03-001 – Analysis and optimization of installed capacity in medical services through discrete event simulation and continuous improvement – Análisis y optimización de la capacidad instalada en servicios médicos mediante simulación de eventos discretos y mejora continua

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Spanish Spanish

Healthcare services face critical challenges due to the sustained growth in demand and the increasing complexity of diagnostic processes. This study explores how Discrete Event Simulation (DES) models can analyze, model, and optimize the installed capacity in diagnostic processes at the tertiary healthcare level, including angiographies, biopsies, and cytologies. Using the DMAIC structure from Six Sigma and Lean Manufacturing tools, key bottlenecks were identified, and validated simulations were employed to evaluate operational and logistical solutions. The results showed significant reductions in waiting times and improvements in the utilization of human and technical resources, underscoring the flexibility and precision of DES models in integrating multiple variables and scenarios. Additionally, the economic and operational implications of the proposed strategies were assessed, demonstrating their feasibility in enhancing service quality and ensuring financial sustainability. This methodological approach provides a robust and replicable tool to address current challenges in healthcare resource management, fostering data-driven decision-making and a continuous improvement model centered on patient care.

Keywords: *Discrete event simulation (des); Installed capacity; Six sigma; Lean manufacturing; Bottlenecks; Healthcare resource management*

Los servicios médicos enfrentan desafíos críticos debido al aumento sostenido de la demanda y la creciente complejidad en los diagnósticos. Este estudio explora cómo los modelos de simulación de eventos discretos (DES) pueden analizar, modelar y optimizar la capacidad instalada en procesos diagnósticos del tercer nivel de atención hospitalaria, como angiografías, biopsias y citologías. Empleando la estructura DMAIC de Six Sigma y herramientas de Lean Manufacturing, se identificaron cuellos de botella clave y se evaluaron soluciones operativas y logísticas mediante simulaciones validadas. Los resultados mostraron reducciones significativas en tiempos de espera y una mejora en la utilización de recursos humanos y técnicos, destacando la flexibilidad y precisión de los modelos DES para integrar múltiples variables y escenarios. Además, se evaluaron las implicaciones económicas y operativas de las estrategias propuestas, demostrando su viabilidad para mejorar la calidad del servicio y garantizar la sostenibilidad financiera. Este enfoque metodológico constituye una herramienta robusta y replicable para afrontar los desafíos actuales en la gestión de los recursos sanitarios, promoviendo decisiones basadas en datos y un modelo de mejora continua centrado en la atención al paciente.

Palabras claves: *Simulación de eventos discretos (des); Capacidad instalada; Cuellos de botella; Gestión de recursos sanitarios; Six sigma; Lean manufacturing*

1. Introduction

Health systems today face growing pressure due to population aging, the rise in chronic diseases, and budget constraints, limiting their ability to provide timely and high-quality care. Particularly, high-complexity diagnostic services—such as angiography, biopsies, and cytology—are critical components for clinical decision-making but often operate under saturated conditions that compromise operational efficiency (Gómez-Chaparro, García-Sanz-Calcedo, & Aunión-Villa, 2020; González-Domínguez et al., 2021; Reponen et al., 2021). The management of installed capacity, defined as the optimal combination of technical, human, and logistical resources available to deliver services, thus becomes a strategic axis for the sustainable functioning of healthcare institutions (Monsef, Suliman, Ashkar, & Hussain, 2023).

The analysis of installed capacity makes it possible to identify gaps between available supply and healthcare demand, facilitating evidence-based decisions for resource redistribution, workflow adjustments, and investment prioritization (Monsef et al., 2023). However, traditional tools fall short in capturing the dynamic complexity of clinical processes. In response, Discrete Event Simulation (DES) has emerged as a robust methodology to model the behavior of hospital systems, as it allows for the representation of sequential events, actor interactions, and demand variability without altering real-world operations (Vázquez-Serrano, Peimbert-García, & Cárdenas-Barrón, 2021).

Recent literature supports the use of DES as an effective strategy to analyze bottlenecks, evaluate configuration alternatives, and estimate the operational impact of management decisions in hospital settings (Gowda et al., 2021). For instance, González-Domínguez et al. (2021) developed a Markov model to analyze the usage of computed tomography equipment in hospital environments, demonstrating the potential of data-driven approaches to support operational decisions.

