International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Process Optimization in Semiconductor Manufacturing: The Role of Big Data Analytics in Yield Improvement

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Abstract
The semiconductor industry faces increasing challenges in maintaining high yields and reducing costs as manufacturing processes become more complex. Big-data analytics has emerged as a powerful tool for process optimization, enabling manufacturers to extract valuable insights from vast amounts of production data and make data-driven decisions. This review explores the role of big data analytics in semiconductor manufacturing, focusing on its applications in yield improvement. We discuss traditional approaches to process optimization, such as Six Sigma and Design of Experiments, and highlight their limitations in addressing the complexity of modern semiconductor manufacturing. We then delve into the transformative potential of big data analytics, examine key data sources in semiconductor fabs, and integrate advanced analytical techniques, such as machine learning and deep learning, for fault detection, classification, and predictive maintenance. This review also covers the importance of real-time analytics and edge computing in reducing latency and improving process control, as well as the challenges associated with data integration and management across manufacturing systems. We present case studies demonstrating the successful implementation of big data analytics in semiconductor fabrication, showing quantitative improvements in yield, cycle time, and overall equipment effectiveness. Finally, we discuss the technical and organizational challenges in implementing big data analytics and highlight emerging trends and future research directions, such as quantum computing and AI-driven process design. This review provides a comprehensive overview of the transformative potential of big data analytics in semiconductor manufacturing and its critical role in driving innovation and efficiency in the industry.

Keywords: Semiconductor manufacturing, Yield improvement, Big-data analytics, Process optimization, Machine learning, Predictive maintenance, Defect detection

Introduction

The continuous advancement of semiconductor technology demands increasingly sophisticated manufacturing processes, which necessitate robust optimization strategies to maintain high yields and reduce costs. Big data analytics has emerged as a powerful tool in this context, enabling manufacturers to extract valuable insights from vast amounts of process data and to make data-driven decisions for yield improvement [1]. By leveraging machine learning algorithms and advanced statistical techniques, semiconductor companies can identify subtle patterns and correlations in their production processes, leading to a more precise control and optimization of critical parameters [2].

This approach to process optimization not only enhances the overall manufacturing efficiency, but also contributes to the development of more reliable and high-performance semiconductor devices. The integration of big data analytics into semiconductor manufacturing processes has led to significant improvements in defect detection, predictive maintenance, and quality control. Furthermore, the application of these advanced analytical techniques has enabled semiconductor companies to accelerate their research and development efforts, facilitating a faster time-to-market for new products and technologies.

The integration of big data analytics has revolutionized the semiconductor industry, enabling companies to extract valuable insights from vast amounts of production data and make data-driven decisions. This technological advancement has not only improved manufacturing processes, but also accelerated innovation cycles, allowing semiconductor firms to remain competitive in a rapidly evolving market [3]. As the industry continues to embrace big data analytics, we expect to see further breakthroughs in areas such as yield optimization, energy efficiency, and the development of next-generation semiconductor materials and architectures.

Overview of the Semiconductor Manufacturing Processes

The semiconductor fabrication process involves several intricate stages, including wafer preparation, photolithography, etching, doping, and metallization. Each of these stages requires precise control and optimization to ensure the production of high-quality semiconductor devices [4]. Advanced process control systems powered by big data analytics play a crucial role in monitoring and adjusting these stages in real time, minimizing defects, and maximizing yield [5].

Critical parameters affecting the yield and quality in semiconductor manufacturing encompass a wide range of factors, including temperature control, chemical purity, particle contamination, and process uniformity [1]. These parameters must be tightly regulated throughout the fabrication process to maintain a consistent device performance and reliability. Advanced metrology techniques and in-line monitoring systems are employed to continuously assess and adjust these parameters to ensure optimal production outcomes [6].

Common challenges in process control and optimization include maintaining precise control over complex multistep processes, managing variability in raw materials and equipment performance, and balancing the trade-offs between yield, quality, and throughput. Advanced process control techniques, such as statistical process control (SPC) and run-to-run control, have been implemented to address these challenges and improve overall manufacturing efficiency [7]. Additionally, the integration of big data analytics and machine learning algorithms is increasingly being used to identify subtle patterns and optimize process parameters in real-time [8].

