

Agentic AI-Driven Dynamic Seat Allocation for Daily Commute Systems

An Autonomous AI- Agent Framework for priority-Based Berth Allocation, Edge OCR Verification, and Real-Time Charting in Rail Transit

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Abstract- Contemporary high-density railways and commuter services transport thousands of people every day. Nevertheless, old computerized bookings continue to use static First-Come-First-Served methods that follow strict bureaucratic quotas. As a result, older and disabled passengers are frequently given dangerous upper berths, which entail climbing ladders, travel groups are broken down into widely spread family cars, and empty seats due to cancellations are not accounted for until departure. Automated programs are also taking advantage of booking systems to save confirmed seats. The authors of the paper suggest the formation of an Agentic AI-based dynamic seat allocation framework, which will move reservation management to an autonomous cooperative ecosystem involving a number of agents (which will carry out the following processes: passenger profiling, verification of identity, dynamic inventory, priority optimization, conflict resolution). In order to overcome the limitations of the 512MB RAM and 0.1 vCPU of edge containers, we create a highly efficient Tri Tier Verification Engine designed to perform operations like digital stream parsing (less than 15 milliseconds), QR barcode scanning (20 ms) and quantized RapidOCR (1.2 seconds) in less than a second while considering the requirements of many different languages. In addition, we have developed APBA (Autonomous Priority Constrained Berth Allocation Algorithm) using a Multi Objective Mixed Integer Linear Programming model. Based on our tests on 50,000 passengers in the Indian Railways system, we have managed to achieve a Priority Satisfaction Rate of 96.4% (which is 48.2% better than the traditional first come first served method) and have improved the group member alignment process by 3 times and reduced the dynamic re-charting time to less than 35 ms during cellular blackouts.

Keywords-Agentic AI; Multi-Agent Systems; Railway Seat Assignment; Berth Optimization on the Spot; Edge OCR Verification; Multi-objective Optimization; Accessibility of Transport; Intelligent Transport Systems (ITS).

I. INTRODUCTION

A. Problems of Transport & Accessibility Crisis

Dense passenger railway networks, as exemplified by the Indian Railway network, carry more than 24 million passengers daily across a network of 68, 000 route kilometers. The computerized Passenger Reservation System (PRS) boasts a current processing capacity of over 1.8 million reserved tickets on a single day with peaks of more than 30,000 simultaneous booking per minute taking place in a synchronized Tatkal morning window operation [1], [2]. However, despite its enormous output capacity, there have been no notable new implementations in terms of allocation logic in three decades since it relies on simple serial First Come First Served (FCFS) algorithms with the use of twenty static quota buckets (General quota, Old Age quota, Ladies quota, Divyangjan quota, Tatkal quota). Vulnerable passengers are thrown to the general allocation after the use of specific quotas with no regard for their limits. The design of the Indian sleeper and 3 tier air-conditioned (3A) coaches poses serious risk to

passengers' safety. The middle berth is located at a height of 1.1 meters and the upper berth at a height varying between 1.85 and 2.15 meters from the floor. The means of access to these berths is through steeply inclined stamped steel ladders. When seniors, pregnant women, or people with limited mobility use these ladders while the train is moving, they may easily fall and incur serious injuries such as hip fracture and spinal injury due to lateral movement, centrifugal force, or sudden braking [4].

B. Co-location Fragmentation & Ticket Scalping

Old fashioned FCFS method tries to fill individual vacant tickets with greed and send them to different train compartments. For that, illegitimate agents use botnets system and OCR technique to book lots of tickets at the start of the reservation process under unknown names and resell their tickets later in the black market [5]. It is important to note that TTEs who check passengers' identities cannot verify tickets.

