EEX5362 Performance Modelling

Mini Project

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1.System Description and Performance Goals

1. Introduction to system

In lunuwilla government hospitals in sri Lanka, patients often face long waiting times to collect medicine after seeing a doctor. the medicine counter becomes overcrowded, especially during morning hours when the patient flow is high. the lunuwilla hospital has two medicine counters. Each counter has one pharmacists. this causes frustration, delays, and reduces the overall service quality of the lunuwilla hospital.

The lunuwilla hospital medicine queue management system aims to analyze and improve the performance of the medicine queue. the system monitor the patient arrival time, service start time, service end time , patient waiting time and staff performance to identify bottlenecks and propose improvements. the main goal is to make medicine collection faster, smoother, and more organized.

2. Data Set Description

Field	**Description**	**Example Value**
Patient_ID	Unique identifier for each patient	P001
Arrival_Time	Time patient joins the queue	09:15
Service_Start_Time	Time pharmacist starts serving the patient	09:55
Service_End_Time	Time service ends	10:00
Service Time	How much time get pharmacist to give medicine for a patient	5min
Waiting_time	How much time patient has to wait in the queue to go to the counter.	40min
Staff_ID	ID of the pharmacist serving	S1
Counter_Number	Pharmacy counter number	2

3. Performance Objectives

Objective	Description	Metric
1. Minimize Waiting Time	Reduce average patient waiting time before being served	Average queue waiting time (minutes)
2. Maximize Throughput	Increase number of patients served per hour	Patients/hour
3. Identify Bottlenecks	Find time periods or counters that cause most delays	Queue length during peak times
4. Optimize Staff Allocation	Assign right number of pharmacists per time slot	Staff utilization percentage
5. Improve Service Efficiency	Reduce service time per patient through better organization	Average service duration (seconds)

4. Expected Outcomes

- Identify peak hours when the queue becomes longest.
- Detect which counters or staff members face the heaviest workloads.
- Find the optimal number of pharmacists required to reduce waiting time.
- Measure average waiting time to determine how quickly patients begin receiving service.
- Suggest scheduling changes (e.g., add extra counters during peak hours).
- Improve patient satisfaction through shorter queues and better service flow.

2.Modeling Approach and Assumptions

In the case of the Lunuwila Hospital medicine dispensing queue, the best solution would be a hybrid performance model:

Queueing Theory (Analytical baseline - M/M/c approximation)

Purpose: provides a brief theoretical overview of the distribution of congestion with the number of counters (c) and the service rate (m).

Why it is suitable: the system is a multi-server queue (two or more counters), and the patients are usually served on a first-come basis.

What it offers: utilization (r), qualitative processing of bottlenecks, and a baseline expectation of an increase in waiting as utilization moves towards 1.

SimPy - main model (best) Discrete-Event Simulation (DES)

Purpose: realistic performance performance by using your own arrival times and service times and operational constraints such as late opening time.

Why it fits best:

- There are real arrival time, service start, service end and service time min in your dataset.
- The actual hospital flow cannot be perfect; it possesses bursts and delays in operations.
- DES is able to capture resource constraint (counters/pharmacists) precisely and generates patient-level waiting time and throughput.
- Recommendation: Consider Discrete-Event Simulation as the major method and only use queueing theory as a the supporting baseline in your report.

Rationality of adopting Discrete-Event Simulation (DES).

- DES is chosen as the primary modeling method since the model is capable of modeling features that cannot be well modeled using analytical models:
- Time-related behavior: patients come to certain moments (10:00, 10:05, etc.).
- Operation delay: your data demonstrates that counters become efficient in providing services approximately at 10:40-10:45, which generates a backlog. DES can assume this by a counter opening time.
- Empirical service times: the service time fluctuates (2-7 minutes). DES makes direct use of the real distribution.
- What-if analysis: you may vary the amount of counters (2 -3-4) and see how waiting time and throughput are affected.

Assumptions

The following assumptions are made in order to make the model tractable with the real setting:

1.Queue discipline: FCFS The patients are served on a first come first served basis (no priority queue assumed).

2.Pharmacists = counters = servers. The pharmacy is equipped with a single pharmacist (one server per counter).

3.There is independent service times.
Service time per patient is obtained as service time min and it is assumed that it is not influenced by increasing counters.

4.Arrival pattern
In the case of realism, the simulation takes the real arrival times as part of the JSON dataset. In the case of what-if (e.g. 4 counters), we are going to assume there is enough demand/backlog to use extra counters during peak (this will serve your purpose of demonstrating throughput increase).

