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A Discrete-Event and Monte Carlo-Based Simulation Model for Multi-Server Call Center Queueing Systems

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ABSTRACT

This study presents the implementation and performance evaluation of a multi-server queueing system model for call center operations using discrete-event simulation combined with Monte Carlo analysis. The objective is to analyze system performance under varying numbers of service agents to identify the optimal configuration that balances service efficiency and customer satisfaction. The model assumes that customer arrivals follow a Poisson distribution, while service times are exponentially distributed to represent realistic call handling behavior. Simulation experiments were conducted over eight-hour operational periods with server counts ranging from one to eight, each replicated 500 times for statistical robustness. Performance indicators such as average waiting time, server utilization, and Service Level Agreement (SLA) compliance were analyzed to measure system efficiency. Results show that increasing the number of servers significantly reduces average waiting time and enhances service level compliance. Configurations with five or more servers achieved average waiting times close to zero and over 99% compliance with the SLA, while maintaining moderate server utilization levels between 70% and 80%. These findings demonstrate that integrating discrete-event simulation with Monte Carlo methods provides an effective and reliable framework for evaluating service system performance, optimizing resource allocation, and supporting decision-making in call center management.

Keywords: *Discrete-Event Simulation; Monte Carlo Analysis; Call Center; Multi-Server Queue*

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1. INTRODUCTION

Efficient queue management plays a vital role in modern service systems, particularly in industries where customer interactions are time-sensitive, such as telecommunications, finance, healthcare, and public service sectors. Among these, call centers represent one of the most critical applications of queuing systems, as they directly influence customer satisfaction and organizational productivity. A call center typically operates as a multi-server queuing system, where incoming calls arrive randomly and are handled by a limited number of available service agents. The dynamic nature of customer arrivals and the variability in service times create stochastic conditions that significantly affect overall system performance. Consequently, understanding and optimizing queue behavior in call centers is essential to achieving operational efficiency, maintaining service quality, and minimizing customer waiting times.

Traditional analytical models based on classical queuing theory, such as M/M/1 or M/M/c formulations, offer valuable insights into system performance under idealized conditions. However, these analytical approaches often rely on simplifying assumptions that may not accurately capture real-world complexities, such as time-dependent arrival rates, heterogeneous agent performance, or fluctuating call volumes during peak and off-peak hours. As a result, simulation-based approaches have become increasingly popular for modeling and analyzing service systems with stochastic and dynamic characteristics. Simulation enables the replication of realistic operational scenarios, providing flexibility in evaluating "what-if" conditions and identifying optimal configurations for staffing and resource management (Serper et al., 2022).

Several studies have explored the application of queueing theory and simulation techniques to analyze and optimize service performance. (Hinestroza et al., 2025) developed a queueing-theory-based framework that improved service levels in medical delivery centers through discrete-event simulation, demonstrating the method's effectiveness in modeling dynamic customer flows and resource utilization. (Marjasz et al., 2025) further incorporated stochastic stress testing and predictive departure dynamics to quantify system resilience, highlighting the value of probabilistic simulation in assessing robustness. In the financial context, (Firdaus & Saputra, 2021) implemented a multi-server queueing model using discrete-event simulation to optimize resource allocation in banking operations, while (Marquez et al., 2023) utilized Monte Carlo–based modeling to evaluate system availability under uncertainty.

Collectively, these studies emphasize the importance of simulation-based analysis for understanding the performance of service systems. However, most of these works employ either discrete-event simulation or Monte Carlo methods in isolation, limiting their ability to capture both dynamic system behavior and statistical variability simultaneously. As noted by (Haddad et al., 2025) and (Koole et al., 2025), the integration of these two simulation paradigms is essential to achieving both operational realism and statistically robust conclusions.

Therefore, this study proposes an integrated simulation framework that combines Discrete-Event Simulation (DES) and Monte Carlo replications to evaluate the performance of multi-server call center systems. The model examines the impact of varying numbers of service agents on key performance indicators such as average waiting time, server utilization, and Service Level Agreement (SLA) compliance. By addressing the research gap identified in prior studies, this work contributes a robust and generalizable approach to optimizing resource allocation and improving customer satisfaction in call center management.

