MACHINE LEARNING VERSUS PHYSICS-BASED CMP MODELING FOR EMERGING TECHNOLOGIES

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ABSTRACT

Machine learning (ML) is now used in a wide variety of applications, including self-driving cars, computer vision, process control, and many others. We discuss the methodology of building ML models for post-chemical mechanical planarization (CMP) topography prediction and hotspots detection using minimal silicon data. Using the GLOBALFOUNDRIES' mmWave RF technology SOC designs as our example, we present a comparative study of ML versus physics-based CMP modeling. Using ML-based CMP models, we were able to achieve ~85% reduction in CMP model development time, while realizing a 3.6x runtime improvement within acceptable accuracy, compared to a purely physics-based CMP modeling approach.

INTRODUCTION

The rapid development of electronic devices and the demand for high-level integration of radio frequency, analog, embedded memory, and advanced logic components within a single system on chip (SoC) requires constant improvement in the semiconductor industry and emergence of new technologies. Chemical mechanical planarization (CMP) technology has evolved rapidly to address these challenges. Using physics-based CMP models for hotspot detection helps designers detect and fix hotspots ahead of design closure. CMP model building starts with a CMP testchip tape out, followed by silicon data collection and calibration of a CMP model to fit the collected data [1]. New technologies are emerging rapidly, and modeling of CMP planarity variations and hotspot detection leads to innovations in CMP hotspot detection [2].

RF chips enables designers to build differentiated, RF-optimized solutions for mmWave applications, delivering outstanding performance, integration and area advantages, and exceptional power efficiency. The combination of radio frequency, analog, and embedded memory systems within a single chip leads to large variations in design patterns, which in turn affects post-CMP planarity. Early detection and fixing of CMP hotspots reduces dishing, minimizing surface non-uniformities and resulting in higher yield and better performance. While physics-based CMP models can be efficiently used for hotspot detection for SOC designs, generating the models requires time and resources. Physics-based CMP models that provide detailed information about the deposition and polishing steps to help engineers understand the origin of hotspots require measurements to build models for the intermediate deposition and planarization steps. On average, building BEOL layer CMP models may require three months for testchip design, tape out, and measurements collection over three wafers for deposition and planarity steps. The current chip shortage has exacerbated CMP modeling issues due to capacity limitations.

Machine learning (ML)-based models may address these limitations because they can be quickly adapted to process changes early in design or process development stages, have faster turnaround time for model updates, have faster runtimes, and capture process trends well. In the following sections, we discuss ML approaches to CMP modeling, data collection for ML model training, and comparative study of physics-based versus ML-based CMP models.

MACHINE LEARNING APPROACHES TO CMP MODELING

ML is a sub-area of artificial intelligence (AI) that enables computer systems to recognize patterns that can be used to autonomously develop solutions using algorithms and data. There are two main ML approaches that can be applied to CMP hotspots prediction: classification and regression.

Classification in ML is the problem of identifying which of a set of categories an object belongs to. In CMP, these categories could be "Hotspot" and "Not Hotspot," or more specific categories like "Hotspot Dishing," "Hotspot Erosion," etc. (Fig. 1).

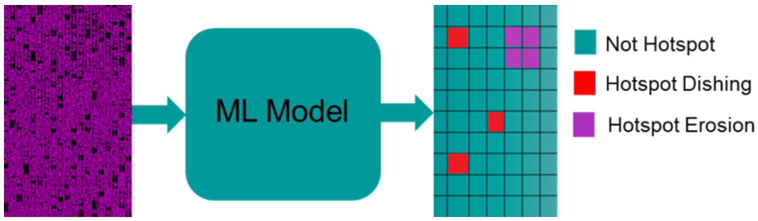

Fig.1 ML classification problem for CMP.

Simulation with the ML-based model should report if a pixel on a layout is a hotspot or not, and the hotspot type. Data should be classified into categories for training the ML model. ML classification model building and applications to CMP are discussed in [3].

Regression in ML is a problem of predicting a continuous outcome based on the input. In the case of CMP, the ML-based model simulation should report heights for each pixel (tile) on the layout (i.e., predicting the topography after CMP) (Fig. 2).

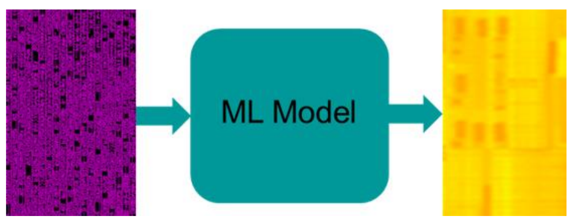

Fig.2 ML regression problem for CMP.

Later, hotspot analysis tools may be used to detect hotspots for a set of threshold values. Surface height data from measurements or physics-based CMP simulations can be used for training the ML model. ML regression models' applications to modeling post-deposition surface topographies of FEOL and BEOL layers are discussed in [4, 5]. Here we focus on the ML regression approach. It enables the user to not only predict hotspots and their types, but also to investigate the neighborhood of the hotspots. This helps to determine the cause of the hotspots and predict ways to fix them, since complete surface topography information is available.

