Enabling process control though predictive design and virtual metrology for high product mix manufacturing

Hyung Joo Lee[1], Sanghyun Choi[1], Sudheesh Krishnankutty[2], Raghavendra Botta[2], Nathan Greeneltch[3], and Srividya Jayaram[3]

[1]Siemens EDA, Korea, [2]Siemens EDA, India, [3]Siemens EDA, USA

Abstract

The semiconductor foundry industry faces challenges in managing diverse customer demands and complex manufacturing processes. Variations in the chemical vapor deposition process affect transistor parameters and yield. Siemens' Calibre® software with machine learning techniques create a virtual metrology model that outperforms traditional methods. An advanced process control system, incorporating design features and real-time data, improves process capability and reduces film thickness variations in high-mix product foundry fabs, as confirmed by control simulations.

Keywords: machine learning, virtual metrology, design features, high product mix manufacturing, process control

Introduction

The semiconductor foundry industry has undergone significant changes in recent years, with high product mix manufacturing becoming increasingly prevalent. The shift towards custom-designed products demands flexibility in manufacturing process. Managing multiple products within the fab is extremely challenging and involves numerous chambers and process steps, different designs and technology nodes, which is complex to coordinate (Figure 1). There is a critical need to develop effective strategies to manage high product mix manufacturing as lack of control in this environment can lead to reduced yields and increased costs.

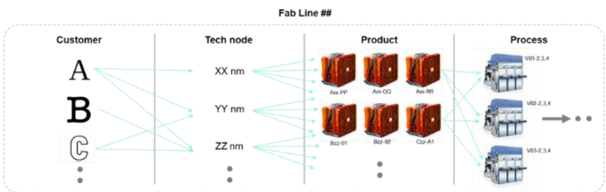

Fig. 1: High product mix manufacturing in semiconductor foundry

Chemical vapor deposition (CVD) processes are greatly affected in high product mix as the deposition thickness variations can occur due to device layout design and CVD process chamber condition drift. Figure 2(a) demonstrates the difference in film thickness between single and double pitches [1]. Figure 2(b) presents transmission electron microscopy (TEM) images that illustrate the discrepancies in silicon nitride film thickness between wide and narrow patterns [2]. Apart from the space width (pitch) between line patterns, several other design features that can impact film thickness variation [3]. The lack of thickness control across different layout designs and the resulting film variability can significantly affect key transistor parameters, such as threshold voltage and overlap capacitance, ultimately leading to yield loss [1].

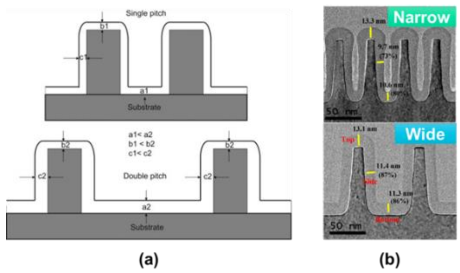

Fig. 2: (a) schematic of the difference in film thickness for a single and double pitch (b) TEM images of silicon nitride film thickness differences between a wide and a narrow pattern

Figure 3 depicts the drift in CVD film growth rate during a preventive maintenance (PM) cycle and the chamber-to-chamber variations in different stages of the PM cycle. This is due to the diminishing surface area and reactive gas consumption on the inner wall of the CVD chamber, which are consequences of the accumulated thickness [4]. Since the utilization of multiple chambers is inevitable, the chamber-by-chamber variation is a concern. PM cycle time-series variation and achieving chamber matching in the CVD process need to be managed to reduce throughput loss [4].

