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Development of Digital Laboratory Modules Using Computer Simulation For Enhanced Learning Experience in Manufacturing Education

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Abstract

The complexity of modern manufacturing environments, characterized by interactions among various entities, variability, and randomness, presents significant challenges for learners. Understanding these dynamics is essential, but traditional classroom-only focused education often falls short in providing students with practical insights. Hands-on experimentation is vital for students to observe interactions and experience process manipulations, yet such experimental setups can be costly and impractical for many institutions. This paper presents the development of digital laboratory modules to enhance students' learning experience in manufacturing education through computer simulation techniques. Two modules were created to address complex manufacturing issues: production design under demand uncertainty, manufacturing layout design, and different maintenance schedules. These modules allow users to control process parameters, design experiments, run simulations, and observe outcomes, promoting informed decision-making without wasting resources. This approach is particularly valuable for resource-constrained industries, facilitating rapid decision-making and process efficiency. Each module uses case studies with background information, problem statements, datasets, and expected results. The paper details the development process and case studies and includes experimentation guidelines for using the modules effectively in educational settings.

1. Introduction

The manufacturing ecosystem is inherently complex due to the rapid and continuous advancement of technology, which introduces multiple interconnected systems, processes, and innovations. Modern manufacturing integrates diverse technologies such as automation, robotics, artificial intelligence (AI), the Internet of Things (IoT), and additive manufacturing, all of which require seamless coordination across various stages of production [1], [2]. The adoption of Industry 4.0 practices has led to smart factories where machines communicate autonomously, generating vast amounts of data that need real-time analysis for process optimization [3], [4]. This technological integration increases complexity by necessitating advanced infrastructure, skilled labor, and cybersecurity measures to protect interconnected systems. Furthermore, supply chains have become globally distributed and heavily reliant on digital platforms for inventory management, logistics, and quality control, adding vulnerability and risk management challenges. Customization demands and shortened product life cycles further strain manufacturing systems [5], requiring flexible production capabilities supported by cutting-edge technology [6]. Balancing these technological advancements with cost-efficiency, product quality, and market competitiveness makes the manufacturing ecosystem more intricate and challenging to manage effectively [7].

Next-generation workforce aiming to manage manufacturing processes must develop a multifaceted skill set integrating technology awareness, process understanding, efficiency improvement, data analytics, and timely decision-making [8], [9]. Technological literacy is paramount; students must be proficient in emerging technologies such as automation, robotics, artificial intelligence (AI), the Internet of Things (IoT), and additive manufacturing to understand how these tools can streamline production. A deep comprehension of manufacturing processes, including lean manufacturing principles and systems dynamics, is essential for identifying bottlenecks and optimizing workflows. To enhance efficiency, students should master process improvement methodologies, enabling them to minimize waste and improve product quality. Proficiency in data analytics tools and techniques is critical for interpreting vast production data to drive informed decisions and predictive maintenance. Additionally, familiarity with digital twin technology and real-time monitoring systems can aid in simulating and refining manufacturing operations [10]. Problem-solving and critical-thinking skills are equally important, empowering students to make rapid, effective decisions in manufacturing environments. Developing soft skills like communication and leadership will enable collaboration across multidisciplinary teams, fostering innovation and adaptability in a technology-driven ecosystem like [11] manufacturing.

Current students are actively preparing for the future of manufacturing through a comprehensive educational approach that blends classroom instruction, laboratory-based learning, and hands-on experience. University curricula increasingly incorporate advanced topics such as Industry 4.0 technologies, automation, artificial intelligence (AI), and supply chain management to build foundational knowledge. Courses often include case studies, simulations, and project-based learning to help students understand real-world manufacturing challenges and solutions. Laboratory-based instruction further reinforces theoretical concepts by offering students practical exposure to cutting-edge equipment like CNC machines, 3D printers, robotics, and IoT devices. These labs simulate real manufacturing environments, allowing students to experiment with process optimization, quality control, and system integration. Hands-on experience is also gained through internships, co-op programs, and industry-sponsored projects, allowing students to apply classroom knowledge in live industrial settings. These experiences foster problem-solving, critical thinking, and adaptability, essential skills for navigating complex manufacturing systems. Additionally, many universities emphasize interdisciplinary learning by integrating engineering, data science, and business courses to prepare students for the multifaceted demands of the industry. Students develop the technical and analytical skills necessary to drive innovation and efficiency in the future manufacturing landscape through this combination of theoretical instruction, practical lab work, and real-world exposure.

However, laboratory-based education poses significant challenges, particularly for low-income institutions [12]. This scenario is even worse for manufacturing education due to the high costs of acquiring and maintaining advanced equipment like CNC machines, robotics, and 3D printers. Limited funding can restrict access to modern technologies, resulting in outdated facilities that hinder hands-on learning. Additionally, recruiting and retaining skilled instructors proficient in emerging manufacturing technologies is costly and competitive. Space constraints and safety regulations further limit the expansion of lab facilities. Moreover, rapidly evolving technologies require constant updates to curricula and equipment, which many institutions struggle to sustain, widening the gap in educational quality and industry readiness. Digital laboratory modules using computer simulations offer a cost-effective and scalable solution to overcome the challenges of traditional manufacturing education. By leveraging simulation tools and virtual labs, institutions can provide students with realistic, interactive learning experiences without expensive physical equipment. These modules allow students to experiment with complex manufacturing processes, design prototypes, and analyze production systems in a risk-free environment. Additionally, digital labs can be easily updated to reflect industry advancements, ensuring curriculum relevance. They also enable remote access, expanding learning opportunities for students in resource-constrained or geographically isolated institutions and enhancing inclusivity and accessibility. This paper addresses these needs and develops three laboratory-based modules to train students in manufacturing education.

