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USING QUEUEING MODEL TO ANALYZE PATIENT FLOW IN EMERGENCY HEALTH CARE DEPARTMENT

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ABSTRACT

In this paper, Overcrowding in emergency departments (EDs) is a prevalent issue that might compromise the standard and accessibility of medical care. Examining the emergency department presentations over the past three years, we have seen a steady rise in the quantity of presentations. It is a struggle for every ED to reduce patient wait times, deliver care on time, and raise patient satisfaction. According to patient satisfaction surveys, the most common concern is over lengthy wait times. We have analyzed 1890 questions for a period of three years (2019-2022). The most common complaints, with an overall satisfaction rating of 78, 66%, are about the lengthy wait times, the waiting staff room which is small area, and the inadequate staff. In order to properly handle these scenarios, we suggested using queuing models for our investigation, since they may yield pretty accurate assessments of the functionality of our system. The case study's data set comprehensive information from January 1 to December 31, 2022, a total of 48.218 patients who were registered during that time. The study's findings can aid in our comprehension of the scope of the issue at hand, the connection between waiting times and available resources, and how to monitor and assess performance in order to identify areas for improvement and resolve day to day crises.

Keywords: Queue Discipline, Emergency Department, Waiting time.

1. INTRODUCTION

The issue of overpopulation in Emergency Departments (EDs) is a global concern that impedes the timely delivery of emergency medical care. Although more individuals are going to emergency rooms, Patients with immediate needs can always receive assistance from the department. Patients may suffer grave consequences from delays in ED care. The Queuing Theory may be used to analyze how well the ED performs in terms of patient flow and accessible resources. An emergency medical care system may be thought of as a network of lines and various kinds of servers where people come in, wait for a server, receive a diagnosis, and either leave the hospital or are admitted. The findings of these studies may be useful to hospitals, as waiting lists are useful instruments for assisting with managerial choices. Studies demonstrate the effective application of the Queuing Theory in the medical field. Danish engineer, mathematician, and researcher

Agner Krarup Erlang examined the queuing theory for the first time in 1913, focusing on telephone traffic. This notion has just recently been applied to health care. The majority of papers were released after 1990, which is attributable to the availability of more software and advances in processing power.

Research has indicated that the queuing theory is applicable in the medical domain. The contributions and applications of queuing theory to problems with health care administration. A variety of queuing theory findings are summed up by [1] in the following areas: system design, appointment system, waiting time and utilization analysis Research on models for assessing how bed assignment rules affect patient turnout likelihood and waiting periods. In addition to determining the distribution of wait times, used a queuing model to create a link between the reneging parameter and the percentage of reneged patients. Through the use of QNA software. Determine the average and fluctuation of the number of clients at every node, as well as server usage, the duration of patient time in a network with several nodes, as well as the mean and variation of each node's waiting period. A queuing model is presented by [2,3] to help establish effective nurse staffing strategies. The flow through an emergency care room may be compared to a queuing process. The model's outputs can then be used to simply visualize and explain the government's 4-hour objective [4]. The length of the line is not significantly affected by increasing service capacity. When usage is high discover that it is feasible to reduce waiting times by prioritizing individuals who need shorter service times [5]. The primary goal of the systematic review was to characterize the body of scientific research on emergency care department congestion from the standpoint of reasons consequences [6], and remedies.

Queuing models will be utilized in this study to design the Emergency Department's capacity in Bareilly City [7], India, to manage patient flow in an ideal manner. For our investigation, we suggested using queuing models to evaluate the effectiveness of the system that were comparatively accurate.

2. PATIENT FLOW MODEL

Healthcare managers frequently anticipate workloads for planning personnel and physical infrastructure [8]. When assessing the current or suggested service systems, they have to take five standard metrics into account.

