Optimizing Service Operations in Banking System: A Discrete Event Simulation Modeling Approach

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Abstract

Queueing is a common problem for busy banks, causing long waiting times for customers. This study focuses on a leading bank in Bangladesh that sees high numbers of customers daily. The goal is to simulate the bank's service system to determine the optimal number of servers during peak hours. Additionally, removing the extra servers to get the optimum service level as the servers remain idle when there are not many customers in a bank is mainly for the cost minimization of the banking operations by maintaining its optimum utilization. Here, a discrete event simulation (DES) approach is utilized to build and analyze the performance of a queueing model over time. Key aspects such as arrival rates, service times, queue capacity, and customer tolerance are also represented. The simulation runs for an extended period to mimic real customer traffic and the performance metrics including average waiting time, queue length, resource utilization, number of busy servers, idle servers, and customer complaints are then quantified. The validated simulation accurately portrays the existing operation and allows testing changes by adding or removing the servers resulting in a reduction of 31.8% in queue length and 33.76% in service time, alongside a notable 20.48% improvement in service utilization. Findings suggest this simulation yields better resource management by speeding up service that proves effective for evaluating complex queueing systems and informing strategic decisions through quantitative analysis of alternatives. Overall, the analysis aimed to enhance seamless bank operations, customer satisfaction, and experience at the busy bank location through data-driven recommendations on queue management.

Keywords
Discrete Event Simulation (DES), Banking Operations, Queueing Systems, Optimization, Bottleneck Analysis

1. Introduction
The banking sector in Bangladesh has experienced rapid growth and expansion over the last decade. However, several challenges remain in delivering efficient and high-quality retail banking services. Issues like long customer waiting times, congestion, and poor resource allocation are frequently experienced at bank branches (Levesque and McDougall 1996). These are not only creating dissatisfaction but also impacting profitability due to lost business opportunities.

Discrete event simulation (DES) provides a powerful quantitative approach to solving complex service issues of banking operations and evaluating improvement strategies (Cassandras and Lafortune 2008). The DES model provides evidence-based decision-making by providing data-driven insights experimenting with different scenarios regarding staff levels, service rates, and other controllable parameters to improve customer experience. Also, optimization experiments with the model determine optimal staffing and resource allocation policies. By representing the system state as a sequence of events over time, DES can capture the dynamics of processes like customer arrivals, queues, and service bottlenecks and this model helps assess key performance metrics like wait times, resource utilization, and service levels under different scenarios (Jahangirian et al. 2010) as shown in Figure 1.

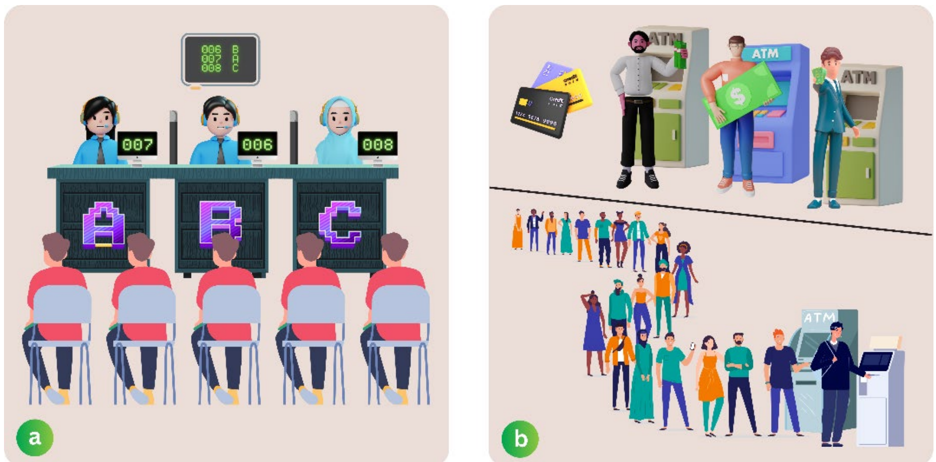

Figure 1. (a) Bank workstation teller counter (b) Automatic teller counter

As retail banking embraces digital transformation, leveraging DES enhances both prescriptive and predictive analyses to optimize service operations in the banking system, harnessing Industry 4.0 technologies (Mehdiabadi et al. 2020). The retail banking landscape is also impacted by evolving supply chain dynamics (Deloitte 2013). Office inventory supply shocks affect branch construction, and delivery disruptions delay cash and consumables replenishment. Integrating supply chain risks into the simulation model ensures service continuity while digital twin mirroring synchronizes physical and digital operations (Argyroudis et al. 2022).

This research employs AnyLogic software to build a DES model for prescriptive analysis of retail bank operation services. Its pre-built components facilitate system construction, with 3D visualization for improved understanding. Data from a Bangladeshi bank, along with the authors' expertise, informs the model. The study aims to assess banking system performance, propose efficiency enhancements, and maintain a balance between customer satisfaction and facilities.