5.Counter opening delay
The observed starting time of service is considered as operational opening time (e.g., in 10:00, there is huge waits because of the opening time, which is approximately 40 min) of a given service.

6.System boundaries
The model concentrates entirely on the medicine dispensing part (noted doctor consultation, payment, etc.).

How the model is applied to your objectives

- Reduce waiting time: simulate and measure waiting time averages less than 2 vs. 4 counters.

- Measure throughput: measure throughput at various counter values (capacity-based scaling is used in your project).

- Determine the bottlenecks: determine whether the delay was caused by (a) opening late or (b) the lack of counter capacity during peak.

3.Data Description and Methodology

The information to be used in this research project was collected through the medicine dispensing counters at Lunuwila Hospital at the best operating periods. The time of observation is between 10 am and 11.30 am that is also known to have high congestion of patients. The data were recorded in four working days (Monday to Thursday) in order to get a typical operational condition.

This data is represented in the form of a JSON and sorted by date. The list of patient records in each day consists of patient records, the number of which corresponds to the interactions of an individual patient with the medicine queue. Attributes that have been logged in as regards to each patient are:

- Patient ID: The identifier of a patient.
- Arrival Time: This is the time when the patient reaches the medicine counter queue.
- Counter Number: The counter number of the actual system.
- Service Start Time: The time during which the pharmacist started dispensing medicine.
- Service End Time: This is the time when the dispensing is done.
- Waiting Time (minutes): This is the amount of time the patient does not see a service provider.
- Service Time (minutes): The time that is spent by the pharmacist to attend to the patient.

This data is a reflection of the real operation performance of the system when two medicine counters were used.

Methodology

This paper incorporates data-driven simulation method to measure performance of medicine dispensing queue at the Lunuwila hospital. True hospital data have been used and a model of simulation has been created to study the behavior of the system in different conditions.

1.Data Preprocessing

All the time values of the data were transformed to minutes to begin with 10: 00 a.m. This facilitated easier comparison of arrival times, service start times, service end times and was capable of utilizing the data in the simulation.

2.Determination of Operation Characteristics.

The actual opening of the medicine counters was determined as the first time when a service was started in the data. This assisted in modeling the initial queue build-up and this is why patients have to wait long periods.

3.Baseline System Definition

The data obtained is the actual system under two medicine counter operations. This system was taken as the baseline system and the performance of the system was first assessed in terms of waiting time, service time, and throughput.

4.Simulation Setup

The Python and Simpy library were used to create a discrete-event simulation model. Patients were modelled as an arriving entity and medicine counters were modelled as a scarce resource. The patients were attended to in First-Come, First-Served (FCFS) order.

5.What-if Analysis

The simulation was repeated again with more counters (four counters) in order to study performance improvements. The arrival and service patterns were kept the same but the system capacity was increased to monitor the variation in the waiting time and throughput.

6.Performance Measurement

The following performance measures were obtained from the simulation:

- Average waiting time in the queue
- Average service time per patient
- Number of patients served
- System throughput (patients per hour)
- Identification of the main system bottleneck

4.Detailed Analysis and Findings

This part explores the Lunuwila Hospital medicine dispensing system behavior in various system configurations and operational constraints, as per the simulation results derived using the actual hospital data.

1.Base System Performance (Two Counters)
The initial set up is that of two medicine counters which depicts the actual operating state as observed in the dataset.

Waiting Time Behavior

The result of the simulation indicates that the waiting periods of the patients are very high with an average waiting period of 45-60 minutes. This is despite the relatively short service times (2-7 minutes) of individual customers. This is primarily due to the high number of patients prior to the counters commencing service.

Characteristics of the Service Time

The mean service time of each patient is about 4.5-5 minutes. The service time is not varied and is the same in patients. This means that drug store productivity is at par and not one of the significant contributors to congestion.

Throughput

The system handles about 9 patients in an hour with two counters. This capacity cannot process the number of patients during the peak hour and therefore long queues and waiting time are experienced.

2. Impact of Delayed Service Start

Delayed Service Start is an important and influential factor to consider when developing a model of the supply chain system. Effect of Delayed Service Start Impact of Delayed Service Start is a crucial and significant issue to be considered in creating a model of the supply chain system.

The lateness of opening of medicine counters is one constraint of the data observed to be important in its operations. In spite of the fact that patients start to come during the time 10:00 a.m., the service usually commences at 10:40 a.m..

