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Linear Programming Model for Semiconductor Aggregate Production Planning with Sensitivity Analysis

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Abstract
This work focuses on optimizing production planning in semiconductor manufacturing and identifying the most significant parameter affecting cost minimization and demand satisfaction. Using IBM ILOG CPLEX Optimization Studio, the study computes optimal solution for the problem and analyses the sensitivity of the inventory cost, work in progress cost and backlogging cost parameters using a small dataset. Findings reveal that higher backlogging costs lead to increased inventory levels and decreased backlogged products, while higher inventory costs result in higher overall production costs and reduced inventory levels. Work in progress costs have a minimal effect on total output. Backlogging cost is identified as the most sensitive parameter, followed by inventory cost and work in progress cost. Variations in work centre capacity significantly impact total costs and backlog quantities, highlighting its importance in production planning. Challenges in meeting demand during high-demand periods are noted, indicating potential struggles in accommodating sudden spikes in demand. The study suggests improvements through sensitivity analysis on parameter interactions, using larger datasets, and exploring dynamic demand patterns for multi-objective optimization.
Keywords: Aggregate production planning; semiconductor manufacturing; sensitivity analysis; linear programming; optimization

Introduction

The expansion of the electronics sector has emerged as a prominent global industry due to technological advancements. Its development plays a vital role in generating employment opportunities and fostering economic progress, especially in developing and newly industrialized nations. This industry encompasses a diverse range of processes, including the fabrication of printed circuit boards, assembly of semiconductor devices and printed circuit boards and the creation of finalized electronic products [1]. Central to this sector is the production of semiconductors, which serves as its foundational core [2]. The semiconductor sector encompasses various enterprises dedicated to the creation and development of semiconductors and related devices, such as transistors and integrated circuits. Figure 1 illustrates the primary four stages involved in semiconductor production. Wafer fabrication and probing are commonly termed as front-end processes, while assembly and final testing are recognized as back-end operations [3].

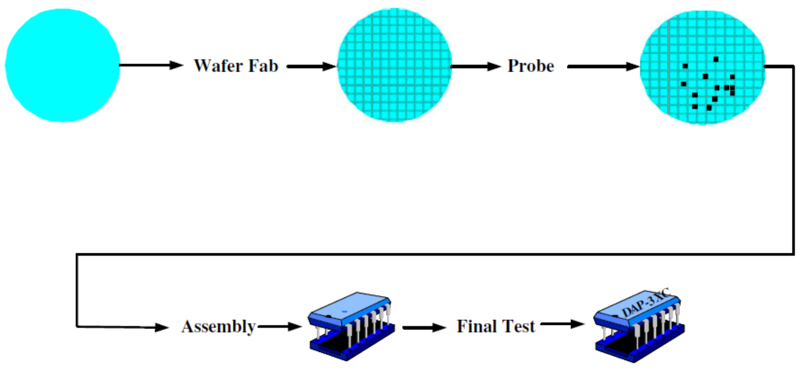


Figure 1 Main stages in semiconductor manufacturing

Semiconductors, also referred to as chips, are vital components present in consumer electronics such as laptops, digital cameras, and smartphones. Their significance extends beyond powering entertainment systems and functions in automobiles. The automotive industry has faced multiple profit warnings due to manufacturers revising down their production and delivery targets owing to chip shortages and supply constraints. The current scarcity of semiconductors stems from both heightened demand and restricted supply. The surge in demand for technology facilitating remote work during the COVID-19 lockdowns in April to June of 2020 sparked a dramatic increase, initiating the shortage. This sudden upsurge led to an unparalleled global shortage, temporarily disrupting the supply chain [4]. Global demand for private computers and medical equipment has increased over the past two years as a result of working and learning from home and medical healthcare services. The demand for game consoles and other multimedia accessories, like graphic cards, has also significantly increased as a result of social distancing and social exclusion.

Since chip shortages are present, it is crucial for every original equipment manufacturer (OEM) to act right away to ensure they are in the most advantageous position. In the face of widespread challenges encountered by multiple companies, there is no straightforward solution to address the shortage of semiconductors and the subsequent increase in costs. As a result, to overcome the difficulties brought on by the shortage of semiconductors, both short-term and long-term production planning strategies are required. Only by improving the planning systems will we be able to overcome these challenges [5].

