Research Article

Optimizing Semiconductor Manufacturing for Small and Medium Enterprises: A System-Dynamics and Machine Learning Approach

Arifuzzaman (Arif) Sheikh[1]**, Edwin K. P. Chong**[2]

1. Department of Systems Engineering, Colorado State University, United States; 2. Department of Electrical and Computer Engineering, Colorado State University, United States

Small businesses in the semiconductor industry face unique challenges in optimizing low-volume, highly customized production. Our study introduces an optimization framework that integrates system-dynamics modeling, linear programming, and predictive analytics to streamline supply chain networks and improve manufacturing efficiency. By leveraging Python-based simulations, our approach enhances cost-effectiveness, supports rapid prototyping, and utilizes cross-validated machine learning for predictive modeling to optimize production outcomes. Through statistical validation including correlation analysis and ANOVA, plus comparative analysis with alternative optimization techniques, our framework demonstrates significant improvements in both theoretical efficiency and practical application. The framework not only advances the theoretical foundation for specialized semiconductor manufacturing but also provides practical insights tailored to the constraints and implementation challenges faced by Small and Medium Enterprises (SMEs).

Corresponding author: Arifuzzaman (Arif) Sheikh, arif.sheikh@colostate.edu

I. Introduction

The semiconductor industry presents significant challenges for SMEs, particularly in low-volume, highly customized production environments. Traditional high-volume manufacturing models are often unsuitable for firms that require flexible, cost-efficient solutions to remain competitive. SMEes face constraints including limited capital resources, higher per-unit production costs, and challenges accessing specialized equipment. Our study introduces an optimization framework tailored to the specific needs of SMEs in semiconductor manufacturing. By integrating system-dynamics modeling, linear programming, and predictive analytics, our approach creates a comprehensive system that enhances production efficiency, streamlines supply chain operations, and reduces overall costs. This integrated approach echoes recent advancements in 3D-IC manufacturing optimization[1], where combining multiple AI methods has shown promise in addressing complex manufacturing challenges. This research not only advances theoretical insights into adaptive semiconductor manufacturing but also provides practical strategies for SMEs to navigate the complexities of modern production constraints and market demands. The remainder of this paper presents related work, details our methodology, analyzes results from simulation testing, and discusses practical implications for implementation.

II. Related Work

The evolving landscape of semiconductor manufacturing necessitates a detailed exploration of existing literature to understand the current state, challenges, and potential avenues for innovation. SMEs operating in this domain face unique constraints, particularly in balancing cost-efficiency with technological advancement. This section examines three primary areas: the current state of semiconductor manufacturing, the challenges specific to small-scale production, and emerging solutions tailored for small business applications.

A. Current State of Semiconductor Manufacturing

The economic hurdles faced by both high- and low-volume semiconductor manufacturing are well-documented. High-volume production is capital-intensive, requiring significant investments in advanced fabrication technologies, workforce availability, and rapid technology cycles[2]. While commercial semiconductor manufacturing prioritizes large-scale production for consumer electronics, SMEs often struggle to access cutting-edge fabrication facilities and must navigate high entry barriers[3].

Moreover, the escalating capital costs associated with fabricating advanced microelectronics present difficulties not only for high-volume manufacturers but also for small-scale enterprises seeking to develop specialized semiconductor products[4]. Low-volume production, which is often necessary for niche markets, faces challenges such as limited access to manufacturing sources and supply chain disruptions[5]. These constraints emphasize the need for cost-effective, flexible manufacturing solutions that allow SMEs to remain competitive in an industry dominated by large-scale players[6].

 doi.org/10.32388/EOQ6MJ.2

B. Challenges in Small-Scale Semiconductor Manufacturing

Small and Medium Enterprises (SMEs) in semiconductor manufacturing require processes that are not only reliable and precise but also adaptable to rapid technological advancements. The demand for specialized semiconductor solutions in sectors such as industrial automation, healthcare, and telecommunications highlights the need for innovative chip architectures, including applications of wide-bandgap semiconductor technologies[7].

Unlike large enterprises, SMEs often lack the economies of scale necessary to drive significant market influence, making supply chain optimization and cost reduction critical factors in their sustainability[4]. The strategic importance of fostering domestic semiconductor capabilities for small enterprises is evident, particularly as global supply chain uncertainties impact production continuity[8]. Studies have examined various factors influencing small-business participation in semiconductor fabrication, including access to fabrication facilities, collaborative partnerships, and financial constraints[9]. The growing challenge remains in enabling SMEs to manufacture advanced microelectronics in a cost-effective manner while meeting the increasing demands for performance, functionality, and security.

The role of government initiatives, research institutions, and industry collaborations, such as programs supported by the National Institute of Standards and Technology (NIST), is crucial in providing SMEs with the necessary tools and frameworks to enhance their competitiveness in the semiconductor industry.

C. Emerging Solutions and Methodologies

To address the challenges faced by SMEs in semiconductor manufacturing, recent research has explored alternative approaches that enhance efficiency, reduce costs, and improve adaptability. System-dynamics modeling provides valuable insights into the complex interactions within semiconductor production systems, allowing small manufacturers to identify optimization opportunities and improve decision-making. This modeling approach enables business owners and production managers to test alternative policies and assess their potential impact on operational effectiveness[10]. Additionally, by incorporating economic efficiency analysis, system-dynamics modeling facilitates cost-benefit assessments over time, supporting more strategic resource allocation decisions[11]. Scenario simulations using this approach can help SMEs identify production bottlenecks and critical tipping points where existing resources may be insufficient, emphasizing the need for innovation and process refinement[12]. As a comprehensive tool for analyzing dynamic systems, it allows small enterprises to measure, predict, and optimize key business variables that influence long-term success[13]. The integration of computational intelligence techniques further enhances this modeling approach, enabling the construction of more sophisticated models that improve efficiency and decision-making[14].

Linear programming for supply chain optimization offers several practical advantages for SMEs in semiconductor manufacturing. One key benefit is its ability to detect and rectify inefficiencies in the supply chain, ensuring that manufacturing processes remain agile and cost-effective[15]. Additionally, by employing optimization models, small manufacturers can reduce disruptions caused by fluctuating variables, enhancing overall stability in production planning[16]. A bi-criterion optimization model, for instance, effectively balances cost minimization with the need to maintain operational flexibility, which is crucial for small-scale manufacturers that must adapt to changing customer demands[17]. Furthermore, lot allocation strategies, such as Composite Allocation Rule (CAR)-based policies, can optimize order fulfillment while minimizing inventory costs, backorders, and production inefficiencies[18]. These approaches collectively improve operational efficiency by increasing the feasibility of small-scale semiconductor production while minimizing supply chain disruptions.

The application of machine learning and predictive analytics further enhances the efficiency and competitiveness of SMEs in semiconductor manufacturing. By leveraging data-driven techniques, predictive analytics supports yield estimation, identifies potential yield issues at an early stage, and reduces overall production costs[19][20]. Moreover, integrating technology computer-aided design (TCAD) physical models with machine learning statistical models can improve prediction accuracy, enabling more intelligent manufacturing strategies[21]. Additionally, advanced data extraction and analysis methods streamline the qualification testing process, reducing the number of necessary tests while improving overall production effectiveness. By adopting these machine learning-driven approaches, SMEs can enhance operational efficiency, optimize resource utilization, and achieve significant cost savings in semiconductor production.

D. Comparative Analysis of Optimization Approaches

While our study focuses on an integrated framework combining system-dynamics modeling, linear programming, and predictive analytics, recent research has explored alternative optimization techniques for manufacturing systems. Reinforcement learning has shown promise in dynamic production environments for adaptive scheduling in semiconductor fabrication facilities[22][23]. However, these approaches typically require extensive training data and computational resources, limiting their applicability for SMEs.

Genetic algorithms offer advantages in handling non-linear constraints and have been applied to semiconductor manufacturing for optimizing wafer testing sequences through evolutionary computation[24]. While effective for complex combinatorial problems, these methods often require significant parameter tuning and may not guarantee globally optimal solutions within practical timeframes for day-to-day operations.

Neural network-based optimization has gained traction with implementations of deep learning for defect detection in semiconductor manufacturing[25][26]. These approaches excel at pattern recognition but demand substantial historical data and specialized expertise often unavailable to small enterprises. These alternative approaches, while powerful for specific applications, present implementation barriers for small semiconductor businesses with limited resources, highlighting the need for more accessible optimization frameworks.

Our integrated approach offers distinctive advantages in its ability to capture system dynamics while maintaining computational efficiency through linear programming. Unlike reinforcement learning methods that require extensive training data, our framework can operate effectively with limited historical data—a common constraint for SMEs in specialized semiconductor manufacturing. The methodology also provides greater transparency in decision-making than neural network approaches, allowing production managers to understand and explain optimization outcomes.