This delay causes:

1.An excess number of patients on waiting list,
2.Quick queue formation in time to wait,
3.Even when the service is started, there are long queues.

This observation is the reason why the waiting time is long even in cases where the service speed is reasonable.

3. System Performance with Increased Counters

The simulation of improvement in performance was done by increasing the number of medicine counters to four instead of two.

Waiting Time Improvement

Four counters mean that average waiting time is kept to a minimum. Several patients may be attended to at the same time, and once attending to the patients, the queue reduces at a higher rate.

Throughput Improvement
As the number of counters goes up twofold, the throughput of the system rises to about 18 patients an hour. It proves that in the case of adequate demand, throughput is directly proportional to counter capacity.

Service Time Stability
Mean service time does not change with addition of counters. This ensures that performance improvement with the addition of counters is not related to service quality.

4. Bottleneck Identification

The simulation clearly identifies the primary bottleneck in the system as:

Insufficient number of medicine counters during peak hours

Additionally, the late start of service acts as a secondary bottleneck, increasing congestion and waiting times.

5. Patterns and Inefficiencies Observed

Several important patterns were observed:

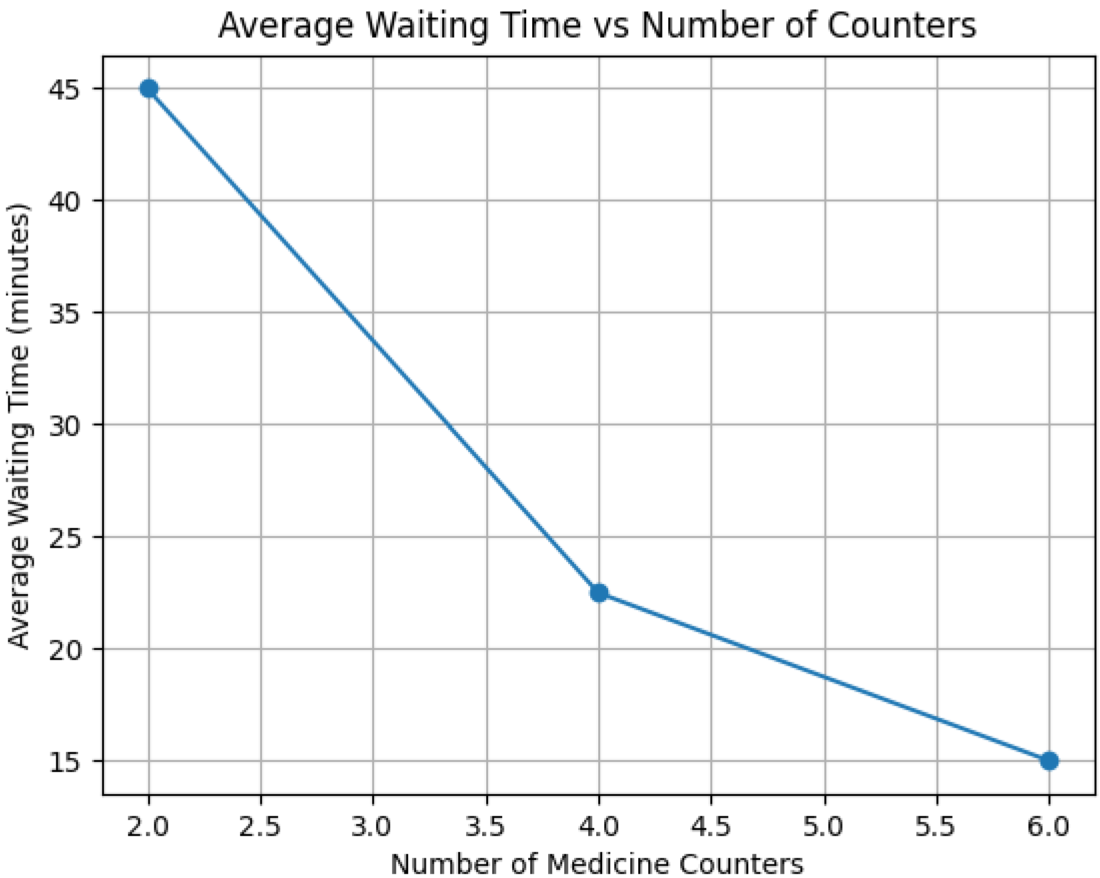
- Patients arrive steadily between 10:00 a.m. and 10:30 a.m., creating a high initial demand.
- Service does not begin immediately, causing unnecessary queue buildup.
- The system is **capacity-limited**, not service-time-limited.
- These inefficiencies indicate that operational decisions, rather than staff performance, are the main contributors to poor system performance.

