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Development of Computer Simulation Model for Capacity and Resource Planning: A Case Study of Intraocular Lens Manufacturing System

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Abstract

Digital simulation is crucial for improving production systems in Industry 4.0 manufacturing. This research focuses on developing a discrete-event simulation model to enhance capacity and resource planning in the Surface Treatment section of making Intraocular Lenses (IOLs) to prepare for high demand. A production system simulation model was developed using FlexSim software. It simulates the production flows of Monofocal and Hybrid IOLs through both automated and manual stages. The developed model can identify the bottlenecks, suggest capacity adjustments, and support resource allocation experimentation. Various scenarios were explored to examine the effects of increased daily batch loads and machine capacity of the main bottleneck through utilization analysis. The statistical analysis showed significant performance improvements when increasing bottleneck machine capacity from 9 to 11 units during high demand. It led to a remarkable 9.95% rise in average daily throughput, which is from 12.771 to 14.042 batches. Also, the bottleneck machine's utilization dropped from 88.94% to 72.83%. This research highlights how simulation serves as an effective decision-making tool for capacity planning. It helps organizations optimize resource use, reduce potential economic losses, adapt to changing demands, and promote sustainable practices in line with Industry 4.0 principles in manufacturing.

Keywords
Discrete Event Simulation, Capacity Planning, Resource Planning, Intraocular Lens Manufacturing, Operation Research

1. Introduction
Effective capacity planning ensures manufacturing operations possess necessary resources to achieve production goals. By optimizing resource allocation and addressing bottlenecks, these processes enhance efficiency and productivity, contributing to competitive advantage. The emergence of Industry 4.0 has instigated a profound paradigm shift in manufacturing, characterized by the integration of advanced digital technologies that prioritize

automation, real-time data exchange, and system adaptability. In this highly dynamic environment, flexible and responsive production strategies have become paramount for maintaining competitiveness. Consequently, advanced capacity planning has emerged as critical, particularly during high-demand periods requiring rapid adaptation. Traditional planning methods struggle with dynamic requirements, prompting manufacturers to adopt simulation approaches for analyzing process performance in virtual environments without operational disruption.

Discrete Event Simulation (DES) offers distinct advantages for analyzing complex production systems by enabling managers to identify inefficiencies, plan resources effectively, and investigate demand scenarios before implementation. This research focuses on developing a detailed simulation model to enhance capacity and resource planning within the Surface Treatment section of an Intraocular Lens (IOL) manufacturing process in anticipation of future high-demand scenarios. The research objectives are: first, to construct a simulation model representing the existing production system, and second, to develop data-driven capacity planning strategies based on model insights.

Modern simulation capabilities enable detailed representations of complex manufacturing systems, providing analysis tools essential for manufacturers aligning with Industry 4.0 principles. These approaches facilitate virtual representation of production lines, enabling analysis of variables such as cycle time, machine availability, and material flow. By modeling real-world production environments, simulation techniques offer insight into system bottlenecks and resource utilization patterns to address capacity planning challenges. Through model development and experimental analysis, this research examines utilization patterns to ensure systems meet increased demand without compromising efficiency. This study demonstrates how simulation development enhances decision-making by providing actionable recommendations for capacity planning, aligning production strategies with enterprise goals.

2. Literature Review

Process modeling and simulation have gained significant attention in manufacturing optimization literature. Gao et al. (2022) established the conceptual foundations of modeling approaches, while Koteleva et al. (2021) advanced methodological frameworks for model construction using specialized software tools—essential given the complexity of modern production systems (Pattar et al., 2019). Model validation represents a critical success factor in simulation projects (Law, 2022), ensuring reliable results that can be effectively applied to production management contexts (Rosova et al., 2020). Qiao and Wang (2021) contributed through classification of simulation models by their distinctive features, complemented by Xiu et al. (2020) who examined industry-specific implementations across various production domains.

