nControl™
For Semiconductor Applications

White Paper
November 2022

nanotronics

nControl™ for Semiconductor Applications

November 2022

sales@nanotronics.co

Nanotronics : Inspection and Control for the Semiconductor Industry

Nanotronics was founded in 2010, initially offering the nSpec™, an automated optical inspection tool for a variety of precision manufacturing applications, including semiconductor wafers and devices.

The nSpec™ incorporates artificial intelligence for recognizing and classifying defects, allowing it to be more flexible than other automated optical inspection tools, usable in R&D labs and on production lines, for a variety of materials and types of substrates, bare and patterned wafers, and devices. We now have over 100 customers around the world.

Beginning in 2018, we developed our suite of process control products, nControl™, as a generalization of our inspection technology. nControl™ tools integrate a variety of sources of process data -- from optical inspection images such as those produced by nSpec™, to live video feeds of production, to data from sensors and actuators in process equipment -- to monitor and predict manufacturing performance, identify anomalies indicating process failures or security breaches, and to optimize production for greater yield.

nanotronics

nControl™ for Semiconductor Applications

November 2022

sales@nanotronics.co

Digital Transformation for Semiconductors

The semiconductor industry is under extraordinary pressures, due to the ongoing effects of the COVID-19 crisis, geopolitical instability, and continuing technological advancement. Manufacturers are faced with the need to adopt new production processes as they bring new products to market and shift their supply chains.

Nimbler adaptation -- reducing ramp times and time to market in new processes -- requires integrating data across numerous facilities and applications. End-to-end data visibility and analytics allows manufacturers to make strategic decisions based on all relevant information.

Physical and digital systems must be integrated; the process data generated by each piece of equipment in a facility, the production data produced by each facility in a distributed manufacturing process, and the data from inputs and downstream products across the supply chiain, need to mesh to enable the production system as a whole to be responsive to changing requirements.

nControl™ for Semiconductor Applications

November 2022

sales@nanotronics.co

Artificial Intelligence in Manufacturing

Since 2012, the performance of deep learning algorithms on nearly every benchmark has grown exponentially. Deep learning algorithms, once an academic curiosity, now outperform humans at Go, drive cars autonomously, and predict protein structures.

In manufacturing contexts, deep learning has become widely adopted in analyzing optical images for quality control. The field of computer vision has existed for decades, but only in recent years have AI-based digital imaging technologies become able to compete with manual inspection.

Another common AI manufacturing application is industrial data analytics for applications such as predictive maintenance and anomaly detection. Production equipment and sensors produce thousands of measurements and log entries per second; that data contains information that can be used to detect equipment in need of repair, recognize impending process failure, and analyze trends in production performance.

AI control over industrial processes can even optimize performance directly; Google's subsidiary DeepMind improved power efficiency by 15% in data centers by controlling the activity of servers, cooling systems, and other equipment.

Unlike traditional process modeling, nonparametric AI models can learn highly multivariate relationships between variables and outcomes empirically, without reference to an a priori theoretical model. AI can detect patterns in data before humans can notice them.

Since AI models update as they incorporate more data, AI-based manufacturing analytics become more effective the longer they're installed. As AI gains adoption across production processes and supply chains, autonomously self-improving factories will become a reality.