Traditional Approaches to Process Optimization

Building on traditional approaches, Six Sigma methodologies and Design of Experiments (DOE) techniques are often employed to systematically identify and eliminate the sources of variation in manufacturing processes. These methods enable engineers to optimize process parameters, reduce defects, and enhance product quality through data-driven decision making. Furthermore, lean manufacturing principles and continuous improvement initiatives are frequently integrated with statistical process control to create a holistic approach to process optimization [9][10].

These advanced statistical techniques allow for the systematic exploration of multiple process variables simultaneously, enabling engineers to identify the optimal operating conditions and understand the complex interactions between factors. The response surface methodology (RSM), in particular, provides a visual representation of how process variables affect the desired output, facilitating more intuitive decision-making and process optimization [11]. Additionally, the integration of computer-aided design and simulation tools with experimental methods has further enhanced the efficiency and effectiveness of process optimization efforts in modern manufacturing environments. The advanced techniques discussed, while powerful and increasingly utilized across industries, present certain limitations and challenges that warrant careful consideration in real-world implementation. A significant constraint is the underlying assumption of a smooth and continuous response surface, which may not accurately represent complex manufacturing processes characterized by discontinuities or abrupt behavioral changes [12]. This assumption can potentially lead to inaccurate predictions or suboptimal solutions when applied to systems with inherent nonlinearities or discrete events [13].

Another challenge associated with these methodologies is the potential for substantial computational and experimental costs, particularly when addressing numerous variables or exploring an extensive range of process conditions. As the dimensionality of the problem increases, the required number of experiments or simulations may grow exponentially, resulting in resource-intensive and time-consuming optimization processes. This scalability issue can be particularly problematic in industries with stringent production schedules or limited R&D resources.

Furthermore, the interpretation of the results obtained from these advanced methods often requires a nuanced approach, necessitating a combination of expertise in statistical analysis and domain-specific knowledge to draw meaningful conclusions and make informed decisions. The multifaceted nature of the data generated by these techniques frequently necessitates interdisciplinary collaboration between data scientists, process engineers, and subject matter experts to fully leverage the insights gained.

In addition, the effectiveness of these methods can be significantly influenced by the quality and representativeness of the input data. Inaccurate or biased data may lead to misleading results, underscoring the importance of robust data collection and validation. Moreover, the selection of appropriate design spaces and experimental designs is crucial because poorly chosen parameters or ranges can result in suboptimal solutions or failure to capture important process behaviors.

Despite these challenges, ongoing research and advancements in computational power and algorithms continue to address many of these limitations, thereby expanding the applicability and reliability of these advanced techniques across various domains.

BIG-DATA ANALYTICS IN SEMICONDUCTOR MANUFACTURING

The integration of big data analytics in semiconductor manufacturing has revolutionized process optimization and quality control. With the vast amount of data generated throughout the production lifecycle, manufacturers can now leverage advanced analytical techniques to extract valuable insights and make data-driven decisions. This approach enables the real-time monitoring of equipment performance, early detection of potential defects, and predictive maintenance strategies, ultimately leading to improved yield and reduced downtime.

Some key sources of data in semiconductor fabs are as follows:

1. Sensors: Modern semiconductor fabs utilize a vast network of sensors throughout the manufacturing process. These sensors monitor various parameters such as temperature, pressure, gas flow rates, and particle counts. Sensor data provide real-time information on the equipment and process conditions.

