Selected Predictive Maintenance Research Cases With Focus on Applications and Potentials in Semiconductor Manufacturing

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Outline of the Talk

• Introduction

• Selected Examples of Condition Based Maintenance (CBM) Research

• Semiconductor Manufacturing Related Research in CBM

• Opportunities for Research in CBM in Semiconductor Manufacturing
Condition Based Maintenance (CBM) Paradigm

Data → Health Assessment → Information → Diagnosis → Performance Prediction → Decisions

Quantitative Health Assessment

Feature Space

Normal Behavior → Most Recent Behavior → Faulty Behavior

Feature f₁ → f₂

Normal Behavior

Model of a Fault

Predicted Probability of Failure

Prediction Uncertainty

Predicted Health
Condition Based Maintenance (CBM) Paradigm

Signal Processing and Feature Extraction Tools

Performance Assessment

Sensor and Communication Channel Health Monitoring

Predictive Machine / Equipment Monitoring

Performance Prediction

Quantitative Health Assessment Tools

Condition Diagnosis Tools

Performance Prediction Tools

Maintenance decision-making

Factory level proactive maintenance decisions

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Selected CBM Research Examples

• Sensor and Communication Channel Health Monitoring
  – Monitoring of sensor dynamics degradation
  – Industrial network health monitoring

• Predictive Machine/Equipment Monitoring
  – Performance assessment and diagnosis of electromechanical systems using physics-based models
  – Immune systems inspired approach to diagnostics in complex dynamic systems

• Maintenance Decision Making
  – Maintenance prioritization
Performance Health Assessment and Diagnosis based on Physical Modeling

- Parameter change pinpoint fault(s)
- From healthy & broken systems models, simulate
  - $y(t)$, $y_i(t)$
  - $n(t) = y(t) - y_i(t)$
- FFT $Y(f)$, $Y_i(f)$, $N(f)$
- $S(f) = |Y(f)|^2$, $N(f) = |N(f)|^2$
- Estimate channel communication capacity:

  \[
  C = \int_{f=0}^{a} \log_2 \left( \frac{S(f)}{N(f)} \right) df
  \]

Dr. Michael Bryant
Motor-Pump System Health Assessment Based on Shannon’s Entropy Theory

- C vs. change in $R_{\text{bar}}$
- 3 regions
  - 0: ideal to actual
  - I: life cycle region
  - II: transition to failure

$$C = \log_2 \frac{S(f)}{N(f)}$$
Immune Systems Inspired Approach to Diagnostics in Complex Dynamic Systems

- High model complexity
- High variability of driving profiles
- High variability of operating conditions
- Cascading faults

- Traditional precedents-based diagnostics reached its limits.
- Need for continuous assessment and control even in situations not observed in the past
Fault Localization through Distributed Anomaly Detection

Block diagram of the Diesel engine system provided by Bosch Research Center, Pittsburgh
Fault Localization through Distributed Anomaly Detection

Negative selection in natural immune systems (Dasgupta, 2006)

Djurjanovic, Ni and Marko, 2006 *(NSF CMMI 0600200)*

Block diagram of the Diesel engine system provided by Bosch Research Center, Pittsburgh
Cascading Faults in an Electronic Throttle System

ECU – Electronic Control Unit

GEVM – Gasoline Engine Vehicle Model

AD – Anomaly Detector
Surge in Computational Effort – “Car Getting a Fever”

- Both controller and plant are set to be faulty (20% random parameter shift, starting at 50s)
- Global ADA, sub-ADA and sub-DA generated sequentially
- System error and subsystem error increase due to the faults
- Computational effort has a surge during detection and diagnosis

Machine got a fever trying to match “the protein” of the newly encountered fault.

GSMMS prediction error and computation power of the immune system for the throttle system
Selected CBM Research Examples

• **Sensor and Communication Channel Health Monitoring**
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• **Maintenance Decision Making**
  – Integrated maintenance and reconfiguration decision-making
Background

- **Load Sharing Systems**
  - Components work under various speeds to share a certain load
  - Power generation, facility pumps, etc.

