Robust Multivariate Process Control in Semiconductor Fabrication

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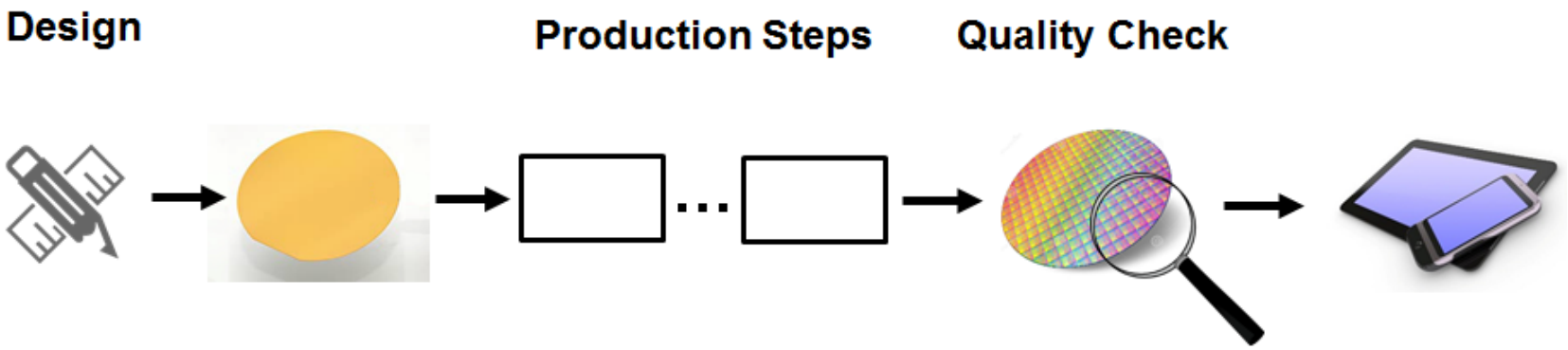
Outline

- Motivation
- Process control during production
- Process control after production
- Conclusion

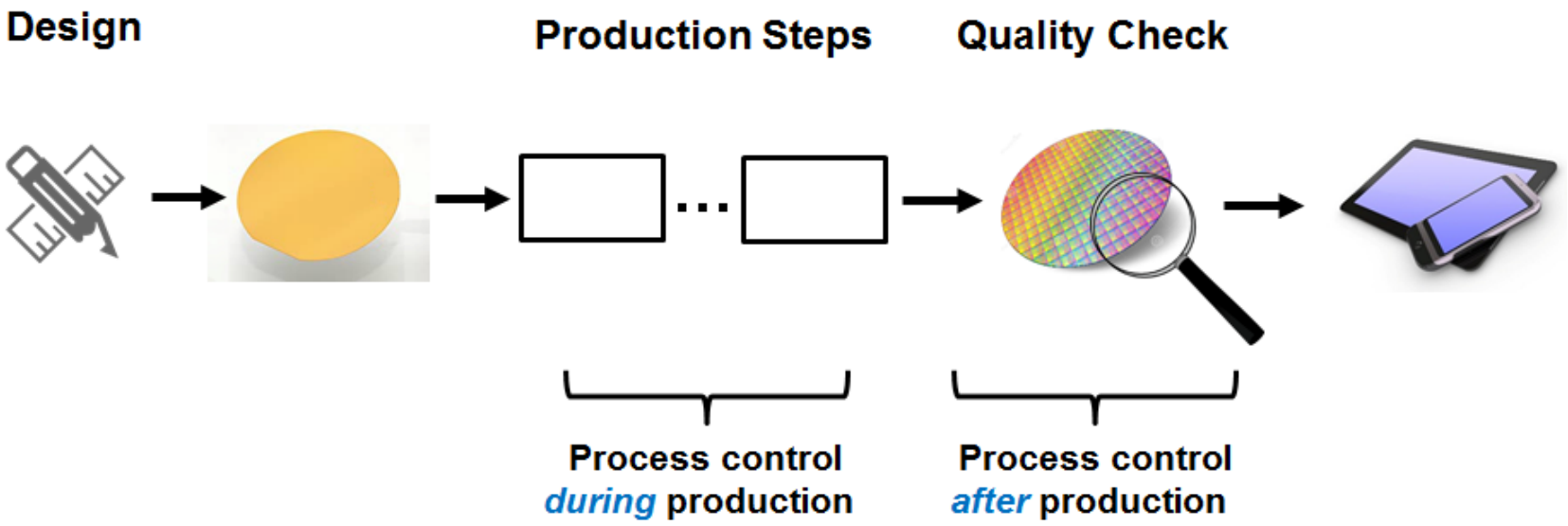
Motivation

Semiconductor manufacturing:



Motivation

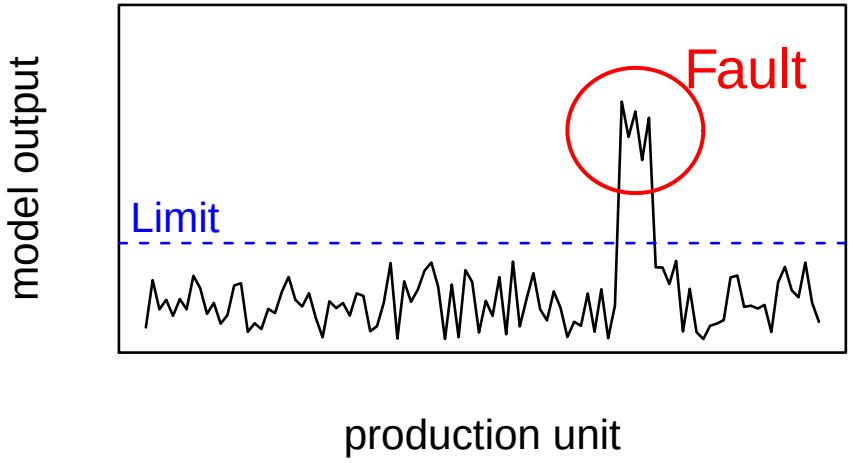
Semiconductor manufacturing:



Motivation

Construct multivariate process control models to

- identify process faults (**fault detection**)
- find the root cause of a fault (**fault diagnosis**)



1. Monitoring *during* production

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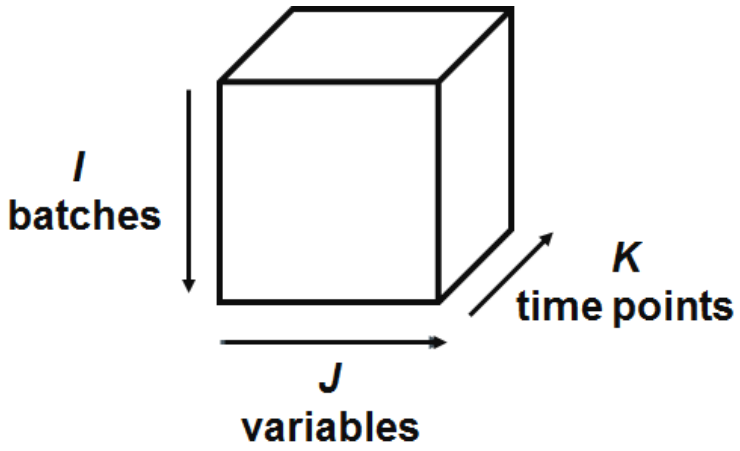
Semiconductor production is **batch processing**



data is organised in 3 dimensions

- observed batches
- measured variables
- time points of measurements

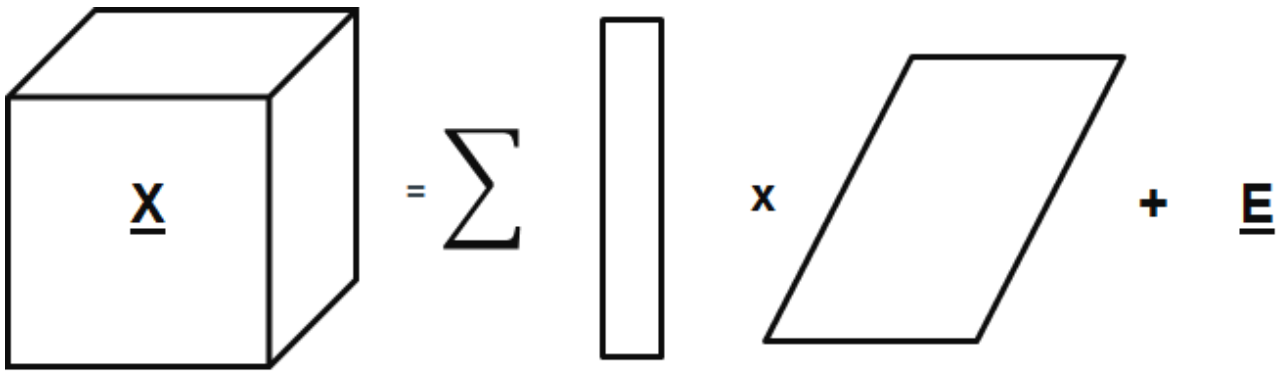
→ **Multi-way data**

1. Monitoring *during* production

Suitable method:

Multi-way Principal Component Analysis

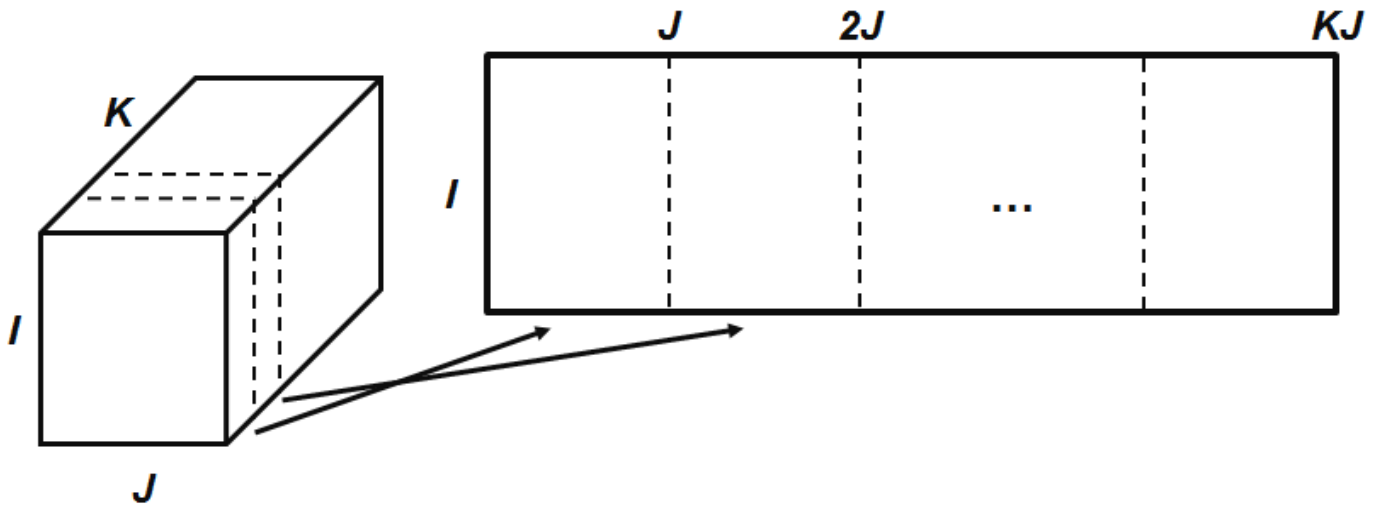
$$\text{data array } \underline{X} \;=\; \text{score vector} \times \text{loading matrix} + \text{error } \underline{E}$$