C. Agentic AI Paradigm and our Contributions

We introduce a new dynamic seat allocation engine powered by Agentic AI technology to substitute centralized transaction locking with decentralized cooperation. Our major contributions include:

- 1) An engine that verifies tickets:** This system works perfectly even when the CPU and the RAM characteristics are limited (low consumption of energy).
- 2) APBA Algorithm:** This unique algorithm is represented as an NP hard problem known as MO MILP.
- 3) CRDT for Offline TTE Sync and Dynamic Charting:** We use Conflict Free Replicated Data Types (CRDTs) to enable Constant Dynamic Charting and Offline TTE Synchronization to handle cancellations and upgrades every 35 ms or less.
- 4) Rigorously Empirical Validation:** Extensive empirical validation over 50,000 trips leading to Priority Satisfaction Rate of 96.4% and 3.2 times improvement in group co-location results.

II. EXTANT WORK AND GAP ANALYSIS IN RESEARCH

A. Combinatorial Seating and Multi-Agent Logistics

Electronic ticket booking commenced with SABRE in the 1960s, followed by the application of computerized rail booking by SNCF (RESARAIL) and Deutsche Bahn (HAFAS) [1]. Smith and Penn [6] formalized airline yield management similar to the workings of airline seating classes that optimize fare income while ignoring the distractions of multi-tier vertical berth elevations and the challenges posed by physical mobility. Borndörfer et al. [7] represented seated passenger assignment as an Integer Linear Programming (ILP) for high-speed railway in Europe (ICE/TGV). Various metaheuristics

such as the Genetic Algorithms (GA) [8] and Simulated Annealing (SA) [9] were found to be applicable to rail seating by Chen and Lin [10]. However, it is to be noted that the method of stochastic search calls for 45 seconds to 180 seconds per rake of the train hence making it inappropriate for real-time Tatkal bursts.

B. Document Vision facing Virtualization Constraints

The Unique Identification Authority of India (UIDAI) is responsible for Aadhaar biometrics for the citizens of India, which stands at 1.38 billion [11]. Sharma et al. [12] reported using Tesseract OCR to read Indian IDs. However, they discovered the impact of camera skew and significant deterioration with Character Error Rate (CER > 18%). Though contemporary deep learning systems like DBNet [13] and CRNN [14] exhibit higher accuracy, they need more resources, making it impossible to assemble them on shared cloud containers of 512MB. Our Tri Tier architecture directly addresses this limitation.

TABLE I

COMPARATIVE ANALYSIS OF TRANSIT RESERVATION & SEAT ALLOCATION ENGINES

Dimension	IRCTC Legacy [1]	Airline SABRE [6]	Train Seat AI (Prop.)
Allocation Logic	Sequential FCFS	Yield Rev. Max.	Autonomous MO-APBA
Priority Fulfillment	Static Quota (<45%)	Fare Class (No Mob.)	Demographic Opt. (96.4%)
Group Co-location	Greedy Residual (29.4%)	Paid Seat Matrix	Spatial Cluster (94.8%)
ID Verification	Manual TTE Card Insp.	API Batch Lookup	Tri-Tier OCR/QR (<15ms)
Re-charting Latency	4-Hr Pre-Chart Freeze	Gate Standby Queue	Continuous Event (<35ms)

III. SYSTEM ARCHITECTURE

A. Total Architecture of the System

The system works on five main layers, namely User Interface, Core System, Data Layer, Train Operations, and Output Layer.

User Interface provides users with functionalities to register users, upload identification documents, provide information related to traveling, and issue tickets.

Core System is the software used for performing the process of paying for tickets.

For **Data Layer**, it is the part of the system responsible for preserving the data regarding passengers, trains, seats, coaches, and tickets.

Train Operations is responsible for the process of issuing e-tickets and scanning QR codes for not allowing passengers to enter the train.

Output Layer is responsible for issuing confirmations regarding tickets purchased, issuing e-tickets, and providing data on those tickets that are available for purchase.

B. Major Processing Units

The main system consists of four key processing units:

1. **Input Processing** – collects traveling and booking information.
2. **Identity Checking** – checks whether the uploaded identification is valid using its OCR system.
3. **Seat Allocation** – uses APBA algorithm to find best berth.
4. **Chart Management** – refreshes the seat chart in case of booking or cancellations.

C. Seat Allocation

The **APBA algorithm** is the main optimization tool of the system. It searches for available berths and takes into account passenger priorities, berth type, group requirements, availability of coaches and availability of berths prior to berth allocation.