The value of simulation is further enhanced when integrated with continuous improvement methodologies such as Lean Healthcare and Six Sigma, widely used in clinical environments to eliminate waste, reduce wait times, and improve service quality (Tlapa, Franco-Alucano, Limon-Romero, Báez-López, & Tortorella, 2022). Within this framework, the DMAIC cycle (Define, Measure, Analyze, Improve, Control) offers a structured and rigorous pathway for managing improvement projects and has been validated as a methodological standard in hospital interventions (Niñerola, Sánchez-Rebull, & Hernández-Lara, 2020).

Studies such as Marin-García, Vidal-Carreras, and Garcia-Sabater (2021) have demonstrated how Lean tools like Value Stream Mapping help identify non-value-added activities and redesign diagnostic processes. Moreover, combined approaches incorporating Big Data, artificial intelligence, and process mining are enhancing the accuracy and predictive power of DES models in healthcare, as reported by Atalan, Şahin, and Atalan (2022) and González-Domínguez et al. (2021).

This study applies these methodologies to analyze installed capacity and propose improvements in three high-complexity diagnostic services at a tertiary-level hospital: a coronary angiography room, a biopsy laboratory, and a cytology service. The models were developed using Arena software and Excel VBA macros, integrating real institutional data collected through medical records, staff interviews, and direct field observations. Models were then statistically validated through mean comparison tests and analysis of variance (ANOVA), ensuring consistency with real-world operations (Sargent, 2020).

In the angiography service, shift saturation due to limited specialized personnel was identified. In the biopsy lab, inefficiencies were caused by batch sample accumulation, while in cytology,

the main bottleneck was the microscopic review stage. Each case was addressed using continuous flow strategies, task redistribution, and auxiliary staffing, improving system performance (Akbulut, Usubütün, Durur, & Kutlu, 2023; Fatima, Malik, & Shafiq, 2021).

These approaches generated improvement scenarios that reduced average service times by up to 40%, increased resource utilization by over 10 percentage points, and significantly lowered idle rates. Moreover, strategic decisions such as shift reorganization, temporary hiring, and task sequencing were guided by validated and replicable simulation scenarios (Kumar, Karunakaran, & Vishnu, 2021).

In conclusion, this research offers an integrated methodological proposal based on Discrete Event Simulation, Lean Healthcare, and the DMAIC cycle, applicable to high-complexity hospital diagnostic services. Its relevance lies in providing a robust tool for addressing operational challenges without requiring major investments, allowing healthcare institutions to enhance their problem-solving capacity sustainably, efficiently, and with a patient-centered approach.

2. Methodology

This study adopts a quantitative-experimental approach using Discrete Event Simulation (DES) to analyze and improve the installed capacity of three high-complexity diagnostic services in a tertiary-level public hospital in Costa Rica: coronary angiography, biopsies, and cytology. The methodological design integrates the DMAIC cycle (Define, Measure, Analyze, Improve, Control) and Lean Healthcare principles, allowing for both accurate system representation and the proposal of feasible improvements without altering real operations.

2.1 Process Definition and Mapping

The initial phase involved the definition of diagnostic processes through field observation and document analysis. The care chain for each service was mapped from patient entry to result delivery. Tools such as SIPOC diagrams and Value Stream Mapping (VSM) were employed to visualize the entire system, identify non-value-added activities, and locate operational bottlenecks. This systemic mapping enabled the segmentation of each service into functional stages, including registration, preparation, diagnostic execution, sample analysis, and patient discharge.

2.2 Data Sources and Parameterization

Model parameters were defined using validated institutional data, complemented by direct observation and interviews with clinical and administrative personnel. This mixed-source strategy provided a comprehensive perspective on the processes under study. The following variables were extracted and adjusted through distribution fitting:

- Patient interarrival time (modeled with exponential distributions)
- Diagnostic and processing times (adjusted to normal, triangular, or beta distributions)
- Daily operational capacity by resource (physician, technician, equipment)
- Shift durations and scheduling rules

For example, the angiography room was modeled based on an interarrival rate of 1.43 patients/hour with a single 6.5-hour shift. In the biopsy service, two distinct diagnostic complexity groups were identified and modeled separately, while in cytology, standard diagnostic times of 12 minutes per sample were assumed.

2.3 Simulation Model Development

The simulation models were developed using Arena Simulation Software and Visual Basic Application (VBA) for Excel, which allowed the logical structuring of process flows through modules representing queues, limited resources, sequential activities, and conditional decisions. Patients were represented as entities with attributes such as procedure type, urgency, and priority, enabling the simulation of realistic routing decisions.

