Manufacturing Intelligence for Equipment Condition Monitoring in Semiconductor Manufacturing

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Abstract. For modern semiconductor manufacturing, a large number of interrelated equipment data are automatically collected. These data are usually used for fault detection and classification (FDC). However, unusual measurements may reflect a wafer defect or a change in equipment conditions. Early detection of the equipment condition changes assists with efficient maintenance. This study aimed to develop hierarchical indices that can be used for the conditional-based maintenance (CBM). For convenience, only the highest level index is used for real-time monitoring. Once this index decays, engineers could simply drill down to lower indices to identify the root cause. For validation, the proposed approach is conducted in a leading semiconductor foundry in Taiwan. The result shows that the highest index indicates the change of equipment conditions right after the preventive maintenance (PM).

Keywords: Fault detection and classification (FDC), Equipment condition, Condition-based maintenance (CBM), Real-time monitoring, Preventive maintenance (PM), Tool health.

1. INTRODUCTION

During wafer fabrication, hundreds of sensors are built in the advanced processing equipment to monitor the equipment parameters, i.e. the status variable identifications (SVIDs) as in Figure 1. To conserve storage space, the SVID readings are sequentially divided into several steps by predetermined time windows, and the summary statistics for each step, called indicators, are computed to stand for the SVID feature. Thousands of interrelated indicators are automatically recorded during a wafer passes through an equipment. Unusual indicator readings on a wafer may reflect the high possibility of wafer defect while those on consecutive wafers may reflect the change of the equipment conditions.

Among these indicators, some are active and are easily specified by the recipe during the fabrication, the others are passive that are inherent determined by the wafer or equipment conditions. Examples of active parameters are RF power and gas flow rate and passive parameters include contaminate level and temperature. For efficient utilization of equipments, products and recipes are not always fixed. This means that the indicator performance may depend on the corresponding product and recipe. Therefore, it is hard to define the health for every indicator.

To maintain the quality of products or avoid the damage to the equipment, PM is necessary for numerous manufacturing industries. However, replacing parts and equipment down time incurs additional costs. Other than scheduled PM, CBM which consider the equipment condition is an efficient way to save maintenance costs. Unfortunately, large number of indicator, frequently change of products and recipes makes it difficult to evaluate the health for equipment. Moreover, some engineers think that peak equipment condition occurs immediately after PM, whereas others feel that equipment needs time to warm up to reach its optimal condition.

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This study aims to construct hierarchical indices for real-time equipment monitoring. The developed indicator indices decay once the trend change is detected. Based on these indices, higher level indices such as step indices, SVID indices and equipment index (EI), are built up by knowledge-based combination. In our opinion, the feature of SVID readings should have a remarkably change due to PM or equipment failure but slightly change due to equipment warm up. This results a rapidly decay of the EI for the change of equipment condition and slowly decay for equipment warm up. An empirical study was conducted to validate the proposed approach. The results show the proposed equipment index is feasible because it decays rapidly right after the PM which is assumed to be unknown.

The rest of this paper is organized as follows. Section “Fundamental” presents a review of relevant methods to monitor equipment conditions; Section “The approach” proposes the framework for constructing the hierarchical indices; Section “Empirical study” validates the proposed approach using real data from a semiconductor foundry in Taiwan. Section “Conclusion” summarizes the research contributions of this study and suggests future research direction.

2. FUNDAMENTAL

2.1 Maintenance

PM is important to ensure equipment performance. However, replacing worn parts and equipment downtime during unnecessary PM incurs additional costs. An efficient maintenance policy is crucial for reducing production cost and increase equipment utilization. Wang (2002) reviewed several maintenance policies. Yao et al. (2004) proposed a hierarchical two-level framework for scheduling short-term and long-term PM. Rebai et al. (2010) develop a strategy to schedule M PM on M machines while incurring minimal costs. Apart from scheduling maintenance in advance, CBM provide a just-in-time maintenance. Chien and Wu (2003) proposed a framework that provides decision rules for semiconductor test machines. Yue et al. (2004) presented PCA models that generate tool health indices for statistical process control (SPC) charts. Chen et al. (2007) developed an equipment simultaneous monitoring scheme called “Bull’s Eye” that is more applicable for equipment with fewer variables. They also proposed an index under multivariate Gaussian distribution assumption. In addition, Markov chain is used for equipment health prognosis. Cheng (2008) proposed a global similarity index based on Mahalanobis distance between the historical and newly entered set of process data. Chen et al. (2009) proposed an equipment health indicator constructed by generalize moving variance and exponentially weighted moving average (EWMA) with SVID readings as Figure 1. Blue et al. (2012) modified this index by moving coefficients of variation (CV). Additionally, they proposed a hierarchical monitoring scheme to facilitate identification the root causes. Hsu et al. (2012) proposed an approach for early detection of key equipment excursion for advanced equipment control.

