Benefits of Implementing AI/ML Controllers for Semiconductor Manufacturing, Including Multi-Tool Co-Optimization

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Many Compounds Semiconductor (CS) Manufacturers are in early adoption of AI and ML solutions to help them optimize their flows and process yields. Most advanced silicon wafer manufacturers have deployed advanced technologies to maximize their profitability through tighter process specs, yields, and improved manufacturing insights that predict equipment and process excursions. Most CS chip makers still require a substantial number of engineering resources to perform highly skilled manual activities in the fab. Automating more of these process control interventions will increase the quality of outcome and reduce the cost of operations. In this paper, we motivate the opportunity of closed loop AI/ML control in run-to-run scenarios, summarize the common challenges of implementation, and share best practices for success that we have learned through multiple implementations. Additionally, we will cover the implementation of AI process control across multiple tool sets and the potential benefits this technology can provide through co-optimization. These shared learnings should help engineers at fabs and at semiconductor equipment companies to plan and execute implementations of AI/ML closed loop process control more effectively.

INTRODUCTION

Artificial Intelligence/Machine Learning (AI/ML) technology is transforming every industry. We are experiencing the impact of AI/ML every day – in our business lives and our personal lives. At the risk of oversimplification, we can describe AI/ML as the most advanced methodologies for improving decision making through data-driven analysis.

In the semiconductor manufacturing space, we are seeing a strong level of interest in AI/ML. Several years back, the interest really began with investment in AI/ML to support predictive maintenance – using AI/ML to make better decisions about when and how to maintain expensive capital equipment. More recently there has been a surge of interest in leveraging AI/ML to make better and faster decisions around process engineering and process control.

For an industry that builds the most advanced hardware in the world for automation, there is a surprisingly large amount of manual decision making and subsequent action within semiconductor manufacturing. At the core of process engineering is the development and maintenance of processes that produce targeted outcomes with minimized variance. Industry estimates indicate that process engineers spend 40-60% of their time reacting to, and fire-fighting process variation issues during high-volume manufacturing. There is a lot of misperception and fear regarding how AI will eliminate many jobs and replace highly skilled labor. The purpose of the methods described in this paper are intended to benefit fab workers by greatly reducing or eliminating many of the manual incentive activities that engineers and technicians spend significant time and effort on when managing a 24/7 manufacturing facility. The benefit of leveraging AI to reduce engineering debug, analysis, and corrective action time by up to 50% will enable those same individuals to work on additional process development, optimization, and/or continuous improvement activities. Their job, the site, and the company will benefit from the addition of these AI/ML capabilities.

In today's Compound Semiconductor fabs, it is common to use data analytics tools such as Statistical Process Control (SPC), Advanced Process Control (APC), Fault Detection and Classification (FDC), and Yield Management Systems (YMS) to monitor process performance. While all these tools have helped to improve the quality and predictability of manufacturing, their impact has a limit because they still require significant human monitoring, expertise, and interaction to implement changes that improve the manufacturing process. AI/ML can enable a greater level of automation and optimization compared to these legacy data analytics tools.

Let us consider autonomous driving. We now have cars that can navigate public streets crowded with people. And do it just as safely as a human driver can. The intelligence that is controlling these cars must not only understand the physics of the world, but also be able to account for the most unpredictable of disturbances – human behavior.

If we can build cars that can autonomously drive, then we should be able to build more autonomous process control for semiconductor fabs. Unlike the world in which a self-driving

car must navigate, the semiconductor fab is one of the most controlled environments in the world.

The intelligence of autonomous cars is based on AI/ML, and more specifically, technologies like deep learning and reinforcement learning. It is possible to effectively apply these same technologies to the process control in the semiconductor fab, but as these technologies are new to the industry, there are not well-established best practices in place yet. As a result, repeatability of applying these technologies is of concern to the industry..

Over the past few years, we have been working to establish best practices for repeatable success through practical engagements. These closed-loop AI/ML process control solutions are being integrated into the hardware of top semiconductor manufacturers. We define “closed loop” as a software controller that can maintain process control in an autonomous fashion, without human intervention on each control step.