2. Equipment logs: Manufacturing equipment in fabs generates detailed logs of their operations, including process recipes, run times, alarms, and maintenance events. These logs contain valuable data on equipment performance and process stability over time.
3. Metrology tools: Specialized metrology equipment is used to measure critical dimensions, film thicknesses, defects, and other physical properties of wafers and devices at various stages of production. Metrology data are crucial for process control and quality assurance.
4. Process control systems: Advanced process control (APC) systems collect and analyze data from multiple sources to optimize and control manufacturing processes in real time. APC systems generate rich datasets of process parameters and outcomes.
5. Yield management systems: These systems aggregate data on defects, parametric measurements, and final test results to track and analyze the yield across the manufacturing process. They provide insights into yield-loss mechanisms.
6. Manufacturing execution systems (MES): MES software manages and tracks the work-in-progress flow through the fab. It generates data on the cycle times, throughput, equipment utilization, and other operational metrics.
7. Environmental monitoring: Systems that monitor cleanroom conditions such as temperature, humidity, air quality, and vibration provide data relevant to process control and contamination prevention.
8. Supply chain systems: Data on raw materials, spare parts inventory, and logistics can affect manufacturing operations and are often integrated with fab data systems.
9. Product engineering databases: Information on product designs, process specifications, and engineering change orders provides a context for analyzing manufacturing data.

Integrating and analyzing data from these diverse sources enables semiconductor manufacturers to optimize processes, improve yields, and enhance overall fab performance through data-driven decision-making.

Big data analytics in semiconductor manufacturing extends beyond process optimization and quality control, encompassing areas such as supply chain management, product design, and customer demand forecasting. By analyzing historical production data and market trends, manufacturers can optimize inventory levels, streamline logistics, and align production schedules with customer needs [14]. Furthermore, big data analytics enables semiconductor companies to accelerate innovation by identifying patterns in research and development data, potentially leading to a faster time-to-market for new chip designs and technologies.

Smart manufacturing and Industry 4.0, concepts are revolutionizing semiconductor production by integrating advanced technologies such as artificial intelligence, the Internet of Things, and cloud computing. These innovations enable real-time monitoring, predictive maintenance, and adaptive process control, leading to improved efficiency and quality of semiconductor fabrication [15]. By leveraging interconnected systems and data-driven decision making, semiconductor manufacturers can achieve greater flexibility, reduced downtime, and enhanced customization capabilities throughout the production lifecycle.

Applications of Big Data Analytics for Yield Improvement

Advancements, such as predictive maintenance and equipment health monitoring in semiconductor production, have also been extended to yield improvements through the application of Big Data analytics. By analyzing vast amounts of data collected from various stages of the manufacturing process described in IV, manufacturers can identify patterns and correlations that impact yield rates. This data-driven approach enables the development of more accurate predictive models for identifying potential defects and optimizing the process parameters in real time.

Predictive maintenance and equipment health monitoring involve analyzing real-time sensor data to proactively forecast potential equipment failures and schedule maintenance, minimizing unplanned downtime, and maximizing production efficiency. Virtual metrology utilizes advanced statistical models and machine learning algorithms to estimate critical process parameters without the need for physical measurements, reducing inspection time and costs while improving overall process control [16][17]. These data-driven techniques not only enhance yield improvement but also contribute to more sustainable and cost-effective semiconductor manufacturing practices.

Fault detection and classification techniques in semiconductors are crucial for maintaining quality control and improving the manufacturing processes. Some key approaches include the following:

1. **Machine learning algorithms**
- Support Vector Machines (SVM)
- Neural Networks
- Decision Trees
- Random Forests

2. **Statistical methods:**
- Principal Component Analysis (PCA)
- Independent Component Analysis (ICA)
- Partial Least Squares (PLS)

3. **Image-Processing Techniques**
- Optical inspection
- X-ray imaging
- Scanning electron microscopy (SEM)

4. **Electrical testing:**
- Automated Test Equipment (ATE)
- Built-In Self-Test (BIST)
- Parametric testing

5. **Data-driven approaches:**
- Big data analytics
- Real-time monitoring systems
- Predictive maintenance

6. **Spectral analysis:**
- Fourier Transform Infrared Spectroscopy (FTIR)
- Raman spectroscopy

7. **Thermal imaging:**
- Infrared thermography
- Lock-in thermography

These techniques can be used individually or in combination to detect and classify various types of faults in semiconductors such as:

- Physical defects (cracks, scratches)
- Electrical faults (short circuits, open circuits)

- Material impurities
- Process-induced defects
- Packaging issues

The implementation of effective fault detection and classification systems can lead to the following:

- Improved yield rates
- Reduced manufacturing costs
- Enhanced product reliability
- Faster time-to-market
- Better quality control

Process window optimization in semiconductor manufacturing using machine learning involves leveraging advanced algorithms and data analysis techniques to enhance the efficiency and yield of the semiconductor production processes. This approach aims to identify and maintain the optimal operating conditions within a complex multidimensional parameter space.