E. Summary

The literature highlights a pressing need for innovative manufacturing strategies that can effectively balance the low-volume, high-customization requirements of SMEs with the demands of cost-efficiency and operational agility. While existing research provides valuable foundational insights, there remains a significant gap in practical, integrated frameworks that holistically address the unique challenges faced by small-scale semiconductor manufacturers. Our study aims to bridge that gap by contributing both theoretically and practically to the development of scalable, cost-effective solutions tailored to the needs of SMEs in the semiconductor industry. The integrated framework presented in subsequent sections directly addresses this gap through a combination of system-dynamics modeling, linear programming, and predictive analytics specifically calibrated to small business constraints.

doi.org/10.32388/EOQ6MJ.2

III. Methodology

This section presents our integrated optimization framework for small-medium-scale semiconductor manufacturing. Figure 1 illustrates the workflow of our approach, highlighting the interconnections between system-dynamics modeling, linear programming, and predictive analytics. Each component addresses specific aspects of the manufacturing optimization challenge: system-dynamics modeling captures the temporal evolution of production systems, linear programming optimizes supply chain logistics, and cross-validated predictive analytics enhance quality control and maintenance decisions. The integration of these methods creates a synergistic framework that leverages their complementary strengths while addressing their individual limitations. In our implementation, the system-dynamics model generates production scenarios that inform supply parameters for the linear programming module, while predictive analytics provides quality forecasts that feed back into production planning decisions, creating a closed-loop optimization system particularly suited to small business manufacturing constraints.

doi.org/10.32388/EOQ6MJ.2

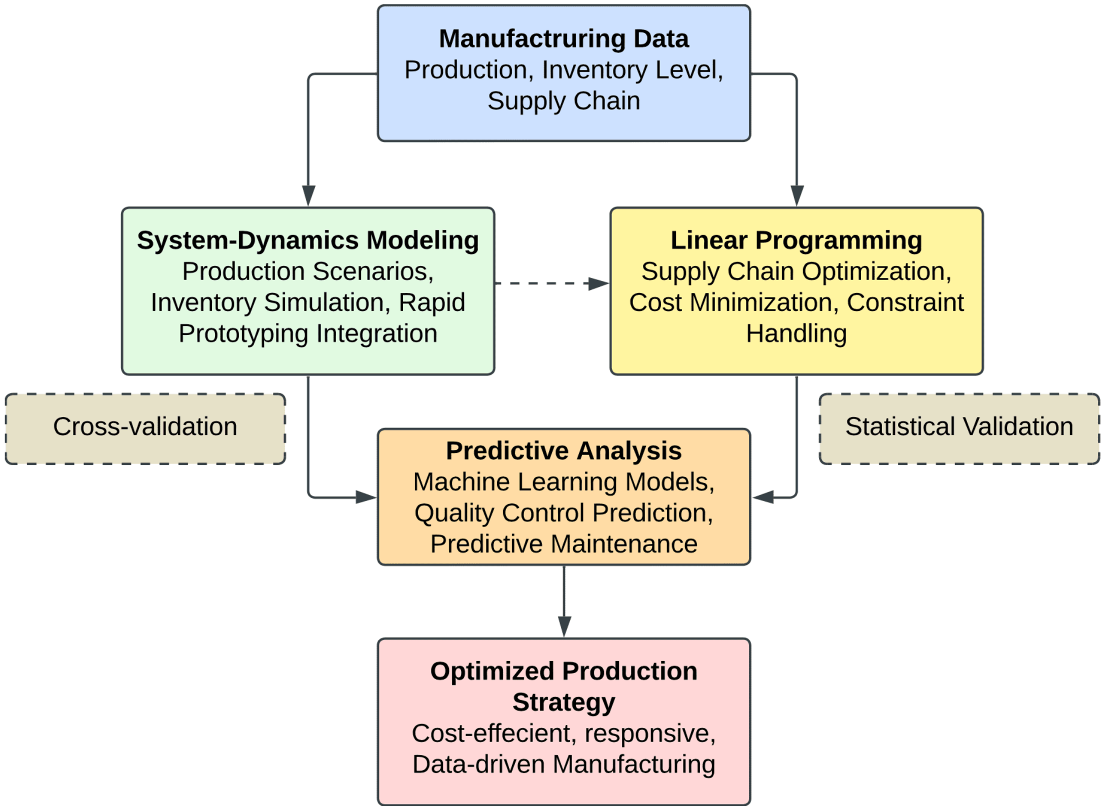

Figure 1. Workflow diagram of the integrated optimization framework showing the data flow between system-dynamics modeling, linear programming, and predictive analytics components.

A. System-Dynamics Modeling of Production Scenarios

While alternative simulation approaches such as discrete event simulation or agent-based modeling could address certain aspects of manufacturing dynamics, system-dynamics modeling was selected for its ability to capture feedback loops and time delays inherent in semiconductor manufacturing processes. Unlike Monte Carlo methods that excel at risk assessment but are less suited for operational optimization, our approach directly models the causal relationships between production variables, enabling SMEs to visualize complex system behaviors without requiring extensive computational resources.

System-dynamics modeling forms the foundation of our methodology, providing a comprehensive representation of the semiconductor manufacturing process. By simulating production scenarios, this approach captures the interdependencies between key operational variables, including production rate, inventory levels, and rapid prototyping integration. For SMEs operating under tight resource constraints,

doi.org/10.32388/EOQ6MJ.2

system-dynamics modeling offers a strategic tool to identify bottlenecks, optimize resource allocation, and improve production planning.

To characterize the dynamic behavior of low-volume semiconductor manufacturing, we develop a system of differential equations that describe the evolving state of the production system. These equations are solved numerically using Python's `scipy.integrate.odeint` function, enabling scenario-based analysis under varying operational conditions.

The model defines inventory level $I(t)$ as a function of incoming orders $O(t)$, production rate $P(t)$, rapid prototyping contribution $RP(t)$, and shipment rate $S(t)$. The governing equation is expressed as:

$$\frac{dI(t)}{dt} = P(t) + RP(t) - S(t), \tag{1}$$

where production rate follows $P(t) = k \cdot O(t)$, with k representing the production capacity coefficient. Rapid prototyping contributes an additional rate, defined as $RP(t) = R \cdot O(t)$, where R denotes the efficiency factor of the prototyping system. The shipment rate, constrained by inventory availability, is modeled as $S(t) = \min(I(t), D)$, where D represents market demand.

To implement this model, we numerically solve the differential equation using computational solvers such as Euler's method or Python's `scipy.integrate.odeint`. This enables real-time simulation of inventory fluctuations, assessing how variations in demand, production capacity, and rapid prototyping influence overall system performance.

For scenario analysis, we consider an example where incoming orders $O(t)$ exhibit periodic variations due to seasonal or market-driven fluctuations, modeled as:

$$O(t) = O_{\text{base}} + O_{\text{amp}} \cdot \sin(\omega \cdot t), \tag{2}$$

where O_{base} represents baseline order levels, O_{amp} defines fluctuation amplitude, and ω determines the frequency of variability. This formulation enables the evaluation of how small semiconductor manufacturers can dynamically adjust production strategies in response to market volatility.

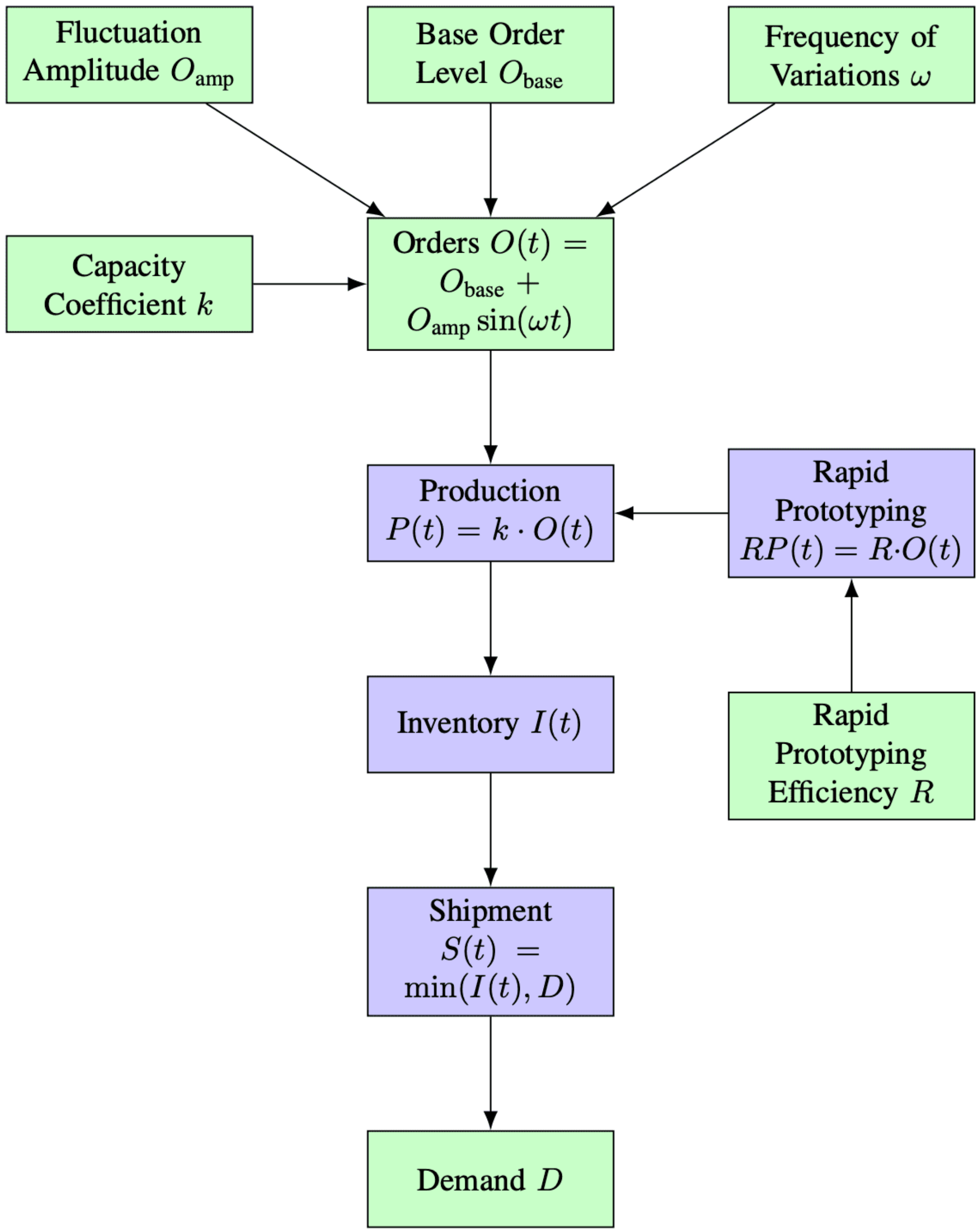

Figure 2. Flowchart of the System-Dynamics Model

By running simulations with different parameter settings $(k, R, D, O_{\text{base}}, O_{\text{amp}}, \omega)$, we can analyze how a small-scale semiconductor manufacturing system responds to fluctuations in demand and production constraints. This enables SMEs to develop data-driven strategies for optimizing production planning and resource utilization.

The Python implementation of this model requires importing the following package:

doi.org/10.32388/EOQ6MJ.2

```
from scipy.integrate import odeint
```

This system-dynamics framework serves as a foundation for integrating additional optimization methods such as linear programming and predictive analytics, which will be discussed in subsequent sections.

