Discrete event simulation vs. queuing models: a resource allocation analysis in a Nigerian Bank

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Abstract

This study addresses a gap in queue management research by comparing Discrete Event Simulation (DES) using Arena software with the Multi-Server Queuing Model (M/M/S) to optimize resource allocation and improve customer satisfaction in a Nigerian bank. Unlike previous studies that used either DES or M/M/S without empirical justification, this research evaluates both methods based on observed inter-arrival and service times collected through stratified purposive sampling. Both models showed reduced customer wait times as the number of servers increased, with a three-server system identified as optimal. However, Arena's Input Analyzer revealed that M/M/S assumptions poorly fit real queue data, leading to performance overestimation. Further DES analysis showed that aligning server performance (replacing Server 1 with one matching Server 2) decreased average wait time from 32.42 to 29.10 minutes. The study concludes that optimizing both server count and individual server performance is key to reducing wait times in multi-server systems.

Keywords

input-analyser, simulation, average waiting time, length of queue

Introduction

Queues are an inevitable part of everyday life, observable in several places such as banks, supermarkets, hospitals, airports, with banks being a focal point due to their vital role in enabling customer transactions. In Nigeria, banks are at the heart of economic activities, yet they are inundated with long queues, leading to customer dissatisfaction, reduced operational efficiency and dwindling profitability [Farayibi, 2019, pp. 1-2; Harley et al., 2014, p. 864]. It is imperative that Nigerian banks employ robust operational strategies to mitigate the problems of queues, as long wait time due to long queues cause customers' dissatisfaction, which consequently leads to loss of customer's goodwill.

The formation of queues often stems from an imbalance where the rate of arrival of customers into the system exceeds the rate at which the system is being able to process the requests of the customers [Aronu et al., 2021, p. 11]. Harley et al. [2014, p. 864] established an inverse linear relationship between the average wait time of customers and bank's profitability, emphasising the critical need for effective queue management. Several studies have adopted either discrete event simulation (DES) or analytical multi-server model (M/M/S) to analyse queue systems, without empirical justification for choice of methods. To address these challenges, this study conducts a comparative analysis of DES model using Arena software package and M/M/S model, to identify optimal approaches for effective customer management and resource allocation in a Nigerian bank, with customer-care queue system of a conveniently selected bank as case study.

DES is a powerful technique for modelling the operations of a system as a sequence of distinct events that take place at specific points in time offering rational simulations of complex environments like bank queues [Software Solutions Studios, 2022]. Using Arena-DES software package, this study leverages its intuitive drag and drop feature, what-if analysis and complete range of statistical distributions to accurately model customer flow in a queuing system. Conversely, queuing theory, a cornerstone of operations research, provides analytical insights into queue behaviour through models like M/M/S, which is well-suited for single-queue, multiple-server systems with exponentially distributed arrival and service times [Muhammad, 2015, p. 1286]. For the selected bank's customer-care section queue system, the use of M/M/S analytical model is justified, as the queue system is characterized by a single waiting line of customers having similar requests and multiple servers – two servers.

This research analysed the customer-care section queuing system of a selected bank through the dual lenses of DES and M/M/S methods, juxtaposing their performance metrics, thereby providing empirical evidence for the more effective method. Performance measures such as average waiting times, utilization factor and length of queue, were used to determine optimal resource allocation and customer management strategies. Investigation through DES into the impact of distinct service attributes of servers in the existing was also carried out. By collecting and analysing data on inter-arrival and service times, this study models the bank's queue dynamics, offering actionable insights into resource allocation and customer management. The findings are expected to guide Nigerian banks with empirical evidence for implementing strategies that minimize waiting times and enhance customer satisfaction and contribute to the broader discourse on queue management in service-oriented industries.

