Key Parameter Identification for Faulty Wafer Detection Using Image Processing

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***Abstract*—Nowadays, the semiconductor industry has become fully automated during the manufacturing process where abundant process parameters are collected on-line by sensor for the Fault Detection and Classification (FDC) purpose. To analyze these parameters and identify a smaller set of key parameters that have crucial influence on wafer quality must bring great benefits in stabling the manufacturing process and enhancing the production yield. Therefore, this article considers an alternative approach to use image processing techniques for analyzing the raw trace data. First, the one-dimensional time series data of a wafer batch was transformed into a two-dimensional image. Fisher's Criterion (FC) ratios of the labelled good and defect wafer images are computed. The parameters that have high FC ratios are deemed the key parameters. The nine key parameters were identified by using the proposed image processing technique, which concurs with the technical experiences from the process engineers.**

KeyWords*: *Semiconductor manufacturing, Key parameter identification, Image Processing, Fisher's criterion

I. Introduction and Proposed Method

Nowadays, in the semiconductor manufacturing practice, wafer manufacturing is a complicated multiple-step sequence of photolithographic and chemical processing steps during which electronic circuits are gradually fabricated on a wafer made of pure semiconducting material; that is, the so-called "raw trace data." Likewise, a gigantic amount of data with a wide variety of process parameters are simultaneously generated. Raw trace data are automatically recorded in every sensor during manufacture processes, so multiple time series data are produced wafer by wafer. The final wafer quality should be, in essence, highly related to some key parameters. In ordinary practice, the engineers use their practical experiences gained from extensive experimental results and historical testing data to decide on potential key parameter. Therefore, the investigation of possible key parameters among the raw trace data poses a challenging task for process engineers in semiconductor manufacturing.

To improve the production yield and maintain the process stability, identifying the key parameters from the raw trace data is an important issue in routine manufacturing. Feature selection aims to downsize the amount of the raw trace data but still maintains the key information. In the Advanced Process Control (APC) practice, the raw trace data are collected by sensor continuously. The process control engineer will use this kind of data to perform the Fault Detection and Classification (FDC) and process control/monitoring tasks. Traditional FDC approaches in semiconductor manufacturing use univariate statistics for monitoring, which is tedious and might be misleading if key parameters cannot be correctly identified. Although the APC of semiconductor manufacturing has advanced considerably in the past decade, this paper attempts to propose an alternative approach by means of image processing techniques to analyze the raw trace data for identifying key parameters.

In the open literature, there exist many researches that transform a two-dimensional image data into one-dimensional data and apply traditional statistical methods for post hoc analysis. For instance, Bartlett et al. [1] proposed using Independent Component Analysis (ICA) to study face recognition. On the contrary, from a reverse point of view, the one-dimensional raw trace data collected for this article will be recast into a two-dimensional image, and then existing image processing methods can be readily employed.

A semiconductor manufacturing process that consists of 38 parameters in the raw trace data set was under investigation. In the data set, there are 155 wafers monitored, labelled with 134 good and 21 defect wafers. For each parameter, the 155×180 measurements of 155 wafers and 180 readings are placed in an image as shown in Figure 1.

 ISBN: 978-1-61208-634-7

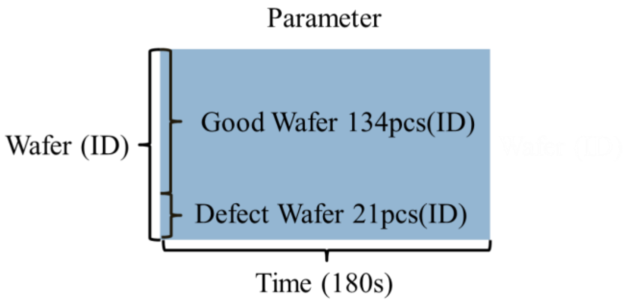

Figure1. Parameter Image.

These 38 parameters are BufPurge N2 MFC Flow, Buffer Chamber Robot Correct EXT, Buffer Chamber Robot Correct ROT, CHILLED WATE R TEMP, CH Inner Heater Zone Temp, CH Outer Heater Voltage Ratio Mode, Chamber heater pid error, H2_Flow Setpoint1, H2_MFCFlow, Heater servo fwd, N2 Flow Setpoint1, N2 MFC Flow, N2 PURGE Flow Setpoint1, N2 PURGE_MFC Flow, NF3_MFCFlow, Number Wafer In Periodic Clean Process, PH3 Flow Setpoint1, PH3 MFC Flow, SiH4 Flow Setpoint1, SiH4 MFC Flow, Temperature Power, Chamber fore line pressure, Chamber heater lift spacing, Chamber heater lift step number, Chamber inner heater zone current, Chamber inner heater zone power, Chamber inner heater zone resistance, Chamber inner heater zone voltage, Chamber lift position, Chamber misc number of wafer count, Chamber outer heater current, Chamber outer heater power, Chamber outer heater resistance, Chamber outer heater voltage, Chamber pm current wafer count, Chamber pressure reading, Chamber recipe elapsed time, and Chamber throttle valve position.