The application of specific simulation tools has been extensively investigated, with Zahraee et al. (2021) demonstrating ARENA software implementation for production optimization, while Sarif Ullah (2019) explored the mathematical underpinnings of model construction. Digital transformations associated with Industry 4.0 reshape manufacturing operations (Ghobakhloo, 2020), blurring boundaries between physical and digital systems while creating growth opportunities. Ferreira et al. (2020) validated simulation modeling's effectiveness in addressing technical challenges, noting well-designed production processes can potentially reduce operating costs by up to 50%. Simulation modeling identifies key performance drivers while enabling scenario testing without disrupting ongoing operations in the mass production system (Zahraee et al., 2021).

Modern production systems present significant challenges due to complexity, resulting in diverse analytical approaches including mathematical modeling and DES. The DES domain encompasses numerous software applications, including ARENA (Pattar et al., 2019; Dias et al., 2022; Suhardi et al., 2019), FlexSim (Ljaskovska et al., 2020; Ruwaida and Akmar, 2021; Wu et al., 2018), and Plant Simulation (Durán et al., 2020; Tande et al., 2021; Pekarcikova et al., 2020). These tools facilitate rapid experimental iterations, though stochastic elements can complicate causal analysis in systems where multiple factors must be considered.

While extensive research exists on discrete event simulation tools across industries, limited attention has been directed toward IOL manufacturing processes. This research addresses this gap by applying FlexSim technology to identify inefficiencies and enhance capacity planning in IOL production environments. The study contributes insights regarding simulation and capacity planning processes relevant to the IOL industry, where traditional MES exhibit limitations compared to material flow simulation capabilities for specific operational areas

3. Methodology

This research employed a four-stage simulation methodology framework (Figure 1), establishing a systematic approach with validation checkpoints to ensure rigor throughout the project lifecycle. The framework progresses through Problem Definition, Model Development, Simulation Experiment, and Deployment phases, each incorporating validation mechanisms that enable iterative refinement when necessary.

The Problem Definition phase begins with understanding the IOL manufacturing process, defining relevant variables and constraints for the simulation model. The Model Development phase constructs a conceptual model representing the Surface Treatment section, guiding FlexSim configuration to replicate real-world conditions. The completed model undergoes verification and validation procedures to ensure accuracy and reliability. The Simulation Experiment phase encompasses systematic design of experimental scenarios examining various machine capacities at Process C under high-demand conditions, followed by simulation execution and rigorous data analysis. The final Deployment phase involves proposing data-driven solutions based on simulation outcomes, particularly recommendations for optimal machine capacity configuration at Process C. This framework ensures consistent progression through defined stages while maintaining scientific rigor through validation mechanisms.