1. Literature review

Like several service-purposed organizations, commercial banks function in red ocean market environments characterized by intense competition. Banks, through quality service and speed of service can ensure customer satisfaction. Quality service and speed of service is adjudged by the waiting time a customer spends across the arrival, queue, service and departure processes, which are typical distinct events in a bank's queue system. The arrival process is characterised by inter-arrival time between successive arrivals, queue process in banks conventionally adopt the First-Come-First-Serve (FCFS) discipline and service process is characterised by variables such as service time and number of servers. Several studies have demonstrated how increment to service rates cause significant reductions in the waiting time of customers on queues, postulating how DES computer numerical approach and M/M/S analytical approach are effective tools for optimising queue systems [Wadi et al., 2019, p. 107; Nascimento et al., 2021, p. 840; Madadi et al., 2013, p. 213; Korzeb et al., 2024].

Simulation is an abstraction of reality that allows us to mimic the behaviour of a real system and carry out scenarios of experiment on the model for the purpose of discovering optimal performance of a system that can be adopted in the real system [Okhuese, 2015, p. 107]. DES, a subset of simulation, is the modelling of systems as a network of queues and entities whereby a change of state of the entities occurs at discrete points in time along the process line. Several studies have highlighted the efficacy of DES in optimisation of queues. DES was applied to manage a supermarket's queuing system, varying number of cashiers from 0 -10, using Arena software package, and reached a conclusion of 88.23 % reduction in average waiting time when number of cashiers is increased from 1 to 3 [Pereira et al., 2020, p. 1667]. Arena was deployed as a DES tool to model and analyse customer service in a banking system, identifying optimal configurations that resulted in significant reduction of queue length with utilisation of 45% [Abdelwanis et al., 2023, p. 187]. Anylogic DES was utilised in the optimisation of banking operations, reporting a 31.8% reduction in the average queue length, 33.76% improvement in service time and a 20.48% enhancement in resource allocation [Jamil et al., 2024, p. 470]. Collectively, these studies underscore the efficacy of DES in the optimisation of queue systems.

Queuing models employ mathematical analytical techniques to providing solutions to queuing problems. Queuing model is the mathematical representation of a queuing system with certain presumptions on the discipline and organization of the queue, the type and number of servers, the arrival and service procedures, and their probabilistic character [Yifter et al., 2023, p. 3]. This study is justified in it's use of M/M/S model for analytical approach as it ideal for a system of multiple servers processing a single waiting line of similar requests, which is the property of the customer-care section queue system of the selected bank of study. Studies have outlined certain assumptions for the M/M/S model, including Poisson-distributed inter-arrival time, exponentially distributed service time, same service rate for all servers, queue discipline is FCFS [Bhat, 2015, p. 94; Akande et al., 2022, p. 76]. The stochastic nature of customer service in a bank was assessed utilising M/M/S, with results highlighting problem of underutilisation of resources [Mekonnen et al., 2018, pp. 16-17]. M/M/S was applied in a banking system to manage waiting lines, with the ATM servers analysed to be idle 69% of the time, inferring underutilisation of ATM service resources [Akande et al., 2022, p. 82]. Collectively, these studies highlight the M/M/S's role in providing actionable insights concerning the state of resource utilisation and customer management in a queue system.

While most studies have been found to focus on application of either the analytical modelling or simulation modelling in analysing queuing problems, few of these studies have comprehensively compared simulation and analytical modelling techniques in optimising resource allocation and customer queue management in banking contexts. Often, existing research have prioritised one methodology over the other without providing empirical evidence to justify the superiority of one over the other or exploring the strengths and weaknesses of both in similar contexts. This study addresses this gap by comparing DES and M/M/S models to optimise customer queue management and resource allocation in a commercial bank's customer-care section, providing a robust framework for decision making in addressing queue problems in banks.

