Big Data Predictive Analtyics for Proactive Semiconductor Equipment Maintenance

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Abstract— Manufacturing Industry generates about a third of all data today and the modern semiconductor manufacturing is one of the most contribution to this tsunami data volume. Terabytes of data is generated on a daily basis during ~500 steps in semiconductor chip processing. During this complex manufacturing process, equipment downtime may cause a significant loss of productivity and profit. In this paper, we are going to explore the predictive analytical algorithms and big data techniques in helping to achieve near-zero equipment downtime in the fabrication unit and to improve OEE (Overall Equipment Effectiveness), which is a key machine manufacturing productivity metric.

Keywords—Big Data, Equipment, Semiconductor, Predictive Analytics (PA), OEE

I. INTRODUCTION

WITH the entire big buzz about 'Big Data' in different industries, there has been little impact about its usage in semiconductor manufacturing. The role and size of data volume in manufacturing has traditionally been understated. The data is very complicated and it is fragmented across the data sources between manufacturing process, quality & inspection, maintenance, testing and process control operations; To stay competitive, It is clearly known fact that there is a need in improving the predictive capabilities based on historical data of equipments to enable the fabrication facility to proactively allocate limited maintenance resources to the right location at the right time and thus maintain the high yield while achieving a high system uptime. The technology transition from 300mm wafers to 450mm demands higher operational efficiencies, minimizing downtime of equipment and improving yield from newer generation of fabrication units. Each fabrication tool can cost millions of dollars. A 300-mm fab manufacturing 20,000 wafers per month at the 65-nm node is expected to require ~$1.8 billion equipment investment. This investment is impelling semiconductor manufacturers to remain focused on maximizing equipment productivity. Industry leaders are realizing that on their own, they cannot afford to do the learning necessary to maximize equipment investment. Current database management systems have limited functionality in their ability to access, analyze, and intelligently extract information from the large variety of manufacturing data sources available within this industry. It is critical that the semiconductor industry rely on big-data technologies access multiple data sources and derive useful defect and yield information to ensure valuable insight. Semiconductor fabrication is one of the most complicated manufacturing processes, in which the current prevailing maintenance practices are preventive maintenance, using either time-based or wafer-based scheduling strategies, which may lead to the tools being either "over-maintained" or "under-maintained", may cause a significant loss of productivity and profit. Currently, the majority of maintenance operations in the semiconductor industry are still based on either historical reliability of fabrication equipment, or on diagnostic information from equipment performance signatures extracted from in-situ sensors. Such a fragmented, "diagnosis-centered" approach leads to mostly preventive maintenance along with reactive maintenance policies that use neither abundant product quality, equipment condition, equipment reliability information, nor the temporal dynamics inside that information in order to anticipate future events in the system and thus facilitate a more proactive maintenance policy. Production efficiency is a measure of the average time a process is producing product. It averages at 60% and there is a large consensus that 80% is a realistic goal. Maintenance accounts for a large portion of the remaining 40%. Tool availability is directly related to the production efficiency of a manufacturing process. It is the percentage of time a tool is available for producing product. Increased tool availability increases production efficiency. Maintenance causes a decrease in tool availability hence a loss in production efficiency and profitability. For this reason a properly functioning maintenance strategy is required for companies to compete for market share. The majority of manufacturing industries carry out maintenance using either a corrective or preventative maintenance strategy. Corrective maintenance is carried out after the failure of an equipment component, also referred to as a reactive based maintenance. In contrast preventative maintenance is carried out on a predetermined periodic time frame. This allows maintenance to be scheduled and carried out before the failure occurs. At Intel, a High Precision Maintenance (HPM) strategy is being utilized to perform preventative maintenance tasks with high precision. This strategy was implemented to reduce maintenance costs. Utilizing these maintenance strategies does not produce the optimal production efficiency, as fully functioning equipment components are replaced regardless of their condition. In recent years industries have begun to utilize predictive maintenance. This allows equipment to be maintained based on its condition.

A review of literature published in this field shows that there rarely exists condition-based maintenance (CBM) utilizing equipment condition as indicator, and almost no predictive maintenance (PdM) utilizing the prediction of future states of the equipment. This paper examines some of the analytical techniques, predictive models and control charts that can be leveraged by the semiconductor industry. This paper is aimed at to survey different big data predictive modeling methods for optimal maintenance in semiconductor manufacturing processes. Deteriorated equipment has a significant impact on the product quality and maintenance policies.

II. PROBLEM DEFINITION

The unscheduled breakdown of an individual piece of manufacturing equipment is a great cost burden, as it results in downtime for dependent/related equipment in the manufacturing chain. Inefficiencies of a single piece of critical "bottleneck" process equipment can have a negative economic impact for an entire production line. Since numerous competitive equipment manufacturers supply the various discrete tools needed in a single fab, service, tool monitoring, and data collection for the tools are inefficient and cumbersome processes.
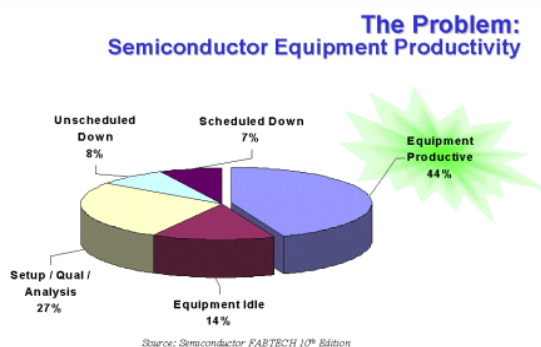

Semiconductor industry statistics show that most semiconductor capital equipment suffers at least 8% unscheduled downtime and loses another 7% to scheduled maintenance. At the January 2000 ISS, Michael Splinter, Senior Vice President and General Manager of Intel's technology and manufacturing group, estimated that each hour of downtime for a critical unit of process equipment can translate into $100,000 of lost revenue in today's chip-hungry market. In a typical fab, just reducing downtime by 1% on the 50 most critical tools can provide revenue opportunities and cost savings nearing one hundred million dollars annually. One way to reduce unscheduled downtime is to improve response time and repair time, and, eventually, to predict when problems will occur before they occur. High system complexity and data volume have prevented the predictive capabilities of equipment maintenance.