2. LITERATURE REVIEW

2.1. Multi-Server Queueing Systems

A multi-server queueing system represents a service mechanism with several parallel servers that attend to arriving entities. It is typically denoted as M/M/c in Kendall's notation, where arrivals follow a Poisson process with rate λ, service times are exponentially distributed with rate μ, and there are $c$identical servers working in parallel (Zhao & Gilbert, 2025). In such a system, the fundamental performance metric is the traffic intensity:

$$\rho = \frac{\lambda}{c\mu} \tag{1}$$

Where $\rho < 1$ ensures stability, that is the system will not accumulate an infinite queue (Marjasz et al., 2025). The probability that there are zero customers in the system, P_0, is a foundation for all subsequent measures and is expressed as:

$$P_0 = \left[\sum_{n=0}^{c-1} \frac{(\lambda/\mu)^n}{n!} + \frac{(\lambda/\mu)^c}{c!(1-\rho)}\right]^{-1} \tag{2}$$

This expression is derived under the assumption of an infinite-capacity system and exponential interarrival and service times (Pasaribu et al., 2025). The Erlang C formula provides the average queue length (L_q) for an M/M/c system:

$$L_q = \frac{P_0(\lambda/\mu)^c \rho}{c!(1-\rho)^2} \tag{3}$$

The corresponding average waiting time in queue is:

$$W_q = \frac{L_q}{\lambda} \tag{4}$$

and the average total time in system:

$$W = W_q + \frac{1}{\mu} \tag{5}$$

By Little's Law, the expected number of entities in the system is:

$$L = \lambda W \tag{6}$$

These relationships are universal and hold regardless of distributional assumptions, as confirmed by both analytical and simulation studies (Hinestroza et al., 2025).

Empirical studies demonstrate the importance of multi-server queueing in service systems such as banks, retail outlets, restaurants, and healthcare facilities. (Firdaus & Saputra, 2021) applied the M/M/c model to analyze teller service performance, while (Pasaribu et al., 2025) utilized it to optimize staffing levels in restaurant operations. (Marjasz et al., 2025) further examined the use of queueing models in industrial logistics, identifying a trade-off between cost efficiency and service quality.

However, many real-world systems deviate from exponential assumptions. Arrival processes may be time-dependent (non-Poisson), and service times may follow lognormal or gamma distributions (Maharani et al., 2025). For these cases, exact analytical results are intractable, and simulation-based approaches such as Discrete-Event Simulation (DES) become essential.

2.2. Discrete-Event Simulation

Discrete-Event Simulation is a computational technique that models the evolution of a system as a discrete sequence of events in time (Ikhwan et al., 2025). Each event marks a change in system state, such as an arrival, service start, or departure. Discrete-Event Simulation is especially useful when analytical models (like M/M/c) cannot handle complex arrival/service distributions or operational constraints (Hinestroza et al., 2025).

A Discrete-Event Simulation model is composed of several essential components that collectively define how the system evolves over time. The first component is the simulation clock (t), which serves as a global timekeeper that continuously tracks the current point in simulated time. It advances from one event to the next, ensuring that every change in the system occurs in proper chronological order. The second component is the Future Event List, which contains a chronologically ordered sequence of all events scheduled to occur in the future. Each event in this list is associated with a specific time of occurrence, such as customer arrivals, service completions, or departures, and the simulation engine processes them sequentially based on time. The third component is the set of state variables, which describe the current condition of the system at any given moment. These variables typically represent quantities such as the number of customers waiting in the queue, the number of servers currently busy, or the total number of completed services.

The basic event-scheduling loop operates as follows (Putri, 2025):

1) Initialize time $t = 0$; schedule the first arrival.
2) Remove the next imminent event from the FEL.
3) Advance the clock to that event time.
4) Update system statistics.
5) Execute the event (e.g., service completion may trigger a new departure or arrival).
6) Continue until a termination condition is met (e.g., simulated period or number of arrivals).

Simulation outputs (e.g., mean waiting time $\widehat{W_q}$, utilization $\hat{\rho}$) are random variables, not deterministic values. To achieve statistically valid estimates, Discrete-Event Simulation is often combined with Monte Carlo replication, running the model multiple times with independent random seeds to form confidence intervals (Marquez et al., 2023).