2. Research methodology

A commercial bank in Nigeria was selected for this study using a non-probability sampling technique (convenient sampling). This study focused on the queuing system of the customer-care section of the selected bank with an existing system of two servers in parallel at the service desk. The stratified purposive sampling method was adopted for the data collection process, as the salary week was chosen for observation of queue in the selected bank of study. This method ensures that data is captured during a period when banking activities are at their peak due to salary-related transactions. Observation and data collection was carried out for a week, from Monday to Friday, 25th – 29th November 2024, within the working hours of 8:00am to 4:00pm each day. Observation was made uniformly for 7 hours (420 minutes) daily. A total of 427 observations were made for the arrival, service start and end time, with the time recorded in minutes.

2.1. Basic parameters of the queuing system

- n = total number of customers in the system (in queue + in service)
- λ = average arrival rate (number of customers expected per unit time)
- μ = average service rate (number of customers served per unit time)
- ρ = utilization factor / traffic intensity (fraction of time for which the server is busy)
- s = number of servers in the system
- $s\mu$ = service rate for multiple servers in the system
- L_s = length of the system (number of expected customers in the system)
- L_q = length of the queue (number of expected customers waiting in the queue)
- W_s = average time spent waiting in the system
- W_q = average time spent waiting in the queue

The objective function of this study is to minimise the average waiting time of customers in the queuing system

$$\text{Minimise } W_s$$

Subject to

$$\lambda < s\mu \quad (1)$$

$$\rho < 1 \quad (2)$$

$$1 < s < 5 \quad (3)$$

Equation 1, which is the system capacity constraint, ensures that the queue does not grow infinitely long. Equation 2, which is the utilisation constraint, ensures that the severs are not overloaded. Equation 3, which is the number of servers constraint, denotes the possible number of servers due to spatial constraint at the customer-care section of the selected bank.

2.2. M/M/S analytical modelling

The model is one of the most adapted analytical models for analysing queuing problems involving multiple service channels servicing a single waiting line. According to existing research, the following are some of the assumptions about the M/M/S modelling of a queue system:

- Arrival time of customers follows a Poisson distribution.
- Service time are exponentially distributed.
- There is at least more than one server in the system attending to a single waiting line (2 servers in this case study).
- Service discipline follows a First-Come-First-Serve (FCFS) basis.
- The servers process a single queue of customers having identical requests.
- Service rates of multiple servers are the same.

From the data captured during observation, average arrival rate, λ, and the average service rate, μ, would be evaluated and used in the computation of the measures of performance of the queue system of the customer-care section of the selected bank. The following formulae of the M/M/S model from equations 4 to 9 were used to compute the measures of performance of the queue system:

Utilization factor, $\rho = \frac{\lambda}{s\mu} < 1$ (4)

The probability that the servers are idle, that is, the probability that there is no customer in the system, $P_o = \left[\sum_{n=0}^{s-1} \frac{1}{n!}\left(\frac{\lambda}{\mu}\right)^n + \frac{1}{s!}\left(\frac{\lambda}{\mu}\right)^s \left(\frac{1}{1-\rho}\right)\right]^{-1}$ (5)

Length of the queue, $L_q = \frac{1}{(s-1)!}\left(\frac{\lambda}{\mu}\right)^s \left(\frac{\lambda\mu}{(s\mu-\lambda)^2}\right) P_o$ (6)

Average time spent waiting in the queue, $W_q = \frac{L_q}{\lambda}$ (7)

Average time spent in the system (service + queue), $W_s = W_q + \frac{1}{\mu}$ (8)

Length of the system, $L_s = L_q + \frac{\lambda}{\mu}$ (9)

2.3. Arena DES modelling

Arena effectively models discrete simulation events. It has several important tools that assist in accurate representation of a real system through modelling, such as, 'Input Analyser' for analysing data behaviour. The input analyser calculates *p*-values using the Chi-square test and provides these values to help make decision about the fitted distribution [Pereira et al., 2020, p. 1672; Abdelwanis et al., 2023, p. 185]. The input analyser was used to conduct a hypothesis testing of distributions of the inter-arrival and service time of customers following Poisson and exponential distribution, respectively. The fitted distributions were subjected to acceptance or rejection by comparing their *p*-values and square error values from the analyser with a chosen alpha-value of 0.05, which is the most conventionally adopted alpha value in statistical analysis for hypothesis testing.