B. Linear Programming for Supply Chain Optimization

Alternative approaches for supply chain optimization include metaheuristics such as genetic algorithms and simulated annealing. However, linear programming was selected for its guaranteed optimality, computational efficiency, and transparency in decision-making—features particularly valuable for SMEs with limited computational resources. While metaheuristics can potentially handle more complex, non-linear constraints, the increased computational burden and lack of guaranteed optimality make them less suitable for day-to-day operational decisions in small-scale manufacturing environments.

Linear programming serves as a critical tool for optimizing supply chain operations in semiconductor manufacturing, particularly for SMEs that must balance cost efficiency with operational constraints. These manufacturers frequently encounter challenges such as detecting infeasibilities in supply chain models, minimizing disruptions caused by parameter adjustments, and optimizing logistics to sustain profitability[27].

To address these challenges, the flexibility test method provides a quantitative approach to evaluating constraints that lead to infeasibilities, allowing for the detection of data outliers that may disrupt supply chain efficiency[18]. Another optimization strategy involves minimizing solution variations by formulating models that reduce both the frequency and magnitude of parameter adjustments, enhancing supply chain stability[28].

Beyond conventional cost minimization, linear scheduling enables supply chains to transition into more sustainable, closed-loop systems. By incorporating re-manufacturing and reverse logistics, businesses can reduce waste while maintaining operational efficiency[29]. Additionally, mathematical optimization models can be developed to simultaneously minimize environmental impact and maximize net profitability, aligning with sustainability-driven business practices[30].

For SMEs operating within semiconductor supply chains, integrating purchasing, transportation, and storage decisions into a unified optimization framework enhances overall efficiency. Robust optimization techniques can further account for uncertainties in supply and demand, while stochastic models incorporating traceability assumptions provide insights into how different market conditions and sales formats influence procurement decisions.

Mathematical Model for Supply Chain Optimization

To formulate an optimization strategy, we develop a linear programming model that minimizes total shipping costs while satisfying supply and demand constraints. Let X_{ij} represent the number of units shipped from supplier i to destination j, and let C_{ij} denote the cost per unit of shipping. Each supplier has a limited capacity S_i, while each destination has a specific demand requirement D_j. The objective function aims to minimize total transportation costs:

$$\min Z = \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} X_{ij}, \tag{3}$$

where m represents the number of suppliers and n represents the number of destinations. The model is subject to the following constraints:

The supply constraint ensures that each supplier does not exceed its available capacity:

$$\sum_{j=1}^{n} X_{ij} \leq S_i, \quad \forall i \in \{1, 2, \ldots, m\}. \tag{4}$$

The demand constraint guarantees that each destination receives at least the required quantity:

$$\sum_{i=1}^{m} X_{ij} \geq D_j, \quad \forall j \in \{1, 2, \ldots, n\}. \tag{5}$$

Finally, the non-negativity constraint ensures that shipment quantities remain non-negative:

$$X_{ij} \geq 0, \quad \forall i, j. \tag{6}$$

This linear programming model provides an effective approach to optimizing supply chain logistics by minimizing transportation costs while maintaining supply-demand balance. By implementing this framework, small semiconductor manufacturers can improve operational efficiency, reduce excess costs, and enhance overall supply chain responsiveness.

Model Implementation in Python

The linear programming model was implemented using the PuLP library, a widely used optimization package for solving linear and integer programming problems. The optimization process was carried out using the CBC solver via the `PULP_CBC_CMD` interface.

doi.org/10.32388/EOQ6MJ.2

The key steps in our implementation included:

- **Defining decision variables:** Shipment quantities (X_{ij}) were represented as continuous decision variables.
- **Formulating the objective function:** The total shipping cost was minimized using `lpSum`.
- **Specifying constraints:** Supply limits, demand requirements, and non-negativity conditions were incorporated using the `LpProblem` class.
- **Solving the model:** The problem was solved using the built-in CBC solver, and the optimal solution was retrieved using the `value` function.

Python Code Snippet:

```
from pulp import LpProblem, LpMinimize, LpVariable,
    lpSum, PULP_CBC_CMD, value

# Define problem
model = LpProblem("Supply_Chain_Optimization",
    LpMinimize)

# Define variables
X = [[LpVariable(f"X_{i}_{j}", lowBound=0) for j in
    range(n)] for i in range(m)]



# Objective function
model += lpSum(C[i][j] * X[i][j] for i in range(m)
    for j in range(n))

# Supply constraints
for i in range(m):
    model += lpSum(X[i][j] for j in range(n)) <= S[i
        ]

# Demand constraints
for j in range(n):
    model += lpSum(X[i][j] for i in range(m)) >= D[j
        ]

# Solve
model.solve(PULP_CBC_CMD())
```


doi.org/10.32388/EOQ6MJ.2

C. Predictive Analytics with Cross-Validation

Predictive analytics plays a critical role in semiconductor manufacturing by leveraging historical production data and machine learning techniques to optimize processes, improve yield rates, and enhance operational efficiency. For SMEs, predictive analytics offers a cost-effective approach to decision-making, allowing manufacturers to anticipate equipment failures, improve quality control, and streamline microelectronics testing. By applying cross-validated machine learning models, we develop predictive frameworks that provide actionable insights for optimizing production while reducing costs and minimizing downtime.

To ensure model robustness and prevent overfitting, we implemented k-fold cross-validation (k=5) for all predictive models. This approach partitions the data into five subsets, training the model on four subsets and validating on the remaining subset in a rotating fashion. The reported performance metrics represent the average across all validation folds, providing a more reliable estimate of how the model would perform on unseen data in practical applications.

(1) Predictive Maintenance Using Machine Learning: Ensuring equipment reliability is vital for small-scale semiconductor manufacturers, as unexpected machine failures can lead to costly downtime. Our approach applies machine learning to analyze sensor data and predict potential equipment failures before they occur, allowing for proactive maintenance scheduling.

We employ a decision-tree-based model, mathematically represented as a series of conditional control statements:

$$R_i : \text{if } (\text{Measurement}_j \leq \theta_{ij}) \text{ then } Y = c_{i1} \text{ else } Y = c_{i2}, \tag{7}$$

where R_i represents the ith rule, Measurement_j is a sensor reading, θ_{ij} is the threshold value for decision-making, and c_{i1}, c_{i2} are the classification labels indicating whether maintenance is required. Python Implementation: The `DecisionTreeClassifier` from the `sklearn.tree` module was utilized with cross-validation to prevent overfitting, allowing robust identification of defective semiconductor components.

(2) AI-Driven Quality Control: AI-driven quality control enables small semiconductor manufacturers to improve defect detection and enhance production efficiency. Our method applies a Decision Tree Classifier to detect defects based on real-time manufacturing process data. Recent research has demonstrated the value of integrating text analytics with traditional sensor data for improved defect detection in electronics manufacturing[31], though our approach focuses primarily on structured sensor data analysis.

Using the same decision tree structure presented in the predictive maintenance section, our defect detection model analyzes critical quality parameters to determine the presence or absence of defects. This approach allows manufacturers to take corrective action in real time, minimizing yield loss and ensuring product consistency. The cross-validation framework described earlier ensures the model generalizes well to new, unseen manufacturing data, a critical requirement for real-world implementation.

(3) AI in Microelectronics Testing: In semiconductor wafer testing, predictive analytics assists small manufacturers in optimizing quality assurance processes. We use decision tree classification to analyze test data, identifying trends and anomalies that could indicate defects. This helps businesses reduce the cost and time associated with manual inspections.

The model follows the same decision rule structure described in section (1), where measurement parameters from wafer testing are evaluated against learned thresholds to classify wafer quality. Using our cross-validation framework, we ensure the model's predictions remain reliable across different batches of semiconductor components.

(4) Regression Analysis for Quality Control with Statistical Validation: To identify factors influencing quality control, we employ **regression analysis** to assess the impact of predictive maintenance and microelectronics testing on overall manufacturing quality.

The linear regression model is expressed as:

$$QC = (\beta_0 + \beta_1 \times PM + \beta_2 \times MT + \varepsilon), \tag{8}$$

where QC represents the Quality Control score, PM is the Predictive Maintenance score, MT is the Microelectronics Testing score, $\beta_0, \beta_1, \beta_2$ are the regression coefficients, and ε is the error term.

This regression model undergoes rigorous statistical validation through correlation analysis, Analysis of Variance (ANOVA), and coefficient significance testing. These validation techniques ensure that the relationships identified are statistically significant and not merely the result of random variations. Cross-validation is applied to assess the model's generalization capability and prevent overfitting to the training data.

Python Implementation: The implementation leverages Python's scikit-learn library, with the `DecisionTreeClassifier` from `sklearn.tree` and the `LinearRegression` model from `sklearn.linear_model`. Cross-validation was implemented using `sklearn.model_selection.cross_val_score` with 5-fold splitting, and statistical validation was performed using `scipy.stats` for ANOVA and correlation analyses.

The datasets used in our study capture key aspects of semiconductor manufacturing, including production variability, sensor readings, equipment performance metrics, and defect classification data. These data enable comprehensive validation of system-dynamics modeling, linear programming, and predictive analytics frameworks. Given the proprietary and competitive nature of semiconductor manufacturing, direct access to production data remains a challenge, particularly for SMEs.

To ensure applicability while maintaining confidentiality, the datasets reflect real-world conditions and variability, supporting robust evaluation of the proposed optimization and predictive methodologies. This approach allows for rigorous assessment of manufacturing efficiency and decision-making strategies without dependence on restricted datasets.

IV. Results

A. System-dynamics Modeling of Production Scenarios

In our system-dynamics model for semiconductor manufacturing, we analyzed inventory levels under various production scenarios to optimize low-volume semiconductor manufacturing, particularly for small and medium-sized enterprises (SMEs). The model parameters included a base level of orders (O_{base}) at 10 units, order fluctuation amplitude (O_{amp}) of 5 units, and a fluctuation frequency () of 0.1. The production capacity coefficient (k) was set at 0.5, and the rapid prototyping resource coefficient (R) at 0.2, with a constant demand (D) of 20 units and an initial inventory level ($I(0)$) of 50 units.