$\rightarrow$ score values hold information of time variation for each batch

1. Monitoring *during* production

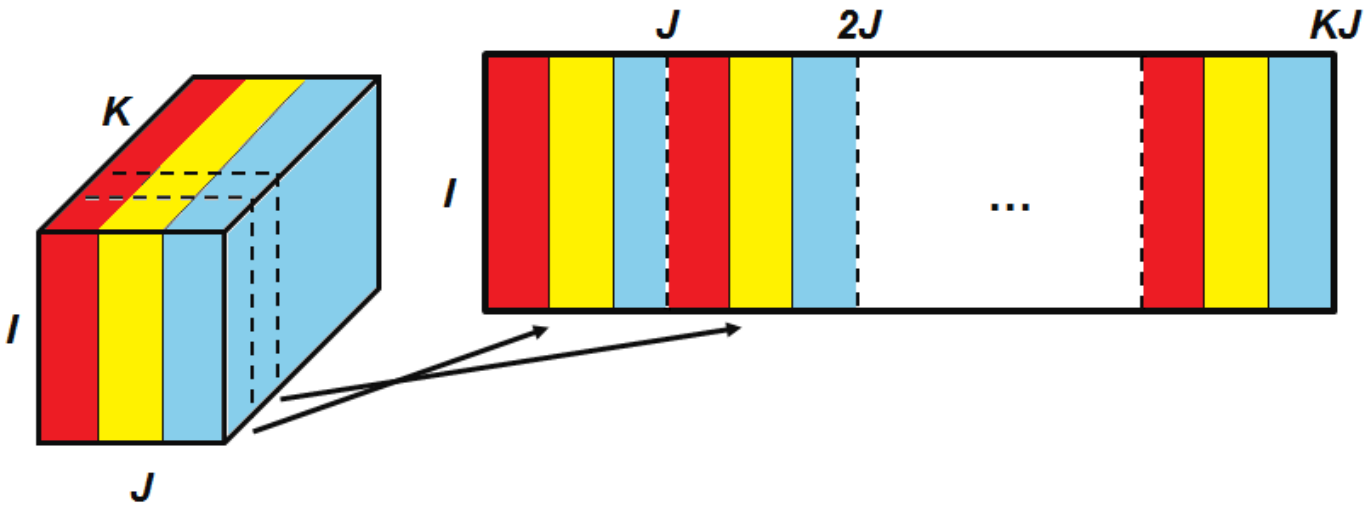
Multi-way PCA: unfold multi-way array by time



→ scores & loadings via ordinary PCA of unfolded matrix

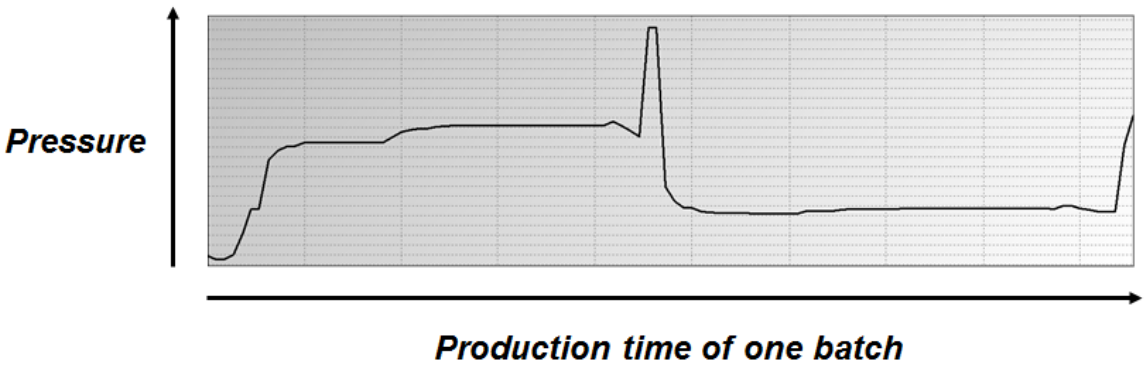
1. Monitoring *during* production

Multi-block PCA allows interpretation



- group variables into conceptually meaningful blocks
- derive block statistics (*consensus* PCA)

1. Monitoring *during* production - Kernel PCA



- variable relationships *not necessarily linear*
- Kernel PCA: transform input data via nonlinear function
- Robust: outlyingness measure to construct robust subset

1. Monitoring *during* production - Hotelling's T^2

Monitor process behaviour via

$$T^2 = [t_1, ..., t_p]\Lambda^{-1}[t_1, ..., t_p]^T$$

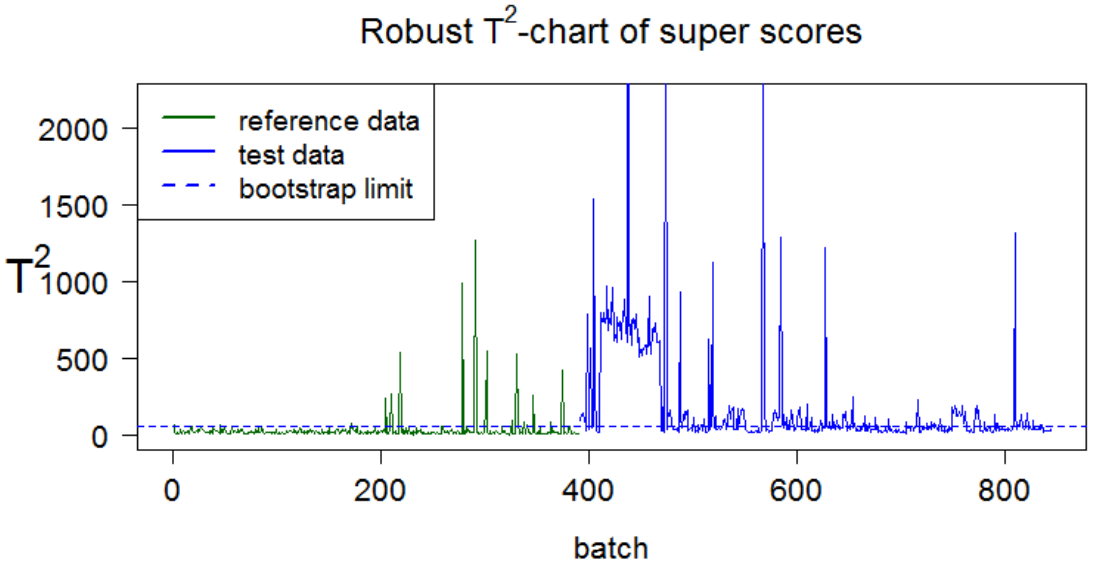
t_i ... centered scores of PC i
Λ ... covariance matrix of scores

