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Queuing Modeling Window Software: Improve And Control Performance In Queuing Models In Healthcare Service

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Abstract
In many industries, queuing is used as most common phenomena. Economic growth and population expansion have caused it to sustain a tremendous transformation in recent years. The past difficulties and factors pertaining to the service industry have made it necessary to look for a scientific method that may help improve performance and get past difficulties and roadblocks in the service delivery process. One of the most important scientific methods for addressing a variety of waiting phenomena connected to real service delivery is considered to be a queueing model. Particularly crowded country like India, where waiting time is the critical issue in all major hospitals providing healthcare services. It might be necessary to wait a while before addressing the ineptitude of hospital administration. Utilizing the Queuing Modelling-Window program, one of the specialized data science programs that makes it easier to obtain indicators of performance. This study uncover insight into the queuing models that highlighting its importance and attributes in tracking and enhancing performance of healthcare service providers.

Keywords: *Performance metrics, QM-window, Arrival rate, Service rate, and M/M/1 &, M/M/S Queuing Model*

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I. Introduction

Queuing theory is composed of plethora of Queue models which uses in various organisations for betterment of their services. Queuing theory predicts what will happen in systems containing waiting phenomena. In overcrowded hospitals, waiting time is major concern. To address the issue arises due to patient responses time. We have conducted study that is based on the queuing theory in Maharani Lakshmi Bai Medical College, Jhansi in India.

In order to provide good medical management of patients, the institution's actual state under investigation constructed in order to pinpoint some of the challenges and try to find answers using software called Queuing Modelling Window software. This research establishes in the organization being reviewed and examined, the queue model the reasons for waiting in order to monitor and improve health services. This study looks at the queuing model to see if it is appropriate for Maharani Lakshmi Bai Medical College, India, and calculates the service supply time there. The capacity of multispecialty hospitals to offer high-quality medical care is impacted by abdominal clinical departments. Hospitals utilize the profits from the abdominal department to fund technological advancements and lower inpatient losses. Even though the abdominal clinical department is extremely important, they do not handle patient concerns over lengthy wait times, which are typically brought on by obvious queues. In order to better serve their patients, hospitals in underdeveloped countries have a great opportunity to reorganize their systems and implement cutting-edge techniques and technology with enhanced workflows. Since the abdominal clinical department serves as a bridge Between the community and the hospital it should be constructed with efficiency and throughput in mind. These objectives are followed in the article's growth and structure. We look at the workflow in the abdominal department. Next, a time analysis will be conducted in the department of abdomen. Ultimately, we will make inferences from the data we gathered, talk about our results, and acknowledge the limits of the study.

II. Literature Review

This review summarizes the current information about the various software used for optimization of time in different organization.

Numerous attempts have been made to use different queue models and queuing theory applications to estimate service quality control. Ahmad et al. (2021) analyzed when a manufacturing facility was studied using a queue model, it was found that the number and calibre of difficulties in manufacturing process planning are related. Annas et al. (2023) proposed healthcare utensils and the most precise solutions for healthcare utensils that were supplied by Indonesia's leading logistics companies. Because of the high urgency of the fulfilment, the logistics providers recognized fast-moving utensils are therefore given priority treatment and must be transported to the intended region. Bahram et al. (2023) analyzed of the randomly generated example problems showed that, although the quality of the solutions provided by the Generalised Additive Models software, the Central Processing Unit execution time of the suggested Non-dominated Sorting Genetic Algorithm II (NSGA-II) algorithm was substantially less than that of Generalised Additive Models. Additionally, the outcomes of the case study model's solution validate that the model can discover the necessary facilities and assign demand areas to them suitably. Barata et al (2022), analyzed The MM1 queuing model determines the variety of services offered at the airport. And, the quality and efficiency of the system can be improved by optimizing the servers utilizing queuing models.

