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A Monte Carlo Simulation Approach to Decision Analytics in Manufacturing and Industrial Automation Project Management

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Abstract

Manufacturing and industrial automation projects face high uncertainty and risk arising from factors such as complex supply chains, equipment variability, and fluctuating production demands. If not properly managed, these uncertainties can lead to costly delays, unplanned downtime, and budget overruns that jeopardize project success. Given the shortcomings of deterministic planning in such volatile environments. If not properly managed, it can lead to costly delays and failures if not properly managed. Monte Carlo Simulation (MCS) serves as a potent instrument for decision analytics in addressing uncertainty within industrial automation and manufacturing contexts. It offers a proactive approach to address this challenge by modeling uncertainties and generating a range of possible outcomes. Unlike traditional single-point estimations, MCS runs thousands of simulations to produce a probability distribution of project outcomes, enabling more robust risk assessment and forecasting. This paper proposes decision analytics framework that integrates MCS into project management for manufacturing and industrial automation. MCS to enhance production planning, mitigate operational risks, and reduce costs, utilizing semiconductor manufacturing as a representative case study. The research illustrates a methodological application of MCS for robust decision-making by assessing multiple production scenarios and deriving probabilistic inferences. The proposed approach encompasses comprehensive data collection, simulation model development, sensitivity analysis, and customized risk mitigation strategies. The findings indicate that MCS enhances decision accuracy despite uncertainty-induced downtime and results in substantial cost reductions. These outcomes further highlight the utility of MCS in industrial automation, where its stochastic insights can facilitate adaptive control systems to promptly adjust operations in response to uncertainty.

Keywords: Monte Carlo Simulation, decision analytics, semiconductor industry, project management, risk management, uncertainty analysis, probabilistic forecasting, supply chain optimization, operational efficiency, sensitivity analysis

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INTRODUCTION

Context

Monte Carlo Simulation (MCS) is extensively employed as an analytical technique in project management for risk assessment and probabilistic forecasting. It enables decision-makers to account for uncertainty by simulating numerous potential outcomes based on varying inputs. In the industrial automation and manufacturing sectors, the complexity of supply chains and production processes, coupled with substantial capital investments, necessitates proactive risk anticipation. In the semiconductor industry, frequent equipment failures, supplier delays, and yield variability can significantly impact project timelines and costs. Although many organizations are eager to implement MCS, challenges such as data complexity, computational demands, and integration issues with existing management systems have hindered its widespread adoption. In rapidly evolving manufacturing markets, it is nearly impossible to prevent all disruptions or delays; however, MCS provides a means to quantitatively assess and prepare for these uncertainties. Consequently, modern industrial environments increasingly depend on adaptive control strategies that automatically adjust process parameters based on real-time feedback to manage variability and maintain stable performance.

Aim

The aim of this study is to apply Monte Carlo Simulation to aid effective decision-making in industrial automation and manufacturing projects. The study models uncertainties such as production yields, machine reliability, and supply chain disruptions in order to improve risk assessment, minimize operational downtime, optimize costs, and enhance overall project outcomes.

Objectives

- To investigate the primary uncertainties influencing the management of industrial manufacturing projects
- To develop a Monte Carlo Simulation model for probabilistic forecasting and scenario analysis
- To determine the effect of different variables on project performance
- To provide effective risk-mitigating strategies to reduce downtime and operational risks
- To offer actionable insights to improve decision-making and optimize costs

PROBLEM STATEMENT

The application of Monte Carlo Simulation (MCS) practices within the manufacturing sector has proven challenging in terms of demonstrating their theoretical benefits. In the realm of industrial automation and manufacturing, significant uncertainties—such as fluctuating production yields, unpredictable development costs, and volatile supply chains—frequently threaten the success of projects. Traditional deterministic models and standard risk assessment techniques are inadequate in addressing these uncertainties or in guiding resource allocation under conditions of risk. Furthermore, the integration of Monte Carlo methods into existing project management frameworks presents complexities that have impeded the broader adoption of MCS. In the absence of a probabilistic approach like MCS, decision-makers are deprived of effective tools to optimize project outcomes, resulting in increased operational risks, cost overruns, and delayed product launches.

PROPOSED SOLUTION

Monte Carlo Simulation (MCS) offers a data-driven framework for addressing uncertainty and quantifying risks in complex industrial projects. Manufacturing project environments are characterized by unpredictable factors such as material yield variations, equipment failures, and supply chain disruptions, which can adversely affect timelines and budgets. By executing thousands of simulations, MCS produces probabilistic forecasts that enable project managers to make informed decisions based on the likelihood of various outcomes. This section delineates a four-step approach for the effective application of MCS in manufacturing project management. Furthermore, the integration of adaptive control methods can enhance the MCS modeling framework and further refine decision analytics. Previous studies suggest that Monte Carlo simulation can be employed for online policy improvement in adaptive controllers when the system's environment can be virtually modeled [1]. By integrating Monte Carlo Simulation (MCS)-derived probabilistic insights into an adaptive controller, the system can proactively adjust control settings in anticipation of predicted disturbances. Concurrently, feedback from the controller serves to update the simulation parameters, thereby enhancing accuracy [2]. Incorporating probabilistic insights derived from Monte Carlo Simulation (MCS) into an adaptive controller enables the system to adjust control settings in advance of anticipated disturbances. Simultaneously, feedback from the controller is utilized to refine the simulation parameters, thereby improving the accuracy of the system.