2. Development of Digital Laboratory Modules

This paper presents the development of two digital laboratory modules designed to improve the operational efficiency of manufacturing systems. These modules aim to educate students on how various parameters influence production output and how to effectively manage production processes to achieve targeted goals. The following sections provide a detailed description of these modules.

Module 1. Improving the process flow by considering different maintenance scheduling

Problem Statement and Objectives: Semiconductor manufacturing involves multiple operational stations; each plays a vital role in producing high-quality wafers. In a facility where wafer production must meet a daily target of wafer production per shift, achieving optimal throughput requires analyzing and balancing station workflows, identifying bottlenecks, and ensuring efficient resource utilization. This study demonstrates the development of a digital laboratory module using simulation and modeling techniques, focusing on shift-wise output and decision-making logic for optimizing productivity. The wafer manufacturing process involves six critical stations operated by individual personnel, which are subsequently used for wafer mounting with alignment, saw blade setup, wafer saw dicing, frame expansion, inspection, and unloading with die handling. Operational times vary significantly, from 2 to 18 minutes, with wafer saw dicing and saw blade setup being the most time-intensive, while unloading and die handling are relatively faster, processing up to 20 wafers per hour. The primary objective is to optimize workflow efficiency to meet an output target of 50–60 wafers per shift, minimize idle times, and address bottlenecks in time-intensive processes. Streamlining operations and balancing workloads across stations aims to enhance production efficiency, reduce waste, and ultimately increase profitability.

Operation data: This is a case study in the semiconductor industry, focusing on wafer manufacturing. The primary objective of the study is to meet client production targets, which involves producing the required quantity of wafers within the allocated timeframe while adhering to stringent quality standards based on various Predefined conditions. This study highlights the challenges faced by the semiconductor industry in meeting customer demands. Time constraints vary depending on factors such as order volume, lead time agreements with clients, and the complexity of wafer designs. A simulation model is developed using AnyLogic Simulation software to support enhanced learning [13, 14]. This model allows students to compare various production line configurations and optimization strategies, incorporating demand variability to determine the most efficient setup. For the simulation-based educational approach, the study focuses on a basic wafer type to simplify the learning process while still reflecting key industrial challenges. By integrating these digital laboratory modules into manufacturing education, the study aims to provide a more interactive and practical understanding of production systems and decision-making in dynamic environments.

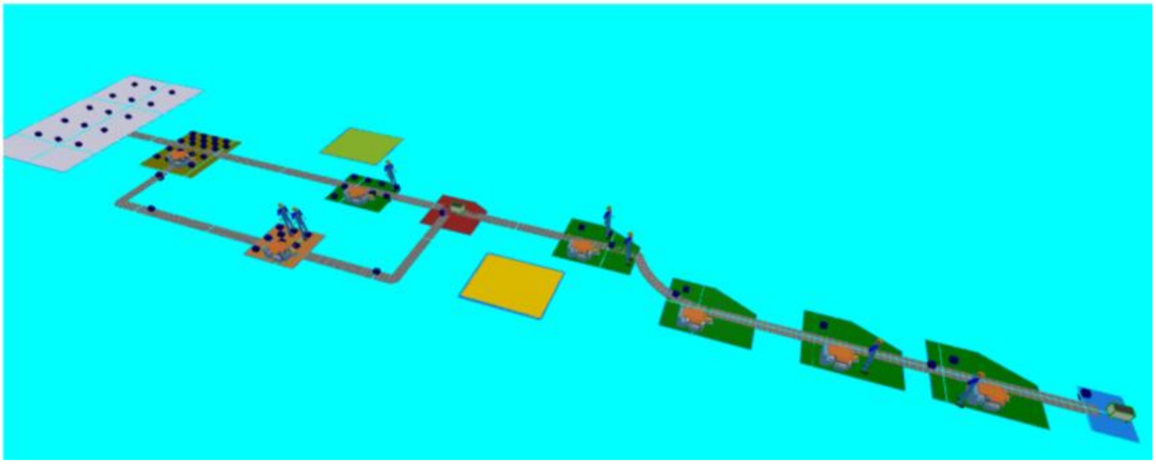


Figure 1: 3D visualization of the model (Process step).

The study is designed to represent typical operations in the semiconductor manufacturing process for student learning objectives. The data used for the model is shown in Table 1. The wafer production process involves six steps across six different workstations. The production line begins with the wafer cleaning operation, where impurities and residues are removed from the wafer surface.

Table 1: Processing Time at each workstation.

