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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 and 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.

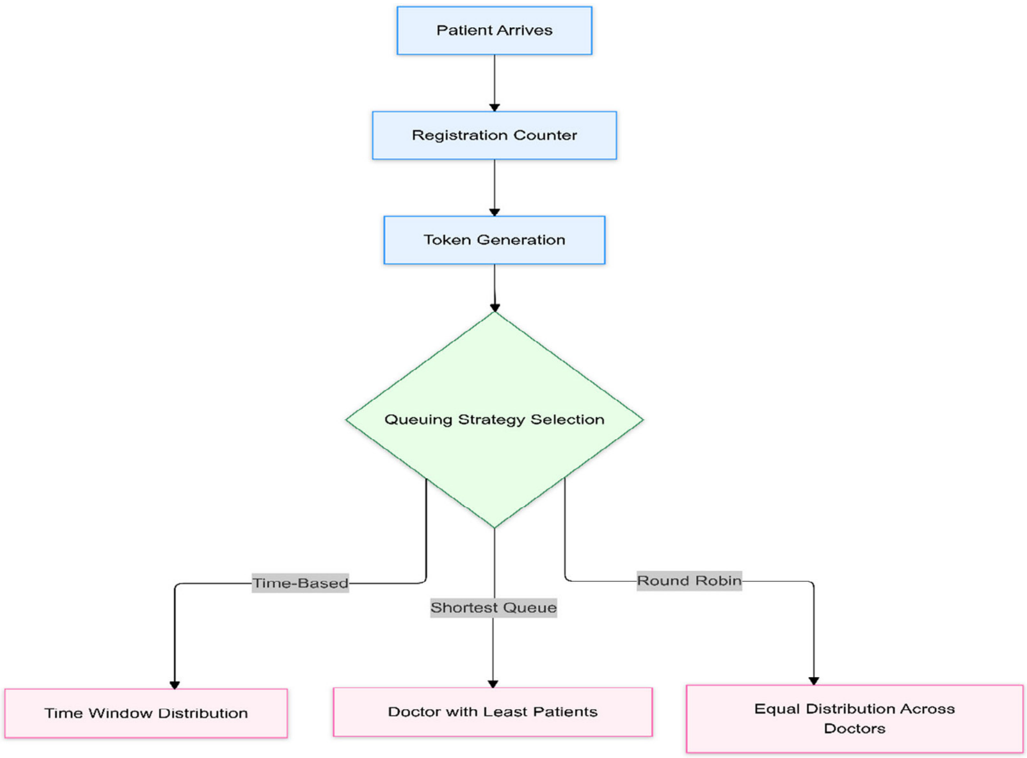


Figure 1: Traditional Token Management at OPD

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, 2]. 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.

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

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.

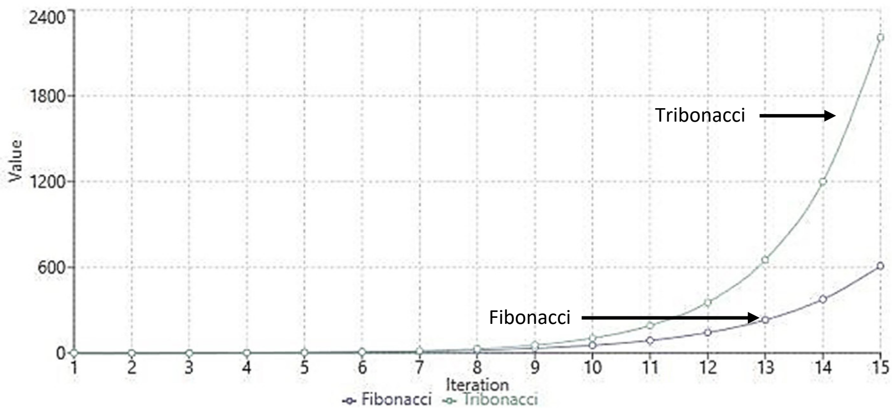


Figure 2: Comparison of Fibonacci and Tribonacci Sequences

Steps of the Algorithm

Step 1: Initial Assignment Using Weighted Round Robin (WRR)

- Patient Assignment: Upon arrival, patients are assigned to doctors based on priority and workload balance.
- Priority Weights: Officers (Priority 2) are assigned first, followed by airmen (Priority 1).
- Load Balancing: Doctors with the lowest workload are selected to ensure balanced initial assignments.

Step 2: Individual Doctor Queues

- Queue Management: Each doctor maintains a separate queue.
- Patient Satisfaction: Patients are immediately informed of their assigned doctor through their mobile phones, enhancing transparency and satisfaction.