The structure of this paper unfolds as follows: Section 2 explores the literature on queueing systems, DES, and recent works. Section 3 delves into the techniques integral to our proposed scheme. Section 4 is dedicated to data collection, while Section 5 develops our banking system model. In Section 6, we presented results, engaged in discussion with numerical and graphical findings, and proposed enhancements. Finally, we concluded and summarized our study.

2. Literature Review

2.1 Discrete Event Simulation (DES)

DES has been widely used as a technique for modeling and evaluating complex systems since the 1960s (Garzia et al. 1986; Robinson 2005). Different methodologies have been developed for implementing DES, including event scheduling, activity scanning, and process interaction (Mansharamani 1997). We employed DES in this study to optimize the bank queue system.

A variety of domain-specific simulation techniques using these methodologies have also been created, such as GPSS, Simscript, SIMAN, and SLAM (Mansharamani 1997; Mayne et el. 1979). The implementation of future event management, or scheduling events by time, is a core component of any DES and various data structures have been proposed for efficient management of future event lists, including priority queues, heaps, and indexed lists (Johnson 1975; Mansharamani 1997).

DES involves modeling systems where changes occur only at specific points in time. Numerical methods analyze simulation models instead of analytical approaches. Analytical methods apply deductive mathematical reasoning, while numerical methods rely on computations to solve models. Simulation models are run to generate artificial system histories based on assumptions, collecting observations for performance estimation (Banks et al. 2005). DES modeling employs a process-oriented methodology to represent system dynamics by a sequence of entity operations (Borshchev 2014).

2.2 Queueing Systems

Queues, essentially lines of people or objects waiting for service, are a common pre-service procedure. This concept**,** also known as queuing theory, is an important part of operations. Operations managers utilize it as a tool to assess and manage waiting times, employing strategies to reduce them (Tom and Lucey 1995). The analysis of queues involves measuring waiting line length, average waiting times, and other factors essential for comprehending the banking service system.

Queue models are valuable tools in both manufacturing and the service industry. In services, queues represent customers waiting their turn for assistance, a common aspect of nearly all service processes. These queues form when customers must wait before receiving service, and when service rates are slower than arrival rates. No queue forms when service rates are higher than arrival rates (Kim et al. 2013). Ray and Bunday (1988) recognized the value of queuing theory in evaluating system performance, considering variables such as the customer volume within the system, the number of customers in line, server utilization, response times, customer waiting times, and system idle time.

The queuing concept involves two distinct costs: the expense of delivering service and the expense incurred when service is not provided. To attract and retain customers, management typically prioritizes providing services with the shortest queues. Operation managers aim for shorter queues to ensure high customer satisfaction, preventing customers from leaving the checkout without service. Enhancing service levels reduces waiting time costs, which serve as a measure of operational efficiency. Heizer and Render (2014) identified three components in the queuing system: arrivals, queuing discipline, and the service facility, as depicted in Figure 2.

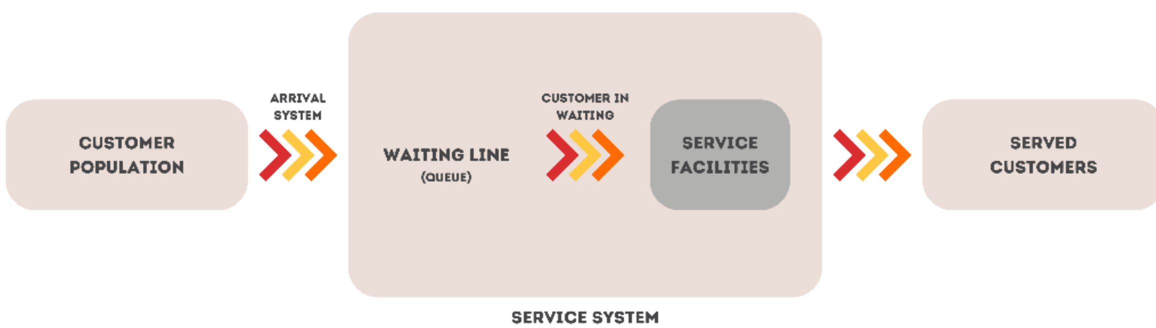

Figure 2. Basic structure of queueing models

2.3 Simulation

2.3.1 Simulation Studies for Queueing Problem

Recent years have witnessed a surge in queuing problem research, with discrete event simulation being a preferred choice for solving these types of issues. Multiple studies have been carried out using simulation to address the queuing problem. Table 1 showcases a collection of recent works in optimizing queueing systems through the application of DES models.