As semiconductor manufacturing continues to evolve, machine learning-based process window optimization will play an increasingly crucial role in maintaining competitiveness and driving technological advancements in the industry.

ADVANCED ANALYTICAL TECHNIQUES

The application of commonly used machine learning algorithms and techniques in semiconductor manufacturing can be further enhanced by integrating real-time data streams from multiple sources such as sensor networks and production line telemetry to create a more comprehensive and dynamic view of the manufacturing process. By leveraging explainable AI models, manufacturers can gain deeper insights into the decision-making processes of these advanced fault detection and classification systems, improving transparency and facilitating better collaboration between human operators and AI-driven systems. In addition, the implementation of federated learning approaches can enable semiconductor manufacturers to collaboratively improve their models while maintaining data privacy and security across multiple production facilities.

Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can be employed for anomaly detection using complex time-series data generated during the manufacturing process [18]. Furthermore, reinforcement learning algorithms can be utilized to develop adaptive control systems that optimize process parameters in real time, leading to improved yields and reduced variability in semiconductor production [19].

Deep learning can also be applied to predictive maintenance, where deep learning models can analyze sensor data from manufacturing equipment to forecast potential failures before they occur. In addition, AI-powered decision support systems can assist operators in real-time process control by providing recommendations based on historical data and current production conditions. The integration of AI in semiconductor manufacturing can lead to significant improvements in overall equipment effectiveness (OEE) and reduce unplanned downtime.

REAL-TIME ANALYTICS AND EDGE COMPUTING

Real-time data processing plays a crucial role in semiconductor manufacturing by enabling rapid decision making and an immediate response to production issues. Edge computing technologies can be deployed on the factory floor to process data locally, reducing latency and allowing for faster insights. This approach not only enhances the efficiency of real-time analytics but also helps in managing massive amounts of data generated by semiconductor production processes.

This approach to real-time analytics and edge computing in semiconductor manufacturing also contributes to predictive maintenance strategies, allowing for early detection of potential equipment failures or anomalies. By processing data closer to its source, edge computing enables more efficient use of network bandwidth and reduces the strain on central datacenters [20][21]. Additionally, the integration of edge computing with AI and machine-learning algorithms can lead to more sophisticated process control and optimization, further enhancing the overall quality and yield of semiconductor production. Edge computing in semiconductor manufacturing enables faster decision making through local data processing, enhanced real-time monitoring, and immediate parameter adjustments. This approach reduces the data transmission time, improves process control, and facilitates advanced analytics on the factory floor, resulting in more responsive and adaptive manufacturing processes.

The implementation of real-time analytics in semiconductor manufacturing presents challenges and opportunities. One challenge is ensuring the reliability and accuracy of data collected from numerous sensors and devices across the production line. However, this also presents an opportunity to develop more robust data validation techniques and improve sensor technology. Another challenge lies in integrating legacy systems with new edge computing infrastructure, but this can drive innovation in the system architecture and lead to more flexible and scalable manufacturing processes.

DATA INTEGRATION AND MANAGEMENT

Data quality and governance are crucial for ensuring the integrity and usefulness of the information collected across the manufacturing ecosystem. Effective data management strategies can help identify and address issues in terms of data accuracy, completeness, and consistency. Implementing robust data governance frameworks enables organizations to establish clear policies, procedures, and responsibilities for data handling, fostering a culture of data-driven decision-making and continuous improvement.

Integrating data across diverse manufacturing systems presents several challenges including disparate data formats, inconsistent naming conventions, and varying levels of data granularity. Legacy systems may also pose compatibility issues when attempting to connect them to modern data platforms. Overcoming these challenges requires a comprehensive integration strategy that addresses data standardization, system interoperability, and implementation of middleware solutions to facilitate seamless data exchange between disparate systems.