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Step 1: Data Acquisition & Preprocessing

Monte Carlo Simulation (MCS) is a powerful tool for modeling complex systems with multiple uncertainties. In manufacturing, several key areas of uncertainty need to be considered for an accurate MCS model. An accurate Monte Carlo Simulation (MCS) model necessitates effective data collection and preprocessing. Within manufacturing domains, it is imperative to capture several key uncertainties for the simulation model, including:

- *Yield variability:* There are many variables in production processes (for example, wafer yields in semiconductor fabrication) can vary. Wafer yields can have variability which may cause production delays and higher scrap rates [3]. Historical yield data and real-time manufacturing data should be obtained.
- *Equipment failure rates:* Equipment malfunctions present significant risks by leading to unplanned downtime. By utilizing predictive maintenance data alongside historical failure logs, it is possible to estimate failure rates for essential machines and components.
- *Supplier lead times:* An important product is critical, the delivery of that very critical product can be delinquent due to supply chain disruptions, geopolitical issues, and logistical challenges [4]. Supplier performance data may also be used to model variability in lead times.
- *Labour productivity:* Uncertainty is further exacerbated by variations in workforce productivity, which can be attributed to factors such as operator experience and absenteeism. By utilizing data from human resource management systems (HRMS), it is feasible to construct models.

The normal distribution is appropriate for variables characterized by symmetrical uncertainty, such as minor equipment failures. The triangular distribution is optimal for estimating uncertain variables with defined ranges, including minimum, maximum, and most likely values. The log-normal distribution is suitable for modeling variables such as lead time, where the occurrence of extreme delays is possible.

Once the relevant data has been collected, proper preprocessing is essential to ensure the quality and reliability of the MCS model. Data preprocessing involves:

- Removal of anomalies and cleaning to avoid data distortion.
- It ensures that data is normalized so that it is compatible between various sources.
- Executing exploratory data analysis (EDA) to see patterns and correlations that can enhance model accuracy.

By carefully considering these key uncertainties, selecting appropriate probability distributions, and properly preprocessing the data, manufacturers can create robust MCS models that provide valuable insights into their production processes and supply chains.

Step 2: Simulation model development

Monte Carlo Simulation (MCS) is a powerful tool for modeling complex manufacturing projects with inherent uncertainties. Following the preparation of data, the subsequent step involves constructing a Monte Carlo Simulation model for the manufacturing project. This simulation model integrates uncertainty with the timeline, costs, and operational parameters, thereby providing a stochastic representation of the project. The step involves key components such as:

- Project timeline simulation: A simulation model is capable of predicting the overall project completion time by utilizing probabilistic estimates for each task. This model can be integrated with factors such as wafer yield, tool maintenance schedules, and human factors variability. By incorporating elements such as production yield, equipment maintenance schedules, and workforce variability, the timeline model can effectively assess their impact on meeting project deadlines. This approach allows for a more realistic estimation of project duration, considering the potential variability in each phase of the manufacturing process.
- Cost modelling: Uncertainties in the prices of raw materials, energy consumption, labor costs, and unintended maintenance impacts should be incorporated. By simulating various cost

scenarios, potential budget overruns can be estimated, and contingency budgets can be planned accordingly [5]. By simulating multiple cost scenarios, managers can better prepare for financial risks and allocate resources more effectively.

- Production capacity simulation: Identify operations that may influence the throughput of the production line under varying conditions. This analysis facilitates the determination of the likelihood of failing to meet production targets across different scenarios and identifies which processes are most susceptible to disruptions. These components work together to create a comprehensive model that accounts for various project uncertainties and their interactions

Advanced manufacturing encompasses a series of intricate and meticulously controlled processes, such as the fabrication of integrated circuits on silicon wafers. Within the Monte Carlo Simulation (MCS) model, input variables are assigned values randomly selected from predefined probability distributions in each iteration, thereby generating a range of potential project outcomes. To mitigate extensive manual labor and ensure model accuracy, specialized simulation software platforms are employed. These tools are integrated with existing Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES) to facilitate real-time data updates [6]. Figure 1 illustrates the semiconductor manufacturing process.

Step 3: Sensitivity & Scenario Analysis

Sensitivity and scenario analysis are important in learning about risks and mitigating risks in manufacturing operations.

