

Intelligent Patient Prioritization: A Dynamic Approach for Military OPDs

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Abstract

The Indian military healthcare framework serves a vital role in providing medical care to active-duty personnel, veterans, and their families. Despite an extensive network of specialized facilities, these systems often struggle with inefficiencies in patient flow, especially in Outpatient Departments (OPDs). Traditional queue management methods, such as first-come-first-serve and token systems, lack the sophistication to address critical factors like patient urgency, workload distribution, and real-time changes in doctor availability. Consequently, patients experience prolonged delays, and healthcare resources are underutilized.

This research proposes an innovative dynamic queuing algorithm designed to streamline patient management in military OPDs. The model incorporates three key elements: Weighted Round Robin (WRR) scheduling to allocate patients based on predefined priorities, a Tribonacci sequence-based aging mechanism to dynamically enhance priority for waiting patients, and a real-time load-balancing system that optimizes the allocation of medical resources. A simulated evaluation of the proposed system demonstrated significant improvements, including reduced waiting times and evenly distributed workloads, underscoring its potential to enhance both patient satisfaction and hospital efficiency.

By replacing static methodologies with a dynamic, adaptive framework, this approach offers a scalable solution tailored to the demands of high-pressure healthcare settings like military hospitals. Furthermore, its multi-faceted design makes it an ideal candidate for deployment in other complex healthcare environments requiring efficient resource allocation and responsive patient management.

Keywords: Dynamic Queue Management, Patient Flow Optimization, Stable Matching Algorithm, Dynamic Resource Allocation

Introduction

The Indian military healthcare system plays a crucial role in safeguarding the health and well-being of those who serve in the military, including active personnel, retired veterans, and their dependents. This extensive network of hospitals and medical facilities spans across all branches of the armed forces—Army, Navy, and Air Force—providing specialized medical care. Despite its broad reach, the system faces challenges, particularly within Outpatient Departments (OPDs), which handle a substantial volume of daily visits. This workload tends to spike during health crises, such as pandemics.

Managing patient flow effectively remains a persistent challenge for military hospitals. Traditional queuing strategies, such as the first-come, first-served and token-based systems, fall short of handling the complexity of patient prioritization, doctor efficiency, and real-time workload adjustments. These methods

often lead to inefficiencies like extended waiting periods, uneven workload distribution among medical personnel, and suboptimal resource use. The manual system's inability to adapt to changing patient demands and the urgency of medical needs further exacerbates these issues.

There is an urgent need for improved queue management solutions in military hospital OPDs. A dynamic queuing algorithm that can adapt to real-time data—such as patient arrivals, doctor availability, and consultation times—could significantly enhance patient flow, reduce waiting times, and improve overall system efficiency. By implementing a flexible queuing approach, military hospitals can better address the needs of their beneficiaries, thereby enhancing both operational outcomes and patient satisfaction.

Traditional Token Management System at OPD

In the conventional outpatient department (OPD) process, patient queue management and doctor assignments are primarily conducted using a token-based system. Once patients complete their registration, they receive tokens that determine their turn for consultation. These tokens are distributed on a first-come, first-served basis, creating a linear queue. However, this approach is prone to inefficiencies, especially during peak hours or when patients are unevenly distributed across different departments or doctors. The manual allocation process can further exacerbate delays, as there is no mechanism to dynamically balance workloads among available physicians.

Several strategies have been employed in some hospitals to improve queuing efficiency. These include time-window-based allocation, round-robin scheduling, and shortest-queue-first mechanisms. In the time-window distribution approach, patients are assigned consultation slots at specific time intervals. The round-robin method cyclically allocates patients to available doctors, aiming to distribute workloads equitably without considering the efficiency of medical practitioners or the military seniority of patients. The shortest-queue-first strategy directs patients to doctors with the fewest patients in their queue, optimizing resource use but neglecting real-time changes in doctor performance metrics.

Despite these techniques, the manual nature of these processes introduces limitations such as errors in queue tracking, a lack of adaptability to real-time changes, and dissatisfaction among patients due to perceived delays or unfairness. These shortcomings highlight the need for a more systematic and automated queue management system that can enhance the overall efficiency and fairness of doctor allocation in OPDs.