In this study, the raw trace data was transformed into an 8-bit gray-level representation. The maximum value is 255, so the grey level range would be from 0 to 255. The minimum value 0 represents black and the maximum value 255 represents white.

For each wafer, a univariate statistic, the Signal-to-Noise Ratio (SNR) is calculated as in (1).

$$SNR = \frac{\mu}{\sigma} \tag{1}$$

In (1), μ is the mean and σ is the standard deviation. Under a particular parameter, the SNR is evaluated wafer-wise, generating a transformation from a time series realization into the feature of wafer's parameter. From a practical viewpoint, a key parameter must be able to clearly differentiate between good and defective wafers. Therefore, it is highly anticipated that the SNR of good wafers exhibits an obvious difference as compared to that of defective wafers.

Next, Fisher's criterion (FC) ratio is used to identify the key parameters from the 38 parameters. As usual, FC tries to find a projection direction, attempting to increase the separation between classes while minimizing the variance within a class [2][3] (see Figure 3). In the paper, the SNR is used to compute each parameter's FC ratio wafer by wafer. Firstly, the SNRs are classified into two categories: good and defective in that labelling was previously done. The good wafers fall into group 1 and the defective wafers fall into group 2. Since there are 38 parameters in total, there are 38 FC ratios as well.

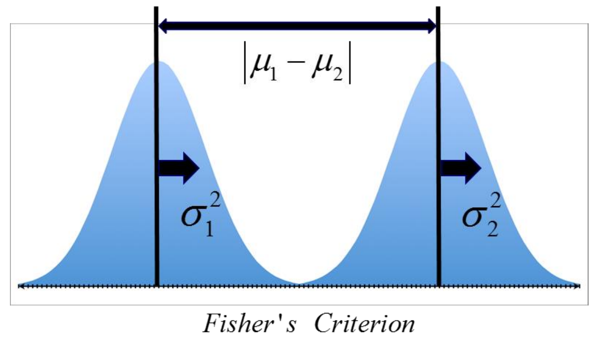

Figure 3. FC Ratio Schematic Diagram

Lastly, the K-means algorithm will be used to set up the threshold for identifying the key parameters. As a clustering method, K-means proposed by MacQueen [4] is a type of unsupervised learning algorithms, which solves the problem of clustering unlabeled data. The goal of this algorithm is to partition the data into ***K*** groups, and assign a cluster to each data point; ***K*** represents the number of clusters.

The procedure of the K-means algorithm and its flow chart (see Figure 4) are shown as follows:

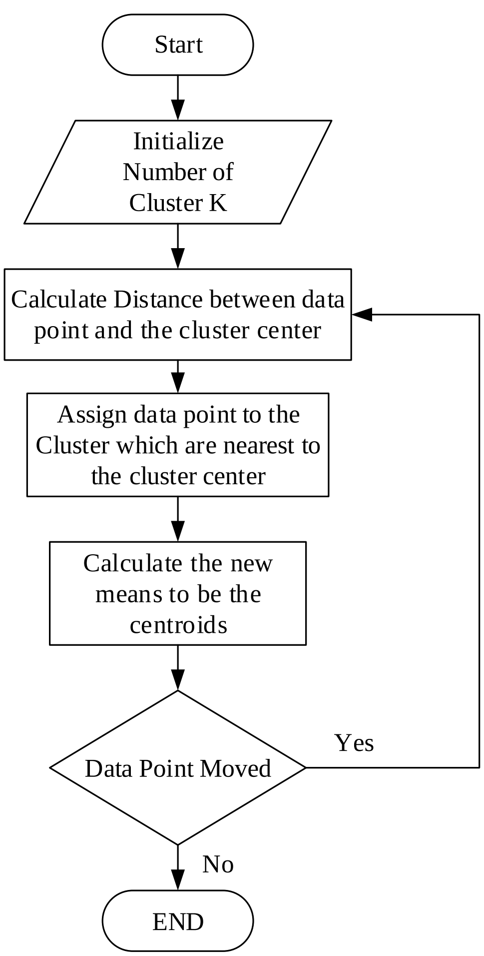

Figure 4. Flow chart of K-means algorithm

 ISBN: 978-1-61208-634-7

1. Select K the number of clusters;
2. Assign each data point to the clusters that has the nearest to the cluster center;
3. Updated the new means of each cluster;
4. Repeat Steps 2 and 3 until no data point moved.

In addition, Figure 5 illustrates the proposed key parameter identification process.

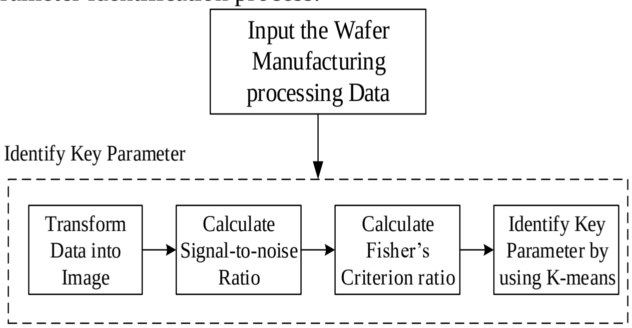

Figure 5. Key Parameter Identification Procedure.