- **Condition-based Maintenance**
  - Components deteriorate with usage and age
  - Deterioration could result in catastrophic failures
  - CBM to keep good balance between over- and under-doing preventive repair based on condition monitoring

- **CBM in load-sharing system**
  - Components deteriorate faster under larger loads
  - Re-allocate loads in response to failures/repairs
  - Dynamically allocate load based on component condition to reduce downtime (risk of catastrophic failure)
Integrated Load Sharing Allocation and Condition Based Maintenance (ILACBM)

To maintain a total load of 280

<table>
<thead>
<tr>
<th>$k$</th>
<th>load ($v_k$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>120</td>
</tr>
<tr>
<td>2</td>
<td>140</td>
</tr>
<tr>
<td>3</td>
<td>160</td>
</tr>
</tbody>
</table>

Reference Policy – CBM Policy
- No dynamic load allocation, always evenly distribute load between two pumps [140, 140]

Optimal Policy

CBM Policy

- : no repair, load allocation: [140, 140]
- : repair the failed pump, load allocation after repair: [140, 140]

ILACBM Policy

- : no repair, load allocation: [160, 120]
- : repair both pumps, load allocation after repair: [140, 140]
- : no repair, load allocation: [120, 160]
Advantages of ILACBM policy over CBM policy
- Reduced operating cost (2.87% in this specific example)
- Reduced downtime → meet target load better
- Balanced system → Reduced repair cost
- Larger operational region → more useful life extracted from pumps

Cost benefit of reconfiguration increases
- As repair setup cost ($\alpha$) increases
  - Uneven load allocation balance the degradation of two pumps, which makes the group maintenance more cost-beneficial
- As total # of degradation levels ($N$) increases
  - Load allocation have more control on the system → more cost benefit for combined decision makings
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Development of Predictive Modeling and Intelligent Decision Making Tools for the High Yield Next Generation Semiconductor Factories

Monitor > Correlation > Prediction > Prevention > Optimization

- Coordinated & Proactive Actions
  - Rapid Response
  - High Yield
  - Zero Downtime
  - Rapid Cycles

Funded by the Semiconductor Research Corporation (SRC) 2004-2007

Paradigm Shift – High Yield Next Generation Fab

Process Inspection
  - Process
  - Inspection
  - Action

Quality Inspection
  - Inspection
  - Detection
  - Action

Equipment Monitoring
  - Sensor
  - Diagnostics
  - Action

Reliability
  - Historical DB
  - Reliability Info
  - Action

Maintenance
  - Historical DB
  - Maint. Info
  - Action

Prognostics Tools
  - P(Yield| Quality, Sensing, Reliability, Process)

Decision Support Tools
  - Decision Tools, Optimization, Synchronization
Bayesian Belief Network Based Causality Discovery and Virtual Metrology

New observations of:
- Process condition
- In-situ sensing
- Time since last maintenance
- Available inspection
- Tool age

Unsupervised clustering tool to transform high dimensional continuous data into low dimensional discrete spaces [Kohonen, 1995]

• To identify causal relationships
• To handle missing/incomplete data
• Prediction of Yield
• To handle inhomogeneous data

Note: SOM is the abbreviation for a Self Organizing Map

Inference of metrology

Yield Models
Application to an Automotive Dataset

- Two illustrative parts selected, with 24 and 20 features, respectively
- 13960 measurements were divided into 2 subsets (50% for training and 50% for testing)

- Order of magnitude faster search than the search corresponding to a list-based database
Semiconductor Manufacturing Dataset

- Three individual data sets were available:
  - **Event Data**
    - ‘Start Time’, ‘Processing Chamber’, ‘Wafer #’ and ‘Lot #’ for each operation
  - **Trace Data**
    - Altered parameter readings with time stamps
  - **Metrology Data**
    - Wafer measurement results along with ‘Wafer #’ and ‘Lot #’

Chamber Tool Process parameters
X-axis: data points over time
Y-axis: altered reading value
Bayesian Network for a Deposition Tool

- Bayesian Network structure was discovered for 9 SOM-discretized process parameters and metrology results using 15,000 data entries (based on the Parker-Clark algorithm).
- Conditional probability table (CPT) for each node was trained using the same data set.
- BN structure and CPT provide the basis for inference.

<table>
<thead>
<tr>
<th>State of PARAM7</th>
<th>State of Metrology</th>
<th>[1]</th>
<th>[2]</th>
<th>[3]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.44%</td>
<td>93.01%</td>
<td>3.54%</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>84.52%</td>
<td>10.32%</td>
<td>5.16%</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>3.61%</td>
<td>34.47%</td>
<td>61.92%</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>12.99%</td>
<td>81.82%</td>
<td>5.19%</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>7.05%</td>
<td>12.70%</td>
<td>80.25%</td>
<td></td>
</tr>
</tbody>
</table>
Model Validation (using another 15000 vector entries)

(a) True distribution and (b) Inferred distribution of metrology given PARAM7 in states 1~5

