Learnings from Multiple Implementations of Closed Loop AI/ML Controllers for Semiconductor Manufacturing

Francis A. Ortega, Ph.D., Eric Holzer, MSME, Mario Faria, MSEE, Jon Herlocker, Ph.D.

Tignis, Inc.
701 N 36th St STE 340, Seattle, WA 98103
(206) 745 - 9866
Francis.Ortega@tignis.com, Eric.Holzer@tignis.com, Mario.Faria@tignis.com, Jon@tignis.com

Keywords: AI/ML, Process Control, Run-to-Run Controller, Reinforcement Learning, Closed Loop

Abstract

Advanced process control has been used successfully for decades to optimize quality and yield in semiconductor manufacturing. However, process control still involves lots of highly skilled manual interventions during construction, operation, and maintenance of the process controller. Here, we show how artificial intelligence (AI) and machine learning (ML) techniques can be used to automate and optimize these processes, further increasing quality and reducing cost of operations and human intervention. Specifically, this paper will cover the results of a closed loop AI/ML controller for a deposition process. 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. These learnings should provide a roadmap for engineers throughout the semiconductor field to plan and execute implementations of AI/ML closed loop process control more effectively.

INTRODUCTION

In the semiconductor manufacturing space, we are seeing a strong level of interest in AI/ML. Several years back, the interest 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 creates the most advanced hardware in the world for automation, there is a surprisingly large amount of manual decision making and manual action within semiconductor manufacturing. At the core of process engineering is the development and maintenance of processes that produce on-target outcomes with minimized variance. We estimate that process engineers spend 40-60% of their time reacting to, and fire-fighting manufacturing variation issues.

In today's semiconductor fabrication facilities (fabs), it is common to have data analytics tools monitoring process performance, such as statistical process control (SPC) charts, advanced process control (APC) tools, fault detection and classification data, and yield management systems. These tools have helped to improve the quality and predictability of manufacturing, but their collective impact is reaching a point of diminishing returns because they require significant human configuration, monitoring, expertise, and interaction in order to further improve manufacturing results. The application of AI/ML can not only better optimize processes, but also enable a greater level of automation in the manufacturing process, providing manufacturing gains that cannot be achieved with traditional methods.

The goal of this paper is to 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. We will cover:

1. How AI/ML run-to-run process control differs from traditional APC, and why it can outperform classic APC for certain classes of processes.
2. Examples of successful implementations of an AI process control controller using a closed loop AI/ML model for a semiconductor deposition process.
3. A summary of the requirements to build a closed loop AI/ML model and the challenges to implementation commonly encountered within the semiconductor manufacturing industry.
4. A set of learnings - best practices - for designing and building AI/ML closed loop process control algorithms that we have developed through iterative experimentation and real-world implementation.

APC VERSUS AI PROCESS CONTROL

APC typically refers to the use of a static control algorithm that adjusts multiple manufacturing recipe parameters in response to measurable observations. As the complexity of manufacturing processes rises, the cost of constructing and maintaining APC controllers has increased. One common issue with APC controllers is the inability to deal with inherent drift. When manufacturing conditions drift over time or abruptly change, controllers must be manually updated to

compensate for these changes. Meanwhile, subpar controller performance leads to increased process variance until manual intervention is applied. Consequently, process drift leads to greater maintenance costs, and in some cases these costs can simply outweigh the benefit of the controller.

TABLE I
COMPARISON OF APC AND AI PROCESS CONTROL

APC	**AI Process Control**
Linear models	Flexible model architecture
Limited inputs (usually <=3)	Unlimited input dimensions
Time-consuming DOEs	Fewer and better DOEs
Static model with exponentially weighted moving average (EWMA)	Continually updated model with guardrails

Table I provides a summary of the key differences between classic APC and AI process control. Several of the advantages of AI process control come from the ability to create significantly more complex mathematical models while still staying within practical computation time. This allows incorporation of significantly more information into the control process imaging. Another underlying benefit is the ability of AI/ML algorithms to automatically retrain as new data becomes available.