Cecula et al. (2021) conducted a comparison of queue management implementation in ticketing systems using traditional and queue techniques. The authors assert that putting queue management into practice greatly raises the service quality. Chakrabarti et al. (2023) analysed about the function and workings of fog/edge computing and the Fog of things (FoT), as well as the necessity of combining them with Cloud of thing (CoT). They have discussed various fog/edge computing architectures, features, applications, and current research issues. A thorough examination of these computing paradigms provides in-depth understanding of their many facets, trends, motivations, visions, and integrated architectures. Gill et al. (2020) analysed to simulate and model thermally sensitive resource management for cloud computing systems, they suggested a framework named ThermoSim. In resource-constrained cloud environments, ThermoSim employs a lightweight RNN-based deep learning model for temperature prediction, resulting in low overhead and effective resource management. Haque et al. (2020) determined that the primary factors influencing wait times were patient characteristics, healthcare provider, and consultations. This analysis focused on doctor-patient appointments at general hospitals. Hauser et al. (2021) analyzed retail businesses around the world had to reevaluate the future function of their network of physical stores as a result of the growing use of omnichannel tactics in recent years. Converting traditional stationary stores into smart stores with additional digital services is one strategic option that many retailers are pursuing. Jiang et al. (2020) analyzed the gaps between actual and target wait times for all priority levels, their study helped us better understand how scheduling strategies may be used to effectively minimize waiting times in MRI institutions. Their main contributions were to anticipate the need for MRI services, Kumar et al. (2020) proposed, A Markovian-based queueing approach was introduced to control an e-health cloud's elasticity. They looked at two scenarios: virtual machine failed, virtual machine can be recovered, and cannot be recovered. The suggested model aids in increasing virtual machine scalability without modifying the machine type. Manh et al. (2023) analyzed to the Based on the examination and computation of study findings on the motorbike parking area pathway for students at Hanoi University of Science and Technology's D3 building Monday through Friday, it can be concluded that the parking lot's queuing model is (M/M/4): (FIFO/∞/∞). Patil et al. (2023) calculated; how many resources would be needed to implement a rigorous testing plan. The simulation model's robustness was successfully confirmed by a number of experiments. An attempt had been made to offer a unique viewpoint on the testing strategy by modifying the Susceptible Exposed Infectious Removed (SEIR) model to include quarantine, testing block, and diagnostic capacity increment. A methodical approach had been taken to outbreak prevention. Sala et al. (2022) analysed the success rate of SIAK implementation in a region can be gauged by the efficacy and efficiency of SIAK. The Ende District's SIAK implementation's efficacy and efficiency have been effectively measured by the HOT-Fit model's domains and components. Eleven indicators, level of usage, attitude, perceived utility, communication, accessibility, safety, punctuality, correctness, thoroughness, compassion, and openness were used to gauge how well information systems are being implemented. Saif et al. (2022) described A key component of the manufacturing sector built on Industrial 4.0 is metrology. Every machine that uses metrological systems needs to be inspected or measured. In the rapidly evolving industrial environment driven by automation, globalization, and product customization, the manufacturing sector was crucial. One of the most important technologies for the growth of industry 4.0 was the Internet of Things (IoT). Additionally, cloud computing and local (edge) communication should be used by contemporary industrial gadgets. Shi et al. (2021) analysed the technique to a wide variety of hospital types via a high-fidelity simulation also yields generalizable findings. They conclude by showcasing a deployment of standard tool at partner hospital to illustrate its wider application through the plug-and-play nature of their framework for integration with processes and data systems in general hospitals. Tuli et al. (2020) describe the project of healthcare as a service was enormous. In their study, they exclusively address the medical needs of heart patients by putting forth Health Fog, a unique fog-based smart healthcare system that uses deep learning and the Internet of Things to automatically identify cardiac conditions. Health Fog efficiently manages patient data and provides healthcare as a fog service. from various IoT devices related to heart patients. Deep learning was integrated into Edge computing devices by Health Fog. Verma et al. (2021) analysis the assessment of several QoS criteria, a study of current auto-scaling, load prediction, and virtual machine migration strategies for IoT-based cloud applications has been conducted. Additionally, future prospects for auto-scaling in cloud environments had also been considered. Vidal et al. (2023) proposed to Optimization–Linear Programming (OP), Queue Model (QM), Economic Production Quantity (EPQ), Optimization OPT, and