III. BACKGROUND

A. Semiconductor Manufacturing

Semiconductor manufacturing is a complex process which consists of hundreds of manufacturing steps. Thus semiconductor manufacturing process is normally under consistent monitoring, it collects sensor signals from process tools, and it measures physical and electrical parameters from wafers through metrology. These tool data and metrology data constitute the ingredients for designing data-driven models that enable virtual metrology and predictive maintenance to control manufacturing line efficiency and product quality.
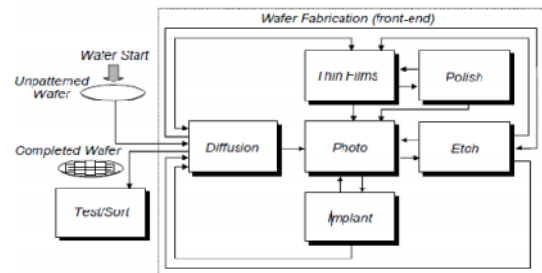
However the data from semiconductor manufacturing often suffer from inherent and difficult problems: high dimensionality due to the number of processing steps and measurements recorded during the entire manufacturing process, imbalanced data due to the nature of manufacturing line with majority of wafers passing and examples of defective wafers occurring rarely, missing data due to production line efficiency constraints that do not allow every measurement to be taken at every step of every wafer. There are various predictive algorithms is applied to various semiconductor equipments (few is listed below)

- ✓ Dry Etch
- ✓ Ion Implantation Tool
- ✓ Chemical Vapor Deposition (CVD) Tool
- ✓ Photolithography

It's likely that predictive maintenance and equipment monitoring will become more prevalent, as manufacturers try to minimize downtime and maximize productivity. Semiconductor factories will apply mathematical models/machine learning models to equipment and factory data to assess health and predict tool failure and then act on those outputs to optimize factory productivity. The application will monitor tools and predict failures.

B. Big Data

As Semi-conductor industry moves to sub-20nm technology nodes and 450mm wafer sizes, the sensor technology that monitors equipments becomes more complex, data volumes will continue to grow in an exponential rate. Due to the sheer size of manufacturing data being generated it is becoming increasingly difficult to analyze it using relational databases. Such huge volumes of data will become impossible for the traditional databases to capture and convert to meaningful information. The rise of big data and its usage can be beneficial to operations and maintenance staff in order to be proactive with regard to ongoing equipment maintenance and upkeep. The use of data can provide more opportunity to predict upcoming issues in a system or equipment and, therefore utilize maintenance in a predictive manner, rather than relying on the costly extremes – such as random Preventative Maintenance or crisis-related Reactive Maintenance. Of course, all of this Big Data is meaningless

without analysis. There are hidden patterns lurking within these facts and figures. Decoding these patterns is what powers predictive maintenance and separates it from more traditional, reactionary approaches to equipment repair and replacement.

Effectively utilizing Big Data can have a huge impact on improving manufacturing effectiveness. The cost of failed equipment leading to unplanned downtime is a major reason that the use of predictive analytics or "big data" has received a great amount of interest, especially when tied directly to preventative maintenance for maintaining motors, equipment, sensors, and the like.
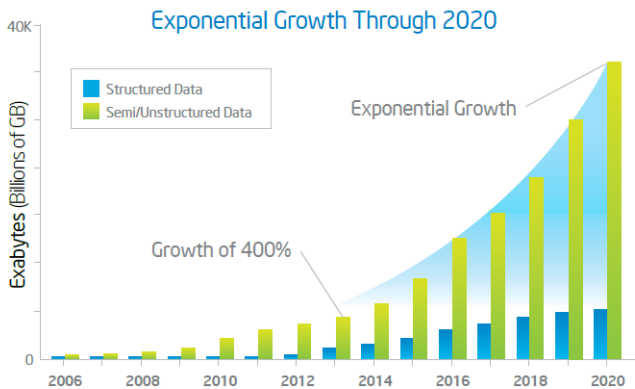

Figure 1. Current and forecasted growth of big data. Source: Philippe Botteri of Accel Partners, Feb. 2013.

With big data, predictive preventative maintenance can optimize maintenance planning while minimalizing consequential costs due to faulty equipment. Traditional relational database management system (RDBMS) technologies such as Oracle, SQL Server, DB2, etc. are approaching their limits when processing massive sets of data in complex data analytics in an OLTP environment. Big data technologies provide a combination of distributed databases, map-reduce based processing, machine learning framework and memory-resident graph databases.