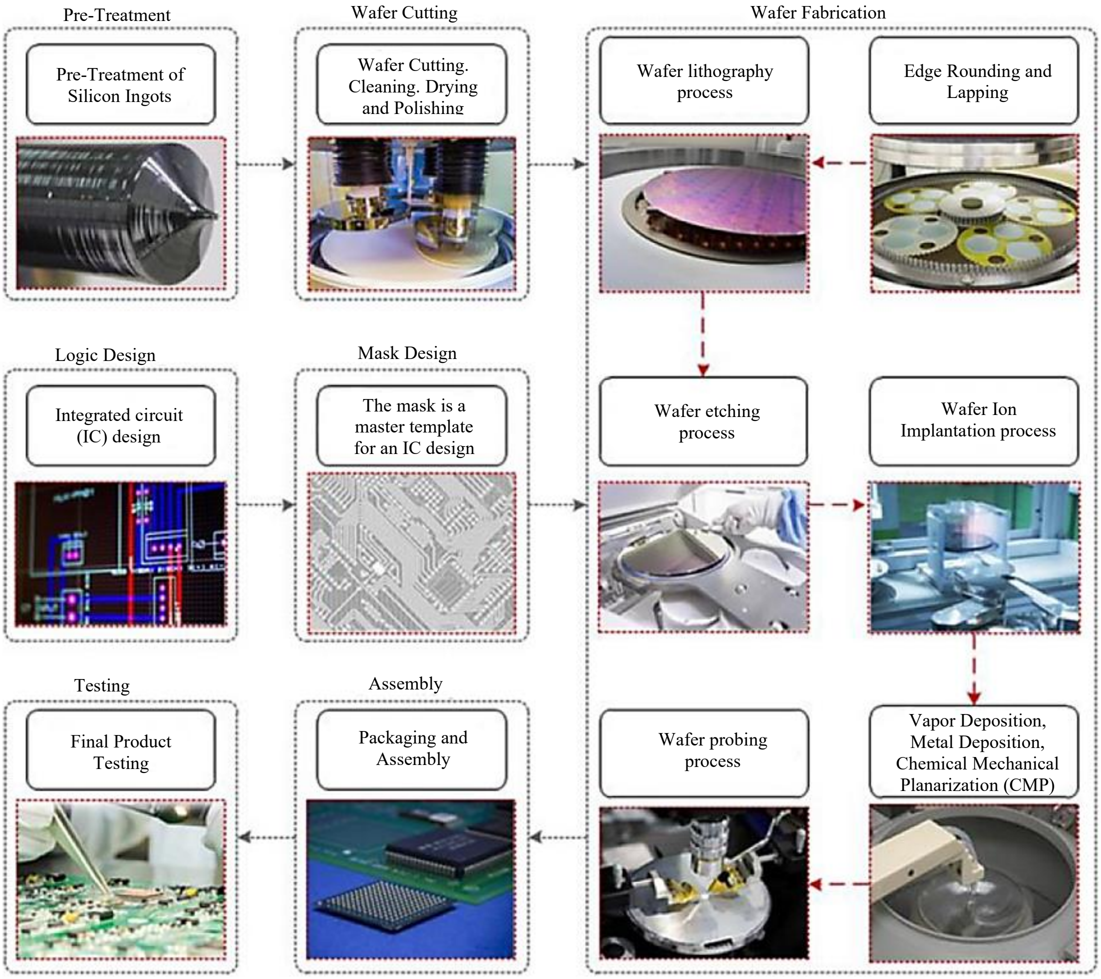

Figure 1. Semiconductor manufacturing process.

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These methods will offer the project managers valuable insights into the most influential factors in determining the outcome of the project, which can be used by them to make data-driven decisions. Sensitivity analysis helps identify which variables have the most significant impact on the overall system performance.

Tornado analysis is a graphical method employed to rank input variables based on their impact on key performance indicators (KPIs) like production yield, operational expenses, or the time required to complete a project. This visual representation allows managers to quickly identify and prioritize the most influential factors in their manufacturing process. In manufacturing systems, numerous interrelated and uncertain variables are often present, such as tool reliability, defect rates, or processing times in a semiconductor fabrication facility. The tornado chart illustrates the effect of each variable, with the ones forming the widest bars being the most significant (Figure 2). For instance, if defect rates and machine downtimes are identified as the primary causes of yield loss, then measures like improved quality control and predictive maintenance can be prioritized to mitigate their effects.

Scenario Comparison provides additional assistance for decision-making by comparing operational scenarios under different risk conditions.

- A *base-case* scenario that uses average values of all variables can serve as a benchmark for typical performance, helping to set realistic expectations for project duration and cost. This includes scenarios such as best machine performance, or as Close stated in his presentation, low defect rates, and efficient logistics. Understanding the best-case scenario helps set aspirational targets and identify areas for improvement.
- Best-case analysis can determine the maximal production yield and cost savings when uncertainties are minimised.