Station Name/ Time (min)	*wafer mount with alignment*	*saw Blade set up*	*wafer saw dicing*	*Frame expansion*	*Inspection*	*Unloading & Die handling*
Min (min)	5	13	11.6	2	3	2
Max (min)	7	18	14	5	6	3
Mode (min)	6	15	12	4	5	3

The cleaned wafer is then passed to the next workstation, where the photolithography process is performed to define intricate patterns on the wafer. The finished wafer progresses through subsequent stations, including etching, doping, deposition, and polishing, among others, before reaching the final inspection stage. This simulation model captures the dynamic production processes and demand fluctuations in wafer manufacturing, enabling the evaluation of various line-balancing strategies to achieve optimal production efficiency. The visual representation enabled real-time monitoring of station activities and ShiftWise analysis, providing insights into the Clear visualization of how wafers moved across stations and Real-time tracking of station-wise outputs, downtime, and bottlenecks, as shown in Figure 1.

Solution approach: This presented module demonstrates three key aspects of the semiconductor manufacturing process: 1) defining decision variables in the interface that facilitates decision-making, 2) Output dashboard showing the shift-wise impact of alternative resource allocation, Maintenance and usage of extra machines, and 3) Scenario Based analysis showing the outcome of the user defined decision variables.

Decision Variables: In this section, the following figure (Figure 2) illustrates the interactive decision parameters that enable users to dynamically modify maintenance schedules and operator settings. Key components include the $StartM\ and\ EndM$ buttons, which allow users to manually control the initiation and completion of maintenance schedules for specific machines or sections, providing flexibility in scheduling. $NOMaintenance\ , ScheduleMS$ buttons further enhance control over maintenance activities. $No\ Maintenance$ turns off planned maintenance to prioritize continuous operations, while $Schedule\ Maintenance$ Activates a predefined maintenance schedule, ensuring periodic equipment servicing. Additionally, Unplanned Maintenance simulates unexpected maintenance events based on an exponential distribution, incurring higher costs than scheduled maintenance. The operator settings, such as operatorF4MFID and operatorFSawDicin, enable adjustments to the number of operators assigned to tasks, directly influencing production rates and efficiency. The Events parameters, including EVST, EVSTPre, EVEND, EVENDPre, represent system triggers for maintenance tasks, incorporating real-world delays and downtime into the simulation. Lastly, the “Extra Machine” and “No Extra Machine” buttons allow users to determine whether an additional machine should be utilized during maintenance or failure of the primary machine, optimizing resource allocation.

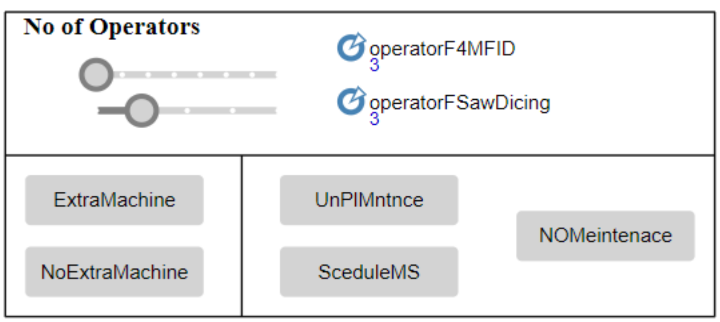


Figure 2: Decision Variables in the model

System Outputs: In this step, Figure 3 demonstrates how changes in decision parameters influence system outputs, presented through shift-based metrics and production analysis. Key components include Shift-based Output Metrics, which track critical data such as operator workloads (e.g., Wkr1, Wkr2), total profit, and costs for each shift, enabling detailed productivity analysis. Production Efficiency Indicators provide real-time visualization of efficiency, correlating operator numbers, maintenance downtime, and working minutes with outputs and profitability metrics Profit_shift1, Profit_shift2, Profit_shift3, offering a clear performance assessment per shift.

Visualization Components, such as bar charts, highlight comparative efficiency and profitability across shifts, with metrics defined as LE1, LE2, and LE3 showcasing labor efficiency trends.