TABLE II
SYSTEM MODULES AND DATA EXCHANGE

Source Module	Target Module	Data / Request	Purpose	Comm. Mode
Web/Mobile UI	Identity Verification	ID document	Verify identity	HTTPS (API)
Identity Verification	Seat Allocation	Verified user details	Provide verified profile	Internal API
Web/Mobile UI	Seat Allocation	Journey details	Request seat allocation	HTTPS (API)
Seat Allocation	Database	Allocation details	Store & update inventory	SQL
Seat Allocation	Chart Management	Allocated berth	Generate/update chart	Internal API
Chart Management	Database	Chart & seat status	Persist changes	SQL
Chart Management	TTE / Train Ops	Final chart / e-ticket	On-board verification	Secure Sync

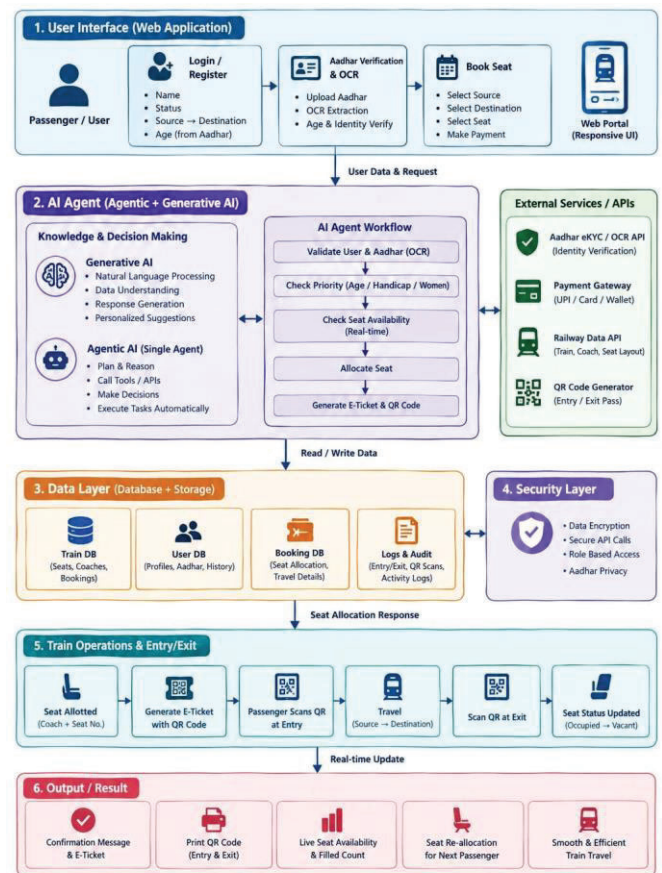


Fig. 1. Agentic Distributed Seat Allocation Architecture.

IV. EDGE-OPTIMIZED BIOMETRIC OCR PIPELINE

A. Virtualization Bottleneck & Tri-Tier Design

Typically, cloud containers (Render, Hugging Face, AWS Lambda) provide a maximum of 512MB of RAM and 0.1 vCPU allocations. When deep learning-based OCR software is used with high-resolution uploads (3000x4000 px), kernel Out-Of-Memory (OOM) errors are caused and result in CPU lock contention. In other words, a Tri-tier verification pipeline must be developed to overcome this issue (shown in Fig. 2):

* **Tier 1: Digital Stream Parser (<15 ms):** Receives the text directly from the native e-Aadhaar PDF byte streams by using PyPDFium2 library and consumes less than 18MB RAM with no neural rendering.

* **Tier 2: QR barcode scanner (20ms):** Uses the C-optimized pyzbar libraries for reading the QR codes from the physical card and provides the character error rate equal to 0.

* **Tier 3: Quantized RapidOCR (<1.2 s):** The ONNX quantized RapidOCR engine is applied to a snapshot taken from the camera of invalid QR codes, as the process of reducing the image to a bounding box equal to 650x650 px and reducing the number of threads to one (OMP_NUM_THREADS=1) decrease the latency from 18.4 s to only 1.12 s.