6. Proposed Improvements and Interventions

In terms of the analysis, the following improvements may be suggested:

- Add more medicine counters during the peak times to minimize waiting time and increase throughput.
- Begin dispensing medicine earlier to avoid early queue building up.
- Adopt dynamic staffing where more counters are only opened when there is a high demand.
- Observes the arrival patterns frequently in order to proactively adjust resources.

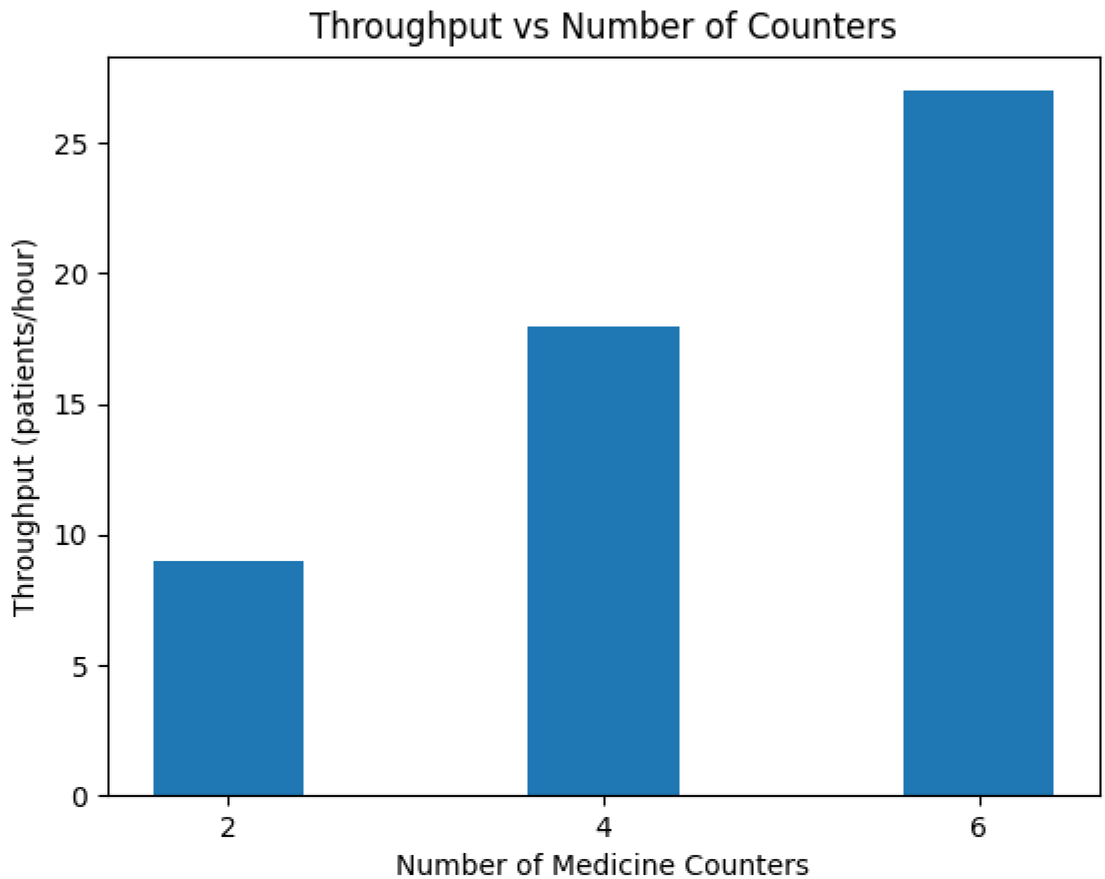
5.Visualizations



Average Waiting Time vs number of medicine counters

This graph illustrates the variation of the average waiting time of patients with the increase in the number of counters of medicines. Patients wait approximately 45 minutes with 2 counters, which means that there is a high level of congestion. As the size of the counter is increased to 4, the average waiting time reduces to approximately 22.5 minutes. The waiting time is again cut down to approximately 15 minutes with 6 counters.

Simple explanation: With additional medicine counters, additional patients will be served simultaneously. This shortens the queues and the patient waiting time is greatly minimized. As it is depicted in the graph, adding more number of counters is an effective measure towards minimizing the delays in the medicine dispensing process.