In order to achieve an optimal maintenance decision-making, a method should be in place to integrate multiple data sources from different data domains.
Production data, machine functional data, and sensor data are all aggregated for analysis and used to build models for predicting machine failure or poor product quality reducing failure times and costs. However handling this volume of data requires an engine that can integrate all the elements of the technology stack, extraction-transformation-loading (ETL), data cleansing, data storage, reporting, statistical modeling and data mining into either a single platform or a seamless stack, that can scale up to 10s of terabytes, handles multiple large tables of billions of rows, and executes 10-100x faster than conventional relational database technology.

C. Predictive Maintenace(PdM)

The pressure to reduce production costs forces manufactures to optimize equipment utilization.

Decreasing of failure rate through predictive maintenance
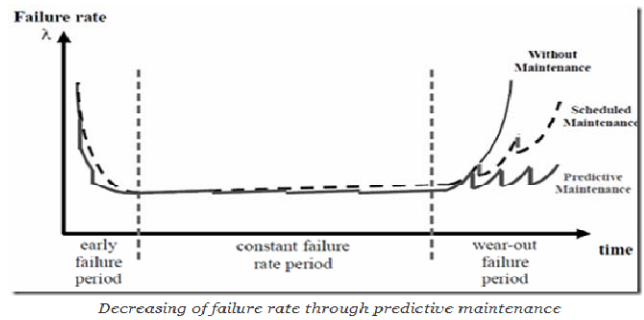
While the concept of Predictive Maintenance is discussed for several years (Mobley 2002, Dekker 1996, Liu 2008), tools in semiconductor processing are usually still controlled by Statistical Process Control (SPC) and Fault Detection and Classification (FDC), but these techniques do not allow prediction of tool failures. Predictive Maintenance is still not implemented in semi-conductor processing due to the complexity of the data volume.

Maintenance Policies can be divided into four categories, with different levels of complexity, Suso et al. (2012a); Mobley (2002)

➢ Run to Failure (R2F) Maintenance
➢ Preventive Maintenance
➢ Predictive Maintenance
➢ Condition-based Maintenance

Run to Failure (R2F) Maintenance:
Corrective maintenance is the classic Run-to-Failure reactive maintenance that has no special maintenance plan in place. The machine is assumed to be fit unless proven otherwise.

- Cons:
    - o High risk of collateral damage and secondary failure
    - o High production downtime
    - o Overtime labor and high cost of spare parts
- Pros:
    - o Machines are not over-maintained
    - o No overhead of condition monitoring or planning costs

Preventive Maintenance:
Preventive maintenance (PM) is the popular *periodic maintenance* strategy that is actively employed by all manufacturers and operators in the industry today. An optimal breakdown window is pre-calculated (at the time of component design or installation, based on a wide range of models describing the degradation process of equipment, cost structure and admissible maintenance etc.), and a preventive maintenance schedule is laid out. Maintenance is carried-out on those periodic intervals, *assuming* that the machine is going to break otherwise.

- Cons:
  - o Calendar-based maintenance: Machines are repaired when there are no faults
  - o There will still be unscheduled breakdowns
- Pros:
  - o Fewer catastrophic failures and lesser collateral damage
  - o Greater control over spare-parts and inventory
  - o Maintenance is performed in controlled manner, with a rough estimate of costs well-known ahead of time

Predictive Maintenance:

Predictive Maintenance (PdM) is an alternative to the above two that employs predictive analytics over real-time data collected (streamed) from parts of the machine to a centralized processor that detects variations in the functional parameters and detects anomalies that can potentially lead to breakdowns. The real-time nature of the analytics helps identify the functional breakdowns long before they happen but soon after their potential cause arises.

- Pros:
  - o Unexpected breakdown is reduced or even completely eliminated
  - o Parts are ordered when needed and maintenance performed when convenient
  - o Equipment life and there by its utilization is maximized
- Cons:
  - o Investment costs for implementing the condition-based monitoring (CBM) system
  - o Additional skills might be required to effectively use the CBM system effectively

Condition-based Maintenance:

Condition based maintenance (CBM) has many similarities to predictive maintenance in that the data gathered during CBM intervals are compared to statistical norms – both averages and trends. CBM is more comprehensive than predictive maintenance since it uses both on-line and off-line test data.

D. Predictive Analytics(PA)

How can we detect faults or failure before the problems happen? This is where maintenance using predictive analytics comes in. Predictive Analytics is the "Open Sesame" for the world of Big Data. In Forrester report, "Big Data Predictive Analytics Solutions," Forrester states: "Big data is the fuel and predictive analytics is the engine that firms need to discover, deploy and profit from the knowledge they gain." There has been significant research in the last decade about the introduction of predictive models in Semiconductor Manufacturing. Predictive Analytics can be used to analyze to detect indicators of tool excursions before they happen. Moving from our current reactive state of manufacturing to a proactive state is what the real value of big data capture and analysis will be found. Predictive analytics, coupled with big data technologies, can help the semi-conductor industry to make smarter decisions to optimize the equipment maintenance.

In the semiconductor industry, turning data into actionable information to support predictive analytics, which is a major challenge that involves both data management and processing. The main challenge arises from the explosive growth of data and it's processing for predictive analytics and decision tree analysis.

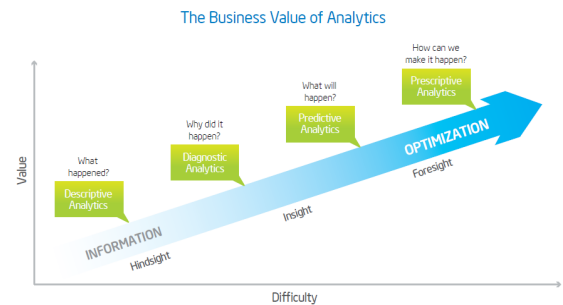The Business Value of Analytics

Figure 3. According to Gartner, the difficulty and business value of analytics both increase as the focus moves from hindsight to foresight.