Each model considered specific operational constraints, such as the maximum number of concurrent patients, shift boundaries, and prioritization logic. State transition diagrams were used to validate the consistency of patient flows and ensure logical behavior across scenarios. Additionally, cross-verification was performed by a second modeler to assess technical robustness and fidelity.

2.4 Validation and Verification Strategy

To validate the simulation models, a multi-method approach was used. Quantitative validation included the application of statistical tests to compare simulation outputs with empirical data collected under normal hospital conditions:

- Kolmogorov-Smirnov tests assessed distributional similarity.
- ANOVA tests compared mean values.
- Shapiro-Wilk tests evaluated the normality of residuals.

Additionally, 12-month hospital data was used to compare model behavior with historical system performance. Qualitative validation was conducted through structured interviews with staff, who confirmed the realism of modeled processes, cycle times, and resource allocation.

2.5 Scenario Design and Performance Indicators

Once the baseline models were validated, alternative scenarios were simulated to evaluate improvement opportunities. These included:

- Implementation of a second work shift in angiography
- Redesign of flow from batch to continuous in the biopsy lab
- Delegation of support tasks to auxiliary staff in cytology

Each scenario was assessed using the following key performance indicators (KPIs):

- Total patient time in system
- Queue time per patient
- Percentage utilization of technical and human resources
- Compliance with scheduled daily production

These indicators provided an objective basis for comparing baseline and proposed conditions.

2.6 Continuous Improvement Tools and Sensitivity Analysis

To support the Analyze and Improve phases of the DMAIC cycle, continuous improvement tools were employed. Pareto charts were used to identify the main causes of delay, while cause-effect diagrams facilitated the exploration of root causes. Sensitivity analyses tested the robustness of the models by simulating parameter variations, such as changes in patient arrival rates or reductions in shift availability.

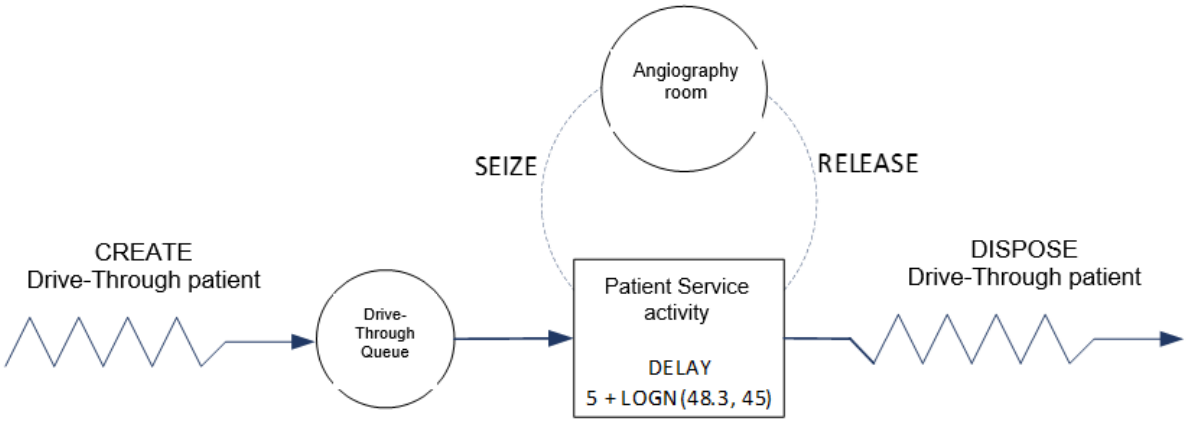
2.7 Health services

The decision-making model was applied to three specific health services: an angiography room, a pathology service focused on biopsies, and a cytology laboratory. Each service was addressed through a tailored methodological approach, based on its operational characteristics and the availability of historical data.

- Angiography Room

The angiography room was modeled as a complete system that integrates infrastructure, equipment, and specialized personnel. A total of 2,044 procedures performed at a hospital in the metropolitan area of Costa Rica were analyzed. The simulation considered variables such as patient flow, available resources, service stages, and procedure durations. Random times were generated using a statistical distribution based on historical data, enabling a faithful representation of procedure durations and “what-if” analyses of available supply versus expected demand. The model was statistically validated using confidence intervals and enabled the exploration of improvement scenarios such as adding a second work shift or incorporating an additionnal room.