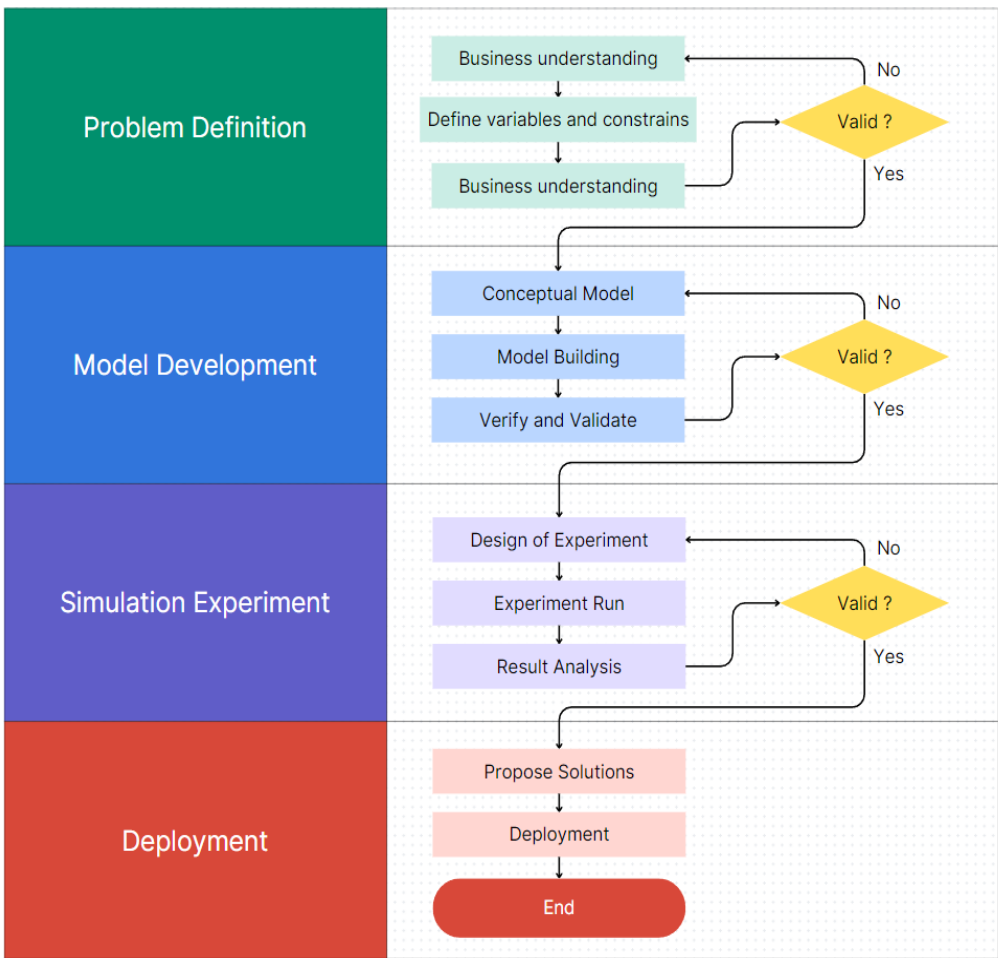

Figure 1. Methodological framework for simulation-based capacity planning in IOL manufacturing, showing four main phases with validation checkpoints and iterative refinement loops.

4. System description

This research focuses on the Surface Treatment section within an IOL manufacturing environment. Figure 2 illustrates the outline process chart of the Surface Treatment section as a critical component within the integrated manufacturing ecosystem. This production segment represents the foundational phase of IOL fabrication. The manufacturing accommodates concurrent processing of two product variants—Monofocal and Hybrid IOLs—utilizing shared resources and equipment.

The process flow chart (Figure 3) illustrates each operational stage from Process A through Process F, receiving material inputs from Monofocal and Hybrid cutting. Processes A, C, and D are automated, while Processes B and F are primarily manual operations. Following the completion of Process F, semi-finished components advance to the subsequent Quality Inspection & Assembly section for continued processing. Table 1 presents the resource allocation framework for the Surface Treatment section, specifying equipment configurations and workforce assignments throughout the production processes