These actions consist of:[9]

(i) an average number of patients (in the system or in a queue) waiting;
(ii) the patients' average wait time (in the system or in the queue);
(iii) capacity use
(iv) expenses of a specific capacity level;
(v) Likelihood of having to wait for care when a patient arrives.

The system utilization metric indicates how many of the servers are in use as opposed to being idle. Health care administrators would seem to aim for 100% system utilization on the surface.100% utilization might not be feasible in most situations; instead, a health care management should aim for a system that minimizes the total cost of capacity and waiting times. A key premise of queue modeling is that a steady state of the system exists, which the health care management must confirm by monitoring the mean arrival and service rates [10].

The primary features of the queuing model are as follows:

(i) The source of the population;
(ii) The number of servers;
(iii) The patterns of arrivals and services;
(iv) The discipline of the queue.

The source of the population may be small or limitless. Patient arrivals are uncontrolled in an endless source scenario and are always capable of surpassing the system's capacity.

Number of servers: The combined capacity of all the servers in operation and their individual capacities define the queuing systems' capacity.

Arrival patterns: The systems get momentarily overloaded due to extremely fluctuating arrival and service patterns, which results in waiting queues. The ED of a hospital is a great place to see instances of how random arrival patterns may lead to such diversity. There are variations in the arrival pattern depending on the time of day.

Service patterns: The length of time needed for therapy differs from patient to patient due to the variety of diseases and conditions that patients face.

The sequence in which clients are served is referred to as queue discipline. The most prevalent norm is the presumption that services are offered on a first-come, first-served basis. Patients in the ED are not all assigned the same risk or degree of triage, so those who pose the greatest risk and are the sickest initially receive treatment.

A brief description of the queuing system is often provided using a few characteristics. Originally a three factor notation A1/B1/C1, Kendall's notation may be used to describe these features. Eventually, the concept was expanded to include D1, E1, and F1 as well, making it A1/B1/C1/D1/E1/F1. Table 1 displays the notation for the queuing model:

Symbol	Explanation
A1	The dispersion of arrival times
B1	The distribution of service time
C1	The number of servers (available agent)
D1	The capacity of the system and the total number of users
E1	The calling population
F1	The queue discipline

For different probability distributions that characterize the arrivals and departures, specific notations have been established. A few examples include the Poisson process-based arrival or departure distribution (M), the Erlang distribution (E), the general distribution (G), and the general independent distribution (GI).

In order to apply queuing models to any given scenario, it is necessary to first outline the procedures for input and output. In our ED, the patient's arrival is the input process; the patient's discharge or admittance to a hospital unit is the output process. The bare minimum number of servers, or providers, needed to create the flowchart showing patients arriving and exiting the emergency department will be determined using the queuing theory. In general, queue models handle new customers arriving at a service facility.

An M/M/n queuing model will be taken into consideration as it will assist us in estimating the required number of providers. Arrivals follow an exponential distribution for the service length, and arrivals follow a Poisson pattern. The Poisson distribution, whose mean and variance are equal, is a discrete distribution that displays the likelihood of arrivals within a specified time frame. With the help of this M/M/n model, we suppose that:

$$\frac{\lambda}{n\mu} < 1 \tag{1}$$

Wherever we mention utilizing:

μ- Service rate;

λ - Arrival rate;

p - System utilization;

1 / μ - Service time ;

P0 - probability in the system of 0 units;

Pk - Probability in the system of k units,

n - Number of server or provider

We are searching for the probability Pk, or the likelihood that a patient joining the line will have to wait for treatment, in order to optimize the procedure and ensure that all of the doctors are active. We will utilize the following relations to compute these probabilities:

$$P_k = P_0 \left(\frac{\lambda}{\mu}\right)^k \frac{1}{k!} \qquad k < n \tag{2}$$

$$P_k = P_0 \left(\frac{\lambda}{\mu}\right)^k \frac{1}{n!n^{k-n}} \qquad k \geq n \tag{3}$$

Considering the attribute that the whole sum of probability ought to confirm:

$$\sum_{k=0}^{\infty} P_k = 1 \tag{4}$$

For every i, we shall compute P0 and the probability Pi. We state that there is no backlog (waiting line) until the number of arrivals (k) is fewer than the number of servers or providers (n). However, in the event that there were more arrivals than servers (or providers), the procedure would need to be optimized in order to shorten wait times.