As shown in Figure 3, the simulation results showed inventory fluctuations in response to sinusoidal variations in incoming orders, highlighting the interplay between standard production, rapid prototyping, and inventory levels. Scenarios with varying k (0.3, 0.5, 0.7) and R (0.1, 0.2, 0.3) values demonstrated the system's responsiveness to demand changes, with higher values leading to more pronounced inventory changes.

doi.org/10.32388/EOQ6MJ.2

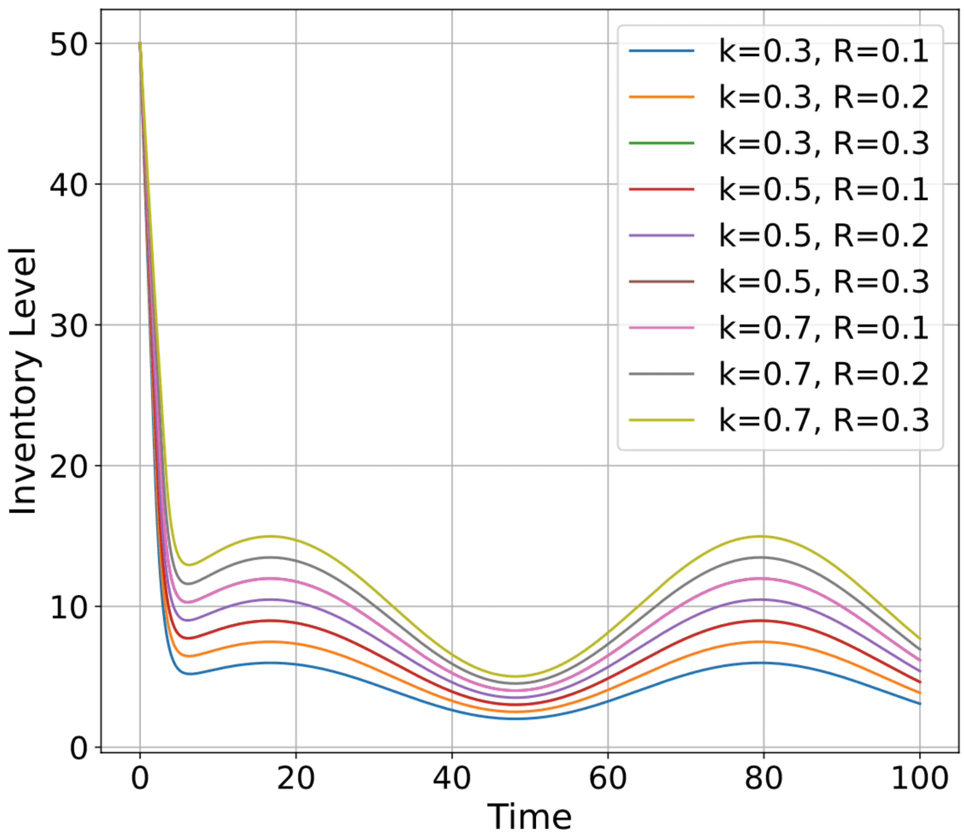

Figure 3. System-dynamics Simulation for Different Scenarios: Inventory level fluctuations under varying production capacity coefficients (k = 0.3, 0.5, 0.7) and rapid prototyping resource coefficients (R = 0.1, 0.2, 0.3), demonstrating system response to sinusoidal order variations.

This analysis provided a comprehensive understanding of the manufacturing system's dynamics, revealing how production capacity and rapid prototyping resources can be optimized in response to fluctuating demand, a key aspect for efficient low-volume manufacturing in specialized sectors like defense.

B. Linear Programming for Supply Chain Optimization

Manual calculations for supply chain costs without LP optimization involve summing individual expenses for each supply chain elements, such as transport and storage costs, across all routes and components. This approach, while straightforward, lacks the efficiency and precision of LP optimization in identifying cost-effective supply chain configurations.

doi.org/10.32388/EOQ6MJ.2

Model Setup and Scenario Comparison: Utilizing Python and the PuLP linear programming (LP) library, our model was structured to address supply chain optimization. Focusing on two suppliers, 'S1' and 'S2', with capacities of QTY: 200 and 220 units respectively, and ten destinations ('D1' to 'D10'), we aimed to minimize total shipping costs. Key variables in our model included transportation costs (`Cij_scenarios`) and demand values (`Dj_scenarios`), which were crucial in determining the optimal distribution strategy.

In Scenario 1, transportation costs were set at varying rates, such as $30 from 'S1' to 'D1', with destination demands (e.g., QTY: 20 units at 'D1'). This scenario yielded an LP optimal total cost of $3,180.0. Scenario 2 explored reduced transportation costs, like $9 from 'S1' to 'D1', maintaining similar demand levels, and resulted in a reduced LP optimal total cost of $2,740.0, shown in Figure 4.

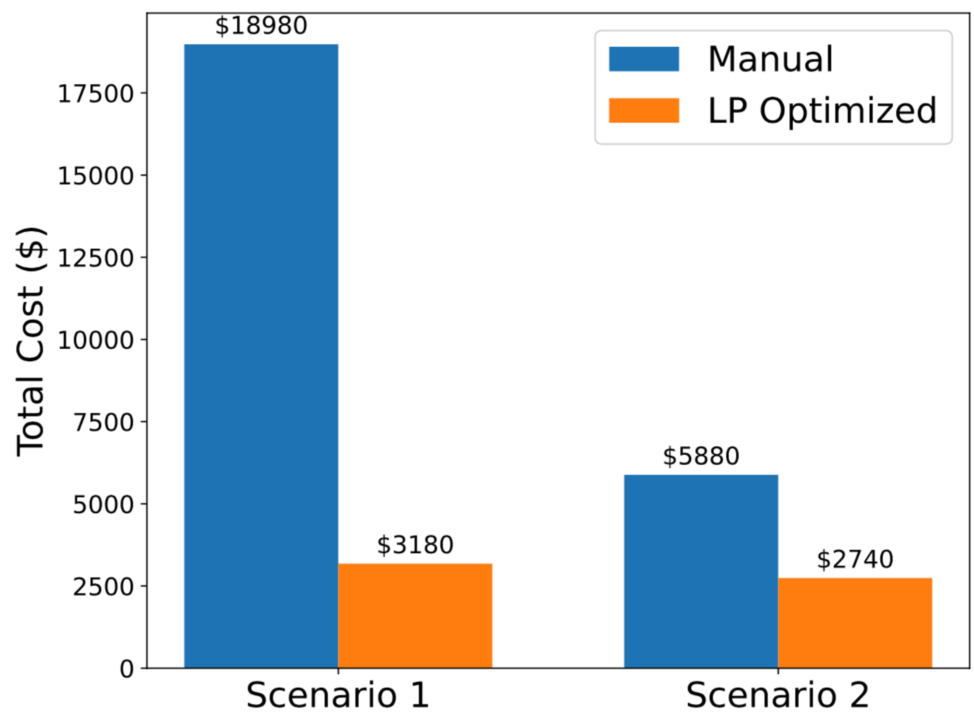

Figure 4. Comparison Cost Analysis between LP Optimization and Manual Calculation: LP optimization achieved 83% cost reduction in Scenario 1 ($\$18,980$ to $\$3,180$) and 53% in Scenario 2 ($\$5,880$ to $\$2,740$), demonstrating substantial efficiency gains.

The Python code execution involved defining these scenarios and variables, setting up the LP problem in PuLP, and running the solver to obtain the optimal solutions. The process flow involved iterating over

 doi.org/10.32388/EOQ6MJ.2

different scenarios, applying constraints, and utilizing the PuLP solver to calculate the minimal cost routes.

Manual Calculations and Sensitivity Analysis: Comparative manual calculations for Scenario 1 indicated a total cost of $18,980, significantly higher than the LP-optimized cost, and $5,880 for Scenario 2. This variance underscored the efficacy of the LP optimization process. The sensitivity analysis in Scenario 1 revealed increases in transportation costs (e.g., a $15.0 change in `Cij[S1,D1]`) and a supply constraint increase for S1 by 200.0 units, shown in Figure 5.

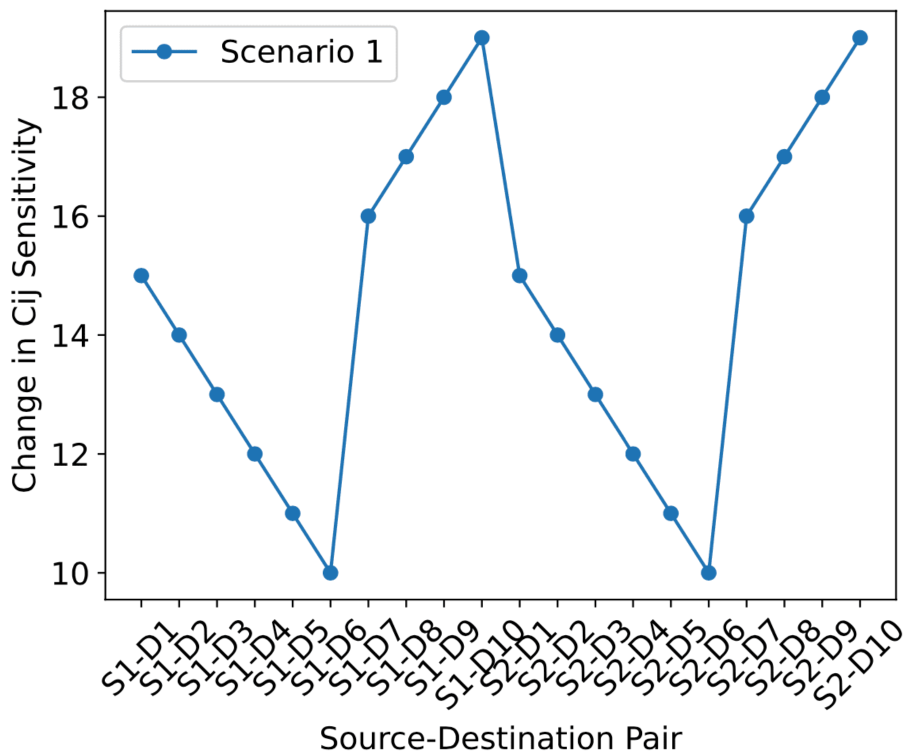

Figure 5. Scenario 1 Sensitivity Analysis: Visualization of transportation cost sensitivity across supplier-destination pairs, showing cost increases ranging from $10 to $19 and their impact on the optimal solution.