Simulation (SIM) models in stochastic supply chain management. In order to aid in decision-making, the research proposes future directions based on shared traits, issues addressed, and common variables. Wang et al. (2021) analysis in their research could assist decision makers in improving the current inspection and quarantine mechanism during the world's economic recovery taking into account both enhancing supervision and improving inspection and quarantine services. By classifying the various categories of foreign visitors with varying risk levels, they can do the risk assessment. Yildirim et al. (2023) analysis to Comparing the buffer stack and chassis exchange terminal (CET) systems revealed that while both systems reduced emissions to similar levels, the CET method reduced truck delays more (83.8% against 28.0%). The findings indicated that buffer stacks were a practical and reasonably priced way for ports to lessen the effects of peak truck traffic brought on by TRTW, cut down on truck emissions, and save money on logistics. Zhou et al. (2021) describe the latest developments in IoT technologies was summed up in their article and referred to as IoT 2.0. Initially, a general IoT 2.0 architecture was contrasted with earlier designs. The main factor propelling the advancement of these systems was edge computing. The seven elements of current IoT technology were then examined machine learning intelligence, mission-critical communication, scalability, security, sustainability, interoperability, and user-friendliness.

III. Model Assumption

Data were analyzed by M/M/1 Model using Queuing Modeling Window software
1. Serving new clients according to the principle of first-in, first-out (FIFO).
2.A customer who signs up for a line stays there until assistance is rendered.
3. The rate of customer arrivals is steady and independent.
4. The rate at which customers arrive is steady and they arrive independently.
5.The Poisson distribution with -rate is used to describe the client arrival rate.
6. The arrival rate, λ, is less than the service time
($\lambda < \mu$) .
Service Facility
Arrivals

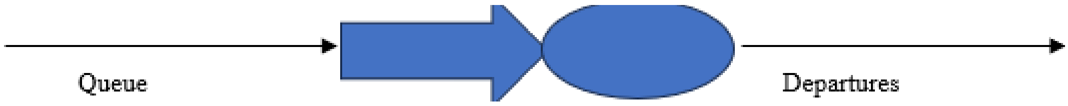

Fig 1: A single channel waiting queue is displayed.

Performance Measure

$L_s = \frac{\lambda}{\mu-\lambda}$

(1)

Where, $\mathbf{L_s}$ is the mean number of Customer in the system

$W_s = \frac{1}{\mu-\lambda}$ **(2)**

Where, W_s is the average time a customer's spend in a system.

$L_q = \frac{\lambda^2}{\mu(\mu-\lambda)}$ (3)

Where, $\boldsymbol{L_q}$ is the mean number of customers in the queue.

$W_q = \frac{\lambda}{\mu(\mu-\lambda)}$ (4)

Where**,** $\boldsymbol{W_q}$ is the average time a customer spends in the queue.

$\rho = \frac{\lambda}{\mu}$ (5)

The coefficient for service supply, or the average number of clients receiving the service in a given amount of time, is represented by the symbol ρ.

$P_0 = 1 - \frac{\lambda}{\mu}$ (6)

Where, P_0 is the idle time when the system isn't working.

IV. Poisson Customers And Exponential Service Times In A Multi-Channel Service Queuing Model (M/M/S)

Each customer in a system with many channels for customer lines is attended to by one or more servers. To clarify our point, let's imagine all of the consumers in queue elect to visit the server that is initially available. The service times of these channels follow the mean of an exponential distribution, 1/μ, and are dispersed independently and identically. The incoming data is described by a Poisson distribution with rate. Every consumer will wait in a single line to be sent to the closest service channel. Again, let's assume that service delivery times follow the exponential distribution and that customers follow the Poisson distribution. Every client in a multiple channel system has equal priority, and every server should run at the same speed. The extra assumptions likewise apply for the single-channel model in addition to the ones that have already been mentioned.