DATA GENERATION FOR MACHINE LEARNING MODEL TRAINING

Training of ML models usually requires big data. This data can be obtained from both silicon measurements and physics-based CMP models. In general, a combination of 2D surface scans by profiler tools and physics-based simulations for different production designs can be used to generate the training, validation, and test data for ML model building. The data should provide good coverage of pattern density, perimeter, line width, and space distributions from multiple products of the same technology node for high quality ML model building.

ARCHITECTURE SELECTION FOR A MACHINE LEARNING MODEL

Selection of the architecture of the network used for the ML model strongly affects the quality of the results. Investigations show that processes where long-range effects are weak can be successfully modeled with deep neural network (DNN) architectures (Fig. 3). The DNN model may have two or more hidden layers (as shown) for several deposition processes used for FEOL layer model building [5]. DNN models may accurately capture the trends in the process and provide good fitting of topography dependence on pattern density, perimeter, line width, and space.

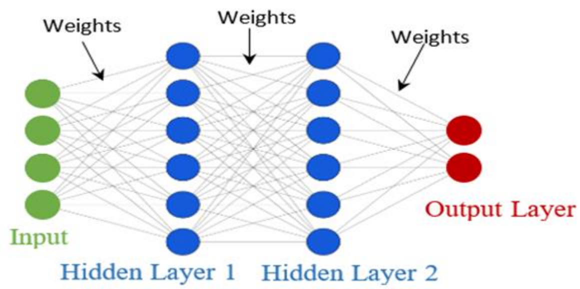

Fig.3 Deep neural network with two hidden layers.

On the other hand, modeling of long-range effects requires consideration of the effect of neighbor sites. A convolutional neural network (CNN) architecture in combination with DNN may provide an optimal solution for predicting both topography trends and long-range effects (Fig. 4).

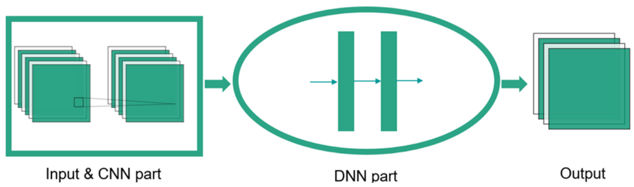

Fig.4 Combined CNN-DNN architecture.

The effect of long-range interactions with different architectures can be seen on ML modeling of wide trenches, where many of the pixels lie inside a trench and have the same geometry data. The DNN architecture will predict a flat profile for those sites since the input to the network will be the same. On the other hand, the combined CNN-DNN architecture will consider the neighbor sites that lie outside the wide trenches and will predict curved polishing topography in agreement with expectations (Fig. 5).

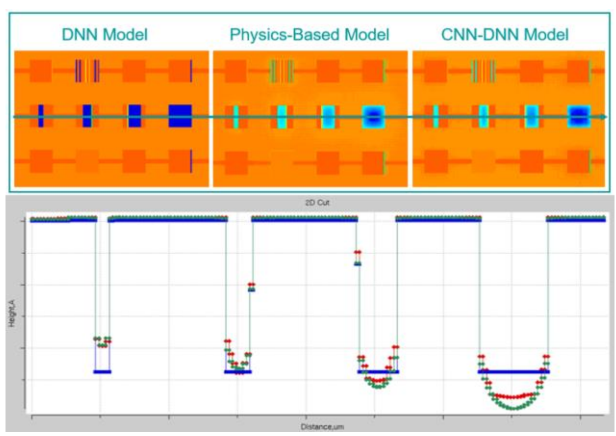

Fig.5 Simulation of wide trenches:
green lines=physics-based model; red lines=CNN-DNN model; blue lines=DNN model.

ML-based models may address physics-based model building limitations and can be quickly adapted to process changes early in the design stages. ML-based models can be developed using existing wafers available in the fab, they don’t need dedicated lot to collect the metrology. This will save wafer cost, time and resources required to run dedicated wafer lot.

Fig. 6 shows ML-based model accuracy against physics-based model on RF product. ML-based model closely follows the physics-based model topography variations trend and within 90% against physics-based model.

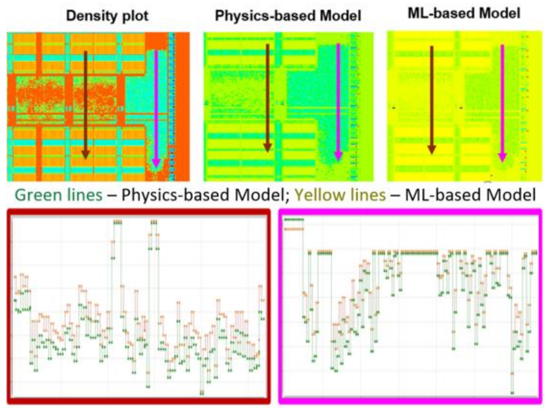

Fig.6 Comparison of topography colormaps and cutlines of physics-based vs. ML-based models.

CONCLUSIONS

In this paper, we presented the application of physics-based CMP models to hotspots detection for mmWave RF technology designs. We discussed the methodology of building ML-based CMP models using minimal silicon data, and their applications to SOC designs. Using an ML-based CMP model, we achieved 85% reduction in CMP development time, while realizing a 3.6x runtime improvement within acceptable accuracy compared to a physics-based model.

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