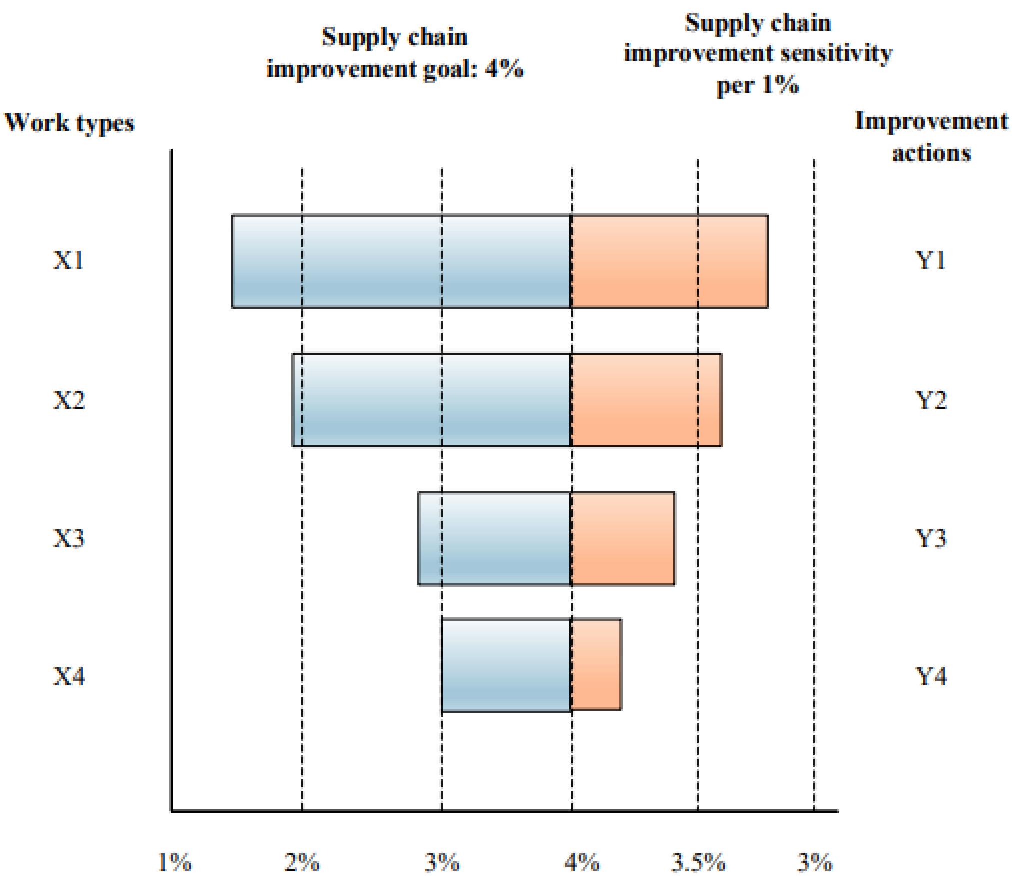


Figure 2. Tornado diagram for supply chain plan improvement.

- Managers are then able to estimate the potential downside risk by simulating severe disruptions (worst-case scenario), such as equipment failures or supply chain bottlenecks. Proactive contingency plans could be developed so that the business will keep running even in adverse situations. By preparing for the worst-case scenario, companies can build resilience into their operations and minimize potential losses.

Confidence intervals and probability distributions are quantitative risk measures [7]. Managers can use these to assess the likelihood of achieving specific targets. For example, a simulation might forecast a 70% probability that a production batch will be completed within 12 months as planned, which is valuable for setting commitments and understanding risk levels. These quantitative risk measures provide a more nuanced understanding of project risks and help in making informed decisions about resource allocation and risk mitigation strategies.

Step 4: Risk Mitigation Strategy

These risk mitigation strategies, informed by MCS, help create a robust framework for managing uncertainties in semiconductor manufacturing. The implementation of a proactive strategy to effectively mitigate risks in manufacturing is significantly reliant on insights derived from Monte Carlo Simulation (MCS). Sensitivity and scenario analyses can be employed to identify high-impact variables, enabling project managers to take measures to minimize disruptions in achieving operational objectives.

Contingency Buffers

Allocate extra time and budget as buffers. Using MCS to estimate worst-case outcomes provides guidance on how much slack to build into project schedules and budgets. For example, an MCS analysis might suggest adding buffer periods for critical equipment maintenance, accommodating yield fluctuations, or handling potential supplier delays in a semiconductor fabrication schedule. These buffers ensure that unexpected events do not derail the project timeline or finances. This approach not only safeguards against potential delays but also enhances overall project resilience, allowing for smoother operations even in the face of unforeseen challenges.

Redundant Suppliers

Diversify the supplier network to reduce single points of failure. Many critical raw materials or components in manufacturing are sourced from specialized suppliers. By qualifying redundant suppliers across different regions, a company can reduce its dependency on any single source. This strategy minimizes the risk of supply chain interruptions caused by geopolitical issues, natural disasters, or other disruptions.

Predictive Maintenance Scheduling

Real-time sensor data and machine learning algorithms are combined in predictive maintenance creating a model that predicts a failure at a given hour before the failure happens. Predictive analytics coupled with integrated predictive models of MCS can be used to simulate the effect of equipment downtime and determine appropriate times to schedule maintenance [8].

Real-Time Monte Carlo Updates

Real-time Monte Carlo updates can be enabled with continuous monitoring of project data. Managers can react to evolving operational metrics by dynamically adjusting simulations such that timely decisions and mitigation plan adjustments can be made as uncertainties are realized. This iterative approach enables transparency in the risks and makes the decision process based on data throughout the project life cycle. This dynamic approach to risk management allows for agile decision-making and continuous optimization of operational strategies, ensuring that the risk mitigation plan remains relevant and effective throughout the project lifecycle.