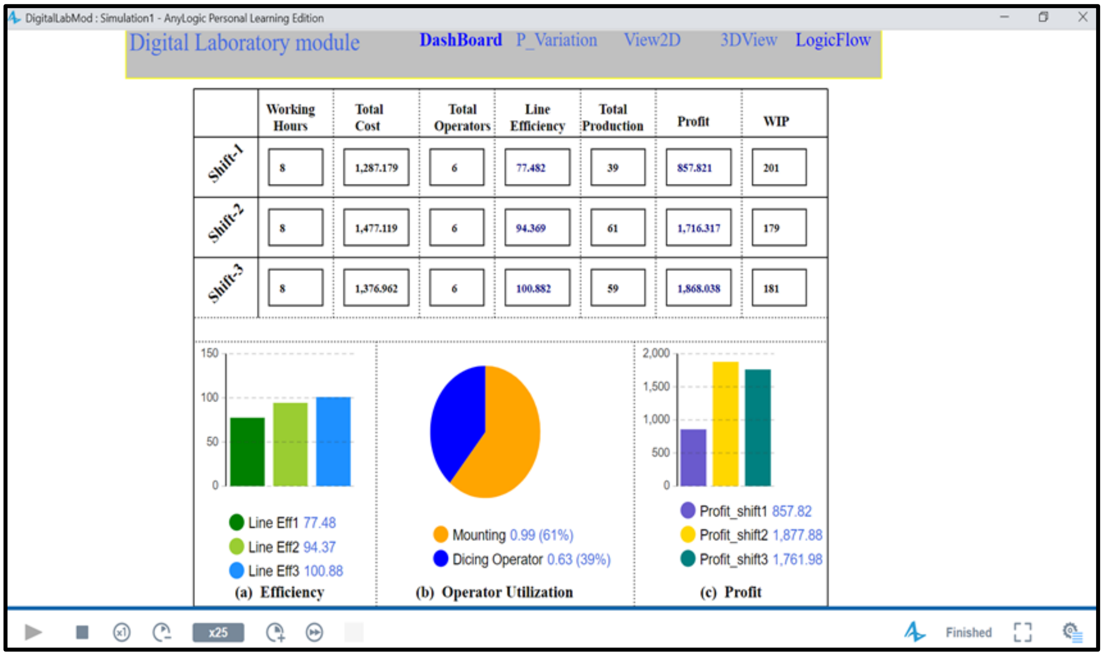


Figure 3: Dashboard showing shift-wise output.

Additionally, pie charts depict the distribution of operator workloads (e.g., mounting vs. dicing), helping to identify bottlenecks or underutilized resources. Metrics are defined as $TotalOprtr, LineEffc,\ waferPD$ offer comprehensive measures of production efficiency and capacity utilization. The interactive interface also enables users to make real-time decisions about operator allocation, Extra machine usage, and maintenance scheduling, directly impacting system performance. For instance, increasing operator availability improves productivity but may incur higher labor costs. Delaying or advancing maintenance affects efficiency, with potential trade-offs between short-term productivity and long-term equipment reliability. This dynamic decision-making process and shift-specific performance visualization support strategic planning and optimization of industrial systems in a simulated environment.

Results & Scenario Analysis: In this Paper, we define the Key variables based on operational characteristics, including time ranges (minimum, maximum, and mode) for each station, standard minute values (SMV), and efficiency calculations. The system calculated the throughput for an 8-hour shift, providing insights into the total number of wafers processed at each station. Parameters such as basic time, allowances (20%), and operator efficiency were included to address variability. The Efficiency formula is defined as:

$$Efficiency\ (\%) = \frac{Manpower \times Working\ Minutes}{Output \times SMV} \times 100 \tag{1}$$

Saw Blade Setup and Wafer Saw Dicing exhibit the lowest efficiencies due to high processing times. Unloading and Die Handling consistently outperformed other stations, processing up to 20 wafers per hour. The model identified bottlenecks by analyzing the output data and offered recommendations for resource allocation and task scheduling.

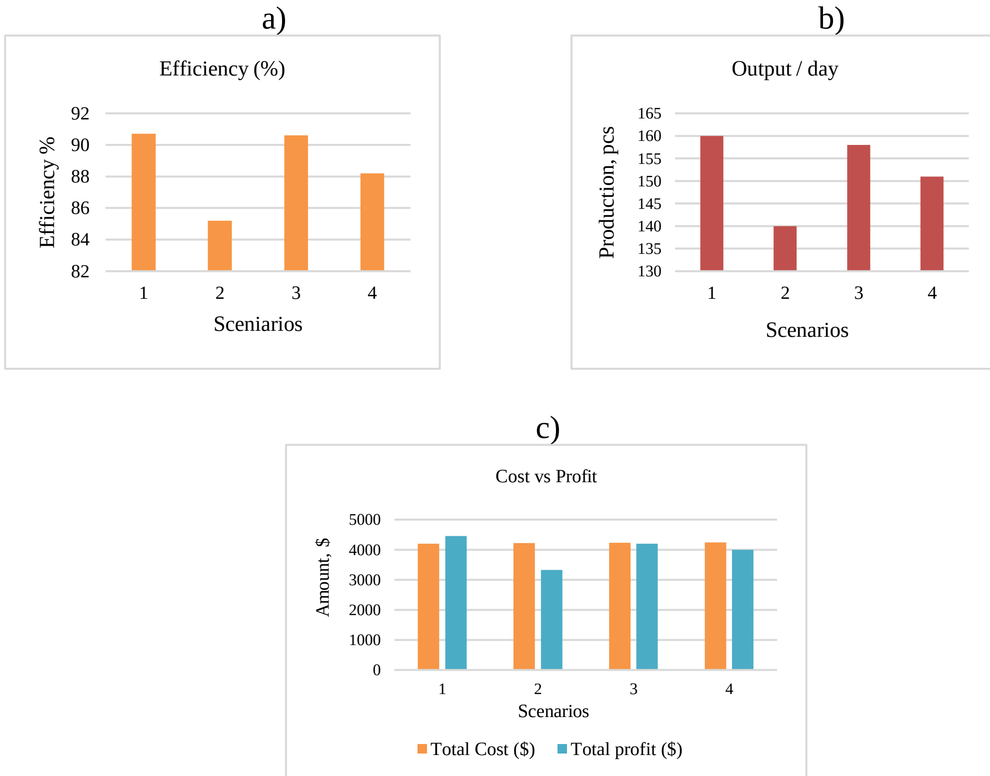


Figure 4: Scenario-based outcome from the simulation, (a) Efficiency, (b) Production, (c) Cost vs Profit.