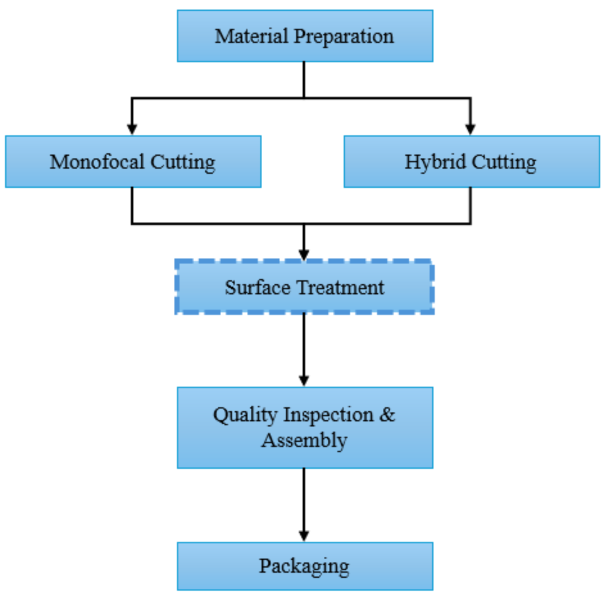

Figure 2. Outline Process Chart of IOL Manufacturing

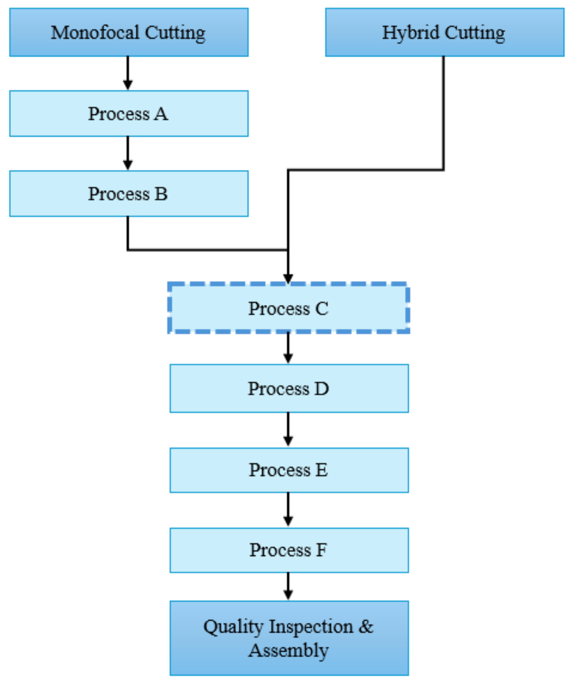

Figure 3. Process Flow of the Surface Treatment Section (Process A-F)

Table 1. Surface Treatment Section Resources

Process	Resource Type	Number of Units	Notes
A	Machines	3	Requires 1 Operators for Setup
B	Operators	1	Manual Operation
C	Machines	9	Requires 1 Operators for Loading/Unloading
D	Automated Units	2	Requires 2 Operators for Loading/Unloading/Monitoring
E	Automated Units	6	Requires 2 Operators for Loading/Unloading
F	Operators	2	Manual Operation

5. Data Collection and Input Data Distribution

To develop a simulation model of the surface treatment stage (Processes A through F), cycle times of each automated machine for each product model were collected from the ERP system, considering machine downtime. Processing times per workpiece were collected for all manual operations. Collecting the per-piece processing time mitigates the variation in lot sizes, especially in the Hybrid model. It provides a more accurate representation of active processing times. Moreover, operations requiring operator involvement, including both manual tasks and automated processes, that necessitate operator actions such as loading, unloading, setup, monitoring, scheduled break times, and a lunch break, were collected and integrated into the simulation model.

The Chi-Square goodness-of-fit test was performed to fit the selected input distributions for the collected data. Table 2 comprehensively summarizes the fitting distributions and their corresponding parameters for all processes.

Table 2. Input Data for Simulation Model

Process	Model	Operation Type	Basis	Distribution/Time	Parameters/Value (seconds)
A	Monofocal	Automated	Per Batch	Constant	1300
B	Monofocal	Manual	Per Piece	Johnson Bounded	Min = 5.829831, Max = 13.177449, Shape1 = 1.119336, Shape2 = 1.152883
C	Both	Automated	Per Batch	Constant	172800
D	Both	Automated	Per Lot	Constant	240
E	Both	Automated	Per Lot	Constant	1655
F	Both	Manual	Per Batch	Johnson Bounded	Min = 1.617465, Max = 5.767154, Shape1 = 1.745864, Shape2 = 1.291986

6. Results and Discussion

6.1 Model Building

The simulation model of surface treatment (Processes A-F) was developed using FlexSim 2022 to represent the stochastic nature and system constraints. The production flow for Monofocal and Hybrid IOLs was modeled sequentially according to the facility layout. Processing times for manual operations (B, F) used statistical distributions from collected data (Section 5), introducing real-world variability. The movement of Monofocal and Hybrid entities was governed by specific batch and lot size requirements at each stage, detailed in Table 3. Operator availability at all workstations was modeled with scheduled breaks (15 minutes every two hours) and 1-hour lunch. Machine downtime for automated processes was incorporated as fixed 15-minute unavailability periods.