This research aims to (1) compute the optimal solution of the problem using generated data through IBM ILOG CPLEX Optimization Studio and (2) identify the most significant parameter affecting cost minimization and demand satisfaction in the production planning model through sensitivity analysis.

Literature Review

Semiconductor manufacturing

The manufacturing of semiconductors involves an exceptionally intricate and multi-stage process. Wafer fabrication facilities employ advanced procedures and cutting-edge machinery, necessitating substantial investments reaching billions of dollars to produce integrated circuits [6]. The complexity inherent in semiconductor manufacturing stems from expansive facilities housing numerous machines and intricate manufacturing characteristics. These facilities often incorporate re-entrant flows, interconnecting numerous operational processes along product lines. As a result, this complexity leads to extended cycle times, spanning several weeks or even months [7].

The semiconductor manufacturing process encompasses three key phases which are the design process, the front-end process and the back-end process. The design phase involves IC design and photomask design, where each layer necessary for circuit construction requires a corresponding photomask. Moving to the front-end process, it includes wafer fabrication, probing, and dicing, where multiple semiconductors align on a silicon wafer to create Large Scale Integrated Circuits (LSIs). Finally, the back-end process involves packaging, assembly, and final product testing, entailing the separation of the semiconductor from the wafer and completing its assembly, fixing terminals, and applying resin coatings [8]. Figure 2 offers an overview of these sequential steps in the semiconductor manufacturing process.

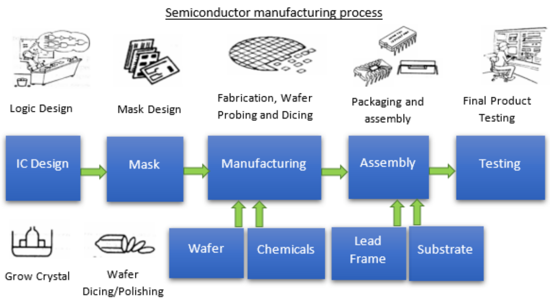


Figure 2 A Brief Overview of Semiconductor Manufacturing Process

Production planning

Production planning encompasses diverse tasks like demand forecasting, devising production strategies, allocating resources, scheduling production activities, and overseeing inventory levels. Its ultimate goal is to efficiently fulfil customer needs, balancing financial efficiency with customer service objectives [9]. Financial objectives typically involve managing production and inventory costs, while customer service objectives revolve around delivering the correct product, in the specified quantity, at the scheduled time and location. Notably, according to Anthony [10] and Salomon [11], production planning predicaments can be classified into strategic, tactical and operational problems.

In the realm of semiconductor manufacturing, production planning studies have primarily focused on congestion modelling. Hung and Leachman [12] introduced an automated production planning methodology that relies on an iterative combination of linear programming (LP) optimization and discrete-event simulation calculations. Similarly, Byrne and Bakir [13] developed a hybrid algorithm combining mathematical programming and simulation models to address the Multi Period Multi Product (MPMP) problem, ensuring both mathematical optimality and practical feasibility. Byrne and Hossain [14] improved a linear programming model, modifying resource requirements and constraints to reduce WIP levels and enhance overall flow time, aiming for more efficient production planning. Furthermore, Bang and Kim [15] introduced a two-level hierarchical production planning (HPP) method that utilizes an iterative approach.

Albey et al. [16] proposed a clearing function considering product mix effects in multi-product systems, while Beraudy et al. [7] introduced diverse production planning models integrating productivity and financial objectives. These models offer multifaceted perspectives, emphasizing both operational efficiency and financial success by maximizing output, considering profit maximization through net present value, and minimizing total costs with fixed lead times. This breadth of approaches illustrates the multifaceted nature of production planning in semiconductor manufacturing and its significant impact on both operational and financial aspects.

Asmundsson et al. [17] and Kacar et al. [18] proposed simulation-based studies focusing on production planning models with lead time clearing functions, capturing nonlinear workload-throughput dynamics in multistage production inventory systems. Their investigations demonstrated the effectiveness of these functions in optimizing planning and maximizing financial outcomes. Furthermore, Zhang et al. [19] also proposed a multi-fidelity simulation optimization approach to efficiently evaluate and select the most effective production plan from a large set, while Bardhan et al. [20] introduced an iterative hierarchical model for semiconductor fabrication facilities. The iterative approach minimizes the performance gap between assumed and obtained processing rates, resulting in improved overall efficiency.