3. QUEUE MODEL FOR EMERGENCY CARE DEPARTMENT

In India, patients can obtain emergency care through EDs, which are part of hospitals. The purpose of the Emergency Department is to treat patients who were treated on the street, at the scene of the accident, or even before they arrived in a non-medical vehicle. It also collaborates with hospital specialists to provide a diagnosis for patients and to monitor them until they are admitted to the hospital or, if their condition does not require hospitalization, until they are released. We took into consideration the Bareilly City Emergency Hospital's ground level ED for the case study. One of the most up-to-date EDs in India, it offers patients who need examination and treatment for a duration of 0 to 24 hours of excellent care. With a floor area of around 1900 square meters and state-of-the-art medical equipment, it functions in a well-defined region. The primary areas that comprise the emergency department include triage, resuscitation room, immediate care unit, pediatric emergencies, Room for minor operations, Space for small crises, Computer tomography, and critical observation. The case study's data set comprises comprehensive information for the period of January 1–December 31, 2022. 51.02% of the patients throughout the study period were transported by ambulance; of these, 6.58% required urgent care upon arrival, and 3.8% of the patients who were treated were walk-ins. In the ED, hospitalization was necessary for 32% of the treated patients.

The ED operates as follows: the triage area is where patients first interact with staff members. There, a triage nurse assesses the patient, assesses the severity of the patient's condition, and assigns a triage code, which is a number between 1 and 5, as shown in table 2. Individuals classified as level 1 go straight to the resuscitation room, while those classified as level 2 go to the immediate care unit. Levels 3, 4, and 5 patients proceed to the waiting room unless a bed becomes available right away.

Table 2: Emergency Department Levels of Triage/ Codes

Triage level / code	Waiting the initial doctor's consultation
Level I / Green	0 minute
Level II / Yellow	Maximum 25 minute
Level III / Red	Maximum 50 minute
Level IV / Blue	Maximum 100 minute
Level V / White	Maximum 200 minute

The ED's workflow will be examined as an exact queuing procedure, where patients arrive, wait, get assessed and treated, and then are either released or sent to another medical unit. Cases with a green code are handled in order of priority. Utilizing patient flow as a foundation, we will apply the queuing theory to calculate the average waiting time and the amount of ED resources (human resources) that are required. The ED department's management has to know the outcomes in order to make the best judgments and set up the workflow.

A total of 48.218 patients were registered throughout the analysis period; hence, 140 patients may be regarded as the daily average (24 hours). In a database, we entered the patient's name, residence, diagnosis, arrival time, and length of stay in the emergency department.

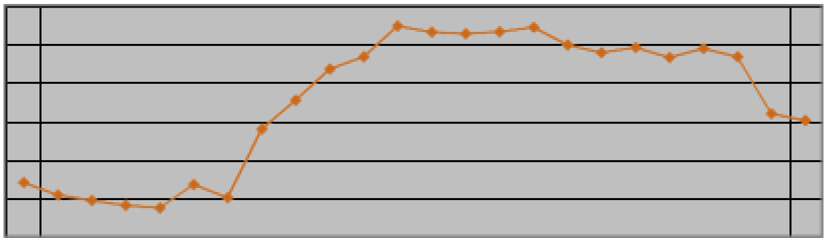
The yearly average number of patient arrivals within the range [ti−1, ti] is represented as xi, where t0=0 denotes the 0 hour, or the start of the day. If we indicate the quantity of patients that came in the time span [ti−1, ti], on day r, we may get the average number of patient arrivals each day :

