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Multi-step virtual metrology for semiconductor manufacturing: A multilevel and regularization methods-based approach

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ABSTRACT

In semiconductor manufacturing, wafer quality control strongly relies on product monitoring and physical metrology. However, the involved metrology operations, generally performed by means of scanning electron microscopes, are particularly cost-intensive and time-consuming. For this reason, in common practice a small subset only of a productive lot is measured at the metrology stations and it is devoted to represent the entire lot. Virtual Metrology (VM) methodologies are used to obtain reliable predictions of metrology results at process time, without actually performing physical measurements. This goal is usually achieved by means of statistical models and by linking process data and context information to target measurements. Since semiconductor manufacturing processes involve a high number of sequential operations, it is reasonable to assume that the quality features of a given wafer (such as layer thickness and critical dimensions) depend on the whole processing and not on the last step before measurement only. In this paper, we investigate the possibilities to enhance VM prediction accuracy by exploiting the knowledge collected in the previous process steps. We present two different schemes of multi-step VM, along with dataset preparation indications. Special emphasis is placed on regression techniques capable of handling high-dimensional input spaces. The proposed multi-step approaches are tested on industrial production data.

1. Introduction

In recent years, Virtual Metrology (VM) techniques have received growing interest from semiconductor manufacturers, thanks to the prospective measurement cost reduction and improvements in production quality (by means of control schemes exploiting VM information) [1].

The goal of a VM module is that of defining the relationships between *process data* (*input*) and *metrology data* (*output*). Given the cost of metrology operations and the increasing availability of recorded data in modern equipment, reliable VM predictions are used in place of real metrology measurements [2,3]. The inputs of the VM algorithms are cost-free data like sensor data, logistic and recipe information, while the predicted output is generally critical dimensions (like layer thickness for Chemical Vapor Deposition, Etch depth of Etch Rate for the Etching) upon which the goodness of the performed process can be assessed. In this perspective, VM tools are seen as information providers, able to yield probabilistic information at process time on wafer quality features.

Thanks to the diffusion in the pasts years of VM modules and the improvement of their prediction accuracy, nowadays VM predictions are not only used to monitor process quality and to decrease the number of physical measures performed, but they are also exploited by intelligent tools like controllers [4,5], dispatching and sampling decision systems [6] that can take advantage of VM estimations to improve the overall process quality.

VM problems, and more in general, modeling of semiconductor manufacturing process quality features, pose a number of challenges, among which the most prominent are the following:

- *High-dimensionality*: The number of potential input process parameters is usually large, given the high number of process variables and even higher number of collected data/statistics and production information. This issue may lead to ill-conditioned problems and data over-fitting [7–9].
- *Data fragmentation*: The typical semiconductor manufacturing production is highly fragmented. Hundreds of different products are processed with different machine settings (*recipes*) on several tools that work in parallel, each one with different

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working stations (*chambers*) (see Fig. 1 for an example). A VM system is required to model the entire production, but separately modeling each *logistic path* (group of wafers with the same combination of recipe, tool and chamber) is unfeasible given the large amount of possible combinations versus the historical data available.

- *Multi-processes influence*: The information regarding the outcome of a process is related to both the process itself and previous steps along the production line that may contain information regarding the current state of the wafer or may physically affect the outcome of the wafer feature in exam. For instance, one physical reason of the superimposition of effects of multiple processes on wafer features is the fact that wafer fabrication is based on multiple layers build one on top of the previous, with a possible concatenation of effects due to layer surface disparities [10].

The first two issues are addressed in Section 2, where a brief review of modeling techniques for VM is given. The main focus of the paper is however on the last issue, namely, the influence of multiple processes on the wafer features predicted by the VM module (the *VM targets*), that has been only partly explored in the VM literature [11,12]. Classical VM modules typically consider the modeling of a single process only, that is, the last one before the physical metrology step, without taking into account the influence of the previous processes on the line may have on the physical/electrical parameters that the VM module aims to predict. If data regarding the previous processes can be retrieved and included in the input set, it is reasonable to expect that the VM systems prediction accuracy can be enhanced.