An increasing number of heuristic methods, such as genetic algorithms, tabu search algorithms and ant colony algorithms, has been applied to address semiconductor production planning challenges. Given the intricacy and computational complexities inherent in these problems, heuristic approaches have proven effective in identifying near-optimal solutions within a reasonable timeframe. Cavalieri et al. [21] illustrated the application of genetic algorithms to enhance plant performance within a flexible semiconductor manufacturing system. Furthermore, Tang et al. [22] introduced a methodology utilizing simulated annealing and genetic algorithms for job scheduling within semiconductor manufacturing lines, aiming for improved optimization results. On the other hand, Guo et al. [23] proposed a decomposition based classified ant colony optimization algorithm specifically for scheduling semiconductor wafer fabrication systems. This approach significantly reduced the time required to identify superior solutions in the optimization process.

Furthermore, Lowe et al. [24] presented a robust optimization approach to production planning under yield uncertainty. The sensitivity analysis, based on an industrial dataset, highlighted that yield uncertainty leads to increased costs, particularly when occurring later in the supply chain, such as at the testing stage. The study demonstrated that robust solutions, despite their higher initial and overall costs, effectively prevent significant demand losses compared to deterministic solutions.

Aggregate production planning

Aggregate production planning (APP) is a medium-term capacity planning process that aims to minimize costs while determining the optimal production, workforce, and inventory levels needed to meet customer demands. It involves establishing the best production and employment plans over a finite planning horizon to satisfy the total demand for all products sharing the same limited resources [25]. The main goal of aggregate production planning is to meet customer demand while utilizing resources such as labour, equipment and inventory efficiently. This involves making decisions about production rates, workforce levels, inventory levels, and subcontracting to ensure that the production plan is feasible and cost-effective. The APP problem involves formulating a plan that satisfies demand over the planning horizon while minimizing costs, considering factors such as production capacity constraints, labour constraints, inventory constraints, demand variability and costs.

Naji et al. [26] introduced an efficiency-based APP model for multi-line manufacturing systems, integrating efficiency factors into the planning process. By using Data Envelopment Analysis (DEA) to calculate efficiency scores based on specific criteria, the model allocates production quantities to the most efficient lines, aiming to optimize both efficiency and production costs. Meanwhile, Marfuah et al. [27] presents an APP model that incorporates a dynamic programming (DP) approach to address uncertainties in demand, production costs and storage costs. By using artificial neural network techniques for demand forecasting and integrating fuzzy logic into the DP framework, the model aims to meet consumer demand and minimize total costs during the planning period.

Research data

The data in this study is randomly generated. Table 1, Table 2 and Table 3 show the dataset used in this study. This data will be used as the baseline dataset.

Table 1: Product and work centre information

Product	P1, P2, P3
Work Centre	W1 = {Operation 1, Operation 2}, W2 = {Operation 3}, W3 = {Operation 4, Operation 5}
Number of Periods	3
Work Centre's Capacity (hours)	W1 = 1000 W2 = 1000 W3 = 1000
Lead Time (days)	Operation 1 = 1 Operation 2 = 1 Operation 3 = 3 Operation 4 = 4 Operation 5 = 0
Initial Inventory (units)	P1 = 0, P2 = 0, P3 = 0
Initial Backlog (units)	P1 = 0, P2 = 0, P3 = 0
Initial WIP (units)	P1 = 0, P2 = 0, P3 = 0
Inventory Cost/Product	P1 = 100, P2 = 100, P3 = 100
Backlogging Cost/Product	P1 = 100, P2 = 100, P3 = 100
WIP Cost/Operation	P1 = 20, P2 = 20, P3 = 20

Table 2: Processing time (hours)

Operation	P1	P2	P3
1	2	2	2
2	4	3	8
3	2	4	3
4	0	2	4

5	0	0	5

Table 3: Product demand (units)

Period	P1	P2	P3
1	50	50	40
2	20	30	50
3	30	30	50

Mathematical model

The mathematical model used in this study is taken from previous research by Kacar et al. [18].

