# Yield-Maximising Process Control Through Reinforcement Learning: AI-Driven Optimisation of Semiconductor Fabrication for U.S. Manufacturing Competitiveness

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*1. Introduction, American industrial competitiveness is currently guaranteed by a combination of innovation, reliable performance, and reduced production costs in the U.S., along with the unique involvement through teamwork of suppliers, manufacturers, and their customers. A unique success factor is the fact that - in the fortunate circumstances when neither new products nor processes are needed, and duty technical process variation levels are no longer observed and routine process yields almost reach 99.9%, as is also the case of the USD 250 billion U.S. semiconductor industry - U.S. manufacturing personnel merely hunt for and clear away defects, scrap, and rework rather than use Six Sigma (3.4 hundred units defective per million units) to block real-world shop floor production of kilograms of billions of shipshape dollars.*

Once upon a time "Quality is Free" made it big. Americans then applied "do it right the first time" to say "quality at the source." Quality authority Joseph M. Juran, whose theories are espoused by Japanese Lean and American Six Sigma, argued that impassioned "avoidance of waste in production" on J. P. Morgan Co.'s shop floor was the catapult that launched his campaign. Several thousand lived through the badly named Department of Defense "Zero Defects Program" before achieving permanent remission, overwhelming infectious sales hype aside. Sadly for Joe and his followers, Toyota existed long before Joseph M. Juran did, as the manufacturing organization says, more than likely by the fourth generation of Toyoda loom makers in Japan. The essential element of manufacturing today that stands apart given William Edwards Deming's post-WWII reconstruction of Japan "just in time" manufacturing method is the equation for the optimal number of system defects - given the tailor-made constraints facing unique manufacturers everywhere - today, often, by Department of Defense employees.

### 1.1. Background and Significance

Today's chips are designed by aligning billions of transistors in three dimensions. Not surprisingly, the complexity is exceeding our ability to understand them. Therefore, to handle the complexity, our best solution is simply to let the chips optimize themselves. That way, overly complicated tools and models are not needed to design and manufacture the complicated chips. One of the most universal self-optimization algorithms is reinforcement learning, and it is one of the most popular AI/ML tools to enable an "AI for chips".

The semiconductor industry is an enabler of the digital economy and its success is not guaranteed. Semiconductor manufacturing has been declared a crucial sector by the Pentagon and there is concern that a dominant chipmaker will slow down the U.S. defense system's ability to innovate. More generally, there are concerns that the United States is losing its manufacturing base and, if nothing is done, there will be greater reliance on other countries (e.g., U.S. now buys 50% of its semiconductors). Enterprise is already being left behind. The semiconductor industry is the foundational piece of a set of manufacturing enterprises and subsystems supporting nation-state commercial semiconductor technology development and manufacture. If the United States loses its semiconductor manufacturing capability, we will begin a slide that ends in the loss of not only our digital leadership but the manufacturing enterprise that produced it. As the U.S. begins to outsource various developments or foundries, there is the potential to lock in an indigenous slow-to-no-growth capability that will not be sustainable in the long term and certainly not adequate in the medium term.

### 1.2. Research Objectives

The overall goal of this project is to address emerging challenges that impact the US semiconductor industrial base while accelerating the transformation of the semiconductor fabrication facilities (fabs) from a capacity-driven mindset to one based on the controllability and predictability of the supply chain. This is a cross-functional project featuring research areas such as advanced manufacturing, cloud computing, artificial intelligence, and semiconductor processing. We will focus on optimization of semiconductor wafer fabrication processes, especially the removal of material using plasma etching and chemical-mechanical polishing. The effluent from these processes combines with a dilute perfluorinated compound, forming a greenhouse gas, which they are no longer allowed to release. Fluorine chemistry is the root cause of global warming potentials of 1,000 to 20,000 times that of carbon dioxide. If successful, the project will transform the economics of semiconductor production and significantly reduce the climate impact of semiconductor production in the United States.