The DES model was developed using the create, process and dispose modules of the Arena software package. Model verification and validation tests were carried out, experimental scenarios were configured and run. The first experimental DES model with assumption about multiple servers having same service rates was carried out and run, varying the number of servers from 2 to 4, in line with the number of servers constraint in equation 3. Resulting performance measures were compared to those of the M/M/S analytical modelling.

2.4. Investigation into the impact of service rates of distinct servers in the customer-care section of the selected bank

A second experimental DES model was built around an assumption that no two servers have the same service rate attributes. Charles-Owaba [2002] explained that tasks with same procedures may require different completion times from different personnel due to the reason that people have different abilities for work. In the existing system, there are two parallel servers at the service desk, server1 and server2, respectively. Out of the 427 observations made during the data collection, 210 customers were observed to be served by server1 personnel, while 217 customers were attended to by server2. The service time of the 210 customers served by the Server1 personnel was analysed using the input analyser tool of the Arena DES software package. The resulting best-fitted service distribution was used to configure the service module. Same procedure was repeated for server2 personnel with 217 customers service time. Performance metrics from these two experimental scenarios were compared against the performance metrics of the first DES model with service time distribution of the 427 customers service time, which is the control scenario.

3. Research results

Table 1 presents the daily recorded data from the customer care section of the selected bank of study, the sum-total of the inter-arrival time of customers and the total service time for processing the 427 customers' requests was observed to be 2067 and 4022 minutes, respectively.

Tab. 1. Daily recorded data from selected bank of study

Days of the week	No of customers	Inter-arrival time (min)	Service time (min)
Monday	91	420	830
Tuesday	85	407	795
Wednesday	76	419	798
Thursday	92	419	769
Friday	83	402	830
Total	427	2067	4022

Source: own elaboration.

The average arrival rate, λ, 0.2066 customers per minute, and average service rate, μ, 0.1063 customers per minute, were computed by dividing the total number of customers by the total inter-arrival time and total service time, respectively. The performance measures of the queue system were computed for each number of servers, s, varied. The average waiting time of a customer in the system, W_s, was observed to be extremely high in the existing system of two servers, with a decrease in value as the number of servers varied from 2 to 4. Other measures of performance such as average waiting time of customers on the queue, W_q, lengths of the queue, L_q, and system, L_s, utilization factor, ρ, were all observed to follow similar trend, as detailed in Table 2.

Tab. 2. Performance measure of the analytical modelling of queuing system

Performance measure	S = 2	S = 3	S = 4
ρ (%)	97.18	64.79	48.59
P_o (%)	1.43	12.04	13.87
L_q (customers)	33	1	0
L_s (customers)	35	3	2

Performance measure	S = 2	S = 3	S = 4
W_q (minutes)	159.50	3.72	0.73
W_s (minutes)	168.91	13.13	10.14

Source: own elaboration.

Arena DES model of the queuing system was developed, constant values of 1 minute were used to configure the model's arrival rate in the create module and service rate in the process module. Performances measures of the queue system such as length of the system and average waiting time of the system were observed to be 1 customer and 1 minute, respectively, proving that the DES model would run as expected. The model was validated by running the model with actual data distribution on the arrival rate and service rate of the 427 observations made. The model generated 424 customer entities, which fell short of the actual number of customer observations made, 427, during data collection by 0.7%, well within the conventionally used validation tolerance of 10%. Seen as detailed in Figure 1.