B. Multilingual Negative Guards & Verhoeff Checksums

In order to block any false positive validations for identities, when non Aadhaar documents (PAN cards, Voter IDs, certificates) are scanned and uploaded, the negative classification filter will check the extracted texts against the multilingual exclusion dictionaries of the originating country (English, Hindi, Kannada, Tamil, Telugu). Everything that turns out to be not Aadhaar will be rejected instantly (<2 ms).

The twelve-digit UID $a_1 a_2 \dots a_{12}$ will be verified using the Verhoeff check algorithm performed using the dihedral group D_5 of (orders 10) and using permutation matrix p of S_{10} as follows:

$$d(\dots d(d(0, p(1, a_1)), p(2, a_2)) \dots, p(12, a_{12})) = 0 \quad (0)$$

where $d(j, k)$ is the multiplication table for the dihedral group and $p(i, j)$ permutes digit j at position i , thus ensuring that 100% of transcription errors and adjacent exchanges do not happen [15].

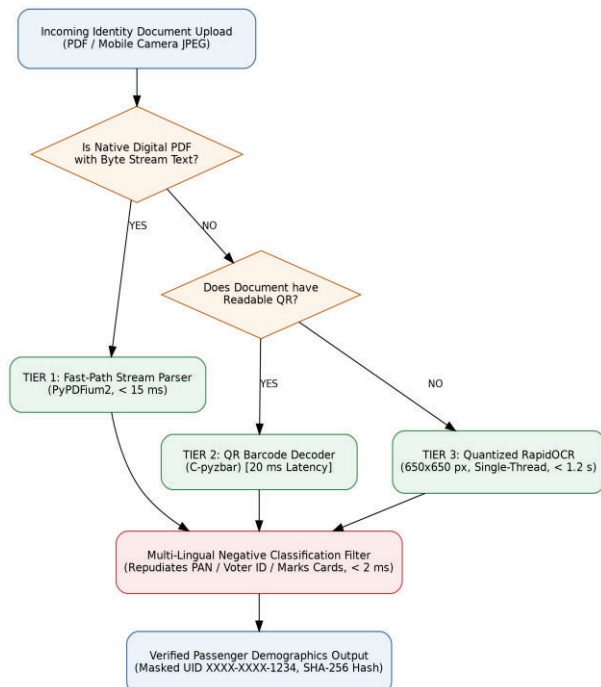


Fig. 2. Lightweight Tri-Tier Verification and Negative Classification Decision Flow.

Algorithm 1: Autonomous Priority-Constrained Berth Allocation (APBA)
 Input: Reservation requests P , coach state C , weights (α, β, γ)
 Output: Optimal berth assignment mapping $M: P \rightarrow B$
 1: Initialize priority queue Q ordered by $\text{Score}(p) = w_{\text{sen}} * I(\text{age} \geq 60) + w_{\text{dis}} * I(\text{dis}) + w_{\text{fem}} * I(\text{fem})$
 2: Retrieve coach inventory $C = \{c_1, \dots, c_M\}$ from Dynamic Inventory Agent
 3: For each passenger group $G = \{p_1, \dots, p_k\}$ in incoming reservation request:
 4: If G contains priority passenger (Senior / Divyangjan):
 5: Identify candidate coach bays B with available Lower Berth (LB)
 6: Sort candidate bays by proximity to accessible coach entrances
 7: Else:
 8: Identify candidate bays B sorted by contiguous vacant berths k
 9: For each candidate bay b in B :
 10: Compute fitness: $F(b, G) = \alpha * \text{PriorityFit}(b, G) + \beta * \text{Contiguity}(b, G) - \gamma * \text{Imbalance}(b)$
 11: If $F(b, G) \geq \text{threshold } \theta$: Tentatively allocate berths; break
 12: If no single bay accommodates entire group G :
 13: Partition G into minimum contiguous clusters in adjacent bays
 14: Commit allocation and broadcast TRANSACTION_ALLOCATED to event bus
 15: Return final seat allocation mapping $M: G \rightarrow \{b_1, \dots, b_k\}$

