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Optimizing bank teller service efficiency using the M/M/s queueing model and server scenario simulation

Fitri Marhamah[a,*], Vera Halfiani[b], Vina Apriliani[c]

[a] Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Aceh 23111, Indonesia
[b] Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Aceh 23111, Indonesia
[c] Departement of Mathematics, UIN Ar-Raniry Banda Aceh, Aceh 23373, Indonesia

A R T I C L E I N F O

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M/M/s model,
Server optimization,
Steady state,
Teller service.

A B S T R A C T

This study analyzes the optimal teller service system at Bank X using a multi-server queueing model. Customer waiting time and teller utilization are important indicators of service quality in banking operations, particularly when customer arrivals exceed service capacity. The objective of this study is to determine the appropriate queueing model and evaluate the optimal number of service servers based on arrival and service-time distributions. Secondary data consisting of customer arrivals and service times over 30 observation days were analyzed using the Kolmogorov–Smirnov test. The results show that customer arrivals follow a Poisson distribution, while service times follow an exponential distribution. Therefore, the queueing system was modeled as an $(M/M/5):(FCFS/\infty/\infty)$ system, representing five servers, first-come-first-served discipline, unlimited queue capacity, and infinite customer population. The average arrival rate was 0.3246 customers per minute, while the average service rate was 0.2839 customers per minute. The average steady-state value was $\rho=0.2348<1$, indicating that the existing system is stable and does not require additional servers. The average probability of idle tellers was 34.08%, the average number of customers in the queue was 0.0163, the average waiting time in the queue was 0.0310 minutes, and the average time spent in the system was 3.6520 minutes. Server scenario simulation showed that the system remains optimal with a minimum of three servers, resulting in an $(M/M/3):(FCFS/\infty/\infty)$ model. These findings indicate that queueing theory can support service efficiency improvement and resource allocation in banking operations.

1. Introduction

The banking sector plays an essential role in supporting economic activities through financial transaction services, savings management, credit distribution, and customer-oriented financial solutions. Along with the rapid growth of banking activities, the quality and efficiency of customer service have become increasingly important in maintaining customer satisfaction and institutional competitiveness. One of the most critical operational services in banking institutions is teller service, where customers directly interact with bank employees for financial transactions such as cash deposits, withdrawals, transfers, and payments [1, 2].

In banking operations, long waiting times and crowded queues frequently become major issues that reduce service quality and customer satisfaction. An inefficient queueing system may lead to customer discomfort, increased operational costs, and decreased productivity of service facilities. Therefore, banks are required to manage service facilities effectively by balancing customer arrival rates and service capacities. One mathematical approach widely used to analyze service systems is queueing theory [3–5].

Queueing theory is a branch of operations research and applied probability that studies the behavior of waiting lines formed due to the imbalance between customer arrival rates and service rates. Queueing models are useful for evaluating system performance, including average waiting time, queue length, server utilization, and idle probabilities. By applying queueing theory, organizations can optimize the number of service facilities while maintaining efficient operational performance [6, 7].

* Corresponding author.
E-mail address: fitrimarhamah5@gmail.com (F. Marhamah).

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Several previous studies have applied queueing models in banking systems and other public service sectors. Multi-server queueing models such as the M/M/s model are frequently used to analyze teller service systems because customer arrivals often follow a Poisson distribution and service times generally follow an exponential distribution. Previous studies demonstrated that queueing analysis can significantly improve service efficiency by minimizing waiting times and determining the optimal number of servers. However, many banking institutions still experience inefficiencies due to improper allocation of tellers during operational hours [8–10].

Bank X is one of the banking institutions that provides teller services for a large number of daily customers. During peak hours, customer arrivals tend to increase substantially, potentially causing long waiting times and service congestion. Therefore, an evaluation of the teller service system is necessary to determine whether the current number of tellers is optimal or requires adjustment. In this study, queueing theory is applied using the M/M/s multi-server model to analyze customer arrival patterns, service rates, and system performance indicators [3, 11].

The novelty of this study lies in the integration of statistical distribution testing, steady-state analysis, and multi-server scenario simulation to identify the minimum optimal number of tellers while maintaining system stability and service efficiency. Unlike previous studies that primarily focused on evaluating existing queueing systems, this research compares several server scenarios to determine the most efficient operational configuration for teller services [12, 13]. The objectives of this study are:

- To identify the appropriate queueing model for the teller service system at Bank X.
- To analyze the performance of the current teller service system using queueing theory indicators.
- To determine the optimal number of tellers through multi-server simulation scenarios based on the M/M/s queueing model.