Table 3. Movement and Processing of Entities

Process	Model	Processing Unit	Batch/Lot Size	Movement Trigger
A	Monofocal	Batch	600 pcs	Full batch completion
B	Monofocal	Piece	600 pcs	Full batch (from Process A) completion
C	Monofocal	Batch	3 Batches	Three batches (any model mix) ready
C	Hybrid	Batch	3 Batches	Three batches (any model mix) ready
D	Monofocal	Lot	50 pcs	Continuously processes new Batches, with initiation triggered only upon completion of a full batch at Process E
D	Hybrid	Lot	10-50 pcs	Continuously processes new Batches, with initiation triggered only upon completion of a full batch at Process E
E	Monofocal	Lot	50 pcs	Full Monofocal batch (or equivalent processing time for Hybrid lots) completion
E	Hybrid	Lot	10-50 pcs	Full Monofocal batch (or equivalent processing time for Hybrid lots) completion
F	Monofocal	Piece	600 pcs	Full Monofocal batch completion
F	Hybrid	Piece	600 pcs	Full Hybrid batch completion

6.2 Model Verification and Validation

Model verification ensured it accurately reflected the intended design and logic of the Surface Treatment section. This was a collaborative effort with the head engineer. Verification involved tracking Monofocal and Hybrid process flows through each step and confirming adherence to Table 3 rules. The processing logic at both manual and automated workstations, including processing times, batching/lotting rules, and movement triggers, was also thoroughly checked. Additionally, the implementation of operator breaks, lunch times, and machine downtime on resource availability was validated. The animation and step-by-step execution features of FlexSim 2022 were used to visually inspect the model's behavior and identify any deviations from real-world operations. Any identified discrepancies were iteratively corrected to ensure the final model properly represented the real shopfloor system.

Model validation compared predicted daily throughput with actual data from the Surface Treatment section. The statistical analysis was subsequently performed to ascertain the presence of a statistically significant difference between these two datasets. Initially, an F-test for homogeneity of variances was conducted on the simulated and historical throughput data. Subsequently, a two-sample t-test was employed to assess the equality of their respective means. The outcomes of these statistical analyses are systematically presented in Table 4.

Table 4. Statistical Results of Model Validation (Simulation vs. Historical Throughput)

Test	Statistic	DF	p-value	Interpretation
F-test (Variances)	0.98	[29, 29]	0.966	No significant difference in variances (Equal variances assumed)
Two-sample T-test (Means)	0.88	[58]	0.384	No significant difference in means
Mean Daily Throughput				
Simulated Model	5342 pcs.			
Historical Data	5244 pcs.			

6.3 Bottleneck Identification

The simulation model identified critical system constraints within the Surface Treatment section under projected demand scenarios. Initial analysis used baseline conditions (Scenario 1: 12 batches daily) to establish normal parameters, followed by elevated demand conditions (Scenario 2: 14 batches daily) to identify bottlenecks under stress. Simulation analysis under elevated batch loading (Scenario 2) revealed Process C as the predominant bottleneck through utilization analysis. Figure 4 illustrates the average resource utilization across all processes under Scenario 2 conditions, clearly demonstrating Process C's significantly elevated utilization rate of 88.94% compared to other system components.