$$x_i^r = \frac{\sum_{k=1}^{12}\sum_{r=1}^{31} P_k^{r,i}}{12} \qquad (5)$$

Where the sum following r denotes the number of days in each month and k stands for the months. As a result, the connection will yield the average number of patients that came within the interval [ti−1, ti]:

$$x_i = \frac{x_i^r}{24} \qquad (6)$$

Figure 1. displays the computed values of xi and the time periods [*t*i−1, *t*i] that were taken into consideration. As seen in figure 1, patient arrivals occur at random.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
number of arrival patients	2,9	2,2	1,9	1,7	1,5	2,8	2,1	5,6	7,1	8,7	9,3	11	11	10	11	11	9,9	9,5	9,8	9,3	9,7	9,3	6,4	6

Figure 1: Average quantity of new arrivals in 2022

Consequently, the mean quantity of arrivals indicated by λ will be:

$$\lambda = \frac{\sum x_i}{24} \tag{7}$$

We have got , therefore we'll assume for the purposes of this analysis that patients come at a pace of five per hour and remain in a single queue. Using the generated database and the same rationality as above, The average yearly service rate that was determined is , Therefore, it takes a physician 22 minutes on average to treat a patient. If the following connection is true, the system is known to be in a steady state:

$$\frac{\lambda}{n\mu} < 1$$

where the amount of human resources is represented by n., the quantity of physicians in the ED. The least amount of doctors in the emergency department may thus be calculated using the inequality.

Given that it takes a doctor, on average, 22 minutes to see a patient, The minimal number of physicians n will be determined by the number of arrivals each hour λ., as indicated by Table 3.

Table 3: Minimum Number of Medical Professionals

λ	5	7	8	9	10	11	12
n	3	3	3	4	4	4	5

We estimated various queue specifications using the M/M/3 queuing model, distinct ED features. Within our case study, we have: λ = 5; μ = 2; n = 3; ∝ = 5/2; and S.E. = λ/nμ = 5/6

$$P_0 + P_1 + P_2 + \left(P_3 + P_4 + P_5 \ldots\ldots\right) = 1 \tag{8}$$

Using n=3 and we get

$$P_0 + P_0\frac{\lambda}{\mu} + P_0\left(\frac{\lambda}{\mu}\right)^2\frac{1}{2!} + P_0\left(\frac{\lambda}{\mu}\right)^3\frac{1}{3!}\frac{1}{3^0} + P_0\left(\frac{\lambda}{\mu}\right)^4\frac{1}{3!}\frac{1}{3} + P_0\left(\frac{\lambda}{\mu}\right)^5\frac{1}{3!}\frac{1}{3^2} + \ldots = 1 \tag{9}$$

$$P_0 + P_0\frac{\lambda}{\mu} + P_0\left(\frac{\lambda}{\mu}\right)^2\frac{1}{2!} + P_0\left(\frac{\lambda}{\mu}\right)^3\frac{1}{3!}[\ \frac{1}{3^0} + P_0\left(\frac{\lambda}{\mu}\right)\frac{1}{3} + P_0\left(\frac{\lambda}{\mu}\right)^2\frac{1}{3^2} + \ldots] = 1 \tag{10}$$

The geometric series introduces the sum of the series and is convergent.

$$P_0 + P_0\frac{\lambda}{\mu} + P_0\left(\frac{\lambda}{\mu}\right)^2\frac{1}{2!} + P_0\left(\frac{\lambda}{\mu}\right)^3\frac{1}{3!}\frac{3\mu}{3\mu - \lambda} = 1 \tag{11}$$

The probability that there are no patients is in the ED is:

$$P_0 = \frac{1}{1 + \frac{\lambda}{\mu} + \frac{1}{2}\left(\frac{\lambda}{\mu}\right)^2 + \frac{1}{6}\left(\frac{\lambda}{\mu}\right)^3 \frac{3\mu}{3\mu - \lambda}} \tag{12}$$