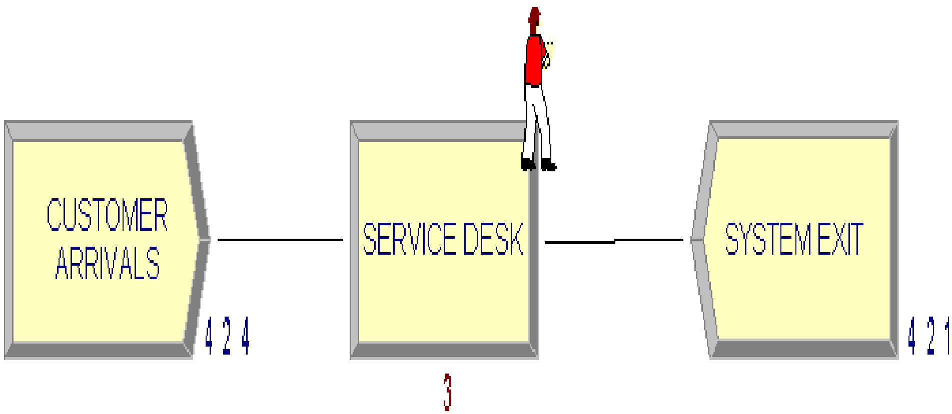

Fig. 1. After-run simulation model of the queuing system
Source: own elaboration.

The input analyser analysed the best fitted data distributions for the inter-arrival time and service time of customers in the real system by calculating the *p*-values and square error values using the Chi-square test. The least square error value of 0.00199 and a *p*-value (0.528) greater than the alpha-value of 0.05 shows that the Weibull provides the optimal fit for the inter-arrival time of customers, while a square error value of 0.0462 and a p-value <0.005 is empirical evidence for accepting to reject the null hypothesis that the inter-arrival time of the customers follow Poisson distribution, as detailed in Table 3 and Figure 2. While for the service time distribution, the least square error value of 0.000939 and a p-value (>0.75) greater than the alpha-value of 0.05 proves gamma distribution to be the best fit, while a square error value of 0.01 and a p-value of <0.005 is empirical evidence for accepting to reject the null hypothesis that the service distribution of the customers is exponentially distributed, as detailed in Table 4 and Figure 3.

Tab. 3. Analysis of distribution functions for inter-arrival time of customers

Distribution Function	Square error	*P*-value
Weibull	0.00199	0.528
Beta	0.00237	0.316
Gamma	0.0025	0.275
Erlang	0.00561	< 0.005
Exponential	0.00561	< 0.005
Lognormal	0.00876	< 0.005
Normal	0.016	< 0.005
Triangular	0.0269	< 0.005
Poisson	0.0462	< 0.005
Uniform	0.0565	< 0.005

Source: own elaboration.

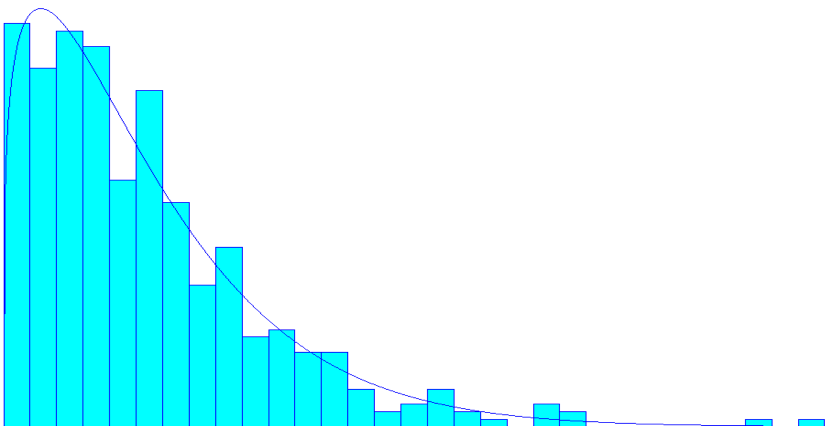

Fig. 2. Fitted distribution of inter-arrival time of customers (Weibull)

Source: own elaboration.

