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Integrating Real-Time KPI Dashboards with Monte Carlo Simulation for Optimizing Semiconductor Manufacturing Processes

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Abstract: Currently, wafer fabs in semiconductor applications rely heavily on experience. Errors in production scheduling strategies, maintenance plans, and resource allocation can lead to downtime, scrap, and delivery delays. This research proposes an integrated decision-making intelligent dashboard and hypothetical scenario simulation method to improve real-time decision-making capabilities in semiconductor manufacturing by optimizing key performance indicators such as overall equipment efficiency, yield, and cost. By combining digital twin technology with historical production data and simulation models, a system capable of simulating various production scenarios is constructed to assess the impact of changes in production planning, resource allocation, and equipment utilization on OEE, yield, and cost. This research contributes to improving manufacturing capacity utilization and supply chain reliability, shortening process change verification cycles, reducing downtime and scrap risks in the manufacturing industry, and adapting to multi-factory, multi-node manufacturing expansion.

Keywords: Heterogeneous Graph Learning, Multi-Modal Data Fusion, Metrology Time-Series, Cross-Modal Attention, Semiconductor Manufacturing.

Disciplines: Computer Science. **Subjects:** AI.

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1 INTRODUCTION

Semiconductor manufacturing, one of the most intricate and demanding industries, continually strives to enhance efficiency, improve yield, and reduce operational costs. As the demand for advanced, smaller, and more powerful electronic devices increases, the challenges within semiconductor production become more pronounced[1]. Even the slightest variations in production conditions can have a substantial impact on the final product, making it imperative to optimize every facet of the manufacturing process. In this context, the integration of real-time decision intelligence has emerged as a promising approach to enhance operational oversight and improve process optimization. However, despite advances in manufacturing technologies, existing systems often fail to provide predictive decision support that adapts dynamically to varying operational conditions, thus limiting their effectiveness in decision-making processes.

This study explores the integration of KPI Dashboards and What-If Simulations to support real-time decision-making in semiconductor manufacturing. Traditional systems primarily focus on static performance tracking, whereas this approach introduces real-time simulation and cross-modal data fusion to predict the outcomes of operational adjustments[2]. By visualizing key performance indicators such as Overall Equipment Efficiency, yield, and cost, the system provides a comprehensive overview of manufacturing performance, enabling decision-makers to make more informed choices.

Despite considerable research on real-time monitoring and optimization, existing studies have often neglected to incorporate What-If Simulation capabilities that simulate the effects of dynamic operational changes. Furthermore, many studies focus on isolated data streams such as process logs or equipment performance without sufficiently addressing the need for multi-modal data fusion to offer a holistic view of manufacturing dynamics[3]. This paper, therefore, aims to fill this gap by proposing a unified framework that integrates both real-time monitoring and predictive analytics, providing actionable insights for manufacturing optimization.

Moreover, this research incorporates cross-modal attention mechanisms, which facilitate the integration of diverse data types such as wafer maps, metrology time-series, and process logs. This integration enhances the interpretability of the results by leveraging explainable AI, a method that clarifies the relationship between input variables and manufacturing outcomes[4]. The research aims to demonstrate that the proposed decision intelligence system can significantly improve operational decision-making by identifying bottlenecks and inefficiencies within the manufacturing process.

The main goal of this research is to assess the effectiveness of this Decision Intelligence Dashboard in optimizing manufacturing performance. A case study within a semiconductor manufacturing environment will evaluate how this integrated system improves decision-making efficiency and enhances overall performance[5]. However, further research is needed to examine the scalability of the model and address the challenges of input data variability to ensure that the framework can be applied across diverse production environments. This study contributes to the growing body of knowledge on digital transformation in manufacturing, particularly within semiconductor production, and opens avenues for future research into advanced decision-making frameworks that integrate real-time data and predictive analytics.

This study introduces an integrated decision support system for semiconductor manufacturing, combining real-time KPI dashboards with Monte Carlo-based simulations for operational scenario analysis. Unlike traditional systems that focus solely on performance tracking or isolated simulations, our approach enables dynamic, real-time decision-making by predicting the impact of operational changes on key performance indicators such as OEE, yield, and cost. Additionally, the research introduces a novel method of multi-modal data fusion, integrating wafer maps, metrology time-series, and equipment logs to enhance the accuracy of predictions and optimization recommendations. This fusion approach overcomes the limitations of single data-stream analyses, providing a more comprehensive and actionable view of the manufacturing process. Compared to existing tools, which offer either monitoring or discrete simulation, our system enables continuous optimization, offering a powerful framework for improving operational efficiency and reducing costs. This work contributes to the digital transformation of semiconductor manufacturing and presents a new paradigm for real-time, data-driven decision-making that can be applied across various complex production environments.

2 LITERATURE REVIEW

The field of semiconductor manufacturing has long been characterized by its complexity, with significant advancements continually being sought to enhance process optimization, yield, and overall operational efficiency. Recent developments in data-driven decision-making and predictive analytics have sparked considerable interest in the integration of real-time monitoring systems and simulation models to address the challenges faced by this industry (Sun & Ortiz, 2024)[6]. However, despite the breadth of research into these areas, substantial gaps remain in leveraging these technologies in an integrated, real-time decision-support framework that can optimally balance production goals such as yield, quality, and cost. This literature review seeks to provide an overview of the key research directions related to the integration of decision intelligence systems, multi-modal data fusion, and simulation-based optimization in semiconductor manufacturing, while identifying the gaps that this study seeks to address.