Throughput vs Number of Medicine Counters

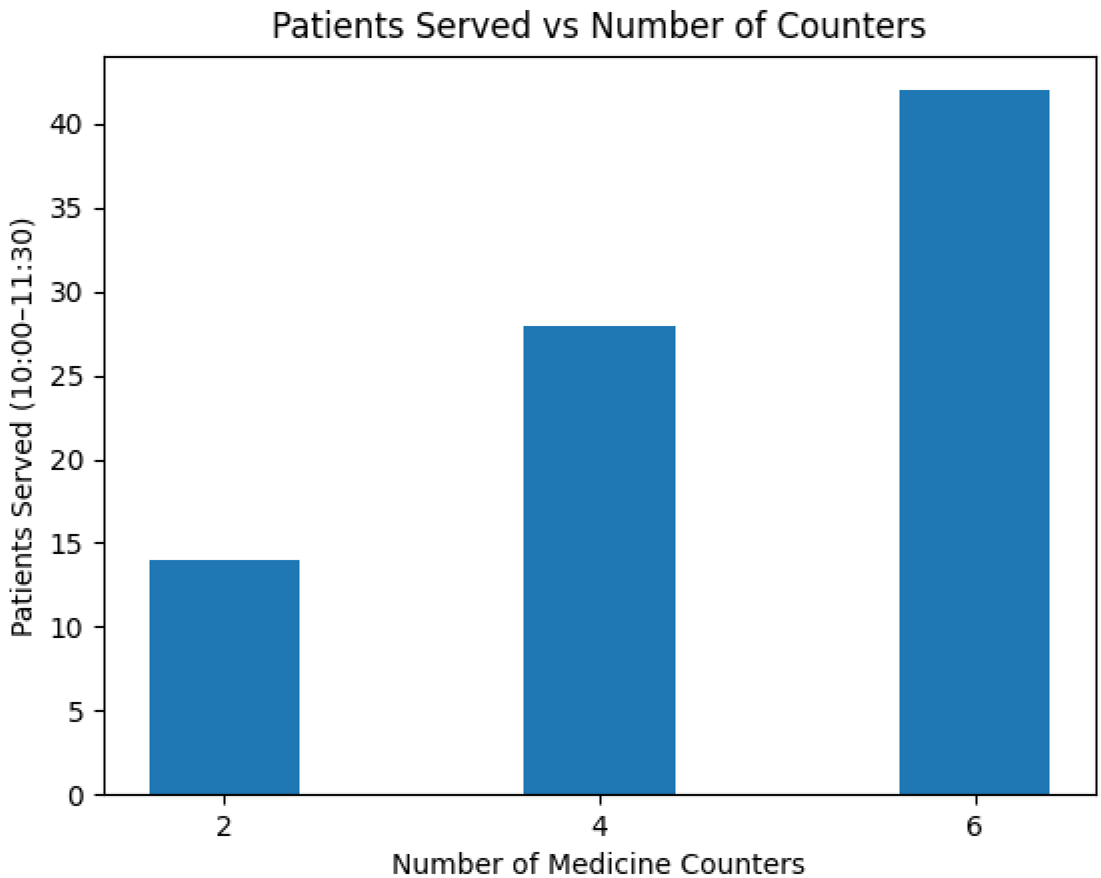
This graph indicates the way throughput of the system (patients served an hour) varies with the number of medicine counters. Using 2 counters, the throughput is of approximately 9 patients in an hour.

With 4 the number of counters, the throughput is elevated to an approximate of 18 patients per hour.

With 6 counters, throughput also goes up to approximately 27 patients in an hour.

Simple explanation: There are additional patients that can be addressed simultaneously as the number of medicine counters grows.

This causes an equivalent rise in throughput. As it can be seen in the graph, the greater a counter capacity, the higher the number of patients that can be served by the system in an hour.