- **crucial:** robust estimation of center and covariance
- adequate mapping of normal operating condition
- effective fault detection for future observations

1. Monitoring *during* production - Case study

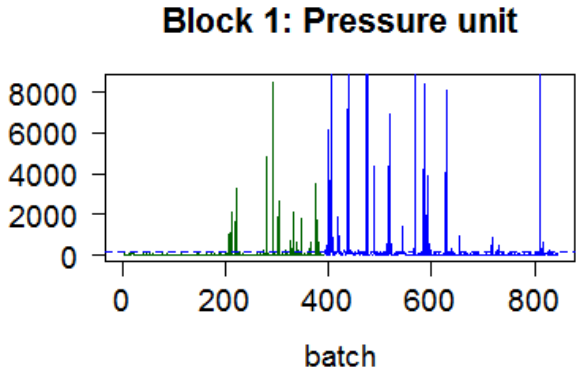
Faulty magnetic field in a plasma etch machine (June 2011)

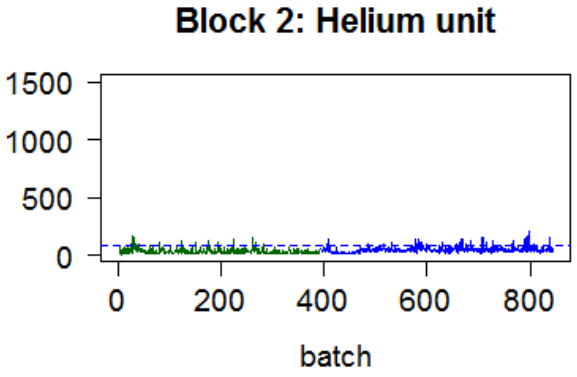
- 392 batches to build model, 424 test batches
- 10 continuous variables in 3 blocks
- 178 time points

