Robust Multivariate Process Control in Semiconductor Fabrication

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22-09-2014
Outline

▶ Motivation
▶ Process control during production
▶ Process control after production
▶ Conclusion
Motivation

Semiconductor manufacturing:

Design → Production Steps → Quality Check
Motivation

Semiconductor manufacturing:

Design → Production Steps → Quality Check

- Process control *during* production
- Process control *after* production
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**

\[
\text{data array } X = \text{score vector } \times \text{ loading matrix } + \text{ error } E
\]

→ 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 $i$

$\Lambda$  ... 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

![Graphs showing contributions of each block via block scores](image-url)
1. Monitoring *during* production - Case study

**On-line monitoring:** 3 single batches during processing
2. Monitoring *after* production
2. Monitoring *after* production

**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
2. Monitoring \textit{after} production

\textbf{But}: univariate monitoring can not identify correlation faults
2. Monitoring after production

**But**: univariate monitoring can not identify correlation faults

What about this observation?

What about a process shift?
2. Monitoring *after* production

**But:** univariate monitoring can not identify correlation faults

→ use *Hotelling’s $T^2$* for multivariate monitoring
2. Monitoring *after* production

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

![Diagram showing two observations A and B in a bivariate normal distribution with T² decomposition for each observation.](image)
2. Monitoring *after* production - Implementation

- model user-interface created in *TIBCO Spotfire*
- simple interface for process engineers
- $T^2$ model construction in R
  - use robust estimation
- Spotfire executes R code & visualizes R results
2. Monitoring *after* production - Implementation
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2. Monitoring *after* production - Implementation
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!

In cooperation with

[Logos of ams and TU Graz]