Despite extensive academic research in published literature, applications of data mining methods to semiconductor data are relatively recent. Unfortunately, there are practical limitations in automating the statistical techniques when complex interactions and nonlinearities are involved in the underlying models. Moreover, the large amount of data in current semiconductor databases makes it almost impractical to manually analyze them for valuable decision-making information. This difficulty is mainly due to the large amount of records, which contain hundreds of attributes that need to be simultaneously considered in order to accurately model the system's behavior. The need for understanding complex interaction effects, and automated analysis and discovery tools for extracting useful knowledge from huge amounts of raw data has led to the development of knowledge discovery in databases (KDD) and data mining methodologies [2].

E. Equipment Health Monitoring (EHM)/ Fingerprinting

The basic idea was that semiconductor manufacturers could learn a great deal by collecting detailed trace and event information from the equipment to understand the behavior of low-level mechanisms, with the assumption that if the low-level mechanisms were exhibiting proper behaviors, then the entire machine would be operating within its specifications.

Equipment Health Monitoring the process of assessing the equipment performance and condition based on equipment measurable states.

Fingerprinting is a systematic approach that uses equipment component data values which are used to calculate additional parameters that determine the equipment health and performance.

Data Mining/Predictive Analytics uses mathematical techniques which are applied to data stored in the factory database searching for indicators of problems or potential issues with the equipment or processing.

IV. DATA SOURCES

Data is the fundamental basis for all other Predictive and Preventative maintenance functions and applications. Equipment utilization in semiconductor manufacturing fabrication units has always been a challenging issue to us. The overall equipment effectiveness (OEE) being in the range of 40-60% shows a lot of potential to improvement. Over the time lack of availability of data from the equipments had kept us from implementing the predictive maintenance procedures to the existing manufacturing equipment in the fabrication units [1]. Semiconductor manufacturing has always been data-intensive. But the data is simply moved into storage "just in case" scenario. And of the data that is actually processed, more than 90% is never accessed again.

For our study, we started collecting the data from the following data sources:

- ✓ Fault Detection and Classification (FDC) data
- ✓ Trace Log data
- ✓ Equipment Tracking (ET) Data
- ✓ Metrology/Probe/Param Data
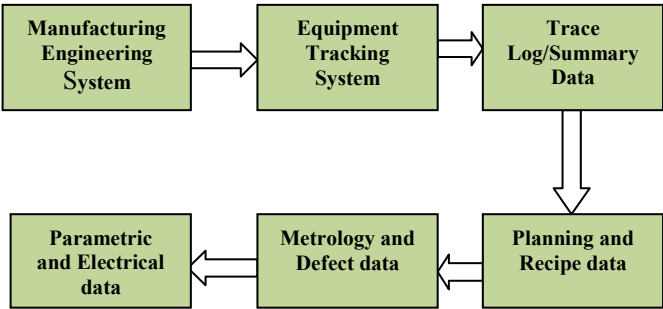
Fault Detection and Classification (FDC) Data:
FDC has been recognized in the semiconductor industry as an integral component of advanced process control (APC) framework in improving overall equipment efficiency (OEE). Massive amount of trace or machine data is made available in today's semiconductor industry and fault detection has been one focus of recent efforts to reduce wafer scrap, increase equipment uptime and reduce the usage of test wafers [1-7].

The semiconductor manufacturing processes are usually through FDC to collect a large number of status variable identification (SVID) as data in real-time processes. FDC contains two functions: fault detection and the fault classification. Engineers focused on results of fault detection testing to take some necessary actions. Different fault requires different corrective actions, while fault classification function is classified based on statistics eigenvalues. So engineers can quickly refer to the machine error code and restore the machine to normal state within the least time [4, 6, 8]. Today,

the fault-detection production databases in most state-of-the-art fabs range from 15-30 terabytes of data.