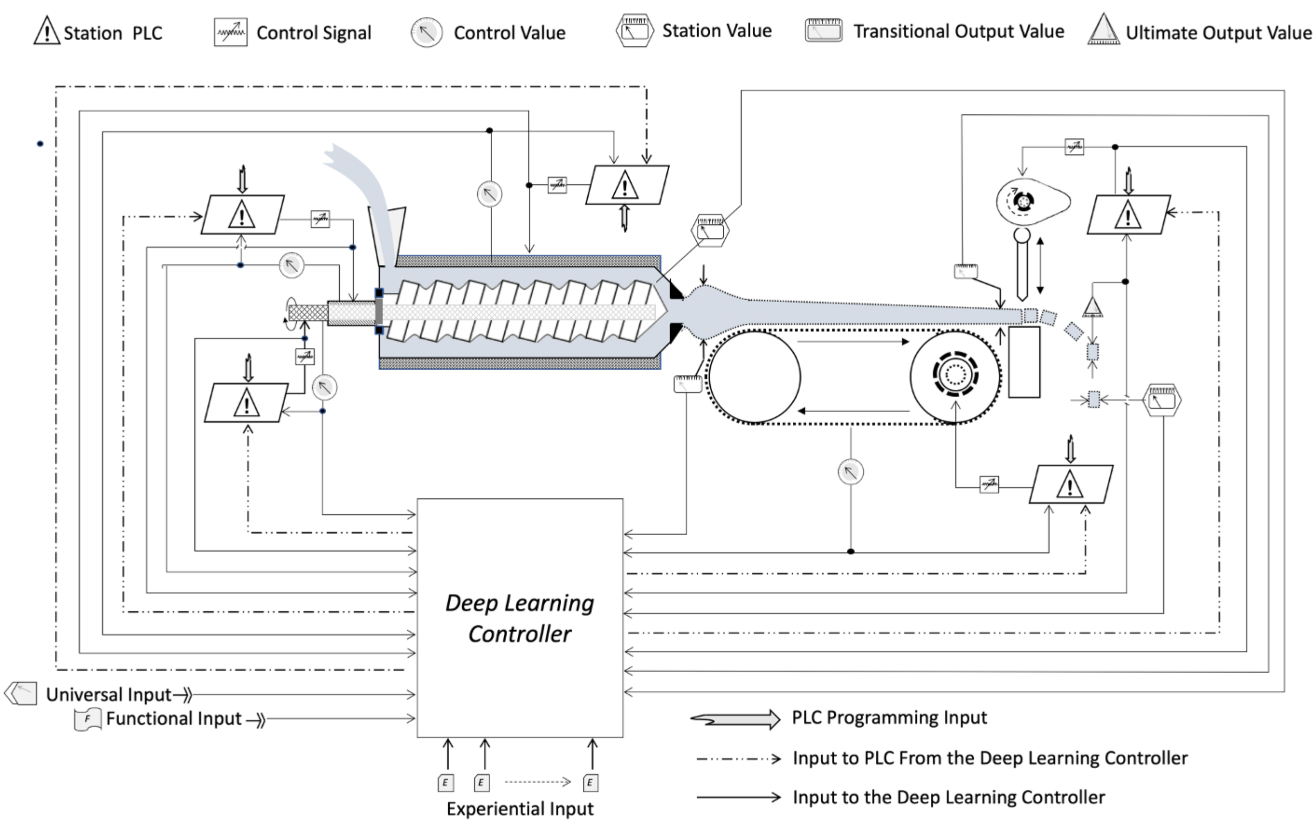
nControl™ : The Next Stage in Semiconductor Process Technology

Semiconductor manufacturing processes require exacting quality standards and constant technological improvement. Semiconductor process control is used to maintain precise and reliable outcomes in each stage of production.

The state of the art in industrial process control, however, is still limited to fixed recipes. The "right" target value for each process variable is hard-coded before production begins, and those target values are derived through a combination of theoretical and experimental analysis.

nControl™, by contrast, uses real-time adaptive control for continuous optimization. That is, it adjusts target values continuously, within individual production runs, to optimize desired quality metrics.

The deep learning model in nControl™ learns the function that relates the recent state of the system to key performance indicators (KPIs) such as defect density and distribution, or other metrics of quality or productivity.