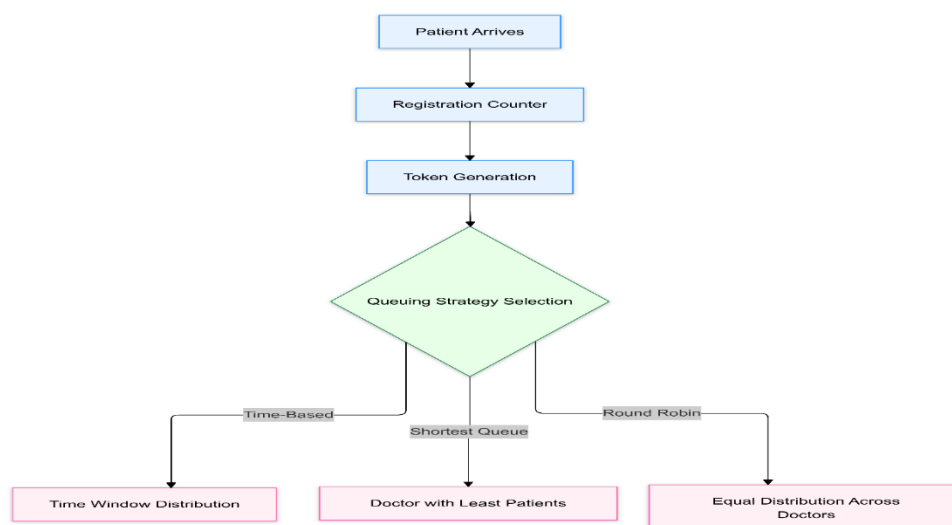


Figure 1: Traditional Token Management at OPD

Waiting time at OPD consultation

In military hospitals' Outpatient Departments (OPDs), consultation waiting times have been notably high. For instance, the average waiting time for consultation at Command Hospital (Army) in Chandimandir was reported to be around 35 minutes [1]. At a tertiary care teaching hospital in Uttarakhand, patients spent an average of 50 minutes and 43 seconds waiting for consultation [3]. These examples highlight the extended waiting times prevalent in OPDs that rely on straightforward token management systems for doctor allocation.

Related Work

Marc Lester Z. Mallari et al. developed a web-based queue management system specifically designed for the Registrar's Office of a university. The system enables real-time tracking of queues and provides timely notifications to staff members in the operational area. Clients visiting the office can also monitor their relative position in the queue through any device that supports web browsing. The queue management system enhances productivity by ensuring that staff are promptly notified and are able to track real-time client activity [4].

Md. Nasir Uddin et al. uses a microprocessor, buzzer and an LCD display to implement a queue management system using both First Come First Serve and Shortest Job First and conducts a comparative analysis of the two methods to compare the respective waiting times [5].

Neha Titarmare et al. presented a survey on patient queue management systems highlighting the methods for optimizing patient flow in healthcare facilities. The study emphasizes the necessity of reducing waiting times through effective queue management, utilizing GSM devices and Android applications for appointment scheduling and notifications. The proposed model features a token-based system, enabling patients to register via missed calls and receive appointment details through SMS, thereby improving convenience and accessibility [6].

V. Rema et al. conducted a comprehensive analysis of patient flow and the impact of technology on queue management in the OPD. The research involved collecting data through surveys and recording patient arrival, service, and departure times using a single-server queuing framework. To further analyze queuing patterns and key performance metrics, a Monte Carlo simulation with 1,000 iterations was performed. The findings indicated an average waiting time of 65 minutes in the queue, with an overall average waiting time in the system of 74.3 minutes. These results underscore the necessity for enhancements in the management of patient queues to improve overall efficiency and patient satisfaction [7].

Sabin TT et al. presented a comprehensive framework for queue management that facilitates online appointment bookings, thereby minimizing wait times and optimizing service flow. This system encompasses features such as organizational registration, service publication, token generation, and real-time management of scheduling slots. Tokens are given on a first come first serve basis and in case the token is not utilized during the scheduled time, the resource is released after a waiting period. To enhance security, the system incorporates one-time password (OTP) verification and reCAPTCHA protocols. Additionally, integration with Internet of Things (IoT) devices and smartphones allows users to monitor queue statuses remotely [8].