Equipment Tracking (ET) Data:
The Equipment Tracking System (ETS) collects and analyzes the data from various semiconductor equipments. Logging equipment is the most important activity in the ETI system. The Equipment Tracking System captures the equipment status and the operation states in an Equipment Tracking database. Using this system, operators log the various event statuses of the equipments, the reason for the current state, and notes about the piece of equipment. The primary task of this system is to correctly reflect tool status. Event data in this system records the 'Start Time' for each operation (i.e., process start or cleaning start), and the 'Processing Area ID', 'Wafer #' and 'Lot #' associated with each operation.
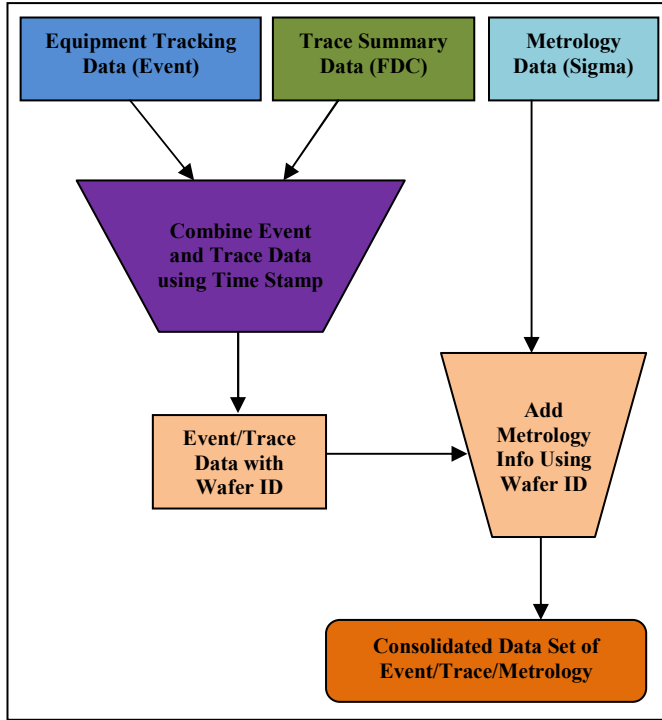
| Equipment	State	Notes	Start Time	End Time
IMHC4C5300	PM_SOURCE	Changing the filament	2/24/2014 2:27p.m	2/25/2014 5:35a.m
IMHC4C5400	PM_SOURCE	Changing the filament	2/23/2014 11:22p.m	2/24/2014 8:23 a.m
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Research Processes:
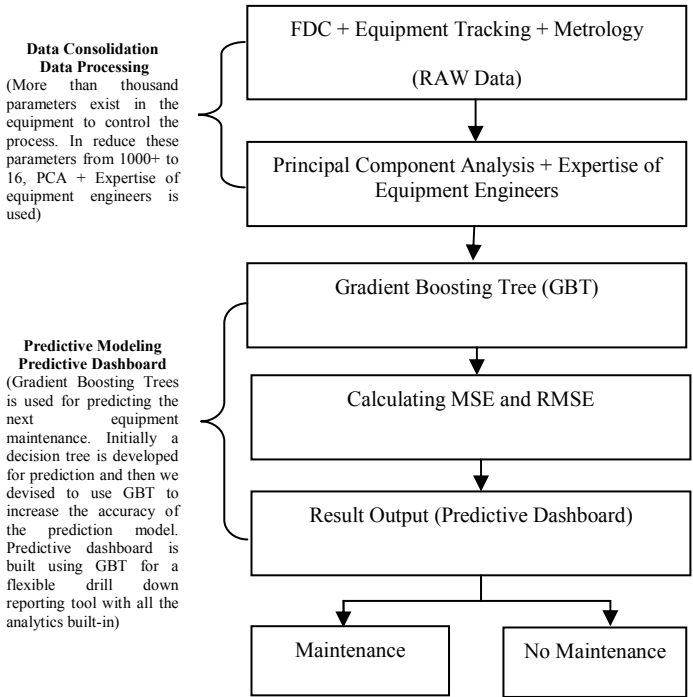
A. Data Consolidation

Data consolidation is the key step in merging all these 4 data sets.

Metrology Data:

Metrology data records wafer thickness measurement results (mean value and standard deviation) along with wafer # and lot #. In order to apply BN analysis, three separate datasets have to be consolidated and synchronized. In so doing, events data, trace data and metrology data are merged together according to wafer # and time stamps.
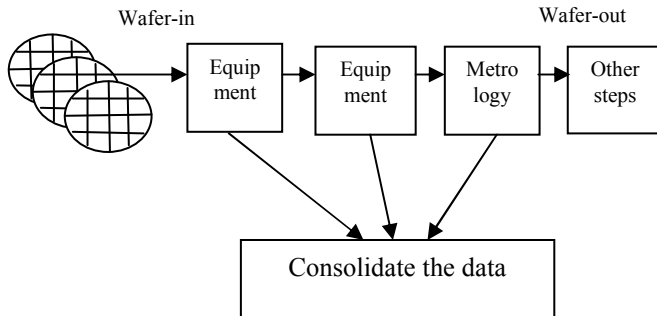
B. Virtual Equipment

Virtual Equipment serves as a testing environment for prediction algorithms prior to their implementation in a semiconductor manufacturing plant (fab). The Virtual Equipment uses input data that is based on historical fab data collected during multiple filament failure cycles. The aim of the Virtual equipment is to test predictive methods in regards to different analysis methods before implementing them in the fab. The virtual equipment is implemented in MATLAB/Simulink.

V. CONCEPTUAL BIG DATA ARCHITECTURE
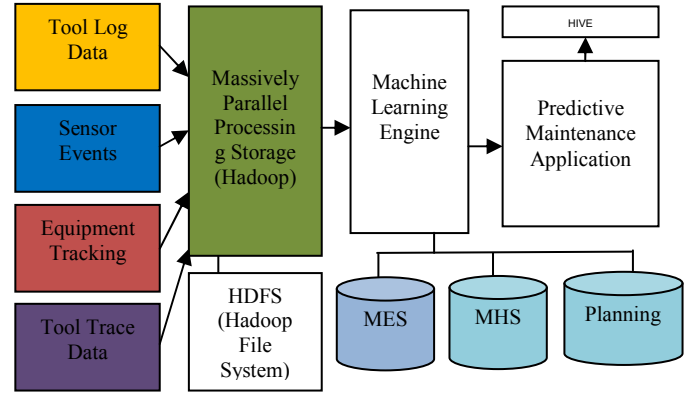
A. Apache Hadoop* sofware

Using Hadoop architecture, we can gather and process data from a variety of sources, including equipment sensors, maintenance logs, trace, FD and equipment tracking. Using that information, the system uses predictive algorithms to determine the likelihood of equipment failure. Engineers and mechanics can then take necessary steps to fix the equipment and prevent catastrophic hardware failure down the line.