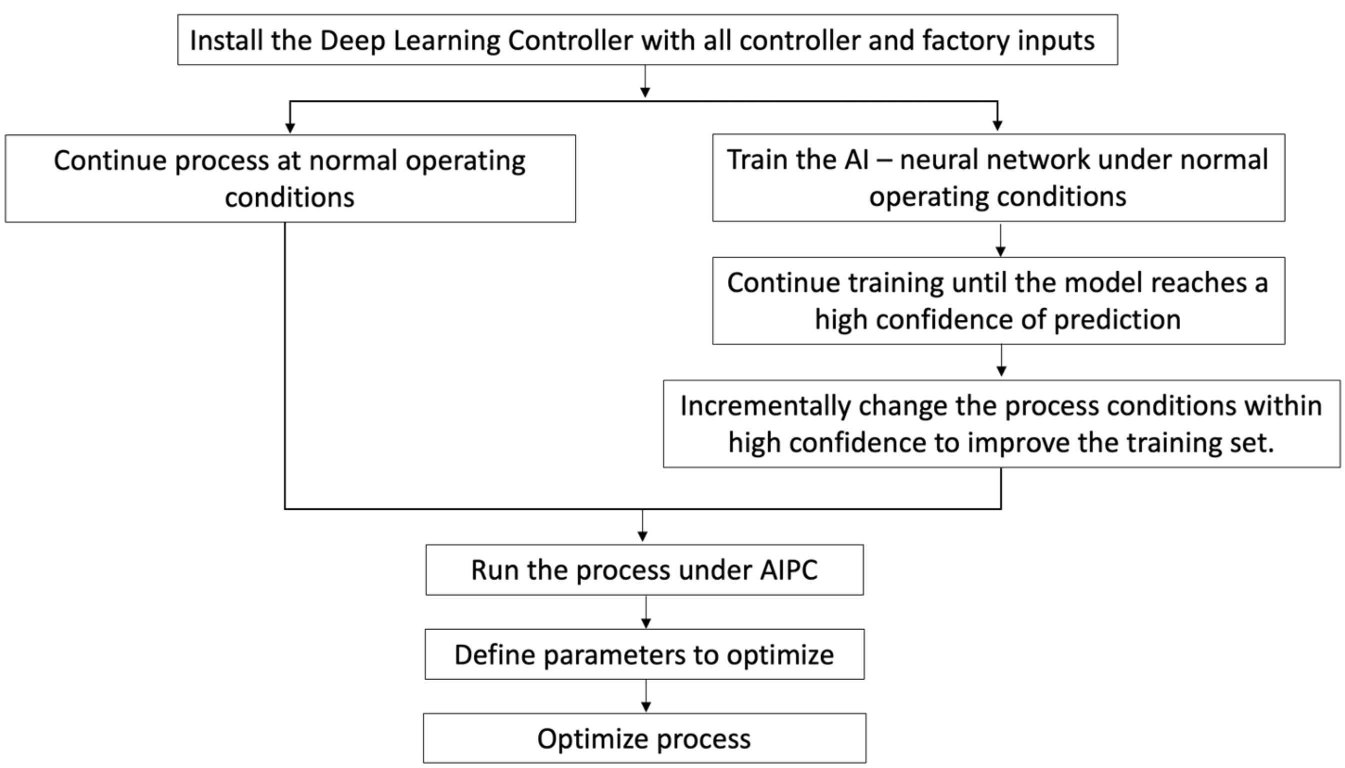
nControl™ : The Next Stage in Semiconductor Process Technology *[cont.]*

nControl™ incorporates data from a variety of sources:

- Live feeds of sensor and actuator data, taken from programmable logic controllers (PLCs) or the facility's data historian
- Ex situ measurements produced by quality control and/or metrology
- Equipment and plant information such as P&ID diagrams and allowable ranges for control variables
- Information from elsewhere in the enterprise resource planning system, such as schedules, deliveries, etc
- Existing statistical process control rules

The nControl™ model ingests this data and learns a low-dimensional representation of the typical function of the process, including ordinary variations like startup and shut-down, different operators, etc.

This means that when process data is anomalous relative to the model's predictions, operators can be alerted early to potential process failures.



nControl™ : The Next Stage in Semiconductor Process Technology *[cont.]*

Additionally, the nControl™ model learns the relationship between in-progress process data and quality and yield measurements of the final result of a production run. This means that at each moment during production, nControl™ has a freshly updated prediction of how the batch will turn out.

nControl™ also simulates how KPIs will be affected by changes to process variables. This allows prediction of the impact of any observed excursion.