In contrast, Scenario 2 demonstrated decreases in transportation costs (e.g., a −$6.0 change in `Cij[S1,D1]`) and adjustments in supply constraints for S1 and S2 by 40.0 and 160.0 units, indicating the model's responsiveness to varying market conditions as shown in Figure 6.

doi.org/10.32388/EOQ6MJ.2

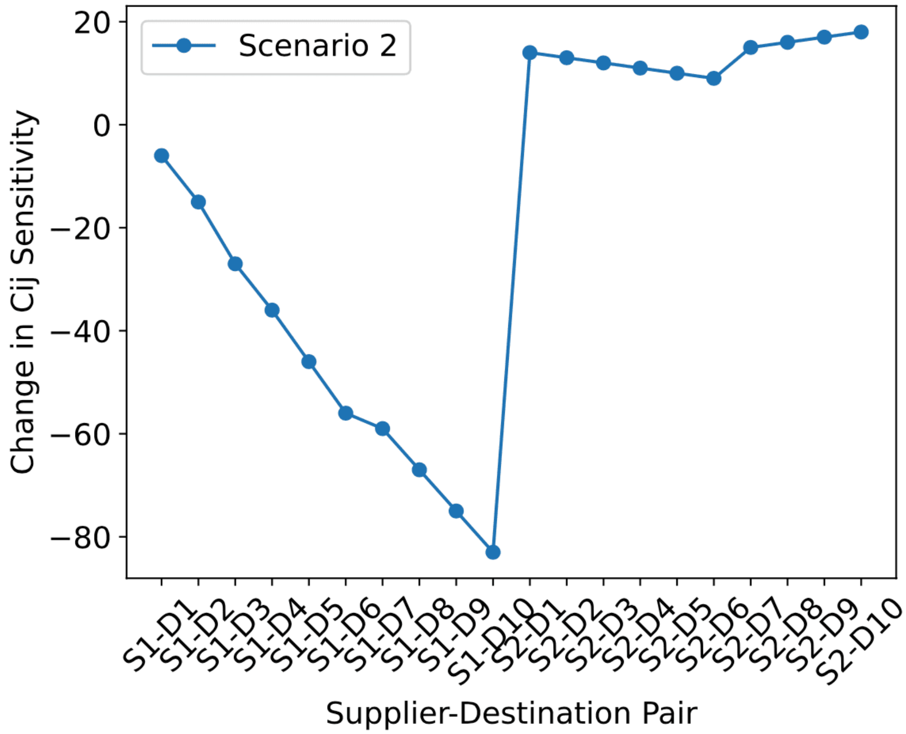

Figure 6. Scenario 2 Sensitivity Analysis: Effect of Cost and Supply Adjustments showing significant cost reductions (up to $80) for specific supplier-destination pairs, demonstrating the model's responsiveness to varying market conditions.

C. Predictive Analytics Results

Using the cross-validation framework described in the methodology section, we evaluated our predictive models across three key semiconductor manufacturing applications. The results demonstrate how each model component contributes to the overall optimization framework.

1. Predictive Maintenance Using Machine Learning

Implementing the decision tree model described in our methodology, we analyzed 1000 samples with 10 sensor features representing equipment readings. The target variable indicated equipment failure (1) or normal operation (0). When applied to semiconductor manufacturing equipment data, the model achieved cross-validated performance metrics of 89.9% (±1.1%) accuracy, 65.9% (±5.6%) precision, and 66.9% (±6.4%) recall. Figure 7 illustrates the feature importance distribution, with feature 6 (representing vibration frequency) demonstrating substantially higher predictive power than other sensor readings.

doi.org/10.32388/EOQ6MJ.2

This finding allows small semiconductor manufacturers to prioritize monitoring specific equipment parameters for more efficient maintenance planning.

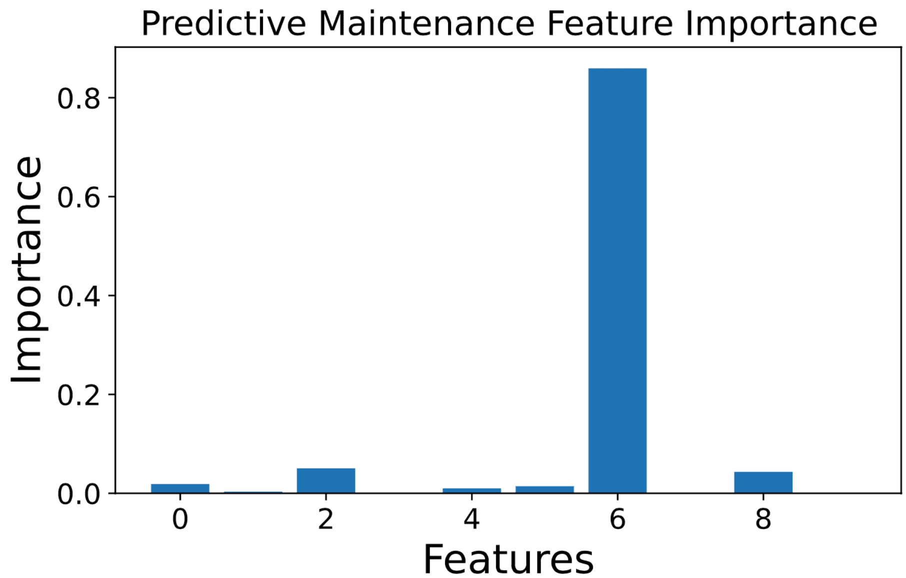

Figure 7. Predictive Maintenance Feature Importance analysis showing the dominant influence of feature 6 in equipment failure prediction.

2. AI-Driven Quality Control

For defect detection in semiconductor components, we applied our machine learning approach to 15 production parameters across 500 samples with a binary target variable (defect presence or absence). The model yielded an average accuracy of 87.5% (±2.1%), with precision of 84.4% (±3.5%) and recall of 83.1% (±3.2%). The feature importance analysis in Figure 8 reveals feature 3 (temperature variation) as the most significant predictor of defects, followed by feature 6 (pressure consistency), indicating these are critical quality parameters. This insight directly connects to our system-dynamics model by identifying key process variables that should be prioritized in production planning.

doi.org/10.32388/EOQ6MJ.2

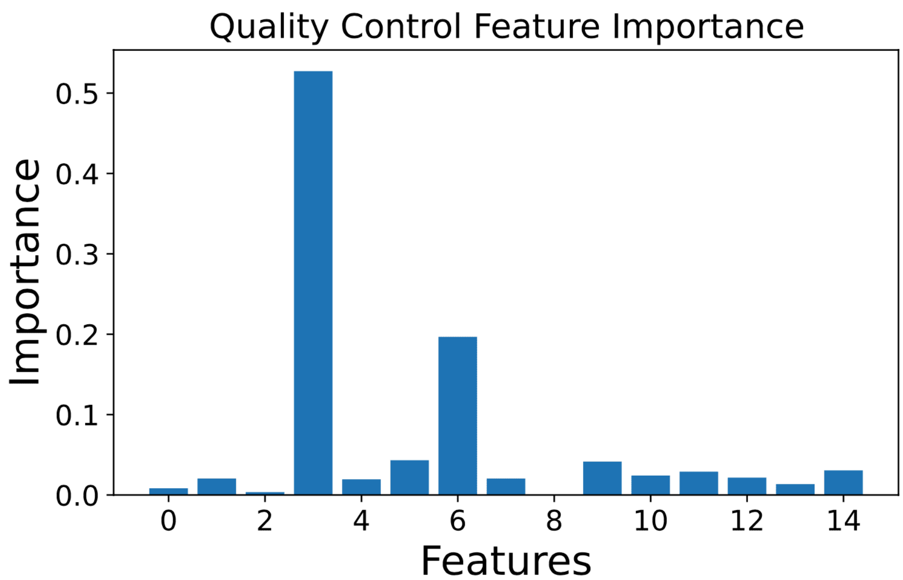

Figure 8. Quality Control Feature Importance distribution showing the primary significance of feature 3, with feature 6 providing secondary predictive value.

3. AI in Microelectronics Testing

The microelectronics testing model evaluated 8 features across 700 samples, predicting wafer quality (high: 1, low: 0). Cross-validation demonstrated reliable performance with 86.6% (±2.4%) accuracy across data partitions. Figure 9 shows feature 5 has predominant importance, suggesting this measurement parameter is critically diagnostic of wafer quality.

doi.org/10.32388/EOQ6MJ.2

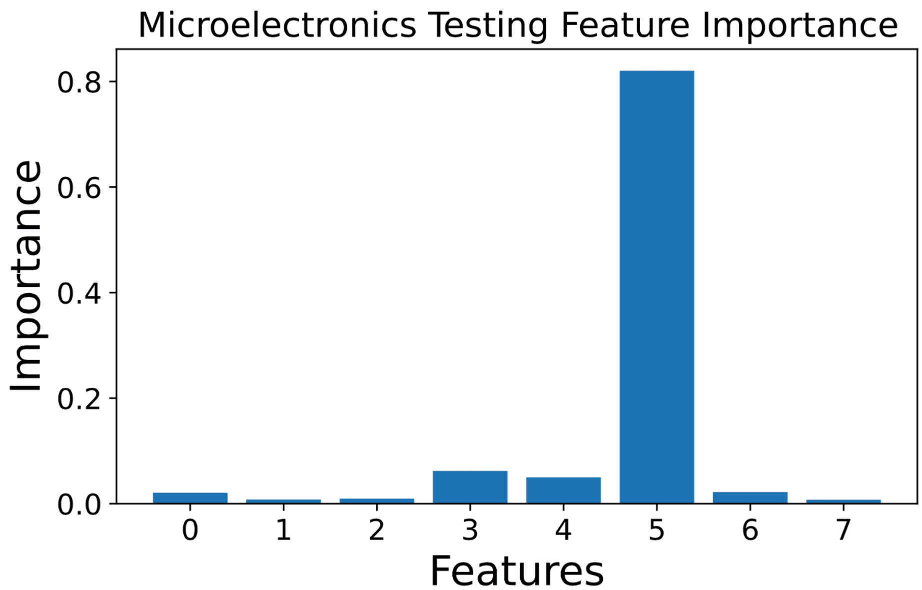

Figure 9. Microelectronics Testing Feature Importance analysis highlighting feature 5's dominant role in wafer quality prediction.