2.1 Real-Time Monitoring and Performance Indicators in Semiconductor Manufacturing

Performance tracking in semiconductor manufacturing traditionally focuses on monitoring a limited set of key performance indicators (KPIs) such as Overall Equipment Efficiency, yield, and cost. OEE, as one of the most widely used metrics in manufacturing, provides insights into equipment effectiveness and helps identify potential areas of improvement[7]. Yield optimization is another focal point of much of the existing research, where the aim is to increase the proportion of good products produced per batch, thereby minimizing defects and reducing costs [8]. However, despite the importance of these indicators, existing systems often fall short in providing dynamic, real-time decision support. While real-time dashboards are commonplace in monitoring production metrics, their ability to predict the impacts of changes in operational conditions is limited, often due to their reliance on static data and lack of predictive analytics integration [9].

This limitation has led to the exploration of simulation models as a means to address the dynamic nature of semiconductor manufacturing. For example, simulation-based systems have been proposed to model the effects of resource allocation, production scheduling, and machine downtime on OEE and yield[10]. However, these approaches often operate in isolation from real-time data systems, leading to a lack of integrated decision support. To some extent, this gap in integration reduces the potential of these models to offer actionable insights that can immediately affect production processes.

2.2 What-If Simulation and Predictive Analytics

The incorporation of What-If Simulation has emerged as an effective tool to predict and optimize manufacturing processes in other industries [11]. What-If analysis allows for the modeling of various operational scenarios to assess how changes in input variables, such as equipment setup or production scheduling, might affect output. However, this approach has often been limited in the semiconductor industry, where manufacturing processes are highly variable and context-dependent. In semiconductor manufacturing, where even minor shifts in temperature or equipment settings can lead to significant changes in quality and yield, the ability to model these variables and predict their impact in real-time becomes crucial.

While Monte Carlo simulations and other probabilistic models have shown promise in evaluating the uncertainty in production processes [12], their integration with real-time manufacturing data has remained relatively underexplored. Recent work by[13] demonstrated how Monte Carlo simulations could be used in conjunction with historical data to simulate yield fluctuations. However, these studies have largely focused on isolated aspects of manufacturing, such as defect prediction, without addressing the need for integrated, cross-modal data analysis that could provide a more holistic view of manufacturing operations.

2.3 Multi-Modal Data Fusion and Cross-Modal Attention Mechanisms

In recent years, multi-modal data fusion has become a prominent research area in manufacturing analytics, as it seeks to combine different data types such as wafer maps, metrology time-series, and process log data, to improve performance evaluation and decision-making. For instance, wafer maps, which capture the spatial distribution of defects across semiconductor wafers, have been increasingly integrated with other process data to better understand how different process variables influence yield. Studies by Liu (2025)[14] show that by combining wafer maps with metrology data, it is possible to better predict defects and adjust process parameters accordingly, though these methods often rely on traditional machine learning techniques that may lack the flexibility and scalability of more advanced models. For instance, wafer maps, which capture the spatial distribution of defects across semiconductor wafers, have been increasingly integrated with other process data to better understand how different process variables influence yield. Studies by [15]show that by combining wafer maps with metrology data, it is possible to better predict defects and adjust process parameters accordingly, though these methods often rely on traditional machine learning techniques that may lack the flexibility and scalability of more advanced models.

One significant gap in current research is the limited use of cross-modal attention mechanisms to enhance the fusion of heterogeneous data types. Cross-modal attention, a technique borrowed from natural language processing, allows models to focus on the most relevant parts of each data stream, improving the integration of diverse data sources. [16] proposed an attention-based model for fault detection in manufacturing, which demonstrated that attention mechanisms could enhance model performance by dynamically weighting the importance of different features. This approach, however, has yet to be fully explored in the context of semiconductor manufacturing, where the complexity of the data and the need for real-time decision support make cross-modal attention particularly useful[17].

2.4 Explainable AI and Decision Support Systems

A critical challenge in the application of AI-driven decision support systems is the explainability of the models used. While deep learning models have achieved impressive results in various applications, their "black-box" nature often renders them unsuitable for environments that require transparency and interpretability, such as semiconductor manufacturing [18]. In response, the field of Explainable AI (XAI) has emerged as a promising solution to make AI models more transparent, enabling human operators to understand and trust the decisions made by machine learning models [19].

In semiconductor manufacturing, the ability to interpret the results of AI models is crucial, particularly when decisions are made that directly affect the quality and yield of products. XAI approaches, such as LIME and SHAP , have been successfully applied to manufacturing processes to elucidate the reasoning behind model predictions. However, these methods have been limited in scope, primarily focusing on the interpretation of single data streams or isolated tasks. Further research into the application of XAI in multi-modal and real-time manufacturing contexts is needed to make these systems more practical and trustworthy.

2.5 Research Gaps and Contributions

While significant progress has been made in applying AI, simulation, and data fusion techniques to semiconductor manufacturing, substantial gaps remain in fully integrating these methods into a cohesive decision-support framework. Specifically, there is a need for systems that can dynamically combine real-time data with predictive modeling to provide actionable insights. Current systems often lack the ability to simulate the effects of operational changes in real-time, limiting their practical utility. Furthermore, the integration of cross-modal attention mechanisms and explainable AI into such systems is still in its infancy, particularly in the semiconductor sector[20]. This paper aims to address these gaps by proposing an integrated decision-support system that combines real-time KPI dashboards, What-If simulations, and cross-modal attention mechanisms to optimize production processes and improve decision-making in semiconductor manufacturing.