Moreover, the ability to simulate the consequences of potential changes allows a reinforcement-learning model to suggest process changes that are predicted to improve batch quality, in real time during production. Suggested changes can either be presented to a human operator for approval, or can be implemented automatically. (Of course, all nControlTM-generated changes to process variables are restricted to lie within fixed ranges defined by the process engineer.)

This real-time adaptive control allows for much greater flexibility and ability to respond to variation. With nControl™, a batch can be "rescued" before quality problems occur.

Real-time adaptive control has advantages in a number of situations:

- Reducing process development time and eliminating ramp time for new products
- Reliably transferring processes to new locations that may have different environmental conditions
- Detecting and remedying process failures quickly
- Maintaining quality despite changes in environmental or other conditions
- Identifying new process improvements to increase yield and productivity

nControl™ For Epitaxial and Thin Film Deposition

Deposition of epitaxial layers or thin films is an ideal nControl™ application because it is prone to defects due to contamination or process conditions causing loss of crystal structure.

Several of the most common epitaxial and thin film deposition processes are known to improve with adaptive control, as it can allow for more rapid and fine-grained adjustment to process variation.

Chemical Vapor Deposition /

Chemical vapor deposition (CVD) is a popular class of methods for thin film deposition in electronics, photonics, and biomedical applications. A vaporized volatile material is chemically reacted with other gases, at which point it becomes non-volatile and is deposited on the substrate. The flow of gas is typically under feedback control according to gas mass. Deposition conditions such as gas flow and composition, temperature, pressure, etc, are optimized experimentally and set by recipe The uniformity and stress of CVD-deposited materials generally depends on the uniformity of conditions inside the reactor, such as temperature.[1]

Run-to-run process control was able to reduce the variation in thickness of PECVD-deposited amorphous silicon thin films from 5% to less than 1% within 10 batches.[2]

Metalorganic Chemical Vapor Deposition (MOCVD) /

More sophisticated process control can make MOCVD reactors more reliable. Switching to adaptive temperature control from PID control reduced the temperature error from 3 degrees C to 0.3 degrees C.[3] Using a computational fluid dynamics model to optimize the starting parameters of the MOCVD reactor reduced the coefficient of variation of a ZnO thin film's thickness from 3.6% to 1.28%.[4]

Adaptive control can be used to more precisely hit pre-set target levels of process variables, and this can be expected to improve the repeatability and control of the process. Also, adaptive tuning of the target levels themselves, to account for irregularities in the fluid dynamics and temperature fluctuations within the reactor, can further reduce the variability in the end product.

Physical Vapor Deposition /

Physical vapor deposition methods such as atomic layer deposition (ALD) or pulsed laser deposition (PLD) involve vaporizing a material from a solid target with ion beams, electron beams, lasers, or magnetically confined plasma, and allowing the target material to condense onto a substrate.

As with chemical vapor deposition, adaptive control of physical vapor deposition can be used to maintain more consistent control of process parameters. For instance, one study using a neural network model achieved temperature control within 0.1 degree C for a molecular beam epitaxy process for gallium arsenide, in half the time it took for a conventional PID controller to reach the target temperature.[5]

sales@nanotronics.co

nControl™ For Dry Etching / Dicing / Photoresist Deposition

Dry Etching /

“Dry” etch procedures involve removal of material from a semiconductor using plasma or gas. It is useful for producing high aspect ratio structures that can’t be created with “wet etch” processes such as photolithography. Precise control of the ion beam or gas flow and its angle of incidence is essential for accuracy in dry etching, and can produce either anisotropic or isotropic results.

Adaptive control methods in dry etching have been found to improve quality. A real-time adaptive model predictive control system (AMPC) in a plasma etch reactor achieved the target levels of variables such as electron density and RF power with much less variability (21.3% reduction in ISE) than model predictive control (MPC).[6]

Using real-time in-situ sensor and image measurements and adaptive algorithms, dry etching process variables can be tuned more precisely to achieve desired quality parameters.