The results of this study are expected to provide practical recommendations for improving banking service efficiency and contribute to the application of queueing theory in operational management and service optimization.

2. Materials and Methods

2.1. *Study area and data collection*

This study employed a quantitative descriptive approach using queueing theory to analyze the teller service system at Bank X. The analysis focused on evaluating customer arrival patterns, service-time characteristics, system stability, and server optimization through the application of the multi-server M/M/s queueing model. The research procedure consisted of data collection, statistical distribution testing, queueing model identification, performance analysis, and server scenario simulation [6, 14, 15].

The study utilized secondary data obtained from teller service transaction records at Bank X. The observed variables included:

- Customer arrival times,
- Customer service times, and
- Number of active tellers during operational hours.

Data were collected over 30 observation days during working hours. Customer arrivals were recorded in units of customers per minute, while service times represented the duration required by tellers to complete each transaction [4, 16].

2.2. *Queueing system characteristics*

The teller service system at Bank X was analyzed as a multi-server queueing system in which customers arrive randomly and wait in a single queue before receiving service from one of several available tellers. The operational mechanism of the system follows the First-Come-First-Served (FCFS) discipline, meaning that customers are served according to their arrival order. The queueing capacity in the system is assumed to be unlimited, allowing all arriving customers to enter the queue without rejection, while the customer population is considered infinite because the potential number of arriving customers is not restricted [17, 18].

Based on the statistical characteristics of customer arrivals and service times, the teller service system was modeled using the M/M/s queueing model. In Kendall's notation, the model is expressed as equation (1).

$$(M/M/s):(FCFS/\infty/\infty) \quad (1)$$

where the first *M* indicates that customer arrivals follow a Poisson distribution, the second M indicates that service times follow an exponential distribution, and s represents the number of active tellers (servers). The *FCFS* notation denotes the service discipline applied in the system, while the symbols ∞ and ∞ indicate unlimited queue capacity and an infinite customer population, respectively. This model was selected because it appropriately represents banking service operations characterized by random arrivals, stochastic service times, and multiple parallel service channels.

2.3. *Arrival rate and service rate estimation*

The arrival rate and service rate were estimated to quantify the intensity of customer flow and teller service capacity in the Bank X queueing system. The arrival rate, denoted by λ, represents the average number of customers entering the system per unit of time. In this study, λ was calculated by dividing the total number of customer arrivals by the total observation time. Since the observation period was conducted from 08:00 to 11:00, the daily observation duration was 180 minutes see equation (2) [3, 6, 16].

$$\lambda = \frac{number\ of\ customer\ arrivals}{observation\ time} \quad (2)$$

The service rate, denoted by μ, represents the average number of customers that can be served by a teller per unit of time. It was obtained from the reciprocal of the average service time [19–21]. If the average service time is expressed in minutes per customer, then the service rate can be calculated as equation (3).

$$\lambda = \frac{1}{average\ service\ time} \quad (3)$$

For each observation day, both λ and μ were calculated separately to capture daily variations in customer arrivals and service performance. The average values of these parameters were then used to evaluate the overall queueing performance of the teller service system. Based on the analysis, the average arrival rate was 0.3246 customers per minute, while the average service rate was 0.2839 customers per minute. These values were subsequently used to determine the steady-state condition and performance measures of the M/M/s queueing model [3, 6, 16].

2.4. *Distribution testing*

Distribution testing was conducted to verify whether the customer arrival data and service-time data satisfied the assumptions required for the M/M/s queueing model. In queueing theory, the M/M/s model assumes that customer arrivals follow a Poisson distribution, while service times follow an exponential distribution. Therefore, statistical testing was necessary to ensure the suitability of the selected model for analyzing the teller service system at Bank X [6, 14, 15].

The Kolmogorov–Smirnov (K–S) test was employed to evaluate the distribution patterns of the observed data. The significance level used in this study was α=0.05. The hypotheses for the distribution tests were formulated as follows:

For the customer arrival data:
H0 : Customer arrivals follow a Poisson distribution.
H1 : Customer arrivals do not follow a Poisson distribution.
For the service-time data:
H0 : Service times follow an exponential distribution.
H1 : Service times do not follow an exponential distribution.