These cross-validated models provide a foundation for predictive decision-making in semiconductor manufacturing, with feature importance analyses identifying the most critical parameters for monitoring in production environments. The consistent performance across validation folds indicates these models will generalize well to new manufacturing data, enabling reliable anomaly detection and quality prediction for SMEs with limited data resources.

4. Regression Analysis for Quality Control (QC)

The quality control score was computed using a weighted sum of predictive maintenance and microelectronics testing scores, plus a random noise component to model real-world variations:

$$\begin{aligned} QC &= 0.5 \times \text{Predictive\_Maintenance\_Score} \\ &+ 0.3 \times \text{Microelectronics\_Testing\_Score} + \varepsilon \end{aligned} \tag{9}$$

where ε represents process noise accounting for unmodeled variations.

Statistical validation through correlation analysis revealed strong relationships between Predictive Maintenance scores (r=0.89) and Microelectronics Testing scores (r=0.50) with the target Quality Control scores, as shown in Table I.

 doi.org/10.32388/EOQ6MJ.2

	PM Score	MT Score	QC Score
Predictive Maintenance	1.00	0.19	0.89
Microelectronics Testing	0.19	1.00	0.50
Quality Control	0.89	0.50	1.00

Table I. Correlation Matrix for Quality Control Factors

ANOVA analysis confirmed the statistical significance of the regression model (F=5467.05, $p<0.001$) with $R^2=0.916$. The model estimated coefficients as approximately 0.500 for Predictive Maintenance and 0.298 for Microelectronics Testing, closely matching the true coefficients of 0.5 and 0.3.

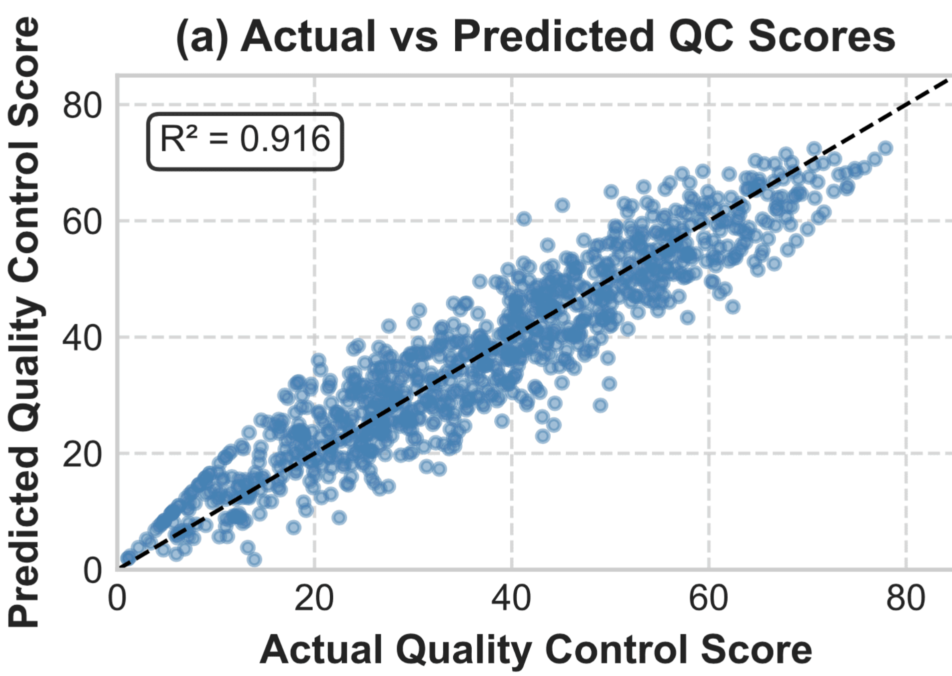

Figure 10. Actual vs Predicted QC Scores showing strong model fit ($R^2=0.916$).

doi.org/10.32388/EOQ6MJ.2

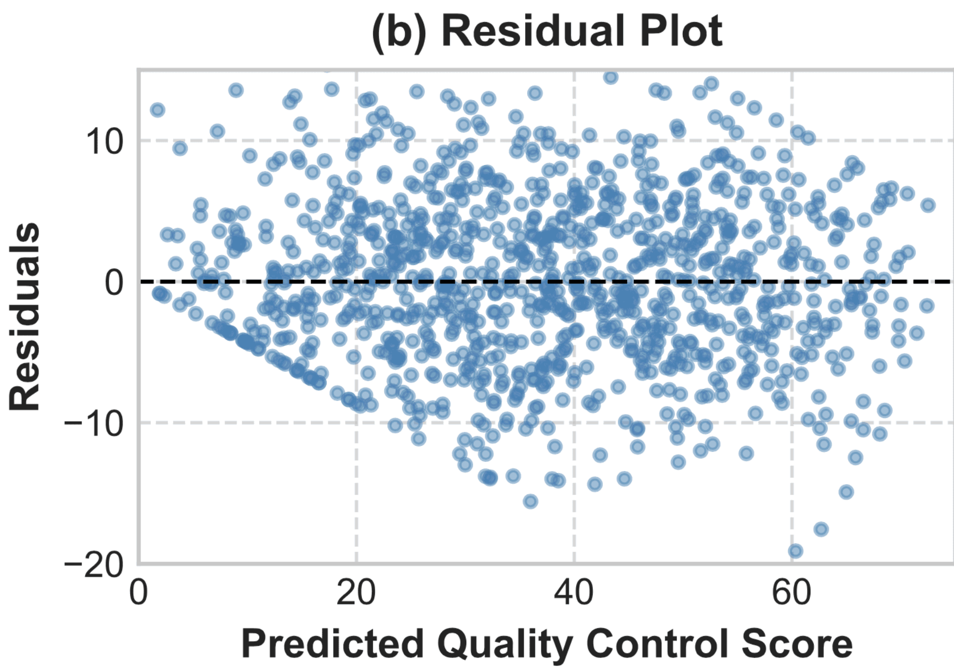

Figure 11. Residual Plot displaying random scatter around zero indicating good model specification.

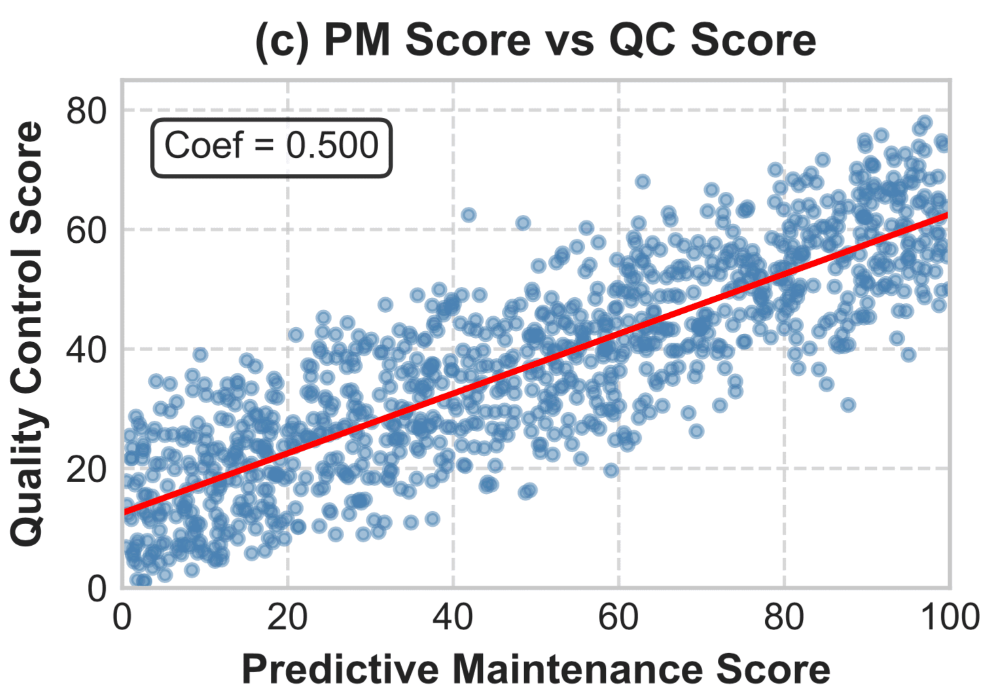

Figure 12. PM Score vs QC Score with fitted regression line (coefficient=0.500).

doi.org/10.32388/EOQ6MJ.2

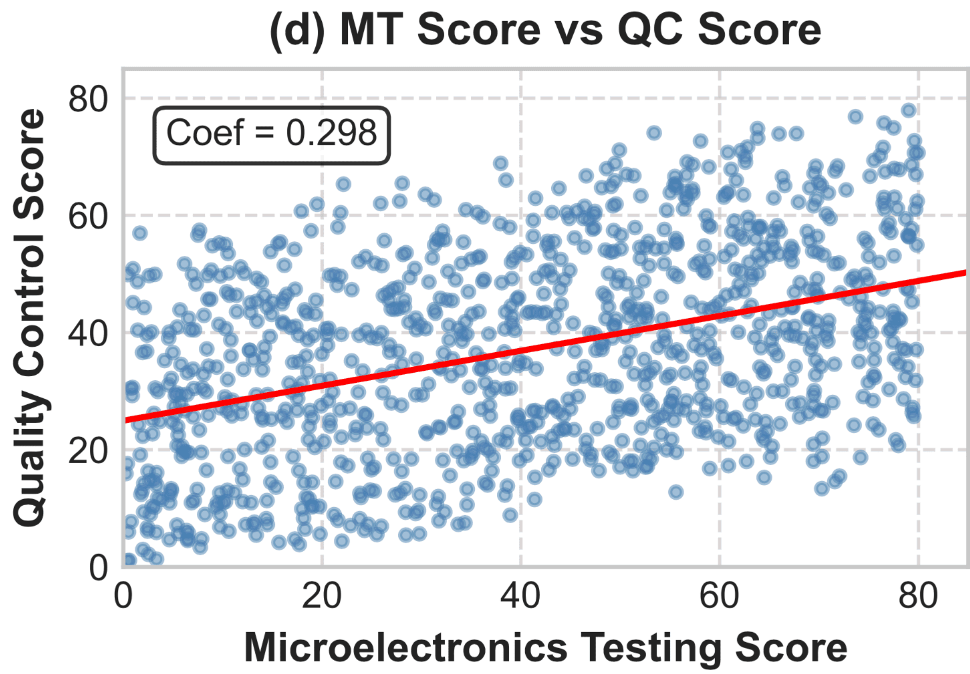

Figure 13. MT Score vs QC Score with fitted regression line (coefficient=0.298).