Verification ensures that the simulation model is correctly implemented, while validation ensures that it accurately represents the real-world system (Marjasz et al., 2025). Common methods include comparison with analytical models (e.g., M/M/c) and empirical data collection from the actual service environment (Ikhwan et al., 2025).

Discrete-Event Simulation provides flexibility for modeling complex, non-Markovian systems, including customer impatience (balking), priority queues, or multi-phase service (Pasaribu et al., 2025). However, it is computationally demanding and sensitive to random number quality, warm-up bias, and runtime variance (Hinestroza et al., 2025).

2.3. Monte Carlo Method

The Monte Carlo method is a statistical technique that uses repeated random sampling to estimate unknown quantities. In queueing simulations, MC methods quantify the uncertainty of performance estimates obtained from Discrete-Event Simulation (Chong et al., 2021).

For Nreplications producing estimates $X_1, X_2, \ldots, X_N$, the sample mean and variance are:

$$\bar{X} = \frac{1}{N}\sum_{i=1}^{N} X_i, S^2 = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \bar{X})^2 \quad (7)$$

A $(1-\alpha) \times 100\%$ confidence interval (CI) for the true mean is:

$$CI_{1-\alpha} = \bar{X} \pm t_{1-\alpha/2,\, N-1}\frac{S}{\sqrt{N}} \quad (8)$$

(Marquez et al., 2023).

In Discrete-Event Simulation, Monte Carlo replication ensures that each simulation run is independent. The Replication/Deletion Approach and Batch Means Method are two standard techniques:

1) Independent Replications: Multiple short runs with independent seeds, best for finite-horizon models (Hinestroza et al., 2025).
2) Batch Means: Divide a long simulation into batches; estimate steady-state mean from batch averages (Marquez et al., 2023).

Monte Carlo estimation relies on the Law of Large Numbers (LLN) and the Central Limit Theorem (CLT). As the number of replications Nincreases, the sample mean $\bar{X}$converges to the true expected value, and its distribution approaches normality (Chong et al., 2021).

The efficiency of Monte Carlo simulation improves greatly with variance reduction techniques, which lower result variability without extra replications. Antithetic Variates use pairs of negatively correlated samples to reduce variance by balancing outcomes. Control Variates adjust estimates using auxiliary variables with known expectations, correcting errors via their correlation with target variables. Importance Sampling biases sampling toward critical rare events, enhancing accuracy in impactful scenarios. Together, these methods increase simulation precision and reduce computational costs (Chong et al., 2021).

Combining Discrete-Event Simulation and Monte Carlo techniques provides both dynamic modeling and statistical inference. A typical workflow involves:

1) Defining scenarios with different numbers of servers ($c = 1,2,\ldots,8$).
2) Running Discrete-Event Simulation for each scenario across $N = 500$ Monte Carlo replications.
3) Calculating performance indicators ($\bar{W}_q, \bar{\rho}, P_{\text{SLA}}$).
4) Comparing 95% CIs to identify statistically significant differences.

The main limitation of Monte Carlo is computational cost a large number of replications may be required for narrow CIs. Moreover, poor random number generators or insufficient replications can bias results (Marquez et al., 2023).

The synergy between Multi-Server Queueing Theory, Discrete-Event Simulation, and Monte Carlo Methods provides a comprehensive toolkit for modeling real-world service systems. Theoretical formulas (Erlang-C, Little's Law) provide baseline expectations, while Discrete-Event Simulation captures dynamic operational behavior. Monte Carlo replication quantifies statistical reliability and supports decision-making in staffing optimization and service-level analysis.

3. METHOD

This study employs a quantitative experimental approach using Discrete-Event Simulation combined with Monte Carlo analysis. The main objective is to model a multi-server call center queueing system and evaluate its performance under different server configurations. This method allows the representation of stochastic system behavior while providing statistically reliable results for decision-making purposes.