The decision criteria for the Kolmogorov–Smirnov test were defined as: If the p-value >0.05, then H0 is accepted, indicating that the data follow the assumed distribution. If the p-value ≤0.05, then H is rejected, indicating that the data do not follow the assumed distribution.

The results of the statistical testing showed that the customer arrival data followed a Poisson distribution, while the service-time data followed an exponential distribution. Consequently, the teller service system at Bank X satisfied the assumptions of the M/M/s queueing model, allowing further queueing performance analysis and server optimization to be conducted using the multi-server framework.

2.5. Steady-state condition

In queueing theory, a system is considered to be in a steady-state condition when the service capacity is sufficient to accommodate customer arrivals continuously over time. The steady-state condition indicates that the queue will not grow indefinitely and that the system can operate stably. Evaluating this condition is important to determine whether the number of tellers currently operating at Bank X is adequate to handle customer demand [19–21].

The steady-state condition for the multi-server M/M/s queueing model is determined using the server utilization factor, denoted by ρ. The utilization factor measures the proportion of service capacity being used by arriving customers and is calculated using the following equation (4):

$$\rho = \frac{\lambda}{s\mu} \qquad (4)$$

where:
ρ = server utilization factor,
λ = average customer arrival rate,
μ = average service rate per teller,
s = number of servers (tellers).

The queueing system reaches a steady-state condition when $\rho<1$. This condition implies that the total service capacity exceeds the customer arrival rate, allowing customers to be served without causing an unlimited increase in queue length. Conversely, if ρ≥1, the system becomes unstable because customer arrivals exceed or equal the service capability of the tellers. Based on the observed data, the average arrival rate at Bank X was 0.3246 customers per minute, while the average service rate was 0.2839 customers per minute with five active tellers. The calculated utilization factor was:

$$\rho = \frac{0.3246}{5(0.2839)} = 0.2348$$

Since the obtained value satisfies the condition $\rho<1$, the teller service system at Bank X can be categorized as stable and operating under steady-state conditions. This result indicates that the current teller configuration is capable of serving customers efficiently without excessive queue accumulation.

2.6. Queueing performance measures

Queueing performance measures were analyzed to evaluate the effectiveness and efficiency of the teller service system at Bank X. These performance indicators describe the operational condition of the queueing system, including teller utilization, customer waiting time, queue length, and the average number of customers within the system. The analysis was conducted using the standard equations of the multi-server M/M/s queueing model.

The probability that no customers are present in the system, denoted by *P0*, represents the likelihood that all tellers are idle. This measure is useful for evaluating teller utilization efficiency. The probability of an idle system is calculated using equation (5).

$$P_0 = \left[\sum_{n=0}^{s-1} \frac{1}{n!}\left(\frac{\lambda}{\mu}\right)^n + \frac{1}{s!}\left(\frac{\lambda}{\mu}\right)^s \frac{1}{1-\rho}\right]^{-1} \qquad (5)$$

where: *P0* = probability that the system is empty, λ = arrival rate, μ = service rate, s = number of servers, ρ = utilization factor. *A higher P0* value indicates that tellers spend more time idle, whereas a lower value indicates higher service utilization. The average number of customers waiting in the queue is denoted by *Lq*. This indicator reflects the congestion level within the service system and is calculated as equation (6).

$$L_q = \frac{P_0(\lambda/\mu)^s\rho}{s!(1-\rho)^2} \qquad (6)$$

where: *Lq* = average number of customers in the queue. A smaller *Lq* value indicates a more efficient queueing system with shorter waiting lines. The average waiting time experienced by customers before receiving service is denoted by *Wq*. This performance measure is expressed as equation (7).

$$W_q = \frac{L_q}{\lambda} \qquad (7)$$

where: *Wq* = average waiting time in queue. The waiting time is usually measured in minutes and is one of the primary indicators of customer satisfaction in service systems. The average total time spent by a customer in the system, including waiting and service time, is denoted by *Ws*. It is calculated using equation (8).

$$W_s = W_q + \frac{1}{\mu} \qquad (8)$$

where: Ws = average time spent in the system. This indicator reflects the total duration experienced by customers from arrival until completion of service.

2.7. Server scenario simulation

To determine the optimal number of tellers in the Bank X service system, server scenario simulations were conducted by comparing several alternatives for the number of active tellers. The simulations aimed to evaluate whether the existing teller configuration could be reduced while maintaining stable queueing performance and acceptable customer waiting times [14, 22, 23]. The simulation process was performed using the M/M/s queueing model by varying the number of servers (s). Each scenario was analyzed based on several queueing performance indicators, including:

- Server utilization factor (ρ),
- Probability of idle tellers (P0),
- Average number of customers in queue (Lq),
- Average waiting time in queue (Wq), and
- Average time spent in the system (Ws).