For predictive analytics usage, we are looking at another Hadoop software component, the Apache Mahout* machine learning library to create predictive algorithms that can run directly on Hadoop. In our semi-conductor data flow, we have both Structured (RDBMS) and Un-structured (Trace log files). We collect the data from traditional RDBMS-based data warehouse, perform data integration and pre-processing of the structured data as a batch process, and then transfer the data to the Hadoop Cluster. The Hadoop cluster integrates the pre-processed data with relevant unstructured data, and applies predictive models, again as a batch job. The results of the analyses are loaded into the online component of the recommendation system, a NoSQL database. The NoSQL database supports low-latency lookups, which allows results to be queried interactively. There are number of NoSQL databases in big data environment, including Cassadra*, HBase, Pig and MongoDB.

B. Not only SQL (NoSQL) databases

NoSQL databases relax the constraints of a traditional RDBMS to deliver higher performance and scalability. NoSQL databases can extend the capabilities of Hadoop clusters by providing low-latency object retrieval or other DW-like functionality. More than a hundred different NoSQL databases are available, offering a wide variety of capabilities to address specific use case requirements. The results of the analyses are loaded into the online component of the recommendation system, a NoSQL database. The NoSQL database supports low-latency lookups, which allows results to be queries interactively. We uses a number of NoSQL

databases in its big data environment including Cassandra*, HBase, and MongoDB*.

C. Memory-Resident Graph Databases

Graph databases (GDB) are now a viable alternative to Relational Database Systems, especially in the field of predictive analytics. The semiconductor databases are huge in terms of both number of entries and number of records. For recommendations in predictive analytics, it's important to look at the performance in searching records that are similar to the most recently observed situations, which is necessary to enable to information discovery and inference process on the use of SOMs and BNs.
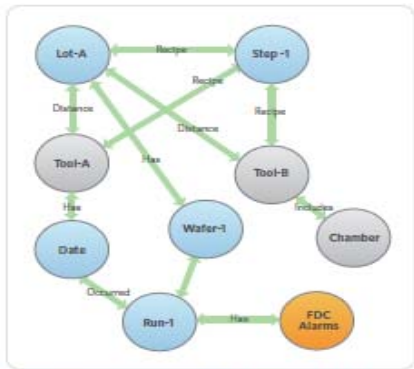
Figure 3: Graph representation of factory data for fast data retrieval and processing.

Graph databases are said to be "schema-less". They don't have the relatively rigid structure that we expect in relational databases. Instead, they can store a wide variety of information, from numbers to video and more, organized in a relatively flexible structure described by a changeable graph. Neo4J is only one of many such databases, others that you may encounter include MondoDB, AllegroGraph and FlockDB. The advantages of the graph structure include rapid creation of and changes to a database, and excellent performance for many routine operations. Almost all databases in manufacturing are organized in a sequential manner as lists based usually on the time of arrival of an entry into the database.

VI. PREDICTIVE MODELS

The goals of predictive modeling in semiconductor manufacturing can be inferring equipment condition based on equipment sensor data log, predicting typical process results such as etch bias after plasma etching or source/drain current after ion implantation, or sampling electrical measurement metrology. Different prediction methods are discussed in the below sub-sections. Typically predictive models used would be Neural Networks, Decision Trees or Regression Analysis to arrive at conclusions. Predictive analytic models mine the data and correlate past failures using multivariate analysis. The models can mine all the variables and conditions that contributed to past failures in order to predict future failures. Incoming data are then run through the model and asset health scores are generated on a real time basis. Predictive analytics technologies apply machine-learning algorithms to produce data-driven models of an asset. By definition, predictive analytics encompasses a variety of techniques from statistics, modeling, machine learning, and data mining that analyze current and historical data to predict future events.

The processing cycle typically involves two phases of processing:

1. Training phase: Learn a model from training data

2. Predicting phase: Deploy the model to production and use that to predict the unknown or future outcome

Signal Processing & Feature Extraction	Health Assessment
Time Domain Analysis	Logistic Regression
Frequency Domain Analysis	Statistical Pattern Recognition
Time-frequency Analysis	Feature Map Pattern Matching (Self-organizing Maps)
Wavelet/wavelet Packet Analysis	Neural Network
Principle Component Analysis (PCA)	Gaussian Mixture Model (GMM)
Performance Prediction	**Health Diagnosis**
Autoregressive Moving Average (ARMA)	Support Vector Machine (SVM)
Elman Recurrent Neural Network	Feature Map Pattern Matching (Self-organizing Maps)
Fuzzy Logic	Bayesian Belief Network (BBN)
Match Matrix	Hidden Markov Model (HMM)

In the below sections, we are going to review some of the predictive algorithms applied for semiconductor equipment maintenance.

A. Dynamic Data Clustering

Data clustering is a field of active research in machine learning and data mining. Most of the work has focused on static data sets. There has been little work on clustering of dynamic data. We define a dynamic data set as a set of elements whose parameters change over time. Predictive analytics provides a much-needed supplement to predictive maintenance technologies. It applies machine learning to cluster large volumes of multi-variable data. Through the cataloging of data clusters, predictive analytics establishes a comprehensive profile for each asset – unique fingerprints left behind during all phases of operation. Those fingerprints provide detailed knowledge of the asset's performance at varying operating rates, with differing products, and under other changing conditions within the production environment.
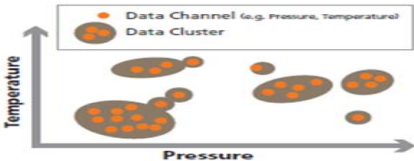
Figure 2. Dynamic data clustering: Shown are clusters associated with just two variables (i.e., data channels). The clusters form from data that describes the true physics of the asset.

