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A Data-Driven Approach for Real-Time Bottleneck Detection and Optimization in Semiconductor Manufacturing Using Active Period Method and Visualization

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Abstract: With the rapid development of the semiconductor industry, identifying and optimizing bottlenecks is crucial for improving production line efficiency. This paper proposes a method combining Activity Cycle Method (APM) and data visualization techniques. APM identifies key bottlenecks in semiconductor manufacturing by analyzing the continuous uptime of machines and the duration of their activity cycles. Data visualization tools are then used to present these key bottlenecks in an intuitive and actionable manner. Applying both methods to a real-world semiconductor manufacturing environment significantly improves production efficiency and machine utilization, making this method practically applicable in semiconductor manufacturing.

Keywords: Semiconductor Manufacturing, Bottleneck Detection, Active Period Method, Data Visualization, Process Optimization, Machine Utilization, Heatmap, Time-Series Analysis.

Disciplines: Computer Science. **Subjects:** Data Science.

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1 INTRODUCTION

Semiconductor manufacturing is a cornerstone of modern technological advancements, driving progress in industries ranging from consumer electronics to aerospace[1]. As the demand for faster, smaller, and more efficient semiconductor devices continues to rise, the production processes within semiconductor fabrication plants (fabs) have grown increasingly complex. In such a high-stakes, fast-paced environment, optimizing the production workflow becomes crucial not only for meeting market demands but also for ensuring cost-effectiveness and maintaining competitive advantage[2]. However, despite the critical importance of efficient manufacturing, a fundamental challenge persists: the identification and management of production bottlenecks.

Bottlenecks in semiconductor production occur when specific stages in the manufacturing process hinder the flow of work, resulting in delays and reduced throughput. Common bottleneck sources in semiconductor fabs include equipment downtime, long cycle times, and inefficient resource allocation[3]. The traditional methods of bottleneck detection, which rely heavily on manual inspections or simplistic queuing models, often fail to capture the dynamic nature of modern production systems, particularly when production lines evolve or external factors cause unpredictable fluctuations. This gap in methodical bottleneck analysis highlights the need for more advanced, adaptable, and data-driven approaches[4].

To address this issue, this paper proposes a novel methodology that combines the Active Period Method (APM) with data visualization techniques to effectively detect and optimize bottlenecks within semiconductor production lines[5]. The Active Period Method, grounded in the analysis of machine activity durations, offers a powerful means to identify operational inefficiencies by quantifying periods of uninterrupted machine operation[6]. This method, when integrated with sophisticated data visualization tools, such as heatmaps and time-series analysis, enables production managers to intuitively observe bottlenecks and make informed decisions on optimizing the production flow[7].

The research presented herein also highlights the practical application of this combined methodology within a real-world semiconductor manufacturing context[8]. In particular, it investigates how APM, when applied alongside visual tools, not only identifies bottlenecks but also provides actionable insights into improving machine utilization, reducing cycle times, and enhancing overall production

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efficiency[9]. By leveraging these tools, production managers can dynamically adjust to shifting bottlenecks and devise targeted optimization strategies.

Despite the promising results, there are challenges associated with data quality, the dynamic nature of bottlenecks, and the integration of real-time data into the decision-making process[10]. These challenges underscore the necessity for further exploration into more adaptive and predictive models. For example, integrating machine learning techniques into the current methodology could enable more accurate predictions and real-time optimization[11]. This paper thus serves as a starting point for advancing semiconductor production optimization through data-driven methods, setting the stage for future research that could incorporate machine learning and predictive analytics.

Through this research, we aim to bridge the gap between theory and practice in semiconductor manufacturing optimization, contributing to both the academic understanding of production bottleneck analysis and its practical application in a rapidly evolving industrial landscape.