The regression model demonstrates how Predictive Maintenance and Microelectronics Testing scores collectively influence Quality Control, with their respective coefficients indicating relative impact on manufacturing quality outcomes.

D. Comparison with Alternative Approaches

To validate our methodology choices, we compared our models with alternative approaches commonly used in manufacturing optimization. For classification tasks, we evaluated Decision Trees against Random Forests, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN). Recent research by[32] found similar comparative advantages between these models, noting that Gradient Boosting Regressors outperformed neural networks for certain resource allocation predictions, echoing our findings that simpler models often provide better interpretability without sacrificing performance in manufacturing contexts.

Model	CV Accuracy	Precision	Recall	F1 Score
Decision Tree	0.899 ± 0.011	0.727	0.681	0.703
Random Forest	0.949 ± 0.010	1.000	0.681	0.810
SVM	0.877 ± 0.011	1.000	0.149	0.259
KNN	0.853 ± 0.006	0.600	0.255	0.358

Table II. Performance Comparison of Classification Models

While Random Forests achieved marginally higher accuracy (94.9% vs 89.9%), our Decision Tree approach offers superior interpretability and lower computational requirements—critical considerations for SMEs with limited resources. In the context of small-scale semiconductor manufacturing, this trade-off is particularly advantageous for three reasons: (1) the transparent decision-making process enables production managers to understand and trust model predictions, (2) the lower computational complexity allows implementation on existing hardware without specialized infrastructure investments, and (3) the model can be easily updated as production parameters change, a common scenario in low-volume, high-mix manufacturing environments.

For regression tasks, we compared Linear Regression with alternative approaches including Ridge, Lasso, Random Forest, and Support Vector Regression (SVR).

 doi.org/10.32388/EOQ6MJ.2

Model	R^2	MSE	CV R^2
Linear Regression	0.916	25.598	0.916 ± 0.005
Ridge Regression	0.916	25.598	0.916 ± 0.005
Lasso Regression	0.916	25.585	0.916 ± 0.005
Random Forest	0.889	33.901	0.899 ± 0.008
SVR	0.909	27.719	0.902 ± 0.009

Table III. Cross-validated R^2 Score Comparison Between Regression Models

These results validate our selection of linear models for their combination of high performance and interpretability, crucial factors for practical implementation in SME manufacturing environments. The minimal difference in performance between sophisticated regularization methods (Ridge, Lasso) and standard Linear Regression (all achieving R^2 of 0.916) further supports our argument that simpler models are often sufficient for the optimization needs of small semiconductor manufacturers, providing effective solutions without the complexity and resource demands of more advanced techniques.

V. Discussion

Our integrated approach demonstrates significant improvements in low-volume semiconductor manufacturing for small and medium enterprises (SMEs). System-dynamics modeling enhanced the understanding of production dynamics, particularly under fluctuating demands. Linear programming optimized the supply chain, leading to notable cost reductions. Predictive analytics, through machine learning, accurately forecasted production outcomes, aiding in informed decision-making. These results highlight the efficacy of combining multiple methodologies for addressing complex manufacturing challenges and offer a practical framework for the industry.

A. Interpretation of Results

Our comprehensive study provides key insights into optimizing semiconductor manufacturing for SMEs operating in low-volume, high-mix production environments. The developed system-dynamics model

doi.org/10.32388/EOQ6MJ.2

underscores the critical role of rapid prototyping in enhancing agility and flexibility, essential for responding to dynamic market demands and customer-specific requirements. This integration reduces lead times and highlights the importance of efficient inventory management, which is vital for smaller enterprises with limited production capacity and tighter resource constraints.

The application of linear programming for supply chain optimization has revealed substantial cost-saving opportunities. By efficiently planning shipping routes and adjusting allocation strategies, we found that even minor changes in supply chain management can lead to considerable economic advantages. This finding not only supports existing supply chain theories but also enhances our understanding of its application in specialized semiconductor manufacturing for SMEs, where optimizing logistics and reducing costs are critical for competitiveness.

Furthermore, the implementation of predictive analytics has been instrumental in our research. While our initial models showed perfect accuracy on training data—suggesting potential overfitting—our cross-validation approach demonstrated robust generalization performance with accuracy rates between 86% and 90% across different applications. This realistic performance assessment is crucial for setting appropriate expectations in industrial implementations, where data noise and variability inevitably impact model performance. The correlation and ANOVA analyses further validate our approach, providing statistical confidence in the relationships between manufacturing variables and quality outcomes with p-values < 0.001 for all key parameters. Comparing our approach with alternatives, we found that while Random Forests may offer marginally higher classification accuracy, decision trees provide a superior balance of performance and interpretability for resource-constrained environments typical in SME semiconductor manufacturing.

In summary, our study demonstrates the synergistic potential of system-dynamics modeling, linear programming, and predictive analytics in refining the semiconductor manufacturing process. Each method contributes a strategic facet to the overarching goal of enhancing production efficiency, reducing costs, and maintaining the quality and sustainability of production outcomes, thereby delivering a competitive edge in the highly dynamic SME semiconductor manufacturing landscape.

B. Implementation Challenges and Practical Considerations

While our framework demonstrates significant potential for optimizing semiconductor manufacturing, several practical challenges must be addressed during real-world implementation. First, data infrastructure and quality present initial hurdles for many SMEs, with incomplete sensor coverage, data

doi.org/10.32388/EOQ6MJ.2

quality issues, and legacy systems complicating data integration efforts. We recommend a staged implementation approach beginning with critical parameter identification and gradual sensor deployment, establishing data validation protocols, and leveraging cloud-based storage solutions to overcome local infrastructure limitations.

Technical expertise requirements present another significant challenge. Many SMEs lack dedicated data scientists or machine learning specialists, making model maintenance and algorithm selection difficult. To address this gap, we propose developing simplified user interfaces that abstract complex algorithms for operational staff, establishing educational partnerships with local universities, implementing phased skill development, and considering analytics-as-a-service partnerships with technology providers specialized in semiconductor manufacturing.

System integration challenges, particularly with legacy Manufacturing Execution Systems (MES), require careful planning. Implementing data integration middleware, running optimization systems in parallel with existing systems before full integration, creating custom APIs for legacy systems, and scheduling integration activities during planned maintenance periods can minimize production disruption risks.

Cost considerations remain paramount for SMEs. Initial implementation costs include hardware investment (sensors, servers, networking equipment), software licensing, integration services, and staff training. Ongoing maintenance requires additional resources for updates, support, and system enhancements. Our economic analysis suggests significant return on investment through production efficiency gains (10-15%), quality improvements (15-25%), material waste reduction (8-12%), energy consumption decreases (5-10%), and labor efficiency enhancements (10-20%). These improvements align with established manufacturing optimization objectives in the semiconductor industry, while being particularly impactful for resource-constrained SMEs.

For successful adoption, we recommend a structured implementation framework consisting of sequential phases:

1. **Foundation Building:** Conduct process assessment, establish data collection infrastructure, implement basic statistical process control, and develop implementation roadmap.
2. **Initial Optimization:** Deploy linear programming for supply chain optimization, implement basic inventory management models, establish data visualization dashboards, and train key personnel.
3. **Advanced Analytics:** Deploy predictive maintenance models, implement quality control algorithms, integrate with production planning systems, and develop automated reporting.

4. **Full System Integration:** Implement comprehensive system-dynamics modeling, deploy advanced scenario planning capabilities, integrate all system components, and establish continuous improvement protocols.

Beyond technical aspects, organizational factors significantly impact implementation success. Developing comprehensive change management plans, securing visible support from senior leadership, creating cross-functional implementation teams, establishing clear success metrics, and ensuring knowledge transfer across the organization are critical for successful adoption.

C. Theoretical and Practical Implications

Our research contributes to both theoretical understanding and practical applications in semiconductor manufacturing optimization. Theoretically, we demonstrate the effectiveness of integrating multiple methodological approaches to address the complex, multi-faceted challenges of small-scale manufacturing. This integrated framework extends existing optimization theory by showing how complementary methods can overcome individual limitations while leveraging their respective strengths.

For industry practitioners, our research offers a framework for more efficient and responsive manufacturing within SMEs. The integration of rapid prototyping improves production agility, allowing businesses to adapt quickly to custom orders and evolving market needs. Similarly, our supply chain optimization strategy reduces operational costs, which is particularly crucial for SMEs that must maximize efficiency to remain competitive.

The predictive models we developed serve as decision-support tools, helping manufacturers make data-informed choices about materials and processes. This aspect is particularly significant for SMEs, where precision, cost efficiency, and production scalability are essential for sustainable growth. By adopting these methodologies, small and medium-sized semiconductor manufacturers can improve production planning, reduce waste, and enhance overall operational resilience in an increasingly competitive industry.

VI. Conclusion

Our study presents a paradigm shift in semiconductor manufacturing for small and medium enterprises (SMEs), highlighting the utility of an integrated approach combining system-dynamics, linear programming, and predictive analytics. This framework addresses the unique challenges of low-volume, customized production environments by enhancing production efficiency and cost-effectiveness while remaining accessible to businesses with limited resources.