Clusters are based on numerous data inputs that respond to the changing conditions of an individual equipment, and they correspond with the various modes, operating ranges, and products to which the asset is applied. Once cataloged in a knowledge or experience database, clusters associated with asset degradation or other negative attribute trigger alerts. Similarly, the formation of new clusters prompts alerts as the predictive analytics technology identifies new conditions that have yet to be classified. Unlike static and limited input

models, the clusters fully account for the asset's condition and recognize both subtle and significant changes in behavior. Dynamically determining the optimal number of clusters in a dataset is a challenging task, since a priori knowledge of the data is required and not always available. Ball and Hall[10] proposed the Iterative Self-Organizing Data Analysis Technique (ISODATA) to dynamically determine the number of clusters in a data set. A similar model to ISODATA is the Dynamic Optimal Cluster-seek (DYNOC) which was proposed by Tou [172].

B. Random Forests CART (Classification and Regression Trees)

For prediction purposes we use a method that utilizes an ensemble of CART models called Random Forests. The aggregation of a large number of different single models usually offers improved prediction accuracy. The methodology allows a transition from a time-based to a condition-based maintenance, a reduction of problem complexity and it offers high predictive performance. As the Random Forest approach is free of parametric or distributional assumptions, the method can be applied to a wide range of predictive maintenance problems. This leads to a reduction of tool downtime, maintenance and manpower costs and improves competitiveness in the semiconductor industry.

C. Multi-Variate Analysis (MVA)

Multi-Variate Analysis (MVA) provides a model-centric approach to quickly identifying the complex-system fault source. Usually process variables will go out of correlation before an actual process fault occurs. Thus an MVA system will give early warning.
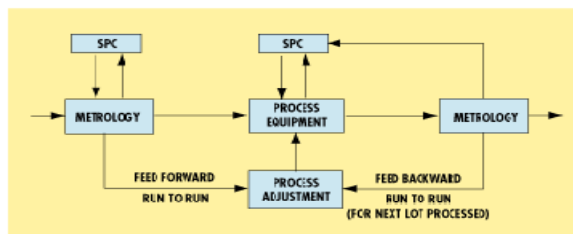

Figure 3: Role of statistical process control in detecting process equipment issues.

Multivariate analysis of equipment parameter data has proven to be an effective technique for providing additional visibility to equipment performance trends in complicated control schemes. Translation of the multivariate output signal into a concise set of corrective actions will further improve equipment effectiveness.

D. Bayesian Networks

Bayesian Networks are already widely considered as suitable for the prediction of equipment condition (e.g. see Vachtsevanos et al. 2006) while methods based on decision trees are rather new for prediction purposes. Probabilistic graphical models are based on directed acyclic graphs. Probabilistic graphical models are based on directed acyclic graphs. Within the cognitive science and artificial intelligence

such models are known as Bayesian Networks (BN). A BN is a directed acyclic graph whose nodes represent random variables and links define probabilistic dependences between variable. Towards Bayesian network methodology for predicting the equipment health factor of complex semiconductor systems. Due to the fact that all variables (predictors, response) are represented as "nodes", and all conditional dependencies between those variables/nodes are represented in (directed) arrows between the nodes, Bayesian Networks are often referred to as a graphical modeling method (Pearl 1988). So models can be set up in a graphical way, defining all nodes and arrows with respect to the real relationships between the predictor and response variables. After model learning, a probabilistic prediction can be made based on new data. For the Predictive Maintenance system described here, a simple network structure was chosen with only few predictors (the first 4 selected variables from Table 1), and the remaining time to failure (TTF) as response variable (Figure 2). The model structure was determined manually utilizing expert knowledge of process and maintenance personnel. For modeling, MATLAB and a modified version of Kevin Murphy's BNT tool box (Murphy 2001) have been used.
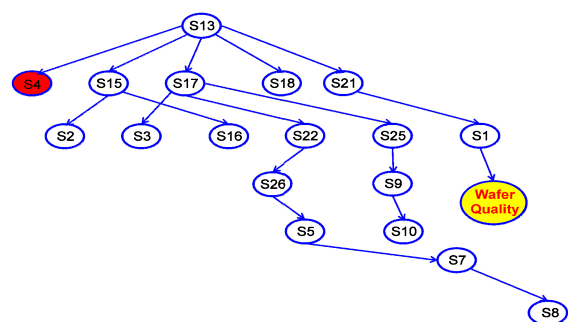


E. Artificial Neural Networks (ANN)

Advanced semiconductor manufacturing processes are all made of very sophisticated machines. Requirements on these processes need hundreds of control parameters of the machine [1]. If a slight deviation of the key values changed, it may cause the process deviation (excursion). And then, the production of wafer may be in reduction or even scrapped. For the normal operation and maintenance of equipment to ensure production, failures of the equipments must be diagnosed correctly and timely.