Knowledge Gaps in Existing Systems

Many existing queue management systems are based on relatively static frameworks, such as First Come First Serve (FCFS) or token-based scheduling. These methods often cater to specific contexts, such as

university registrars or appointment booking, but lack flexibility in response to real-time changes in patient arrivals, doctor availability, or consultation durations. This static nature limits their applicability in dynamic environments requiring continuous adjustments to resource allocation and workload distribution. Moreover, traditional queue management techniques like FCFS and Shortest Job First provide a basic framework but fail to account for real-time queue dynamics. These limitations restrict their effectiveness in environments that require ongoing modifications to resource distribution and patient prioritization. Additionally, these methods do not emphasize fairness in patient allocation or the simultaneous optimization of multiple performance metrics, such as minimizing waiting times while balancing workloads among healthcare providers

Overview of Queuing Models

Queuing models serve as analytical tools designed to evaluate systems where entities—such as patients, customers, or data packets—await service from one or more servers. These models typically define two key parameters: the arrival rate (λ), which measures how frequently entities arrive at the system, and the service rate (μ), representing the efficiency with which servers process these entities. Queuing models are commonly classified using Kendall notation ($A/B/c$), where A represents the nature of the arrival process, B denotes the service process characteristics, and c indicates the number of servers. For example, an $M/M/1$ model assumes a Poisson distribution for arrivals (M), an exponential distribution for service times (M), and a single server (1). Such models are instrumental in determining key performance metrics, including average waiting time, system utilization, and queue length.

These traditional queuing models find application in various domains, including telecommunications, customer service, and healthcare. In the healthcare sector, they are used to optimize patient flow, aiming to minimize wait times and achieve a balanced workload distribution among doctors. However, these models have inherent limitations, as they rely on stationary assumptions and may not adapt well to real-time changes. They struggle to incorporate dynamic factors such as doctor efficiency and patient priority, making them less suitable for handling variability in patient demand and resource availability

Stable Matching Algorithm

The Stable Matching Algorithm, introduced by David Gale and Lloyd Shapley, aims to find a stable pairing between two sets of participants. In the context of healthcare, it can effectively match patients with doctors to ensure optimal and mutually satisfactory pairings.

- Let $P = \{P_1, P_2, \dots, P_m\}$ represent the set of patients.
- Let $D = \{D_1, D_2, \dots, D_n\}$ represent the set of doctors.

A stable match is defined as a set of pairs $M = \{(P_i, D_j) \mid P_i \in P, D_j \in D\}$ such that no patient and doctor not belonging to the same matched pair would prefer each other over their current match. This ensures that:

- No patient would prefer a different doctor who also prefers that patient over their current match.
- No doctor would prefer a different patient who also prefers that doctor over their current match.

The Stable Matching Algorithm (SMA) provides a structured approach to pairing patients and doctors, but its application in military outpatient departments (OPDs) reveals several limitations, including neutral doctor preferences, a static preference framework, potential starvation of lower-priority patients, and an inability to dynamically balance workloads among doctors. To address these challenges, a dynamic queuing algorithm is proposed, which prioritizes patients based on rank or urgency and adapts to varying consultation speeds. This algorithm incorporates modules such as Weighted Round Robin (WRR) to

assign patients based on predefined weights favoring higher-priority individuals, Dynamic Load Balancing to ensure equitable workload distribution, and a Tribonacci-Based Aging Mechanism to adjust patient priorities dynamically based on waiting times. The algorithm proceeds through steps that include initial patient assignment using WRR based on priority and workload balance, management of individual doctor queues to enhance patient satisfaction, and the aging mechanism to ensure longer-wait patients receive higher priority, ultimately ensuring fair patient flow and efficient resource utilization.

Proposed Dynamic Queuing Algorithm

Managing patient queues in military OPDs poses unique challenges due to the need for prioritization by rank (e.g., officers and airmen) and the varying speeds of doctors’ consultations. The queuing system should:

- Prioritize patients based on rank or urgency.
- Balance waiting times to prevent delays.
- Dynamically adapt to doctors’ performance.

This methodology proposes a flexible queuing algorithm that ensures fair patient flow and efficient resource utilization by incorporating the following modules:-

- Weighted Round Robin (WRR). WRR assigns patients to doctors based on predefined weights. Higher-priority patients (e.g., officers) receive greater weights, allowing their earlier allocation in a cyclic manner.
- Dynamic Load Balancing. Dynamic Load Balancing ensures equitable workload distribution by adjusting patient assignments based on real-time doctor performance, queue lengths, and patient priorities.
- Tribonacci-Based Aging Mechanism. The Tribonacci Sequence is used to dynamically adjust patient priorities based on their waiting time. It is based on the Fibonacci sequence, however it provides a better delay factor, as can be seen from Fig 2. The Tribonacci sequence follows the formula:

$$T_n = T_{n-1} + T_{n-2} + T_{n-3}$$

Where $T_0=0$, $T_1=1$, and $T_2=1$. This sequence is used to adjust a patient’s priority, where the waiting time affects the patient's priority according to the progression of the Tribonacci sequence. The longer a patient waits, the higher their priority becomes, ensuring they are not overlooked indefinitely.