In the next section, some preliminary experimental results are demonstrated to validate the proposed procedure.

II. EXPERIMENTAL RESULTS OF KEY PARAMETER IDENDIFICATION

The key parameter identification result will be presented in this section. Every parameter was investigated by using the proposed procedure. An exemplary parameter, Chamber heater pid error, is illustrated in Figure 6. In the table, the original data profile is shown in (a), and the image representation in (b). In (a), the red lines indicate the profiles of the defective wafers, whereas the blue lines represent the profiles of the good wafers.

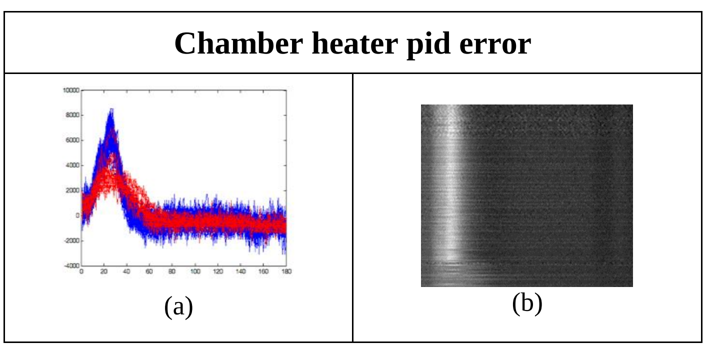

Figure 6. Chamber Heater Pid Error.

In this study, potential key parameters are mainly identified based upon Fisher's Criterion, and then Table I tabulates the FC values of all the 38 parameters. To set up a threshold for identification, the K-mean algorithm is used to classify all the 38 FC values into two clusters: key parameters and non-key parameters. As mentioned in subsection *D*, the cluster with a larger FC value is deemed the key parameter cluster.

TABLE I. FISHER'S CRITERION LISTS OF 38 PARAMETERS

Parameter	Fisher's Criterion
1. BufPurge N2 MFC Flow	0.03922
2. Buffer Chamber Robot Correct EXT	0.10435
3. Buffer Chamber Robot Correct ROT	0.01229
4. CHILLED WATER TEMP	0.01998
5. CH Inner Heater Zone Temp	3.74436
6. CH Outer Heater Voltage Ratio Mode	0.001468
7. Chamber heater pid error	5.01448
8. H2_Flow Setpoint1	0.001038
9. H2_MFCFlow	0.000226
10. Heater servo fwd	0
11. N2 Flow Setpoint1	0.009865
12. N2 MFC Flow	0.009985
13. N2 PURGE Flow Setpoint1	0.022763
14. N2 PURGE_MFC Flow	0.01684
15. NF3_MFCFlow	0.013256
16. Number Wafer In Periodic Clean Process	0
⋮	⋮

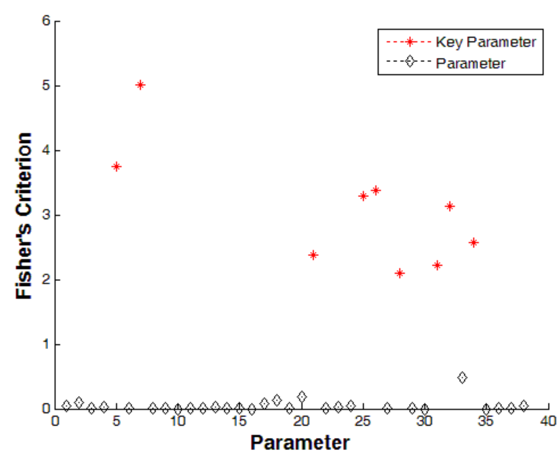

Figure 7. Identify Key Parameter by Using K-means.

Figure 7 exhibits the classification result via K-means as $K = 2$. The red points denote the key parameters as the black point represents the non-key parameters. In the figure, the Y axis stands for the FC value and the X axis denotes the parameter ID. The identified 9 key parameters are also shown in Table II. The identified parameters are all related to the inner heater sensors, which were also confirmed by the on-site engineers. Based upon this process investigation, the process engineer can proceed to constructing adequate control charts for a much smaller set of process parameters. By doing so, the false alarm of FDC can be greatly reduced.

 ISBN: 978-1-61208-634-7

TABLE II. KEY PARAMETERS IDENTIFIED

Result of Research Method	Engineer's Experience
Chamber heater pid error	✓
Chamber Inner Heater Zone Current	✓
Chamber Inner Heater Zone Power	✓
Chamber Inner Heater Zone Voltage	✓
⋮	⋮

III. CONCLUSION

In this research, the proposed method clearly identifies 9 key parameters. This result concurs by the well-known process engineer's domain knowledge and practical experiences. Through this case study, the proposed method proves to be a viable tool capable of correctly identifying the key parameters out of abundant process parameters in the semiconductor manufacturing practice. An immediate study for future research could be the identification of possible key steps for the key parameters revealed from this paper.

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 ISBN: 978-1-61208-634-7