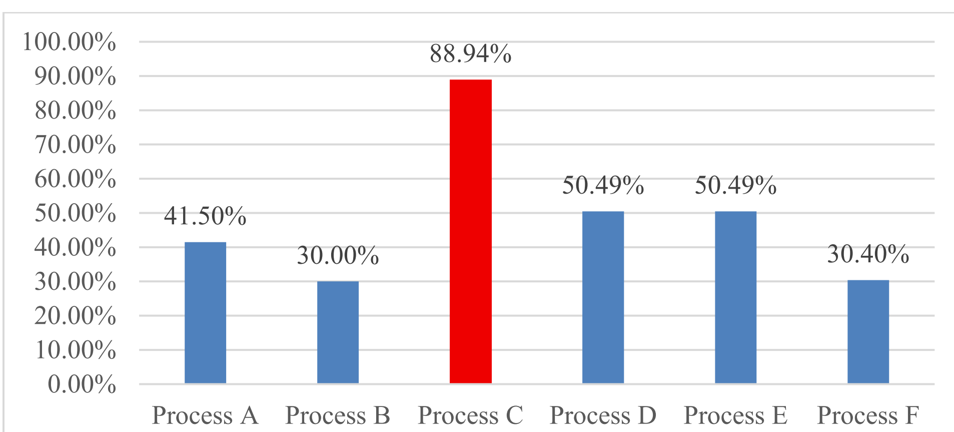

Figure 4. Average Resource Utilization Across Processes of Scenario 2

Process C's identification as the primary constraint was substantiated through utilization analysis and simulation observations:

1. Highest Utilization Rate: Process C demonstrated an average utilization of 88.94%, significantly exceeding other processes in the system, indicating near-capacity operation under elevated demand conditions
2. Queue Formation: Simulation runs consistently showed work-in-process accumulation upstream of Process C, suggesting insufficient capacity relative to incoming flow rates
3. Processing Bottleneck: Dual product flows (Monofocal and Hybrid) competing for Process C's 9-machine capacity created delays that propagated throughout the system

The utilization pattern indicated Process C's role as the governing constraint limiting system throughput under increased demand without capacity augmentation. This identification established the foundation for targeted capacity enhancement strategies to address the primary limitation.

6.4 Experimental Design

To quantify capacity limitations and evaluate bottleneck mitigation strategies, a structured experimental design was implemented. The investigation employed a controlled experimental approach to assess the effects of demand variation and targeted capacity enhancement at the identified constraint. The experimental design examined three scenarios through manipulation of two factors: daily batch volumes (demand level) and machine allocation at Process C (capacity level). This factorial approach isolates the capacity enhancement effect while controlling for demand variations, providing clear evidence of the intervention's effectiveness.

Table 5 presents three experimental scenarios designed to isolate and quantify capacity enhancement impact at Process C. Scenario 1 establishes baseline performance under normal demand conditions with 12 batches daily and the current 9-machine configuration at Process C. Scenario 2 examines high demand conditions (14 batches daily) while maintaining the existing capacity, enabling identification of system stress points. Scenario 3 evaluates the same high demand scenario with enhanced capacity (11 machines at Process C), directly testing the proposed bottleneck mitigation strategy.

Table 5. Experimental Scenarios

Scenario	Daily Load (Batches)	Number of Machines at Process C	Purpose
1	12	9	Baseline Performance under normal demand
2	14	9	High demand with current capacity
3	14	11	High demand with enhanced capacity

Each scenario was replicated 48 times to ensure statistical robustness for detecting meaningful differences between scenarios. A 14-day warm-up period was established based on preliminary analysis showing the first completed batch emerged around day 7, ensuring the system reached steady-state before data collection. Each replication consisted of 30 operational days following the warm-up period.

Daily throughput (batches per day) was selected as the primary response variable for capacity planning decisions. Experimental data was analyzed using descriptive statistics, one-way ANOVA to test for significant differences across scenarios ($\alpha = 0.05$), and Tukey's HSD for pairwise comparisons. Independent random number streams were employed for each replication to ensure proper randomization and reproducibility of results.

6.5 Simulation Results

Simulation experiments were executed across three scenarios with 48 replications each, following a 14-day warm-up period to achieve steady-state conditions. Mean daily throughput results demonstrated progressive improvement across scenarios, with higher demand and increased machine capacity yielding correspondingly greater throughput performance, as summarized in Table 6.