Tab. 4. Analysis of distribution functions for service time of customers

Distribution Function	Square error	*P*-value
Gamma	0.000939	> 0.75
Erlang	0.0013	0.605
Weibull	0.00133	0.672
Lognormal	0.00229	0.136
Beta	0.00232	0.179
Normal	0.00871	< 0.005
Exponential	0.01	< 0.005
Triangular	0.0105	< 0.005
Uniform	0.0279	< 0.005
Poisson	0.0358	< 0.005

Source: own elaboration.

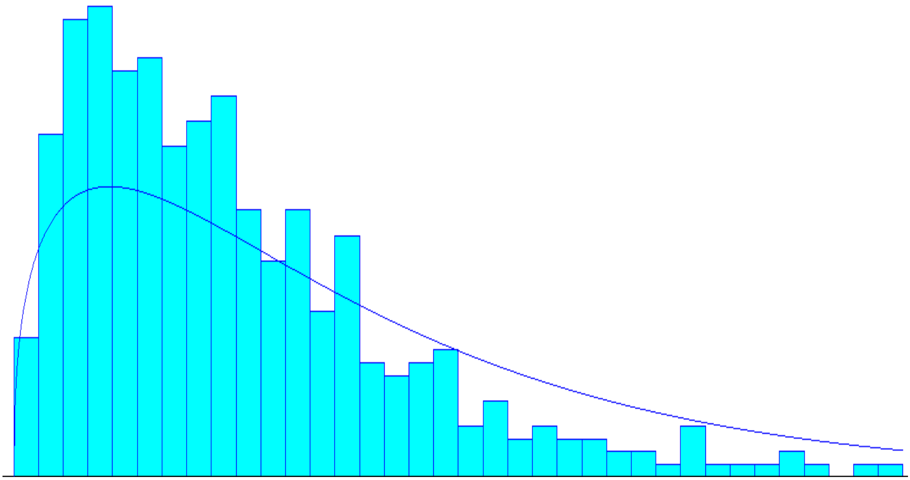

Fig. 3. Fitted distribution of service time of customers (Gamma)

Source: own elaboration.

The DES model was run varying the number of servers from 2 to 4, with performance measures from the DES model juxtaposed with those of the M/M/S analytical model. The results demonstrated a clear inverse relationship between the number of servers and the average waiting time in the system for both models. The values of the performance measures of the queue system of the customer-care section of the selected bank were higher in the M/M/S analytical model compared to corresponding performance measures from the Arena DES model for each number of servers, as detailed in Table 5.

Tab. 5. Performance measures of Arena simulation and analytical models of the customer-care section of selected bank

Performance metrics	Arena simulation model			M/M/S Analytical model		
Servers, S	2	3	4	2	3	4
Utilization factor, ρ (%)	94.42	63.16	46.33	97.18	64.79	48.59
Length of the queue, L_q (customers)	5	0	0	33	1	0
Average time spent waiting in the queue, W_q (minutes)	23.05	1.61	0.40	159.50	3.72	0.73
Length of the system, L_s (customers)	7	2	2	35	3	2
Average time spent in the system, W_s (minutes)	32.42	11.01	9.71	168.91	13.13	10.14

Source: own elaboration.

Investigation into the impact of distinct service rate attributes of the servers of the existing system on the performance of the queuing system of the customer-care section of the selected bank, through a second DES experimental model was carried out with the assumption that no two persons are the same, and by logic, it is expected that no two servers should have same service rate, even for same tasks with same procedures. The service time of the 210 customers served by server1 personnel of the existing system, which was analysed by the input analyser, was observed to be Weibull distributed, (0.999 + WEIB(8.94, 1.18)). The input analyser also analysed the distribution of the service time of the 217 customers served by server2 personnel to be Weibull distribution, (0.999 + WEIB(8, 1.2)). Three scenarios were modelled: a control scenario, which was the first DES experimental model with combined service rates of server1 and server2 (0.5 + GAMM(5, 1.78)), and two experimental scenarios with service rates of server1 (0.999 + WEIB(8.94, 1.18)) and server2