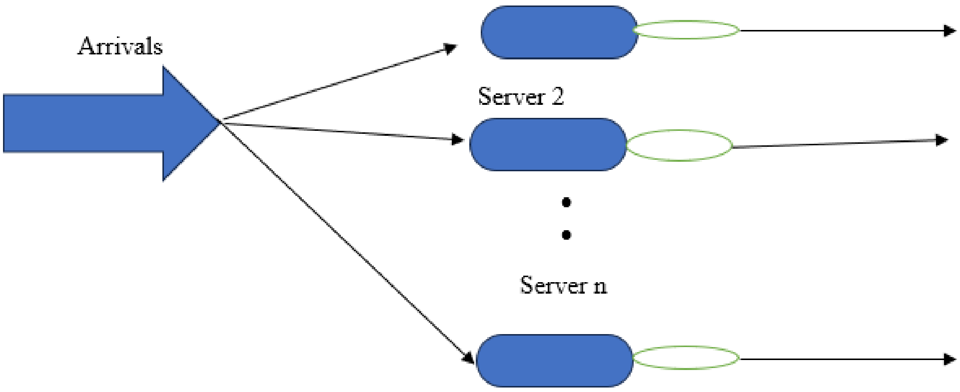

Fig 2: Waiting Line with Multiple Channels

Assumptions of the Model

1. The (M/M/1) model is used under the identical conditions, with the exception of a waiting queue, where the arrival rate (λ) is smaller than the service supply rate μ < s), where s is the number of service channels.
2. There are multiple service channels in the queue.

Model Form

1. The likelihood that there aren't any customers in the system (since it's not busy).

$$P_0 = \frac{1}{\left[\sum_{n=0}^{n=s-1} \frac{1}{n}\left(\frac{\lambda}{\mu}\right)^n\right] + \frac{1}{s}\left(\frac{\lambda}{\mu}\right)^s \frac{s\mu}{s\mu-\lambda}} \qquad (7)$$

2. The likelihood that the system contains (n) units given that

$$P_{n=} \frac{1}{n} \left(\frac{\lambda}{\mu}\right) P_0 \qquad n<s \qquad (8)$$

3. The anticipated average number of clients in the system (L_s)

$$L_S = \frac{\lambda\mu \left(\frac{\lambda}{\mu}\right)^s \quad P_0}{(s-1)\,(s\mu - \lambda)^2} + \frac{\lambda}{\mu} \qquad (9)$$

4. Average wait time for customers in the system (W_s)

$$W_{s=} \frac{W_q}{1/\mu} \qquad (10)$$

5. Average amount of time spent in line by customers (W_q)

$$W_q = W_s - \frac{1}{\lambda} = \frac{L_s}{\lambda} \qquad (11)$$

6. Coefficient of utilization (system busy) (ρ)

$$\rho = \frac{\lambda}{s\mu} \qquad (12)$$

V. A Statistical Analysis Of Maharani Lakshmi Bai Hospital Waiting System

It is necessary to define the probability distributions that accompany each arrival and service supply time in advance due to the many mathematical models that explain the waiting phenomena in terms of these distributions.

Calculates the overall time spent observing

Over the course of three weeks, starting on July 5, 2024, and ending on July 25, 2024—the hospital's official working days the anticipated number of patients seen in MLB College's The table below lays down the formula for this computation.

Table 1: Calculating the Total and Partial Observation Durations Over the Course of the Study

Working day of the week	**Every day, excluding Wednesday and Friday**
Study-Specific "Working Days"	Monday, Tuesday, Thursday, Saturday, and Sunday
Hours of Official Work	Between 5 and 11 p.m.
Specific Hours for Studying	From 6 to 9 p.m.
Time of Observation in Hours	Three hours and
Perceived Duration in Minutes	180 minutes
Measured Time in Minutes	Ten minutes
The Maximum Daily Observed Period Count	There are 18 periods a day and
The Most Periods Per Week That We Can Observe	54 periods a week.

The Arrival Phenomenon: A Statistical Analysis

In the theory of queue models, the phenomena of service channel arrival are major importance because the process of patients arriving sporadically and at unequal intervals cannot be foreseen in advance. For the purpose of calculating the probability distribution, we monitored the occurrence of patients arriving at the service channel throughout time Out of an anticipated total of 344 observing sessions, 80 were chosen at random during the three-week period. To get the arrival rate, the following table will be used: Arrival rate (λ) is the average number of patients entering the system over an anticipated 10-minute period (λ).