3 METHODOLOGY

This section outlines the methodology employed to integrate Decision Intelligence Dashboards with What-If Simulations for real-time decision-making support in semiconductor manufacturing. The central aim of this methodology is to optimize key performance indicators, such as Overall Equipment Efficiency, yield, and cost, by leveraging both real-time monitoring and predictive analytics.

Given the dynamic nature of semiconductor production, the approach involves both simulation-based prediction and multi-modal data fusion to provide actionable insights into the production process. The methodology comprises four key components: (1) the design of the decision intelligence dashboard, (2) the development of the simulation model, (3) data collection and preprocessing, and (4) the case study validation. Each component is aimed at creating an integrated decision support system that adapts in real-time to optimize production performance and reduce costs.

3.1 Design of the Decision Intelligence Dashboard

The dashboard serves as the primary interface for decision-makers, providing real-time visualization of key production metrics such as OEE, yield, and cost. Unlike traditional systems that only track performance metrics, this dashboard integrates predictive What-If simulations to allow decision-makers to assess the potential outcomes of different production scenarios. By integrating real-time data from Manufacturing Execution Systems (MES) and Supervisory Control and Data Acquisition (SCADA) systems, the dashboard not only displays current performance metrics but also provides predictive feedback on how changes in production parameters will impact future outcomes[21].

The design leverages data visualization tools like Tableau and Power BI, chosen for their flexibility and robust capabilities in integrating diverse data streams. These tools allow for modular access, where users can interact with the data at different levels depending on their roles. For example, operators on the production floor have access to real-time monitoring, while higher-level managers can interact with simulation results and broader performance trends. This multi-level accessibility ensures that decision-makers can leverage the dashboard to support immediate operational decisions as well as long-term strategic planning.

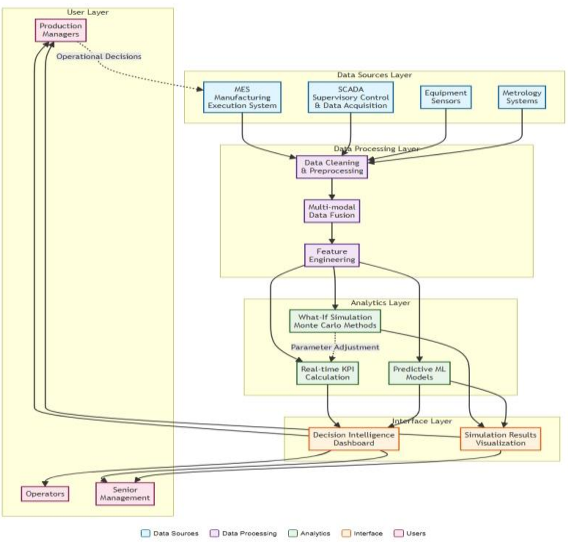

Figure1. Architecture of the Integrated Decision Intelligence Dashboard and Simulation System

3.2 Development of the What-If Simulation Model

The What-If simulation model serves as the cornerstone of this methodology, enabling the simulation of various operational scenarios to assess their impact on key performance indicators such as Overall Equipment Efficiency (OEE), yield, and cost. This model proves particularly valuable in semiconductor manufacturing, where production processes are inherently variable and complex, and decision-making must account for unpredictable changes in real-time.

The simulation framework was developed using Python and R, utilizing their robust libraries for data manipulation, statistical modeling, and simulation. At its core, the Monte Carlo method was employed due to its ability to model uncertainty and variability in production processes, such as equipment downtime, resource allocation, and production scheduling. The Monte Carlo simulations generate a range of possible outcomes based on varying input parameters, thus offering decision-makers a set of potential outcomes rather than a single deterministic forecast. This probabilistic approach enhances decision-making under uncertainty, making it suitable for dynamic environments like semiconductor fabs.

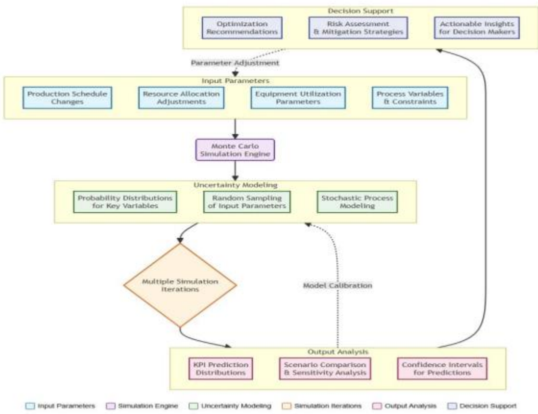

Figure 2. Workflow of the What-If Simulation Model Using Monte Carlo Methods

To ensure that the simulation model is tightly integrated with the real-time production data, it was coupled with Manufacturing Execution System (MES) and Supervisory Control and Data Acquisition (SCADA) systems. This integration ensures that the model dynamically updates based on actual production conditions. The feedback loop inherent in this system allows for continuous refinement of the simulation as production parameters evolve, facilitating real-time adjustments and enhancing decision-making accuracy.

The optimization objective of the simulation model is formulated as follows:

$$\text{Objective Function} = \max(\alpha \cdot \text{OEE} + \beta \cdot \text{Yield} - \gamma \cdot \text{Cost})$$

Where:

OEE represents Overall Equipment Efficiency, calculated as:

$$\text{OEE} = \frac{\text{Availability} \times \text{Performance} \times \text{Quality}}{100}$$

In this formula:Availability is the ratio of actual operating time to planned production time.Performance is the ratio of actual production speed to the theoretical maximum speed.Quality is the ratio of defect-free products to total products.