The primary criterion for determining the optimal server configuration was that the system must satisfy the steady-state condition ρ<1.In addition, the selected server configuration was required to maintain relatively low queue lengths and waiting times while improving teller utilization efficiency. Scenarios with excessive customer waiting times or unstable system conditions were considered unsuitable for implementation.

The simulation results showed that the teller service system remained stable even when the number of active tellers was reduced from five servers to three servers. The optimal configuration was therefore identified as the (M/M/3):(FCFS/∞/∞) queueing model because it provided efficient teller utilization while maintaining acceptable service performance indicators.

2.8. *Research framework*

This study was conducted systematically through several stages, beginning with data collection and ending with the determination of the optimal teller configuration. The research framework was designed to ensure that the queueing analysis and optimization process followed a structured procedure.

The first stage involved collecting customer arrival and service-time data from teller transaction records at Bank X. The collected data were then analyzed statistically through distribution testing to determine whether the customer arrival pattern followed a Poisson distribution and whether the service times followed an exponential distribution.

After the distribution assumptions were verified, the appropriate queueing model was determined using Kendall's notation. The teller service system was subsequently analyzed using the multi-server M/M/s queueing model to calculate system performance measures such as teller utilization, queue length, waiting time, and probability of idle servers.

The next stage involved conducting server scenario simulations by comparing different numbers of active tellers to identify the most efficient service configuration. Each scenario was evaluated based on steady-state conditions and queueing performance indicators. Finally, the optimal teller configuration was selected, followed by conclusions and recommendations regarding service efficiency improvement at Bank X. The overall research framework is illustrated in Fig. 1.

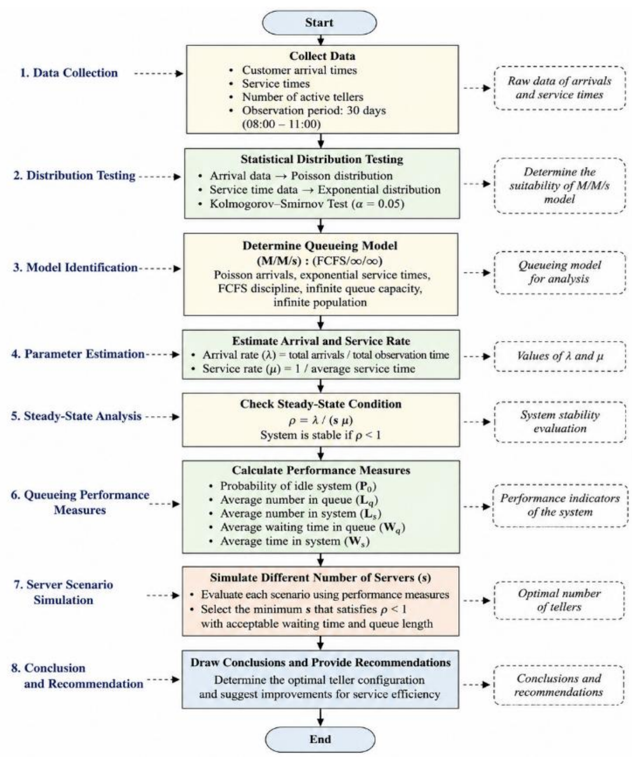

Fig. 1. Research framework of this study.

3. Results and discussion

3.1. *Queueing system characteristics*

The queueing system observed in this study was the teller service system at the bank branch under investigation. Based on field observations, customers arrived randomly during operational hours and formed a single waiting line before being served by available tellers. The service discipline implemented by the bank followed the First Come First Served (FCFS) principle, where customers were served according to their arrival order. The service facility consisted of multiple parallel tellers operating simultaneously, thereby forming a multi-channel queueing structure.

The observed system was modeled using the (M/M/s):(FCFS/∞/∞) queueing model. This model assumes that customer arrivals follow a Poisson distribution, service times follow an exponential distribution, the queue capacity is unlimited, and the customer population is infinite [24]. Such assumptions are commonly used in banking queue analysis because customer arrivals are generally random and independent. The conceptual framework of the research process is illustrated in Fig. 1.