Sets:
P: set of all products
K: set of all work centres
L: set of all operations
$L(k)$: set of operations l processed on work centres $k \in K$

Indices:
t: period index
p: product index
k: work centre index
l: operation index

Parameters:
α_{pl}: Processing time of operation l of product p
C_k: Maximum capacity of work centre k in units of products
LT_l: Lead time of operation $l \in L$
D_{pt}: Demand of product p at the end of period t
h_{pt}: Unit inventory cost of product p at the end of period t
b_{pt}: Unit backlogging cost of product p at the end of period t
w_{pl}: Unit work in progress cost of product p at the end of operation l

Decision variables:
X_{plt}: Quantity of product p released in period t to operation l
$X_{p1t} = X_{pt}^{in}$: Quantity of product p released into first station in the line at period t
Y_{plt}: Quantity of product p completing its operation l at period t
$Y_{pLt} = Y_{pt}^{out}$: Output quantity of product p at period t
W_{plt}: Work in progress of product p, at operation l at the end of period t
I_{pt}: Inventory level of product p at the end of period t
B_{pt}: Backlogging level of product p at the end of period t
Model:

$$Min \sum_{p\in P}\sum_{l\in L}\sum_{t=1}^{T} w_{pl}W_{plt} + \sum_{p\in P}\sum_{t=1}^{T}(h_{pt}I_{pt} + b_{pt}B_{pt}) \tag{1}$$

subject to

$$X_{plt} = Y_{p(l-1)(t)} \quad \forall p \in P \quad \forall l \in L \quad \forall t \in \{1,\dots,T\} \tag{2}$$

$$W_{plt} = W_{pl(t-1)} + X_{plt} - Y_{plt} \quad \forall p \in P \quad \forall l \in L \quad \forall t \in \{1,\dots,T\} \tag{3}$$

$$X_{p(t-LT_l)} = Y_{plt} \quad \forall p \in P \quad \forall l \in L \quad \forall t \in \{1,\dots,T\} \tag{4}$$

$$Y_{pt} + I_{p(t-1)} - B_{p(t-1)} - I_{pt} + B_{pt} = D_{pt} \quad \forall p \in P \quad \forall t \in \{1,\dots,T\} \tag{5}$$

$$\sum_{p\in P}\sum_{l\in L(k)}\alpha_{pl}Y_{plt}\leq C_k \qquad \forall k\in K \quad \forall t\in\{1,\ldots,T\} \tag{6}$$

$$X_{plt}, Y_{plt}, W_{plt}, I_{pt}, B_{pt}\geq 0 \quad \forall p\in P\ \forall l\in L\ \forall t\in\{1,\ldots,T\} \tag{7}$$

The goal of objective function (1) is to minimize the total cost related to inventory, backlogging, and work in progress. Equation (2) establishes the relation between the output X_{plt} of one operation and the input Y_{plt} of the subsequent operation. Equation (3) ensures the work in progress balance across the time horizon for each operation. The fixed lead times for each product's operations are maintained by Equation (4). Equation (5) encapsulates flow conservation for final products, ensuring that demands are met through inventory, current production, or backlogging for future periods. Capacity constraints for each work centre are formulated using Equation (6). Equation (7) ensures the non-negativity of decision variables.

Results and discussion

Baseline solution

In determining the baseline solution, IBM ILOG CPLEX Optimization Studio is utilized to solve the model. Table 4 shows the results obtained from the baseline dataset.