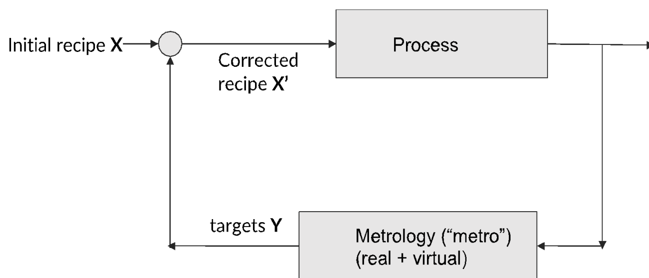

Fig. 1. High Level AI Process Control Design Flow

Furthermore, Tignis has explored the capability of AI process control to co-optimize multiple tools in series vs performing single tool process control in a vacuum. AI process controllers are capable of accounting for a wide array of environmental and upstream parameters to co-optimize multiple controller parameters from multiple steps in order to increase the probability of quality product. Training these multi-tool control algorithms on real world historic data showed a strong signal between available input parameters and desired outcome.

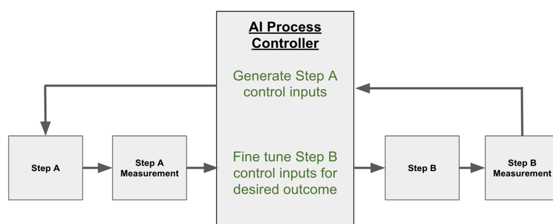

Fig 2: High Level Multi-Step AI Process Control Design Flow

Our work has shown a clear plan for implementation of an AI process controller for the co-optimization of the two processes. A single control implementation with access to process, environment, and metrology parameters from multiple steps and ownership for parameter definition for the manufacturing process presents a clear advantage to manual control or even legacy APC controllers.

Leading-edge Logic and Memory Fabs have incorporated APC control techniques such as Run-to-Run (R2R) control for many years. This was developed to incorporate incoming process measurement steps (inline SPC data) as a tuning parameter for control of the current process step. Some of examples of co-optimization process areas that yield improvements are:

- Lithography - Etch (Tighter process control)
- PVD - Wafer Probe (Wafer yield)
- Epi - Diffusion Furnaces (Thermal control)
- Diffusion Furnaces - Etch (Etch yield)
- Deposition - CMP (Tighter process control)

The goal of this paper is to highlight these benefits and motivate the opportunity of closed-loop AI/ML control in R2R multi-process steps scenarios, and all indicators show that the compound semiconductor space is primed for these co-optimizing types of process controllers. SiC, GaAs, GaN, and other emerging process technologies can be challenging to control when it comes to optimizing yields and processes in high volume manufacturing, and these are ideal candidates for the usage of AI/ML controllers. We will summarize the common challenges of implementation, and share best practices for success that we have learned through multiple fab implementations.

AI/ML R2R process control differs from traditional Advanced Process Control, and can outperform classic APC for certain classes of processes.

AI PROCESS CONTROL BENEFIT OVER APC

APC typically refers to the use of a control algorithm that adjusts multiple manufacturing recipe parameters in response to measurable observations. Many APC solutions are considered more static, meaning the relationship between features/inputs and a desired controlled outcome are pre-determined. As the complexity of manufacturing processes rises and drift occurs over time or abruptly changes, APC controllers typically break. A closed loop AI/ML model can be leveraged to reduce or even eliminate the maintenance burden of traditional APC controllers. With AI process control, machine learning is utilized to continually evaluate and adjust process recipes. This is particularly useful in processes with inherent drift as the AI process control controller can automatically compensate for long-term change over time.

For successful design of AI process controllers, there are certain requirements and best practices to follow to ensure a robust solution.

MODEL FITTING

The initial step in establishing a multi-step AI process controller is to analyze a historical dataset. Designing the right model that fits the type of data and optimization of the output variable/s is critical to have an accurate and robust controller. While marathon datasets[1] are used to fit more complex f(...) models[2], typically we enhanced this data with DOE-style data. These DOEs explore the ranges of important features or parameters that are outside the normal "production" environment.

When creating a dataset for a controller, it is important that the only recipe parameters that will be varied are those that will be controlled. In DOE datasets, we target the recipe parameters to be modified. If these parameters result in strong relationships to the output targets, its impact on the dataset will result in a higher sensitivity to the controller.

As an example, we illustrate Table I showing the R-squared values of fitting using a ridge regression model. Training and test data were randomly sampled from the DOE dataset. The fit model was able to explain almost all the variance in the 3 measured responses.

TABLE I

Response	**Explained Variance (r^2)**
CD	0.99785
Uniformity	0.99015
Thickness	0.99599

REQUIREMENTS FOR AI PROCESS CONTROLLERS

Table II defines requirements and associated challenges to designing a controller utilizing AI process control. The requirements for process control in general are assumed to be fulfilled.