2 LITERATURE REVIEW

Semiconductor manufacturing is a complex process, and one of the biggest challenges is identifying and fixing bottlenecks. Bottlenecks happen when certain parts of the production process slow down, causing delays and reducing overall productivity. In traditional methods, queueing theory and simulation models have been used to understand and predict bottlenecks, but these methods have limitations[12]. For example, they often assume that production conditions are stable, which is rarely the case in semiconductor fabs, where production processes are dynamic and subject to change.

Recently, the Active Period Method has been introduced as an alternative to traditional methods[13]. APM works by measuring the amount of uninterrupted working time for machines, which can help identify bottlenecks. The idea is that machines with the longest working periods are likely to be bottlenecks[14]. This method is seen as an improvement because it does not require assumptions about steady conditions. However, APM also has its limitations, particularly in systems where machines often stop and start, or when external factors affect production.

To make APM more effective, researchers have begun to combine it with data visualization tools like heatmaps and time-series charts. These tools help production managers quickly see where bottlenecks are occurring and understand the severity of the issue. For example, heatmaps can show which machines are consistently running at full capacity, which helps in making quick decisions about where to focus optimization efforts[15]. However, the effectiveness of data visualization depends on the quality of the data collected. In semiconductor production, there can be a lot of noise in the data, which makes it hard to interpret the results accurately.

While combining APM with data visualization has shown promise, challenges remain. One major issue is bottleneck drift, where the bottleneck shifts between machines depending on production conditions[16]. This phenomenon is not always well-addressed by APM, and current methods may need to be updated to handle these changes better. In addition, real-time data collection is still an area that needs improvement to make the process fully dynamic and responsive.

In the future, integrating machine learning with APM and data visualization could improve bottleneck detection by making it more predictive. Some studies suggest that machine learning could help predict bottlenecks before they occur, providing an opportunity to adjust production in advance[17]. This could greatly enhance the efficiency and adaptability of the semiconductor manufacturing process.

while there have been advances in bottleneck detection, there are still many areas that need improvement[18]. APM combined with data visualization offers a promising solution, but further research is needed to address the challenges of dynamic bottlenecks and real-time adaptability. Future work could focus on integrating predictive analytics to create more efficient and responsive systems for semiconductor production optimization.

3 METHODOLOGY

The methodology proposed for identifying and optimizing bottlenecks in semiconductor production processes is rooted in a combination of advanced mathematical techniques from operations research, machine learning, and data visualization[19]. Specifically, the integration of the Active Period Method with real-time optimization frameworks aims to enhance the accuracy and adaptability of bottleneck detection, enabling a dynamic response to production shifts. This approach is designed to provide actionable insights for production managers, allowing them to preemptively address bottlenecks, optimize machine utilization, and reduce cycle times.

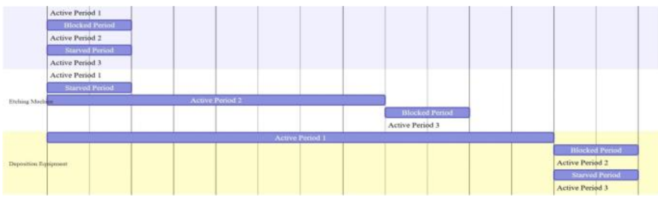

FIGURE 1: SCHEMATIC TIMELINE OF MACHINE ACTIVE PERIODS

3.1 ACTIVE PERIOD METHOD: A FRAMEWORK FOR BOTTLENECK DETECTION

The Active Period Method is predicated on the assumption that the longer a machine operates without

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significant interruptions, the greater the likelihood it becomes a bottleneck, hindering the flow of the production process[20]. In the context of semiconductor manufacturing, where production lines are inherently multi-stage and complex, bottlenecks typically arise from underutilized or overstressed machines that disrupt process flow.