Data lakes and cloud computing play crucial roles in managing large datasets by providing scalable storage and processing. These technologies enable manufacturers to centralize data from various sources, facilitating easier access and analysis. Cloud-based solutions offer the flexibility to scale resources on-demand, allowing organizations to handle fluctuating data volumes efficiently and cost-effectively.

CASE STUDIES

The adoption of big data analytics in semiconductor manufacturing has led to significant improvements in yield optimization and predictive maintenance [22]. Advanced machine learning algorithms can analyze historical process data to identify patterns and predict potential defects, thereby enabling proactive intervention. Real-time monitoring and analysis of equipment sensor data has also helped semiconductor fabs reduce downtime and optimize production schedules, resulting in increased overall equipment effectiveness. These advanced analytical techniques have also enabled semiconductor manufacturers to

optimize their supply chain management and improve inventory control and demand forecasting. Additionally, big data analytics has facilitated the development of more sophisticated quality control processes, allowing the detection of subtle defects that may have previously gone unnoticed. By leveraging these data-driven insights, semiconductor fabs have been able to reduce costs, increase productivity, and maintain a competitive edge in increasingly complex and demanding industries.
The implementation of data-driven methodologies has led to significant quantitative improvements in key performance indicators within semiconductor fabs. Yield rates have seen notable increases, with some manufacturers reporting improvements of up to 5-10% through the application of predictive analytics and real-time defect detection systems. Cycle times have also been substantially reduced, with some fabs achieving reductions of 20-30% by optimizing production schedules and minimizing bottlenecks through data-driven insights [23]. The overall equipment effectiveness (OEE) has similarly benefited, with many semiconductor manufacturers reporting OEE improvements of 10-15% through predictive maintenance and optimized equipment utilization strategies.

Challenges and Future Directions

The improvements in data analytics have led to significant cost savings and increased production capacity for semiconductor manufacturers. However, the implementation of big data analytics in semiconductor manufacturing is challenging. The sheer volume and velocity of data generated in modern semiconductor fabs can overwhelm traditional data processing systems, requiring advanced infrastructure and analytics capabilities to effectively capture and analyze information in real time.
To effectively implement big data analytics in semiconductor manufacturing, organizations must address significant skill gaps in data science and analytics in their workforce. In addition, cultural resistance to adopting new technologies and data-driven decision-making processes can hinder the successful integration of big data solutions. Overcoming these challenges requires a comprehensive approach to employee training, change management, and foster a data-driven culture within the organization. Developing a robust talent pipeline and partnering with educational institutions can help address skill gaps in data science and analytics. Implementing a change management strategy that emphasizes the benefits of big data analytics and involves key stakeholders throughout the implementation process can help overcome cultural resistance. Additionally, establishing cross-functional teams that combine domain expertise with data science skills can facilitate the integration of big-data solutions into existing manufacturing processes.
Future research could explore the integration of quantum computing in manufacturing analytics, potentially revolutionizing complex optimization problems and enhancing predictive capabilities. The application of an AI-driven process design may lead to more adaptive and efficient production systems that are capable of real-time adjustments based on market demand and resource availability. In addition, investigating the intersection of big data analytics with emerging technologies such as augmented reality and digital twins could offer new avenues for improving manufacturing operations and decision-making processes.

Conclusion

The integration of big data analytics in semiconductor manufacturing has revolutionized process optimization and yield improvement. This review explores the transformative potential of advanced analytical techniques to address the increasing complexity of the semiconductor fabrication processes.
The key findings of this review are as follows:

1. Traditional approaches such as Six Sigma and Design of Experiments, while valuable, have limitations in addressing the complexity of modern semiconductor manufacturing.
2. Big data analytics enables manufacturers to extract insights from vast amounts of production data, leading to data-driven decision making and significant improvements in yield, cycle time, and overall equipment effectiveness.
3. Advanced analytical techniques, including machine learning and deep learning, have proven effective for fault detection, classification, and predictive maintenance.
4. Real-time analytics and edge computing play crucial roles in reducing latency and improving process control, enabling rapid decision making and immediate response to production issues.
5. Data integration and management across manufacturing systems remain challenging but are essential for leveraging the full potential of big data analytics.
6. Case studies have demonstrated quantitative improvements in key performance indicators, with some manufacturers reporting yield improvements of 5-10% and cycle time reductions of 20-30%.