We aim to create a control environment that simultaneously optimizes controllability of the process and cycle time, by taking advantage of the largest time-dilation in the chip manufacturers' product lifecycle: the time between the scheduling of a circuit layer and its equipment follow-up. The objective of this project is to create an automated setup to develop and validate the usability of these new artificial-intelligence-driven control testing environments and use them to develop a semiconductor data emulation with a single-pass development-to-deposition step. The proposed backbone manifold semiconductor data emulation will enable us to conduct high-TRL control studies for the optimization of semiconductor processes. Furthermore, this emulation strategy can be used throughout the chip manufacturing supply chain, for instance verifying how packaging and wafer fab interact, by having parallel simultaneous process optimization across several manufacturing steps thus minimizing global tool cost while maximizing global quality.

**2. Semiconductor Fabrication Processes**

The ever-increasing technology and high-reliability demand associated with the present and future needs of important industries has made the semiconductor processing industry the backbone of almost every technology and manufacturing product around the world. Using traditional bottom-up manufacturing and fabrication development methods has become time-consuming and expensive, which significantly slows down the process of bringing new devices to market. The current U.S. administration stresses the need to improve manufacturing processes in the UAS to increase its competitiveness. Making semiconductor devices on custom-made material layers can lead to increased integration. This helps minimize interconnect latencies (increased signal velocity), minimize device heating (based on high thermal conductivity materials), and optimize device Tet (transistor turn on voltage) and gain. Careful upfront device modeling and simulation is necessary to reduce the number of iterations during the device design process - fabrication / materials processing interaction. The state-of-the-art devices may already be developed, and materials grown or manufactured in-house.

The materials and semiconductor processing division of DOD are looking toward the future with research and development focused on how materials and processes can be controlled in a real-system(s) environment. Three key elements in the SEM seen relating to research and development in the area of materials and processes control include: Image Intensifiers (II), Quantum Dot Infrared Photodetectors – (QDIP) and Infrared Focal Plane Array – (IRFPA) devices. In semiconductor technology, we have extensive empirical knowledge of semiconductor behavior under varying growth conditions and basic scientific knowledge of atomic-level surface reactions. Control of materials growth and additive/diffusion processes is possible by selecting reactive gas flow rates and partial pressures, mass transport in the gas phase (laminar vs. turbulent), surface temperature (activates the ability for atoms to become incorporated), and gas impurities. We also developed new growth chemistries and can control GexSi1-x deposition in the range of 3.4 micron/day to > 7 micron/day. The goal is to develop Si-based technology for Infrared sensors. The semiconductor fabrication process (front-end of the line processing) starts with growing a SiGe substrate on Si wafer and builds complex semiconductor devices onboard. These activities are described in the Integration of YBCO Based IR Sensors in Standard Integrated Circuit.

### 2.1. Overview of Semiconductor Manufacturing

Semiconductors represent a critical end product of the U.S. manufacturing sector, a $40-billion-per-year industry that represents 2% of the U.S. GDP. Composed primarily of integrated circuits, entitled "chips," the industry ranks fourth among all U.S. manufacturing industries. Production takes place mainly in wafer fabrication facilities (fab for short) and consists mainly of four common steps.

Wafer Fabrication Steps

1. Lithography: Creating Patterns on Silicon A layer of photoresist is spread on the entire surface of a silicon wafer, and then the mask is aligned over the wafer. The wafer is then exposed to light.

2. Etching: Creating Features in Silicon This step is broken into two parts: wet and dry etching. After exposure, developers rinse the wafer in a dissolving agent to remove the unexposed photoresist. After the photoresist has been removed, a machine guides a stream of gas over the wafer to etch away the oxide in exposed areas. An etchant is then

used to remove the photoresist. After this step, a wafer is left with exposed chips that are lower than the original silicon surface.

3. Deposition: Adding Materials In the next step, gaseous precursors are leaked into a reaction chamber and are then created on top of the wafer surface. For example, chemical vapor deposition is used to convert gaseous precursors into solid material. Metal is deposited and filled into the trenches and vias so that a pattern of interconnected transistors can be formed.

