Virtual metrology and predictive maintenance: Novel methods for equipment control

Workshop der GMM–Fachgruppe 1.2.3 Abscheide- und Ätzverfahren, 7.12.2011

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Virtual metrology and predictive maintenance: Novel methods for equipment control

- Motivation
- Virtual metrology (VM) and predictive maintenance (PdM)
  - Concept of VM and PdM for IC-manufacturing and equipment control
  - Framework for implementation of VM and PdM in IC-manufacturing
- VM and PdM application examples
  - Structured approach for VM and PdM development
  - Prediction of etch depth by VM
  - PdM for prediction of filament break-down in ion implantation
- Conclusions and outlook

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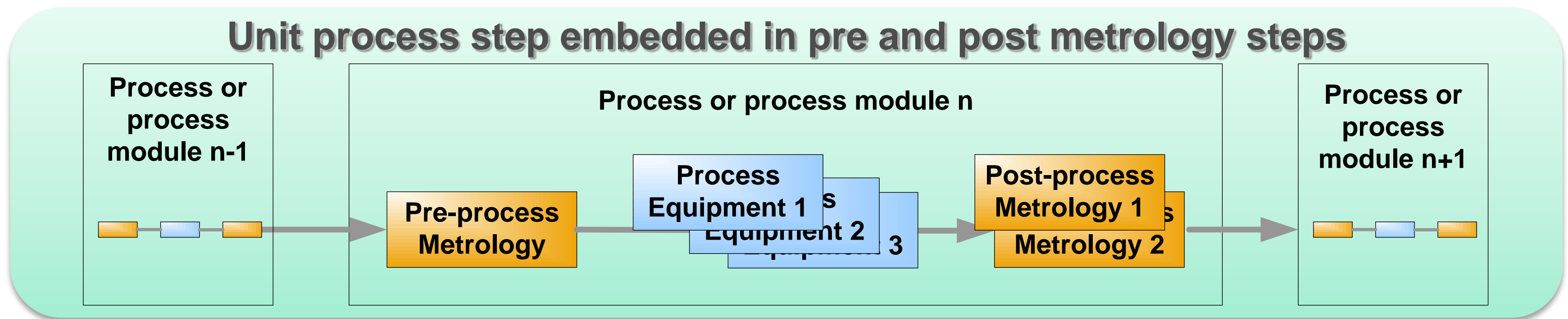
Concept of VM for IC-manufacturing and equipment control
Overview

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

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



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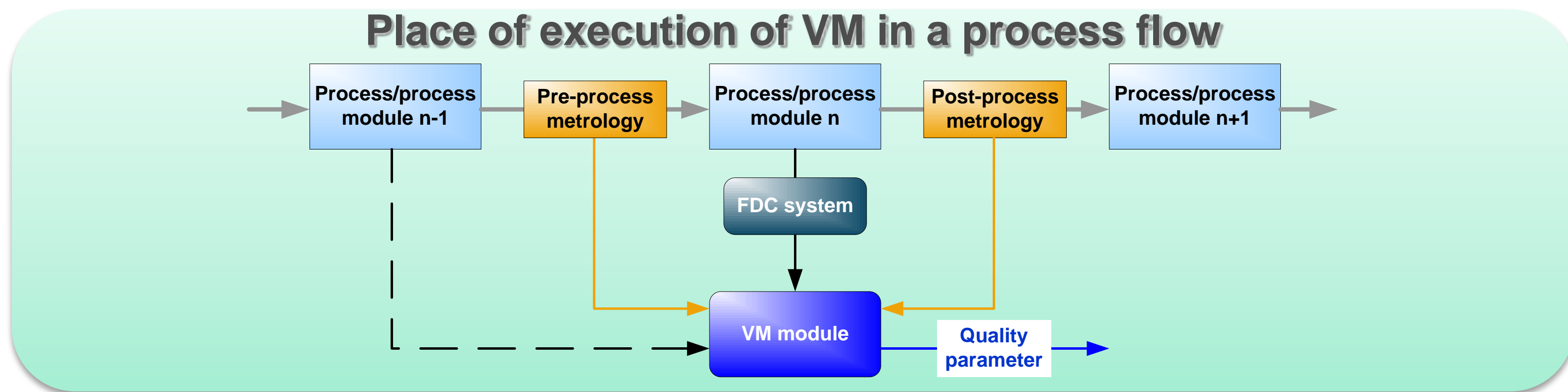
Concept of VM for IC-manufacturing and equipment control
VM objectives and benefits

VM objectives

- Predict post process physical and electrical quality parameters of wafers and/or devices from information collected from the manufacturing tools including support from other available information sources in the fab

VM benefits

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



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Concept of PdM for IC-manufacturing and equipment control
Overview

State-of-the-art

- Preventive Maintenance: time-based maintenance decisions
  - Early maintenance for security reasons leads to increased tool downtime
- Reactive Maintenance (run to fail): error-based maintenance decisions
  - Causes scrap production and unscheduled downtime

Deficiencies for maintenance planning

- Wear part end-of-life unknown, usually not measurable

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Concept of PdM for IC-manufacturing and equipment control