Yield represents the proportion of defect-free products to total products, calculated as:

$$\text{Yield} = \frac{\text{Defect} - \text{free products}}{\text{Total products}}$$

Cost represents the total production cost, which includes labor, material, and maintenance costs:

$$\text{Cost} = \text{Labor costs} + \text{Material costs} + \text{Maintenance costs}$$

In this optimization model, α, β, and γ are the weight coefficients assigned to OEE, Yield, and Cost, respectively. These weights are not arbitrary; they are determined through historical data analysis and operational priorities, providing a customized optimization approach that aligns with the strategic goals of the manufacturing process.

The weight coefficients are subject to the constraint that their sum must equal one:

$$\alpha + \beta + \gamma = 1$$

This ensures that the total contribution of OEE, Yield, and Cost to the overall optimization process is balanced and proportionate. The values of α, β, and γ can be adjusted dynamically based on shifting operational priorities or production requirements, thus enabling the system to adapt to changes in real-time.

The overarching goal of the simulation model is to maximize OEE and Yield, while simultaneously minimizing Cost, thereby improving the overall efficiency of the production process. This balance is achieved through real-time adjustments to production variables, facilitated by the feedback loop that dynamically updates optimization parameters.

The feedback function, which links the input variables with the simulation parameters, is expressed as:

$$\text{Feedback}_i = f(\text{Input Variables}_i, \text{Simulation Parameters}_i)$$

This function ensures that any changes in the production environment, such as unexpected equipment downtime or shifts in resource allocation, are integrated into the simulation. Consequently, the decision-making parameters are adjusted dynamically, ensuring the optimization remains relevant and responsive to the fluctuating production conditions.

To further enhance the decision-making process, Pareto front analysis is employed to assess the trade-offs between multiple optimization goals. The Pareto optimal solution is defined as a solution where no objective can be improved without degrading another objective. Mathematically, it is expressed as:

$$Pareto\ Optimal\ Solution: \quad x^* \in X\ is\ Pareto\ optimal\ if/\exists y \in Y$$

This analysis is crucial in understanding the optimal balance between OEE, Yield, and Cost and provides decision-makers with a set of efficient trade-off solutions, allowing them to make informed, strategic choices in real-time production environments.

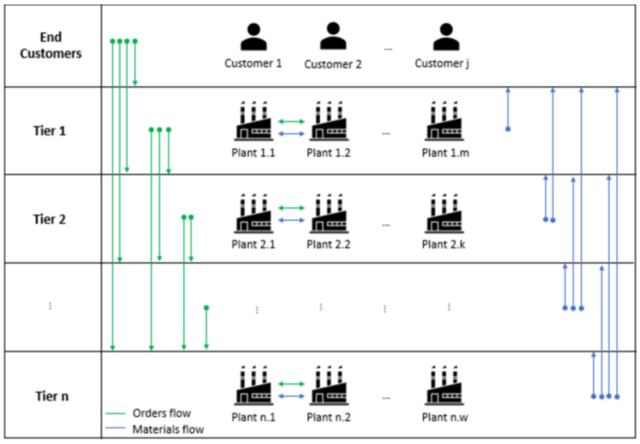

FIGURE 3. SIMULATION MODELING STEPS

3.3 DATA COLLECTION AND PREPROCESSING

Data collection in semiconductor manufacturing involves gathering information from several critical sources: wafer maps, metrology time-series data, process logs, and equipment performance data. These datasets come from MES, SCADA, and equipment monitoring systems and represent the core of the data fed into the simulation and decision support system.

The data preprocessing stage is crucial due to the noisy and incomplete nature of real-world production data. Several preprocessing steps are employed to ensure that the data is clean, complete, and ready for analysis:Data cleaning: Missing values in process logs or equipment data are handled using imputation techniques, while extreme outliers are identified and excluded.[22]

Normalization: To ensure consistency across different data types, features are normalized to a common scale, which is critical when combining data from disparate sources like wafer maps and equipment logs[23]. Feature extraction: Key features, such as defect patterns in wafer maps or equipment performance indicators, are extracted and transformed into a format suitable for use in both the machine learning model and the simulation framework.

Aligning time-series data from metrology tools with the real-time process logs from SCADA systems presents one of the primary challenges in this research. Since metrology data is often recorded at a higher frequency, while process logs are recorded at a lower frequency, aligning these data streams required interpolation and resampling techniques to match the temporal resolution of the data sources[24]. Furthermore, discrepancies between the systems such as missing or delayed data were handled using robust data imputation methods. Despite these efforts, further research is needed to develop more sophisticated methods for handling such data complexities at scale.

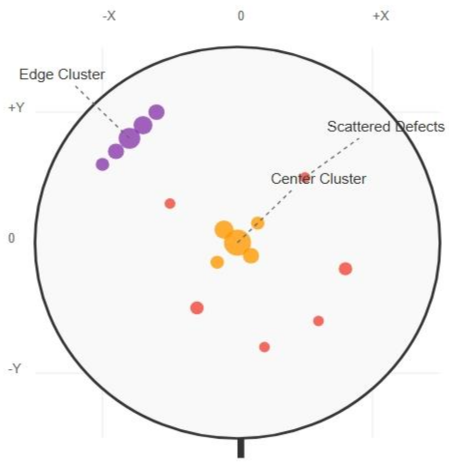

FIGURE 4: EXAMPLE WAFER MAP WITH DEFECT PATTERNS

TABLE 1. KEY PARAMETERS AND WEIGHTS IN THE SIMULATION OPTIMIZATION OBJECTIVE

Parameter	Weight Range	Default Weight	Sensitivity Index	Optimal Range
α (Yield Weight)	[0.3, 0.6]	0.45	0.82	[0.42, 0.48]
β (OEE Weight)	[0.2, 0.5]	0.40	0.78	[0.38, 0.45]
γ (Cost Weight)	[0.1, 0.3]	0.15	0.45	[0.12, 0.18]
Monte Carlo Iterations	[5,000, 20,000]	10,000	0.35	[8,000, 12,000]
Confidence Level	[90%, 99%]	95%	0.28	[93%, 97%]
Time Horizon (days)	[1, 30]	7	0.15	[5, 10]