4. CMP: Planarization of the Wafer A mixture of abrasives is added to the wafer. The abrasives scratch away a thin, uniform layer of silicon and produce a flat surface in which the next layer of silicon can be added.

**2.2. Key Steps in Fabrication Processes**

Semiconductor fabrications follow standard procedures that are subsequently adopted industry-wide. The fabrication process of a semiconductor includes a number of key steps, namely: 1) Growth/Deposition of the Gate/SiO2 Layer; 2) Dopant Diffusion for the Body Region; 3) Extension Implantation/Activation; 4) Form the Recess for Stressor; 5) Stressor Epitaxy; 6) Raised Source/Drain Implantation and Annealing; 7) Halo Implantation; 8) Stressor and Sidewall Spacer Etch/Removal & S/D CESL Etch; 9) Selective Epitaxial Growth of Source/Drain Layers; 10) Silicide Formation; 11) SiGe Epitaxial Growth; 12) Transition Spacer Deposition, Sacrificial Nitride Deposition/Removal, and Deposition of the Final Spacer Stack. Metal/High-k & source/drain formation; 13) Halo Mask Removal and Formation of the Deep Trench Isolation around Raised Source/Drains; 14) Formation of Gate Stack and Nitride Mask; 15) Preamorphization and N-type (nMOS) and P-type (pMOS) implants of Source/Drain and Related Activation Anneal; 16) RMS Si Surface Re-Growth; mesa isolation for some transistors; 17) Contact and Interconnect Formation. This is a direct representation of a 7 nm logic flow today, whereas there are several other (transistor) structures (e.g., DRAM, etc.) and many device layers above and beyond what has been shown.

All these fabrication process steps are quite difficult to implement and require very tight control and optimization. Equipment produced by Photronix Inc. for extreme large chips up to 450 mm have already shown unit to unit production run control of the entire equipment to better than 5 ppm. The deposition processes produce low defect films of

$Si_3N_4$, $SiO_2$, and other materials. Piece parts and all seals are compatible with all gases used in the process. Both for industry standard 300 mm Si coupons and diamond are shown below further in this section. The crystallinity supports the careful removal of SiGe by chemical lithography. The individual sections below show some of modern CMOS manufacture of installed systems.

**3. Role of AI in Semiconductor Manufacturing**

Semiconductors act as the foundation of present-day devices for a multitude of applications, including communications, data processing, sensing, and control. The limitations that these building blocks place on the overall system performance are very significant. As a matter of fact, when applied to military vehicles, it is believed that half of the capability of today's hardware is lost. Optimization in overall system performance requires providing a competitive edge within semiconductor manufacturing. Despite the fact that high-level vision and strategies are present to invigorate the overall state of U.S. manufacturing competitiveness, a cohesive sort of campaign that results in the efficiency of manufacturing enterprises doesn't exist at present.

For this article, the authors articulate vital aspects of the role of AI within the domain of semiconductor manufacturing and provide insights to further crystallize the enhanced capability of AI-driven process control to deepen the current global competitive edge in semiconductor fabrication. There are reasons to believe that by conventional ways, further enhancements and efficiencies in manufacturing, especially of semiconductors, which are the building blocks of high-volume systems, will have a direct bearing on the cost and performance of any platform that relies on computing and centralized data processing.

Applicants mentioned that several conventional and non-conventional techniques exist that allow them to delve deeper into the applications of AI for process control. Here, the authors provide an AI-dominant architecture and capabilities envisioned that would further underscore the process control and extend the frontiers of modern semiconductor devices. If we briefly articulate the perspective from the work based on the broader impacts, we anticipate that the hybrid versions of multiple-goal optimization and models, when put to effect onsite, would pierce through the state-of-the-art performance and significantly shape the future.

### 3.1. Applications of AI in Semiconductor Fabrication

In the fabrication of semiconductor devices, data is continuously collected at each stage of each wafer's production processing, whether it be photos or other measurements. Similarly, to other subfields of precision manufacturing, large data sets are available that can be used to train ML models such as ANNs. The U.S. digital services organization 3M has proposed that ML-based process optimization in semiconductor fabrication is a critical technology to be developed in order to ensure U.S. technological and manufacturing competitiveness.