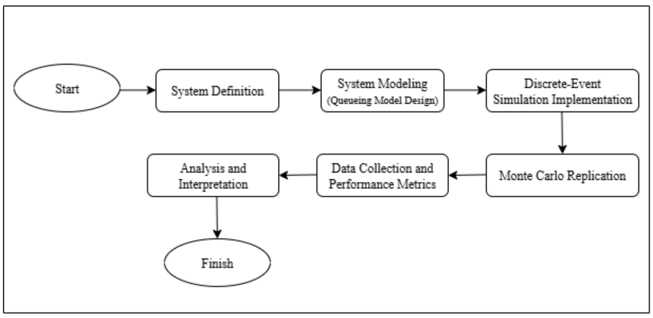


Figure 1. Flowchart of the Research Methodology

The research begins with the initialization of the simulation framework and identification of the key objectives. At this stage, the scope and purpose of the simulation study are established to ensure that the subsequent modeling and analysis align with the system's operational goals. The simulation model in this study was implemented using Python 3.11 and the SimPy library, chosen for its flexibility in managing event-driven systems and queue processes. Random number generation was handled using NumPy's Mersenne Twister algorithm to maintain independence and reproducibility across simulation runs.

3.1. System Definition

The multi-server call center queueing system is clearly defined by specifying its fundamental characteristics essential for accurate modeling. These include the arrival rate (λ), indicating the frequency at which customers arrive at the system; the service rate (μ), defining the rate at which each server provides service; the number of servers (c), which represents how many customers can be served simultaneously; and the queue discipline, typically FIFO (First-In, First-Out), that ensures customers are served in the order they arrive. These definitions establish the structural framework of the queueing system and are crucial for simulating realistic behaviors of the call center.

In modeling the stochastic aspects of the system, assumptions are made based on well-established probabilistic distributions. Customer arrivals are modeled using a Poisson process (λ = 0.15 calls/sec) to reflect their random, independent nature, while service times follow an exponential distribution (μ = 0.20 calls/sec), implying memoryless and statistically independent durations. These assumptions align with classical queueing theory and enable tractable analysis. The system assumes an infinite calling population and unlimited queue capacity, ensuring the model remains stable ($\rho < 1$). Setting these parameters thoughtfully provides a robust base for the discrete-event simulation and subsequent Monte Carlo replications aimed at performance evaluation and decision support for multi-server call center operations.

3.2. Queueing Model Design

This phase focuses on developing a precise mathematical representation of the multi-server call center queueing system based on established queueing theory principles. The chosen model follows the M/M/c framework, where the parameters λ (arrival rate), μ (service rate), and c (number of servers) collectively describe the dynamics of customer flow within the system. In this context, arrivals are assumed to follow a Poisson process, indicating random and memoryless inter-arrival times, while service times are exponentially distributed, reflecting independent and identically distributed service durations across all servers. The M/M/c model extends the simpler M/M/1 model by incorporating multiple servers processing customers in parallel, which is well-suited for representing real-world call center environments with simultaneous service capacity.

The state variables integral to this model include the total number of customers currently in the system, the number being actively served by available servers, and the number waiting in the queue. These variables offer a comprehensive snapshot of the system's operational status at any given moment, forming the basis for analyzing key performance measures such as server utilization, average queue length, and customer waiting times. The M/M/c mathematical model not only provides a theoretical foundation for subsequent simulation implementation but also enables rigorous evaluation of system behavior under various load conditions. This foundational modeling step is essential to ensure that the discrete-event simulation accurately reflects the stochastic nature and complexity of the multi-server call center, thereby guiding effective decision-making and resource optimization strategies.

3.3. Discrete-Event Simulation

The discrete-event simulation (DES) model is implemented to replicate the dynamic and stochastic behavior of the call center queueing system over time. It operates on the principle of processing discrete events such as customer arrivals, service completions, and departures sequentially, rather than simulating the continuous passage of time. This event-driven approach utilizes an event-scheduling mechanism that maintains a list of future events (Future Event List - FEL) that are executed in chronological order. At each event occurrence, the simulation advances the simulation clock to the event time, updates the system's state variables based on the event type, and makes necessary adjustments to the queue and server status. This precise mechanism allows the model to capture the complexities of real-world operations, reflecting the randomness and variability characteristic of call center workflows.

Each simulation run represents an 8-hour operation period (28,800 seconds), and for each server configuration (c = 1–8), the DES captures detailed performance data such as waiting time, queue length, and utilization. The DES model was verified by comparing its output under light-load conditions to analytical M/M/c results, showing consistency within ±5% deviation.