The simulation revealed a substantial disparity in station performance, underscoring the need to reallocate resources with maintenance considerations. Note that we considered different scenarios based on extra machine set-up and maintenance types of categories (Table 1). Another table (Table 2) compares four scenarios in the wafer manufacturing process, evaluating the impact of maintenance strategies, additional machines, and operator count on efficiency, output, work-in-progress (WIP), total cost, and profit. The first scenario, featuring scheduled maintenance without extra machines, appears as the best-performing option. It achieves the highest efficiency of 90.7%, the highest profit of $4450, and the second-lowest total cost of $4197.12 while maintaining a manageable WIP level (562). In contrast, in Scenario 2, with extra machines, the factory suffers from reduced efficiency of 85.2% and a profit of $3326, highlighting diminishing returns despite slightly lower WIP. Scenario 3, with unplanned maintenance and no extra machines, closely matches that of scenario 1, with an efficiency of 90.6% and a profit of $4200, but it incurs higher costs, which are $4226.23. In Scenario 4, combining unplanned maintenance and extra machines, the reduced efficiency is 88.2%, a moderate profit of $4000, and the highest total cost is $4240.15.

Thus, Scenario 1 is the most optimal solution, balancing high efficiency, cost-effectiveness, and maximum profitability, making it the preferred choice for sustainable operations.

Table 2: Evaluation Matrix for different Scenarios (24 hrs. Timeframe)

Scenarios	Maintenance	Extra machine	Operators	Efficiency (%)	Output	WIP	Total Cost ($)	Total profit ($)
Scenario-1	Schedule	No	18	90.7	160	562	4197.12	4450
Scenario-2	Schedule	Yes		85.2	140	580	4221.31	3326
Scenario-3	Un-Planned	No		90.6	158	560	4226.23	4200
Scenario-4	Un-Planned	Yes		88.2	151	569	4240.15	4000

Module 2. Optimization of the floor operators to maintain the proportional production target

Problem Statement and Objectives: The case study focuses on an electrical structure manufacturing company that manufactures five styles: Chassis, Mainbreaker, Utility, Combo, and Stacks. This facility operates five production lines for five types of structures. Four are connected to two sub-assembly lines, while the fifth line is connected to a single sub-assembly line, as shown in Figure 5. The facility operates a batch production model and needs to divide the batch among five production lines according to the required proportion of the output to meet the customers' demand. To accommodate high customization, every type of structure comes with five complexity levels mixed according to the required proportion. Production begins with integrating several processes embedded into a frame, and not every process in the production line may be necessary for a specific frame of structures.

The facility operates on a standard schedule of two eight-hour shifts daily and produces about 35 electrical structures. If the demand exceeds, the existing systems must extend their working hours and even work on Saturdays. Despite these efforts, they fail to meet the demand, resulting in backlogs and unfulfilled orders. In such a situation, managers face difficulties balancing the production line to achieve the targeted output. Hence, this study aims to streamline operations by optimizing the number of workers in each workstation to fulfill its production goals within a standard workweek and avoid the additional labor costs associated with overtime and weekend shifts.