Step 3: Aging Mechanism for Effective Priority

- Tribonacci-Based Aging: Patient priority increases dynamically over time using the Tribonacci sequence: Effective Priority= Base Priority+ Twaiting time Where Twaiting time adjusts based on the Tribonacci progression [4].
- Base Priority: Officers start with a priority of 2, airmen with 1.

• Example: After 3-time units, the priority increment is T3=4, boosting waiting patients' priority.

Step 4: Periodic Performance Monitoring and Reallocation

• Monitoring Interval: Reassessment occurs at fixed intervals (e.g., every 5 minutes).

• Performance Metrics:

➢ Average consultation time per doctor.

➢ Queue lengths and patient waiting times.

• Reassignment: Patients not yet in consultation may be reassigned based on:

➢ Effective priority (Tribonacci-based).

➢ Doctor's workload and performance.

• Constraints:

➢ No reassignment for patients already in consultation.

➢ Reassignments are minimized to reduce confusion.

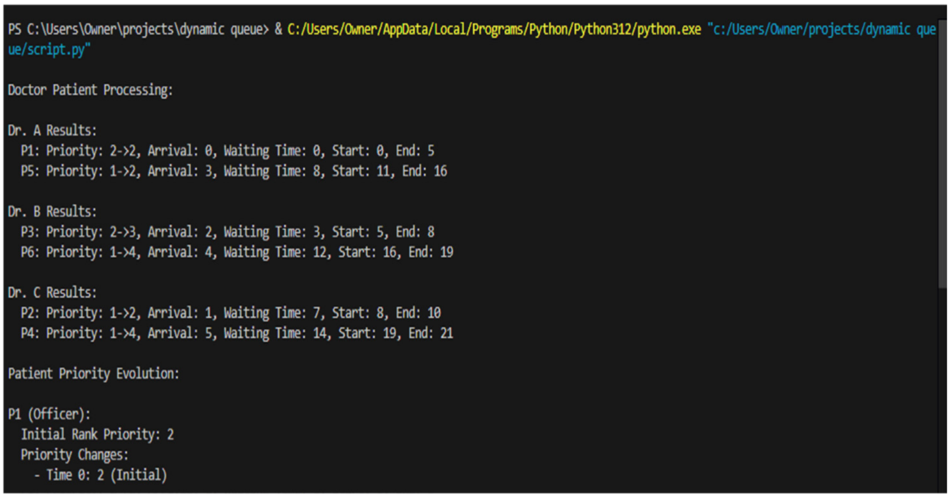
Step 5: Dynamic Load Balancing

• Faster Doctors: Maximum queue lengths are enforced to prevent overloading faster doctors.

• Slower Doctors: Patients are assigned to slower doctors when queues are shorter, provided waiting times remain within acceptable limits.

Results and Analysis

A scenario of three doctors and six patients 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 [5-8]. 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: -



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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

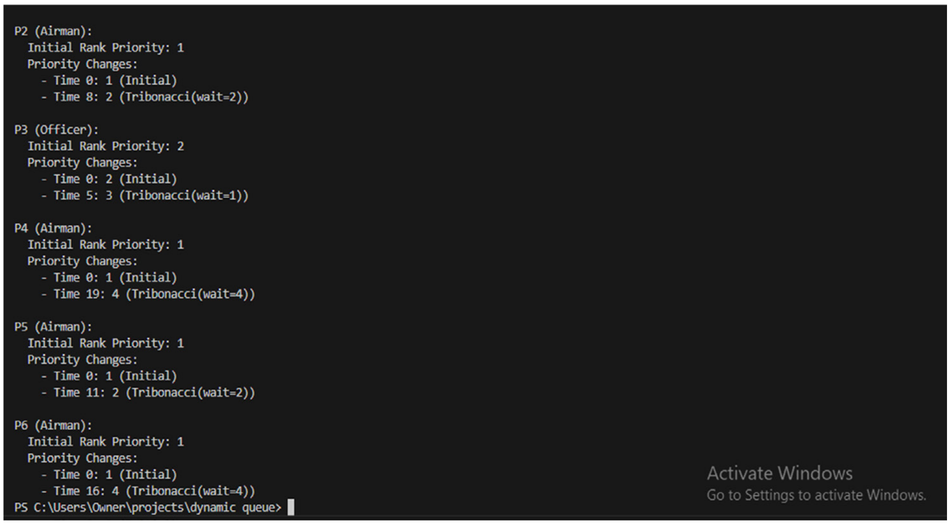
Dr. B Results:
  P3: Priority: 2->3, Arrival: 2, Waiting Time: 3, Start: 5, End: 8
  P6: Priority: 1->4, Arrival: 4, Waiting Time: 12, Start: 16, End: 19

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



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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>
```


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 [9-14]. 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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