Table 1. A comparison of related research

Researchers	Summary	Analytical Solution/Tool	Outcomes
Wittevrongel and Bruneel (1999)	Examined discrete-time ATM queues with arrival streams that are both independent and correlated.	Queuing theory concepts and mathematical analysis.	Provided insights into the behavior of ATM queues under different arrival stream conditions.
Cascone et al. (2014)	Presented a case study on using DES for single queue management in a bank agency.	Arena Simulation Software	Demonstrated the application of DES for improving queue management.
Nascimento et al. (2021)	Aimed to improve queue management at a Brazilian bank branch through DES.	Arena Simulation Software	Recommended providing 9 to 11 operators to attend to customers based on arrival and service rates.
Dorfman and Medanic (2004)	Utilized a DES model for railway traffic to schedule trains on a railway network.	A DES model for scheduling trains on railway networks.	Demonstrated the DES model's capability to manage schedule disruptions and avoid deadlock, leading to effective train scheduling.
Huang et al. (2016)	The primary focus of this dissertation was the application of DES and optimization techniques to enhance the healthcare system's performance.	A DES model and optimization techniques to improve healthcare system performance.	Improved healthcare system performance through simulation and optimization.
Jacobson et al. (2013)	This study offered a broad perspective on the use of DES modeling in healthcare clinics and integrated healthcare systems.	Single or multi-facility health care clinics using DES to improve system performance.	Involved recognizing management alternatives, reconfiguring healthcare systems, enhancing system performance and design, and strategizing for new systems.
Kadry et al. (2017)	The paper focused on the simulation and analysis of staff scheduling in hospitality management, specifically in Hotel X in Kuwait.	Arena Simulation Software	Optimized staff scheduling that decreases visitors' waiting time.
Mohamad and Filza Saharin (2019)	This study focused on enhancing the queuing system at a hypermarket using DES.	Arena Simulation Software	Enhanced the waiting time for each customer by a significant 26%, which translates to a reduction of 5.24 minutes.
Yang et al. (2014)	The study focused on passenger flow simulation in urban subway stations using Anylogic software.	A simulation-based approach using Anylogic software to model and analyze passenger flow in urban subway stations.	Provided insights into passenger flow patterns, identified bottlenecks, and proposed optimization strategies to reduce waiting times and improve overall efficiency in urban subway stations.
Jamshidi et al. (2019)	The research aimed to optimize ticket sales at Tehran Azadi Stadium by simulating queuing systems and utilizing multi-criteria decision-making (MCDM).	Simulation modeling was employed to simulate the ticket sales process, and MCDM techniques were used to rank and select the best scenarios for improving ticket sales.	Provided an optimized approach to ticket sales at Tehran Azadi Stadium, reducing waiting times for customers in queues for improving ticket sales efficiency.

2.3.2 Simulation Software

AnyLogic is a versatile tool known for its broad applications in control systems, traffic, manufacturing, logistics, and more, making it a popular choice in recent optimization research. This software offers a professional virtual prototype developed for managing discrete, continuous, and mixed scenarios in complex systems due to its robust support as depicted in Figure 3 for agent-based, system dynamics, dynamic systems, discrete event simulation, and the availability of specialized modeling libraries tailored for service systems (Ivanov 2017). So, we utilized AnyLogic simulation software for our bank service system analysis.

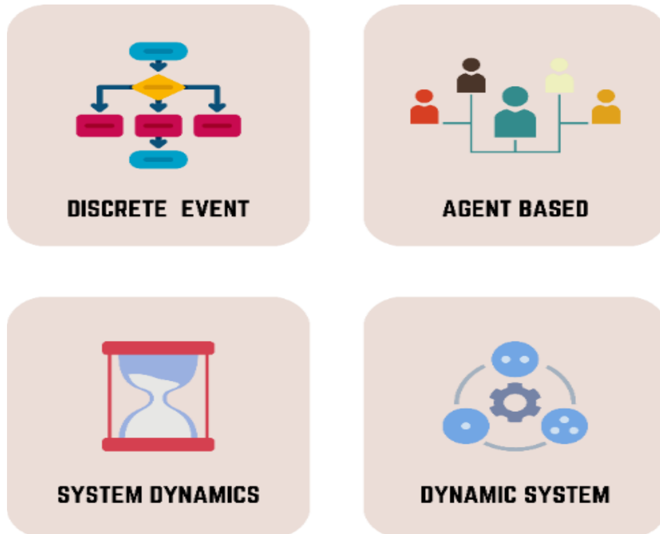

Figure 3. Multimethod simulation modeling in AnyLogic

AnyLogic's versatility spans various multi-method models, as indicated by (Borshchev 2014). It provides a graphical modeling interface and drag-and-drop building blocks that enable the quick construction of DES models by connecting objects like sources, queues, servers, and other elements. This visual approach to simulation modeling reduces development time compared to traditional programming-based methods.

2.3.3 Simulation System Components

Figure 4 depicts the key components from AnyLogic's Process Modeling library that are used to develop our banking simulation model including Source, Queue, Delay, Select Output, Service, Resource Pool, Sink, and Time Measure blocks. The Source block generates customer arrival events, while Queue blocks model waiting lines at the bank servers. Delay blocks add walking time between service points. The Select Output block routes incoming customers probabilistically to the bank server's queue. Service blocks represent the server service processes. Resource Pool blocks limit the number of server staff. Sink blocks collect statistics and dispose of customers after service completion. Finally, Time Measure blocks track metrics like waiting times and cycle times.