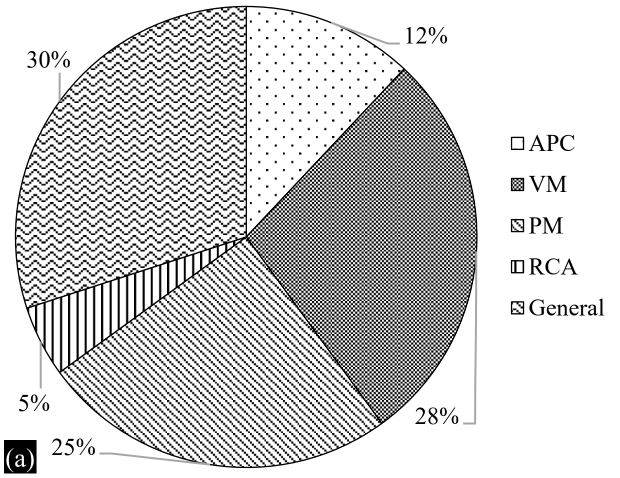
By integrating these MCS-informed strategies into semiconductor manufacturing processes, companies can significantly enhance their ability to anticipate, manage, and mitigate risks. This comprehensive approach not only improves operational efficiency but also contributes to long-term sustainability and competitiveness in the rapidly evolving semiconductor industry.

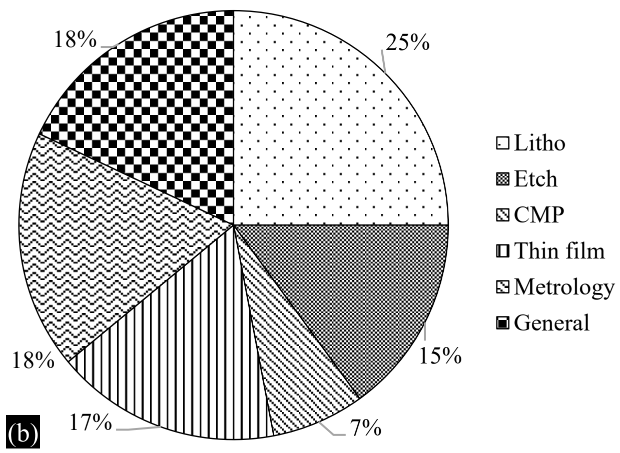
CASE STUDY APPLICATIONS: SEMICONDUCTOR PRODUCTION PLANNING

Case Study 1: Machine Learning for Process Optimization

This case study demonstrates the successful integration of machine learning (ML) with Monte Carlo Simulation (MCS) in the semiconductor manufacturing industry, showcasing its potential for process optimization. A semiconductor manufacturer integrated machine learning (ML) with MCS to optimize its wafer fabrication process. The company applied ML algorithms to analyze large-scale sensor data, identifying anomalies, predicting yield variations, and estimating equipment failure rates [9]. By leveraging these ML-derived insights, the company gained a more comprehensive understanding of its production process, enabling more accurate predictions and better-informed decision-making. The insights were incorporated into MCS that helped simulate the production scenarios whereby changes in the process parameters could influence yield as well as operational efficiency. This provided a probabilistic view of the outcomes of production and helped inform data-driven decision-making using the simulation results. This integration of ML and MCS created a powerful synergy, combining data-driven insights with probabilistic modeling to enhance the overall manufacturing process.

The implementation of this combined ML and MCS approach led to significant improvements in the manufacturer's production outcomes. Figure 3 shows the Pie charts of the manufacturer's wafer defects. It was reduced by 20 percent and operational efficiency increased by 15 percent. The insights from the combined ML and MCS approach enabled the company to adjust resource allocation and reduce costly downtime. This case illustrates how integrating advanced analytics with simulation can identify process vulnerabilities and enable proactive measures to improve yield, thereby mitigating operational risks.