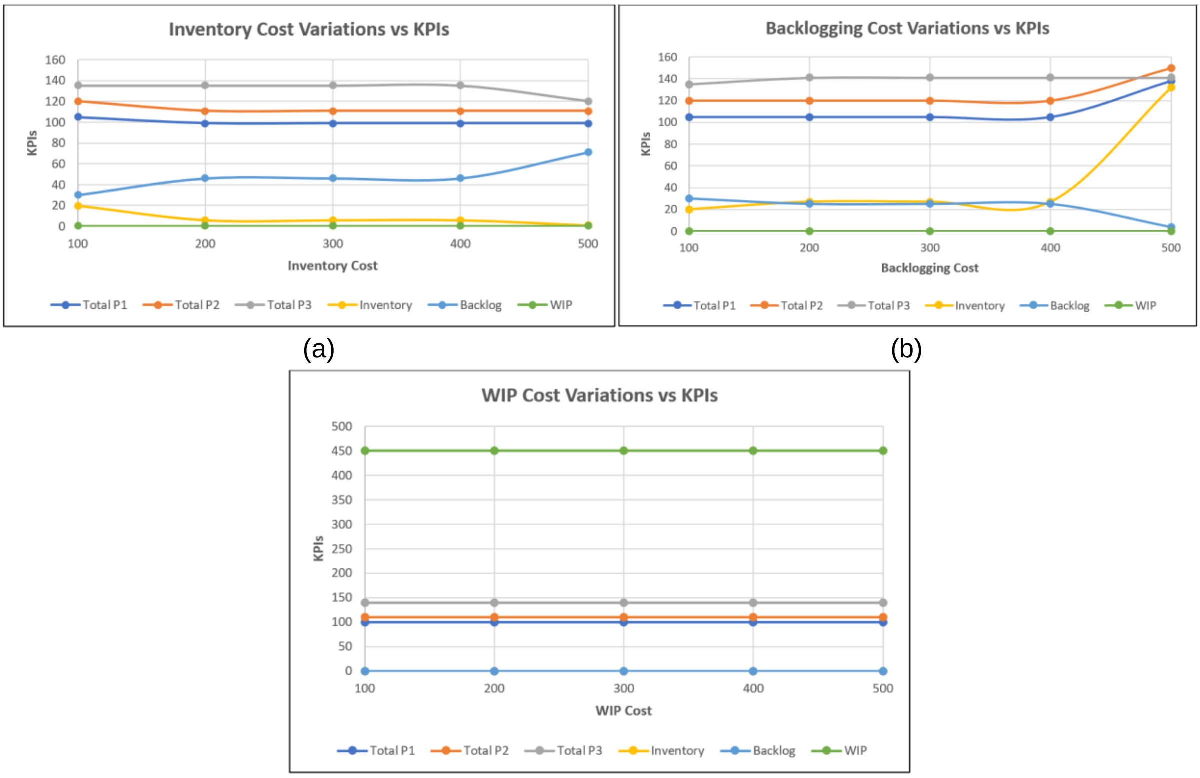
Table 4: Baseline solution

Total Cost	Product Quantity	Product Type	Period, t		
			1	2	3
5000	Production Output	P1	35	35	35
		P2	40	40	40
		P3	45	45	45
	Inventory	P1	0	0	5
		P2	0	0	10
		P3	5	0	0
	Backlog	P1	15	0	0
		P2	10	0	0
		P3	0	0	5
	WIP	P1	0	0	0
		P2	0	0	0
		P3	0	0	0

Based on the results from Table 4, it is observed that the production system is unable to satisfy demands while prioritizing cost minimization. This can be seen by the imbalances in production across the three periods. Therefore, there is a need for further improvement in capacity planning and demand forecasting in order to meet demands effectively.

Sensitivity analysis on cost parameters

The sensitivity analysis involved incrementally increasing or decreasing the values of inventory cost, backlogging cost and WIP cost, each one at a time, to observe their effects on production decisions and overall system performance.



(a) (b)

(c)

Figure 3 Effect of cost variations on KPIs

Based on Figure 3(a), when the inventory cost is increased to 200, there is a notable decrease in the total inventory product, indicating that higher inventory costs lead to reduced inventory levels. By reducing inventory levels, the system can minimize the higher inventory holding costs and optimize the overall production costs. Meanwhile, the amount of total backlog increases, suggesting that higher inventory costs may result in more products being backlogged due to production limitations. This is because the production system reduces the inventory levels to minimize costs, leading to an inability to produce enough to meet demand.

Further increases in inventory cost to 300 and 400 result in no changes on the production quantity, inventory, backlog quantities and WIP. This suggests that the production system has reaches an optimal configuration, where further increases in inventory costs do not give significant impact. However, when the inventory cost reaches 500, there is another notable increase in total backlogs and a small decrease in total inventory. This implies that the production system has reach a tipping point, leading to a compromise between cost minimization and meeting product demand. As a result, the production system has limits in its capacity to adjust to the increasing inventory cost.

Based on Figure 3(b), when the backlogging cost is incrementally increased to 500, there is initially small change in the total inventory, WIP, and backlog products. This indicate that the production system is designed to prioritize meeting demand within a reasonable range of backlogging costs, without drastically altering the production strategy. However, after the backlogging cost reaches 500, the number of inventory products increases significantly, while the total backlog becomes zero. This finding indicates that higher backlogging costs encourage the production of more inventory to prevent backlog, leading to an increase in inventory levels and a decrease in backlogged products. The production system aims to minimize the high penalty associated with backlogged products by ensuring that demand can be met from the available inventory.