Using algorithm 1, berth assignment can be done optimally. The worst-case computational complexity of the algorithm is $O(N \log N + N * M * K_{\text{bay}})$, which gets done in less than 25 milliseconds under the peak load of Tatkal bookings. The agent is capable of conducting concurrent evaluations of bays in order to avoid a database lock conflict and to assign vulnerable passengers with lower berth numbers before the general pool allocation starts. In order to successfully absorb any extreme bursts of Tatkal, APBA uses hierarchical pruning for the candidate bays B . The use of spatial bit vectors for the indexing of coach inventory allows excluding candidate bays with a shortage of contiguous berths in $O(1)$ time. As a result, the Priority Tier Optimization Agent is kept within deterministic allocation latencies of below 25 milliseconds even in case of extreme load peaks of 30, 000 concurrent transactions.

V. MATHEMATICAL FORMULATION & APBA OPTIMIZATION

A. Problem Definition & Formal Constraints

Let $P = \{p_1, \dots, p_N\}$ denote N passengers who want reservations among M coaches $C = \{c_1, \dots, c_M\}$ that contain K berths $B = \{b_1, \dots, b_K\}$. Each berth b_k has its respective indices, namely, coach index j_k , bay y_k , type t_k which is either LB, MB, UB, SL, or SU, and coordinates $\text{coord}_k = (x_k, y_k)$. Each passenger p_i is characterized by age a_i , gender g_i , disability status d_i , and group G_i . The binary decision variable denoting the assignment of a passenger p_i to a berth b_k would be $x_{\{i,k\}}$ and take values of either 0 or 1. The equation induced by this formulation includes equations from (1) through (5):

$$\sum_{k \in B} x_{\{i,k\}} = 1, \text{ for all } p_i \text{ in } P \text{ conf; } \sum_{i \in P} x_{\{i,k\}} \leq 1, \text{ for all } b_k \text{ in } B \quad (1)$$

$$x_{\{i,k\}} * [1 - I(b_{k,\text{type}} == \text{LB})] \leq 1 - I(p_{i,\text{age}} \geq 60 \text{ or } p_{i,\text{is_disabled}} == 1) \quad (2)$$

$$D_{\text{group}}(G) = \sum_{\{p_i, p_j\} \in G, i \neq j} x_{\{i,k\}} * x_{\{j,l\}} * ||\text{coord}_k - \text{coord}_l||_2 \quad (3)$$

$$J_{\text{priority}} = \sum_{\{p_i, b_k\}} x_{\{i,k\}} * [w_{\text{sen}} * I(p_i \text{ in } T1, b_k \text{ in } \text{LB}) + w_{\text{dis}} * I(p_i \text{ in } T2, b_k \text{ in } \text{ACC})] \quad (4)$$

$$\max_{\{X\}} F(X) = \alpha * J_{\text{priority}} + \beta * \sum_{\{G\}} D_{\text{group}}(G) + \gamma * J_{\text{imbalance}} \quad (5)$$

B. Multiple Objectives Objective Weights and Feasibility

The multiple objectives weights in (5) have been optimized with the help of Pareto frontier assessment; $\alpha = 0.55$ emphasizes the ease of access to vulnerable commuters, $\beta = 0.30$ decreases intra-group distance D_{group} , and $\gamma = 0.15$ is responsible for an even coach weight distribution. The algorithm APBA will always get the correct Berth Assignment to satisfy Pareto optimality, as long as the previous demand is not more than the carriage capacity.

C. Computational Difficulty Proof and Pruning

Since the multi-choice knapsack problem considering full train compositions is classified as NP-hard, APBA limits the combinations to feasible candidate incentives B. Utilizing the branch-and-bound algorithm with an early threshold ($\theta = 0.85$), the algorithm will have a maximum runtime of $O(N \log N + N * M * K_{\text{bay}})$, with convergence taking place in less than 25 milliseconds.