With regard to ED, based on data from a single year, the probability that there are no patients at the Ed, no queues is:

$P_0 = 0.045$

When three or more patients are currently in the system, a new model patient joining the M/M/3 queue must precisely queue for service. In our relation, using Erlang's C formula, we obtain:

$$C\left(3, \frac{\lambda}{\mu}\right) = \sum_{k=3}^{\infty} P_k = 1 - \sum_{k=0}^{2} P_k \tag{13}$$

$$= P_0 \frac{1}{3!}\left(\frac{\lambda}{\mu}\right)^3 \frac{3\mu}{3\mu - \lambda} \tag{14}$$

Introducing in the model of relation (14) the data we obtain:

$$C\left(3, \frac{\lambda}{\mu}\right) = 0.064$$

With regard to M/M/3, the queue's length is

$$L_q = P_0 \frac{1}{3!}\left(\frac{\lambda}{\mu}\right)^3 \sum_{k=1}^{\infty} k\left(\frac{\lambda}{3\mu}\right)^k \tag{15}$$

When we compute the series' sum, we get:

$$L_q = P_0 \frac{1}{3!}\left(\frac{\lambda}{\mu}\right)^3 \frac{3\lambda\mu}{(3\mu - \lambda)^2} \tag{16}$$

And using relation (14) we have:

$$L_q = \frac{\frac{\lambda}{3\mu}}{1 - \frac{\lambda}{3\mu}} C\left(3, \frac{\lambda}{\mu}\right) \tag{17}$$

The average number of patients in the ED waiting queue in steady state is , consequently, there is a good chance that a newcomer will have to wait in line.

We are currently interested about the queue's waiting time. The mean waiting time in the queue can be found using little's Law by:

$$W_q = \frac{L_q}{\lambda} \tag{18}$$

From equation (17) we have:

$$W_q = \frac{1}{3\mu - \lambda} C\left(3, \frac{\lambda}{\mu}\right) \tag{19}$$

The average wait time at the ED i.e. $W_q = 0.064$ hours, it means 3.840 minutes. The typical duration of each patient's therapy, it is denoted by is W_t is $W_t = \frac{1}{\mu}$ thus $W_t = 1/2 = 0.5$ hours (30 minutes).

As a result, the system's overall waiting time may be found at $W = W_q + W_t$. Introducing the data we obtain hour (33.6 minutes).
The mean overall count of patients in the emergency department is $L = W\lambda$. According to the data, the total number of patients in the ED will be $L = 2.80$.

4. CONCLUSIONS

At this paper study, the patient flow at the emergency department located in Bareilly city (District Hospital) India, is characterized using the M/M/3 queuing model.
Total registration card 48.218 or the total number of patients aided and treated in the ED in 2022, were used to establish a database. The research provides an example of how decision makers might utilize data analysis and queuing models to identify the best course of action. We took into consideration in the case study that the quantity of beds and human resources are equal. We plan to expand the research in future studies to include scenarios in which the number of physicians is not the sole factor influencing the waiting time. Experience demonstrates that most of the time, doctors can see more than one patient in a 20-minute period. Determining the best possible distribution of resources, including the number of doctors and beds, in the ED based on demand is crucial to ensuring that patients have the best possible wait times. When planning capacity, the queuing model is a helpful tool. A computer simulation can be used to carry out the planning activity. Figure 1 demonstrates the requirement for a dynamic medical staff allocation.
Nonetheless, as several years of experience have shown, models may be incredibly helpful in offering decision assistance in intricate settings like the ED. This study offers assistance to ED managers by demonstrating how to use the model as a helpful tool for decision-making in ED management. By illustrating how to use the model as a useful tool for decision-making in ED management, this study helps ED managers. It is critical to identify strategies for enhancing performance using the available resources in light of the present financial restrictions.

CONFLICT OF INTERESTS

None

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