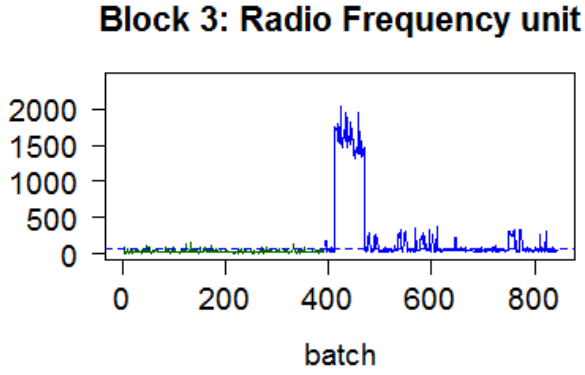


1. Monitoring *during* production - Case study

Fault diagnosis: contributions of each block via block scores

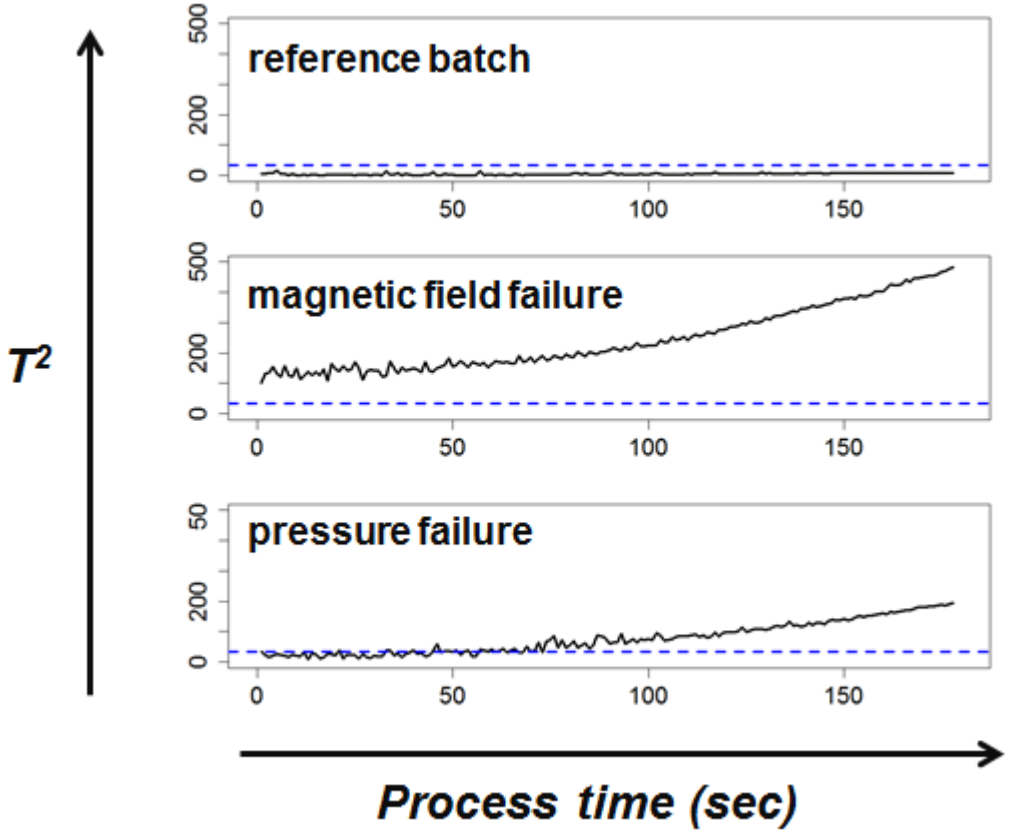




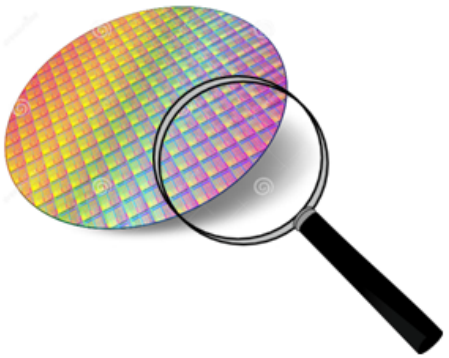


1. Monitoring *during* production - Case study

On-line monitoring: 3 single batches during processing



2. Monitoring *after* production



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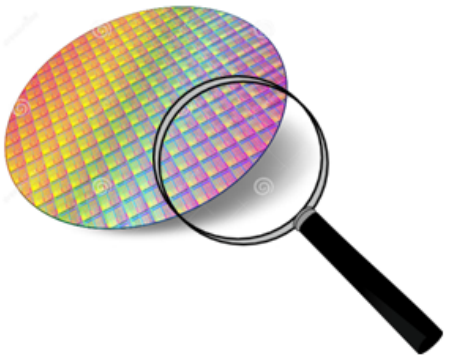
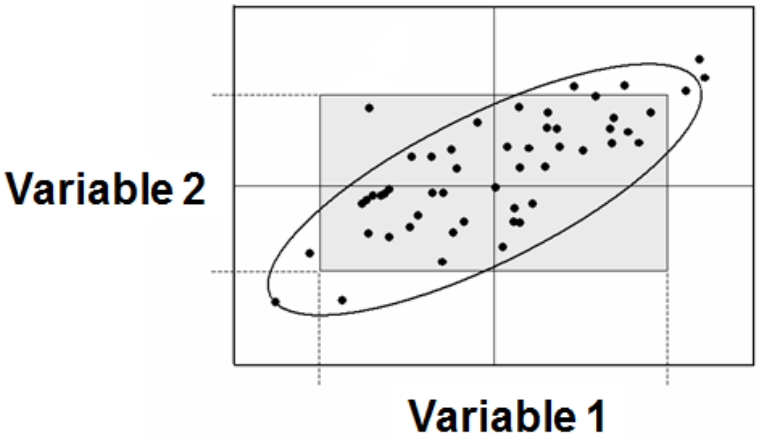


Wafer Acceptance Test

- crucial quality check
- decision if chips fulfill design requirements
- univariate limits to monitor variables

2. Monitoring *after* production

But: univariate monitoring can not identify correlation faults



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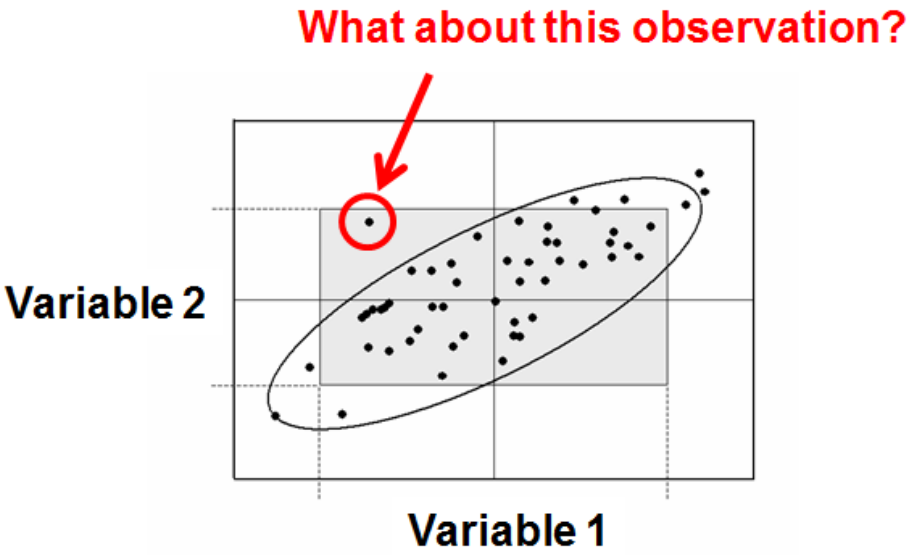

