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Development of digital laboratory modules using computer simulation for enhanced learning experience in manufacturing education ☆

S.M. Atikur Rahman [a], Selim Molla [b], Jakia Sultana [c], Richard Y. Chiou [d], Tzu-Liang (Bill) Tseng [e], Md. Fashiar Rahman [e,*]

[a] *Department of Aerospace and Mechanical Engineering, The University of Texas at El Paso, TX 79968, USA*
[b] *Computational Science Program, The University of Texas at El Paso, TX 79968, USA*
[c] *Teaching, Learning, and Culture Program, The University of Texas at El Paso, TX 79968, USA*
[d] *Department of Engineering Technology, Drexel University, Philadelphia, PA 19101, USA*
[e] *Department of Industrial, Manufacturing and Systems Engineering, The University of Texas at El Paso, TX 79968, USA*

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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]. 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 [2]. This technological integration increases complexity by necessitating advanced infrastructure, skilled labor, and cybersecurity measures to protect interconnected systems [3]. Customization demands and shortened product life cycles further strain manufacturing systems, requiring flexible production capabilities supported by cutting-edge technology [4]. Balancing these technological advancements with cost-efficiency, product quality, and market competitiveness makes the manufacturing ecosystem more intricate and challenging to manage effectively [5]. These challenges extend to manufacturing education, where institutions often lack the resources to acquire and maintain costly equipment like CNC machines, robotics, and 3D printers. To address this gap, digital simulation-based laboratories offer a practical alternative. By leveraging tools such as AnyLogic and FlexSim, students can explore complex manufacturing scenarios in a risk-free, interactive environment. These virtual labs not only lower barriers to access but also foster critical skills in production planning, system optimization, and data-driven decision-making. These modules allow

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* Corresponding author.
E-mail address: mrahman13@utep.edu (M.F. Rahman).

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students to experiment with complex manufacturing processes and analyze production systems in a risk-free environment. 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.

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

3.1. 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, achieving optimal throughput requires analyzing and balancing station workflows, identifying bottlenecks, and ensuring efficient resource utilization. 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, ranging from 2 to 18 min, with wafer saw dicing and saw blade setup being the most time-intensive processes, while unloading and die handling are relatively faster, allowing for the processing of 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.

3.2. Operation data

This case study focuses on wafer manufacturing in the semiconductor industry. To demonstrate it, a simulation model is developed using AnyLogic Simulation software to support enhanced learning [6]. This model allows students to compare various production line configurations and optimization strategies, incorporating demand variability to determine the most efficient setup. In this study, the wafer production process consists of six steps, each performed at a separate workstation. The production line begins with the wafer cleaning operation, where impurities and residues are removed from the wafer surface. Visual representation of the simulation 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 Fig. 1.

3.3. Solution approach

This module highlights the core components of the semiconductor manufacturing process. To begin with, the interactive decision parameters enable users to dynamically modify maintenance schedules and operator settings. The key components include the *StartMandEndM* buttons, which allow users to manually control the initiation and completion of maintenance schedules. *NOMaintenance*, *ScheduleMS* buttons further enhance control over maintenance activities. Additionally, operator settings, such as *operatorF4MFID* and *operatorFSawDicing*, enable adjustments to the number of operators assigned to tasks. We also demonstrated how changes in decision parameters influence system outputs, presented through shift-based metrics and production analysis.

3.4. Results & scenario analysis

In this section, we define the Key variables based on operational characteristics, including time ranges (min, max, mode) for each station, standard minute values (SMV), and efficiency calculations. The simulation revealed a substantial disparity in station performance, underscoring the need to reallocate resources with maintenance considerations. Among the four scenarios evaluated in this module (Table 1), scheduled maintenance without extra machines yielded the best performance, highest efficiency (90.7 %), highest profit ($4450), and low cost. Other scenarios showed reduced efficiency or higher costs. Scenario 1 offers the most balanced outcome, making it the optimal choice for sustainable wafer manufacturing operations.