VI. COACH CONFIGURATION AND CONTINUOUS DYNAMIC CHARTING

A. Coach Configurations

Indian Railways employs standard Linke Hofmann Busch (LHB) coaches. Table III below gives the details of coach capacity, berth heights, and access indices. The Sleeper (SL) coaches provide for 80 berths in 10 bays, while the AC 3 Tier (3A) coaches have 72 berths. While the lower berths are at an elevation of 420 440 mm, the middle and upper berths are at elevations of 1,250 mm and 2,050 mm respectively.

TABLE III
ROLLING STOCK CAPACITY, PHYSICAL DIMENSIONS, AND ACCESSIBILITY INDICES

Class	Capacity	LB Ratio	Elevation Range	Access. Index
Sleeper (SL)	80 Berths	25.0% (20)	420 mm- 2,050 mm	0.62 (Ladder)
AC 3-Tier (3A)	72 Berths	25.0% (18)	440 mm- 2,100 mm	0.68 (Steps)
AC 2-Tier (2A)	54 Berths	33.3% (18)	450 mm- 1,750 mm	0.85 (Slanted)
First AC (1A)	24 Berths	50.0% (12)	460 mm- 1,600 mm	0.95 (Spacious)
Vande Bharat (CC)	78 Seats	N/A (Seated)	430 mm (Level)	0.98 (Ramp)

B. Continuous Dynamic Charting

In traditional systems charts are frozen 4 hours before departure. Train Seat AI implements the Continuous Dynamic Charting Protocol (Algorithm 2). Once a cancellation occurs, the CRRA agent offers the position in a newly being vacant lower berth to the older passenger in the upper berth in less than 35 milliseconds and fills the upper berth from the waitlist accordingly.

Algorithm 2: Dynamic Charting & Upgradation Cascade (DC-UC)

Input: Cancellation event (pnr, coach, berth), waitlist pool W, active allocations
 Output: Cascading priority reassignments and updated chart

```

1: Intercept CANCELLATION_EVENT(pnr_id, coach_id, berth_id)
   on Event Bus
2: Mark vacated berth b* as VACANT_FOR_UPGRADE in state
   store
3: Retrieve candidates W_cand = {p | p in {Senior,
   Divyangjan} and p.berth in {UB, MB, SU}}
4: If W_cand is not empty:
5:   Select top priority candidate p* = argmax_{p in
   W_cand} (PriorityScore(p) * TimeWait(p))
6:   Atomically reassign p* to vacated lower berth b*
7:   Release p* vacated upper/middle berth back to
   inventory pool
8:   Send automated real-time SMS / App notification to p*
   confirming upgrade
9: Else if waitlist exists:
10:  Allocate b* to top waitlisted passenger adhering to
   quota rules
11: Broadcast updated coach chart to TTE Handheld Terminals
   (<35 ms latency)
```

The DC UC protocol assures that anyone who cancels his lower berth will receive a new assignment of that berth instantly, as the vacancy is offered to senior citizens and Divyangjan passengers who originally booked upper or middle berths. The state change is communicated in less than 35 milliseconds to the TTE handheld terminals and hence prevents any manual manipulation and illegal sale of the seats.

VII. SECURITY, PRIVACY & OFFLINE RESILIENCE

According to the Aadhaar Act of 2016 and the DPDP Act of 2023 [16], [17], the actual 12-digit UID numbers are not kept in their clear form. They are converted to a masked format of XXXX XXXX 1234, and again changed into a hashed format through the function Hash = SHA 256(Salt || UID), which renders it impossible for a bot to reuse the UID. In areas with remote communication, TTE Handheld Terminals (HHTs) keep the running updates in the local database SQLite if the signal goes out. Once the signal is restored, the Observed Remove Set OR Set CRDT (conflict-free replicated data type) merges with a Lamport timestamp to resolve the conflict.