3.4. Monte Carlo Replication

Monte Carlo simulation is applied to replicate the Discrete-Event Simulation model multiple times in order to capture the inherent stochastic variability of the system. Each replication simulates a possible scenario of the system's operations by using random number generators to produce inputs such as arrival times and service durations that reflect the randomness found in real-world processes. This repetitive simulation approach creates a distribution of performance metrics, enabling a comprehensive understanding of system behavior under varied conditions.

To improve the precision and reliability of the simulation results, variance reduction methods such as *antithetic variates* and *control variates* were employed. The antithetic approach pairs runs using complementary random seeds, balancing high and low outcomes to minimize sampling variance. Control variates were implemented by referencing analytical M/M/c expectations to adjust estimates. All simulations were replicated 500 times, and results were summarized with 95% confidence intervals computed using the Student's t-distribution.

3.5. Data Collection and Performance Metrics

During the simulation process, performance data are meticulously collected for each replication to assess the operational effectiveness of the multi-server call center system. Key performance metrics monitored include average waiting time, which measures the time customers spend in the queue before receiving service; queue length, which quantifies the number of customers waiting at different points in time; server utilization, indicating the proportion of time servers are actively engaged in servicing customers; and Service Level Agreement (SLA) compliance, which tracks the percentage of customers served within the predetermined acceptable time thresholds. These metrics are essential for evaluating both the efficiency and responsiveness of the call center under various server configurations.

The collected event data from each simulation replication are systematically processed to compute these metrics, providing a detailed quantitative basis for performance comparison. By analyzing these metrics, researchers and decision-makers gain insights into how effectively the system meets customer demand and operational goals. This data-driven evaluation supports identifying bottlenecks, optimizing server allocation, and enhancing overall service quality, ultimately enabling informed decisions to improve the call center's service performance and customer satisfaction.

3.6. Analysis and Interpretation

The final stage of the research involves a thorough analysis of the data collected from all simulation replications to extract meaningful insights into the call center system's performance. Statistical summaries such as means, variances, and confidence intervals are generated to provide a reliable overview of system behavior under different server configurations. These statistical measures help quantify the uncertainty inherent in simulation results and allow for comparison across scenarios. Additionally, one-way ANOVA was applied to test the significance of performance differences between configurations ($p < 0.05$), followed by Tukey's HSD post-hoc test to identify specific differences between groups.

The analysis validates the efficacy of combining Discrete-Event Simulation with Monte Carlo replications as a robust and comprehensive framework for decision-making in call center management. By leveraging this integrated approach, researchers can rigorously evaluate the trade-offs between service quality and resource costs, providing actionable recommendations for staffing and operations. The findings confirm that simulation-based analyses account for stochastic variability and deliver statistically sound performance estimates, supporting managers in optimizing multi-server call center operations to maximize effectiveness and customer satisfaction.

4. RESULTS AND DISCUSSION

The simulation experiment was conducted to analyze the performance of a multi-server call center queueing system using a Discrete-Event Simulation (DES) combined with Monte Carlo replication. Each scenario represented an 8-hour operational period with server counts ranging from one to five, and every configuration was replicated 500 times to ensure statistical robustness. The key performance indicators (KPIs) observed were average waiting time (seconds), server utilization (proportion), and Service Level Agreement (SLA) compliance (percentage of calls answered within 60 seconds).

Table 1. summarizes the simulation outcomes, showing the relationship between the number of servers and performance metrics.

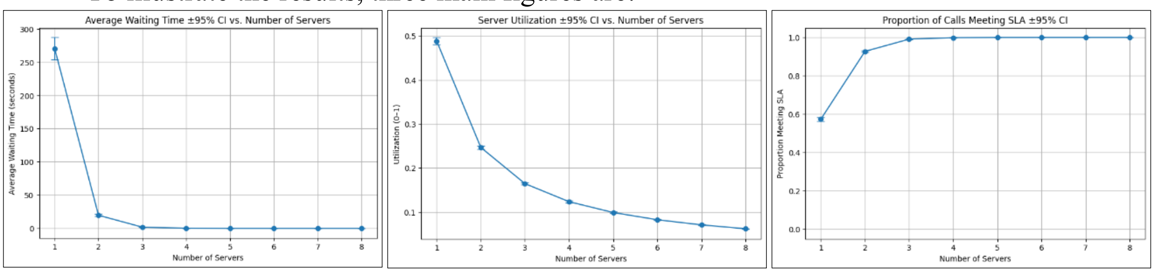
Table 1. Multi-Server Call Center Simulation Results