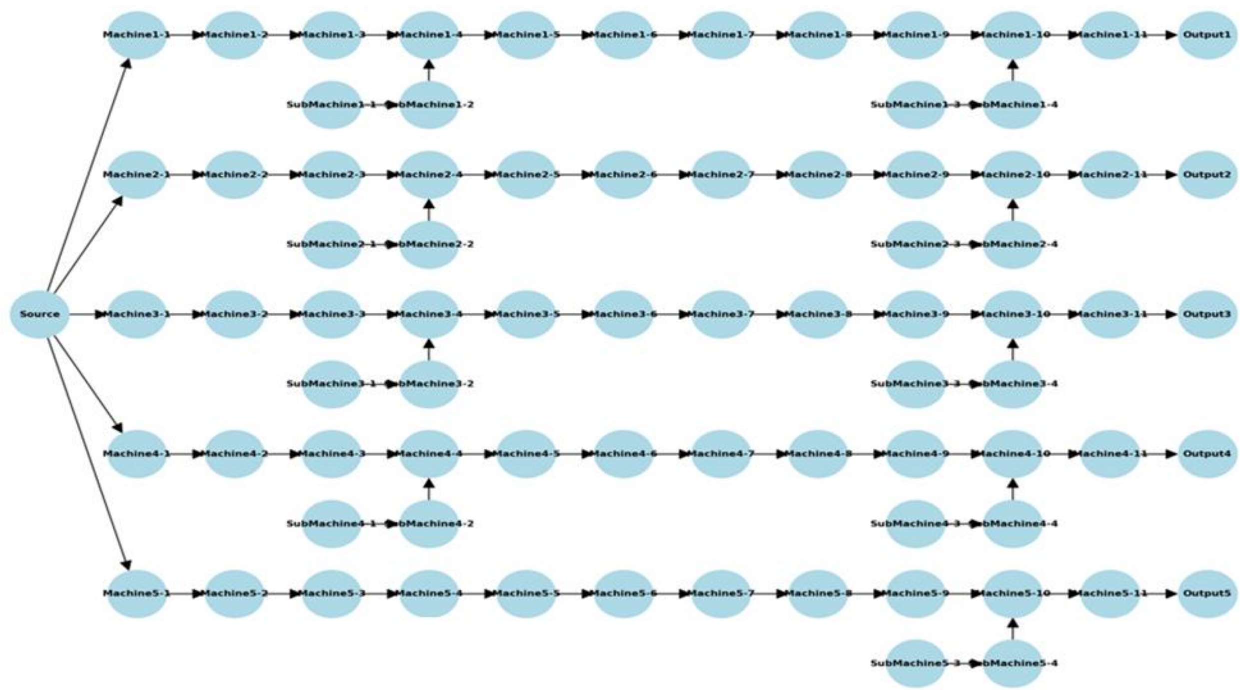


Figure 5. Facility layout of production lines

Operational data: The production process starts with discrete event simulation [15] by integrating various processes within a frame, which differ in complexity and type. Work-in-progress (WIP) parts are moved to the next station in sequence as each processing stage finishes. Processors (workstations) in every production line follow triangular distribution ($T \sim \text{Triangular}(a, b, c)$). In this case, the mode is the average of the lower and upper values ($i.e.\ c = \frac{a+b}{2}$).). Each batch for input will be allocated to the production lines based on the percentages, as shown in Table 3. The five complexity types for each assembly line also follow the same percentage distribution.

Table 3. Targeted output quantities and complexity proportion for production lines

Assembly lines	**Target Qty /shift**	**%**
Chassis	28	39%
Mainbreaker	21	30%
Utility	10	14%
Combo	10	14%
Stacks (SCMMs)	2	3%
Total	71	100%

The processors are arranged sequentially in each production line to maintain a streamlined workflow. However, specific processors in the main assembly and sub-assembly lines are configured to operate in parallel. This setup facilitates a higher degree of customization, enabling the production lines to efficiently meet varying demands and complexities. For instance, the arrangement of workstations in the Mainbreaker line and the distribution of its workflow across parallel processors are organized in Figure 6 and Table 4, respectively.

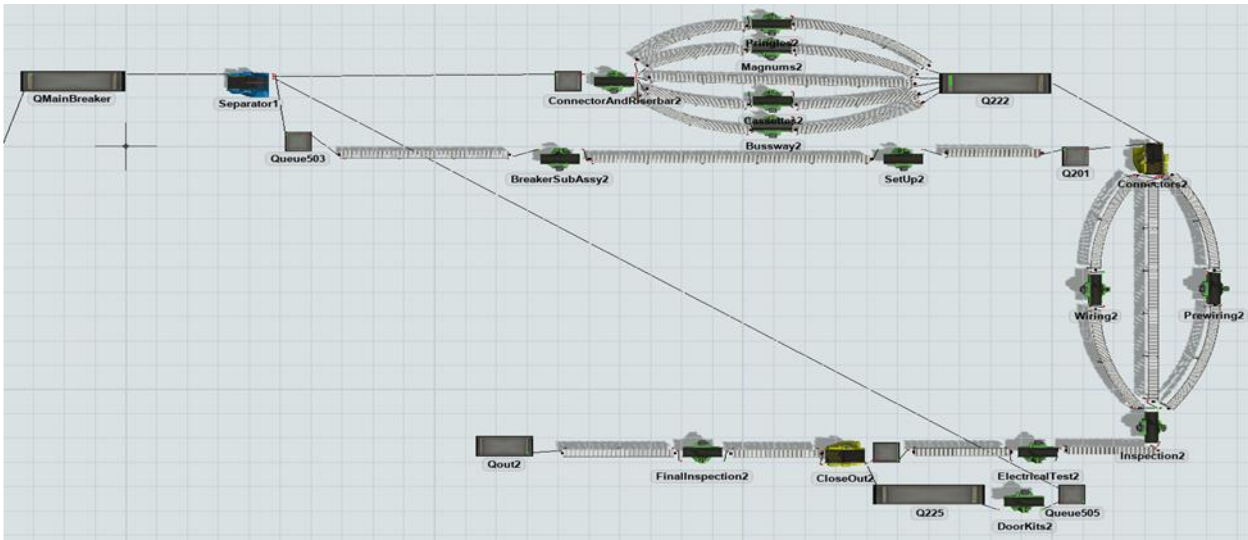


Figure 6. Layout of the Mainbreaker production line

Table 4. Product flow distribution for parallel paths in Mainbreaker

Assembly lines		Parallel path	%
Mainbreaker	Main assembly line	Connectors2 → Prewiring2	25
		Connectors2 → Inspection2	25
		Connectors2 → Wiring2	50
	Sub-assembly line	ConnectorsAndRiserbar2 → Pringles2	5
		ConnectorsAndRiserbar2 → Magnums2	5
		ConnectorsAndRiserbar2 → Q222	45
		ConnectorsAndRiserbar2 → Cassettes2	5
		ConnectorsAndRiserbar2 → Bussway2	40

Solution approach: The methodology for this study focuses on simulating and optimizing worker allocation in a stochastic manufacturing system to meet production targets efficiently. FlexSim Simulation [16] Software has been used to model and analyze the production system. This tool helps visualize the flow, identify bottlenecks, and test potential solutions. The operational and flow distribution proportions were collected from the company's historical records. This data served as the foundation for understanding processing times, complexity levels, and production flow, ensuring the simulation model accurately reflects real-world operations. The methodology consists of the following steps.

