Approaches for development and implementation of Virtual Metrology and Predictive Maintenance in semiconductor manufacturing

Ulrich Schöpka, Georg Roeder, Markus Pfeffer, Martin Schellenberger, Richard Öchsner, Lothar Pfitzner (Fraunhofer IISB)
Outline

• Introduction
• Virtual Metrology and Predictive Maintenance: Motivation and concept
• Approaches for VM/PdM development
• VM/PdM examples
Introduction

Virtual Metrology and Predictive Maintenance: novel APC methods

Semiconductor manufacturing

- Advanced Process Control (APC) systems have become essential for cost effective manufacturing at high quality
- To further increase technological and productivity requirements, novel APC methods Virtual Metrology (VM) and Predictive Maintenance (PdM) gain more and more attention

Complex systems for process control in semiconductor manufacturing

- Comprising SPC, fault detection and classification, run-to-run control, and others
- To enhance control: Development of novel methods and algorithms for virtual metrology (VM) and predictive maintenance (PdM)
Virtual Metrology (VM)

Motivation for application of VM

VM definition
• Technology of prediction of post process metrology variables (either measurable or non-measurable) using process and wafer state information that could include upstream metrology and/or sensor data.

State-of-the-art
• In current IC manufacturing, achievement of process stability and high production yield relies on reliable wafer monitoring by physical metrology
• Critical parameters are assessed using monitor or product wafers
• No broad implementation of concepts like virtual metrology
Virtual Metrology (VM)
Concept of VM for IC-manufacturing

Deficiencies for monitoring and process control
• Limited possibility for process monitoring and control on wafer-to-wafer or on real-time basis
• Critical parameters may not be measurable with in-line measurements

VM benefits
• Support or replacement of stand-alone and in-line metrology operations
• Support of SPC, FDC, run-to-run control, and PdM
• Improved understanding of unit processes
• Improved equipment control for VM running on equipment level
Predictive Maintenance (PdM)

Motivation for application of PdM

PdM definition

• Application of equipment degradation models for prediction of equipment’s remaining useful lifetime utilizing all relevant manufacturing data

State-of-the-art

• Preventive Maintenance: performance of preventive actions to reduce the likelihood of equipment failure during operation ➔ maintenance potentially too early, leading to increased tool downtime

• Reactive Maintenance (run to fail): error-based maintenance decisions ➔ can cause scrap production and unscheduled downtime

PdM statistical modeling workflow

PdM Algorithms

Sensor data, VM prediction

Pre-processing: feature extraction, transformation

Model creation and parameter learning

Prediction of faults, component health
Predictive Maintenance (PdM)

Concept of PdM for IC-manufacturing

Deficiencies for maintenance planning
• Wear part end-of-life unknown, often not measurable

PdM benefits
• Improved uptime and availability – by reducing or eliminating unplanned failures
• Reduced operational cost – by enhanced consumable lifetimes and efficiency of service personnel
• Improved product quality – by eliminating degraded operation and tightening process windows
• Reduced scrap – by maintenance actions before a failure occurs
Approaches for VM/PdM development

Structured approach for VM/PdM development and application

Phases in VM/PdM development as adapted from the Cross-Industry Standard Process for Data-Mining (CRISP-DM)

- **Equipment/process understanding**
  - Objective and success criteria for VM
  - Analysis of equipment parameters and process steps
  - Work plan

- **Data understanding**
  - Initial data collection
  - Data description and exploration
  - Analysis of data quality

- **Data preparation**
  - Data selection
  - Data formatting
  - Construction of derived variables

- **Modeling**
  - Selection of modeling technique
  - Test design generation
  - Model building and assessment

- **Evaluation**
  - Process and model review
  - Determination of next steps (model refinement vs. move to deployment)

- **Deployment**
  - Planning of deployment
  - Monitoring and maintenance
  - Project documentation and review

---

Fraunhofer IISB
Approaches for VM/PdM development

Different kinds of data available

**Historical fab data:**
- Equipment and process data (from tool, FDC system)
- Measurement data (from offline measurements and quality control)
- Logistic data (from MES system)
- Maintenance data

→ Merging of data from all available sources requires identical time stamp

**Model development:**
- Find function \( g(X) \) to approximate the true function \( f(X) \) to describe the process output \( Y \), health status or time to failure

\[
\begin{bmatrix}
  y_1 \\
  y_2 \\
  \vdots \\
  y_n
\end{bmatrix} = g
\begin{bmatrix}
  x_{11} & \cdots & x_{1m} \\
  x_{21} & \cdots & x_{2m} \\
  \vdots & \ddots & \vdots \\
  x_{n1} & \cdots & x_{nm}
\end{bmatrix} + \begin{bmatrix}
  \varepsilon_1 \\
  \varepsilon_2 \\
  \vdots \\
  \varepsilon_n
\end{bmatrix}
\]