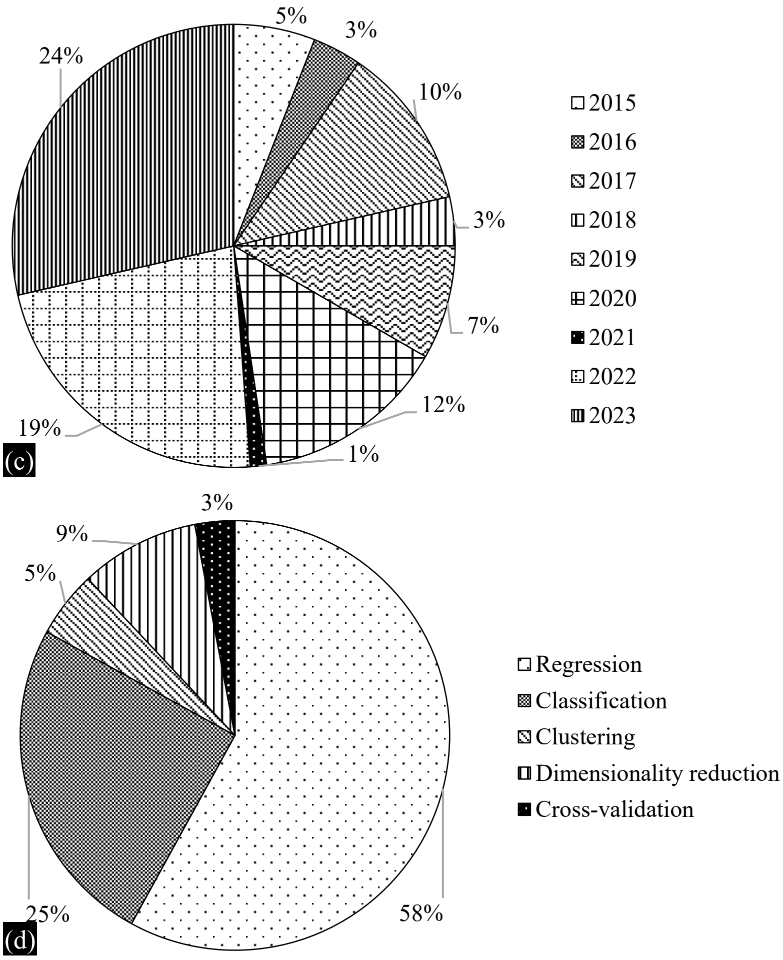


Figure 3. Pie charts of manufacturer's wafer defects.

Furthermore, this case study highlights the potential for ML and MCS integration to drive continuous improvement in complex manufacturing processes, offering a blueprint for other industries facing similar optimization challenges.

Digital Twin and Uncertainty Control

In another application, a semiconductor manufacturer integrated MCS with a digital twin of its production line to better manage uncertainty [10]. This integration allowed for a more comprehensive and dynamic representation of the manufacturing process, capturing real-time data and simulating various scenarios. It served as a shorthand for a real-time virtual replica of the manufacturing process incorporating stochastic variables of machine downtime, process variability, and supply chain disruptions. Thousands of probabilistic scenarios where produced by MCS simulations that permitted managers to evaluate potential risks and what contingency strategies may mitigate those risks.

These scenarios encompassed a wide range of potential outcomes, from minor fluctuations to major disruptions in the production process. This approach helped identify operational deficiencies and enabled adaptive scheduling solutions; as a result, lead time deviations were reduced by about 25%. Resource utilization also improved through proactive adjustments to production plans based on the simulation insights. The digital twin also enabled real-time monitoring and predictive maintenance, further reducing unexpected downtime and improving overall equipment effectiveness (Figure 4). By leveraging digital twin technology alongside MCS, decision-makers gained actionable intelligence that made production lines more reliable and resilient against unanticipated disruptions [11].

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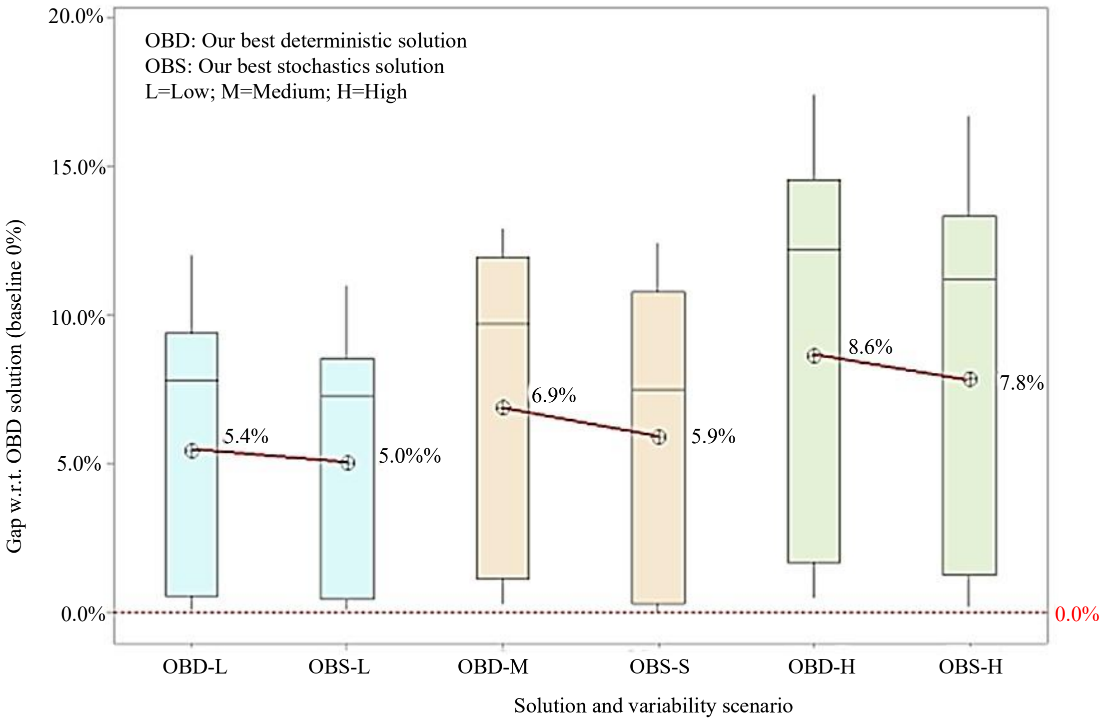

Figure 4. Solution and variability scenario.