Figure 1: Simulation model developed for the angiography room.



- Pathology Service (Biopsies)

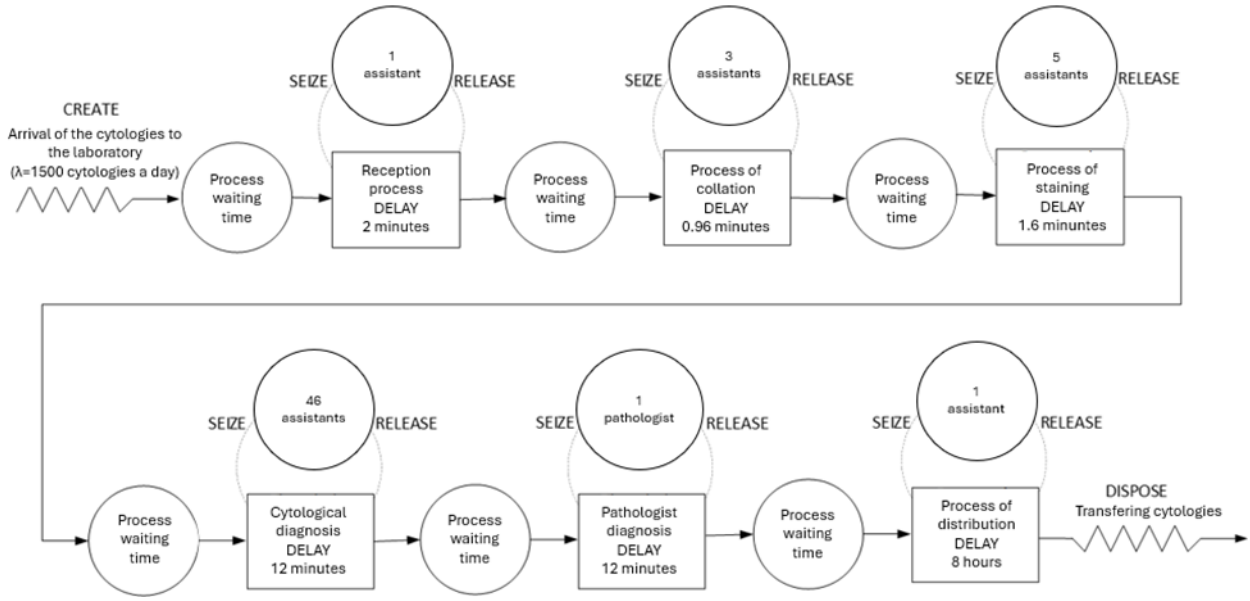
The biopsy analysis process was modeled using a Visual Basic for Excel application, which incorporated the Box-Müller algorithm (Equation 1) to simulate normally distributed data. Six critical process stages were analyzed: tissue sample collection, sample cutting, paraffin block preparation, slide creation, diagnosis by the pathologist, and report delivery. The model allowed for the simulation of changes in staffing and equipment availability, evaluating their impact on diagnostic response times, which had reached up to 120 days between 2015 and 2019. The model demonstrated that activities performed by the pathologist represented the main bottleneck in the process, significantly affecting the system’s capacity.

$$\begin{cases} \mu + \sigma x_1, & x_1 = \sqrt{-2\ln U_1}\ \sin 2\pi U_2 \\ \mu + \sigma x_2, & x_2 = \sqrt{-2\ln U_3}\ \sin 2\pi 4 \\ \mu + \sigma x_3, & x_3 = \sqrt{-2\ln U_5}\ \sin 2\pi U_6 \end{cases} \quad (1)$$

- Cytology Laboratory

In the cytology laboratory, an integration of DES and Lean Manufacturing principles was applied. A Value Stream Map was used to characterize the workflow and extract key indicators. Based on this, a simulation model was built using constant times that reflected the average operational metrics of the process. The analysis identified bottlenecks related to the review of cytologies by pathologists and assessed the impact of eliminating batch-based workflows, which introduced unnecessary waiting times. The model also evaluated the availability of cytotechnologists and the need to redistribute tasks to improve the efficiency of the service.

Figure 2: Descriptive diagram of the simulation model developed for the cytology laboratory.