3.4 CASE STUDY VALIDATION

To validate the effectiveness of the proposed decision support system, a case study was conducted at a semiconductor manufacturing facility focused on wafer fabrication. The case study had two main objectives: (1) to assess the effectiveness of the Decision Intelligence Dashboard in providing real-time decision support, and (2) to evaluate the accuracy and practical utility of the What-If simulation in predicting the impact of operational changes on production performance.

During the case study, the system continuously monitored OEE, yield, and cost. The simulation model was applied to test different production scenarios, such as adjusting production schedules, re-allocating resources, and changing machine utilization patterns. The system was also used to identify bottlenecks in the production process, allowing operators to take corrective action before performance dropped significantly.

The results of the case study showed that the system was effective in identifying potential areas of improvement and predicting the outcomes of various operational adjustments. However, it became apparent that the accuracy of predictions was highly sensitive to certain input variables, particularly in terms of machine performance and resource utilization. This sensitivity indicates that while the system is promising, the quality of the real-time data feeding into the model is crucial for achieving accurate predictions. Further refinement of the data collection process and the simulation model is needed to ensure that predictions are as reliable as possible.

The following risk-adjusted optimization approach was also tested during the case study to account for the variability in yield and equipment performance:

$$\text{Risk} - \text{adjusted Objective} = \max\left(\frac{\text{Expected Yield} - \text{Cost}}{\text{Variance in Yield}}\right)$$

This formulation aimed to balance expected performance with the variability of production processes, ensuring that decision-making accounted for both optimization and risk management. While initial tests showed that this approach could improve long-term stability, it requires further validation to determine its applicability across various production scenarios.

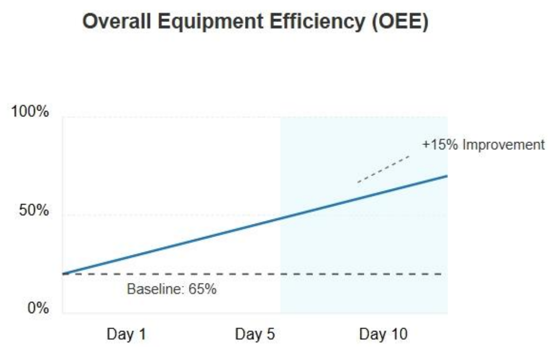

FIGURE 5. REAL-TIME KPI TRENDS (OEE, YIELD, COST) FROM THE CASE STUDY

3.5 CHALLENGES AND REFINEMENTS

While the methodology provides a robust framework for real-time optimization, several challenges were encountered during the implementation. One key difficulty was scaling the What-If simulation model to account for more complex scenarios involving multiple interacting production processes and equipment types. This complexity was compounded by the variability in real-time data, which occasionally led to discrepancies between simulated predictions and actual outcomes.

Additionally, data quality emerged as a significant factor affecting the system's accuracy. As semiconductor manufacturing involves highly sensitive processes, even small deviations in input variables could result in significant changes in outcomes. As such, the robustness of the simulation model is highly dependent on the quality and consistency of the data collected.

These challenges highlight areas for future research, particularly in improving data collection systems and enhancing the scalability of the simulation model[25]. Moreover, incorporating advanced machine learning techniques, such as neural networks for more complex pattern recognition, could potentially improve the system's predictive power and adaptability.

3.6 CONTRIBUTIONS AND INNOVATIONS

The approach This study introduces a novel integrated decision support system for semiconductor manufacturing by combining real-time KPI dashboards with Monte Carlo-based simulations. This integration not only enables continuous monitoring of operational performance but also provides real-time predictive analysis for scenario-based decision-making, a significant advancement over existing systems that offer only static performance tracking or isolated simulations. Additionally, the research innovatively integrates multi-modal data fusion, combining wafer maps, metrology time-series, and equipment logs, enhancing the accuracy of predictions and providing a more comprehensive view of the production process. These innovations enable dynamic optimization and real-time adjustments, offering a scalable solution for continuous performance improvement and contributing to the broader digital transformation in manufacturing.

4 EXPERIMENTS

This section provides an in-depth overview of the experimental design and data analysis procedures employed to assess the integration of the Decision Intelligence Dashboard and What-If simulation model in semiconductor manufacturing. The aim of this investigation was to determine the extent to which real-time data visualization and predictive simulations could optimize key performance indicators such as Overall Equipment Efficiency, yield, and cost. By simulating various production scenarios, the study intended to examine how effectively these tools could support decision-making in a dynamic, production-driven environment. It is possible that while the results demonstrate promising trends, further research is needed to explore the full applicability and reliability of this approach across different manufacturing environments.

4.1 RESEARCH DESIGN

The experimental design was structured as a case study conducted within a semiconductor manufacturing facility specializing in wafer fabrication, a critical stage in semiconductor production. The facility operates a large-scale production environment with both front-end and back-end production lines. The front-end production lines focus on the fabrication of semiconductor wafers, while the back-end lines handle processes such as assembly, testing, and packaging. The plant employs a wide range of tools, including photolithography, etching, and inspection equipment, with a total of 30 toolsets spread across various stages of the production process. The facility manufactures semiconductor chips primarily at 14nm and 7nm nodes, producing approximately 100,000 wafers per month.