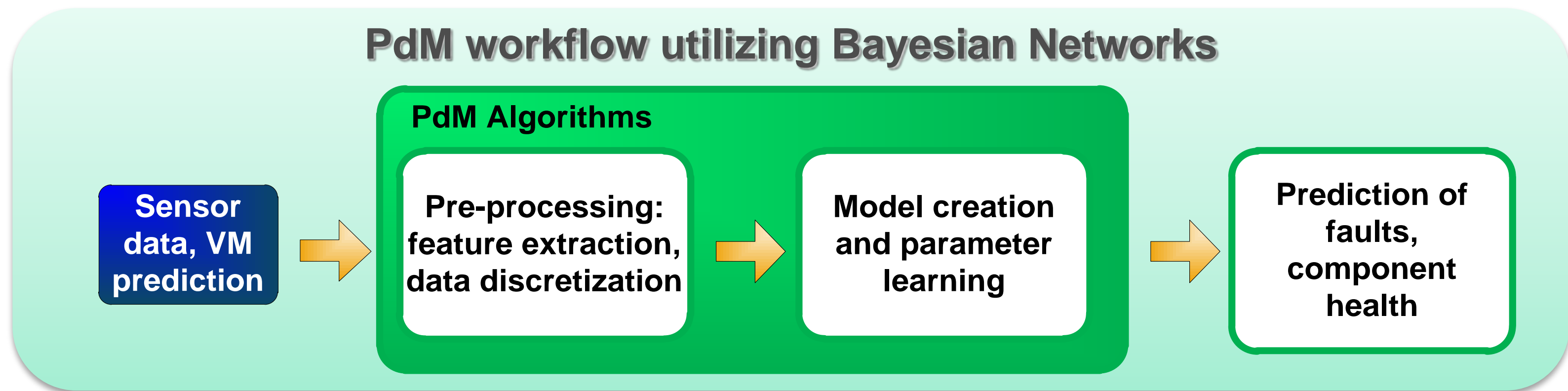
PdM objectives and benefits

PdM objectives

- Predict tool failures and wear part end-of-life from manufacturing tool data, from metrology data, and VM results

PdM benefits

- Prevention of unscheduled downtime
- Better maintenance planning
- In-time allocation of maintenance personnel and spare parts
- Prevention of scrap production



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Concept of PdM for IC-manufacturing and equipment control

PdM/VM modeling: Similarities and differences

Predictive Maintenance (PdM)

- Prediction of tool failures for better maintenance planning
- Enabled by long-range parameter drift in tool/sensor parameters
- Question: „When do I have to perform maintenance without risking a tool breakdown?“

Virtual Metrology (VM)

- Prediction of actual process outcome
- Based on actual tool/sensor data
- Question: „What process result will I get based on the actual parameter setting and tool condition?“

Regression/ Classification problem

Statistical modellig

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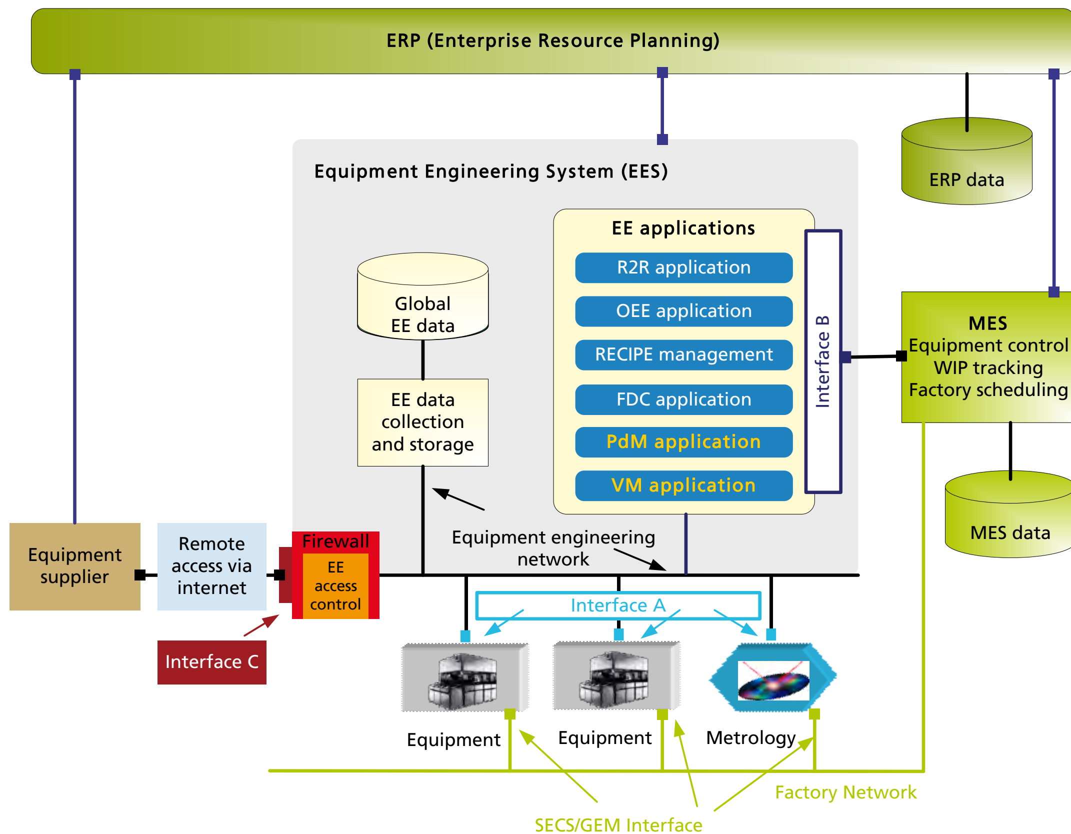
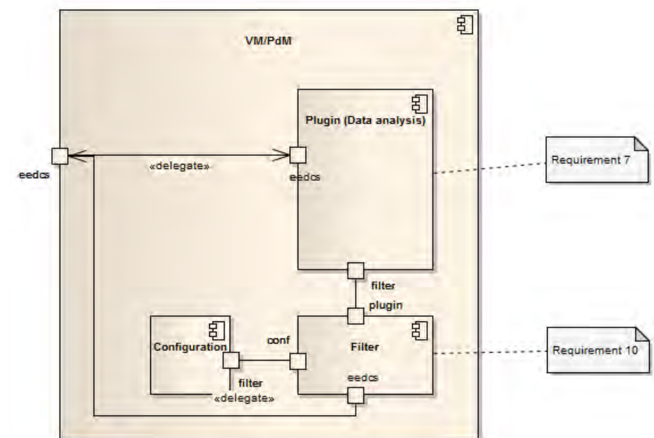
Concept of VM for IC-manufacturing and equipment control