AI methods, including ANNs, have also been applied to models of the photolithography process used in fabrication. For example, van Engelen et al. describe a model that can be used to predict energy release point spread function for multiple excitations of a deep-UV light source, while Aimeur effectively characterized mask quality with a quality factor based on a trained ANN model. Karuppannan et al. provide an overview of applications of AI in lithography and outline the benefits to the semiconductor foundries if they are able to deploy AI to their manufacturing processes. They also point out the bottlenecks that exist in the photolithography process lifecycle that can potentially be streamlined with the use of AI. For example, reduced overlay errors of the order of 10^-12 were achieved with the support of machine intelligence at Vicarious FPC. Karuppannan et al. state that a 2018 model-based Metrology (MB-Metro) system could decrease the number of measurements in the front-end-of-line by 40%.

## 4. Challenges and Opportunities

The semiconductor technology industry is currently facing a "zero-sum game," where every increase in capability must be balanced by a decrease in device size or pitch between devices to maintain Moore's Law scaling. The demanding limits on how small a feature can be formed on a semiconductor device are increasingly affected by process variations that arise within the fabrication process.

Over the course of the 2010s, industry attention shifted from focusing on innovation solely at the device level and limits there, to integrating device-level innovations with new localized process controls to mitigate the impact of device-level variability and process drift, and extracting margins previously reserved for variability (called 'guard-bands') to ensure device reliability. Still, even with the implementation of new process control schemes, device-to-device variation has been increasing.

One of the fundamental goals of this initiative is to improve the number of good or working devices coming off a wafer by leveraging the latest technologies in artificial intelligence (AI) and machine learning (ML). Overcoming the above "zero-sum" constraints in minimally invasive ways requires a realistic view of the entire industry and emphasizes the opportunity for the U.S. to continue to remain a key player in global manufacturing competitiveness. Given the current challenges facing semiconductor manufacturers, the industry is seeking analytical methodology improvements designed to minimize investment while preserving profit margins.

### 4.1. Current Challenges in Semiconductor Manufacturing

Semiconductor manufacturing is an intricate and complicated process. To become more competitive in the industry, the U.S. consortia are providing a distributed smart factory (DSF) of autonomous machines that are supported by decentralized and secure cyber infrastructure, smart energy and logistics, and AI hubs. The AI hub, in turn, means learning the AI prior concentration of integrated predictive and other algorithms to best optimize process equipment efficiency and yield. To develop a competitive edge, AI functionality must be developed so that a DSF team can leapfrog from AI technology already existing in factories to much smarter learning capabilities that can only emerge in a DSF.

The equipment within a DSF factory will undergo AI Research & Development (R&D) to excel at three levels of active machine intelligence. Currently, the most predominant in factories or poised for immediate use are "AI Advanced" predictive capabilities, including algorithms on advanced process control, predictive maintenance, and new recipe design. The target domain of four necessarily aligned NextFlex AI R&D is machine predictive operational behavior task that further enhances equipment availability, throughput, and quality capabilities beyond predictive maintenance and recipe development. Often, factories have machine adoption capabilities below the PM levels of advanced control and into simple smart sensing that define the AI Basic operational capabilities of "Sensing-Available," taking the AI Advanced prediction and recipe equipment capabilities and coupling them with dynamic equipment condition manufacturer and permitted servicing equipment logistics will help enable full DSF equipment optimization.

### 4.2. Opportunities for AI Integration

4.2.1 Manufacturing Equipment

An AI agent could be taught to understand, predict, and control manufacturing equipment settings in ways that mitigate the current gaps in expertise on rapid processing changes to stave off production equipment drift and manage dry-particulate contaminate regimes.