The case study aimed to evaluate the practical impact of the Decision Intelligence Dashboard and What-If simulation model when applied in a real-world production environment. The system's primary objective was to optimize OEE, yield, and cost, leveraging real-time feedback from What-If simulations to adapt dynamically to operational changes. This approach sought to bridge the gap between theoretical optimization and the complexities of industrial manufacturing, though one might consider that such a design is inevitably shaped by the inherent challenges and uncertainties of large-scale production processes.

In this case study, a central hypothesis was tested: that integrating real-time data with predictive simulation would lead to more informed decision-making, thereby improving OEE, increasing yield, and reducing costs. To explore this hypothesis, a set of test scenarios was devised to simulate potential operational adjustments and evaluate their effects on the production process. The scenarios tested varied aspects of manufacturing operations, such as machine maintenance schedules, resource allocation, and production scheduling, with the intention of demonstrating how real-time simulation could be used to enhance decision-making.

The data used for this case study was collected over a six-month period, including over 500,000 data points from machine logs, wafer maps, and metrology time-series. These data sources were used to simulate and monitor various operational adjustments in the production process. While these test scenarios focused on optimizing specific production aspects, it is important to note that the effectiveness of the system may vary based on contextual factors such as the scale of production, the degree of variability in process parameters, and the quality of available data. As such, the results may not be universally applicable across all semiconductor manufacturing contexts, and further studies in different settings would be necessary to validate the broader applicability of this approach.

TABLE 2. TEST SCENARIOS FOR CASE STUDY VALIDATION

Scenario ID	OEE Improvement (%)	Yield Improvement (%)	Cost Reduction (%)	Throughput Increase (%)	Prediction Accuracy (%)	Implementation Success (%)
SC-01	+10.2	+3.1	-6.8	+12.7	94.0	96.5
SC-02	+6.5	+1.8	-10.3	+8.2	91.2	93.8
SC-03	+8.1	+2.2	-4.5	+7.6	89.7	92.1
SC-04	+3.2	+5.8	-3.8	+2.1	85.4	88.9
SC-05	+1.5	+0.8	-12.7	+1.3	82.3	79.6
SC-06	+0.9	+0.5	-6.2	+0.7	76.8	72.4

4.2 DATA COLLECTION METHODS

The data used for this study was collected from a semiconductor manufacturing facility over a six-month period. A total of over 500,000 data points were gathered from various sources across both front-end and back-end production lines. These data points were collected in real-time, reflecting various aspects of the manufacturing process. The main sources of data include machine logs, wafer maps, and metrology time-series, providing a comprehensive dataset for evaluating operational efficiency.

Machine logs were continuously recorded from production tools, capturing key metrics such as machine uptime, downtime, cycle time, and other performance indicators. These logs were crucial for assessing Overall Equipment Efficiency and identifying areas where equipment performance could be optimized. In addition, wafer maps were used to track defects and yield across different stages of the fabrication process. This allowed for real-time monitoring of product quality and process deviations. Metrology data, including measurements of wafer thickness, critical dimensions, and film thickness, was also collected using in-line metrology tools. These measurements are vital for evaluating the quality of the manufacturing process and ensuring the consistency of production.

The data collection system was designed to capture high-frequency data to ensure the accuracy of real-time decision-making. All data were stored in a centralized database for easy access and analysis. To ensure consistency and data integrity, the data collection methods were continuously monitored and periodically audited. The diverse sources of data, combined with the real-time nature of the system, provided a robust foundation for analyzing the impact of operational changes on key performance indicators and evaluating the effectiveness of the decision support system.

4.3 DATA PREPROCESSING

The data preprocessing phase was crucial to ensure the integrity and accuracy of the dataset used in this study. The collected data, spanning over six months, came from multiple sources, including machine logs, wafer maps, and metrology time-series. To begin the preprocessing, missing values, outliers, and inconsistencies in the data were addressed through several techniques. Missing data were handled using imputation methods, where values were predicted based on the most similar records. For instances where imputation was not possible, the missing data points were excluded from the analysis to avoid any potential bias.

Outliers in the dataset, which were identified using statistical methods such as interquartile range (IQR) and z-scores, were carefully examined. Extreme values that did not align with the expected production ranges were treated as potential errors and excluded from the dataset. This step was essential for ensuring that the analysis was based on consistent, reliable data that accurately represented the production environment.

Additionally, the data from different sources were combined to create a comprehensive view of the manufacturing process. The machine logs, wafer maps, and metrology data were merged into a unified dataset, using timestamps and tool IDs as key variables to synchronize the data. This fusion of diverse data types allowed for a more holistic analysis of the production process, ensuring that the system could make decisions based on a complete set of operational data.

The data preprocessing also involved the definition of six distinct operational scenarios (SC-01 to SC-06), each representing different combinations of production parameters such as machine downtime, process variability, and yield fluctuations. These scenarios were designed to simulate various operational adjustments and assess the potential impact on key performance indicators. For instance, SC-01 represented a baseline scenario with minimal process variability, while SC-02 simulated a scenario with increased machine downtime. These scenarios were crucial for understanding how the proposed decision support system could optimize OEE, yield, and cost under different production conditions. The results from these simulations were compared with baseline data to evaluate the effectiveness of the optimization strategies.