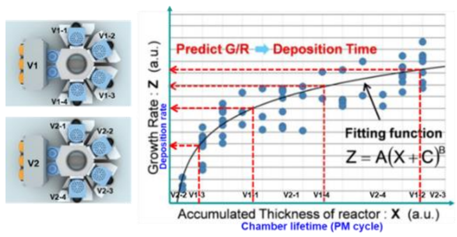

Fig. 3: PM cycle and chamber-to-chamber film growth rate variations

Variation in CVD film thickness is from a combination of design features and chamber characteristics which can be challenging to control using run-to-run (R2R) advanced process control (APC) methods. Having several new product introductions (NPI) in a single day is also a challenge. In this paper, a machine learning (ML) based virtual metrology (VM) approach is proposed as an effective process control solution for high product mix fabs. This is demonstrated on CVD process control loop through control simulation.

Methodology

Ideally, for precise control each wafer should be monitored for process control, but this requires additional metrology resulting in longer processing times and overall cost. A trade-off between cost and quality can be obtained using VM. VM utilizes data from the process chamber, known as fault detection and classification (FDC), to predict the metrology results. These can then be integrated in process control system, particularly in R2R [5]. Moreover, specific design features, such as pattern density and perimeter, can be extracted and utilized for prediction across multiple dies and technologies and can be used during NPI and in subsequent production stages [3]. In this study, Siemens' Calibre® software is used to extract design features from a variety of layouts across different technology nodes. Calibre® Fab Insights [6-8] is used to incorporate these design features into the chamber-level FDC data, using ML techniques such as a modified gradient boosted tree algorithm, to construct the VM model. The data used for modeling is sourced from a high-volume foundry fab that includes three different technology nodes and involves 70 distinct products running on 15 CVD chambers (with 5 equipment units, each equipped with 3 chambers). 70% of the data is utilized for model training and remaining 30% for model testing.

Figure 4 illustrates the results of the VM modeling. The X-axis and Y-axis represent the actual and predicted thickness. Due to confidentiality, the specific thickness targets for each node have been omitted. Each color indicates the chamber, and the shape represents the product. R^2 metric is used to assess the model fitness. VM model with both design features and FDC data shows significantly superior performance.

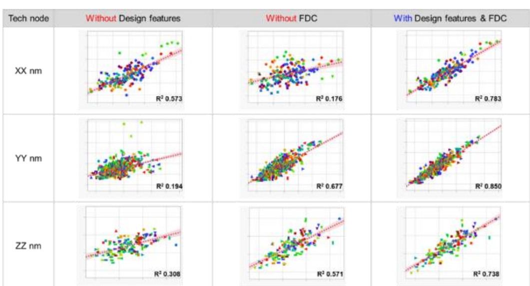

Fig. 4: VM modeling with and without incorporating design features and FDC

Comparing VM model with design data shows better results against without design data. When comparing the VM model with and without FDC, it shows that a VM model solely based on design features lacks practicality.

Figure 5 shows comparison by product, evaluating the RMSE of the VM model with and without design features. Figure 6 provides a comparison by chamber, assessing the RMSE of the VM model with and without FDC. Across the board, the VM model with both design features and FDC data consistently exhibits significantly better performance.

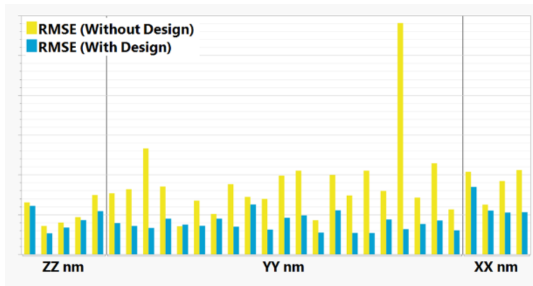

Fig. 5: Segmented comparison of the VM model with and without design features by product

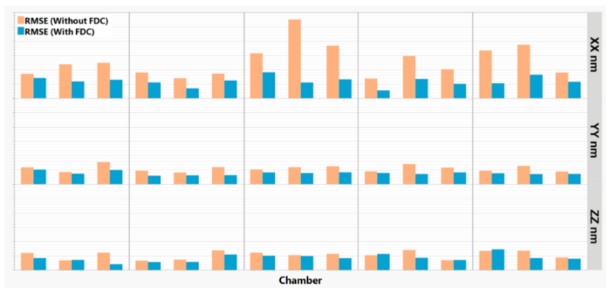

Fig. 6: Segmented comparison of the VM model with and without FDC by chamber

Results

Figure 7 illustrates proposed APC system, using VM model for R2R control. This model uses design features, FDC, and the incoming measurement to achieve the desired target thickness. Difference between the actual and predicted thickness (prediction error) goes out of spec, then the VM model is updated automatically by incorporating additional data within a predefined time window.