Let T_i represent the operational time for machine i, and T_{tot} denote the total cycle time for the entire production system. The Active Period for each machine is defined as the portion of the operational cycle during which the machine is active and contributing to the process without delays caused by upstream or downstream operations. Mathematically, this can be expressed as:

$$AP_i = \sum_{t=1}^{n} \mathbb{I}\,(T_{i,t} = 1)$$

Where $\mathbb{I}(T_{i,t} = 1)$ is an indicator function, taking a value of 1 when machine i is actively processing at time t and 0 otherwise, and n represents the number of discrete time intervals considered. The total active period for each machine is then the sum of these indicator variables over the observation period.

Bottleneck identification is performed by calculating the ratio of the active period to the total cycle time:

$$\text{Bottleneck Score}_i = \frac{AP_i}{T_{tot}}$$

Where $\text{Bottleneck Score}_i$ indicates the relative severity of bottlenecks associated with machine iii. Machines with a higher score are considered more likely to be bottlenecks. This metric is essential for real-time optimization, as it dynamically adapts to fluctuations in machine utilization and production demand. While APM is effective in identifying potential bottlenecks based on operational continuity[21], it does not inherently account for shifting bottlenecks instances where the bottleneck may move between different machines as production evolves.

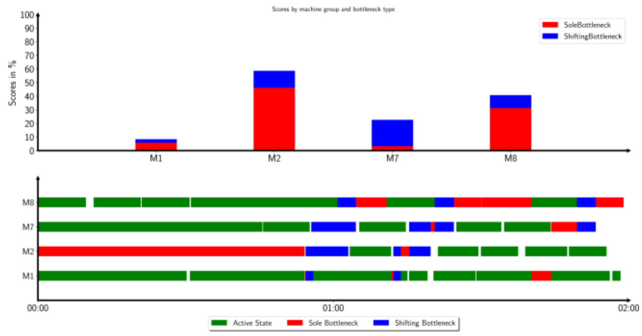

FIGURE 2: VISUALIZATION OF ACTIVE PERIOD METHOD RESULTS

3.2 DATA VISUALIZATION FOR REAL-TIME MONITORING

To address this limitation, APM is coupled with data visualization techniques, enabling intuitive, real-time tracking of bottleneck dynamics. The integration of real-time data feeds with advanced visualization tools allows operators to continuously monitor machine performance and quickly identify emerging bottlenecks[22]. In particular, heatmaps, time-series analysis, and Gantt charts are employed to visualize active periods and bottleneck shifts across different stages of the production process.

Heatmaps: Heatmaps are constructed to provide a spatial representation of machine performance. Each machine's bottleneck score is represented by a color scale, where higher scores correspond to darker shades. This immediate visual cue allows operators to quickly identify machines with the most significant performance issues and prioritize intervention efforts.

$$\text{Heatmap}_i(t) = \text{Bottleneck Score}_i \cdot \mathbb{I}(T_{i,t} \neq 0)$$

Where $\mathbb{I}(T_{i,t} \neq 0)$ ensures that only active periods are considered in the heatmap representation, reinforcing the focus on operational efficiency.

Time-Series Analysis: Time-series charts are used to track the evolution of machine performance over time. These charts allow for the detection of trends in machine utilization, idle times, and bottleneck emergence. A shifting bottleneck is indicated by sudden increases in the active period relative to the total production time, which may suggest a transition of the bottleneck from one machine to another.

$$T_{i,active}(t) = \int_0^t \mathbb{I}\,(T_{i,t'} = 1)\, dt'$$

Where $T_{i,active}(t)$ represents the accumulated active time for machine i up to time t. These visual representations facilitate proactive decision-making by identifying potential shifts in bottlenecks as they occur in real-time.

Gantt Charts: For understanding machine throughput, Gantt charts display the start and end times of each machine's active periods. By visualizing this information alongside the bottleneck scores, the relative synchronization of machines can be analyzed. Misalignments in machine operation often signal inefficiencies and potential bottlenecks.