Framework for implementation of VM and PdM in IC-manufacturing

Concept for generic VM and PdM implementation



- Adoption of architectures following SEMI and SEMATECH, cconsideration of user requirements for framework
- Develop SW for framework implementation with component- and service-based models for VM and PdM



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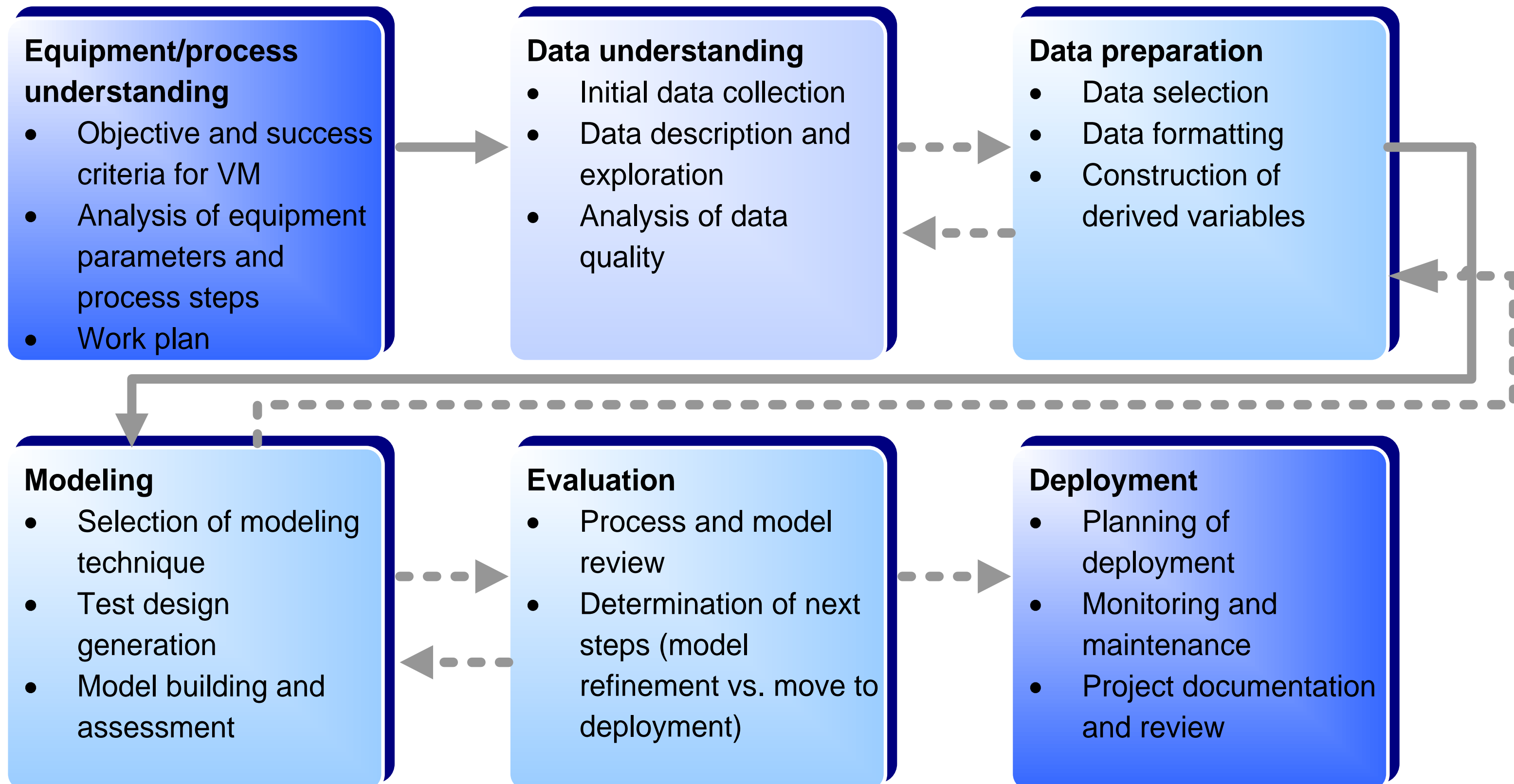
VM and PdM application examples