One-way ANOVA revealed statistically significant differences in mean daily throughput across scenarios. The interval plot with 95% confidence intervals for each scenario is presented in Figure 5, visually demonstrating the progressive increase in throughput performance with non-overlapping confidence intervals that confirm the statistical significance of the differences. Tukey's HSD post-hoc analysis identified significant pairwise differences between all scenarios (Table 7 and Table 8). The critical comparison between Scenarios 2 and 3, which isolated the effect of increasing Process C capacity under identical demand conditions, demonstrated a statistically significant throughput improvement, representing a substantial increase in daily production capacity.

Table 6. Summary of Mean Daily Throughput Results by Scenario

Scenario	Daily Load (Batches)	Machines at Process C	Mean Daily Throughput (Batches)
1	12	9	11.896
2	14	9	12.771
3	14	11	14.042

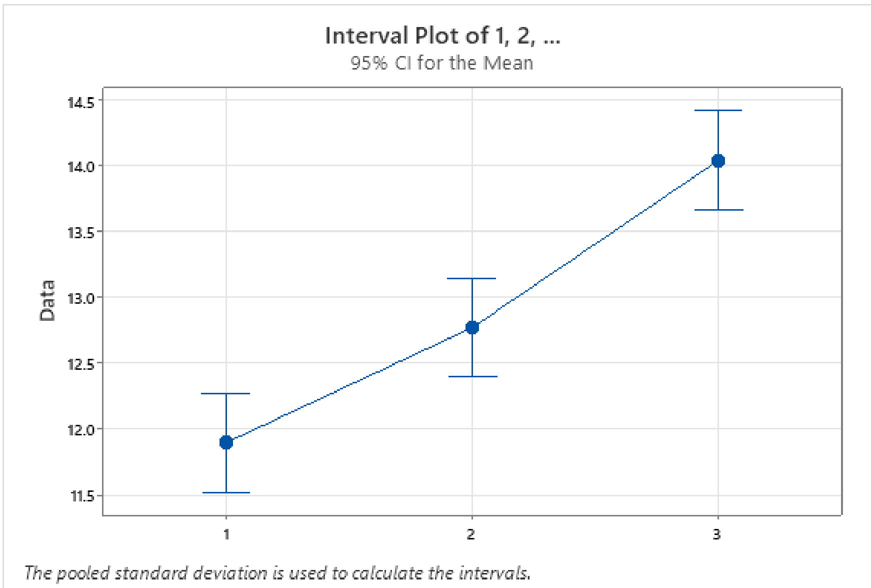

Figure 5. Interval Plot of Mean Daily Throughput with 95% Confidence Intervals Across Scenarios

Table 7. One-Way ANOVA Summary for Mean Daily Throughput Across Scenarios

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	2	111.8	55.882	32.18	0.000
Error	141	244.9	1.737		
Total	143	356.6			

Table 8. Turkey's HSD Post-Hoc Test for Pairwise Comparisons of Mean Daily Throughput

Difference of Levels	Difference of Means	SE of Difference	95% CI	T-Value	Adjusted P-Value
2 - 1	0.875	0.269	(0.238, 1.512)	3.25	0.004
3 - 1	2.146	0.269	(1.509, 2.783)	7.98	0.000
3 - 2	1.271	0.269	(0.634, 1.908)	4.72	0.000

6.6 Proposed Improvements
The simulation analysis provides empirical evidence supporting strategic capacity planning interventions within the Surface Treatment section, specifically targeting the identified bottleneck at Process C to accommodate escalating demand. The statistically significant performance improvements observed through discrete event simulation modeling substantiate the primary recommendation to augment machine capacity at Process C.