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

4.1. Problem statement and objectives

This case study examines an electrical structure manufacturing facility that produces five product styles – Chassis, Mainbreaker, Utility, Combo, and Stacks – across five production lines. Four lines connect to two sub-assemblies, while one connects to a single sub-assembly. The plant operates under a batch production model, aiming to meet demand proportions for each style. Each style has five complexity levels. The facility operates two 8-hour shifts per day, producing approximately 35 structures; however, demand requires 142 units daily, resulting in overtime and weekend work. The study focuses on optimizing worker allocation to eliminate extra labor costs while meeting production goals.

4.2. Operational data

The production process uses discrete-event simulation. Work-in-progress parts advance sequentially, with some processors working in parallel to handle customization. Workstation processing times follow a triangular distribution ($T \sim \text{Triangular}(a, b, c)$), with mode $c = \frac{a+b}{2}$. Inputs are distributed among lines according to demand proportions: Chassis 56 units (39 %), Mainbreaker 42 (30 %), Utility 20 (14 %), Combo 20 (14 %), and Stacks 4 (3 %). Customization flow distributions along parallel paths within each production line follow specified percentages. For example, Table 2 presents the customization percentages for the Mainbreaker line.

4.3. Solution approach

The study adopts a simulation-based methodology to optimize worker allocation in a stochastic manufacturing system, ensuring production targets are met efficiently. FlexSim Simulation Software is used to model and analyze the system, providing visualization of production flows, identification of bottlenecks, and evaluation of alternative solutions. Operational and flow distribution data drawn from historical records form the foundation, allowing the model to realistically represent processing times, complexity levels, and production behavior. The methodology consists of the following steps.

1. *Identify decision variables:* The primary decision variable is the number of workers assigned to each workstation across the five

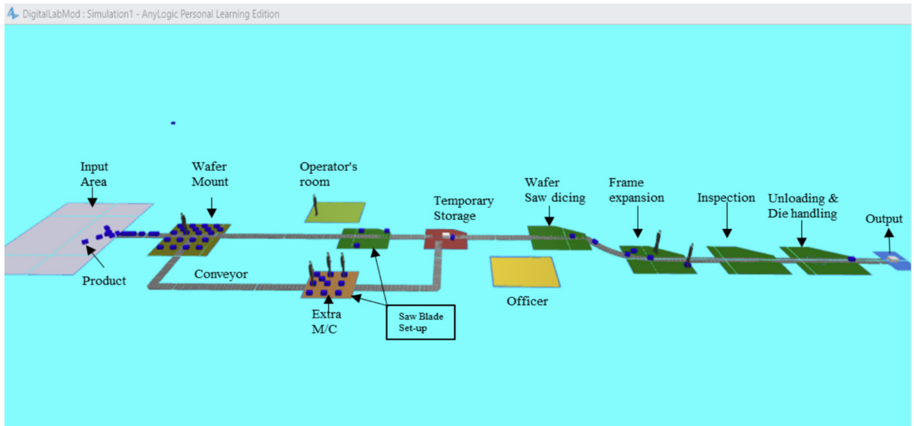

Fig. 1. 3D visualization of the model (Process step).

Table 1
Evaluation Matrix for different Scenarios (24 hrs. Timeframe).

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

Table 2
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

production lines (Chassis, Mainbreaker, Utility, Combo, and Stacks). Adjusting this allocation directly impacts throughput, bottlenecks, and utilization. FlexSim parameter tables enable scenario testing by automatically varying operator counts, ensuring efficient distribution of workloads across both main and sub-assembly lines.

2. *Model development:* The simulation replicates the entire facility layout, incorporating main and sub-assembly lines, parallel product flow paths, and worker-resource availability. Each line represents its product-specific complexity levels, flow distributions, and processing times, which are modeled using triangular distributions. The system can detect bottlenecks, monitor machine utilization, and analyze operator efficiency, enabling structured experimentation and optimization. As a representative among the five production lines, Fig. 2 shows the Flexsim model of the Mainbreaker production line.

3. *Performance measures:* Two key measures guide evaluation – (1) meeting target output for each production line, and (2) workstation utilization. Outputs benchmark production goal achievement, while utilization rates highlight underloaded or overloaded stations. These measures support workforce redistribution or process adjustments to improve efficiency.

