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Automatic equipment fault fingerprint extraction for the fault diagnostic on the batch process data

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ABSTRACT

Equipment condition monitoring in semiconductor manufacturing requires prompt, accurate, and sensitive detection and classification of equipment and process faults. Efficient and effective fault diagnostic is essential to minimizing scrapped wafers, reducing unscheduled equipment downtime, and consequently maintaining high production throughput and product yields. Through analyzing the equipment sensor signals as the batch process data, i.e., process timestamp × sensor × wafer, this paper firstly applies the well-known Support Vector Machine (SVM) classifier to detect the abnormal observations. In the second stage, the normal process dynamics are decomposed into different clusters by *K*-Means clustering. Each part of the process dynamics is further modelled by Principal Component Analysis (PCA). Fault fingerprints then can be extracted by consolidating the out of control scenarios after projecting the abnormal observations into the PCA models. An empirical study is conducted in collaboration with a local IC maker in France to validate the methodology. The result shows that the proposed approach can effectively detect abnormal observations as well as automatically classify the proper fault fingerprints to give evident guidelines in explaining the known faults.

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1. Introduction

Semiconductor manufacturing consists of highly complex and lengthy wafer fabrication processes with at least 300 process steps and a large number of interrelated variables. The complicated setting in the manufacturing environment further increases the difficulty of maintaining process stability and controlling quality. Equipment condition monitoring and product quality analysis are vital for detecting critical abnormal events in wafer fabrication for optimal tool utilization and high product yield [1]. As a consequence, the fault diagnostic procedure shall be implemented and executed in the precisest manner because an oversight in fault detection or classification will then cause cascading product loss in the production line.

Conventional fault diagnostic methods are usually performed in a two steps [2]: (i) *fault detection* to determine whether a fault has occurred and (ii) *fault classification* to categorize the root cause to the observed out-of-control status. Automated and intelligent fault diagnostic systems can overcome the wastage and barriers caused by the poorly maintained, degraded, and/or improperly controlled equipment [2]. Besides to *fault detection* and *fault classification* steps, two other important steps are *process dynamic decomposition* as well as *fault root extraction*.

In semiconductor manufacturing, one process contains a set of consecutive steps with different settings. For example, a deposition process requires heating the chamber to a temperature high enough to ensure the reaction can be triggered. If the temperature sensor readings are collected and reviewed after the process, a nonstationary profile can be seen in three steps: warming-up, main deposition, and cooling-down. This non-stationarity shown in the temporal sensor readings does not come from the seasonality, periodicity or abnormal drifts. Instead, it is a normal phenomenon encoded in the recipe in relation to the chemical and physical laws. Therefore, we define this type of non-stationarity as the process dynamic. Accordingly, *process dynamic decomposition* proposed in the paper is to cluster the nonstationary sensor readings into stationary partitions. PCA, which requires a stationarity assumption, can be then employed to model all the partitions. *Process dynamic decomposition* step is necessary in order not to consider the process normal dynamics (i.e., normal ups and downs) as the faults.

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Fault root extraction comes to practice once the fault is detected and classified to extract the faulty variables in order to diagnose the root causes of the fault. In this paper, we propose a novel method for combining these four steps for efficient and effective detection, classification and root extraction of specific faults in semiconductor manufacturing process.

There is a plenty of literature on process fault diagnosis ranging from analytical methods to artificial intelligence and statistical approaches. Generally, fault diagnostic methods in nearly all industries can be mainly classified into three categories, based on the process knowledge that is required a priori [3]: model-based, knowledge-based and data-driven methods. The model-based is usually developed based on some fundamental understanding of the physics of the process and this understanding is expressed in terms of mathematical functional relationships between the inputs and outputs of the system. Model-based methods are very accurate; however, determining the appropriate values of the model parameters is timely inefficient and labor-demanding [4]. Therefore, a model-based method is too costly and unpractical to apply in real systems comprehensively. On the other hand, different natures of the faults and the manufacturing uncertainty require developing numerous models to diagnose all the faults for various types of equipment in semiconductor manufacturing.

In knowledge-based methods, once a process issue happens, engineers have to identify the root causes of the problem as soon as possible to reduce the production loss. Most of the engineers only rely on their own domain knowledge and experience to identify the specific characteristics of abnormal products and to classify the fault causes. As one can imagine, such judgments are subjective and requires strong expertise in the problem domain [5]. In particular, the knowledge-based methods should provide evident results for relatively unskilled operators to make reliable decisions without intervene of the domain specialist when a fault occurs.