Connecting these Process Modeling Library components enabled the construction of a realistic flow model of customers through the bank service system. The modular, drag-and-drop approach provided an efficient way to interpret the conceptual model into an executable simulation model for experimentation and analysis.

Figure 4. Basic components of the AnyLogic process modeling library

3. Methods

DES allows representing the bank service system as a sequence of events over time, such as customer arrivals, waiting in queue, and being serviced at counters. This simulation-based approach provides a data-driven, quantitative methodology to gain insights into the system dynamics and evaluate different what-if scenarios to find the best configuration. Figure 5 shows the summarizes of the overall methodology:

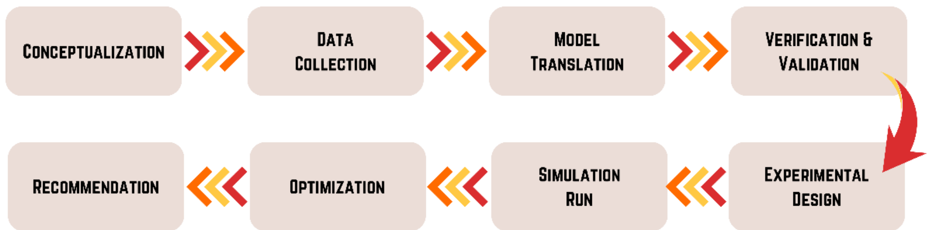

Figure 5. Logical progression of discrete event simulation (DES)

The simulation modeling methodology followed a systematic process comprising conceptualization, data collection, translation, verification and validation, experimental design, simulation run, optimization, and recommendations. First, a branch of IFIC Bank PLC was studied to conceptualize the key processes and constraints, developing an initial conceptual model. Next, datasets were collected on model parameters like arrival rates and service times. Furthermore, the conceptual model was then translated into a DES model using AnyLogic's graphical modeling interface. Additionally, the model was verified to ensure proper implementation and validated by comparing outputs with real-world observations. Moreover, a comparison has been made between the current system and a proposed system with subsequent analysis of model outputs, from which the optimal resource allocation and staffing were determined. Finally, recommendations to improve real-world system performance were provided based on the optimized results. This systematic methodology enabled the simulation model to evaluate operational efficiencies and provide data-driven decision support.

4. Data Collection

IFIC Bank PLC has been facing increasing customer complaints related to long wait times at their most popular service counters during peak hours. Upon investigation, it was found that the Pay Bill, Receive Money, and Account Creation/Deletion counters were consistently experiencing long queues that exceeded tolerable service times for customers. To address this issue, we have gathered arrival rate data, queue capacity, service time, waiting tolerance limit, and number of currently present servers for these specific services and utilized it as input for our simulation process aimed at improving the overall efficiency of the bank's service system by identifying bottlenecks.

All the flowchart blocks of the model have been configured as per the data provided by a bank correspondent. They are configured as follows in Table 2.

Table 2. Data collection and analysis for a bank simulation model configuration

Input Parameters		**Number of Participants**	**Number of Servers (Before Improvement)**	**Percentage Rate of Total Arrival**		**Service Time (minute)**				**Queue Capacity**
Arrival Rate of Each Working Day (8 H)		445				**Min**	**Avg**	**Max**	**Tolerance**	
Gateway 1 Participants	**Pay Bill Service**	187	4	78.2% Total participants	53.73% of Gateway 1	2	4	8	30	20
	Receive Money Service	161	4		46.26% of Gateway 1	2	3	6	30	20
Gateway 2 Participants	**Create/ Delete Account**	32	2	21.8% of Total participants	32.98% of Gateway 2	5	10	15	40	10
	Miscellaneous	65	2		67.02%of Gateway 1	3	5	10	30	10

Here, participants will be divided to reach their respective destinations according to predefined percentages of choosing each service, and each service block has been configured based on the respective amount of time needed for each service. Here the service has been assumed to be following the triangular distribution which consists of three values (min, avg, max). While configuring the service block, the customer tolerance limit for each service has been added. If the service takes longer than the tolerance limit, customers will come out of the queue and go to the customer complaint service to file complaints about the poor performance of the system.

4. Model Development

In this study, the model takes into account the bank service layout and incorporates a service process flowchart, which is visually represented in Figure 6. This comprehensive approach ensures that our simulation model encompasses all relevant elements of the service system. The services are given as follows:

- Pay Bill Service (PaybillService): Handling payments for electricity bills, taxes, and money collection and storage in specific accounts, along with hall dues and library fees of university students.
- Receive Money Service (RecieveService): Involving cash pick-ups and receiving money from designated accounts.
- Create a New Account or Delete Account (CreatingNewAccount): Assisting customers in the process of creating new accounts or deleting existing ones.
- Customer Complaint (CustomerComplain): Serving as a platform for dissatisfied customers to file complaints about subpar service experiences.
- Miscellaneous: Encompassing a range of services, including insurance, passport, visa, bank loans, and mortgages.