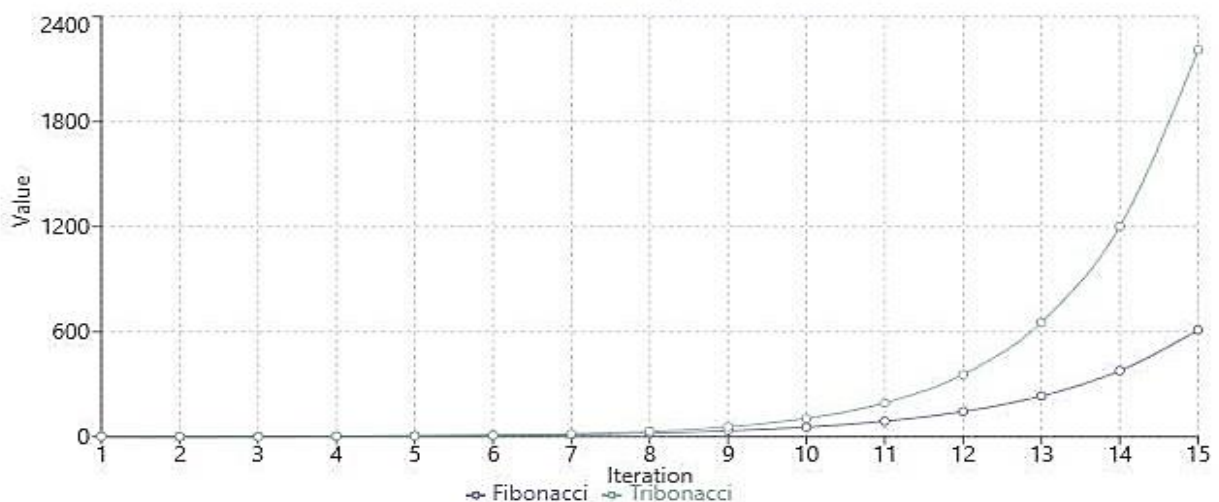


Figure 1: Comparison of Fibonacci and Tribonacci Sequences

Steps of the Algorithm

The detailed working of the Dynamic Queuing Algorithm are brought out in the following steps:-

1. Step 1 - Initial Assignment Using Weighted Round Robin (WRR). When patients arrive, they are assigned to doctors based on priority and workload balance. Officers are given Priority 2 and are assigned first, followed by airmen, who have Priority 1. Doctors with the lowest current workload are chosen to ensure a balanced distribution of patients during initial assignments.
2. Step 2 - Individual Doctor Queues. In the queue management system, each doctor maintains a separate queue, ensuring organized patient flow. To enhance transparency and satisfaction, patients are immediately informed of their assigned doctor through their mobile phones.
3. Step 3 - Aging Mechanism for Effective Priority. Tribonacci-Based Aging is used to increase patient priority dynamically over time using the Tribonacci sequence:

$$\text{Effective Priority} = \text{Base Priority} + T_{\text{waiting time}}$$

Where $T_{\text{waiting time}}$ is calculated based on the Tribonacci progression. For example, after 3 time units, the priority increment is $T_3=4$, boosting waiting patients' priority.

