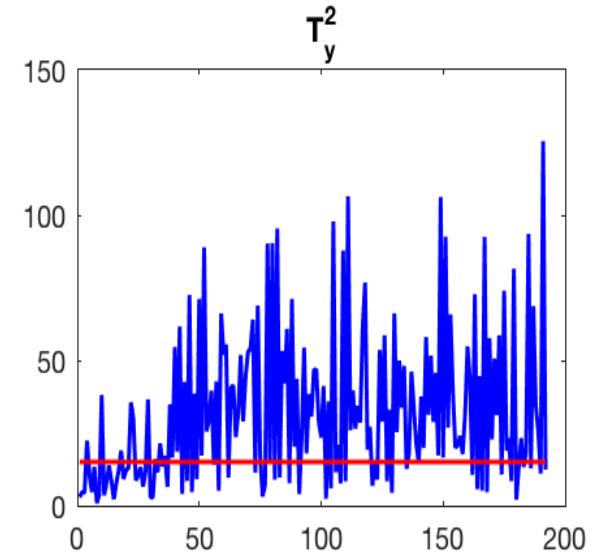


Fig.49.  $T_y^2$  plot for IDV(13)



# Thank You

USC

School of Engineering

University of Southern California