Systematic approach to VM/PdM development



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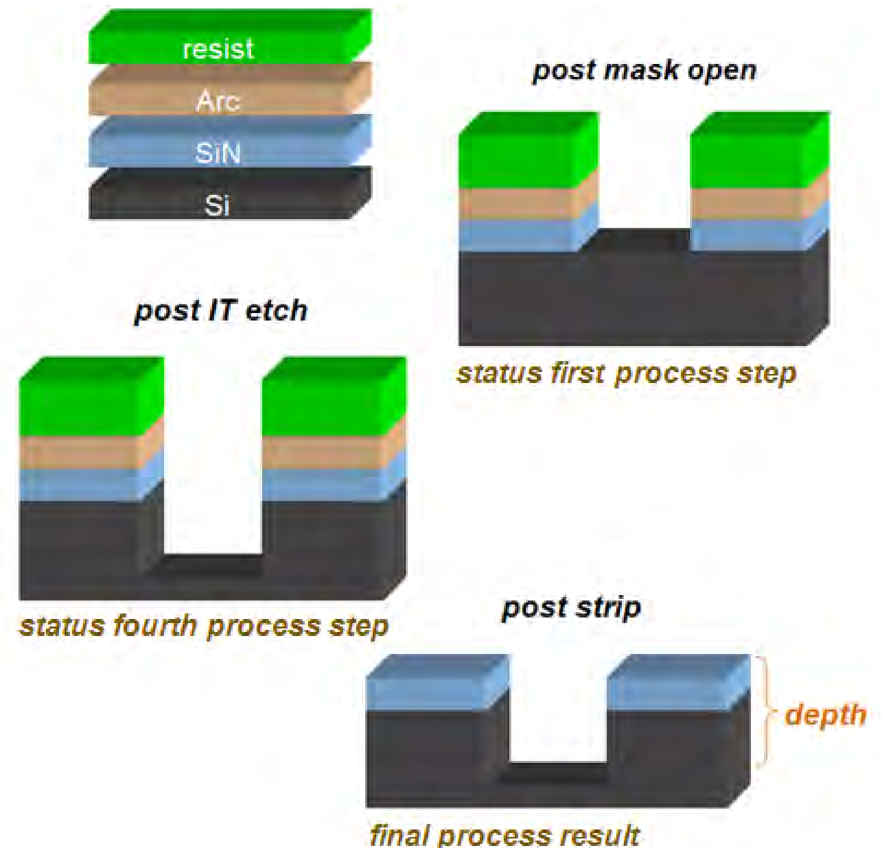
VM and PdM application examples
Introduction to the etch process

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
- Steps 4 (and step 1) are expected to primarily define the etched depth which should be predicted by VM



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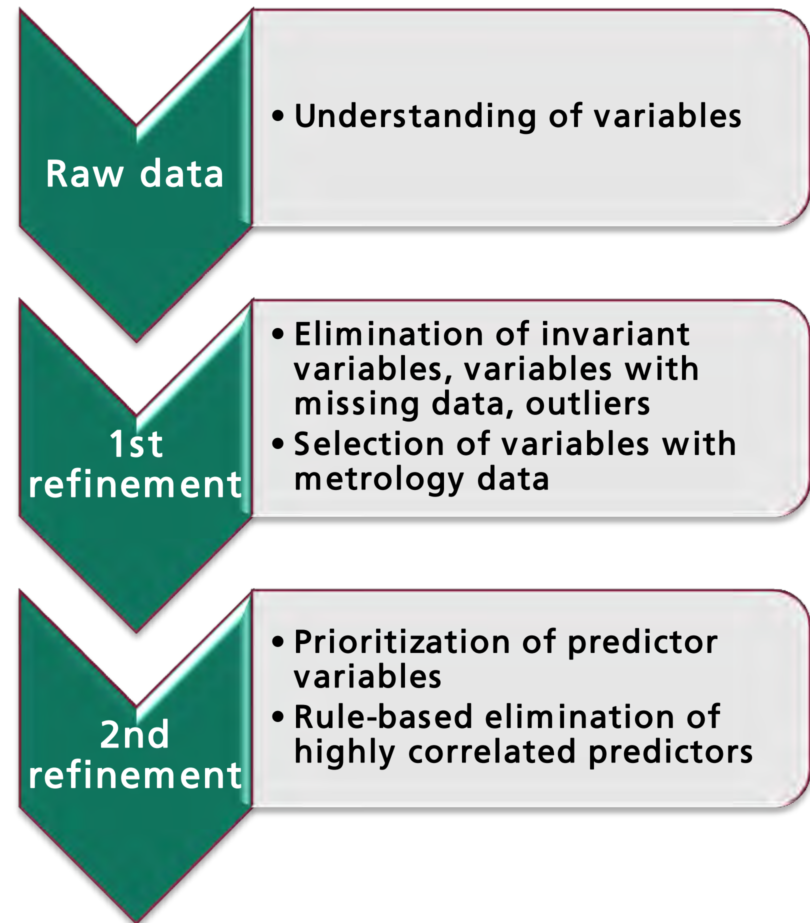
VM and PdM application examples
Data preparation steps

Overview of data

- Step and summary data (logistic, equipment, process, sensor) is collected for two slightly different etch recipes performed on four chambers
- App. potential 120 predictor variables and 65000 cases are available for VM modeling (2900 with metrology data)

Data cleaning

- Elimination of invariant variables, variables with missing data, outliers
- Selection of cases with metrology data
- Predictor selection by a rule based elimination of correlated data



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VM and PdM application examples
Data overview