The resulting data collection problem is a difficult one. In fact, from the modeling point of view, the collected multi-step data more markedly present the aforementioned issues of high-dimensionality and fragmentation. The increase in dimensionality is clearly related to the inclusion of a larger number of parameters into the dataset, that are related to the previous processing steps. To illustrate the issue of data fragmentation, consider the example of Fig. 2 that regards three of the most important classes of semiconductor processes, namely, Chemical Vapor Deposition (CVD), Lithography (Litho), and Etching (Etch). The diagram represents a possible process flow in the case of 11 different work-stations for the aforementioned processes. Since different process tools can perform the same process step for a specific wafer, the number of possible paths grows exponentially with the number of steps. As a consequence, a homogeneous dataset referred to a specific path would comprise an insufficient number of observations.

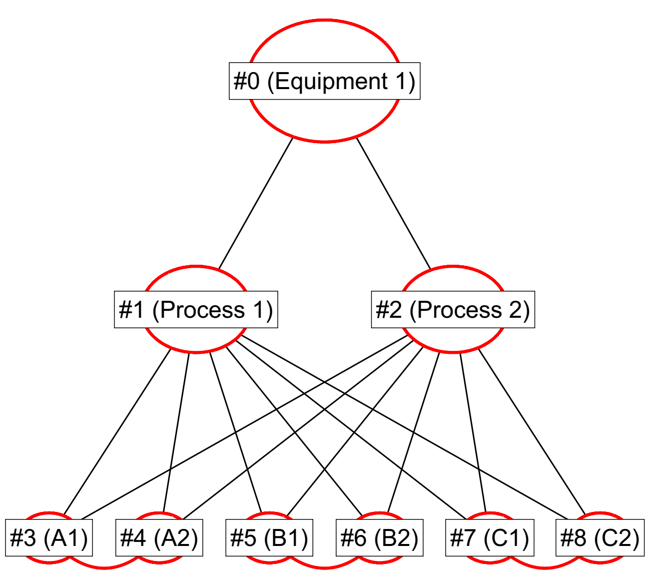

Fig. 1. Tree representation of a CVD (Chemical Vapor Deposition) tool with three chambers (A, B, C) with two subchambers each (1 and 2), involved in two processes (Process1 and Process 2). Therefore, for the processed wafers, twelve distinct logistic configurations (i.e., paths) are possible.

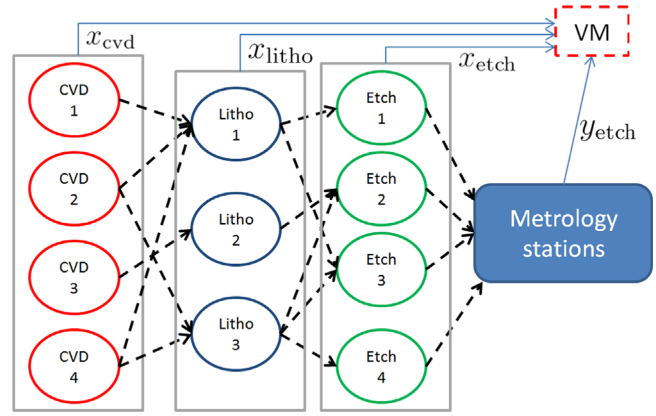

Fig. 2. Example of process flow in semiconductor manufacturing: the black dashed lines represent wafer dispatching events, while the solid blue lines represent information flows. The Virtual Metrology (VM) block collects process data (x) for several consecutive steps, and metrology data (y) for the latest step. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

In this paper we present a novel framework to address multi-step VM situations similar to the one shown in Fig. 2. The proposed approach relies on regularized machine learning methodologies to deal with high-dimensionality, and on a multilevel transformation of the input space to deal with data fragmentation. The goal is that of estimating quality indicators of wafers that have undergone several processes, by making use of data related to a subset of those processes that may have influenced the VM target (based on data availability and a priori physical knowledge).

The paper is organized as follows:

- Section 2.2 is devoted to review regularized machine learning techniques with focus on Regularization Methods.
- In Section 3 a brief description of Multi-Level techniques is provided and the proposed Multi-Step approaches are presented, in terms both of dataset preparation and model assumptions.
- In Section 4 a user case is presented and the proposed methodologies are validated exploiting a industrial manufacturing dataset.

Finally, in Section 5, final remarks and comments are provided. This paper extends the results presented in [13].

2. Modeling techniques for VM

In this section, the basic features of the modeling techniques employed for VM technologies are reviewed.

2.1. Literature review

Several features are required for a VM system to be successfully employed in a production environment (i.e. scalability to new production settings, fast computation, interpretability). Among them, prediction accuracy is the first and most important one, and consequently, the issue of modeling for VM has been at the heart of the debate in the scientific community in the past years.