Data quality: Metrology and equipment data needs to be accurate and complete
Approaches for VM/PdM development

Potential methods for model building

Data analysis and feature subset selection:
• Clustering methods (e.g. k-means clustering)
• Feature selection methods

Machine learning methods (regression and classification models)
• Univariate/multivariate modeling e.g. by
  • Linear/nonlinear regression
  • Stepwise regression
  • Decision tree methods (CART, Random Forest, Boosted Trees, …)
  • Support Vector Machines (SVM)
  • Neural Networks
  • Bayesian Networks
  • …

Time series modeling methods applicable
• Require measurable wear indicator
• Forecasting e.g. by ARMA/ARIMA, Kalman filtering
• Univariate or multivariate methods available
VM example
Prediction of etch depth in a trench etch process

Trench etch process
- The IT etch defines the active regions
- The process is carried out in four steps:
  1. Etching of the organic ARC and nitride layer (mask open)
  2. Conditioning step
  3. Conditioning step
  4. Etching of the poly silicon (IT etch)
- Strip of resist and of anti-reflective coating (ARC) by etching in a plasma
- Step 4 and step 1 are expected to primarily define the etched depth which should be predicted by VM
VM example
Prediction of etch depth in a trench etch process

Modeling and validation
• Inclusion of all etch steps, prioritization in correlation analysis
• Boosted Trees regression model

Result
• Precise prediction of etch-depth is possible
• Limitation of the prediction horizon and continuous model update significantly improves the VM accuracy and precision

VM prediction results for model application applying model update

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Training</th>
<th>Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of residuals</td>
<td>&lt; 0.1 nm (&lt; 0.1 %)</td>
<td>&lt; 0.2 nm (&lt; 0.1 %)</td>
</tr>
<tr>
<td>Std. dev. of residuals</td>
<td>2.5 nm (0.51 %)</td>
<td>4.0 nm (0.81 %)</td>
</tr>
</tbody>
</table>

With contributions from Infineon Technologies AG
PdM example
Prediction of filament breakdown in ion implanter source

Motivation
• Implanter “Source PM” is a frequently recurring maintenance activity
• Predicting the source breakdown allows to precisely schedule the maintenance action before the breakdown occurs.
• No wear index in data ➔ prediction of Time to Failure (TTF)

Methods
• Comparison of different machine learning methods
  • Random Forest
  • Bayesian Networks with soft discretization
  • Multiple Linear Regression

With contributions from ams AG
Pictures: ams AG
PdM example
Prediction of filament breakdown in ion implanter source

Test metrics:
- Root Mean Square Error (RMSE) for models applied to learn (RMSE\textsubscript{learn}) and test data (RMSE\textsubscript{test})
- Performance within last 20% of the maintenance cycle (RMSE\textsubscript{20%})
- Time-resolved test metrics necessary, since precision near breakdown is crucial

Modeling results:
- Random Forest model chosen due to best overall performance

With contributions from ams AG
Conclusion

Virtual Metrology and Predictive Maintenance:
• Data driven APC methods for prediction of post process quality parameters (VM) and remaining useful equipment lifetime (PdM)

Modeling methods and process:
• Different machine learning and time series methods available for modeling
• Utilization of process, equipment, logistic, maintenance, and metrology data
• CRISP-DM data mining standard defines modeling process

VM/PdM examples:
• VM demonstrated on trench etch process
• PdM to predict time to failure in ion implanter source demonstrated

VM and PdM are powerful new APC methods
• Data analysis during VM/PdM development enhances process understanding
• VM/PdM support meeting future technological and productivity challenges
The IMPROVE project was funded by the ENIAC Joint Undertaking (project ID: 12005) and by the Public Authorities of the countries involved: Austria (Österreichische Forschungsförderungsgesellschaft mbH), France (Direction Générale de Compétitivité, de l'Industrie et des Services), Germany (Bundesministerium für Bildung und Forschung), Ireland (The industrial Development Authority), Italy (Ministero dell'Istruzione, dell'Università e della Ricerca), Portugal (Fundação para a Ciência e a Tecnologia).

More information: [www.eniac-improve.eu](http://www.eniac-improve.eu)

Contributions by:

- S. Winzer, S. Jank (Infineon)
- P. Scheibelhofer, G. Hayderer, G. Leditzky (ams AG)