Data preparation: clustering according to the type of data

#	datatyp	name	meaning/usage	unit	comment
20	equipment	O_GAS_AR_ST3_A	gas flow argon; measured	sccm	average
21	equipment	O_GAS_AR_ST3_R	gas flow argon; measured	sccm	range
22	equipment	O_GAS_CF4_ST3_A	gas flow CF4; measured	sccm	average
23	equipment	O_GAS_CF4_ST3_R	gas flow CF4; measured	sccm	range
24	equipment	O_GAS_CHF3_ST3_A	gas flow CHF3; measured	sccm	average
25	equipment	O_GAS_CHF3_ST3_R	gas flow CHF3; measured	sccm	range
26	equipment	O_GAS_N2_ST3_A	gas flow N2; measured	sccm	average
27	equipment	O_GAS_N2_ST3_R	gas flow N2; measured	sccm	range
28	equipment	O_GAS_O2_ST3_A	gas flow O2; measured	sccm	average
29	equipment	O_GAS_O2_ST3_R	gas flow O2; measured	sccm	range
46	process data	O_PRS_CHB_A	chamber pressure; measured	Torr	average
47	process data	O_PRS_CHB_A_M		Torr	average_median
57	process data	O_RFREF_A	RF- reflected (derived value; measured)	W	average
58	process data	O_RFREF_A_M		W	average_median
59	process data	O_RFREF_ST3_A		W	average
60	logistics	O_RUNNUMBER		-	
67	logistics	O_Slot	slot	-	
70	logistics	O_TIME		days	
71	logistics	O_TIME_PREV_DIFF_A		s	average
72	logistics	O_TIME_PREV_DIFF_X		s	maximumum
73	equipment	O_TMP_CATH_A	temperature cathode (i.e. chiller); measured	°C	average
74	equipment	O_TMP_CATH_A_M		°C	
75	equipment	O_TUNE_A	set-up RF match		average
76	equipment	O_TUNE_A_M			average_median
77	equipment	O_TUNE_ST3_A			average
88	logistics	Lot		-	
89	logistics	O_EQUIPMENT		-	
90	logistics	O_2818_00_EQUIPMENT		-	
91	measurement data	O_2818_00_DP_E_MEAN		nm	
92	measurement data	O_2818_00_DP_E_RANGE		nm	
93	measurement data	O_2818_00_DP_E_MAX		nm	
94	measurement data	O_2818_00_DP_E_MIN		nm	
95	measurement data	O_2818_00_DP_E_STDEV		nm	

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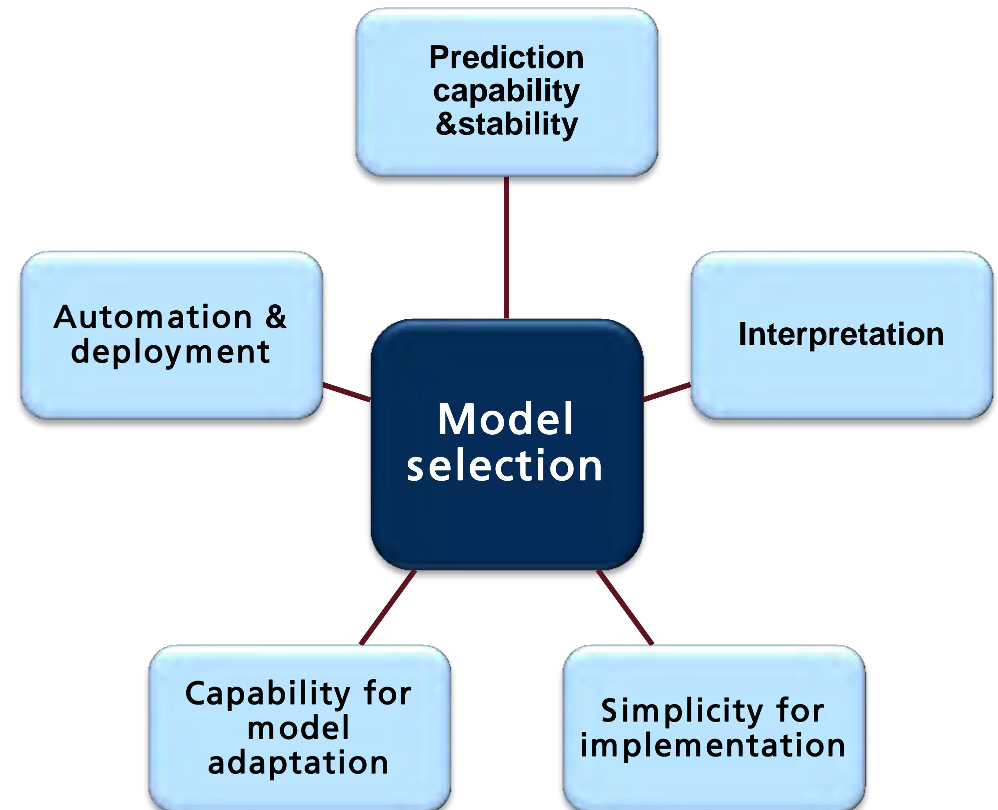
VM and PdM application examples
Modeling approach - overview

Modeling approaches

- Inclusion of all etch steps, prioritization in correlation analysis
- Investigation of several learning algorithms
  - stepwise linear regression
  - neural networks
  - support vector machine
  - gradient boosted trees
- Currently boosted trees are investigated in detail because main algorithm selection criteria are met



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VM and PdM application examples
Overview of boosted regression trees

Principle of boosted trees (BT)

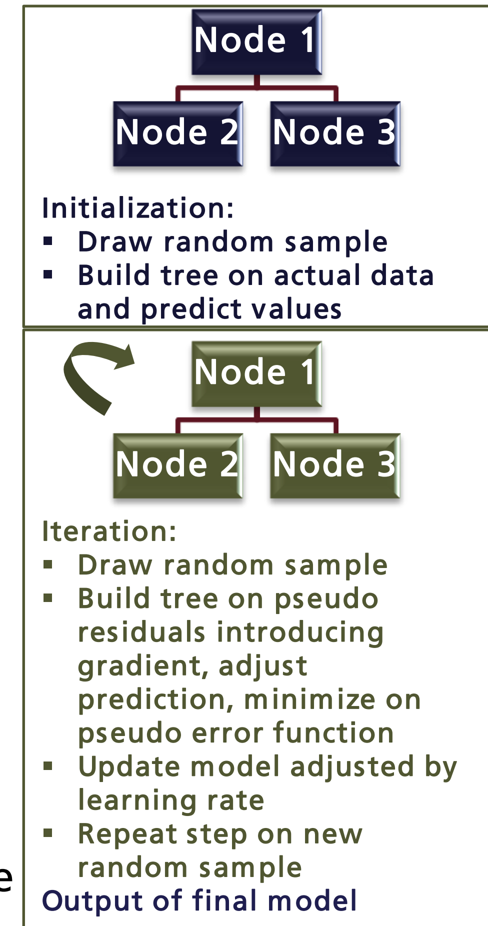
- Ensemble learning: improve performance of a single model by fitting and combining many simple models
- BT applies two algorithm types:
  - algorithms for classification and regression trees
  - boosting algorithm to build a collection of models