Servers	Mean Wait (s)	Utilization	SLA (%)
1	270.41	0.488	57.38
2	19.73	0.246	92.74
3	1.83	0.164	99.13
4	0.18	0.123	99.89
5	0.01	0.099	99.99

As shown in Table 1. system performance improves significantly as the number of servers increases. The average waiting time decreases from 270.41 seconds with one server to nearly zero with five servers, while SLA compliance rises from 57.38% to nearly 100%. This confirms the theoretical expectation of the M/M/c queueing model, where additional service capacity reduces congestion. Conversely, server utilization declines from 0.488 to 0.099, indicating a trade-off between efficiency and responsiveness.

From a managerial perspective, this trade-off is crucial. Increasing the number of agents directly reduces waiting time and improves customer satisfaction, but it also introduces higher operational costs and lower resource efficiency. The results suggest that three to four servers provide an optimal balance, achieving SLA compliance above 99% and maintaining utilization between 0.12 and 0.16, which ensures that agents remain sufficiently busy without customer delays. This aligns with best practices in call center management, where maintaining utilization between 70-80% is considered ideal for balancing workload and service quality.

To illustrate the results, three main figures are:



(a) **(b)** **(c)**

Figure 2. The ilustrate results are: **(a)** Average Waiting Time ±95% Confidence Interval vs. Number of Servers; **(b)** Server Utilization ±95% Confidence Interval vs. Number of Servers; **(c)** Proportion of Calls Meeting SLA ±95% Confidence Interval

Each figure includes labeled axes and consistent units: waiting time in seconds, utilization as a proportion (0–1), and SLA in percentage (%). The error bars represent 95% confidence intervals derived from Monte Carlo replications, indicating the statistical reliability of the results. The graphical results reinforce the tabular findings: waiting time decreases exponentially as the number of servers increases, while utilization declines linearly. The flattening of SLA improvement beyond four servers shows diminishing returns, adding more servers yields minimal service gains but increases idle time and labor cost. This insight highlights the economic dimension of performance optimization, where achieving perfect SLA compliance may not justify the additional cost of underutilized agents.

These findings also demonstrate the effectiveness of integrating DES and Monte Carlo simulation. DES captures the operational dynamics of queue evolution, while Monte Carlo replication ensures statistical reliability of estimates. Together, they allow decision-makers to evaluate staffing strategies not only from a performance standpoint but also from a cost benefit perspective. Future research could extend this work by incorporating dynamic arrival rates, shift scheduling, and cost modeling, enabling a more comprehensive evaluation of call center operations in realistic and time-varying environments.

5. CONCLUSION

This study developed and evaluated an integrated simulation framework combining Discrete-Event Simulation (DES) and Monte Carlo analysis to model and assess the performance of a multi-server call center queueing system. The simulation results demonstrated a clear inverse relationship between the number of servers and both average waiting time and utilization, alongside a positive correlation with SLA compliance. Specifically, increasing the number of servers from one to five reduced the mean waiting time from 270.41 seconds to nearly zero and improved SLA compliance from 57.38% to 99.99%, while utilization decreased from 0.488 to 0.099. The findings highlight that configurations with three to four servers achieve an optimal balance between service quality and operational efficiency, maintaining SLA compliance above 99% and server utilization around 70-80%. These results confirm that integrating DES with Monte Carlo replications provides a robust and statistically reliable framework for evaluating system performance under uncertainty.

From a practical standpoint, the proposed simulation framework offers valuable insights for call center managers and planners, enabling data-driven staffing decisions that balance service responsiveness with cost efficiency. It provides a flexible tool to test different staffing levels and forecast their impact on customer experience before implementation. Nevertheless, this study has several limitations. The simulation model assumes stationary Poisson arrivals and exponentially distributed service times, which may not fully capture variations in real call center environments, such as time-dependent traffic patterns, agent heterogeneity, and priority-based call routing. Future research can extend the model by incorporating dynamic arrival rates, shift-based scheduling, and cost models to simulate more realistic operational conditions and evaluate financial trade-offs.