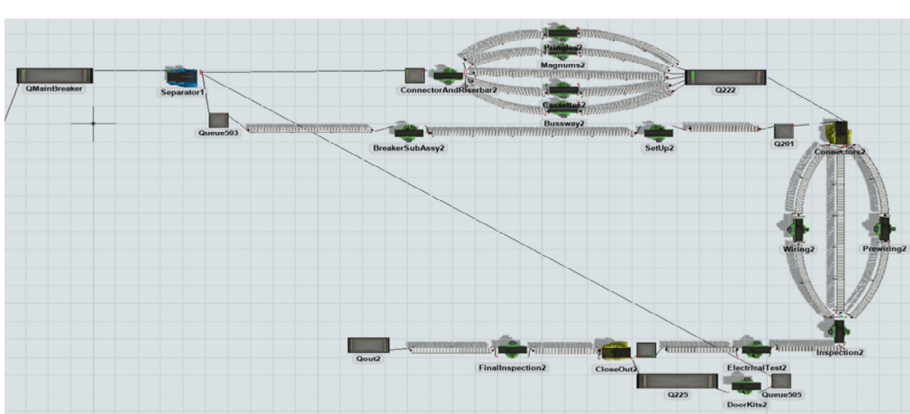

Fig. 2. FlexSim model for the Mainbreaker line.

4. Experimentation and optimization: Multiple scenarios are tested by redistributing workers across workstations. The goal is to achieve the daily target of 142 structures without overtime. Scenarios aim to minimize idle times, balance workloads, and resolve bottlenecks. Iterative analysis ensures recommendations are validated and practical, leading to optimal worker allocation that fulfills production requirements within normal shift limits.

5. Analysis of student learning outcomes

To assess the effectiveness of the digital laboratory modules developed using Simulation, a structured evaluation was conducted involving both individual interviews and post-activity surveys. Students highlighted their improved understanding of operational trade-offs, the complexities of system dynamics, and the practical challenges of layout-based decision-making.

*Survey Questions for Students***:** The survey was designed to evaluate students' perceptions of the digital laboratory modules developed using AnyLogic and FlexSim. Students responded to four questions on a 5-point Likert scale *(*1 – Strongly Disagree; 2 – Slightly Disagree; 3 – Neutral; 4 – Slightly Agree; 5 – Strongly Agree).

(1) These modules helped me better understand how process parameters affect manufacturing system performance and optimization (line balancing, maintenance scheduling).
(2) I feel more confident in applying concepts like line balancing, maintenance scheduling, and resource allocation after using the modules.
(3) The modules improved my ability to make data-driven decisions in a simulated manufacturing environment.
(4) I was able to connect the digital lab experience to real-world manufacturing challenges.

Survey Response: The survey responses show consistently positive feedback across all questions. Q1 and Q3 both received an average score of 4.3 out of 5.0, while Q2 scored slightly lower at 4.0. Q4 received the highest rating with an impressive 4.8, indicating strong satisfaction in that area. Overall, the results suggest that participants were highly satisfied, with particularly strong approval for the aspect measured in Q4.

Findings and Observations: Prior to participating in simulation-based modules, students had limited theoretical exposure to modeling tools, with no prior hands-on experience using professional platforms such as simulation. Nevertheless, all six students successfully built and ran functional models. They reported spending roughly 65–75 % of their time on scenario experimentation and decision-making, indicating a strong focus on system-level thinking rather than software-related hurdles. Overall, the modules bridged the gap between theory and practice, providing a realistic and engaging environment for learning smart manufacturing principles.

6. Conclusion

The digital laboratory modules developed in this study effectively model the complex workflows involved in semiconductor and electrical structure manufacturing. 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. Students are expected to gain practical, hands-on learning experiences through these modules.

CRediT authorship contribution statement

S.M. Atikur Rahman: Writing – original draft, Software, Methodology, Formal analysis. **Selim Molla:** Writing – original draft, Software, Methodology, Formal analysis. **Jakia Sultana:** Visualization, Methodology, Investigation. **Richard Y. Chiou:** Writing – review & editing, Validation. **Tzu-Liang (Bill) Tseng:** Writing – review & editing, Resources, Funding acquisition. **Md. Fashiar Rahman:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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