4.2.2 Process Integration

AI could drive new formulations for rapid sintering of microelectronics ceramic-green body indirect layer and direct interface joining materials and metallization layers, ultimately enabling computer modeling and simulation of components that hardware in the loop evaluate system performance to relevant industrial standard tests, such as mil-grade qualification procedures and protocols simulated flight clearance testing and military system-compatible protocols. Advantages of using heterogeneous materials and their potential in new emerging fields of electronic packaging, it would be particularly powerful if AI could identify scalable, manufacturable materials without manual human-in-the-loop assessment.

4.2.3 Technique Optimization

Machine learning could identify robust in-situ, in-process, and end-of-line quality monitoring techniques that provide two-channel (at least) redundancy for quality assurance. Also, deep-learning algorithms could be used to determine how to fabricate MOS capacitors on silicon on insulator wafers so their conductance (indicative of measurement chemistry interference) solely reflects an added dielectric. The feedback from this study could aid in integrating miniaturized, packageable sensors directly into devices for future quality control. Identifying the most performance-sensitive process conditions, along the same rapid-firing ceramic flip-chip alignment process, is the first step needed to use AI for spectrometry optimization (learning advanced signal-processing techniques). If high-energy computed tomography is discovered by AI to be useful, this could expand in possible applications to inspect fuel injectors, biomedical devices, automotive parts, and energy-dispersive electronics test boards.

## 5. Case Studies

A number of successful case studies were reviewed in our survey. Five such studies were selected to be presented here. We note that each study reported significant reduction in cycle time, latency, and/or electricity costs, on the order of 20% of some performance metric. However, this fact alone neglects the broader industry context in which tech giants can afford to invest more broadly in R&D than small or mid-sized companies. Nonetheless, we briefly present these case studies here to investigate how AI has already been successfully implemented in semiconductor manufacturing, offering a closer, practical understanding of where AI is very useful in this context. This understanding will serve as a determinant of where and how energy efficiency in the manufacturing of these systems will grow as the adoption of AI grows.

### 5.1. Successful Implementations of AI in Semiconductor Manufacturing

Though AI and analytics for semiconductor fabs was on the "up-and-coming" list of technology block enhancements in the ICT roadmapping exercise, which outlines future semiconductor-focused R&D needs, successful implementations are already making their way into production fabs. The effect of leveraging AI technology ranges from the incredible enhancement of measurement systems to capacity improvements due to cycle time and dispatching optimizations. Several industry papers dedicated to the successes of AI in semiconductor manufacturing show how it is affecting individual parts of the fab. A few examples cited include huge reductions in spare parts consumed and a halving of wafer edge test time from 4 to 2 min. Across all pursuits, a common theme is evident: the factories are changing in a major fashion as both cutting-edge research and contributions are ushered into production.

Via previous and current contributions by RPI's members to the productivity fashion show of public literature, AI continues to revolutionize the entirety of the semiconductor process from raw poly-Si crystal growth to epitaxial and assembly operations. Robbins states that "modern deployed AI and control systems show this future," where the future "needs radical revisions of wafer fab operations" owing to future customer demands and process capabilities that future computers provide. already seem to be here. In one study conducted by Robbins et al. in a multiyear endeavor, a production facility came to the promising conclusion that "by leveraging Fabwide Optimization (FWO) algorithms, 'economic dispatch' of the entire facility inventory without extra resequencing has been achieved." Another resin-embedded illustration embraces an AI deployment into a three-manshift fab, tracking the "augmented objective" capability demonstrated by AI that "balance[s] the trade-offs of profit maximization, and lead time minimization while incorporating trends and recalculating new optimal production plans once a week over a 15-week planning horizon." In all cases, the deployments were successful and incorporated directly into manufacturing execution system (MES) frameworks, and/or were extended to more wafers and more areas in the factory once implemented.

## 6. Impact on U.S. Manufacturing Competitiveness

U.S. manufacturing sector supports more than 18.6 million jobs and contributes over $2.4 trillion in output. Moreover, the sector has a tremendous impact on the nation's overall economy - every $1.00 spent in the manufacturing sector adds $2.74 to the economy. To maintain U.S. manufacturing's competitiveness and economic impact, new technologies and approaches must be developed and adopted. In particular, the adoption of AI in manufacturing settings promises to revolutionize the practice of manufacturing. In essence, manufacturers can leverage AI-driven optimization to reduce costs, minimize downtime, increase production output, reduce variability, improve part quality, and reduce waste. U.S. manufacturing firms, particularly those specializing in semiconductor fabrication and advanced materials, will be most affected by AI-driven optimization.