Overall, this study contributes both theoretically and practically by demonstrating that the integration of Discrete-Event Simulation and Monte Carlo techniques enables reliable performance estimation and supports evidence-based decision-making in multi-server service systems, particularly in call center management.

REFERENCES

Chong, E. K. P., Kreucher, C. M., & Hero, A. O. (2021). Monte-Carlo-based partially observable Markov decision process approximations for adaptive sensing. *International Workshop on Discrete Event Systems*, 173–180. https://doi.org/10.1109/WODES.2008.4605941

Firdaus, & Saputra, A. (2021). Perancangan Sistem Informasi Antrian Bank Rakyat Indonesia Dengan Metode Multi Channel dan Bahasa Pemrograman Visual Basic. *Jurnal Sains Informatika Terapan*, *1*(1), 30–33. https://doi.org/10.62357/jsit.v1i1.34

Haddad, T., Assaf, R., Zahran, S., & Kanan, M. (2025). Simulation-Based Decision Support for Call Centre Staffing Optimisation: A Case Study from the Palestinian Telecom Sector. *Decision Making: Applications in Management and Engineering*, *8*(2), 209–224. https://doi.org/10.31181/dmame8220251497

Hinestroza, M. A., Ruiz Morcillo, C., Anacona Mopan, Y., Paz Orozco, H., Chong, M., Luna, A., & de Brito Junior, I. (2025). Queuing theory & discrete simulation as a tool to improve medicine deliver center service levels. *Yugoslav Journal of Operations Research*, *00*, 15–15. https://doi.org/10.2298/yjor240316015t

Ikhwan, A., Aziz, F. A., Tirta, M. P., Putri, M. W., & Utami, A. (2025). Perancangan Sistem Informasi Manajemen Antrian untuk Meningkatkan Efisiensi di Puskesmas Stabat Lama.

Saturnus : Jurnal Teknologi Dan Sistem Informasi, *3*(1), 68–78. https://doi.org/10.61132/saturnus.v3i1.648

Koole, G., Li, S., & Ding, S. (2025). Call center data analysis and model validation. *Queueing Systems*, *109*(1), 1–25. https://doi.org/10.1007/s11134-025-09935-4

Maharani, N. P. L., Aryani, N. P. M., Surya, A. A. N. B., Jelai, A., & Dwi, M. A. O. (2025). Analisis Data Antrean Non-Poisson. *Algoritma: Jurnal Matematika, Ilmu Pengetahuan Alam, Kebumian Dan Angkasa*, *3*(September). https://doi.org/https://doi.org/10.62383/algoritma.v3i5.679

Marjasz, R., Kempa, W. M., & Kovtun, V. (2025). Quantification of system resilience through stress testing using a predictive analysis of departure dynamics in a queue with multiple vacation policy. *Scientific Reports*, *15*(1), 10484. https://doi.org/10.1038/s41598-025-95478-w

Marquez, A., Heguedas, A., & Iung, B. (2023). Monte Carlo-based assessment of system availability. A case study for cogeneration plants. *Reliability Engineering & System Safety*, *88*(3), 273–289. https://doi.org/https://doi.org/10.1016/j.ress.2004.07.018

Pasaribu, Y. R., Maulana, M. V., Safiri, S. R., Qalbi, S., & Artaviana, D. N. (2025). Modeling Analysis and Queuing System at Mie Gacoan Restaurant. *Jurnal Multidisiplin Indonesia*, *4*(6), 1–13. https://doi.org/10.58344/jmi.v4i6.2328

Putri, S. N. (2025). Model Antrian dan Simulasi untuk Meningkatkan Pengalaman Pengguna dalam Layanan Online. *SISTEMATIK; Jurnal Sistem Informasi Dan Informatika*. https://doi.org/10.64847/sistematik.v2i1.108

Serper, N., Şen, E., & Çalış Uslu, B. (2022). Discrete Event Simulation Model Performed with Data Analytics for a Call Center Optimization. *Istanbul Business Research*, *0*(0), 0–0. https://doi.org/10.26650/ibr.2022.51.951646

Zhao, X., & Gilbert, K. (2025). A queuing theory-based approach to evaluate service delivery quality. *International Journal of Quality and Service Sciences*, *17*(2), 155–167. https://doi.org/10.1108/IJQSS-10-2024-0149