2.7 Methodological Limitations

While the study is based on robust data sources and validated methodologies, it is limited to a single institutional context. Nevertheless, the structure of the models and the analytical tools used are generalizable and replicable in similar diagnostic settings. Future research may incorporate real-time data streams or predictive analytics to further enhance model precision and responsiveness.

3. Results

This section presents the outcomes of the Discrete Event Simulation (DES) models developed for three high-complexity diagnostic services in a tertiary hospital in Costa Rica: coronary angiography, biopsy pathology, and cytology. The simulation models were built upon institutional records, direct observations, and expert feedback, and were statistically validated

to ensure their fidelity. Each model was structured under the DMAIC framework and evaluated through Key Performance Indicators (KPIs) aligned with the objectives defined in the introduction and methodology.

3.1 Coronary Angiography Service

- Baseline Scenario

In the coronary angiography unit, demand pressure and limited specialized personnel had caused consistent saturation of the available capacity. The service operated with a single diagnostic room, functioning under a 6.5-hour daily shift. Based on hospital records, the modeled patient arrival rate was 1.43 patients/hour, equivalent to an interarrival time of approximately 0.7 hours. This configuration generated an estimated monthly volume of 148 patients, which aligns closely with observed historical figures.

Simulation runs revealed a mean system time per patient of 2.46 days, reflecting the cumulative effect of queue time, preparation, diagnostic procedure, and recovery. The average queue length remained at 24 patients, and in peak periods, reached a maximum of 71 individuals. Most notably, the angiography room operated at a utilization rate of 99%, underscoring critical saturation and confirming that capacity expansion or process reengineering was urgently needed.

- Improvement Scenario: Double Shift Implementation

To address saturation, a scenario incorporating a second daily shift was simulated. The new configuration extended the operating hours to 13 hours per day, effectively doubling time availability while maintaining the same infrastructure. Simulation results projected an increase in monthly throughput to approximately 198 patients, with a 95% confidence interval ranging from 167 to 222. Importantly, average patient system time dropped from over two days to 2.06 hours, and maximum wait time fell to 16.5 hours—an improvement of nearly 88%.

In this improved scenario, the angiography room's utilization rate adjusted to 64%, indicating restored balance between resource availability and patient demand. Such a redistribution of time and capacity not only alleviated bottlenecks but also provided greater operational resilience for managing emergency cases or fluctuations in demand.

Table 1: Coronary Angiography – Baseline vs Improved Scenario.

Scenario	Monthly Throughput	Utilization (%)	Avg System Time	Max Wait Time
Baseline	148	99	2.46 days	6.75 days
Improved	198	64	2.06 hours	16.5 hours

3.2 Biopsy Laboratory

- Baseline Scenario

In the biopsy pathology lab, diagnostic complexity varied considerably, with two dominant processing profiles observed: Group 1, consisting of simpler biopsies requiring approximately 9.26 minutes for diagnosis, and Group 2, involving more complex cases averaging 27.39 minutes. Historical data indicated a 2:1 ratio in favor of the simpler group. Despite a stable team configuration of one histotechnologist and one pathologist per shift, the existing workflow relied on batch processing, where samples were accumulated before being analyzed.

This batching strategy contributed to process inefficiencies. Simulation of the current conditions estimated that, despite an installed capacity for 8000 annual diagnoses, only 62% of received samples were processed within the required timeframe. Utilization rates for key personnel were 77% for pathologists and 74% for histotechnologists, reflecting high workload yet inadequate diagnostic throughput.

- Improvement Scenario: Transition to Continuous Flow

An alternative scenario was tested by implementing a continuous flow model, where biopsies were routed directly to diagnostic workstations without unnecessary accumulation. Simulation outputs demonstrated that average system time decreased by 37.8%, largely due to reductions in queuing and diagnostic wait time.

With continuous flow, pathologist utilization rose to 85%, and histotechnologist utilization to 82%. Mean patient system time dropped to 61 minutes, with a 95% confidence interval between 59.4 and 62.6 minutes. The average wait time per biopsy was reduced to 29 minutes. These results suggest that minor process adjustments—without the need for additional personnel—can yield significant performance improvements. ANOVA testing between observed and simulated data yielded a p-value of 0.292, supporting the claim that the simulation accurately reproduced real-world conditions.

Table 2: Biopsy Lab Performance – Baseline vs Improved.