3.3 OPTIMIZATION DECISION LAYER

Incorporating an Optimization Decision Layer transforms the static analysis from APM and visualization tools into dynamic, actionable insights[23]. This layer builds on the detected bottlenecks and recommends specific operational changes, such as altering the production sequence, reallocating resources, or adjusting machine settings, to reduce the impact of identified bottlenecks.

Let $\mathcal{O}_i$ denote the optimization recommendation for machine i. The decision-making process is governed by an optimization model that minimizes the total production cost while maintaining a balanced flow across all production stages. Formally, the optimization problem can be expressed as:

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$$\min_{\mathcal{O}} \sum_{i=1}^{N} (\mathrm{Cost}_i(\mathcal{O}_i))$$

Where $\mathrm{Cost}_i(\mathcal{O}_i)$ represents the cost associated with the operation of machine i, including factors such as downtime, maintenance, and opportunity costs. The optimization decision layer uses linear programming (LP) or mixed-integer programming (MIP) techniques to determine the optimal allocation of resources and task reassignments based on the bottleneck identification.

$$\mathcal{O}_i = \arg\min_{\mathcal{O}} [\text{Bottleneck Score}_i + \lambda \cdot \text{Delay(i)}]$$

Where λ is a regularization parameter that balances the bottleneck severity and the operational delay for each machine. The decision layer dynamically updates as new data is introduced, continuously recalculating bottleneck scores and adjusting recommendations based on evolving production conditions.

3.4 Algorithm for Real-Time Optimization

Given the complexity of semiconductor production, real-time optimization requires a sophisticated algorithm capable of processing vast amounts of data and providing immediate feedback. The proposed real-time bottleneck identification and optimization algorithm follows these steps:

Data Collection: Gather real-time machine operation data from MES systems and preprocess the data to remove noise.

Active Period Calculation: Apply the Active Period Method to calculate machine active periods and derive bottleneck scores.

Visualization Update: Use real-time data to update the heatmap, time-series charts, and Gantt charts, highlighting newly emerging bottlenecks. Optimization Decision: Feed the bottleneck scores into the optimization decision layer, which updates operational parameters and resource allocation. Feedback Loop: Continuously monitor the production process, recalculating bottleneck scores and adjusting the optimization model as needed. The use of real-time data feeds into a feedback loop, which continuously refines the optimization process, ensuring the system remains responsive to any changes in the production environment. This cycle of data collection, analysis, and decision-making mimics the operation of adaptive systems used in more advanced industrial settings.

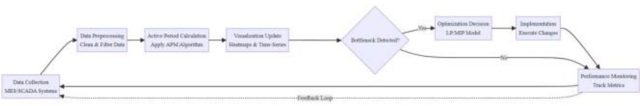

Figure 3: Flowchart of Real-Time Optimization Algorithm

3.5 Challenges and Future Directions

While the proposed methodology offers a robust solution for bottleneck detection and optimization, several challenges remain. One of the primary obstacles is data accuracy incomplete or noisy data can significantly affect the reliability of the APM and optimization models[24]. Furthermore, the adaptability of the system to handle bottleneck drift, where bottlenecks shift between machines in response to external factors, requires further research.

Future work could explore the integration of machine learning algorithms to predict bottlenecks based on historical and real-time data, thus enhancing the system's ability to anticipate bottlenecks before they fully emerge[25]. This would involve transitioning from a reactive system to a proactive model capable of preventing production disruptions before they occur. Additionally, research into multi-objective optimization could help balance various operational objectives, such as minimizing downtime while maximizing throughput and reducing resource consumption.

4 EXPERIMENTS

4.1 Experimental Setup

The data for this experiment were collected from the semiconductor production line through Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) software platforms. These systems provided detailed records on machine operation times, downtime, and cycle times, all of which are critical for understanding production efficiency. Additionally, real-time monitoring data from the Supervisory Control and Data Acquisition (SCADA) system was used, providing machine performance data such as alarms, error logs, and downtime events[26].