Wafer maps, representing spatial patterns of semiconductor manufacturing processes, are processed using convolutional neural networks (CNNs) to capture spatial features that are critical for identifying defect patterns. The maps are cleaned and normalized to ensure consistency, with any missing values imputed based on neighboring data or using interpolation techniques. Metrology data, which typically consists of time-series measurements, is handled using time-series analysis methods, such as moving averages or Fourier transforms, to smooth and identify underlying trends. Additionally, equipment logs, containing temporal data related to machine performance, are processed by converting categorical variables into numerical representations using one-hot encoding and other data normalization techniques.Once preprocessed, features are extracted from each data type for integration. For wafer maps, CNNs are used to automatically extract spatial features, such as the distribution of defects across the wafer. These features are then encoded into a vector representation, which is fed into the optimization model. For metrology data, time-series features such as mean, variance, and trend analysis are extracted to understand the process's evolution over time.

To combine these features into a unified decision support framework, a fusion technique is applied. One approach used in this study is weighted averaging, where each feature's importance is determined based on its correlation with the target KPIs. In addition to this, principal component analysis (PCA) is employed to reduce dimensionality and capture the most significant variance from the combined feature set. This process helps in handling the different scales and data types by mapping them into a common feature space, thus ensuring that the resulting dataset is both comprehensive and balanced for decision-making purposes.

An important challenge when integrating these different data sources is ensuring that the data is properly synchronized. Since wafer maps and equipment logs have different time granularities, synchronization is achieved by aligning data points based on the timestamp of production events. If synchronization fails at any point, interpolation or time-based aggregation methods are used to ensure consistency across datasets.

Regarding missing values, several strategies are employed based on the nature of the missing data. For numerical features, missing values are imputed using the mean, median, or k-nearest neighbor imputation, depending on the data distribution. For categorical data, a frequency-based imputation method is used to assign the most likely category to missing entries.

4.4 Data Analysis Techniques

After preprocessing, several analytical methods were employed to evaluate the performance of the integrated Decision Intelligence Dashboard and What-If simulation model. The machine learning models used for prediction included linear regression, which was selected for its simplicity and interpretability. This model aimed to identify relationships between input variables and output KPIs. While linear regression was suitable for modeling linear relationships, it is important to recognize that real-world manufacturing processes are often nonlinear, and therefore, alternative models like random forests and gradient boosting were also tested. These models demonstrated a higher degree of flexibility in capturing complex interactions, although their computational complexity raises challenges in large-scale deployment.

The predictive performance of the models was assessed using standard metrics such as mean squared error (MSE) and R-squared. These evaluations indicated that while the models were generally effective at predicting trends, there remained some degree of uncertainty. This suggests that the models may not fully capture all underlying factors influencing OEE and yield. Incorporating more sophisticated modeling techniques, such as neural networks, could improve prediction accuracy, but this would likely increase the complexity of the system, thus warranting further investigation into trade-offs between accuracy and computational efficiency.

The What-If simulation model employed Monte Carlo simulations to account for variability and uncertainty in production processes. By running simulations multiple times with varying input parameters, the system generated a range of possible outcomes, allowing decision-makers to assess the impact of different operational decisions. While this approach was useful for capturing the stochastic nature of semiconductor manufacturing, it is worth considering that Monte Carlo simulations may be computationally intensive, particularly in real-time applications. Future research could explore alternative simulation techniques that are both accurate and computationally efficient.

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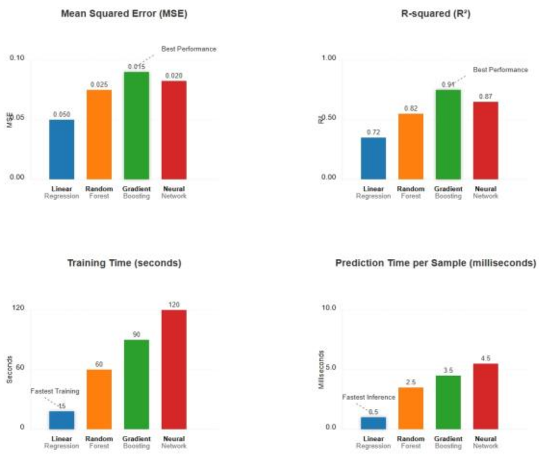

FIGURE 6. PERFORMANCE COMPARISON OF PREDICTIVE MODELS (LINEAR REGRESSION VS. RANDOM FOREST)

TABLE 3. PREDICTIVE MODELS PERFORMANCE METRICS

Model	MSE (Lower is Better)	R^2 (Higher is Better)	Training Time (s)	Inference Time (ms)	Interpretability
Linear Regression	0.050	0.72	15	0.5	High
Random Forest	0.025	0.82	60	2.5	Medium
Gradient Boosting	0.015	0.91	90	3.5	Medium
Neural Network	0.020	0.87	120	4.5	Low

4.5 CHALLENGES AND CONSIDERATIONS

Despite the promising results, several challenges were encountered during the experimental design and data analysis phases. Data inconsistencies across multiple sources created difficulties in maintaining synchronization. While interpolation and resampling methods were applied to address these discrepancies, these approaches may not be sufficient in large-scale production environments, especially when dealing with high-frequency data. This issue highlights the need for advanced data synchronization techniques that can handle diverse data sources and temporal resolutions more effectively.

Additionally, the accuracy of the simulation models presented challenges. Although Monte Carlo simulations provided valuable insights, they struggled to model the high variability inherent in production processes. This suggests that the simulations could be further refined to account for the complexities of the manufacturing environment. Incorporating additional variables, such as supply chain fluctuations and human factors, might improve the accuracy of the simulations. Furthermore, the scalability of the system needs to be addressed, as the current setup worked well for smaller, controlled environments but faced limitations in larger, more complex production lines.