Metric	Baseline	Improved
Pathologist Utilization (%)	77	85
Histotechnologist Utilization (%)	74	82
System Time (minutes)	98	61
Queue Time (minutes)	48	29

3.3 Cytology Service

- Baseline and Improved Conditions

The cytology laboratory handled microscopic reviews under high workload and limited diagnostic personnel. A standard diagnostic time of 12 minutes per sample was documented and modeled accordingly. Under the existing configuration, 60 cytologies were processed daily, resulting in a cumulative cycle time of 31.68 hours when including batching and idle periods. Of this, only 24.05 hours were attributed to value-added diagnostic work, with the remaining time lost to waiting or inefficient task switching.

The improved scenario restructured the lab workflow to include auxiliary support staff and introduced balanced task sequencing to reduce transition times. With this reconfiguration, simulation results showed a dramatic decrease in total cycle time to 12.55 hours—a reduction of more than 60%. Waiting time decreased by 44%, and value-added time dropped to 8.26 hours, reflecting the efficiency of distributed workload.

Furthermore, diagnostic productivity doubled, increasing from 60 to 120 samples per day. The change demonstrated how non-technological interventions—such as task reassignment and process flow redesign—could have substantial impact on system performance.

Table 3: Cytology Lab Efficiency – Baseline vs Improved.

Metric	Baseline	Improved
Value-added Time (h)	24.05	8.26
Waiting Time (h)	7.63	4.30
Total Cycle Time (h)	31.68	12.55
Samples per Day	60	120

3.4 Model Validation and Statistical Consistency

To ensure model fidelity, all simulations were subjected to a structured statistical validation framework. Each model underwent 30 replications, and the means of simulation outputs were compared to empirical data obtained from hospital records

These statistical comparisons validate the consistency of the simulation models with real-world data, reinforcing their reliability for decision-making and scenario planning. To ensure model fidelity, all simulations were subjected to a structured statistical validation framework. Each model underwent 30 replications, and the means of simulation outputs were compared to empirical data obtained from hospital records.

- **Confidence Intervals**: All real means (e.g., biopsy mean of 60.4 minutes) were contained within the simulation's 95% CI (59.4 – 62.6 minutes), confirming consistency.

Table 4: Confidence Interval Comparison – Simulated vs. Observed Means.

Service	Observed Mean	Simulated Mean	95% CI Simulated	Conclusion
Angiography	2.46 days	2.44 days	[2.31, 2.57]	Within CI
Biopsies	60.4 min	61.0 min	[59.4, 62.6]	Within CI
Cytologies	31.7 h	31.68 h	[30.21, 33.14]	Within CI

- **Kolmogorov-Smirnov Tests**: p-values > 0.05 were obtained for all tests, indicating that the distributions of simulated and observed data were statistically similar.

Table 5: Kolmogorov-Smirnov Test Results.

Service	D statistic	p-value	Conclusion
Angiography	0.067	0.409	No significant difference
Biopsies	0.078	0.317	No significant difference
Cytologies	0.071	0.361	No significant difference

- **ANOVA**: No significant differences were detected between simulated and observed means across services (e.g., $F = 1.14 < F_{\_critical} = 2.13$, $p = 0.292$).
- **Shapiro-Wilk Normality Test**: Residuals were normally distributed ($p > 0.10$), meeting the assumptions for parametric tests.

Table 6: ANOVA and Shapiro-Wilk Tests.

Service	ANOVA F	ANOVA p	Shapiro-Wilk p	Conclusion
Angiography	1.02	0.312	0.188	Normal residuals, no differences
Biopsies	1.14	0.292	0.113	Normal residuals, no differences
Cytologies	0.98	0.338	0.266	Normal residuals, no differences

3.5 Synthesis and Management Implications

The results across all three services demonstrate that DES, combined with Lean and DMAIC principles, can produce validated, actionable insights for hospital decision-makers. The findings indicate that:

- Patient wait times can be reduced by up to 65%
- Diagnostic throughput can be increased by 100% in cytology
- Resource utilization improved by 8–12 percentage points without adding infrastructure
- Process bottlenecks were resolved through operational changes alone

Moreover, the study confirms that the simulation models are not only technically robust but also replicable in other hospital environments. They offer a rigorous basis for testing operational scenarios, guiding strategic decisions, and implementing changes in a low-risk, high-impact manner. In doing so, the study provides a replicable framework for improving the productivity and resilience of hospital diagnostic services through data-driven simulation and continuous improvement methodologies.