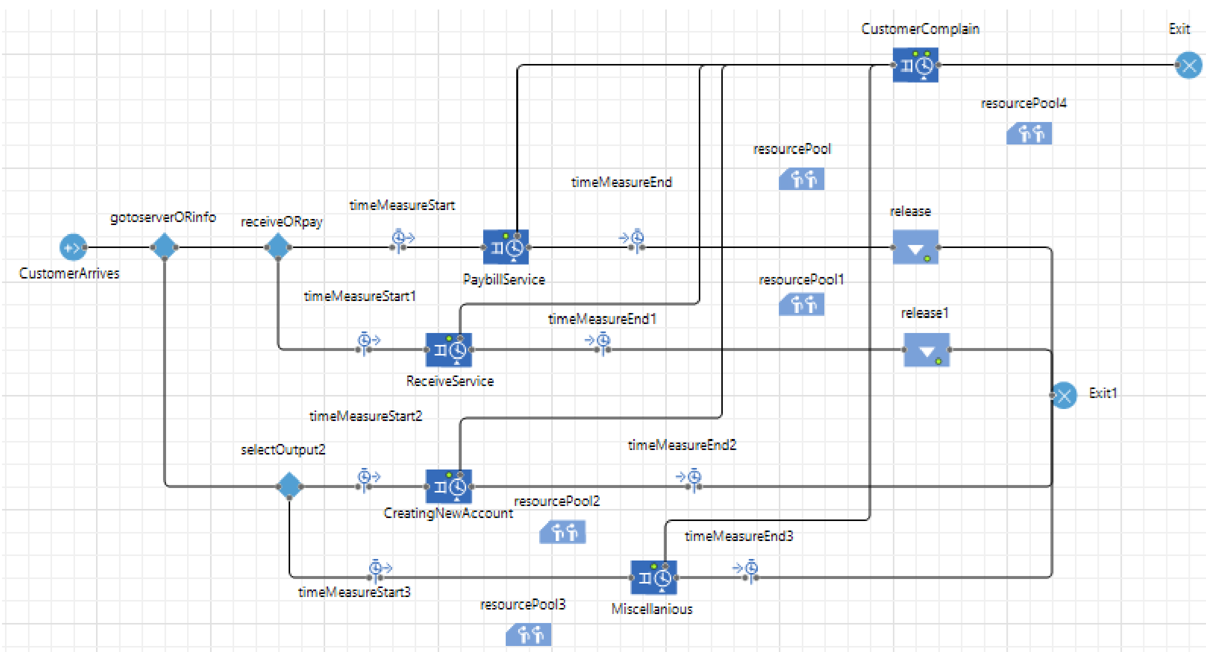

Figure 6. Process flowchart for bank workstation simulation

6. Simulation and Discussion

In the configuration of our IFIC Bank PLC simulation model, we've set crucial process parameters to ensure an accurate representation of the system as shown in Table 3. The simulation is set to run over 40,000 minutes in virtual execution mode which is worth a four-month-long simulation if we consider 8 hours a working day and 5 working days a week, mirroring close to a real-world condition. We've incorporated an arrival rate of 56 participants per hour, with a total of 445 participants entering the system daily.

Table 3. Process parameters for the bank simulation model configuration

Hyper Parameter	Value
Simulation Run Time	40000 min
Execution Mode	Virtual
Participant Arrival Rate	56/hr
Total Participants	445/day

The time plot graph shows the 'Service time for Receive' and the 'Service time for Paybill' in a simulation as shown in Figure 7(a). According to Table 2, the tolerance time for both Paybill and Receive services is set at 30 minutes. Initially, the service time for receiving is out of the tolerance has been spotted in the first 3000 minutes of the simulation. This implies that the processing time for received transactions exceeds the acceptable limit. Throughout the simulation, the service time for paying bills remains within an acceptable range.

Figure 7. Time plot of service time for (a) Paybill and Receive (b) Create/Delete Account and Miscellaneous

As depicted in Figure 7(b), the plotted time graph displays the 'Service Time for Create or Delete Account' and 'Service Time for Miscellaneous'. As indicated in Table 2, the tolerance time allowances for creating or deleting an account and miscellaneous activities are 40 and 30 minutes, respectively. Notably, both the service time for creating or deleting accounts and miscellaneous operations consistently fall within the acceptable range throughout the simulation. The fact that the service time remains within range for both operations indicates the system's capability to effectively manage the volume of transactions in these categories.

In the context of this analysis, two distinct scenarios were simulated to assess the effectiveness of different resource allocations for the received money servers. In the initial scenario as shown in Figure 8, the simulation involved four ReceiveService servers, revealing a significant strain on the resourcePool1's capacity. As a result, this led to high utilization, which in turn extended service times. This scenario presented an unsustainable system in the long run, and an increase in customer complaints due to prolonged queue times which ultimately led to bottlenecks in the system.