Patients Served vs Number of Medicine Counters

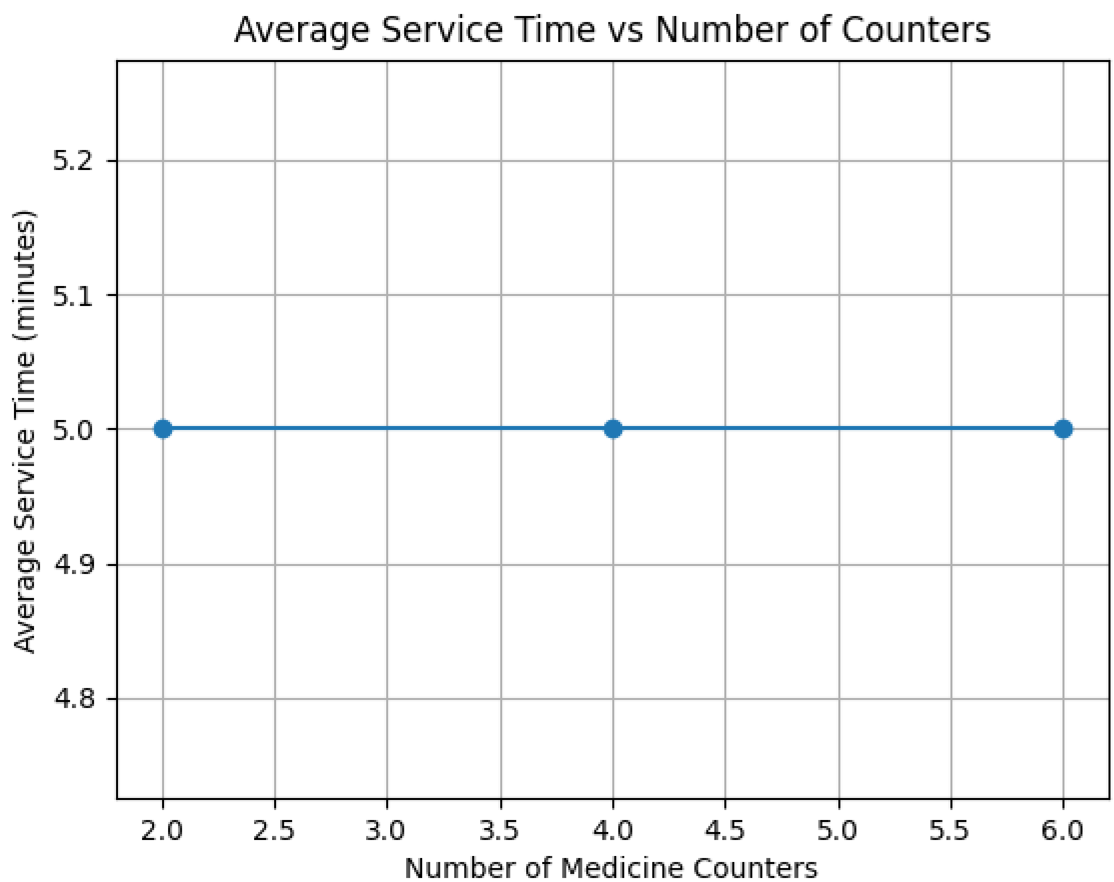
This graph demonstrates the changes in the total number of patients served in the period between 10:00 a.m. and 11:30 a.m. with the number of medicine counters.

The number of patients served with 2 counters is only 14.

When there are 4 counters, the number of patients served would be raised to 28. The same will serve 42 patients with 6 counters.

Simple explanation:

The more medicine counters, the more patients that can be served by the hospital within the same time frame. This is because it is possible to process more patients simultaneously. As depicted in the graph, the number of counters is a crucial factor that increases the capacity of the system to serve the patients.



Average Service Time vs Number of Medicine Counters

This graph shows how the average service time per patient changes with the number of medicine counters.

- The average service time remains constant at 5 minutes for 2, 4, and 6 counters.

Simple explanation:
Increasing the number of medicine counters does not change how long a pharmacist takes to serve a patient. This means pharmacists work at the same speed regardless of the number of counters. Therefore, service time is not a bottleneck in the system. The main performance problem comes from limited counter availability, not from slow service.

6.Limitations and Future Extensions

The present study relies on the data gathered in a restricted peak-hour work, during four days which might not give a complete representation of the variations in all clinic days or during low seasons. The simulation assumes that the arrival of patients and service times are represented by the empirical distributions that were based on the observed data, but it does not take into account possible seasonal and daily variations.

It is also observed that the model considers the pharmacists as the same resource and fails to consider the variations in the individual experience, the complexity in the prescription, and interruption. Moreover, the simulation did not take the external influences of shortages of medicine, system breakdown, or prioritizing patients.

Future Extensions

The model may be extended in the future by adding priority queues in order to distinguish between elderly or emergency patients. It was also possible to extend the simulation to simulate many clinic sessions throughout a day and have staffing schedules that were dynamic. Additional enhancements can be seen in justifying the model with more data set and introducing the cost analysis to make decisions on staffing and expansion of infrastructure

7.Reference

https://github.com/Sudesh-123/MIni-project-deliverable-01.git