4. Discussion of Results

The results obtained through the simulation models provide valuable insights into the operational behavior and improvement potential of high-complexity diagnostic services. Across the three services studied—angiography, biopsies, and cytology—the validated DES models demonstrated both accuracy in replicating real-world operations and robustness in projecting performance under alternative configurations.

One of the most important findings is the confirmation that process inefficiencies, rather than absolute resource shortages, are major contributors to system saturation and patient delays. In the case of the angiography room, the extremely high utilization rate (99%) and long patient wait times (up to 6.75 days) suggested an overburdened system. However, the addition of a second shift redistributed workload effectively, reducing system time to just over 2 hours and cutting maximum wait time by over 80%. This scenario did not require additional physical infrastructure, only a temporal reorganization of existing assets.

Similarly, the biopsy lab, which originally processed only 62% of samples within the expected timeframe, showed marked improvement after transitioning from batch processing to a continuous flow. The resulting 37.8% reduction in system time and increased resource utilization illustrated the gains achievable through lean-inspired process redesign. Notably, these changes were driven not by technology, but by workflow sequencing and task alignment.

The cytology service stands out for its dramatic performance leap. The integration of auxiliary staff and rebalanced task assignments led to a 65% reduction in total cycle time and a doubling

of diagnostic throughput. These gains were made possible by eliminating non-value-added time, as confirmed by the drop in idle and wait times. Importantly, this reinforces the idea that even without increasing personnel numbers, reallocating responsibilities and structuring workflows based on diagnostic complexity can yield measurable productivity improvements.

The statistical validation further supports the reliability of these findings. The fact that observed data consistently fell within the 95% confidence intervals of the simulation results, combined with non-significant results in K-S and ANOVA tests, indicates a high degree of fidelity between the model and actual system performance. Residuals were also normally distributed across services, fulfilling key assumptions for the inferential tests applied.

These outcomes align with the initial problem framing in the introduction, which emphasized the constraints faced by health systems and the promise of methodologies like DES, Lean Healthcare, and Six Sigma for process optimization. Moreover, they validate the methodological framework presented in the study, which integrated institutional data, process mapping tools (e.g., SIPOC and VSM), and scenario-based simulation as a unified diagnostic and planning approach.

In sum, the discussion confirms that simulation is not merely a technical modeling tool, but a strategic enabler for healthcare management. By providing a virtual environment for experimentation, it allows institutions to test interventions safely, predict impacts reliably, and implement changes with greater confidence and stakeholder alignment.

5. Conclusions

This study confirms that Discrete Event Simulation (DES), when integrated with Lean Healthcare principles and the DMAIC methodology, constitutes a powerful and adaptable tool for improving operational efficiency in high-complexity hospital diagnostic services. The models developed for the angiography room, biopsy lab, and cytology service not only replicated actual hospital behavior with statistical rigor but also revealed concrete improvement opportunities without requiring large-scale investments.

Key conclusions include:

1. Process inefficiencies—not infrastructure limitations—are primary contributors to delays. In all three services analyzed, patient wait times and system saturation were largely attributable to scheduling, batching practices, or misaligned task distribution rather than insufficient physical resources.
2. Simulated improvement scenarios delivered measurable gains. Shifting from single to double shifts in angiography, moving from batch to continuous flow in biopsies, and integrating auxiliary staff in cytology all led to reduced wait times, increased throughput, and better resource utilization.
3. Validation reinforces model reliability. Confidence intervals, ANOVA tests, and distribution analysis consistently demonstrated that simulation outputs matched real-world data. This validates DES as a credible decision-support tool in clinical environments.
4. The methodology is transferable and replicable. The structured approach—based on real data, visual mapping tools (SIPOC, VSM), and iterative scenario analysis—can be applied to other hospital services facing similar capacity challenges.
5. Simulation supports sustainable healthcare management. By offering a low-risk environment for testing changes, DES empowers hospitals to optimize care delivery

and resource use with minimal disruption, contributing to more agile, patient-centered health systems.

Overall, this research offers not only a diagnostic model but also a pathway for continuous improvement in healthcare operations, strengthening the ability of institutions to address growing demand and complexity through data-driven strategies.

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Use of Generative Artificial Intelligence

Generative artificial intelligence was not used in the preparation of this work, with the sole exception of conventional text processing tools for language editing and reference management, which do not affect the methodological design, data analysis, or interpretation of results.

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