The semiconductor manufacturing processes are usually through FDC to collect a large number of status variable identification (SVID) as data in real-time processes. We can evaluate artificial neural networks (ANNs) on how well it's efficiently analyzes SVID data and can provide good results for further controls. Artificial neural back-propagation network has some functions, including possess learning, fault tolerance, and the parallel computing [4, 5]. Applying these functions, artificial neural back-propagation network can develop a predictive method for outliers' machines and thus

help the overall enhancement of yield in semiconductor manufacturing [6]. The idea of implementing ANN is to have an effective predictive model to detect abnormal values of FDC. Neural networks offer a number of advantages, including less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms. Disadvantages include its "black box'' nature, greater computational burden, proneness to over-fitting, and the empirical nature of model development [7].

F. Self-Organizing Maps (SOM)

In semiconductor industries, one is always faced with large volume of high dimensional data from in-situ sensors, maintenance records, inspections database, etc. Currently, there are a number of methods like Principal Component Analysis (PCA) that have been employed to reduce the dimensionality of the data in order to make it amenable to exploratory analysis. One class of such methods typically projects the data to a low-dimensional space, either linearly or in a non-linear fashion, at the same time preserving their mutual relations as well as possible. The SOM is a set of unique methods that reduce the amount of data by clustering, and reduce data dimensionality through a nonlinear projection of the data onto a low-dimensional space [98]. The methods in this category include principal component analysis, multidimensional scaling, etc.
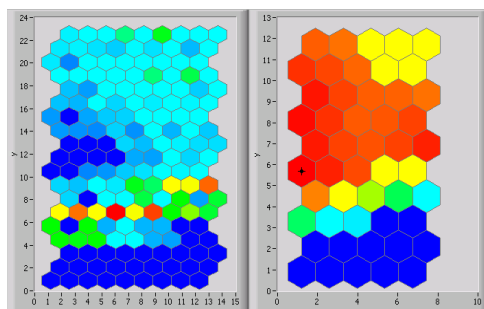
G. Support Vector Machine

SVM is a supervised learning method that can be used for classification and regression analysis. It generally involves a training phase that requires health indicators with the corresponding label or equipment condition (good/bad/fault). The objective of using SVM is to use the trained model to predict equipment condition given only the current health condition.

H. Health Score Model (Binary logit Model)

The Health Score model is based on the linear regression model and measures the likelihood that an asset or process will fail. The health score value, typically referred to simply as the Health Score, can also be used to predict the future health of the asset. The Health Score is presented as a number between 0 and 1. The higher, the number, the healthier the asset. A well-established statistical method for predicting

binomial outcomes is required to predict the health score value, and the solution uses a binomial logistic algorithm for this purpose. In the binomial or binary logistic regression, the outcome can have only two possible types of values (e.g. "Yes" or "No", "Success" or "Failure"). Multinomial logistic refers to cases where the outcome can have three or more possible types of values (e.g., "good" vs. "very good" vs. "best"). Generally outcome is coded as "0″ and "1″ in binary logistic regression. This kind of algorithm is limited to models where the target field is a flag or binary field. The algorithm provides enhanced statistical output when compared to a multinomial algorithm and is less susceptible to problems when the number of table cells (unique combinations of predictor values) is large relative to the number of records.

I. Lifespan Analysis (Cox Regression Model)

The Lifespan Analysis model analyzes time-to-failure event data. Lifespan analysis is an offline, back-end process and can be performed at regular intervals or on demand. The model is based on the Cox Regression Model. In many cases where the time to a certain event(such as failure) can be predicted, the Cox Regression technique is particularly well-suited.

J. Time Series Models

Time series models are used for predicting or forecasting the future behavior of variables. Time series models estimate difference equations containing stochastic components. Two commonly used forms of these models are autoregressive models (AR) and moving average (MA) models. The Box-Jenkins methodology (1976) developed by George Box and G.M. Jenkins combines the AR and MA models to produce the ARMA (autoregressive moving average) model which is the cornerstone of stationary time series analysis. ARIMA(autoregressive integrated moving average models) on the other hand are used to describe non-stationary time series. In recent years time series models have become more sophisticated and attempt to model conditional heteroskedasticity with models such as ARCH (autoregressive conditional heteroskedasticity) and GARCH (generalized autoregressive conditional heteroskedasticity) models frequently used for financial time series. In addition time series models are also used to understand inter-relationships among economic variables represented by systems of equations using VAR (vector autoregression) and structural VAR models.

CONCLUSION

Explosive data growth in the semiconductor industry will continue to be a major challenge and the ability to manage large data volumes and move the industry from a reactive to a predictive state has the potential to drive significant value for semi-conductor industry. However, little has been published about the use of machine-learning techniques in the manufacturing domain. Predictive maintenance with the advent of big data has reached a crossroads that will provide more intelligence for companies to make predictive maintenance decisions that will avoid the need to make the most costly

decision of reactive maintenance. There is a continuous collaborative research efforts going on between semiconductor industries and academia in the areas of Virtual Metrology, Predictive Maintenance, Fault Detection, Run-to-Run control and modeling. There is lot of research going on turning the fault detection with fault prediction to reduce scrap and equipment downtime. Predictive Maintenance will augment preventative maintenance to further reduce downtime. The predictive approach helps prevent unplanned downtime and will help to identify failing parts before they impact wafer quality or cause the tool to fail. It can also extend the useful life of critical parts based on cumulative data. The predictive approach have potentially immense benefits to both semiconductor manufacturers and equipment suppliers, ensuring them to improve the chip quality, increase the yield and extend the useful life of semiconductor equipment.

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