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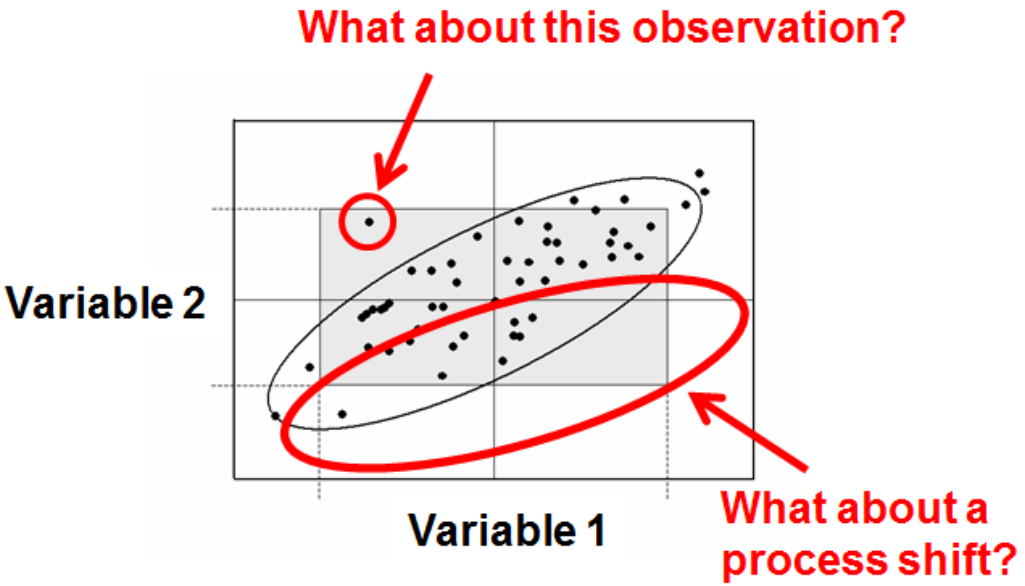

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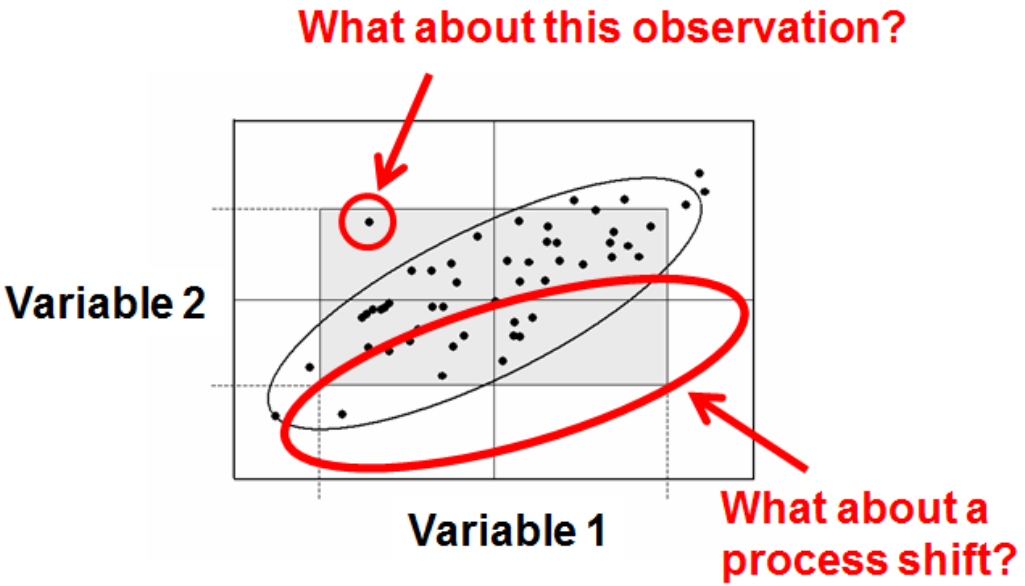
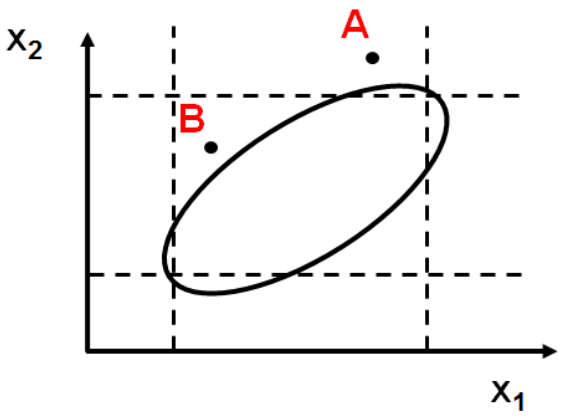
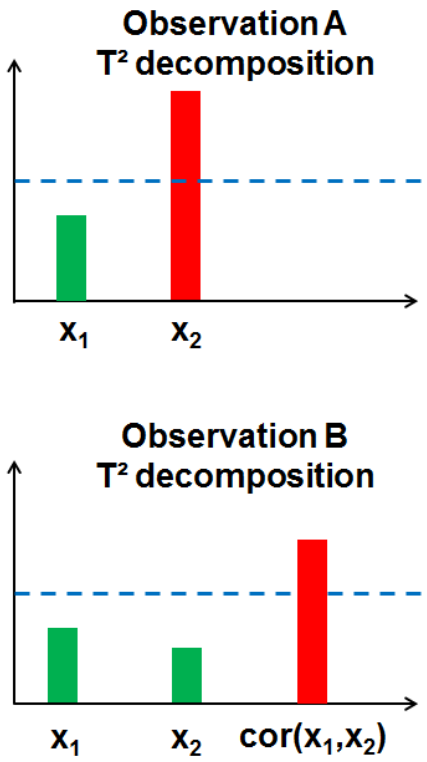


→ use *Hotelling's* T^2 for multivariate monitoring

2. Monitoring *after* production

Fault diagnosis via **Mason-Young-Tracy decomposition**:

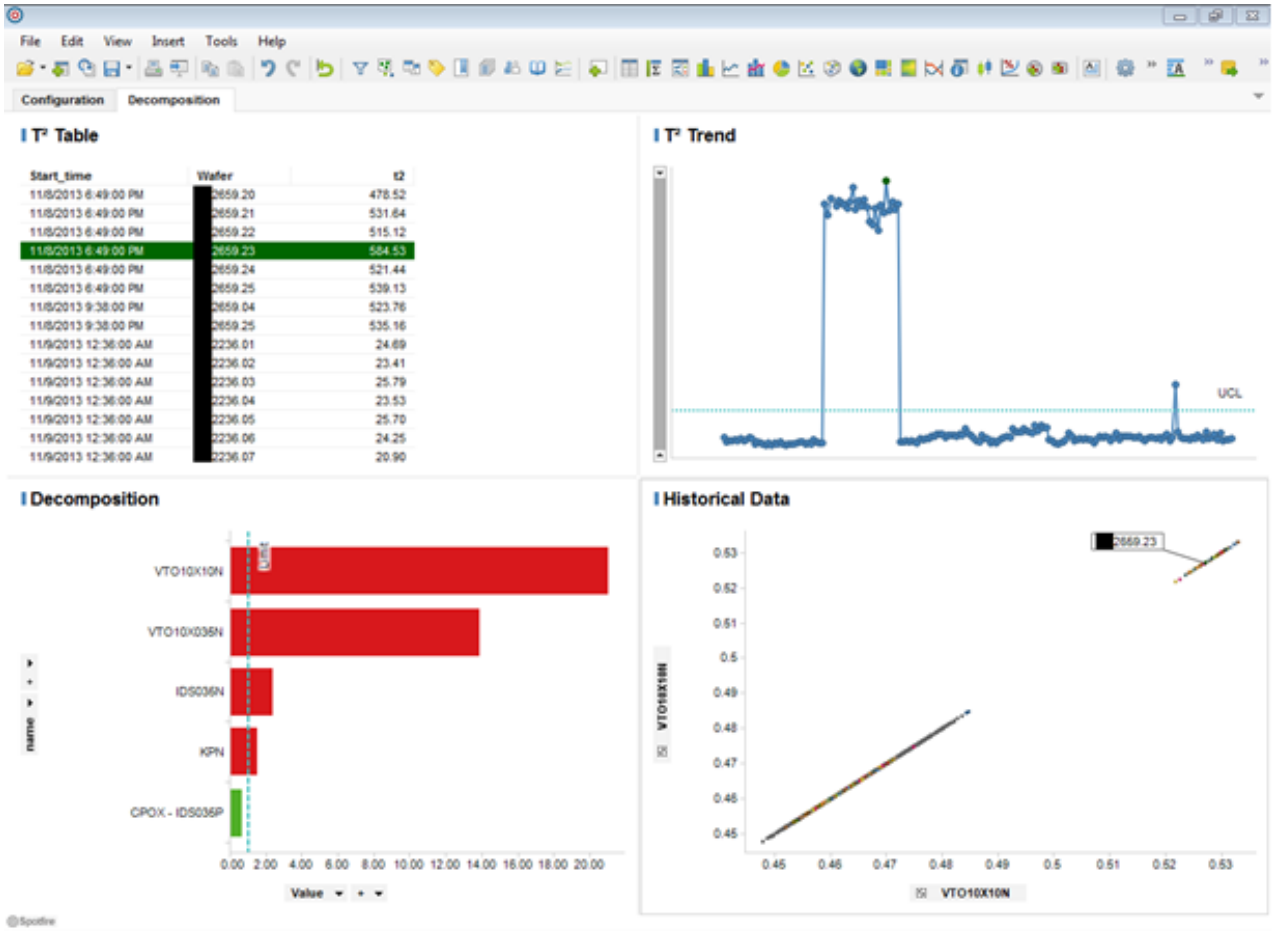




2. Monitoring *after* production - Implementation

- model user-interface created in *TIBCO Spotfire*
- simple interface for process engineers
- T^2 model construction in R
  $\rightarrow$ use robust estimation
- Spotfire executes R code & visualizes R results

2. Monitoring *after* production - Implementation



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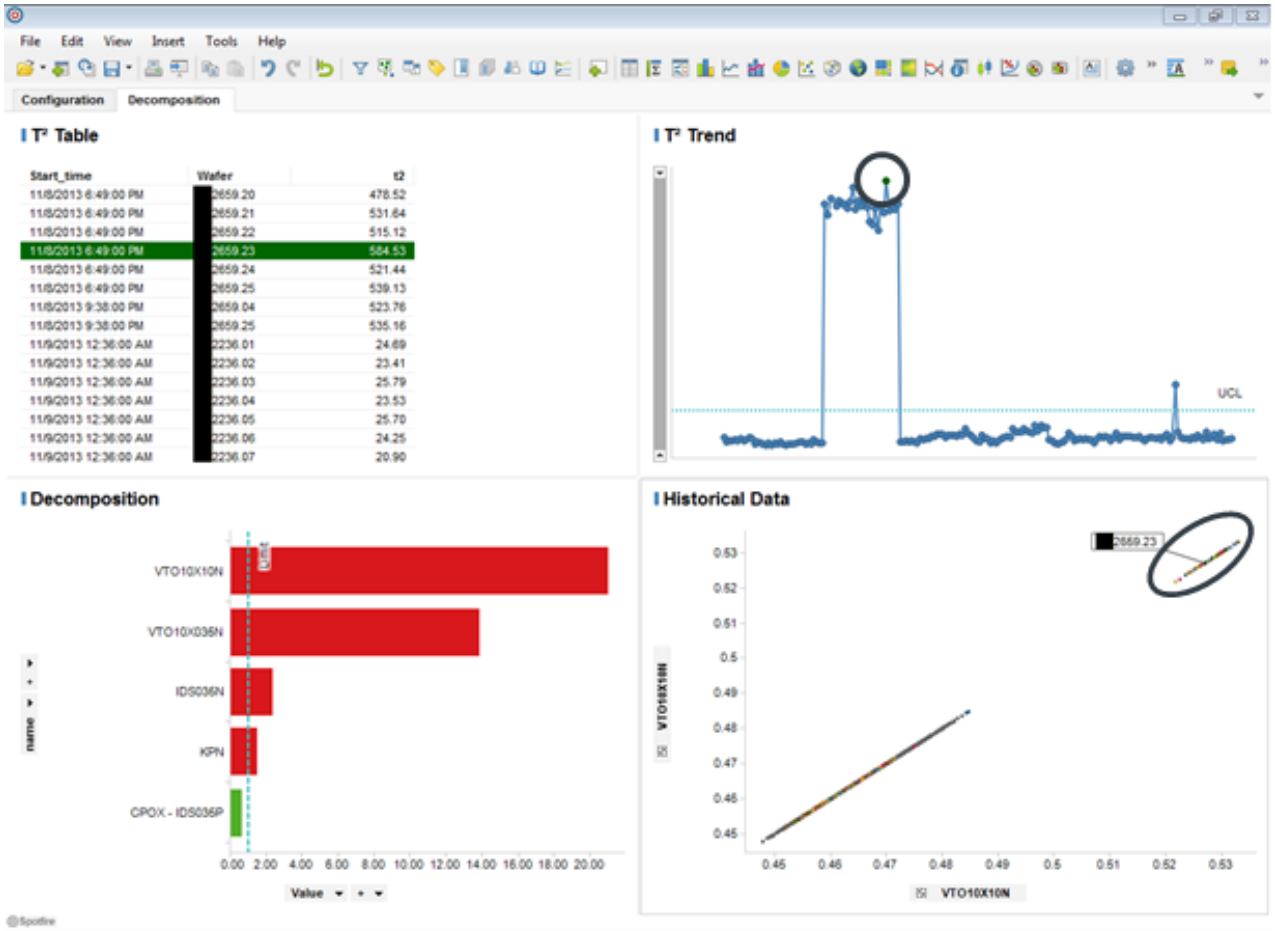