Given its existing infrastructure and talent, the U.S. is ideally suited to lead in the development and application of AI-driven optimization of semiconductor fabrication processes that can be applied to the manufacture of any technologically sophisticated device or system. One of the nation's competitive advantages lies in its ability to design, manufacture, and test extremely small, low-power-consuming sensing and communication systems. Furthermore, many smaller companies who work with large end customers to design and manufacture these systems are located here in the United States. Manufacturing components of these systems in the U.S. where AI-driven optimization methods have been used for process development and control provides an additional differentiator that, in turn, distinguishes U.S.-manufactured devices from those produced overseas. In order to accomplish this, the right methods for addressing distributed optimization problems with applications in the semiconductor manufacturing industry must be employed.

**6.1. Economic Benefits**

With the rapid digitization of multiple sectors of the U.S. economy and society, there is an aligning—and urgent—need to match the efficiency of the computational systems that are becoming fundamental in most economic sectors. The efficiency of AI in predicting and optimizing materials and processes enables the first large-scale application of data-driven models in semiconductor manufacturing. This has economic benefits for the industry and helps increase the competitiveness of U.S. semiconductor manufacturing. The first notable economic benefit is the considerable growth in U.S. materials sector sales, which is forecasted at approximately $3.1 billion in year four.

AI-driven predictive process optimization also reduces manufacturing costs. Refinement of a recent process model using less than 10% of the input factors and constrained settings predicts savings equal to almost $43 thousand in raw material costs per 150 mm worth of wafers produced. Aluminium nitride Process Development Kits will accelerate the rate of growth in the HEMT market as manufacturing cycles of new devices on a commercial scale fall by at least 25-33%. Therefore, the models developed directly increase the productivity of semiconductor fabrication facilities, and by extension the competitiveness of semiconductor manufacturing in the United States. In addition to the economic benefit these models provide, they also significantly shorten the development cycle of new devices, therefore reducing the time-to-market for new semiconductor product offerings in certain sectors of the electrical power and electronics industry.

**6.2. Technological Advancements**

A wide variety of products consumed by U.S. citizens and supplied through worldwide export to foreign consumers contain semiconductors. The Intelligent Control Research Laboratory (ICRL) will be working with an exciting company from the Silicon Prairie that is navigating the rapidly evolving industry. EMCO is a world-class company that specializes in the total solution provider approach. Their focus includes advanced composites, additive manufacturing, peripheral technologies, and a variety of industries including Aerospace, Oil & Gas, Defense, and more. EMCO has recently been ramping up its "chip" (semiconductor) production line and is going "Super Bowl-Style" with its heavy investment in us so it can deliver its products to customers even faster. Dr. Jacobs, Dr. Frueh, and all the undergraduate and graduate team members from the ICRL are excited for this engaging opportunity. The ICRL has a strong presence in semiconductor research, especially in plasma processing of these materials, and is situated in one of the major high-tech swaths of the Midwest surrounded by advanced manufacturers. Furthermore, the only laser surface texturing system in the US semiconductor industry is owned and operated by Nebraska Engineer, Alex Halmel. Such high-tech research and development facilities bolster the technological competitiveness of U.S. manufacturing, and are supported with transdisciplinary expertise for scale-up and innovation.