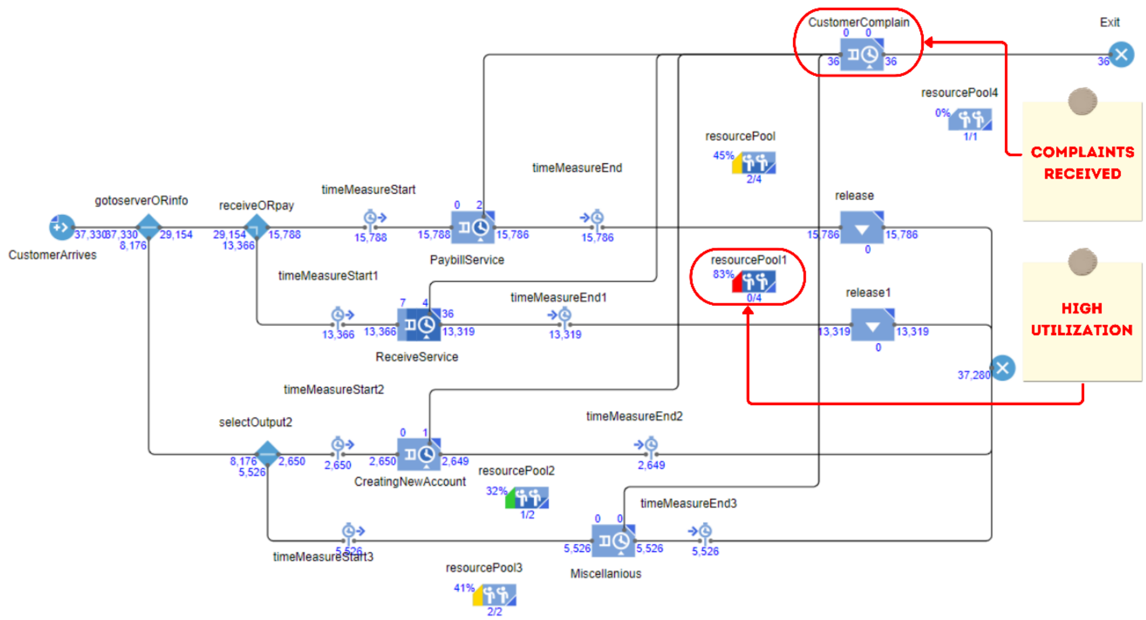

Figure 8. Identifying system's poor performance (Before improvement)

The findings in Table 4 indicate that receiving money experiences the highest utilization and takes the longest. While paying bills also faces substantial utilization, it's processed faster than receiving money. Creating new accounts has lower utilization and quicker processing compared to receiving money and bill payments. Miscellaneous tasks have the least utilization and are processed the fastest.

Table 4. Simulation scenario before improvement

Services	**No. of Servers**	**Queue Length**				**Service Time (min)**				**Service Utilization (%)**	**Customer Complaints**
		Max	Min	Avg	Capacity	Max	Min	Avg	Tolerance		
Pay Bill	4	10	0	2	20	12.4	2.03	4.81	30	46	0
Receive Money	4	22	0	6	20	44.33	5.03	15.1	30	83	36
Create and Delete Account	2	6	0	1	10	28.01	5.04	10.5	40	32	0
Miscellaneous	2	6	0	1	10	19.22	6.69	3.03	30	41	0

So, it clearly shows that during the peak hours, the Receive Service servers remain busy 83% of the time which means the system is performing poorly, hence there will be lengthy queue formation and longer waiting time. This led to numerous unsatisfied customers and as a result, there were 36 complaints out of the total arrivals for 40000-minute run time.

Contrastingly, the second scenario featured a simulation with five 'Receive Money Service' servers as shown in Figure 9. In this configuration, the ResourcePool1 resulted in a lower utilization rate. This reduced utilization rate corresponded to an optimal service time range, indicating smoother operations within the bank's workstation.