• The overall similarity was evaluated by the metric

\[ S = \sum_{k=1}^{M} P_k \times S_k(I,T) \]

where \( P_k \) is probability of parent node in state \( k \); \( M \) is number of states of parent node; and \( S_k \) is similarity between inferred and true distribution given by

\[ S_k(I,T) = \sum_{j=1}^{N} \left( \sqrt{I_j \cdot T_j} \right) \]

• In this case study, the overall similarity is 0.9978 (average of 4-fold CV)
CBM Decision-Making with Yield Inference (SRC Force 2)

- Step 1: Data preprocessing
  - Data consolidation and synchronization
  - Feature extraction
- Step 2: Chamber state estimation
  - HMM based chamber state estimation using observable parameters
- Step 3: Predictive yield model
  - Bayesian network inference using new observations
- Step 4: Simulation
  - Simulation model of production and maintenance
- Step 5: Maintenance optimization
  - Finding optimal maintenance policies using Genetic algorithm
HMM Based Chamber State Estimation

- HMM is a doubly embedded stochastic process, characterized by transition probability, emission probability and initial state distribution.
- The directly unobservable chamber state (degradation process) is modeled using observable parameters.
HMM Based Chamber State Estimation

- HMM topology is set to be left-to-right based on physical understanding of the system.

- System will return to its initial state only if maintenance is executed.

- A five state HMM model is trained using Expectation Maximization algorithm (Baum-Welch)
HMM Based Chamber State Estimation

- Random initialization has been applied, and the model with maximum likelihood is chosen to avoid local optimum
- Most likely state sequence for given observable parameters is estimated using Viterbi algorithm
- Corresponding to each state, a yield distribution can be obtained using Bayesian network prediction
Simulation Model

- Simulation model for a single chamber

- Semiconductor data from a single chamber

Transition Probability Matrix

\[ P = \begin{bmatrix}
0.9719 & 0.0195 & 0.0086 & 0 & 0 \\
0 & 0.9256 & 0.0544 & 0.0200 & 0 \\
0 & 0 & 0.9872 & 0.0119 & 0.0009 \\
0 & 0 & 0 & 0.9744 & 0.0256 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix} \]

Yield Information

<table>
<thead>
<tr>
<th>State</th>
<th>Yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.9300</td>
</tr>
<tr>
<td>1</td>
<td>0.9293</td>
</tr>
<tr>
<td>2</td>
<td>0.7783</td>
</tr>
<tr>
<td>3</td>
<td>0.5583</td>
</tr>
<tr>
<td>4</td>
<td>0.0040</td>
</tr>
</tbody>
</table>

Taken from www.seconsemi.com
Simulation Result

• Objective function

\[
\text{minimize } E[1000e^{2(1-Yield)} + T_{\text{CBM}} + 2T_{\text{RM}}]
\]

\(T_{\text{CBM}}\): Total time spent on Condition-Based Maintenance
\(T_{\text{RM}}\): Total time spent on Reactive Maintenance

• Simulation results

  - Feasible solution space is small \(\rightarrow\) 50 replications for each CBM policy

<table>
<thead>
<tr>
<th>CBM policy</th>
<th>State 1</th>
<th>State 2</th>
<th>State 3</th>
<th>State 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yield</td>
<td>0.93</td>
<td>0.93</td>
<td>0.85</td>
<td>0.77</td>
</tr>
<tr>
<td>Time(_{\text{CBM}})</td>
<td>230</td>
<td>188</td>
<td>71</td>
<td>0</td>
</tr>
<tr>
<td>Time(_{\text{RM}})</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>196</td>
</tr>
</tbody>
</table>

Optimal CBM policy
Publications


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State of the Art Research Opportunities for CBM in Semiconductor Manufacturing

Integration of Solutions for Data to Decisions Transformation

New Diagnostic and Prognostic Methods

Level or Research Activity

- Significant Activities in new sensing
- Gaps in methods for data management

Data → Information → Decisions

- Fragmented work on methods for assessment, diagnosis and prediction.
- Emphasis on fault diagnosis and classification
- Significant amount of Operations Research

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Unique Features of CBM Research in Semiconductor Manufacturing

- Equipment Suppliers
- Chip Makers
- Level of Expertise
  - Equipment Characteristics
    - Equipment Physics
    - Reliability Test Results
    - Fault Types
    - Process Knowledge
  - Usage Patterns
    - Fault Implications on the Product
    - Fault Implications on the System
  - Fault Types
  - Process Knowledge
  - Equipment Suppliers
  - Chip Makers

- Level of Expertise
- Equipment Suppliers
- Chip Makers

Cockrell School of Engineering
Questions