The capacity enhancement strategy demonstrates quantifiable improvements in resource utilization for Process C. Under Scenario 2 conditions (14 batches daily utilizing 9 machines), Process C exhibited 88.94% utilization, indicating near-capacity operation. The expanded machine configuration comprising 11 units in Scenario 3, while maintaining equivalent throughput targets, yielded substantial reduction in Process C utilization to 72.83%. This reduced utilization rate (Figure 6) provides empirical validation of the proposed intervention's efficacy in mitigating the identified constraint

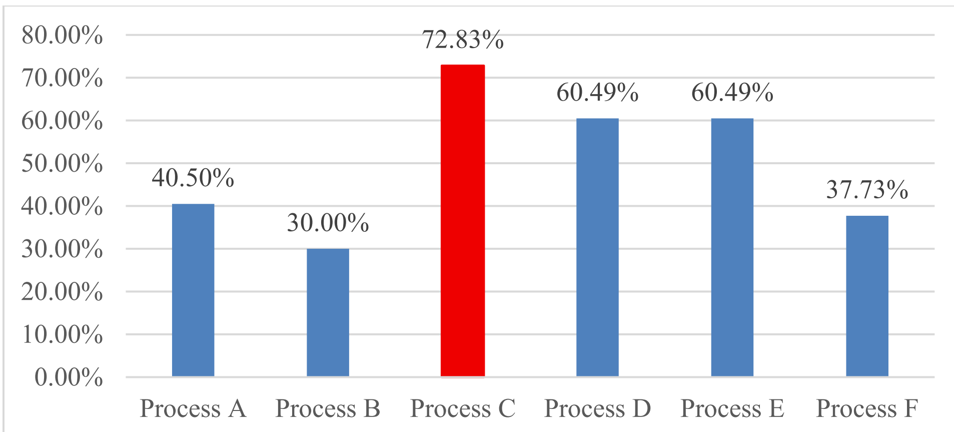

Figure 6. Average Resource Utilization Across Processes of Scenario 3

The comparative analysis reveals significant operational improvements between scenarios. Daily throughput increased from 12.771 batches to 14.042 batches, representing a 9.95% enhancement in system capacity. This improvement results from alleviating the Process C bottleneck that previously constrained production flow.

The capacity enhancement strategy aligns with operational requirements from increasing market demand. These simulation-based findings provide data-driven recommendations for engineering management consideration and potential implementation

7. Conclusion
This study developed a discrete-event simulation model to analyze capacity dynamics within the Surface Treatment section of an IOL manufacturing process. The primary objective was to identify critical bottlenecks and assess capacity requirements under increasing demand.

The simulation model successfully identified Process C as the primary system constraint and quantified potential throughput improvements through targeted capacity enhancement. Results demonstrated 9.95% improvement in daily throughput when machine capacity was increased at the identified bottleneck

The framework provides a foundation for evidence-based decision-making in complex manufacturing systems. The developed framework provides a foundation for evidence-based decision-making in complex manufacturing systems. Future research could extend the model to broader system interactions or investigate process variability impact on performance.

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Biographies

Parid Jaisuda is a master's student in Industrial Engineering at Prince of Songkla University, specializing in simulation modeling and process optimization. He is currently a trainee in a manufacturing environment, where he contributes to developing simulation models for optimizing production workflows. Parid's research focuses on using digital simulation tools to enhance capacity planning and resource planning, which forms the foundation of the work presented in this paper.

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Narttakarn Khunjun received a Doctor of Philosophy in Industrial and Systems Engineering from Prince of Songkhla University, a Master of Engineering in Industrial and Production Systems Engineering, and a Bachelor of Science in Physics, both from King Mongkut's University of Technology Thonburi, Thailand. Her professional background includes experience in both industry and academia. She is currently a Policy and Plan Analyst at the Science Park, Prince of Songkhla University. Previously, she has served as a Research Assistant. Her industrial experience includes roles as a Senior Process, Tooling Engineer and Packaging Engineer. She specialized in statistical process control and quality assurance for hard disk drive components. Additionally, she has worked as a collaborative researcher and served as a Teaching Assistant for quality control courses.