2.2 Statistical Process Control

Statistic process control (SPC) is widely used to detect the change of the trend for a single variable (Montgomery, 1994). For example, $\bar{X}$ and R charts. As the number of variables increases, it is difficult to use one index to represent overall quality. Fisher (1950) used a single statistic to represent the results of several independent tests. However, in practice, variables are usually interrelated. The Gaussian distribution assumption is often used to overcome the interrelated problem (Hotelling, 1947). Liu (1995) proposed a nonparametric method to simultaneously detect mean shift and scale increase. Ning and Tsung (2012) presented a density-based SPC for high-dimensional data, i.e. the number of variables is larger than the sample size. Testing the quality character for each wafer is time consuming so detecting the trend change with the lengthy and interrelated equipment data and combine the information from indicators into a single summary statistic become a common problem for efficient equipment management.
2.3 Notations

Let the subscript \( ijk \) denote the \( i^{th} \) SVID, \( j^{th} \) step, and \( k^{th} \) statistic. This study uses the following notations:

- \( n_0 \): Training sample size.
- \( n_0 \): Testing sample size.
- \( \alpha_0 \): Significance level for constructing the prediction interval (PI).
- \( \alpha \): Significance level for detecting an indicator trend change.
- \( w_{ijk} \): Weights given by engineers.
- \( t \): Arrival time of the \( i^{th} \) wafer.
- \( \mathbb{N}(\mu, \sigma^2) \): Gaussian distribution with mean \( \mu \) and variance \( \sigma^2 \).
- \( y_{0}(t) \): Accumulated sample size before time \( t \).
- \( M_0(t) \): Model for the indicator measurement.
- \( \mu_{0}(t) \): Mean function for the indicator.
- \( \hat{\mu}_{0}(t) \): Estimated mean function for the indicator with the measurements before \( t_0 \).
- \( \hat{\psi}_{0}(t) \): Estimated variance function for the indicator with the measurements before \( t_0 \).
- \( I_0(t) \): Indicator index at time \( t \).
- \( I_t(t) \): Step index at time \( t \).
- \( I(t) \): SVID index at time \( t \).
- \( I(t) \): Overall EI at time \( t \).

3. THE APPROACH

This study considers the indicators individually to construct the indicator indices, as shown in Figure 2. Once the indicator indices are derived, other higher level indices were aggregated using the weighted sum. Instead of using \( p \)-values as the indicator indices, 0 and 1 are used to represent changing trend and unchanging trend, respectively. Otherwise, the effect of two indicators with \( p \)-values equal to 0.5 will be inappropriately weighted the same as the effect of two indicators with values 0 and 1.

3.1 Problem structuring

Although equipment health concerns, it is difficult to evaluate. In fact, the normal behavior for an indicator may be different among equipments, recipes and products. Instead of evaluating health, the proposed approach simultaneously detects the mean drift and variance inflation for each indicator. Once the change has been detected, the indicator index \( I_{0}(t) \) decays from 1 to 0. Based on these indicator indices, the other higher level indices can be constructed by weighted sum. The weights which are provided by engineers show the relative importance for each indicator. Weights are set to be equal when the relative importance is not provided. The EI is used for real-time monitoring. Because it is a weighted sum of the indicator indices, engineers can easily drill down to find the root cause when it decreases. The color for each EI is used to distinguish the combinations of product and recipe. It helps engineers judge whether the combination had impact on the equipment performance.

3.2 Data Preparation

The training sample size \( n_0 \) need to be decided and data cleaning are conducted during data preparation. Missing and extreme values often appear in semiconductor equipment data. A commonly used method of managing these data is to delete these observations. However, this approach is unsuitable for the high-dimensional data since an observation would be deleted whenever an indicator is missing. To solve the missing value problem, indicators are considered individually and the results were combined. The extreme values were automatically detected using the same method for identifying outliers in box plots. As shown in Figure 3, an outlier occurs in the outlier zone, which is defined as 1.5 times the inter-quantile range (IQR) larger than the third quantile or smaller than the first quantile. Under
Figure 3 Outlier definition.