The semiconductor industry is poised for further transformation as emerging technologies such as quantum computing and AI-driven process design are integrated into manufacturing analytics. These advancements promise to enhance the optimization capabilities, improve the predictive accuracy, and enable more adaptive production systems.

Looking forward, the semiconductor industry is likely to see the emergence of "smart fabs" that autonomously optimize production processes in real-time. Increased interconnectedness and data sharing may foster a collaborative innovation ecosystem. As big data analytics becomes more sophisticated, it could enable predictive maintenance at an unprecedented scale, minimizing downtime, and maximizing equipment lifespan across the entire semiconductor manufacturing landscape.

In conclusion, big data analytics have proven to be a powerful tool for addressing the challenges of modern semiconductor manufacturing. Its continued development and integration will be crucial for driving innovation, improving efficiency, and maintaining competitiveness in this rapidly evolving industry.

References

1. C.-F. Chien, C.-W. Liu, and S.-C. Chuang, “Analysing semiconductor manufacturing big data for root cause detection of excursion for yield enhancement,” *International Journal of Production Research*, vol. 55, no. 17, pp. 5095–5107, Nov. 2015, doi: 10.1080/00207543.2015.1109153.
2. Y. Zhu and J. Xiong, “Modern big data analytics for ‘old-fashioned’ semiconductor industry applications,” Nov. 2015, vol. 6, pp. 776–780. doi: 10.1109/iccad.2015.7372649.
3. L. Chiang, B. Lu, and I. Castillo, “Big Data Analytics in Chemical Engineering.,” *Annual Review of Chemical and Biomolecular Engineering*, vol. 8, no. 1, pp. 63–85, Feb. 2017, doi: 10.1146/annurev-chembioeng-060816-101555.
4. J. Yu, “Fault Detection Using Principal Components-Based Gaussian Mixture Model for Semiconductor Manufacturing Processes,” *IEEE Transactions on Semiconductor Manufacturing*, vol. 24, no. 3, pp. 432–444, Aug. 2011, doi: 10.1109/tsm.2011.2154850.
5. S. J. Qin, G. Cherry, R. Good, J. Wang, and C. A. Harrison, “Semiconductor manufacturing process control and monitoring: A fab-wide framework,” *Journal of Process Control*, vol. 16, no. 3, pp. 179–191, Aug. 2005, doi: 10.1016/j.jprocont.2005.06.002.
6. M. Khakifirooz, Y.-J. Chen, and C.-F. Chien, “Dynamic Support Vector Regression Control System for Overlay Error Compensation With Stochastic Metrology Delay,” *IEEE Transactions on*

Automation Science and Engineering, vol. 17, no. 1, pp. 502–512, Sep. 2019, doi: 10.1109/tase.2019.2935179.