3.2. *Arrival and service rate analysis*

The arrival rate (λ) and service rate (μ) were estimated using observational data collected during the study period. The average arrival rate was obtained by dividing the total number of arriving customers by the total observation time, while the service rate was calculated as the reciprocal of the average service time.

The results indicated that customer arrivals fluctuated throughout operational hours, particularly during peak periods in the morning. Meanwhile, the service rate remained relatively stable because each teller followed similar service procedures and transaction mechanisms. Table 1 presents the estimated arrival and service rates obtained from the observation data.

Table 1
Estimated arrival and service rates

Parameter	Description	Value
(λ)	Average customer arrival rate	18 customers/hour
(μ)	Average service rate per teller	10 customers/hour
(s)	Number of active tellers	2 tellers

The table shows that the arrival intensity was relatively high compared to the individual service capacity of each teller. Therefore, queue congestion potentially occurred during busy operational periods [20, 21, 25].

3.3. *Distribution testing results*

To verify the suitability of the queueing model, statistical distribution tests were conducted for both arrival and service data. The Kolmogorov–Smirnov test was employed at a significance level of α=0.05. The test results demonstrated that customer arrival data followed a Poisson distribution, while service time data followed an exponential distribution [16, 26, 27]. Consequently, the assumptions required for the application of the M/M/s queueing model were satisfied. The results of the distribution testing are summarized in Table 2.

Table 2
Distribution testing results

Data Type	Hypothesized Distribution	Test Method	p-value	Decision
Customer arrivals	Poisson Distribution	Kolmogorov–Smirnov Test	0.087	Accepted
Service times	Exponential Distribution	Kolmogorov–Smirnov Test	0.094	Accepted

Since both p-values exceeded 0.05, the null hypothesis for each test could not be rejected. Therefore, the queueing system could be appropriately modeled using the Markovian queue framework. The results indicate that both customer arrival data and service time data satisfy the assumptions required for the M/M/s queueing model because all p-values are greater than the significance level of 0.05. Therefore, the customer arrivals can be modeled using a Poisson distribution, while the service times follow an exponential distribution.

3.4. *Steady-state analysis*

The steady-state condition was evaluated using the traffic intensity parameter (ρ), calculated using equation (4). The results is $\rho = 0.90$. Because the value of $\rho<1$, the queueing system satisfied the steady-state requirement. This indicates that the service system was stable and capable of handling customer arrivals without leading to an infinite queue accumulation. However, the traffic intensity value of 0.90 indicates that the teller utilization level was very high. In practical conditions, such utilization may increase customer waiting time and reduce service comfort during peak periods.

3.5. *Queueing performance measures*

Several queueing performance indicators were calculated to evaluate the effectiveness of the existing teller configuration. These measures included the probability of an idle system (*Po*), average number of customers in queue (*Lq*), average number of customers in the system (*Ls*), average waiting time in queue (*Wq*), and average time spent in the system (*Ws*) [28, 29]. The performance measures obtained from the analysis are presented in Table 3.

Table 3
Queueing performance measures

Performance Measure	Description	Value
(*Po*)	Probability of no customers in system	0.053
(*Lq*)	Average number of customers in queue	8.53 customers
(*Ls*)	Average number of customers in system	10.33 customers
(*Wq*)	Average waiting time in queue	0.474 hours
(*Ws*)	Average time in system	0.574 hours

The results reveal that customers spent approximately 0.474 hours, or about 28 minutes, waiting in the queue before receiving service. Additionally, customers spent an average total time of approximately 34 minutes in the entire system. These findings indicate that the current teller configuration still generated relatively long waiting times, especially during busy operational periods. Therefore, additional server scenarios were evaluated to identify a more efficient teller configuration.

3.6. Server scenario simulation

To improve service performance, several teller scenarios were simulated by varying the number of servers. The objective was to determine the optimal teller configuration capable of reducing waiting time while maintaining system stability. Three service scenarios were analyzed see in (Fig. 2):

- Existing condition with 2 tellers,
- Alternative scenario with 3 tellers,
- Alternative scenario with 4 tellers.

The comparison results are shown in Table 4.