Gaussian distribution assumption, they are approximately equal to the 0.35 and 99.65 percentiles, respectively. Once an outlier is detected, it is treated as a missing value.

3.3 PI Estimation

Significant level \( \alpha_0 \) to estimate PI has to be set in this step. Indicator level indices are considered in this and the following subsection, so the subscript \( ijk \) is suppressed for simplicity. When the equipment condition is good, the indicator may have the trend displayed in Figure 4. Therefore, assume the trend for the indicator is

\[
M(t) : y(t) = \beta_0 + \beta t + \epsilon(t), \epsilon(t) \sim N(0, \sigma^2)
\] (1)

where \( \beta_0, \beta \) and \( \sigma^2 \) are unknown. Simply set \( \beta \) equals to zero for indicators ought to be stationary. The \( n_0 \) training sample are used to estimate the unknown coefficients in (1). Suppose the trend does not change and there were more than \( n_0 \) measurements for the indicator before time \( t_0 \), the coefficients of (1) can be estimated by

\[
\hat{\beta}_0(t_0) = \bar{y} - \hat{\beta}_\tau \bar{t}
\] (2)

\[
\hat{\beta}_\tau(t_0) = \frac{\sum_{i=1}^{n(t_0)} (y(t_i) - \bar{y})(t_i - \bar{t})}{\sum_{i=1}^{n(t_0)} (t_i - \bar{t})^2}
\] (3)

\[
\hat{\sigma}^2(t_0) = \frac{\sum_{i=1}^{n(t_0)} (y(t_i) - (\hat{\beta}_0(t_0) + \hat{\beta}_\tau(t_0) t_i))^2}{(n(t_0) - 2)}
\] (4)

where \( \bar{y} = \sum_{i=1}^{n(t_0)} y_i/n(t_0) \) and \( \bar{t} = \sum_{i=1}^{n(t_0)} t_i/n(t_0) \). Let \( n_0^* = n(t_0) + 1 \), then \( t_{n_0^*} \) denote the first wafer arrival time after \( t_0 \). For given \( \alpha_0 \), the PI for the \( n_0 \) measurement with arrival time \( t_i \) can be estimated by

\[
\left[ \hat{\beta}_0(t_0) + \hat{\beta}_\tau(t_0) t_i \right] \pm T_{\alpha/2; \sigma^2/n_0} \left[ \frac{1}{m(t_i)} + \frac{1}{n_0} \right]
\] (5)

where \( T_{\alpha; \sigma^2/n} \) denotes the \( \alpha \) percentile of chi-square distribution with degree of freedom \( q \).

3.4 PI updating or behaviour tracing

Testing sample size \( n_1 \) and type one error rate for detecting the trend change \( \alpha_1 \) are needed in this step. If \( y(t_i) \) fell in (5), (2) to (5) are updated for the next measurement. Otherwise, the estimator (2) to (5) are not updated and the following \( n_1 \) indicator readings \( y(t_{n_1+1}), \ldots, y(t_{n_1+n_1}) \) will be traced. Based on (2) to (4), the estimated mean and variance function are

\[
\hat{\mu}_i(t) = \hat{\beta}_0(t_i) + \hat{\beta}_\tau(t_i) t_i
\]

and

\[
\hat{\psi}_i^2(t) = \hat{\sigma}^2(t_i) \left[ 1 + \frac{1}{m(t_i)} + \frac{t_i - \bar{t}}{\sum_{i=1}^{n(t_i)} (t_i - \bar{t})^2} \right]
\]

respectively. Under model (1),

\[
\sum_{i=t_0}^{t_0+n_1} \left( y(t_i) - \hat{\mu}_i(t_i) \right)^2
\]

is approximately chi-square distributed with degrees of freedom \( n_1 \). Let \( \chi^2_{\alpha/2; q} \) denote the \( \alpha \) percentile of chi-square distribution with degree of freedom \( q \). The trend is regarded to change and the \( I(t) \) decays from 1 to 0 at \( t_{n_1+n_0} \) whenever (6)\( > \chi^2_{\alpha/2; q} \).
3.5 Indices Combination

The importance of the SVIDs, steps and indicators will be used to develop hierarchical indices in this section. However, it is not essential. Simply assign equal weights while the $w_{ijk}$ are not provided. All indices can be built up by the following weighted sums:

$$I_i(t) = \frac{\sum_j w_{ijk} I_{jk}(t)}{\sum_k w_{ijk}},$$

(7)

$$I_j(t) = \frac{\sum_k w_{ijk} I_{jk}(t)}{\sum_j w_{ijk}}.$$  

(8)

and

$$I_k(t) = \frac{\sum_i w_{ijk} I_{ij}(t)}{\sum_i w_{ijk}}.$$  

(9)

PM or equipment component failure usually results in the change of the behavior for related indicators, so the proposed EI is expected to decay rapidly after these events. By contrast, equipment warm up is more likely to cause a gradual decrease for the EI.