7. Y.-C. Su, T.-H. Lin, W.-M. Wu, and F.-T. Cheng, "Accuracy and Real-Time Considerations for Implementing Various Virtual Metrology Algorithms," *IEEE Transactions on Semiconductor Manufacturing*, vol. 21, no. 3, pp. 426–434, Aug. 2008, doi: 10.1109/tsm.2008.2001219.
8. M. Khakifirooz, C. F. Chien, and Y.-J. Chen, "Bayesian inference for mining semiconductor manufacturing big data for yield enhancement and smart production to empower industry 4.0," *Applied Soft Computing*, vol. 68, pp. 990–999, Nov. 2017, doi: 10.1016/j.asoc.2017.11.034.
9. C. J. Spanos, "Statistical process control in semiconductor manufacturing," *Proceedings of the IEEE*, vol. 80, no. 6, pp. 819–830, Jun. 1992, doi: 10.1109/5.149445.
10. S. Limanond, J. Si, and K. Tsakalis, "Monitoring and control of semiconductor manufacturing processes," *IEEE Control Systems*, vol. 18, no. 6, pp. 46–58, Dec. 1998, doi: 10.1109/37.736011.
11. K. K. Vadde, D. C. Montgomery, and V. R. Syrotiuk, "Optimizing protocol interaction using response surface methodology," *IEEE Transactions on Mobile Computing*, vol. 5, no. 6, pp. 627–639, Jun. 2006, doi: 10.1109/tmc.2006.82.
12. Q. P. He and J. Wang, "Fault Detection Using the k-Nearest Neighbor Rule for Semiconductor Manufacturing Processes," *IEEE Transactions on Semiconductor Manufacturing*, vol. 20, no. 4, pp. 345–354, Nov. 2007, doi: 10.1109/tsm.2007.907607.
13. Q. P. He and J. Wang, "Statistics pattern analysis: A new process monitoring framework and its application to semiconductor batch processes," *AIChE Journal*, vol. 57, no. 1, pp. 107–121, Dec. 2010, doi: 10.1002/aic.12247.
14. C.-H. Wang and J.-Y. Chen, "Demand forecasting and financial estimation considering the interactive dynamics of semiconductor supply-chain companies," *Computers & Industrial Engineering*, vol. 138, p. 106104, Sep. 2019, doi: 10.1016/j.cie.2019.106104.
15. D. Cemernek, H. Gursch, and R. Kern, "Big data as a promoter of industry 4.0: Lessons of the semiconductor industry," Jul. 2017, pp. 239–244. doi: 10.1109/indin.2017.8104778.
16. P. Kang, D. Kim, H.-J. Lee, S. Doh, and S. Cho, "Virtual metrology for run-to-run control in semiconductor manufacturing," *Expert Systems with Applications*, vol. 38, no. 3, pp. 2508–2522, Sep. 2010, doi: 10.1016/j.eswa.2010.08.040.
17. M. Maggipinto, A. Beghi, G. A. Susto, M. Terzi, and C. Masiero, "A Computer Vision-Inspired Deep Learning Architecture for Virtual Metrology Modeling With 2-Dimensional Data," *IEEE Transactions on Semiconductor Manufacturing*, vol. 31, no. 3, pp. 376–384, Aug. 2018, doi: 10.1109/tsm.2018.2849206.
18. K. Liang, N. Qin, D. Huang, and Y. Fu, "Convolutional Recurrent Neural Network for Fault Diagnosis of High-Speed Train Bogie," *Complexity*, vol. 2018, pp. 1–13, Oct. 2018, doi: 10.1155/2018/4501952.
19. N. Stricker, A. Kuhnle, R. Sturm, and S. Friess, "Reinforcement learning for adaptive order dispatching in the semiconductor industry," CIRP Annals, vol. 67, no. 1, pp. 511–514, Jan. 2018, doi: 10.1016/j.cirp.2018.04.041.
20. C. S. M. Babou, S. Kashihara, I. Niang, D. Fall, and Y. Kadobayashi, "Home Edge Computing (HEC): Design of a New Edge Computing Technology for Achieving Ultra-Low Latency," springer, 2018, pp. 3–17. doi: 10.1007/978-3-319-94340-4_1.
21. S. Patonico, K. Steenhaut, and A. Braeken, "Identity-based and anonymous key agreement protocol for fog computing resistant in the Canetti–Krawczyk security model," *Wireless Networks*, vol. 29, no.

3, pp. 1017–1029, Jul. 2019, doi: 10.1007/s11276-019-02084-6.

22. J. Moyne and J. Iskandar, "Big Data Analytics for Smart Manufacturing: Case Studies in Semiconductor Manufacturing," *Processes*, vol. 5, no. 3, p. 39, Jul. 2017, doi: 10.3390/pr5030039.
23. Z. Huang, M. Li, V. C. Angadi, M. Danishvar, and A. Mousavi, "Zero Defect Manufacturing of Microsemiconductors – An Application of Machine Learning and Artificial Intelligence," Nov. 2018, pp. 449–454. doi: 10.1109/icsai.2018.8599292.