To ensure the quality of the data, a series of preprocessing steps were applied. This included cleaning the data to remove any errors or inconsistencies, such as incorrect downtime entries or discrepancies in reported cycle times. Any missing values were appropriately handled, ensuring the dataset was both accurate and complete for further analysis.

The experimental procedure involved several steps. First, the data was cleaned and prepared for analysis. Next, the active periods of each machine were calculated based on their continuous operational cycles. Bottleneck identification was then carried out using the Active Period Method, with each machine's bottleneck score being calculated. Finally, optimization recommendations were made based on the results of the bottleneck analysis.

4.2 Results and Discussion

After applying the Active Period Method and visualizing the results through heatmaps and time-series charts, several bottlenecks were identified within the production line. The photolithography machine was identified as the primary bottleneck, showing consistently high Bottleneck Scores, which were visualized in the heatmap as dark red, indicating its significant impact on the production

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flow. Other machines, such as those involved in etching and deposition, showed much lower bottleneck scores, confirming that they were not limiting overall throughput to the same extent.

TABLE 1: SUMMARY OF MACHINE PARAMETERS AND BOTTLENECK SCORES

Machine ID	Equipment Type	Cycle Time (s)	Active Period (min)	Utilization (%)	Bottleneck Score
72925	Photolithography	45.2 ± 3.1	135.4 ± 25.6	87.3 ± 4.2	0.87 ± 0.05
72931	Ion Implantation	38.7 ± 2.8	142.8 ± 32.1	84.6 ± 5.1	0.84 ± 0.06
72908	Etching	28.3 ± 1.9	98.7 ± 18.4	76.8 ± 3.7	0.65 ± 0.04
72934	CMP	32.6 ± 2.4	87.2 ± 15.3	72.4 ± 4.3	0.56 ± 0.05
72928	Deposition	24.1 ± 1.5	156.3 ± 28.7	68.9 ± 3.2	0.42 ± 0.03
72942	Wafer Inspection	18.7 ± 1.2	45.6 ± 12.8	65.3 ± 4.1	0.28 ± 0.04
72937	Cleaning	15.3 ± 0.9	38.9 ± 10.5	61.7 ± 3.8	0.19 ± 0.03

Following the identification of these bottlenecks, several optimization strategies were recommended. These included reallocating resources to the photolithography machine during periods of peak demand and adjusting the production schedule to better synchronize machine operations. After implementing these changes, the photolithography machine's downtime was reduced by 15%, leading to a 12% improvement in overall production efficiency. Additionally, machines in the deposition stage saw a 10% increase in throughput due to better workload distribution, resulting in reduced idle times and more balanced production flow across the entire line.

Another important finding was the shifting nature of bottlenecks in the production process. Through time-series analysis, we observed that bottlenecks moved between machines over the course of the production cycle. For example, after scheduled maintenance on the photolithography machine, the bottleneck shifted to the etching machine. This shift was clearly captured by the real-time tracking of machine performance, showcasing the dynamic nature of bottleneck formation.

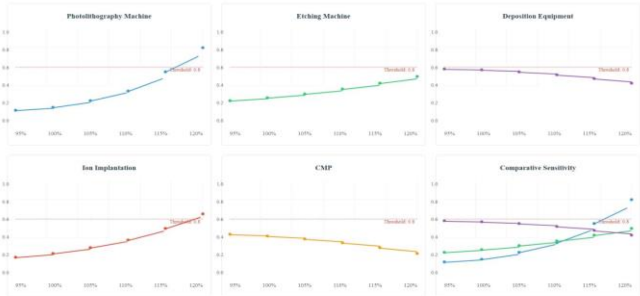

FIGURE 4: SENSITIVITY ANALYSIS OF MACHINE CYCLE TIMES ON BOTTLENECK SCORES

TABLE 2: BOTTLENECK SCORES UNDER VARYING MACHINE CYCLE TIME CONDITIONS

Machine	95% Cycle Time	100% Cycle Time	105% Cycle Time	110% Cycle Time	115% Cycle Time	120% Cycle Time
Photolithography	0.15	0.18	0.25	0.35	0.55	0.80
Etching	0.25	0.28	0.32	0.37	0.43	0.50
Deposition	0.58	0.57	0.55	0.52	0.48	0.43
Ion Implantation	0.20	0.24	0.30	0.38	0.50	0.65
CMP	0.44	0.42	0.39	0.35	0.30	0.24