Advantages

- Applicability to classification and regression problems
- Accommodation of continuous and categorical predictors
- Tree methods are nonparametric and nonlinear
- Inherent variable ranking
- Improved predictive performance vs. C&RT

Limitations

- Model is complex and cannot be visualized like a single tree



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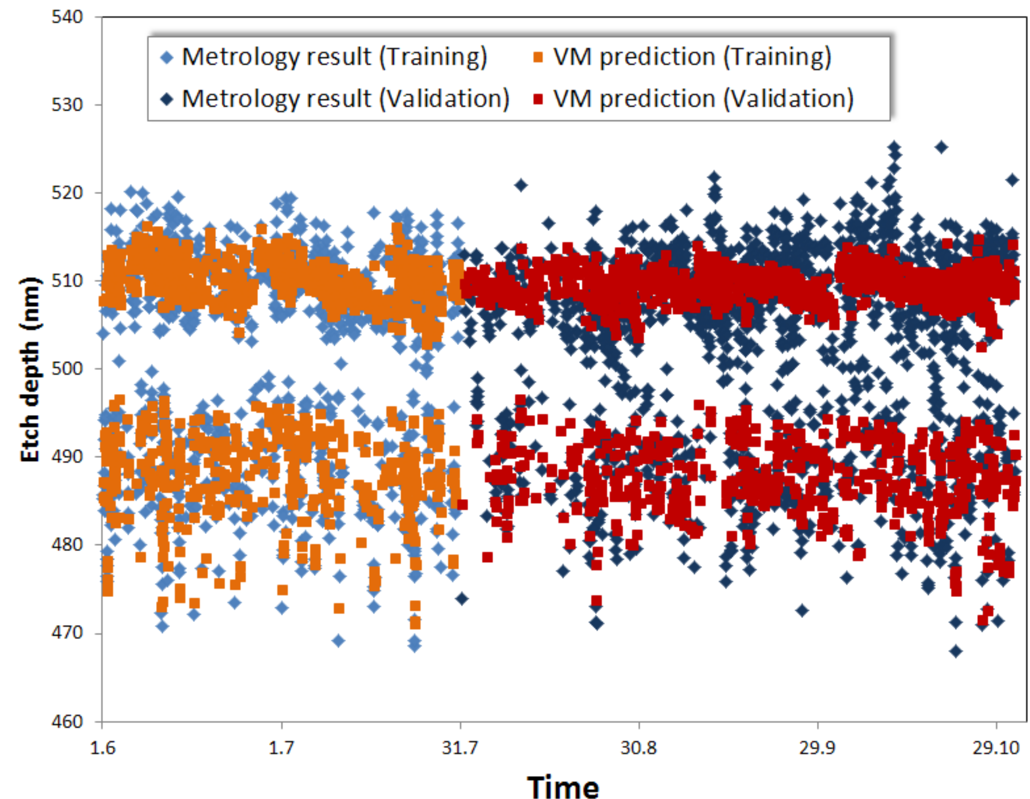
VM and PdM application examples
Prediction capability of VM - overview

Modeling and validation

- Training on data set taken from 06-07/2011
- Validation on rest of sample for period 08-10/2011

Result

- Prediction of etch-depth is possible
- Variable ranking shows importance of predictors
- Logistic variables with untrained characteristics can be modeled from missing data handling algorithms



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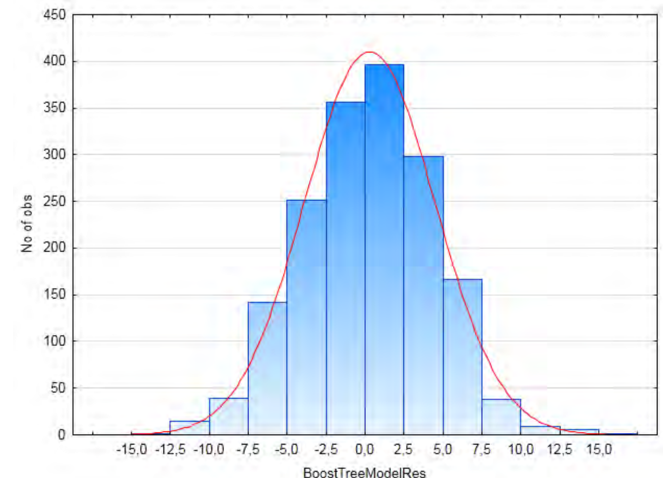
VM and PdM application examples