(0.999 + WEIB(8, 1.2)), respectively. For all the experimental scenarios, inter-arrival distribution of customers, (-0.5 + WEIB(5.71, 1.22)), and a parallel system of two servers were kept constant. The control scenario, reflecting the existing system, showed a utilization factor of 94.42%, with average queue and system waiting times of 23.05 and 32.42 minutes, respectively, and lengths of queue and system to be 5 and 7 customers, respectively. The first experimental scenario, with two server1 personnel, exhibited a high utilization factor of 97.83%, significantly increasing waiting times to 68.63 minutes (queue) and 78.36 minutes (system), and lengths of queue and system to 14 and 16 customers, respectively, when compared to the control scenario. Conversely, the second experimental scenario, with two server2 personnel, yielded a lower utilization factor of 88.85%, reducing waiting times to 20.27 minutes (queue) and 29.10 minutes (system), and lengths of queue and system to 4 and 6 customers, respectively, when compared to the control scenario. The results are as detailed in Table 6.

Tab. 6. Performance measures across different service rate configurations

Performance measures	**Two parallel servers with configuration of combined service rate distribution of server1 and server2 (0.5 + GAMM (5, 1.78))**	**Two parallel servers with configuration of service rate distribution of server1 (0.999 + WEIB(8.94, 1.18))**	**Two parallel servers with configuration of service rate distribution of server2 (0.999 + WEIB(8, 1.2))**
Utilization factor, ρ (%)	94.42	97.83	88.85
Length of the queue, L_q (customers)	5	14	4
Average time spent waiting in the queue, W_q (minutes)	23.05	68.63	20.27
Length of the system, L_s (customers)	7	16	6
Average time spent waiting in the system, W_s (minutes)	32.42	78.36	29.10

Source: own elaboration.

4. Discussion of results

Comparative analysis of the first Arena DES modelling and M/M/S analytical modelling of the queue system of the customer-care section of the selected bank, based on the assumption that servers in a parallel system have same service rates, presented results that conformed to findings of existing research on how the average waiting time of customers decreases with increasing number of servers [Yifter et al., 2023, p. 1]. However, the input analyser tool of the Arena DES software package provided empirical evidence to show that assumptions about distributions of the inter-arrival time and service time of the queuing system were not ideal representation of the real data recorded during data collection, negating assumptions of some existing studies [Muhammad, 2015, pp. 1285-1286; Bhat, 2015, p. 94; Akande et al., 2022, p. 76]. The input analyser instead expressed Weibull and gamma distributions as the best-fitted distributions for the inter-arrival and service time of the 427 observations, respectively. The inaccurate representation of data distribution on the inter-arrival and service time reflected in the overestimation of values of performance measures of the analytically modelled queue system for each number of servers varied, when compared to the DES model.

Both the DES and M/M/S approaches showed that a proposed system of three servers in the queuing system of the customer-care section of the selected bank of study is the best resource allocation strategy, as it shows good customer queue management in terms of reduced average waiting time in the system with a fair utilization factor of servers, which is neither overutilisation nor underutilisation of the server resources. Although results showed that a proposed system of four servers had the least average waiting time of a customer in the system for both models, the extremely low utilization factors of less than 50% indicate the problem of extreme underutilization of the servers, which is not an ideal desire of any organisational management, as it does not reflect optimal resource allocation strategy.