Table 2: Detailed Estimate of the Number of Arrivals Making Service Requests

Number of Arrival	0	1	2	3	Summation
Observed frequency	12	11	84	55	162
Summation	0	11	168	165	344

The formula that follows is used to get the arrival rate (λ):

$\boldsymbol{\lambda}=\frac{\sum_{i=1}^{i=4} x_i f_i}{\sum_{i=1}^{i=4} f_i}\ x_i\ =\frac{344}{162}=$ 2.12 person per period

The following hypothesis was evaluated after the arrival rate was established and the distribution of the phenomena of arrival of the patient at the service channel is assessed using the chi-square test:

$\boldsymbol{H_0}$**:** The Poisson distribution is used to determine when a patient will arrive at the service channel.

$\boldsymbol{H_1}$**:** The patient's arrival at the service channel does not correspond to the Poisson distribution.

We calculated the test's statistic using the following formula.

$$\mathrm{T}\ = \frac{\sum_{i=1}^{r}(O_i - E_i)^2}{E_i}$$

Where,

O_i : is the Observed value,

E_i : is the expected value,

$E_i = \mathrm{n}\ p_i$

$p_i = \frac{e^{-m}}{r!} m^r$

Where (m) shows the previously established patient arrival rate; the test statistic's value isT = 3.05, However, the chi-squared value in tabular form is 3.25. The null hypothesis, which states that the arrival phenomena follow the Poisson distribution, has been accepted since the test statistic's value is lower than the value of the tabular chi-square.

The Analysis of Service Providing Time through Statistics

Service performance timings are random since they are not set and differ from patient to patient. Following the same procedures as in the statistical analysis the phenomenon of arriving, where the service duration is determined using the patient enters until the time exits, we have chosen 80 service duration times at random to ascertain the probability distribution that is responsible for service performance times. The results are displayed in the following table:

Table 3: Specified Service Duration in Minutes

7	5	6	18	7	8	5	6	5	16
9	8	8	6	8	3	4	3	2	6
7	9	4	2	7	8	6	5	4	4
12	6	4	8	7	4	5	11	12	6
9	8	8	4	5	4	8	6	6	6
6	8	4	4	4	3	7	5	7	8
8	8	6	7	4	6	3	7	7	8
8	4	8	8	8	5	6	8	8	5

The table displays the average providing service time after the data is processed. (4).

Table 4: Calculating the Mean Service Duration

Interval of Service duration	Observed frequency	Midpoint of the Intervals	Frequency of the Midpoint
2-4.18	19	3.0925	58.784
4.18-6.37	23	5.2775	121.371
6.37-8.55	30	7.4625	223.865
8.55-10.74	3	9.647	28.935
10.74-12.925	3	11.832	35.496
12.925-15.11	0	14.0175	0
15.11-23.	2	16.2025	32.405
summation	80		500.82

We may determine the average giving service time using the preceding data in the manner described below:

$\mu = \frac{\sum_{i=1}^{i=7} x_i f_i}{\sum_{i=1}^{i=7} f_i} = \frac{500.86}{80}$ = 6.25 minutes per person

We evaluated the following two hypotheses distribution using the chi-square test of service time phenomenon after calculating the average providing service time.

$\boldsymbol{H_0}$ **:** There is an exponential distribution in the service time distribution.

$\boldsymbol{H_1}$**:** An exponential distribution does not apply to the distribution of service times.

The statistic was determined using

T = $\frac{\sum_{i=1}^{r}(O_i - E_i)^2}{E_i}$

Where,

E_i=np_i

p_i=$\mu e^{-\mu x}$

The test statistic is T = 0.932, while the tabular chi-square value is$\chi^2_{1-\alpha,k}$,=$\chi^2_{0.05,5} = 1.455$ Since we agree with the null hypothesis, the arrival times follow an exponential distribution.