As we will highlight, the use of AI/ML techniques in AI process control provides advantages over APC:

- Reduction in implementation time and cost by streamlining data collection during design of experiments (DOE).
- Tighter process control throughout the lifetime of a controller through closed-loop feedback
- Reduction in maintenance costs by replacing manual interventions through automation.

AI PROCESS CONTROL IN SEMICONDUCTOR DEPOSITION PROCESSES

Tignis has successfully implemented AI process control for various semiconductor deposition processes. Deposition processes are prone to drift due to the significant buildup of byproducts that can be deposited within the system. The result is a gradual drift in the relationship between recipe parameters and outputs, such as the desired thickness of a deposited layer. To correct this, maintenance such as dry or wet cleans are periodically performed. Static APC controllers perform poorly in these scenarios, particularly when the drift itself changes in unpredictable ways after maintenance or configuration changes. In contrast, a closed loop AI process controller can continuously self-evaluate and adapt using historical and recent data.

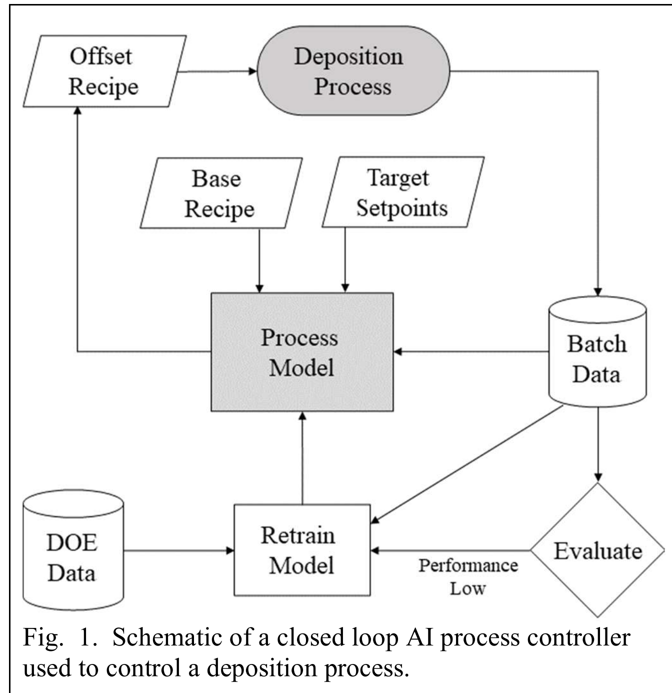

Fig. 1. Schematic of a closed loop AI process controller used to control a deposition process.

CLOSED LOOP AI PROCESS CONTROL PARADIGM

Figure 1 is a schematic of a closed loop AI process controller for a deposition process. At the heart of the schematic is the process model, which must accurately describe the relationship between the controllable recipe inputs and the desired target outputs. To offset the recipe and control the deposition process, the model utilizes the base recipe, desired target setpoints, and recent batch data. The batch data composition and the frequency with which it is collected varies. Practically, data from the last previous batch (~20 wafers) is used to inform the model for the current batch. Along with the recipe and target setpoints, this data must include metrology data and optionally sensor data, which was the case in all our implementations.

In the bottom half of Figure 1, the retraining aspect of the AI process controller is described. Process variance is continuously evaluated after each batch (Batch Data to Evaluate decision). When performance dips below an arbitrary threshold, retraining can be initiated. In a fully automated setting, the model will periodically undergo retraining incorporating recent batch data.

DATA REQUIREMENTS FOR THE PROCESS CHARACTERIZATION MODEL

The first step in constructing a controller is collecting data that allows for sufficient characterization of the process. This is also where we come across the first big misconception when

working with process owners to build AI process controllers. Process owners overvalue historical data from DOE or production runs and may believe it contains sufficient information to model their process. Given that production recipes are normally static, it does not contain enough variation to map inputs to outputs. DOE datasets, however, are intended to explore the sensitivity of recipe variables on metrology targets. Unfortunately, the parameter space is large, and the high cost of tool time limits exploration. Thus, most DOE datasets are typically small and focused on the launch of a new process. In our experience, additional experiments were **always** required. Provided historical data was insufficient.