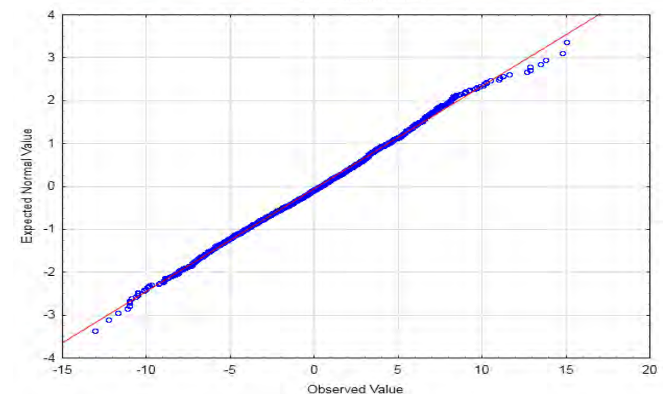
Prediction capability of VM - details

Parameter	Training	Model application
Bias abs.	0.1 nm	0.2 nm
Bias rel.	< 0.1 %	< 0.1%
Std. dev. abs.	2.5 nm	4.2 nm
Std. dev. rel.	0,5 %	0.8 %

- Good prediction of etch-depth is achieved

Distribution of prediction residuals





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VM and PdM application examples
Investigation of model retraining

Motivation of retraining

- Increase database for training and include more equipment behavior scenarios
- Include rare logistic types

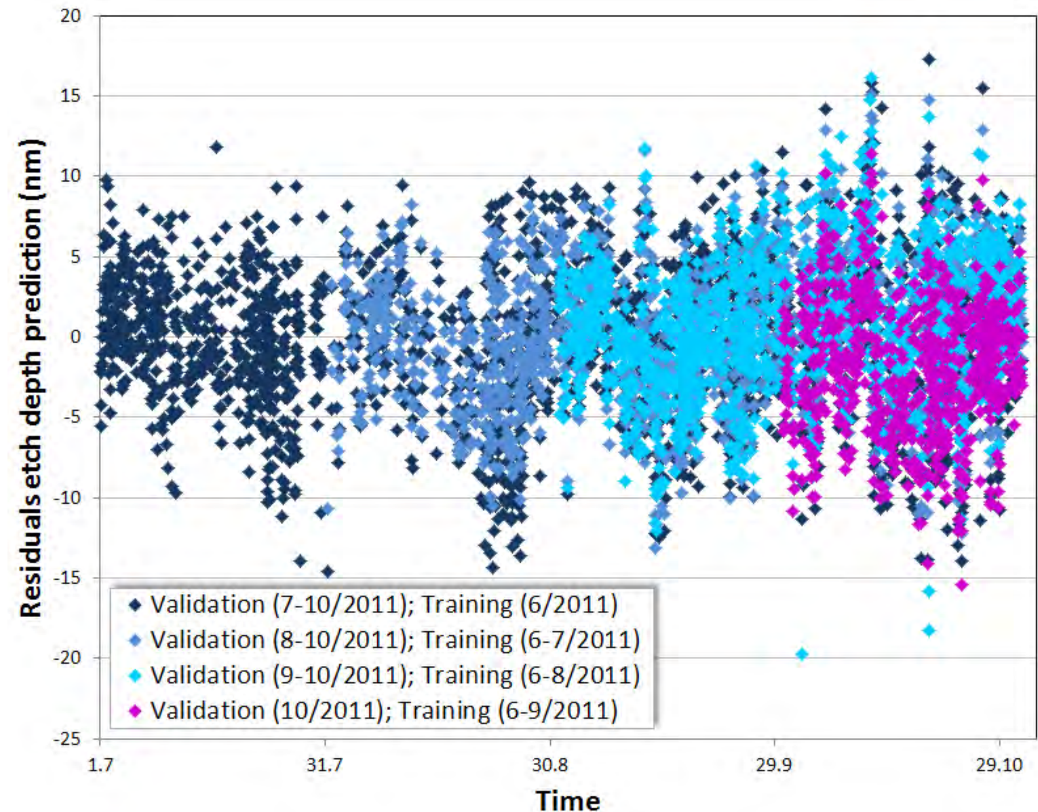
Approach

- Time-based (monthly) retraining

Result

- Monthly retraining continues stability of prediction
- Investigate additional retraining scenarios, e.g. for fast retraining and optimized timing

VM prediction residuals for different training and model application periods



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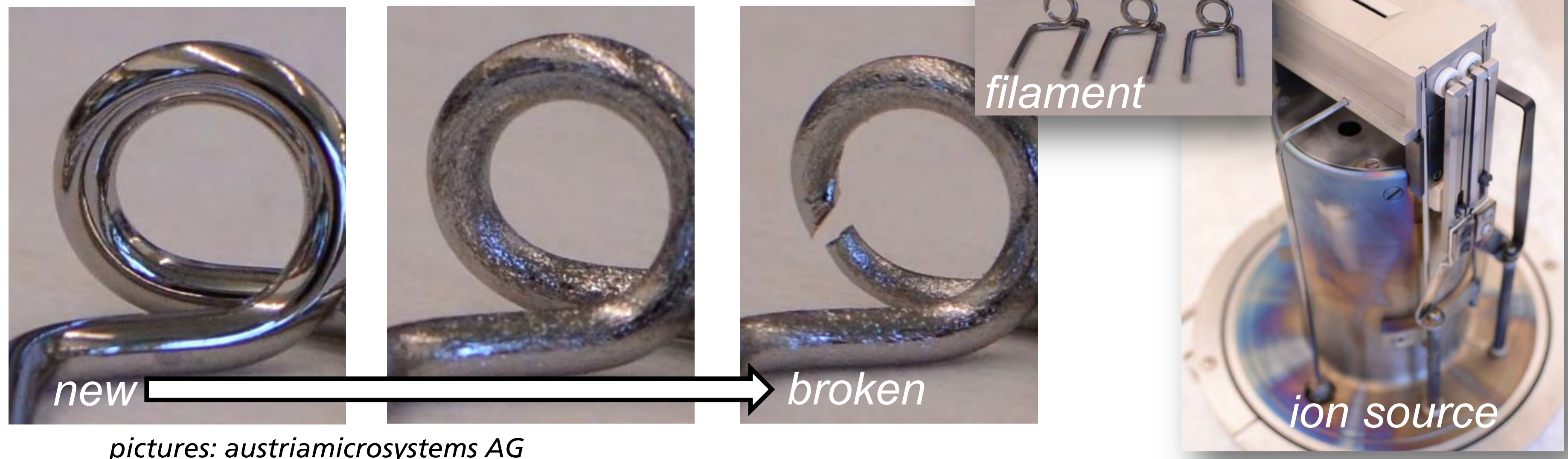
VM and PdM application examples

