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Feature Construction for Dense Inline Data in Semiconductor Manufacturing Processes

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Abstract: Management and analytics for inline manufacturing process data has become a critical but increasingly complex task in the semiconductor fabrication industry. The importance of new methods for construction of informative features has been accentuated by advancements in the data collection technology employed in this industry, which has recently increased sampling rates for inline data from values below 1 Hz to frequencies in excess of 10Hz. In this paper, a new feature construction method is proposed that aims to extract as much of the information accessible with these increased sampling rates as possible, while simultaneously minimizing redundancy and user involvement. The proposed method results in a meaningful dynamics inspired feature set, which provides insight into the underlying process and equipment dynamics. The advantages offered by this feature set are established using data collected at several modern 300mm fabs, for chamber and tool matching tasks, as well as wafer defect level prediction.

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1. INTRODUCTION

Semiconductor fabrication equipment, like many other manufacturing tools, are equipped with a vast array of sensors, often simultaneously generating hundreds of signals to capture the equipment and process behavior. Furthermore, in recent years, the industry has seen significant increments in the sampling rates of these sensor readings, e.g. in technology from Applied Materials, Inc. as discussed in Dietz and Ducrot (2014), and tools developed by Lam Research Corporation (http://www.lamresearch.com/products/products-overview). These recent developments in the data collection technology have led to massive amounts of inline data being gathered from tools through significantly raised sampling rates. The higher sampling rates hold promise to enable better process control through improved fault detection and diagnosis, virtual metrology and virtual quality control, which are possible because of the enriched information contained in densely sampled signals.

The exploitation of the data for process control and decision making is highly contingent upon the extraction of useful information from the available signals. Due to the dominance of low sampling rates in the semiconductor fabrication industry, traditional methods for dealing with the signals have focused on their statistical characteristics, including mean values, standard deviations, peak-to-peak values, and occasionally even higher order statistics such as skewness, kurtosis and entropy. These characteristics are obtained for the entire signal or certain portions of it, as specified by user defined windows, often requiring significant heuristics or physics based knowledge. The inability of low sampling rates to accurately depict the transient portions of the signals led to the fact that traditional methods were unable to capture the dynamics involved, as evidenced in Fig. 1. On the other hand, high-frequency sampling captures the transient portions of the signals more faithfully, thus allowing for the extraction of meaningful dynamics inspired features and offering insight into the dynamics of the underlying process, as well as their impact on the tool and product. At the same time, the prohibitive amount of data collected at these raised sampling rates has also limited the active use of traditional methods in industry, since it requires considerable expert knowledge and supervision on the part of the users. This has left the collected data to serve solely in post-mortem analysis, and industry feedback indicates that even that often fails when high sampling rates are used. It is worth noting that the size and dimensions of the data to be handled in practice are expected to continue to grow, making it of ever increasing interest to develop an automated method for signal parsing and feature construction that minimizes the required user involvement.

While there are numerous powerful frequency domain based methods that have been developed for the analysis

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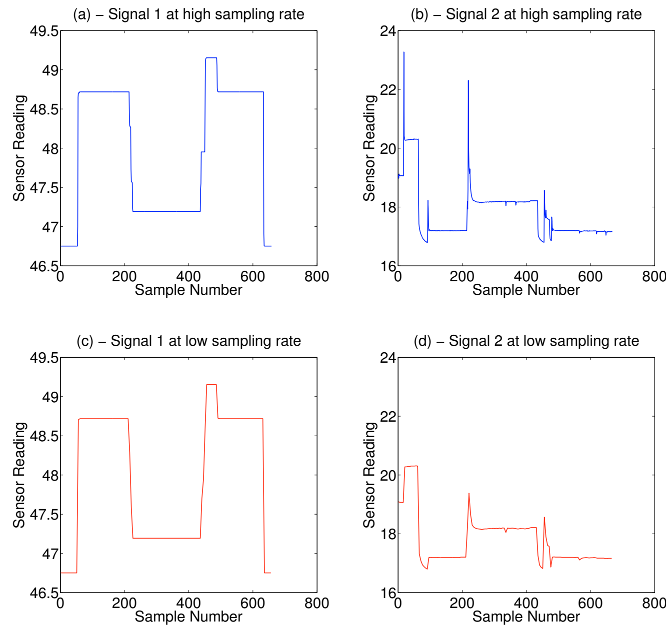

Fig. 1. The impact of the high sampling rates, the blue lines are signals collected at high sampling rates and the red dashed lines are collected at one-fifth that sampling rate. It is seen that much data from the transient regions will not be observed at the lower sampling rates.

of densely sampled signals collected from various types of rotating machinery, the non-rotating and non-cyclic nature of the equipment and processes make these inappropriate for data analysis in most semiconductor manufacturing applications. Additionally, the sampling rates employed, even after the introduction of the new technologies, is not high enough to allow the use of time-frequency domain tools to study the transient sections of the signals. With regards to feature construction in the time-domain, the IEEE standard IEEE Std 181TM - 2011 (2011) on describing transition or pulse based waveforms and the literature referenced therein are among the very few works that look at extracting dynamics inspired features from data generated by non-rotating equipment. This creates an urgent incentive to develop a new information extraction method aimed at obtaining dynamics inspired features from densely sampled data sets in semiconductor manufacturing applications.

To this end, this paper introduces a novel approach for information extraction from inline semiconductor manufacturing process data, with the objective to extract as much useful information as possible, while minimizing redundancy and user involvement. The feature set constructed by the proposed method includes the features considered in IEEE Std 181TM - 2011 (2011), along with other features determined through expert advice and analyses performed on data collected from equipment in multiple 300mm fabs. The advantages of the proposed feature set over traditional methods for chamber/tool matching and wafer defect level prediction will also be established.

The remainder of this paper is organized as follows. The following section will discuss the methodology for signal parsing and construction of informative features from it. Section 3 shall then present benefits of augmenting the traditional features with the newly constructed features in applications of chamber/tool matching and determining wafer defectivity. All results presented are based on data collected from multiple tools performing different processes in modern 300mm fabs. Finally, conclusions will be drawn and future work will be proposed in Section 4.

2. FEATURE CONSTRUCTION METHODOLOGY

Prior to the recent increases in the inline sampling rates in semiconductor manufacturing equipment, much of the information in the transient portions of the signals was not accessible, as is illustrated in Fig. 1. Now, the high sampling rates employed for inline data collection efforts allow useful features to be constructed from these sections of the signal as well. A new method able to do so is proposed in this paper, with the intention to maximize the extraction of useful information, while also preventing redundancy in the feature set and minimizing the required user involvement.

The feature set proposed here develops further on those considered in the standard IEEE Std 181TM - 2011 (2011). The list of features constructed in this work is provided in Table 1, with many of those features being associated with the transition regions. These features are conceptually illustrated in Fig. 2.

The method for the construction of these features is outlined in Fig. 3, with the user involvement being limited to the option to manually define the sensor noise threshold or signal type. The signals that are encountered are labeled as either step-like or impulse-like, examples of which are shown in Fig. 4 and an example of sensor noise threshold is also displayed in Fig.5. Statistically, data points in a step-like signals follow a multimodal distribution, as opposed to points following a unimodal distribution in an impulse-like signal. In this way, a classical dip test of unimodality

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