Data-driven methods come to practice whenever a large amount of historical process data is available. There exist different ways in which this data can be mined and transformed as a priori knowledge to a diagnostic system. This transformation is called as the feature extraction process from the historical process data, and the extracted features are utilized to facilitate later diagnosis. The data-driven methods mostly rely on the signal-based diagnosis. The data-driven methods are also known as the data mining or the machine learning methods, which uses historical data to automatically learn a model of system behavior. The Data-driven methods have been employed in a wide variety of industries [1,4–9] because the data always contains valuable knowledge and using data-driven methods is much less difficult than model-based methods, particularly in the complex industries [3]. Semiconductor manufacturing equipment consists of hundreds of built-in sensors for regulating the tool signals as well as the process states. Since historical data have kept valuable information about the equipment status and the corresponding processes, it is believed that data-driven based fault diagnostic is more applicable compared to the other methods based on the rigorous process models or domain knowledge [5–7].

One of the greatest challenges of fault diagnostic in semiconductor manufacturing is to cope with the four types of variation: 1) variations from the faulty events; 2) variation from the process dynamic induced from the recipe setting; 3) variations from the process change, in particular, the change from one recipe to another in the normal process runs; and 4) variations from the equipment degradations/deterioration. Accordingly, any fault diagnostic must be capable of differentiating one of the four variations without confounding the other three; however, the data-driven methods are more capable of handling this challenge. Using model-based methods usually needs different models for different settings and recipes of the process and normally defining a unique mathematical model distinguishing all the variations is impossible [3].

This research focuses on proposing an efficient data-driven fault diagnostic method to monitor the equipment condition, and consequently to detect and classify the faults. For this aim, we incorporate several useful soft computing algorithms to develop a data-driven fault diagnostic method.

The rest of this paper is organized as follows. In Section 2, the most recently papers studying fault diagnostic in the semiconductor manufacturing following by the literature gap analysis are reviewed. The proposed data-driven fault diagnostic method is explained in Section 3. A case study and result analysis based on the real data from a local semiconductor manufacturing in France is conducted in Section 4. Concluding remarks are made in Section 5.

2. Literature review

The related literature is firstly categorized based on different criteria and the works studying fault diagnostic in semiconductor manufacturing are carefully summarized. Each paper is reviewed in terms of the three following perspectives [10–12]:

- Fault diagnostic method: as mentioned in Section 1, the fault diagnostic is categorized into 1) model-based, 2) knowledge-based, and 3) data-driven methods.
- Diagnosis steps: as already elaborated in Section 1, the necessary steps for an efficient fault diagnosis method are categorized as 1) fault detection, 2) fault classification, 3) process dynamic decomposition, and 4) fault root extraction [13].
- Industrial domain: the application domain the reviewed papers can be mainly grouped into 1) continuous chemical processing, 2) mechanical manufacturing, and 3) semiconductor fabrication. To save the space, only the papers discuss the chemical and semiconductor processes are summarized. Moreover, the data coming from the two domains share very similar properties, ex: the batch process structure. In this regard, we would like to focus on the approaches carried out in relation to the batch process data, which is the study vehicle of this research.

Based on the three perspectives above, the related literature is carefully reviewed and finally they are summarized in Table 1.

In the literature, data-driven methods, such as Principal Component Analysis (PCA) and Partial Least Squares Regression (PLSR), have been widely applied in chemical and semiconductor industries. Yue et al. [14] introduced the batch process monitoring to semiconductor fabrication for plasma etchers by using emission spectra and the multi-way PCA (MPCA) method to analyze multiple scan sensitivity within a wafer for several typical faults. They tested two MPCA schemes for the purpose of fault detection and wavelength selection. The proposed method selected critical wavelengths to detect the fault. However, due to the selected wavelength constraint and ignorance in the normal drifts, the proposed method is not guaranteed to be robust. Spitzlsperger et al. [15] presented an adaptive Hoteling's T^2 control chart for the semiconductor etching process. In the paper, they emphasized the insufficiency of Hotelling process control charts for monitoring the status of the oxide etching process due to the Hotelling statistic movement. It is unstable for the period after the maintenance. The proposed method updates only the univariates that are given to drift, but the problem has not been completely resolved.

Chien et al. [16] combined MPCA and Self-Organizing Map (SOM) to construct the model to detect faults and to derive the rules for fault classification. In their method, the 3D historical data was unfolded and projected onto the score and residual spaces in order to reduce the high data dimension to a few PC's. While D (Hotelling's T^2) and Q (residual) statistics were used for abnormal

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