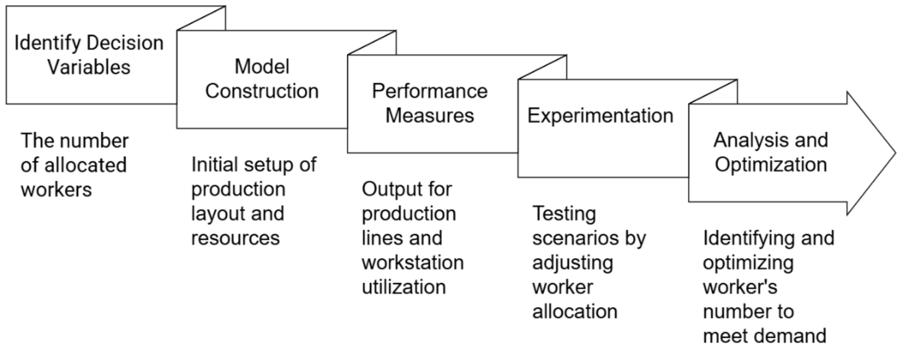


Figure 7. Steps of the solution approach

Identify decision variables: In this study, the primary decision variable is the number of workers allocated to each workstation across the five production lines. This variable plays a critical role in determining the efficiency and throughput of the system. By adjusting the number of workers at different stages of the production process, the simulation evaluates how operator distribution impacts key performance measures such as output levels, bottlenecks, and utilization rates. This decision variable is central to balancing the workload across the main and sub-assembly lines, ensuring the production system operates efficiently under varying levels of complexity and demand. In FlexSim, we manage this decision variable (number of operators) using parameter tables. The parameter table is used to change variables for different scenarios automatically.

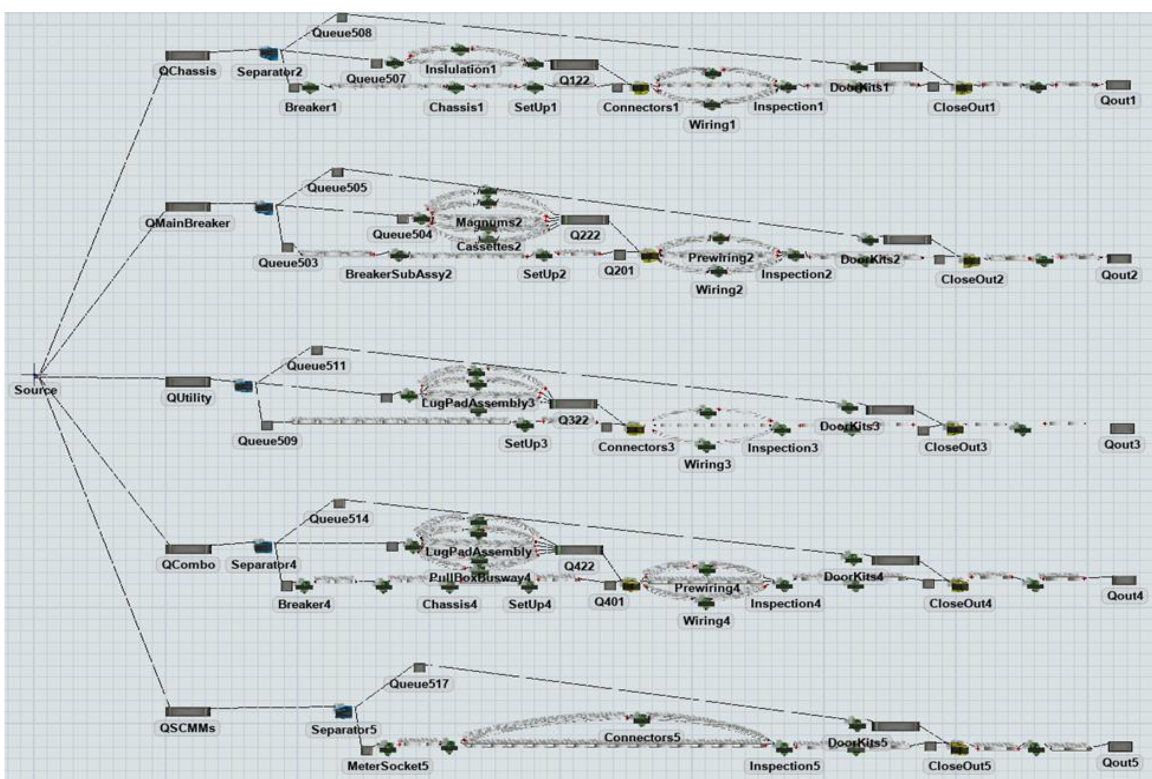
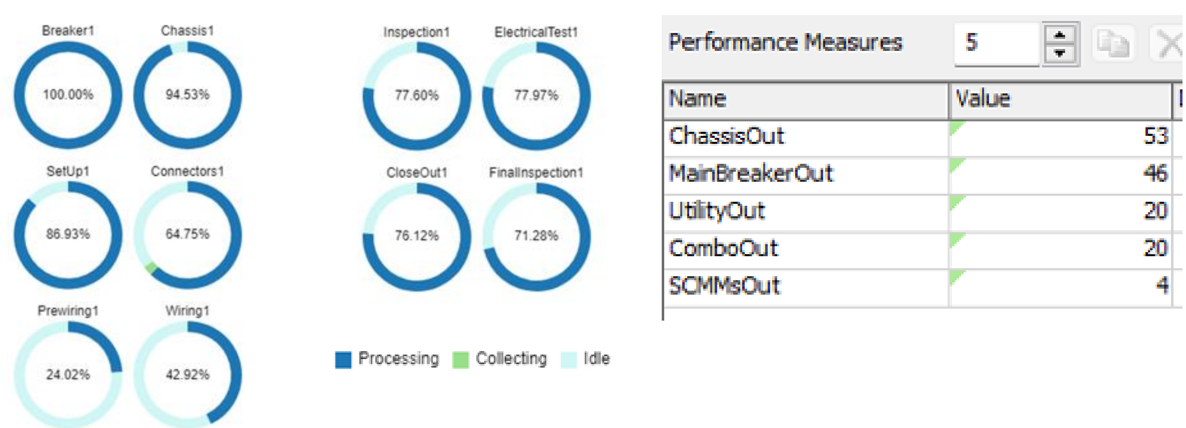