As alluded to, DOE datasets are limited due to their high cost. Therefore, any new requested experiments should be minimized. Using data that is initially available, an initial process model can be constructed. Then, ML techniques can be employed to quantify the uncertainty of the initial model (1). Uncertainty quantification is used to identify the portions of the parameter space most important for additional experimentation. This strategy has allowed us to successfully petition for a minimal set of experiments to fully characterize several deposition processes.

AI Process Control Model Architecture

With sufficient data in hand, the next major decision point in controller construction is choosing the process control model architecture. The complexity of the model used to explain the relationships between inputs and outputs is vitally important in construction of any controller. While complex non-linear models may perform very well in predicting outputs relative to inputs, a controller must take the additional step of using an inverse model to infer the actual impact of the inputs. This poses a challenge for the inverse of complex models that result in multiple solutions. At worst, the inverse model will yield unusable solutions. At best, model complexity will increase variance. This is exemplified in a case study by Onto Innovation where they compared the performance of a process controller using a linear and deep learning model (2). Due to the simplicity of the process that they were modeling, the linear model outperformed the deep learning model.

At Tignis, we've developed an innovative model architecture that decomposes the AI process control into multiple collaborating sub-models. This decomposition provides several advantages: 1) it allows us to choose appropriate levels of complexity for the different sub-models, 2) we can selectively retrain models, and 3) it enables us to predictably transform machine learning predictive models into optimizing controllers. Overall, this paradigm provides flexibility to tackle the control problem, while maintaining simplicity.

Validation Experiments

To understand the impact of AI Process Control, we present results for deposition thickness from multiple implementations of our AI process controller designed to compensate for changes in the process model.

In each case the historical data provided by the process owners was not sufficient. That data was used to generate an initial model that was then analyzed to recommend a minimum set of experiments to re-characterize the process. Once process characterization was complete, a longitudinal dataset was collected to incorporate the drift-compensating component of our controller. The controller was then deployed and validated through experimentation.

Validation Results

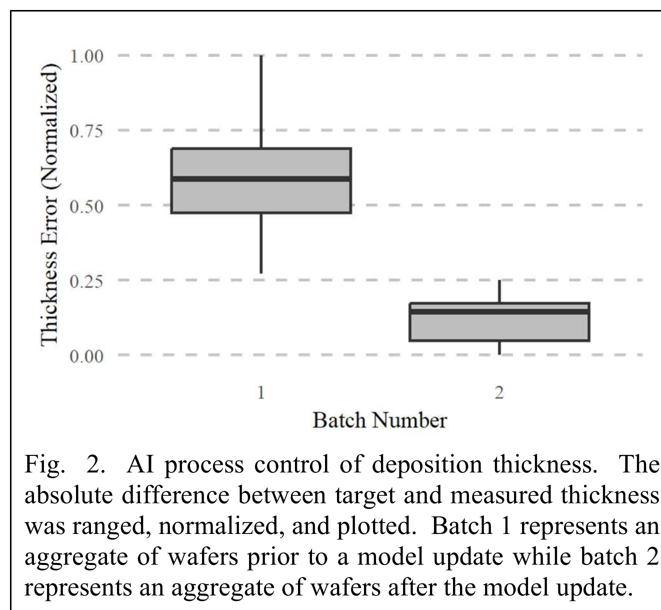

Fig. 2. AI process control of deposition thickness. The absolute difference between target and measured thickness was ranged, normalized, and plotted. Batch 1 represents an aggregate of wafers prior to a model update while batch 2 represents an aggregate of wafers after the model update.

Figure 2 plots the difference between desired target deposition thickness and actual deposition thickness (measured directly with a separate metrology step) in two wafer batches utilizing a Tignis AI process controller. We normalized the results so that we can analyze the aggregate improvement in error reduction across disparate equipment.