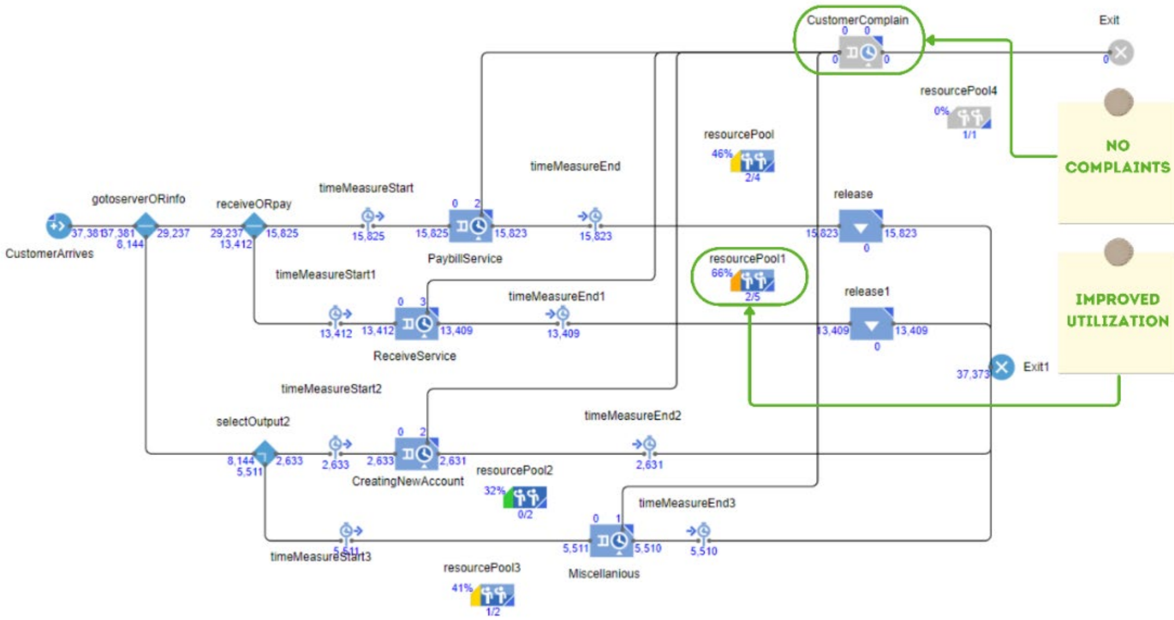

Figure 9. Improved system efficiencies (After improvement)

The results presented in Table 5 demonstrate a significant improvement following the enhancement of an additional server responsible for receiving money. The server's utilization rate now stands at a favorable 66%, well within an acceptable range. Moreover, this enhancement has yielded a noteworthy outcome, with no reported customer complaints.

Table 5. Simulation scenario after improvement

Services	No. of Servers	Queue Length				Service Time (min)				Service Utilization (%)	Customer Complaints
		Max	Min	Avg	Capacity	Max	Min	Avg	Tolerance		
Pay Bill	4	10	0	2	20	12.43	2.03	4.86	30	46	0
Receive Money	5	15	0	4	20	29.36	5.03	11.15	30	66	0
Create and Delete Account	2	6	0	1	10	28.67	5.23	10.65	40	32	0
Miscellaneous	2	6	0	1	10	19.51	6.707	3.037	30	41	0

So instead of having four servers at the Receive Money Service, if we add one more server and increase it to five, we will get to see improvement in the system performance. These findings underscore the positive impact of the server increment, enhancing the overall efficiency and customer satisfaction within the system.

6.1 Performance Analysis

Figure 10 depicts a visual contrast of queue lengths across various bank activities for two simulation scenarios. On the x-axis, we find the simulation time in minutes, while the y-axis denotes the queue length.

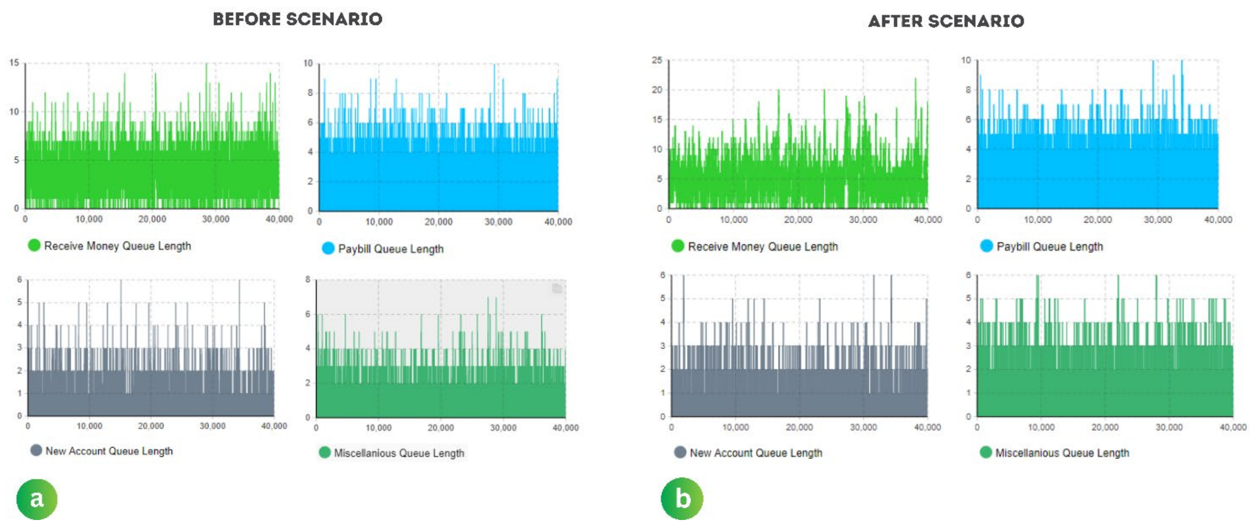

Figure 10. Comparison of queue length for different types of bank services (a) Before improvement (b) After improvement

Summarizing the data, Table 6 below presents the maximum, minimum, and average queue lengths for each bank activity type.