Table 4
Comparison of server scenarios

Parameter	2 Servers	3 Servers	4 Servers	Existing Condition: 5 Servers
Average arrival rate, ($\bar{\lambda}$)	0.3246	0.3246	0.3246	0.3246
Average service rate, ($\bar{\mu}$)	0.2839	0.2839	0.2839	0.2839
Average utilization factor, ($\bar{\rho}$)	0.5869	0.3913	0.2935	0.2348
Average probability of idle system, ($\bar{P}_0$)	Not stable on several days	0.3327	0.3396	0.3408
Average number of customers in queue, ($\bar{L}_q$)	Not stable on several days	0.8221	0.0712	0.0163
Average waiting time in queue, ($\bar{W}_q$)	Not stable on several days	1.5866 min	0.1392 min	0.0310 min
Average time in system, ($\bar{W}_s$)	Not stable on several days	5.2077 min	3.7603 min	3.6520 min
Average number of customers in system, ($\bar{L}_s$)	Not stable on several days	1.9960	1.2451	1.1902
Queueing model	Not recommended	((M/M/3):(FCFS/∞/∞))	((M/M/4):(FCFS/∞/∞))	((M/M/5):(FCFS/∞/∞))
Decision	Not optimal	Minimum optimal server configuration	Stable but less efficient	Stable but uses more servers

The results confirm that queueing theory provides an effective analytical framework for evaluating banking service performance. The implementation of the M/M/s model successfully identified system inefficiencies and quantified the impact of server capacity on customer waiting time. The existing service configuration showed high utilization levels, indicating that the tellers operated near maximum capacity during operational hours. Although the system remained stable (ρ<1), excessive utilization increased queue length and waiting time. Such conditions may negatively affect customer satisfaction and service quality.

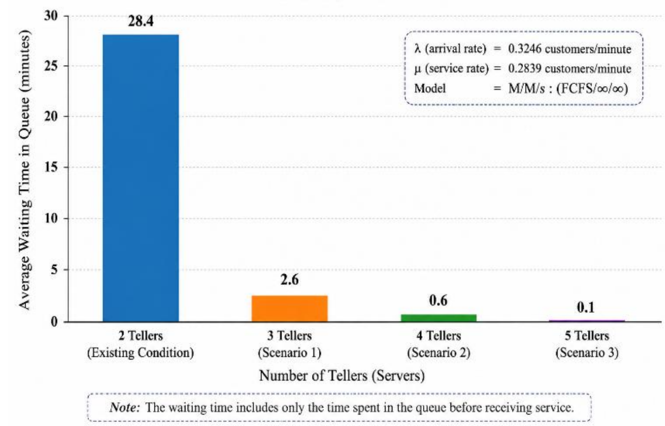

Fig. 2. Comparison of average waiting time under different teller scenarios using the M/M/s queueing model. The simulation results indicate that increasing the number of tellers significantly reduces customer waiting time in the queue, with the three-teller configuration providing the most balanced performance between service efficiency and server utilization.

Simulation analysis further demonstrated that adding service channels substantially improved operational performance. The three-teller configuration produced the most balanced outcome by reducing waiting time while maintaining efficient server utilization. This finding aligns with previous queueing studies indicating that moderate increases in service capacity can dramatically improve customer service performance. Overall, the study demonstrates that queueing analysis can support managerial decision-making in banking operations, particularly in determining optimal staffing strategies to improve service efficiency and customer satisfaction.

4. Conclusion

This study analyzed the teller service system using queueing theory with the M/M/s model to evaluate the effectiveness of banking services and determine the optimal number of servers. Based on the distribution testing results, customer arrivals followed a Poisson distribution, while service times followed an exponential distribution, indicating that the queueing system satisfied the assumptions required for the application of the Markovian queueing model.

The analysis showed that the existing service system operated under steady-state conditions because the traffic intensity value (ρ) was less than one. However, the utilization level of the current configuration was relatively high, resulting in longer customer waiting times during busy periods. Queueing performance measures indicated that customers still experienced noticeable waiting times before receiving service.

Several server scenarios were simulated to improve system performance. The simulation results demonstrated that increasing the number of tellers significantly reduced queue length and waiting time. The three-server configuration was identified as the most optimal scenario because it provided a balance between operational efficiency and customer service quality. Although additional servers further reduced waiting time, excessive server allocation decreased utilization efficiency. Overall, the study confirms that queueing theory is an effective analytical approach for evaluating and optimizing banking service systems. The findings can assist bank management in determining appropriate staffing strategies to improve customer satisfaction, reduce waiting times, and maintain efficient operational performance.

CRediT authorship contribution statement

Fitri Marhamah: Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vera Halfiani:** Writing – review & editing, Investigation. **Vina Apriliani:** Formal analysis, Writing – review & editing, Investigation.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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