In Batch 1, with the controller using the initial fitting, there is significant deviation between the target and actual values. However, after retraining the controller on the Batch 1 metrology data, Batch 2 shows significant improvement to thickness quality.

In Figure 3, results are shown for an already tuned AI process controller after an abrupt tool configuration change. In Batch 1, there is significant error between desired target setpoints and actual thickness. However, controller retraining

was able to automatically compensate for the abrupt change as shown with the much-reduced error in Batch 2.

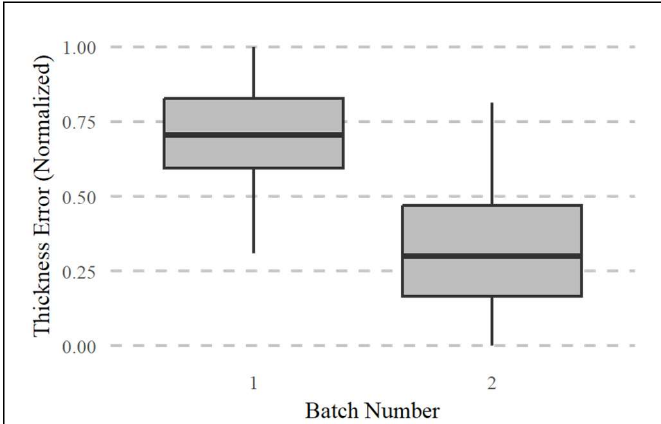

Fig. 3. AI process control of deposition thickness after selected tool configuration changes. Absolute difference between target and measured thickness was ranged normalized and plotted. Batch 1 represents aggregate of wafers prior to a model update while batch 2 represents an aggregate of wafers after the model update

Overall, we have been able to consistently achieve over 25% improvement in baseline error through implementation of AI process controllers for deposition processes. This improvement was quantified by calculating the percent difference in the absolute wafer-to-wafer thickness variation before and after implementation of a Tignis AI process controller. In essence, reducing the process window size by more than one quarter. Furthermore, the controllers can be trained very quickly, the models updates can be fully automated, and can be deployed by a fab process engineer without internal data science support.

Requirements for AI Process Control

Table II lists the requirements and associated challenges to constructing a controller utilizing AI process control. The work discussed above was vital in developing this list. The requirements for process control in general are assumed to be fulfilled.

Conclusions

In summary, the controller described here is an example of how AI/ML closed-loop control can be applied in manufacturing environments now. Semiconductor fabs can deploy these applications to improve product quality, yield, resource efficiency, labor cost, and uptime of tools. As an example, we have demonstrated how AI process control can reduce deposition thickness variance by more than 25%. The requirements and lessons presented here should help others in the implementation of their own AI/ML closed-loop control.

TABLE II
AI Process Control Requirements and Associated Challenges

Requirement	**Challenge**
Process impacted by abrupt change or long-term drift that would complicate traditional APC.	Prior understanding of the stability of a process will inform whether APC or AI process control is the better option.
Dataset with sufficient input and output variation to characterize the process.	DOE data is costly to collect, and available data for process characterization is typically small.
Ability to provide new experimental data when required.	Uncertainty quantification can be used to identify priority experiments to adequately build process characterization models.
Process model that can be successfully inverted and used for inference.	Classic AI/ML models are good for prediction, hard to use for optimization
Longitudinal dataset to characterize batch-to-batch drift.	In lab environments where data is collected, it can be difficult to collect data with completely static inputs.
Sensor data that provides sufficient signal.	Sensor data may not have any relationship with target drift, and their inclusion may result in worse control

References

[1] D.J. Stracuzzi, et al., *Uncertainty Quantification for Machine Learning*. Sandia National Lab, Albuquerque, NM, June 2017

[2] Y. Sun. *A Case Study of Deploying Run-to-Run Strategy with Deep Learning Model in High-Mix Semiconductor Manufacturing*. 2021 APCS Conference. Austin, TX, USA. October 2021.

Acronyms

AI: Artificial Intelligence
ML: Machine Learning
SPC: Statistical Process Control
APC: Advanced Process Control
DOE: Design of Experiment