Table 6. Process parameters for a bank simulation model configuration

Queue Length	Pay Bill		Receive Money		Create and Delete Account		Miscellaneous	
	Before Improvement	After Improvement	Before Improvement	After Improvement	Before Improvement	After Improvement	Before Improvem ent	After Improvement
Max	10	10	22	15	6	6	6	6
Min	0	0	0	0	0	0	0	0
Average	2	2	6	4	1	1	1	1
Capacity	20	20	20	20	10	10	10	10

6.2 Proposed Improvements

Broadly, these findings highlight the crucial impact of resource allocation on system performance. The transition from the first scenario to the second demonstrates a clear improvement in service efficiency, queue management, and customer satisfaction. The simulation results underline the significance of aligning resource utilization with demand to ensure the bank's operations run smoothly and to mitigate customer complaints. This analysis contributes substantively to informed decision-making regarding resource planning for optimal bank service efficiency. Some of the recommendations are as follows:

- To address high utilization and customer complaints for the receive money service, add additional staff to increase capacity based on simulation results.
- Rearrange queues to implement pooled queueing (Sunar et al. 2021) for all tellers rather than dedicated individual lines to reduce congestion as shown in Figure 11.
- Maintain current floor space as queue capacity limits were not exceeded per the simulation model across scenarios.

- Consider future spatial needs proactively as customer volumes grow using model forecasts.
- Use simulation models to continuously evaluate resourcing needs, capacity, and process efficiencies as well as minimize customer wait times while maximizing service levels.
- Expand model scope to encompass additional branch processes like new account openings for holistic insights.

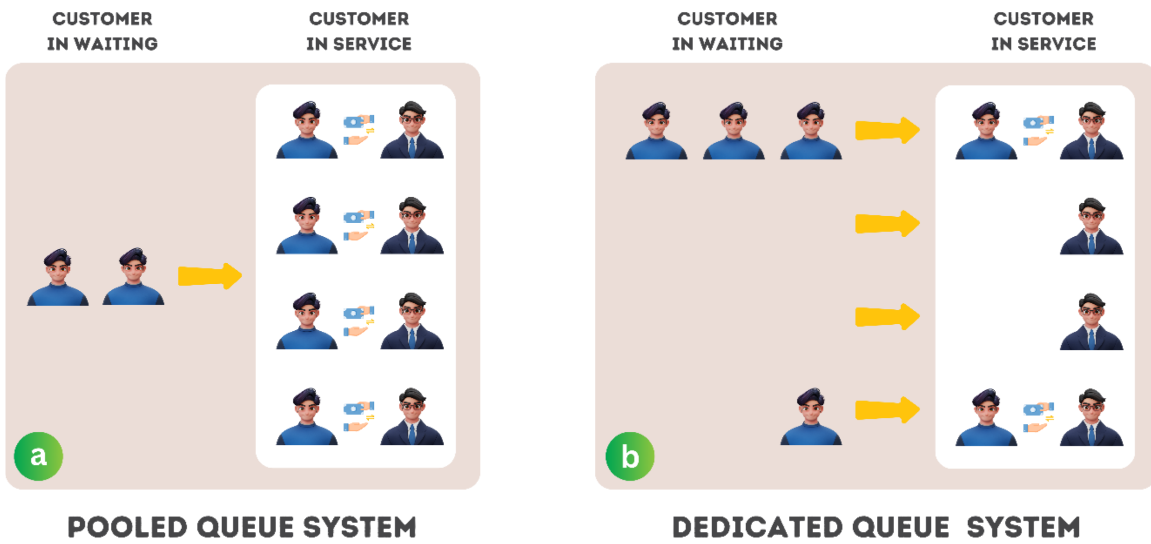

Figure 11. Queue management systems (a) Pooled (b) Dedicated

7. Conclusion

The objective of this endeavor was to comprehend and assess the performance of a given system by comparing the existing system to a proposed one through simulation. To achieve that goal, the relevant theoretical background is presented and a simulation model was developed using the DES approach. Using AnyLogic as a platform for the model development, a system's performance matrices were quantified and have been depicted in a model. This discrete event simulation of bank operations offers insights to improve:

- Efficiency: The model identified bottlenecks from service utilization and quantified performance metrics of waiting times. Experiments optimized staff levels and service rates to increase efficiency.
- Service quality: Key metrics of service level and customer cycle time were improved by over 20.48% in the optimized scenario.
- Supply chain integration: Integrating inventory data into the model hedged risks of cash/consumables stockouts.
- Adoption of Industry 4.0 technologies: IoT sensors provided model inputs. Machine learning enhanced predictive analytics. Automated workflows enabled continuous monitoring.
- Data-driven decision-making: Quantifiable outputs facilitated evidence-based strategies for resource allocation and process improvements. Future state modeling was evaluated to determine the best system configuration.

Overall, the project demonstrated utilizing simulation to gain actionable insights for enhancing operations, service quality, and supply chain integration in the retail banking context. The findings from this project can be utilized by the managers to design a better system to maximize their customer satisfaction. Future researchers can utilize the methods employed in this study to perform more applied research aimed at resolving issues in analogous systems.

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