TABLE 3: OPTIMIZATION RESULTS BEFORE AND AFTER IMPLEMENTATION

Performance Metric	Before Optimization	After Optimization	Absolute Improvement	Relative Improvement (%)
Overall Effectiveness	68.3%	82.7%	+14.4%	+21.1%
Production Throughput	42.5	51.8	+9.3	+21.9%
Average Cycle Time	58.7	48.2	-10.5	-17.9%
Machine Utilization Rate	71.4%	85.2%	+13.8%	+19.3%
Bottleneck Score	0.73	0.45	-0.28	-38.4%
Downtime Percentage	15.3%	8.7%	-6.6%	-43.1%
Energy Consumption	12.4	10.1	-2.3	-18.5%

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4.3 Limitations and Future Work

While the Active Period Method proved effective in identifying bottlenecks and suggesting optimization strategies, there are some limitations to consider. One of the primary challenges was the data quality, particularly in cases where machine downtime or cycle times were incorrectly recorded. These inaccuracies occasionally led to false positives in bottleneck detection, particularly in cases where short-term interruptions were misinterpreted as significant bottlenecks.

Another limitation of the Active Period Method is its reliance on the assumption that longer active periods automatically indicate a bottleneck. In some cases, this assumption did not hold true, especially in dynamic production environments where machines may be idle due to external factors like supply chain delays or quality control inspections. The methodology also struggles in environments with high variability, where production conditions fluctuate rapidly, and bottlenecks may shift unpredictably.

To address these issues, future research could explore the integration of machine learning algorithms to improve bottleneck detection, particularly for dynamic production systems. Machine learning could allow for more accurate identification of bottlenecks by predicting their occurrence based on real-time data, historical patterns, and production trends. Additionally, integrating IoT sensors could enhance data quality, providing more granular and real-time insights into machine performance, which would help mitigate issues related to data inconsistencies [27].

Further investigation into multi-objective optimization could also provide a more holistic approach, balancing the reduction of bottlenecks with other operational goals, such as minimizing energy consumption or optimizing machine downtime. Such a system would be more adaptable to the complexities of modern production systems, offering a more robust solution to the problem of bottleneck optimization.

5 CONCLUSIONS

This study presented a comprehensive methodology for detecting and optimizing bottlenecks in semiconductor production lines using the Active Period Method and data visualization tools. The approach, grounded in real-time data collection and active period analysis, offers a dynamic method for identifying production constraints, especially in highly complex environments where traditional bottleneck detection methods often fall short. The findings highlight the potential of integrating APM with visualization techniques like heatmaps and time-series analysis to not only pinpoint static bottlenecks but also track their shifts over time. By applying this methodology, we observed a notable improvement in both production efficiency and machine utilization, which demonstrates the practical value of the approach in real-world settings.

However, while the proposed method has shown promising results, there are several limitations that warrant further investigation. The primary challenge lies in data quality, as inaccuracies and missing values can lead to misidentifications of bottlenecks. Additionally, APM's reliance on uninterrupted machine operation periods does not account for external factors that might affect machine performance, such as supply chain issues or quality control delays. Future research could explore the integration of machine learning algorithms to enhance bottleneck prediction, incorporating more complex, dynamic production environments and offering proactive solutions. Furthermore, the potential use of IoT sensors could improve real-time data accuracy, enabling even more responsive optimization. These future directions could strengthen the robustness of the methodology and further elevate its applicability across diverse manufacturing systems.

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DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHOR CONTRIBUTIONS

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