4. Step 4 - Periodic Performance Monitoring and Reallocation. The system operates with fixed monitoring intervals every five minutes, during which performance metrics like average consultation time per doctor, queue lengths, and patient waiting times are evaluated. Based on this assessment, patients who have not yet entered consultation may be reassigned considering their effective priority (determined using a Tribonacci-based approach) and the workload and performance of doctors. However, patients already in consultation are not reassigned, and reassignments are minimized to reduce potential confusion.
5. Step 5 - Dynamic Load Balancing. To ensure balanced workloads, maximum queue lengths are enforced to prevent overloading faster doctors, while patients are assigned to slower doctors when their queues are shorter, as long as waiting times remain within acceptable limits

Results and Analysis

A scenario of three doctors and six patient was simulated in python using the proposed algorithm. The system adjusts patient priorities as they move through different doctors, allowing for flexible resource allocation based on factors such as arrival times and assigned priority levels. For instance, patients initially given a lower priority can have their status elevated based on their waiting time and order of arrival. This dynamic approach ensures efficient patient flow through different doctors, optimizing waiting times to prioritize those with urgent needs. By enhancing patient throughput and reducing overall waiting times, this system could significantly improve the efficiency of the hospital's outpatient department (OPD) and overall patient care. The results of the simulation are appended below:-

```
PS C:\Users\Owner\projects\dynamic queue> & C:/Users/Owner/AppData/Local/Programs/Python/Python312/python.exe "c:/Users/Owner/projects/dynamic queue/script.py"
Doctor Patient Processing:
Dr. A Results:
P1: Priority: 2->2, Arrival: 0, Waiting Time: 0, Start: 0, End: 5
P5: Priority: 1->2, Arrival: 3, Waiting Time: 8, Start: 11, End: 16
Dr. B Results:
P3: Priority: 2->3, Arrival: 2, Waiting Time: 3, Start: 5, End: 8
P6: Priority: 1->4, Arrival: 4, Waiting Time: 12, Start: 16, End: 19
Dr. C Results:
P2: Priority: 1->2, Arrival: 1, Waiting Time: 7, Start: 8, End: 10
P4: Priority: 1->4, Arrival: 5, Waiting Time: 14, Start: 19, End: 21
Patient Priority Evolution:
P1 (Officer):
Initial Rank Priority: 2
Priority Changes:
- Time 0: 2 (Initial)
```

Figure 3: Dynamic Queue Implementation

```
P2 (Airman):
Initial Rank Priority: 1
Priority Changes:
- Time 0: 1 (Initial)
- Time 8: 2 (Tribonacci(wait=2))

P3 (Officer):
Initial Rank Priority: 2
Priority Changes:
- Time 0: 2 (Initial)
- Time 5: 3 (Tribonacci(wait=1))

P4 (Airman):
Initial Rank Priority: 1
Priority Changes:
- Time 0: 1 (Initial)
- Time 19: 4 (Tribonacci(wait=4))

P5 (Airman):
Initial Rank Priority: 1
Priority Changes:
- Time 0: 1 (Initial)
- Time 11: 2 (Tribonacci(wait=2))

P6 (Airman):
Initial Rank Priority: 1
Priority Changes:
- Time 0: 1 (Initial)
- Time 16: 4 (Tribonacci(wait=4))
PS C:\Users\Owner\projects\dynamic queue> |
```

Activate Windows
Go to Settings to activate Windows.

Figure 4: Dynamic Queue Implementation

Conclusion

Efficient patient flow management in military healthcare facilities is vital to ensuring timely, equitable medical care while maintaining operational efficiency. This study identifies critical limitations in traditional queuing systems, including their static nature and inability to account for real-time patient demands, doctor availability, and priority-based needs. To address these challenges, this research builds upon foundational concepts from stable matching algorithms and queuing models, introducing a novel dynamic queuing algorithm tailored to the complexities of military OPDs.

The Stable Matching Algorithm (SMA), while effective in creating stable pairings in static environments, lacks the flexibility to handle real-time variability in healthcare settings. This study adapts key principles from SMA—such as optimal pairings—while incorporating dynamic reassignment mechanisms to address bottlenecks and workload imbalances.

The proposed algorithm combines Weighted Round Robin scheduling for rank-based prioritization, a Tribonacci-based aging mechanism to ensure fairness over time, and periodic performance monitoring for dynamic load balancing. Simulation results demonstrate significant improvements, including reduced waiting times, balanced workloads, and enhanced patient satisfaction. By dynamically adjusting patient-doctor assignments and prioritizing fairness, the algorithm resolves critical inefficiencies of traditional systems and addresses the unique demands of military healthcare facilities.

Future research can explore scaling this approach to multi-department hospital settings, incorporating additional patient attributes like medical urgency, and leveraging advanced predictive analytics for further optimization. By building upon stable matching frameworks and extending traditional queuing models into adaptive, real-time systems, this research provides a transformative solution for military OPDs and offers a blueprint for broader applications in complex healthcare environments.

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