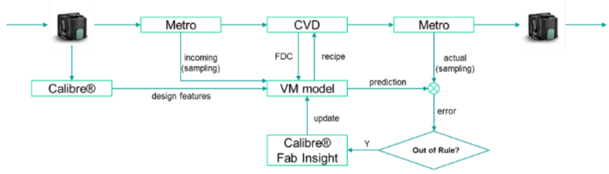

Fig. 7: Schematic diagram of APC system

Figure 8 presents the time-series evaluation results of the APC system through control simulation. Process capability

(Cpk) is improved from 0.86 to 1.30. Variations in the R2R deposition film thickness is mitigated and desired target thickness is achieved by the integration of the APC system, which updates the VM model and the CVD process recipe. Due to the limited size of the dataset, though the control simulation focuses on a single technology node (YY nm), multiple products are still processed across multiple chambers.

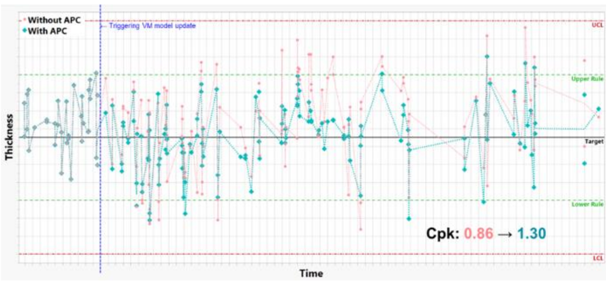

Fig. 8: Control simulation result of APC system

Figure 9 and Figure 10 illustrate the improvement in thickness variation achieved through control simulation, comparing the results with and without the implementation of the APC system.

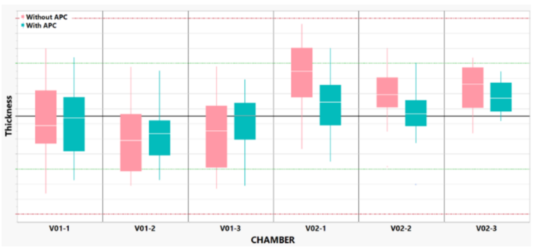

Fig. 9: Control simulation result of APC system by chamber

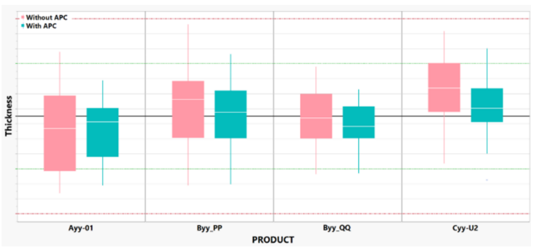

Fig. 10: Control simulation result of APC system by product

Figure 9 shows the improvement in thickness variation by chamber, and Figure 10 shows the improvement by product. In the absence of the APC system, the thickness is inadequately adjusted to the target value in each chamber due to inability of operators or traditional control methodologies to manually trace and compensate for all sources of variations. In contrast, when the APC system is employed, both the chamber to chamber and product to product film thickness variations are significantly reduced. This confirms the effectiveness of integrating the APC system with the VM model into the CVD process, particularly in a high-mix product foundry fab with numerous equipment units.

Conclusion

There is growing demand for increased manufacturing flexibility due to custom design products. Integrating an ML-based VM model with design features and FDC into the APC system is proposed as an effective process control solution for high-product-mix manufacturing. Simulation results confirm the remarkable effectiveness of this solution in the CVD process, within a high-product-mix foundry fab.

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