Based on Figure 3(c), when WIP cost increases, shows that higher WIP costs do not affect the total output of the product, suggesting that the production system can maintain desired output levels despite higher costs associated with WIP. Meanwhile, total inventory and backlog remain zero throughout, which implies that the production system is able to balance the production and demand effectively.

After comparing the effects of changes in each cost parameter on production decisions and system performance, the analysis shows that the backlogging cost is the most sensitive parameter for the production system. The system has made significant adjustments in its inventory and production strategies to minimize the high cost associated with backlogged products. In contrast, the production system appears to be relatively less sensitive to changes in WIP cost, demonstrating a higher degree of flexibility and resilience in maintaining the desired output levels. Lastly, the sensitivity of inventory cost falls in between, as the system adjusts inventory levels and experiences a compromise between cost minimization and meeting demand when the inventory cost increases significantly.

Sensitivity analysis on capacity variations

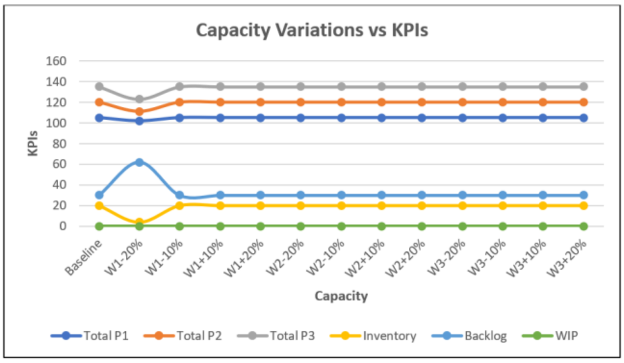


Figure 4 Effect of capacity variations on KPIs

Based on Figure 4, among all the variations in work centre capacities for W1, W2, and W3, only the decrease in W1's capacity by 20% had a notable impact on the production planning model. This decrease in capacity led to an increase in total cost and backlog quantities, suggesting that work centre W1 plays a critical role as a bottleneck in the production process.

The results highlight the importance of aligning work centre capacities with product demand. In scenarios where demand exceeds capacity, such as this case with W1, production efficiency is compromised. Therefore, optimizing the capacity of work centre W1, and potentially other bottleneck areas identified through sensitivity analysis, is crucial for improving overall production efficiency and meeting demand requirements.

Sensitivity analysis on demand variations

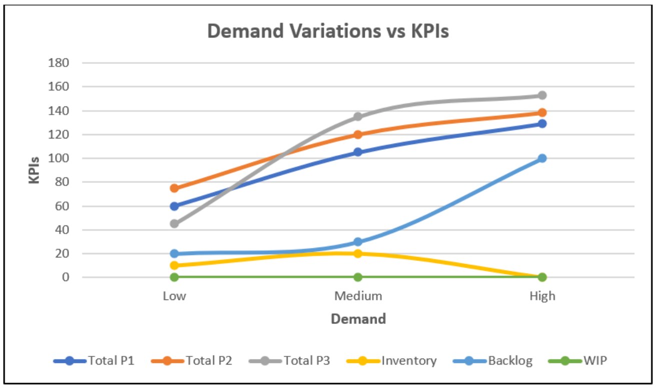


Figure 5 Effect of demand variations on KPIs

Based on Figure 5, the analysis shows that the production outputs increase to meet the higher demand, indicating that the production system can adjust production levels accordingly. However, challenges arise during high-demand periods, as evidenced by increased backlog quantities. This suggests that the production system may struggle to cope with sudden spikes in demand, leading to backlogs of unfulfilled orders.

Conclusion

In summary, semiconductor production planning is crucial in decision-making and production strategy, as it directly impacts the efficient utilization of resources and overall operational efficiency. Understanding each aspect of production planning is essential for optimizing resource allocation, minimizing costs and meeting demand effectively. Backlogging cost is found as the most sensitive parameter to cost variations, highlighting the need for adjusting production planning strategies in response to changes in backlogging cost. The results also highlight the importance of aligning work centre capacities with product demand to prevent potential bottlenecks. During high-demand periods, the production system may find it challenging to manage sudden demand spikes, resulting in backlogs of unfulfilled orders. However, this study has limited scope of data and the model used may have simplifications and assumptions that do not fully capture the complexities of semiconductor manufacturing processes. Therefore, future research can explore using larger and more diverse datasets that better capture the complexity and variability of real-world production environments. Future research can also improve on conducting sensitivity analysis on potential interactions between different parameters to give better insights.

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