Dicing /

Wafer dicing, which singulates wafers via sawing or laser cutting, is another process that depends on precise real-time control in order to avoid defects. Variables such as feed speed, rotation speed, and coolant flow can be tuned automatically. Irregularity in dicing can lead to cracks, misalignments, and other performance-limiting defects.

Adaptive control systems in dicing often improve reliability and quality.

A system for adaptive control of a multi-wire saw for silicon wafers produced far less variability in tension and position motion than a PID controller.[7] Similarly, an adaptive control system for a diamond abrasive wire saw used on silicon carbide wafers intended to maintain a constant normal force, compared to a system that used a constant part feed rate, had less variation in normal force, 41% shorter processing time, and 20% less surface roughness.[8]

A deep-learning based model for laser micromachining, which learned the relationship between microscopic images of the surface and the location of the laser, was able to stop machining in real time at precisely the point at which a copper layer was completely machined through.[6]

Using live sensor data (including imaging) and adaptive control systems, dicing and machining processes can be made more accurate, resulting in higher yields.

Photoresist Deposition /

The deposition of photoresist can benefit from adaptive real-time control. Thickness, uniformity, deposition rate, and adherence are highly dependent on variables like humidity, viscosity, and the flow of adhesion-promoting substances. With in-line sensors and continuous optimization of process variables, nControlTM could improve the quality and reliability of photoresist deposition.

Conclusion

Across the board, when adaptive control methods in semiconductor manufacturing processes are compared to simpler PID or MPC control algorithms, the adaptive methods achieve the target process values faster and/or with less variance than the simpler methods.

Moreover, adaptive control methods where feedback depends on real-time sensor measurements can produce better quality and reliability in the final product.

Flexible, continuous optimization techniques in which target values themselves shift in response to sensor measurements have not yet been implemented for most semiconductor applications, but our internal experiments on additive manufacturing [9] have found that continuous optimization can improve quality parameters such as tensile strength in the final product. These results likely generalize to additive or subtractive manufacturing technologies in semiconductor applications which similarly involve the gradual buildup of 3-dimensional structures.

Process control systems such as nControlTM that flexibly adjust target values to empirical observations ought to be even more robust to variation in environmental conditions and provide even higher quality than process control based on reaching fixed target values.

References /

[1]Sun, Luzhao, et al. "Chemical vapour deposition." Nature Reviews Methods Primers 1.1 (2021): 1-20.
[2]Crose, Marquis, et al. "Multiscale modeling and run-to-run control of PECVD of thin film solar cells." Renewable Energy 100 (2017): 129-140.
[3]Chiu, Jung-Ching, et al. "The multi-segment adaptive control of the high temperature heat source in a MOCVD vacuum reactor." 2017 China Semiconductor Technology International Conference (CSTIC). IEEE, 2017.
[4]Li, Jian, et al. "Study on the uniformity of ZnO films grown by MOCVD." Ceramics International 45.11 (2019): 13971-13978.
[5]Wu, Guoqing, et al. "An Intelligent Temperature Control Algorithm of Molecular Beam Epitaxy System Based on the Back-Propagation Neural Network." IEEE Access 10 (2022): 9848-9855.
[6]Koo, Junmo, et al. "Design of a self-tuning adaptive model predictive controller using recursive model parameter estimation for real-time plasma variable control." Computers & Chemical Engineering 123 (2019): 126-142.
[9]Jiang, Jin, et al. "Multi-motor synchronization of multi-wire saw based on model-free adaptive control." Advanced Materials Research. Vol. 69. Trans Tech Publications Ltd, 2009.
[9]Li, Shujuan, et al. "Force modeling and control of SiC monocrystal wafer processing." Journal of Manufacturing Science and Engineering 137.6 (2015).
[]Xie, Yunhui, et al. "Deep learning for the monitoring and process control of femtosecond laser machining." Journal of Physics: Photonics 1.3 (2019): 035002.
[9]Limoge, Damas W., et al. "Inferential Methods for Additive Manufacturing Feedback." 2020 American Control Conference (ACC). IEEE, 2020.

A REVOLUTION IN SIGHT