Determines the Patient Waiting Queue Model's Features

These are the main features of the model for the patient waiting queue in the Adnominal Clinic at Maharani Lakshmi Bai Medical College JHANSI Hospital, based on an examination of arrival and service times using statistics:

1. A distribution of Poisson with parameter the arrival probability distribution is modelled with a rate of 2.12 patients each period.
2. The distribution is exponential that provides the time probability distribution has a parameter of 6.26 minutes per person.
3. First-in-first-out (FIFO) is the service organization's (MLB Medical College) service priority.
4. There is no restriction to the number of service applicants.
5. There are countless alternatives for the service channel. This indicates that (M / M /1) (FIFO /∞/∞) is the model that most accurately depicts the waiting queue for the service channel under investigation.

Performance Indicators at MLB Hospital's Abdominal Clinic

The QM Window program is used to obtain performance indicators Following the service performance time is found to be 6.26 and the arrival time to be 2.12

Table 5: Results of the QM-Window

Parameter	Value	Parameter	Value	Minutes	seconds
Exponential service times, or M/M/1		Average Number of Servers Used	0.32		
Rate of arrival (λ)	2.12	Average Number of Patients Waiting in Line (L_q)	0.18		
Rate of service (μ)	6.26	The mean quantity of patients within the system (L_s)	0.49		
Number of Servers	1	Average time spent in line	0.07	4.90	283.34

		(W_q)			
		Average Number of patients in the System (W_s)	0.23	14.40	869.57
		Probability (% of time) when System is empty (P_0)	0.57		

The above table shows the following.
1. Utilization Coefficient P=0.32
2. The mean number of patients in the queue, L_q= 0.18 patient.
3. The mean number of people waiting in line is L_s= 0.49 patient.
4. Average patient wait time in line, L_q= 0.07 hour.
5. Customers' average wait time in the system W_s=0.23 hours.

Probabilities can also be computed when:
1.Number of service channels (K) = Number of patients in the system (N), where N=K
2. There are less patients (N) in the system than service channels (K) (N ≤ K).
3. The total number of patients (N) in the system is Beyond the quantity of service channels (K) K≥N
4. K ≤ 9 ≤ 0

Table 6: The Number of Service Channels (K) Probabilities for Different Cases

K	Prob. (N =K)	Prob. (N≤K)	Prob. (N≥ K)
0	0.66	0.66	0.34
1	0.22	0.89	0.11
2	0.08	0.96	0.04
3	0.03	0.99	0.01
4	0.01	1	0
5	0	1	0
6	0	1	0
7	0	1	0
8	0	1	0
9	0	1	0

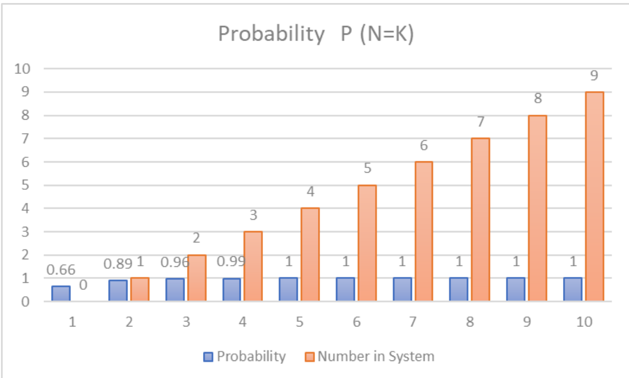

Fig 3: Patient count (N) in the system equals service channel count (K), hence N=K

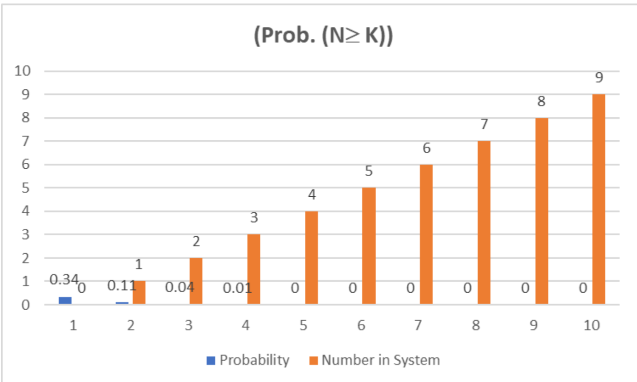

Fig 4: N < K, the number of patients in the system (N) is less than the number of service channels (K).