PdM: Modeling of filament breakdown in ion implantation

Problem description:

- Filament used for generation of electrons in ion source of implanter tool
- Plasma in source causes ongoing degradation of filament through ion sputtering
- Failure mechanism: breakdown of filaments



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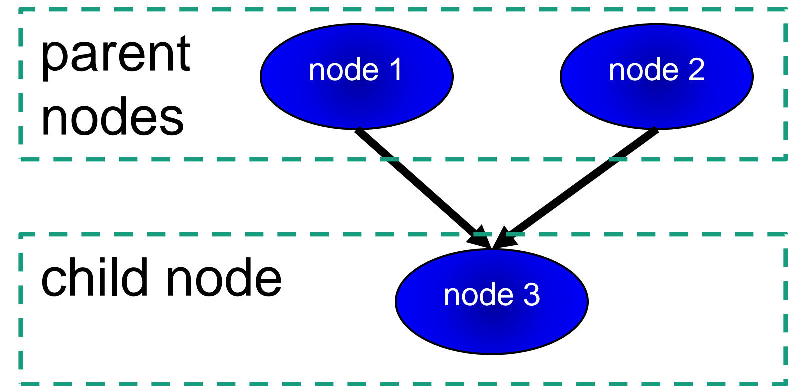
VM and PdM application examples

PdM: Modeling of filament breakdown in ion implantation



Bayesian Networks basics:

- Probabilistic graphical modeling
- Representation of random variables in nodes
- Edges (arrows) between nodes represent conditional dependence between variables
- Parent and child nodes: state of child nodes depends on state(s) of parent node(s)
- Based on historic data, conditional probabilities in Bayesian networks can be learned
- For time series data: dynamic BN (one model instance per time step)

p(node3|node1,node2) => *„probability of node3 given node1 and node2“*

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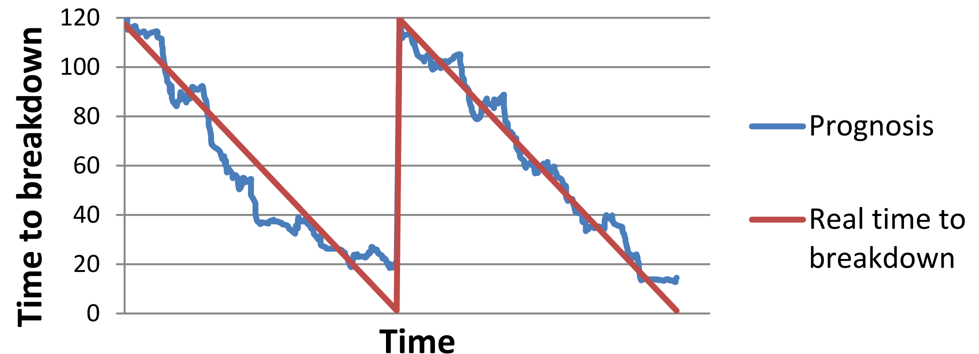
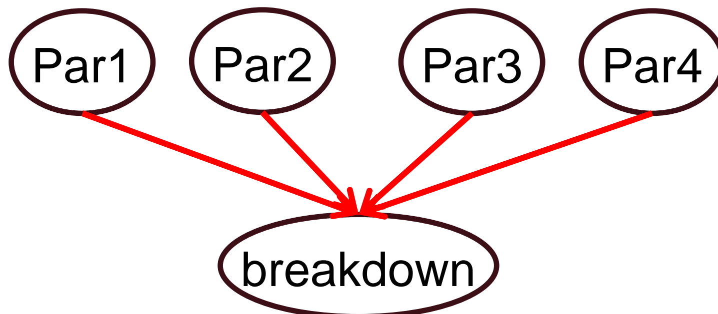
VM and PdM application examples
PdM: Modeling of filament breakdown in ion implantation

Modeling approaches

- Method: Bayesian Networks with soft discretization
- Input data: tool parameters (different voltage/current values, pressure values, gas flow rates)
- Output: remaining time to breakdown
- Model properties:
  - Prognosis in hours
  - Error: RMSE=8.3h



red curve: remaining time to failure as observed
blue curve: remaining time to failure prognosis
x-axis: time



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Conclusions and outlook

Achievements

- Common architecture to integrate VM and PdM into the different existing fab systems developed
- Software for implementation of VM and PdM modules in fab environments available
- VM and PdM modules for important fabrication steps demonstrated
  - Development may follow a structured approach
  - Data quality and preparation is of key importance
  - Prediction quality but also other properties (e.g. model adaption, automation) are key to model selection

Further research

- Optimization of VM retraining; re-visit other machine learning algorithms
- Continued testing of VM algorithm for etch-depth prediction

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Acknowledgment

- This research is funded by the German Federal Ministry of Education and Research (BMBF) and the European Nanoelectronics Initiative Advisory Council (ENIAC)

- The work is carried out in the ENIAC project "IMPROVE" (Implementing Manufacturing science solutions to increase equipment PROductiVity and fab pErformance); project ID: 12005

- More information: www.eniac-improve.eu

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