TABLE II

Requirement	Challenge
Data with sufficient input and output variation	DOE data is costly to collect, and available data for process characterization is typically small.
Process model that can be successfully inverted and used for inference.	Complex models may outperform simple models in prediction, the inverse of complex models are difficult to use.
Process impacted by other steps or long-term changes.	Prior understanding of stability of process to select if APC or AI process control is the better option.
Sensor data that provides sufficient signal.	Sensor data may not have any relationship with target drift, and their inclusion may result in worse control
Other data (maintenance, Ops, etc)	Merge other data to enhance model features and sensitivity

VALIDATING AI CONTROLLER MODEL

An experimental plan is typically used to test the performance of the AI controller. As an example, we use a Deposition-CMP optimization AI controller. Target values would be intentionally changed to replicate batch-to-batch drift. 3 sets of experiments, each consisting of 2 batches of 2 full lots or 25 wafers. The model must then be updated between each batch upon receiving metrology data. Experimental fab results show the ability of the AI process controller to reduce the variability of thickness and stress for a deposition tool. In addition, the co-optimization of the two processes reduced the variance of thickness and uniformity for the downstream CMP process.

Another example of AI process co-optimization is with Chemical Vapor Deposition (CVD) and Chemical Mechanical Planarization (CMP) process steps. The CVD inputs or features used in the model are pressure, gas delivery, chamber wall readiness, temperature, time, and pressure. The control decision made at the CVD step, as well as the measured CVD thickness and uniformity are used as inputs to the CMP process controller. The CMP control variables are removal rate, polishing time, downforce, pad height and pad life and conditioner sweep rate.

Additionally, co-optimized AI Process Control uses the incoming tool information such as raw trace data, associated metadata, and key hardware configuration differences, to further augment the existing incoming metrology data to provide a more meaningful 'Variability Aware R2R modeling.' Implementing previous process steps data enhances the interaction for more complex processes and AI allows the

[1] Marathon Datasets are process data captured during a long continuous run of wafers where recipe paramaters are held static allowing models to capture process variance due to other factors.

[2] Complex f(…) models can have a massively multi-variate input space. Unlike legacy APC models they can include inputs in addition to feedforward and feedback measurements such as process traces and environmental readings.

process to optimize the desired outcome on areas with more variability.

GENERAL RESULTS/IMPROVEMENTS

The normal range of improvements is measured in terms of mean absolute error (MAE) of the desired outcome, this compares a baseline for the process/es using normal operation or even APC and then applying the AI Process Controller. For the case of deploying AI Process Control on a single tool and compared to a non-APC process, we have seen improvements in the range of 40-65%. For scenarios when comparing against an APC solution we see improvement ranges of 20-30%. These gains translate into tighter distributions of the output target. AI Process control additionally excels in the detection or elimination of large excursions that result in scrapping full lots. This is how some of the world's most advanced fabs maintain a competitive advantage, they control their processes using AI/ML techniques.

Furthermore, in our example co-optimization of CVD and CMP, varying thickness and stress targets when depositing films can be used to improve accuracy of control at the CMP step. The AI process controller is capable of comprehending process drift, changes due to equipment pauses, time between PMs and other consumable changes like Pads. We have seen using this knowledge to control two process tools cooperatively to show additional 10% control improvement relative to controlling the steps in a vacuum. Our results indicate an additive improvement to the thickness and stress at CVD and after CMP for thickness and uniformity when controlled together. Typical AI Process control improvements shown in Table III are measured in terms of MAE.

TABLE III

AI-Process Control	**% Improvement vs Non-APC**	**% Improvement vs APC**
Single Tool	40-65%	20-30%
Multi-tool	50-75%	30-40%

In summary, AI/ML process controller applications are commercially available now, and semiconductor fabs can start taking advantage of them today. The benefits from deploying these applications include significantly improved fab process variability, improvement in engineering resources efficiency, ability to detect major excursion events resulting in scrap, cost reduction with improved utilization and uptime of tools. Additional benefits can be had if AI process controllers are given the opportunity to co-optimizing multiple control steps. Throughout this paper we wanted to illustrate some initial success from deployed applications used in real-time manufacturing. We focus the paper on the lessons learned for those examples with high deployment success rate including defining scope, dataset, data management and validation of models with fabs.

In our experience, AI provides fabs with a cost-effective and very beneficial process control solution with observable data and process performance gains. Tignis expertise and technology IP further supplements these AI Process Controllers with differentiated data compression and curation capabilities that enable faster and more efficient monitoring and process control capabilities, enabling an complete AI eco-system that leapfrogs legacy methods and automation infrastructures.

ACRONYMS

AI: Artificial Intelligence
ML: Machine Learning
SPC: Statistical Process Control
APC: Advanced Process Control
R2R: Run to Run
FDC: Fault Detection and Classification
DOE: Design of Experiments
YMS: Yield Management Systems