Figure 8: FlexSim model for the facility layout

Model development: The simulation model was constructed to replicate the production facility, incorporating five distinct production lines—Chassis, Mainbreaker, Utility, Combo, and Stacks, as shown in Figure 8. The simulation model includes the production layout for all five styles, including main assembly lines and sub-assembly lines, parallel product flow paths based on predefined percentages for each production line, and worker allocation and resource availability as key decision variables. Each line was designed to reflect its respective products' associated complexity levels, processing times, and flow distributions. The model integrates operational data, including triangular distributions for processing times and proportional flow allocations derived from historical data. The model can also identify bottlenecks, track machine utilization, and analyze worker performance, ensuring a comprehensive representation of the manufacturing process. This structured approach enables precise experimentation and optimization to meet production goals efficiently.

Performance measures: The performance measures for this study are centered around achieving the target output for each production line and evaluating workstation utilization. The target output serves as a benchmark for assessing whether each production line meets its production goals based on the allocated resources and processing times. On the other hand, workstation utilization provides insights into resource use efficiency across different production stages. The simulation can identify underutilized or overburdened workstations by monitoring these metrics, allowing for worker allocation or process flow adjustments to optimize performance. These measures ensure the system operates efficiently while meeting demand within the given constraints. As an example, the performance measures (FlexSim output) are displayed in Figure 9.

(a) (b)



Name	Value
ChassisOut	53
MainBreakerOut	46
UtilityOut	20
ComboOut	20
SCMMsOut	4

Figure 9: Performance measures (a) machine utilization and (b) line throughput

Experimentation and optimization: The experimentation phase involves testing various scenarios within the simulation model to evaluate the impact of different worker allocation strategies on production performance. The study aims to identify the optimal allocation that achieves the target output of 142 structures per day by adjusting the number of workers across workstations in the five production lines. Scenarios include redistributing workers between main and sub-assembly lines to balance workloads, minimizing idle times, and addressing bottlenecks. Performance measures such as output numbers, workstation utilization, and line efficiency are monitored for each scenario to determine the most effective configuration. This iterative approach ensures the final recommendations are based on comprehensive and validated results. This way, the worker allocation is optimized to ensure that each line meets its targeted output without overloading any workstation or requiring additional shifts.

3. Conclusion

The digital laboratory modules developed in this study effectively model the complex workflows involved in the manufacturing processes of semiconductor and electrical structures. By integrating simulation and modeling techniques, these modules offer a comprehensive understanding of the necessary actions to optimize productivity. Incorporating 3D visualization significantly enhances the user experience, allowing stakeholders to monitor processes in real-time and make informed decisions. This study highlights the pivotal role of simulation and modeling in modern manufacturing facilities, demonstrating their potential to streamline operations and achieve target outputs in highly variable environments. Future integration plans involve incorporating these digital laboratory modules into the existing "Strategic Design for Manufacturing" course. The modules will serve as case studies in classroom settings, where students will interact with the user interface to explore various parameters and observe their impacts on the manufacturing process. Students will also be instructed to identify appropriate parameters to manage processes efficiently. Students are expected to gain practical, hands-on learning experiences through these modules. The learning outcomes and students' perceptions of the modules will be thoroughly examined and presented in a future study.

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