1.0 Introduction. The AI-Driven Innovation Laboratory (AIDL), leading this work, develops advanced artificial intelligence and machine learning (AI/ML) for software-based optimization, control, and predictive health monitoring. Very quickly this technology has resulted in collaborative research projects within the DoD, accelerated regional and national supply chain integration, and has been a cornerstone in over $10M of redirect funding, making up 20% of overall research funding as of 2022 for the Advanced Manufacturing Industry Partnership at Nebraska. For example, ICRL and AIDL PhD researchers and leaders have work at the Center for Nano Ferro and Integrated Systems (CNMfIS), as the enlisted technical partners of a Lincoln, Nebraska-based, leading semiconductor manufacturing company. This technical engagement has already come with its own announcement through the manufacturer signaling more than $6.2M in investments getting ready to place them as the preeminent device manufacturer in the silicon prairie. Through these engagements, it has materialized that there are currently a number of statistical, heuristic, or rule-based solutions currently marketed to this major semiconductor company. However, these models are not keeping up with either next-generation product lines or the recent slump in global supply chains as a result of the Covid-19 epidemic. In turn, many manufacturers (mostly international) showed reduced spending on control and optimization capabilities, especially when other companies claimed in their public literature, to have the most advanced software currently on the market. As such, several mid- to large-sized client companies now wish to adopt our software, showcasing substantial industry acceptance, future return on investment, and cultivation of a need in the marketplace.

**7. Regulatory and Ethical Considerations**

Artificial intelligence is increasingly being adopted in a range of industries because it can reduce costs, increase process reliability, and enhance product quality. AI technologies might also contribute to semiconductor manufacturing efficiency. The U.S. government and industry need to consider many factors when integrating AI throughout a semiconductor fabrication process. Some are related to domestic legal and ethical considerations, and others are related to global semiconductor market dynamics.

The use of AI in edge fabrication presents few regulatory concerns from a US legal perspective. This is due, in part, to the relatively fewer opportunities for abusive practice or human rights violations. The US's requirement that the FCC test all products approved for the US market for electronic emissions. However, certain AI-powered technologies used to maintain the operation of a fabrication facility may implicate existing medical device regulations. As discussed, an increasing number of companies use AI-powered wearable technology to passively track employees' adherence to health and safety protocols. These practices implicate FDA's oversight role over, inter alia, wearable devices that are intended to compensate for functional limitations—and thus may be classified as a type of wearable medical device—medical devices that are intended for direct-to-consumer use, and devices that rely wholly or partly on artificial intelligence to support clinical decision-making. In addition, the ownership and operation of semiconductor fabrication facilities in other countries introduces a set of considerations pertaining to existing and evolving legal and policy frameworks overseas, including export controls and potential national security considerations. Team members on the project shared their insights into international legal and policy obligations in the following section. In the semiconductor industry, several governmental and ethical advisors develop and recommend values-driven principles and trustworthy AI regulatory requirements that are influenced by previous examples or proposals, industrial-focused legal or ethical research and analysis, and private sector-led initiatives. Several proposals that could provide valuable guidelines or points of contact for the industry development are discussed. However, there appears to be little or no concrete policy, legal or regulatory frameworks directed towards AI applications or semiconductors.

## 8. Future Directions and Emerging Trends

In summarizing the current state of the art in AI for semiconductor manufacturing, it is useful to consider anticipated future directions which have been demonstrated in other manufacturing domains. Several emerging trends in AI for optimization-based problems appear useful in this regard. For example, AI for medicine and simulation-based science problems are capable of running highly efficient optimization and uncertainty quantification (UQ) problems, including optimizations and quality scenarios. AI for approximately solving PDE-based control problems portend a new wave of embedded intelligence for optimizing quality while maintaining low-power usage. This would transform a reactive domain following optimization, improving relevant measures that are related to the optimal run-time decision—critical or secondary. Resilience tools within the DOE are beginning to demonstrate their ability to make strategic choices under uncertainty.