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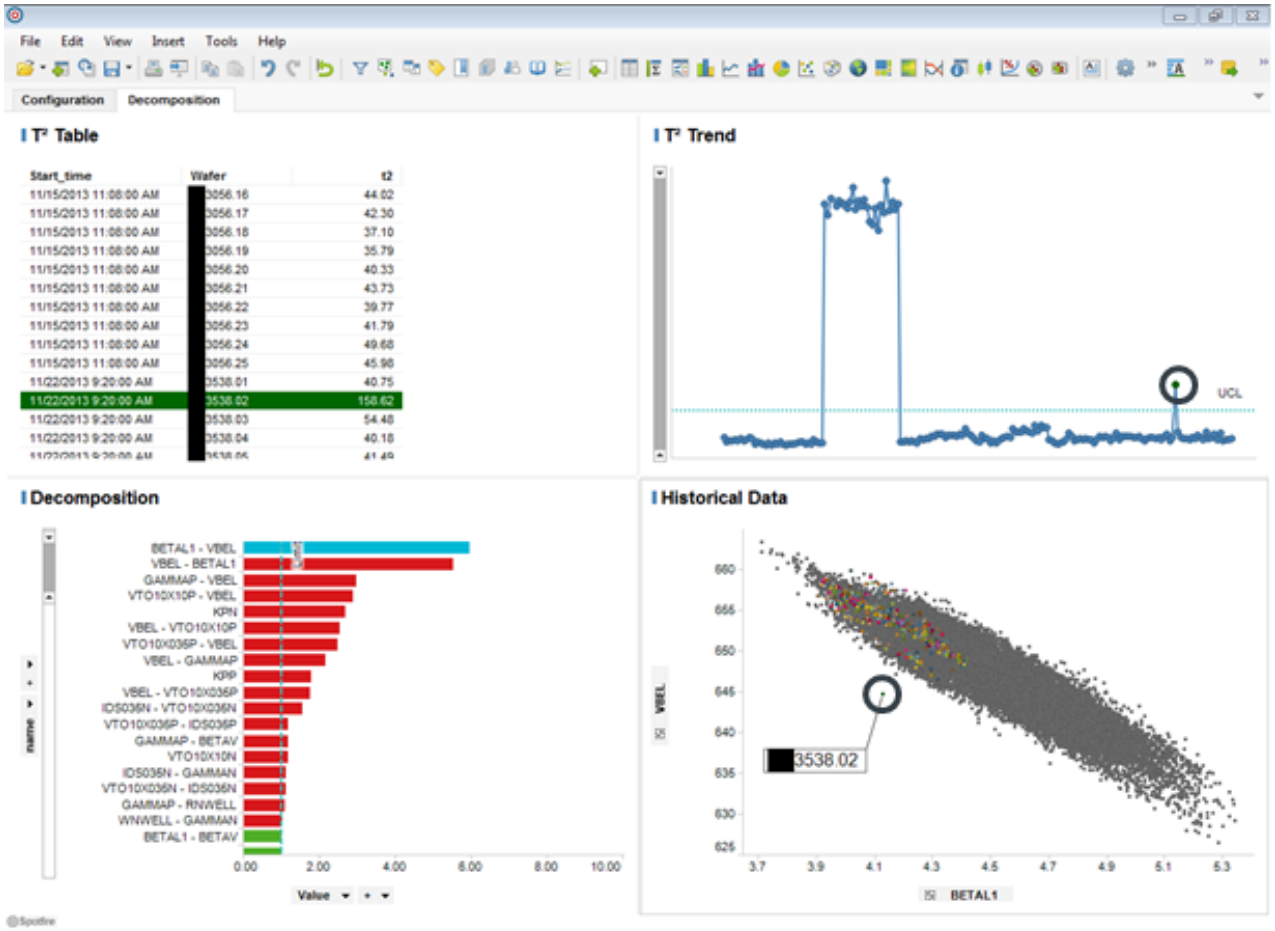

Conclusion

Kernel PCA-based monitoring model for multi-way data

- captures nonlinearities
- robust estimation of normal operating condition
- fault diagnosis & on-line monitoring

T^2 model for quality monitoring after production

- detection of correlation problems
- fault diagnosis via T^2 decomposition
- implementation easy-to-use for process engineers

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Thank you!

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