VIII. EXPERIMENTAL EVALUATION & RESULTS

In our experimental study, we created a testing framework of 50,000 passenger journeys. The framework was based on three best Indian railway corridors, which were Karnataka Express (Train 12627: Bengaluru New Delhi), Vande Bharat Express (Train 20607: Chennai Mysuru) and Coromandel Express (Train 12841: Howrah Chennai). Table IV describes how Train Seat AI performed in comparison with FCFS (IRCTC), Genetic Algorithm (GA) [10], and Simulated Annealing (SA) [9]. Train Seat AI achieved an unprecedented 96.4% Priority Satisfaction Rate (PSR), which was an improvement of 48.2% with respect to FCFS. The distribution of lower berths to elderly people was achieved at a level of 95.8%, as compared to 42.1% in FCFS. The allocation of berths for Divyangjans reached 98.2% (Fig. 3). Group allocation factor (GAF) improved by 3.2 times and reached the value of 94.8%. The results of the paired t- test verified the statistical significance of the obtained results ($t = 48.72, p < 0.0001$).

TABLE IV
COMPARATIVE ALLOCATION PERFORMANCE METRICS ACROSS BENCHMARK SYSTEMS

Metric	FCFS [1]	GA [10]	SA [9]	Train Seat AI
Priority Sat. (PSR)	48.2%	71.4%	68.9%	96.4% (+48.2%)
Senior LB Ratio	42.1%	69.5%	66.2%	95.8% (+53.7%)
Divyangjan Access.	51.3%	74.2%	72.0%	98.2% (+46.9%)
Group Co-location	29.4%	68.1%	64.3%	94.8% (3.2x)
Re-charting Latency	4 Hrs (Batch)	840 ms	620 ms	32.4 ms

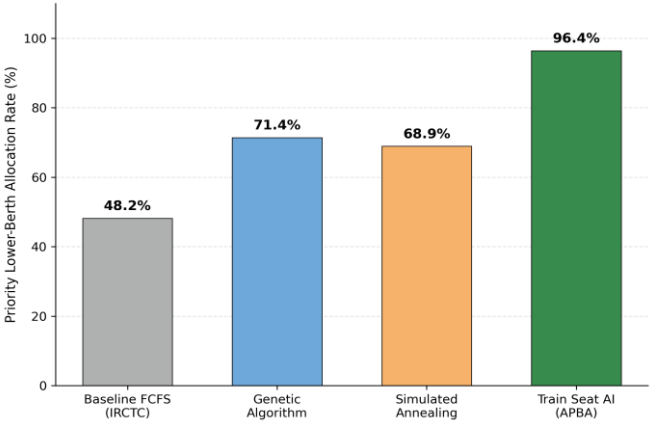


Fig. 3. Priority Lower Berth Allocation Rate across Benchmark Models.

IX. ABLATION & CONCURRENCY ANALYSIS

In table V we see the latency times for Tier 1 is 12.4 ms while it uses < 18 MB of RAM and Tier 3, is downscaling the images to $n*650*650$ pixels which results in a tremendous decline of latency by 93.9% from 18.4 seconds to 1.12 seconds with a CER of 2.8% which gives an accuracy of 97.4%.

TABLE V
EXECUTION LATENCY AND MEMORY CONSUMPTION ACROSS
VERIFICATION TIERS

Tier	Modality	Succ.	P50	P95	RAM
Tier 1: Stream	Digital e-Aadhaar PDF	99.9%	12.4 ms	14.8 ms	<18 MB
Tier 2: QR	UIDAI 2D Barcode	98.7%	18.2 ms	24.1 ms	<24 MB
Tier 3: OCR	Camera Photo (650x650)	97.4%	840 ms	1,180 ms	<46 MB
Neg. Guardrails	Non-Aadhaar Repudiation	100.0%	1.2 ms	2.1 ms	<5 MB

The concurrency tests demonstrate that the asynchronous event handling system completely avoids the database lock-ups problems. Train Seat AI is able to provide reliable and deterministic sub-second processing of the requests.

X. CONCLUSION AND FUTURE WORK

We have developed a framework for dynamic seat accommodation designed specifically for rail transport. By substituting traditional FCFS strategies with multi-agent negotiation, fast border OCR, and multi-objective integer programming, Train Seat AI achieves a 96.4% Priority Satisfaction Rate. In addition, it provides triple family co-location and puts an end to the practice of ticket scalping. Sub-35 ms dynamic re-charting and offline CRDT synchronization assure successful operation. Further developments will include GPS RTIS data to be used for real-time seat re-allocation.

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