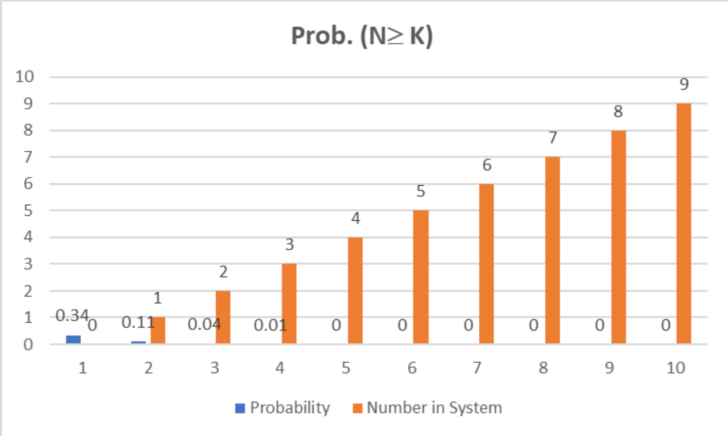

Fig 5: N > K, meaning that the number of patients in the system (N) exceeds the number of service channels (K).

VI. Results

Our Statistical Analysis Allows Us to Derive the Following Result.

1. Coefficient of Utilization P = 0.32 indicates that there is no significant traffic during regular business hours in the abdominal clinic at Maharani Lakshmi Bai Hospital, meaning that the likelihood that the system (the clinic) is as busy as 0.32. This suggests that the clinic is open 32%
2. There are typically just 0.18 patients in the waiting line, which is a low quantity.
3. The mean quantity of patients in the healthcare system is 0.49, meaning that there is no overcrowding overall.
4. The mean amount of time spent waiting in line is 0.07 hours, which is an appropriate amount of time to provide the service and shows that the patient receives it without any problems.
5. The method uses 0.23 hours of time, which is not a significant amount of time and is not comparable to the department's capabilities.

VII. Recommendations

1. Queuing models' technology must be implemented by all institutions facing congestion in order to monitor and improve the quality of their services.
2. Governmental staff training stresses how to employ the queuing mechanism to arrive at the best time possible in order to provide high-quality services.
3. Conducting research on how well operations research methods work to address typical problems in the service industry, such as personnel shortages, inefficiencies in transportation, and linear programming.

References

[1] Ahmad, S., Alnowibet, K., Alqasem, L., Merigo, J. M., & Zaindin, M. (2021). Generalized OWA Operators For Uncertain Queuing Modeling With Application In Healthcare. Soft Computing, 25, 4951-4962.

[2] Asian Journal Of Management, Entrepreneurship And Social Science, 3(01), 551-564. Annas, M., Humairoh, H., Sundram, V. P. K., & Wahab, S. N. (2023). POM-QM Utilization On Healthcare-Utensils Demand Identification And Distribution In Indonesia

[3] Bahrami, I., Ahari, R. M., & Asadpour, M. (2021). A Maximal Covering Facility Location Model For Emergency Services Within An M (T)/M/M/M Queuing System. (3), Journal Of Modelling In Management, 16963-986.

[4] Barata, F., Ricardianto, P., Mulyana, A., Perwitasari, E., Arubusman, D., Purwoko, H., & Endri, E. (2022). Berthing Time In The Port Of Tanjung Priok, Jakarta, Indonesia. Uncertain Supply Chain Management, 10(4), 1387-1396.

[5] Cecula P, Yu J, Dawoodbhoy FM, Delaney J, Tan J, Peacock I, Et Al. Applications Of Artificial Intelligence To Improve Patient Flow On Mental Health Inpatient Unitsnarrative Literature Review, Heliyon. 2021;7(4):E06-626.

[6] Chakraborty, A., Kumar, M., Chaurasia, N., & Gill, S. S. (2023). Journey From Cloud Of Things To Fog Of Things: Survey, New Trends, And Research Directions. Software: Practice And Experience, 53(2), 496-551.