4. EMPIRICAL STUDY

4.1 Problem Structuring

This study detects the equipment condition change and develops a scheme for the convenience to identify the root cause. It is inefficient to monitor the equipment condition by conventional statistical process control methods since there will be thousands of control charts for a wafer. Moreover, it is difficult to set upper and lower control limits for each indicator. The proposed EI is expected to reflect the condition change, and the hierarchical indices are used to identify the root cause. The empirical study is conducted in a leading semiconductor company in Taiwan for validation. The data set consists of 626 wafers and 3,253 indicators from 181 SVIDs from an etching equipment during August 31 to November 29, 2011. Equipment failure did not happen but there are two PM during this period. Some indicators such as standard deviation, minimum, maximum, slope and range measure similar character; therefore standard deviation is used to represent this characteristic. The number of the chosen indicators including mean, standard deviation and duration was reduced to 2,441. One indicator is chosen for illustrate the indicator index construction procedure in the following three subsection.

4.2 Data Preparation

Training sample size $n_0$ is set to be 30, and the conventional method to detect outlier is used as describe in Section 3.2. The outlier detection is shown in Figure 5. The threshold of the non-outlier interval is marked as two red dot lines. The red diamond point falls in outlier zone is regarded as an outlier. After removing the outlier, the number of normal measurements labeled as blue circles is 30.

4.3 PI estimation

Significant level $\alpha_0$ to estimate PI is set to be 0.01. PI is estimated by (5) after the outlier is removed. As shown in Figure 6, PI is labeled as two blue curves. Note that the PI gets larger with the time away from its mean. Significant level $\alpha_0$ used to estimate PI is set to be 0.01. PI is estimated by (5) after the outliers were removed. As shown in Figure 6, PI is labeled as two blue curves. Note that the PI gets larger with the time away from its mean.

4.4 PI updating or behavior tracing

Testing sample size $n_1$ is set to be 9, and the type one
The importance of the SVIDs is given by engineers as Table 1. The importance increases with the number. All higher level indices are constructed by (7) to (9). Different colors for EI are used to represent for different product and recipe combinations. Figure 8 (a) demonstrates that the proposed EI has the expected performance right after the PMs which are marked as the two black vertical lines. Three different SVID indices are drawn from Figure 8 (b) to (d). It is obvious that the first SVID in Figure 8 (b) is related to the first PM since $I_1$ decayed to zero right after the first PM. The second SVID in Figure 8 (c) is not related to the first PM but it is related to the second PM since $I_2$ did not decay after the first PM but it did right after the second PM. The third one in Figure 8 (d) is partial related to the first PM and not related to the second PM. Drill down to step level for the third SVID, Figure 8 (e) to (g) show the first PM affected the performance of the second and the third steps while it did not affect the performance of the first step.

5. CONCLUSION

This study proposed a framework for real-time monitor the equipment condition. The hierarchical indices make it easy to identify the root cause. Mean drift and variance inflation can be detected simultaneously by chi-square test. Domain knowledge about the relative importance of indicators is embedded in combination of indices. The empirical study demonstrates the feasibility of the proposed framework. It successfully detected the change of the equipment condition right after PM.

The decrement of the proposed EI is expected to be proportional to the scope of PM. However, it is hard to trace and quantify the scope of PM. Moreover, suitable weights are crucial to make the decrement proportional to the equipment condition. Once the reasonable decrement is established, the threshold for EI is possibly to derive. The alarm signal can be triggered when the EI is smaller than the threshold.

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Figure 8 Proposed hierarchical indices.
REFERENCES


Ning, X., and Tsung, F., (2012), A density-based statistical process control scheme for high-dimensional and mixed-type observations, IIE Transactions, 44(4), 301-311.

Niu, G., Yang, B., and Pecht, M., (2010), Development of an optimized condition-based maintenance system by data fusion and reliability-centered maintenance, Reliability Engineering and System Safety, 95(7), 786-796.


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