Findings from the second DES model, based on assumption that no two servers are expected to have the same service rate attribute, highlight the critical influence of distinct servers' service rate attributes on queuing system performance. The experimental scenario of two parallel servers with configuration of server2's service rate distribution yielded a less congested and more efficient system with lowest average waiting time of a customer in the system, 29.10 minutes. Investigation into the distinct service rate attributes of the servers at the customer-care section of the selected bank of study showed that the average waiting time at the customer care section of the selected bank can be decreased by replacing the server1 personnel with a server who has identical service rate attribute as server2 personnel. Thus, in addition to increasing the number of servers in a system, to reduce the average waiting time of customers, this study has shown that by investigating the individual impact of service attributes of distinct servers in a multi-server queue system, management can make evidence-based decisions on how to optimise the effectiveness of the existing number of servers in their queue system to reduce the waiting time of customers.

Summary

This research compared two methodologies: Discrete Event Simulation (DES) using the Arena software package and the multi-server queuing model (M/M/S) in the study of the queuing system of the customer-care section of a selected bank. With both methodologies demonstrating reduced waiting times as the number of servers increased, the study validated inverse relationship between average customer waiting time and the number of servers. However, the M/M/S model overestimated the values of the performance measures of the queuing system due to its inaccurate assumptions of the distributions of the inter-arrival and service time of customers, which were not supported by the collected data. This highlights the importance of appropriate distribution analysis for reliable analysis of queue systems. Banks and other service organisations should adopt DES approach over the M/M/S analytical approach for analysing queue systems as it provides accurate representation of distribution functions based on accurate statistical computations, rather than assumptions that may not accurately represent real-time data collected about their queue systems.

In balancing optimal customer queue management strategy with optimal resource allocation strategy, through a minimised average waiting time of a customer in the system with a fair personnel utilisation, this study identified three servers as the optimal configuration for the customer-care section of the selected bank. Additionally, analysis of service attributes of server personnel using DES revealed that a configuration with two server personnel mirroring the service rate distribution of the more efficient server (server2) reduced average waiting times compared to the existing mixed-server setup, while a configuration with two server1 personnel increased waiting times. These findings underscore that in the context of service organisations, server personnel do not exhibit same service rate attributes as opposed to theoretical assumptions [Bhat, 2015, p. 94].

This study emphasizes the need for empirical validation when selecting modelling approaches for analysing queuing systems. While both DES and M/M/S models align with theoretical expectations, the accuracy of results is contingent on the alignment of assumptions about distribution functions with real-world data. The study also demonstrates the value of investigating individual server attributes to enhance service efficiency, offering practical implications for resource allocation and customer management in banking operations.

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Symulacja zdarzeń dyskretnych a modele kolejkowe: analiza alokacji zasobów w banku nigeryjskim

Streszczenie

Niniejsze badanie wypełnia lukę w dotychczasowych analizach zarządzania kolejkami, porównując symulację zdarzeń dyskretnych (DES) w oprogramowaniu Arena z modelem kolejkowym z wieloma serwerami (M/M/S), w celu optymalizacji alokacji zasobów i poprawy satysfakcji klientów w nigeryjskim banku. W przeciwieństwie do wcześniejszych badań, które stosowały jedną z metod bez uzasadnienia empirycznego, niniejsza analiza ocenia skuteczność obu podejść na podstawie danych dotyczących czasu między przybyciami i obsługi klientów, zebranych metodą celowo-warstwową.
Oba modele wykazały skrócenie czasu oczekiwania wraz ze wzrostem liczby serwerów, przy czym system trójserwerowy uznano za optymalny. Jednak narzędzie Input Analyzer z pakietu Arena ujawniło, że założenia modelu M/M/S słabo odwzorowują rzeczywiste dane, co

skutkuje przeszacowaniem miar efektywności. Dalsza analiza DES wykazała, że zastąpienie pracownika serwera 1 osobą o parametrach serwera 2 skraca średni czas oczekiwania z 32,42 do 29,10 minut. Badanie pokazuje, że oprócz zwiększania liczby serwerów, istotne jest również dopasowanie ich indywidualnej wydajności w celu minimalizacji czasu oczekiwania w systemach wieloserwerowych.

Słowa kluczowe

analizator danych wejściowych, symulacja, średni czas oczekiwania, długość kolejki