Stochastic Flow Shop Optimization

The company, being a semiconductor manufacturer had to contend with uncertainties in processing times on a hybrid flow shop. For stochastic modelling, the company applied a biased randomized simheuristic with MCS. The introduced form of controlled randomness in production scheduling was through the simheuristic algorithm that simulated (thousands of) production scenarios, accounting for variations of both machine availability and processing speeds. The simheuristic algorithm introduced controlled randomness in production scheduling by simulating numerous production scenarios, accounting for variations in both machine availability and processing speeds.

MCS supplied probabilistic insights about the effect of uncertainties on throughput, lead times, and operational efficiency. Decision-makers utilized these results to optimize job sequencing and task prioritization, leading to significant improvements in machine utilization and throughput. The results were used by decision-makers to optimize job sequencing and task prioritizing these machines to decrease machine idle time by 20% and increase throughput by 7.8%. It also found possible bottlenecks and suggested alternate scheduling procedures to avoid delays [12]. The adaptation to unexpected disruptions was quick and fast and this simulation-based optimization approach guaranteed production cycles to be more predictable and overall supply chain reliability was improved.

Monte Carlo–guided Adaptive Process Control

Monte Carlo simulation (MCS) can be effectively combined with adaptive process control to enhance performance in complex industrial systems. Monte Carlo–guided adaptive process control: An example from process control illustrates the combined use of adaptive control and MCS. Researchers developed a feedforward–feedback adaptive controller for a semiconductor electroplating process that dynamically couples a kinetic Monte Carlo simulation with the control system. This integration allows for real-time adjustments based on microscale simulations, improving overall process control. The Monte Carlo model continuously simulated the copper deposition dynamics at the microscale, allowing the controller to adjust the plating current in real time based on simulated predictions of layer thickness variability. By continuously updating the model based on actual process data, the system can adapt to changing conditions more effectively than traditional control methods. This Monte Carlo–guided adaptive control scheme achieved robust regulation of the plating process – the closed-loop system's behavior matched the simulation's predictions within stochastic variation, and the adaptive adjustments reduced response times and improved stability despite uncertain process dynamics.

This approach demonstrates the power of combining statistical simulation with adaptive control techniques to handle complex, stochastic processes. This case demonstrates how integrating MCS with an adaptive controller in an industrial automation scenario (semiconductor manufacturing) can maintain product quality and process efficiency under highly variable conditions, by providing a more accurate and responsive control mechanism that adapts to real-time changes in the system.

RESULTS AND DISCUSSION

Across these case studies presented in this paper, Monte Carlo Simulation has shown significant benefits in improving operational efficiency, decision-making, and cost management in manufacturing contexts. The outcomes provide strong evidence for the utility of MCS in managing uncertainty and enabling more proactive planning in industrial operations.

Reduced Downtime & Operational Risk

Proactive risk modeling with MCS can greatly decrease unplanned downtime and operational risk. For instance, using machine learning in conjunction with MCS enabled manufacturers to predict yield fluctuations and equipment failures more accurately [13]. Early detection of anomalies allowed timely interventions that cut unplanned downtime by as much as 20%. Likewise, integrating MCS with digital twin simulations provided scenario-based risk assessments that helped prevent unexpected disruptions, thus maintaining continuous production [14].

Enhanced Decision-making

Traditional deterministic models lack the ability to capture the range of possible outcomes, whereas MCS provides probabilistic insights that improve decision quality. By analyzing thousands of simulated iterations, managers developed a much deeper understanding of how projects could unfold under different conditions. This empowered them to make more data-driven decisions, especially in the face of uncertainties in production and supply chain operations [15]. Because of greater visibility into the best case, worst case, and most likely scenarios, companies were able to put in place contingency measures that dramatically cut lead time deviations.

Cost Optimization

MCS was also important in another critical area of cost management. Production variability and supply chain uncertainties were simulated, and the inventory levels and production schedules varied using company optimums using simulation. This resulted in a 15-20 percent decrease in operational costs due to a reduction of material waste and better resource allocation [16]. Additionally, in identifying and remediating process inefficiencies from using MCS, organizations were able to prevent overproduction and keep down holding costs.

Optimized Inventory and Supply Chain Efficiency

By integrating adaptive control, the simulation-driven approach became even more effective in practice. For instance, in the semiconductor case studies, the ability to adjust control actions based on MCS outputs led to closer alignment between predicted and actual outcomes – the adaptive controller kept the real system performance within the probabilistic bounds forecasted by the simulation. The feedback loop between MCS and adaptive control also improved operational responsiveness. Overall, the inclusion of adaptive control mechanisms enhanced the accuracy of the simulation's predictions and provided faster, more robust responses to disturbances, confirming the complementary benefits of coupling MCS with real-time adaptive decision-making.