[7] Gill, S. S., Tuli, S., Toosi, A. N., Cuadrado, F., Garraghan, P., Bahsoon, R., ... & Buyya, R. (2020). Thermosim: Deep Learning Based Framework For Modeling And Simulation Of Thermal-Aware Resource Management For Cloud Computing Environments. Journal Of Systems And Software, 166, 110596.

[8] Haque O, Akter S, Hossen A, Rahman Z. A Case Study On Outpatient Waiting Time For Treatment With Single Server Queuing Model At Public Eye Hospital In Bangladesh, American Scientific Research Journal For Engineering. 2020;6(1):4-9.

[9] Hauser, M., Flath, C. M., & Thiesse, F. (2021). Catch Me If You Scan: Data-Driven Prescriptive Modeling For Smart Store Environments. European Journal Of Operational Research, 294(3), 860-873.

[10] Jiang, Y., Abouee-Mehrizi, H., & Diao, Y. (2020). Data-Driven Analytics To Support Scheduling Of Multi-Priority Multi-Class Patients With Wait Time Targets. European Journal Of Operational Research, 281(3), 597-611.

[11] Kumar, M. S., & Raja, M. I. (2020). A Queuing Theory Model For E-Health Cloud Applications. International Journal Of Internet Technology And Secured Transactions, 10(5), 585-600.

[12] Manh, C. D., & Thi, M. N. (2023, May). The Queueing Model On The Parking Area: A Case Study At Hanoi University Of Science And Technology. In International Conference On Emerging Challenges: Strategic Adaptation In The World Of Uncertainties (ICECH 2022) (Pp. 127-135). Atlantis Press.

[13] Patil, A., Shardeo, V., Madaan, J., Dwivedi, A., & Paul, S. K. (2023). A Study To Forecast Healthcare Capacity Dynamics In The Wake Of The COVID-19 Pandemic. International Journal Of Physical Distribution & Logistics Management, 53(10), 1187-1216

[14] Sala, E. E., & Subriadi, A. P. (2022). Hot-Fit Model To Measure The Effectiveness And Efficiency Of Information System In Public Sector. The Winners, 23(2), 131-141.

[15] Saif, Y., Yusof, Y., Latif, K., Kadir, A. Z. A., Binti Lliyas Ahmed, M., Adam, A., ... & Memon, D. A. (2022). Roundness Holes' Measurement For Milled Workpiece Using Machine Vision Inspection System Based On Iot Structure: A Case Study. Measurement, 195, 111072.

[16] Shi, P., Helm, J. E., Deglise-Hawkinson, J., & Pan, J. (2021). Timing It Right: Balancing Inpatient Congestion Vs. Readmission Risk At Discharge. Operations Research, 69(6), 1842-1865.

[17] Tuli, S., Basumatary, N., Gill, S. S., Kahani, M., Arya, R. C., Wander, G. S., & Buyya, R. (2020). Healthfog: An Ensemble Deep Learning Based Smart Healthcare System For Automatic Diagnosis Of Heart Diseases In Integrated Iot And Fog Computing Environments. Future Generation Computer Systems, 104, 187-200.

[18] Verma, S., & Bala, A. (2021). Auto-Scaling Techniques For Iot-Based Cloud Applications: A Review. Cluster Computing, 24(3), 2425-2459.

[19] Vidal, G. H. (2023). Deterministic And Stochastic Inventory Models In Production Systems: A Review Of The Literature. Process Integration And Optimization For Sustainability, 7(1), 29-50.

[20] Wang, C. H., Chen, Y. T., & Wu, X. (2021). A Multi-Tier Inspection Queueing System With Finite Capacity For Differentiated Border Control Measures. IEEE Access, 9, 60489-60502.

[21] Yıldırım, M. S. (2023). Investigating The Impact Of Buffer Stacks With Truck Restriction Time Window Policy On Reducing Congestion And Emissions At Port Of Izmir. International Journal Of Civil Engineering, 21(7), 1107-1122.

[22] Zhou, I., Makhdoom, I., Shariati, N., Raza, M. A., Keshavarz, R., Lipman, J.& Jamalipour, A. (2021). Internet Of Things 2.0: Concepts, Applications, And Future Directions. IEEE Access, 9, 70961-71012.