In similar trend, industry should be poised to optimize systems based not only on nominal predictors but also considering the cost of being wrong. For example, having controllers with the ability to adjusting in case of uncertainty from a future event, like disturbances from corona. Given that many operations success must have a substantial reliance on vital yet costly quality assurance testing, verifying that the desired quality is achieved prior to expensive testing is crucial, leading to anticipatory system optimization. Quantifying the ability to probabilistically certify the value of IQT and directly speed-up the approach towards obtaining high-quality worst-case values is essential. We further believe that robust AI of the near-future will be probabilistically aware or capable and thus able to aid in uncertainty quantification. Able to quantify statically the risk of a decision (like a systemic shutdown) instead of testable limit cases to the system overall effectiveness. AI-driven optimization of the numbers and frequency of testing platforms to meet FDA's STRIDE policy initiated in October 2021 are also likely and should adapt the use of multifidelity and domain-characteristic surrogate models similar to those exploited by aerospace.

### 8.1. Potential Innovations in AI for Semiconductor Manufacturing

The landscape for AI in semiconductor manufacturing is continuously evolving as new computational methods using AI emerge and as experimental methods become more established. Exploring some of the possible future innovations can help us better understand where the field is heading and the role we play in making those future innovations possible. Although the groundwork for some of the innovations is in early stages, they hold promise for new research directions, massively efficient data analysis strategies, and next-generation control and optimization methods.

Innovation 1: AI-driven Feedback and Deprocessing Although much research focuses on the beginning of the line, the processing phase itself can be a rich source of new research. The manufacturing process is divided into many sections, and there is substantial waste when a wafer is determined to be unrepairable at the end of the line. If AI could determine in real time that an abnormal processing condition occurred, it might be possible to build in corrective "deprocessing" steps or workaround strategies to save the wafer. This idea has been the source of multiple recent studies related to machine learning and experimentation for "feedback control" of wafer characteristics. A natural extension of this work would be in driving deprocessing decisions with AI. This could involve linking deprocessing decisions to fault detection systems or developing a closed-loop "feedback" control model. Finally, it is possible that AI-driven processors could yield faster deprocessing behavior; typically, a wafer is moved to a deprocessing step several tools downstream, which may involve substantial time and physical effort. A better way to mechanistically deprocess might involve moving tools closer to the processing area or improving deprocessing capabilities on the processing tools themselves. Although this area would take an investment in tooling and process improvements, it might yield a substantial yield benefit.

## 9. Conclusion and Recommendations

Conclusion. The conceptual findings in this essay highlight pressing questions about the appropriate level of AI governance in IIoT, particularly in assisting optimization of mature semiconductor fabrication processes. In the context of the U.S. government's industrial policy interests, we have underscored several initial avenues of research and action. We posit that U.S. policymakers should consider the following pertinent topics:

- The exploration of historical analogies to guide answers to our framework of normative standards for AI regulation, which considers "self-defined ethical standards" conducive to promoting AI in IIoT. Instead of viewing industrial users of AI as adverse agents, authorities may require "official compliance and governance action" from the developers or distributors of IIoT and AI solutions.

- Empirical studies that are designed to optimize existing high-quality semiconductor fabrication equipment and processes may create actionable intelligence for U.S. chip and equipment manufacturers. As such, U.S. entities operating in the large-scale integrated circuits and electronics industry (inclusive for defense) are better positioned to extract valuable insights from AI-driven optimization of mature process technology, as relatively few such tools are available for advanced process nodes.

- U.S. entities can conduct case studies on how the lessons learned from using off-the-shelf computationally efficient materials in a complex multi-material and multi-process part can inform future design and optimization at more advanced process nodes. Results from such studies, which leverage publicly sourced codes, can potentially enhance resilience and, therefore, competitiveness.

Based on this research, U.S. entities should continue using deterministic industrial perspectives in fundamental and use-inspired research in AI-driven process-tooling materials. Moreover, more research is needed to assess how AI tools might be - with less human oversight - "valuable AI blackboxes" to aid the work of equipment operators, R&D engineers, and others. The key question is, what is the threshold of commercial interest such that further 'governors' to ensure AI safety are no longer a priority? Continued research in this area should focus on patents, academic publications, and the burgeoning U.S. National AI Research Resource (NAIRR) Incubation Labs, planned federal AI R&D investment in AI Institutes and Joint University Microelectronics Program (JUMP), which focuses on using standards based on defect simulation to improve defect detection sensitivity and physical awareness.