Real-time Adaptive Decision Making by Integrating Adaptive Control

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CONCLUSION

Monte Carlo Simulation (MCS) has demonstrated its value as a powerful tool for managing uncertainty and improving decision-making in industrial automation and manufacturing. Integrating MCS with real-time data and advanced analytics allows organizations to mitigate operational risks, meet production targets, and minimize downtime. This paper presented a structured framework for implementing MCS in high-risk industrial projects—encompassing data acquisition, model development, sensitivity analysis, and risk mitigation—and illustrated its application through several case studies. The results showed that MCS enables more proactive decision-making, cost-effective operations, and efficient resource allocation by leveraging insights from simulated scenarios. As manufacturing industries continue to face supply chain disruptions and technological complexities, broader adoption of MCS will be critical to maintaining resilience and competitive advantage. This research provides a practical guide for applying MCS in project and operations management, offering actionable strategies to achieve greater operational excellence. Looking ahead, future applications of MCS in manufacturing analytics should incorporate adaptive feedback control loops to continuously refine and dynamically optimize operations under ever-changing conditions.

REFERENCES

1. Tesauro, G., & Galperin, G. R. (2025). On-line policy improvement using Monte-Carlo search. arXiv preprint arXiv:2501.05407.
2. Liu, J., & Braatz, R. D. (2003). Robust nonlinear feedback-feedforward control of a coupled kinetic Monte Carlo–finite difference simulation. Journal of Process Control, 13(7), 607–619.
3. Tin, T. C., Tan, S. C., Yong, H., Kim, J. O. H., Teo, E. K. Y., Lee, C. K., Than, P., San Tan, A. P., & Phang, S. C. (2021). A realizable overlay virtual metrology system in semiconductor manufacturing: Proposal, challenges and future perspective. IEEE Access, 9, 65418–65439.
4. Goodchild, M., Langham, G. M., Appelbaum, R., Crampton, J., Herbert, W. A., Janowicz, K., Kwan, M. P., Michael, K., & Schamess, L. (2025). Locational data and the public interest. IEEE Transactions on Technology and Society.
5. Zanbouri, K., Noor-A-Rahim, M., John, J., Sreenan, C. J., Poor, H. V., & Pesch, D. (2024). A comprehensive survey of wireless time-sensitive networking (TSN): Architecture, technologies, applications, and open issues. IEEE Communications Surveys & Tutorials.
6. Tariq, A., Khan, S. A., But, W. H., Javaid, A., & Shehryar, T. (2024). An IoT-enabled real-time dynamic scheduler for flexible job shop scheduling (FJSS) in an Industry 4.0 based manufacturing execution system (MES 4.0). IEEE Access.
7. Xu, Q., Yu, N., & Hasan, M. M. (2023). Evolutionary computation-based reliability quantification and its application in big data analysis on semiconductor manufacturing. Applied Soft Computing, 136, 110080.
8. Nam, T. Y., Cho, D. I., Shin, J. W., Yoon, K. H., Kim, J. C., & Moon, W. S. (2024). Maintenance scheduling strategy for MMCs within an MVDC system using sensitivity analysis. IEEE Access.
9. Chen, Y. L., Sacchi, S., Dey, B., Blanco, V., Halder, S., Leray, P., & De Gendt, S. (2024). Exploring machine learning for semiconductor process optimization: A systematic review. IEEE Transactions on Artificial Intelligence.

10. Firouzi, F., Daneshmand, M., Song, J., & Mankodiya, K. (2023). Guest editorial: Special issue on empowering the future generation systems: Opportunities by the convergence of cloud, edge, AI, and IoT. IEEE Internet of Things Journal, 10(5), 3681–3685.
11. May, M. C., Kiefer, L., & Lanza, G. (2024, December). Digital twin based uncertainty informed time constraint control in semiconductor manufacturing. In 2024 Winter Simulation Conference (WSC) (pp. 1943–1954). IEEE.
12. Ammouriova, M., Panadero, J., Leißau, M., Laroque, C., Schumacher, C., & Juan, A. A. (2022, December). A biased-randomized simheuristic for a hybrid flow shop with stochastic processing times in the semiconductor industry. In 2022 Winter Simulation Conference (WSC) (pp. 1888–1898). IEEE.
13. Ashfaq, M., Khan, I., Alzahrani, A., Tariq, M. U., Khan, H., & Ghani, A. (2024). Accurate wheat yield prediction using machine learning and climate-NDVI data fusion. IEEE Access, 12, 40947–40961.
14. Gao, X., Chen, Z., Huang, G., & Hezam, I. M. (2024). Blockchain-enabled safeguard mechanism in SCP-based relief supply chain designs in response to long-term disasters. IEEE Access.
15. Xu, J., & Bo, L. (2024). Enhancing supply chain efficiency resilience using predictive analytics and computational intelligence techniques. IEEE Access.
16. Bakon, K., Holczinger, T., Süle, Z., Jaskó, S., & Abonyi, J. (2022). Scheduling under uncertainty for Industry 4.0 and 5.0. IEEE Access, 10, 74977–75017.