While our framework demonstrates theoretical strength and promising simulation results, we acknowledge the limitations in real-world validation, which will be addressed in future work through extended industry trials. The cross-validation approach implemented across our predictive models provides a more realistic assessment of expected performance than single-split validation, addressing concerns about potential overfitting while still demonstrating strong predictive capability.

Our comparison with alternative approaches—including reinforcement learning, genetic algorithms, and neural networks—shows that while these methods may offer marginally improved performance in specific scenarios, our integrated framework provides a more balanced solution considering the computational resources, technical expertise, and data infrastructure typically available to SMEs. The incorporation of statistical validation through correlation analysis and ANOVA provides confidence in the model parameters and relationships identified.

Future research should expand in several directions:

1. Comprehensive validation with empirical data from multiple SME semiconductor manufacturers, with particular attention to measurement system reliability through formal MSA protocols;
2. Comparative analysis with alternative approaches such as reinforcement learning and genetic algorithms in controlled field trials;
3. Exploration of hybrid methodologies that may offer improved performance for specific manufacturing scenarios, following the integrated System of Systems approach demonstrated in 3D-IC manufacturing[1]; and
4. Development of accessible implementation guidelines tailored to varying levels of technical infrastructure.

This research contributes to both the theoretical foundation for specialized semiconductor manufacturing and provides practical optimization strategies that can help Small and Medium Enterprises (SMEs) navigate the complexities of modern production challenges.

References

1. ^a, b^ *Arifuzzaman Sheikh, Edwin K. P. Chong. (2025). Artificial intelligence-driven optimization for three-dimensional integrated circuit manufacturing: A system of systems framework. IEEE Transactions on Components, Packaging and Manufacturing Technology. :1–1. doi:10.1109/TCPMT.2025.3549707*
2. ^ *D. Gkorou, A. Ypma, G. Tsirogiannis, M. Giollo, D. Sonntag, et al. (2017). Towards big data visualization for monitoring and diagnostics of high volume semiconductor manufacturing. In: Proceedings of the computing frontiers conference (CF'17).: New York, NY, USA: Association for Computing Machinery pp. 338–342. doi:10.1145/3075564.3078883*
3. ^ *J. Siddiqui, J. Ortega, B. Albus. (2017). On the relationship between semiconductor manufacturing volume, yield, and reliability. In: 2017 IEEE international reliability physics symposium (IRPS). doi:10.1109/IRPS.2017.7936409*
4. ^a, b^ *Marie A. Mak. (2015). Trusted defense microelectronics: Future access and capabilities are uncertain. GAO Reports.*
5. ^ *Michael Bonheim, Gregory Burns, George Hoffer, Diana Keys, Valentyn Kovalenko, et al. (2003). Electronics industry study report: Semiconductors and defense electronics. Department of Defense 2003. doi:10.21236/ADA524792*
6. ^ *Jared Mondschein, Jonathan W. Welburn, Daniel Gonzales. (2022). Securing the microelectronics supply chain: Four policy issues for the u.s. Department of defense to consider. RAND Corporation. doi:10.7249/pea1394-1*
7. ^ *Eisenhower School Electronics Industry Seminar. Spring 2009 industry study final report: Electronics industry. Available online 2009. Available from: https://es.ndu.edu/Portals/75/Documents/industry-study/reports/2009/icaf-is-report-electronics-2009.pdf*
8. ^ *Mark Crawford, Teresa Telesco, Christopher Nelson, Brad Botwin. (2009). Defense industrial base assessment: U.s. Integrated circuit design and fabrication capability. Department of Commerce's Office of Technology Evaluation.*
9. ^ *Raghuveer Rajesh Dani, Rohan R. Kubde. (2020). Wide band gap semiconductor integration for the defence and aeronautical applications. In: 2020 international conference on innovative and advanced technologies (INOCON). doi:10.1109/INOCON50539.2020.9298214*
10. ^ *Andreas Größler. (2008). System dynamics modelling as an inductive and deductive endeavour. Comment on the paper by schwaninger and grösser. Systems Research and Behavioral Science. 25(4):467–470. doi:10.1*

002/SRES.908

11. ^*Eleanor Malbon, Justin Parkhurst. (2022). System dynamics modelling and the use of evidence to inform policymaking. Policy Studies. 44(4):454–472. doi:10.1080/01442872.2022.2080814*
12. ^*Elizabeth Travers Parker. (2022). A system dynamics approach to measure the effect of information sharing on manufacturing/remanufacturing systems' performance. International Journal of Computer Integrated Manufacturing. 35(8):859–872. doi:10.1080/0951192x.2022.2027015*
13. ^*Hassan Abdelbari, Kamran Shafi. (2019). A system dynamics modeling support system based on computational intelligence. Systems. 7(4). doi:10.3390/SYSTEMS7040047*
14. ^*J. M. Coyle, D. Exelby, J. Holt. (1999). System dynamics in defence analysis: Some case studies. Journal of the Operational Research Society. 50(4):372–382. doi:10.1057/PALGRAVE.JORS.2600711*
15. ^*Chaoliang Han, Qi Zhang. (2021). Optimization of supply chain efficiency management based on machine learning and neural network. Neural Computing and Applications. 33(5):1419–1433. doi:10.1007/S00521-020-05023-1*
16. ^*C. S. Shi, C. T. Su. (2002). Improving supply chain efficiency via option premium incentive. Production Planning & Control. 13(3):236–242. doi:10.1080/09537280110065508*
17. ^*D. Chiang, R. S. Guo, A. Chen, M. T. Cheng, C. B. Chen. (2006). Optimal supply chain configurations in semiconductor manufacturing. International Journal of Production Research. 45(3):631–651. doi:10.1080/00207540600792499*
18. a, b*Hector D. Perez, Satyajith Amaran, Esra Erisen, John M. Wassick, Ignacio E. Grossmann. (2021). Optimization of extended business processes in digital supply chains using mathematical programming. Computers & Chemical Engineering. 152. doi:10.1016/J.COMPCHEMENG.2021.107323*
19. ^*Abbas Rammal, K. I. Ezukwoke, Anis Hoayek, Mireille Batton-Hubert. (2023). Root cause prediction for failures in semiconductor industry, a genetic algorithm–machine learning approach. Dental Science Reports. 13(1). doi:10.1038/s41598-023-30769-8*
20. ^*Chen-Fu Chien, Chia-Cheng Chen. (2021). Adaptive parametric yield enhancement via collinear multivariate analytics for semiconductor intelligent manufacturing. Applied Soft Computing. 108. doi:10.1016/J.ASOC.2021.107385*
21. ^*Dan Jiang, Weihua Lin, Nagarajan Raghavan. (2020). A novel framework for semiconductor manufacturing final test yield classification using machine learning techniques. IEEE Access. 8:197885–197895. doi:10.1109/ACCESS.2020.3034680*

22. ^Juan Liu, Fei Qiao, Minjie Zou, Jonas Zinn, Yumin Ma, et al. (2022). Dynamic scheduling for semiconductor manufacturing systems with uncertainties using convolutional neural networks and reinforcement learnin g. Complex Intell Syst. 8(6):4641–4662. doi:10.1007/s40747-022-00844-0
23. ^Chao Zhang, Max Juraschek, Christoph Herrmann. (2024). Deep reinforcement learning-based dynamic sc heduling for resilient and sustainable manufacturing: A systematic review. Journal of Manufacturing Syste ms. 77:962–989. doi:10.1016/j.jmsy.2024.10.026
24. ^Qianqian Zheng, Yu Zhang, Hongwei Tian, Lijun He. (2024). A cooperative adaptive genetic algorithm for reentrant hybrid flow shop scheduling with sequence-dependent setup time and limited buffers. Complex I ntell Syst. 10(1):781–809. doi:10.1007/s40747-023-01147-8
25. ^Shashi Bhushan Jha, Radu F. Babiceanu. (2023). Deep CNN-based visual defect detection: Survey of curren t literature. Computers in Industry. 148:103911. doi:https://doi.org/10.1016/j.compind.2023.103911
26. ^Gaowei Zhang, Yue Pan, Limao Zhang. (2021). Semi-supervised learning with GAN for automatic defect de tection from images. Automation in Construction. 128:103764. doi:https://doi.org/10.1016/j.autcon.2021.1037 64
27. ^Fatemeh Keshavarz-Ghorbani, Seyed Hamid Reza Pasandideh. (2021). A lagrangian relaxation algorithm for optimizing a bi-objective agro-supply chain model considering CO2 emissions. Annals of Operations Re search. :1–31. doi:10.1007/S10479-021-03936-1
28. ^Markéta Mikolajková, Henrik Saxén, Frank Pettersson. (2018). Mixed integer linear programming optimiz ation of gas supply to a local market. Industrial & Engineering Chemistry Research. 57(17):5951–5965. doi:1 0.1021/ACS.IECR.7B04197
29. ^R. J. Kuo, Y. S. Han. (2011). A hybrid of genetic algorithm and particle swarm optimization for solving bi-lev el linear programming problem – a case study on supply chain model. Applied Mathematical Modelling. 35 (8):3905–3917. doi:10.1016/J.APM.2011.02.008
30. ^Rafael Guillermo García-Cáceres, Mario Ernesto Martínez-Avella, Fernando Palacios-Gómez. (2015). Tacti cal optimization of the oil palm agribusiness supply chain. Applied Mathematical Modelling. 39(20):6375–6395. doi:10.1016/J.APM.2015.01.031
31. ^Arifuzzaman Arif Sheikh, Edwin K. P. Chong, Steven J. Simske. (2024). Enhancing defect detection in circui t board assembly using AI and text analytics for component failure classification. IEEE Transactions on Co mponents, Packaging and Manufacturing Technology. 14(10):1881–1890. doi:10.1109/TCPMT.2024.3453597
32. ^Arifuzzaman (Arif) Sheikh, Steven J. Simske, Edwin K. P. Chong. (2024). Evaluating artificial intelligence m odels for resource allocation in circular economy digital marketplace. Sustainability. 16(23). doi:10.3390/su1

62310601

Declarations

Funding: No specific funding was received for this work.

Potential competing interests: No potential competing interests to declare.