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Predictive Modeling for Intelligent Maintenance in Complex Semiconductor Manufacturing Process – Jun Ni

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Introduction

A semiconductor manufacturing system is a highly complicated and integrated system with many tools and products. The products travel through the same tool groups repetitively using re-entrant flows, which usually involves more than one hundred tools and requires several months of processing time for a single product. During the manufacturing process, equipment downtime may cause a significant loss of productivity and profit, and result in disruptions and idle time on many other tools in the process flow. Furthermore, the operational tools cannot always guarantee to produce chips with satisfactory quality due to the degradation of tool performance. Thus, extensive efforts have been devoted to improving the maintenance strategies to keep tools in their acceptable operating conditions as well as to prevent tools from catastrophic failure. The current prevailing maintenance practice is preventive maintenance (PM). However, most existing PM policies do not utilize the current equipment condition to schedule maintenance, which results in either over-maintained or under–maintained situation. Predictive maintenance that assesses remaining useful life of machines should be developed to perform maintenance actions proactively.

Predictive Modeling of Multivariate Stochastic Dependencies Using Bayesian Network

The Bayesian Network (BN) is used to develop predictive modeling methods to discover the stochastic causal dependencies between the yield at the metrology station and data from a series of processing stations as shown in Figure 1. In addition, the self-organizing maps (SOM) have been utilized to discretize continuous data into discrete values, which will tremendously reduce the computational cost of Bayesian network learning process. This modeling tool is designed to facilitate rapid and accurate yield prediction. For example, The BN structure in Figure 2 based on real manufacturing process data shows that the probability distribution of metrology can be inferred by only measuring the state of G with the conditional probability in Table 1. A BN enables us to decouple a system by finding causal relationship among variables, which helps to reduce the dimensionality of a complex system.

HMM Based Prediction of Tool Degradation under Various Operation Conditions

A Hidden Markov Model (HMM) is employed to model unobservable degradation process in chamber tools by measuring the directly observable process information and product quality information as shown in Figure 3. Since particle contamination in semiconductor fabrication tools is a major source of yield loss, a great deal of efforts in both research and industry communities have been devoted to developing in-situ particle monitoring techniques to ensure product quality and yield. However, stochastic correlation between unobservable degradation and measurement from in-situ particle sensor in chamber has not been studied. HMM tool enables to track and predict the discrete levels of particle contamination and help proactively to clean the chamber exactly when maintenance is required.

Improved Maintenance Decision Using Predicted Process Condition and Product Quality Information

With above two novel methods, a methodological framework to perform better maintenance in semiconductor manufacturing processes is established as depicted in Figure 4. Using the tool degradation estimation and yield prediction obtained from integrating the process information, different maintenance scenarios can be evaluated and compared to determine which action is relatively better in terms of certain customized criteria via the simulation model (Figure 5).

The case study as shown in Figure 6, Figure 7, and Table 2 demonstrates the utilization of BN based yield prediction model and HMM based tool degradation model, providing an improved maintenance policy over currently used PM strategy. For instance, the Condition-based Maintenance at S_4 is able to provide a maintenance solution with lowest cost while retaining the highest possible yield.

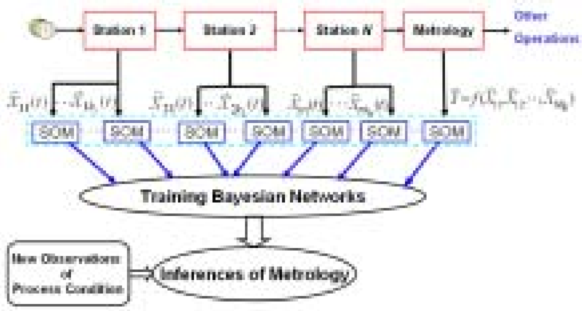

Figure 1: multivariate stochastic dependencies model

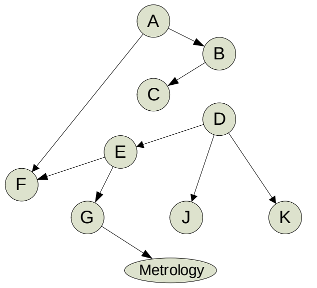

Figure 2: BN showing causal relationships among 10 random variables

Table 1: Condition probability for Metrology given state of G

State of G	State of Metrology		
	1	2	3
1	3.44%	93.01%	3.54%
2	84.52%	10.32%	5.16%
3	3.61%	34.47%	61.92%
4	12.99%	81.82%	5.19%
5	7.05%	12.70%	80.25%

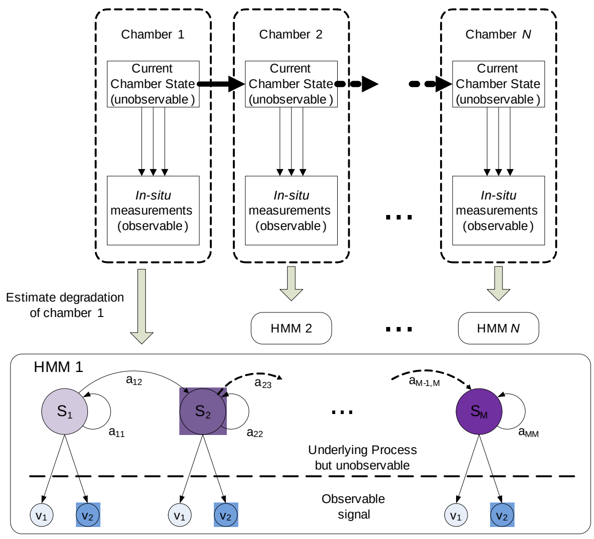

Figure 3: Framework of chamber degradation prediction based on HMM

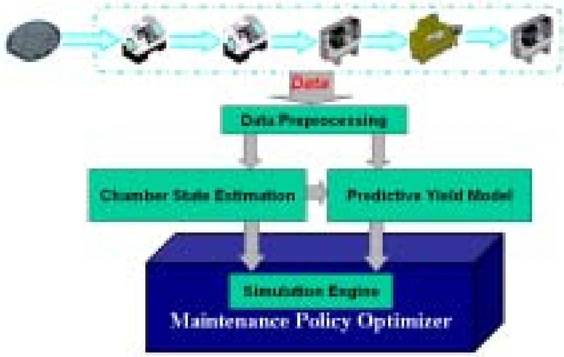

Figure 4: Methodology framework of improved maintenance decision-making

Figure 5: Simulation model of single chamber tool

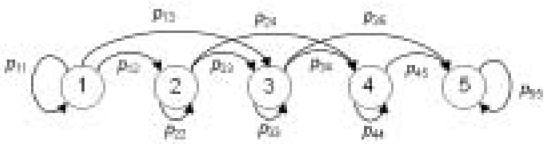

Figure 6: 5 states Markov chain for degradation model

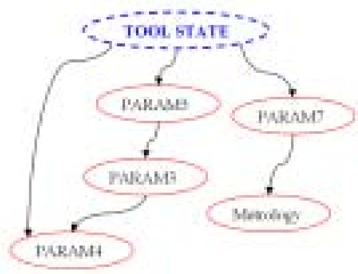

Figure 7: BN structure for predictive yield model

Table 2: Comparison of maintenance cost for different policies

Maintenance Policy	Total Time of Cleaning	Total Time of Repair	Total Maintenance Cost
CBM at S_2	230	0	230
CBM at S_3	188	0	188
CBM at S_4	71	8	87
RM	0	196	392
PM	424	0	424