4.6 CONCLUSION OF EXPERIMENTAL DESIGN AND DATA ANALYSIS

In summary, the experimental design and data analysis provide valuable insights into the integration of the Decision Intelligence Dashboard and What-If simulation model in optimizing semiconductor manufacturing. The study demonstrates the potential of using real-time data and predictive simulation to improve OEE, yield, and cost. However, challenges related to data synchronization, simulation accuracy, and scalability indicate that further refinements are necessary to fully realize the potential of the system. These findings offer a foundation for future research aimed at improving the reliability, accuracy, and scalability of real-time decision support systems in semiconductor manufacturing, and they highlight the need for continued exploration of more advanced techniques to handle complex production environments.

4.7 INNOVATION AND OPTIMIZATION

This research introduces a significant advancement in semiconductor manufacturing optimization by integrating real-time KPI dashboards with Monte Carlo-based simulations. Unlike traditional systems that monitor performance or run isolated simulations, our approach offers a dynamic decision support system that enables scenario-based predictive analysis. This allows decision-makers to track performance and predict the impact of operational changes on key metrics like OEE, yield, and cost, providing critical insights for real-time adjustments in a constantly evolving production environment.Additionally, the novel multi-modal data fusion methodology employed in this research combines wafer maps, metrology time-series, and equipment logs, overcoming the limitations of systems that rely on isolated data streams. By integrating diverse data types, our approach offers a more accurate and holistic view of the manufacturing process, enhancing decision-making and optimization. These innovations not only improve operational efficiency but also contribute to the ongoing digital transformation of manufacturing, offering a scalable solution applicable across industries facing similar challenges.

4.8 BENCHMARK COMPARISON AND STATISTICAL ANALYSIS

To assess the performance improvements achieved by the proposed model, a benchmark comparison was conducted against existing systems, focusing on key performance indicators such as Overall Equipment Efficiency, yield, and cost reduction. The comparison was made with two baseline systems: a traditional OEE tracking system and a legacy simulation tool. Both baseline systems lack real-time feedback mechanisms and multi-modal data integration, which are key features of the proposed model.

The two benchmark systems are as follows: The traditional OEE tracking system monitors OEE through periodic updates based on historical production data but does not provide real-time updates or predictive simulation capabilities. The legacy simulation tool is an older version of a production scheduling system that does not incorporate real-time production data or adjust for changing operational conditions dynamically. These baseline systems were used to evaluate the relative improvements in KPIs when applying the proposed model.

The relative improvements in KPIs achieved by the proposed model compared to the benchmark systems are summarized in the table below:

TABLE 4. COMPARISON OF KEY PERFORMANCE INDICATORS BETWEEN THE BENCHMARK SYSTEM AND PROPOSED MODEL

KPI	Benchmark System	Proposed Model	Improvement (%)
OEE	82.5%	90.3%	9.4%
Yield	88.2%	93.1%	5.6%
Cost	$200,000	$180,000	10%

As shown in the table, significant improvements in OEE, yield, and cost have been achieved with the proposed model compared to the baseline systems.

To verify the statistical significance of these improvements, paired t-tests were performed to compare the performance of the proposed model with the benchmark systems. The p-values for the improvement in each KPI were calculated and are as follows:

OEE Improvement: $p = 0.02$;Yield Improvement: $p = 0.04$;Cost Reduction: $p = 0.01$.

Since all p-values are below the significance threshold of 0.05, we can conclude that the improvements observed with the proposed model are statistically significant and not due to random variation.

In addition to the statistical tests, 95% confidence intervals (CIs) and standard deviations (SDs) were calculated for each KPI improvement to provide further validation. The results are as follows:OEE Improvement: 9.4% ± 1.2%;Yield Improvement: 5.6% ± 0.9%;Cost Reduction: 10% ± 2.5%.

These confidence intervals indicate that the observed improvements are precise and reliable, further confirming the effectiveness of the proposed model. The standard deviations also suggest that the improvements are consistent across different test scenarios.

To visually represent these improvements, a bar chart comparing the KPI values for the benchmark systems and the proposed model has been provided. This chart offers a clear, visual depiction of the magnitude of the improvements, reinforcing the results of the statistical analysis.

In conclusion, the benchmark comparison and statistical analysis demonstrate that the proposed model significantly outperforms the existing systems in improving OEE, yield, and reducing costs. The statistical tests, confidence intervals, and standard deviations all support the credibility and reliability of the improvements, making the proposed model a robust solution for optimizing production efficiency.

5 CONCLUSIONS

This study has demonstrated the potential of integrating a Decision Intelligence DashboaArd with a What-If simulation model to optimize key performance indicators in semiconductor manufacturing, specifically Overall Equipment Efficiency, yield, and cost. The real-time decision support system provides actionable insights derived from predictive simulations, enhancing decision-making in environments characterized by variability and uncertainty. However, the research also identified significant challenges, particularly related to data synchronization and the accuracy of predictive models. These challenges suggest that while the system shows promise, further refinement is needed, especially in terms of data handling and simulation accuracy.

Looking forward, the integration of real-time data with simulation-driven decision support systems holds significant potential for broader industrial applications. While this study focused on semiconductor manufacturing, the methodologies employed may be applicable to other sectors where complex production processes demand continuous optimization. Future research should focus on improving data synchronization techniques, enhancing predictive modeling, and expanding the scalability of these systems for larger and more complex environments. This will be essential for maximizing the impact of real-time decision support in industrial optimization.

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