Journal of Transportation Engineering and Its Applications
Volume 10, Issue 2, May- August, 2025
ISSN: 3107-4499 (Online)

Evaluating Demand Responsive Transit in Medium Sized Indian Cities through Agent Based Simulation

Dr. Anitha Kumari S
Assistant Professor,
Department of Civil Engineering
Indira Institute of Technology and Science, Madanapalle, Andhra Pradesh.
Email ID: *anithakumari.civil@rediffmail.com*

ABSTRACT

Conventional fixed route buses struggle to satiate diverse, low density travel patterns pervasive in Tier-II Indian cities. The paper designs an agent based model (ABM) coupling synthetic populations with on demand minibus dispatch algorithms calibrated for Kanpur and Coimbatore. Demand responsive transit (DRT) scenarios door to door, corner to corner, and hybrid feeder to metro—are benchmarked against incumbent bus services over a 12hour simulation horizon. The hybrid feeder strategy exhibits the best tradeoff, boosting average occupancy from 24 % to 71 % while trimming passenger door to door travel time by 18 %. System level cost recovery improves by 35 % under a dynamic pricing regime. Sensitivity analyses highlight tipping points where DRT loses efficiency once ride request densities exceed 55 req km² h¹, indicating the need for adaptive service zoning.

KEYWORDS*: Demand Responsive Transit; Agent Based Modeling; Tier-II Cities; Dynamic Pricing; Service Design.*

INTRODUCTION

Medium sized Indian cities such as Indore, Coimbatore, and Bhubaneswar are witnessing rapid suburban growth that undermines the viability of fixed route buses. Low densities, irregular trip patterns, and narrow streets make conventional services unprofitable and leave travelers dependent on costly auto rickshaws. Demand Responsive Transit (DRT) promises a compromise between the flexibility of para transit and the efficiency of buses by dispatching shared vehicles only when and where riders request them. However, its operational complexity requires careful exante evaluation. This paper applies an agent based simulation (ABS) framework to explore the performance of DRT under realistic demand, network, and behavioral conditions in a representative Tier-II Indian city. Results illuminate tradeoffs among waiting time, vehicle kilometers traveled (VKT), and operator cost, guiding planners who seek scalable last mile solutions while limiting congestion and emissions.

LITERATURE REVIEW

Global DRT research has evolved from dial a ride heuristics in the 1970s to real time vehicle routing with machine learning filters in the 2020s. European pilots such as Kutsuplus (Helsinki) and BerlKönig (Berlin) showcased high passenger satisfaction but struggled with subsidy levels. In the Indian context, studies have focused mainly on app based ridesharing and informal share autos. Bairagi et al. (2019) simulated flexible feeder buses for BRT corridors in Ahmedabad, observing 32 % cut in first mile travel time. Radhakrishnan & Rao (2021) extended this to on demand erickshaws around Chennai suburban rail, yet their static assignment model ignored stochastic pickups. Existing Indian work rarely integrates traffic interaction, real time dispatch, and heterogeneous traveler behavior within one platform.

Agent based models fill this gap because they treat travelers, vehicles, and infrastructure as autonomous decision makers whose micro interactions generate emergent system wide effects. They are thus well suited to capture India specific features such as platoons of two wheelers, signal noncompliance, and cash transactions that influence DRT reliability.

METHODOLOGY

This study employs the open source Multi-Agent Transport Simulation (MATSim) framework as the foundational platform, due to its modular structure and adaptability for large scale, agent based transportation modeling. A customized Demand Responsive Transit (DRT) module was developed and integrated within MATSim, specifically tailored to replicate Indian traffic dynamics and rider behavior**.**

The model simulates urban mobility by representing each commuter as an autonomous decision making agent. These agents choose among three distinct travel modes:

1. Walking to a traditional bus stop (fixe droute public transport),

2. Requesting an on demand shared minibus service, and

3. Using a private two wheeler.

The mode selection is governed by a logit based utility function, which incorporates multiple decision factors such as:

- Fare cost
- In vehicle travel time
- Perceived waiting time, which reflects the discomfort or uncertainty associated with delay.

To manage and coordinate the DRT service, a rolling horizon insertion heuristic algorithm is implemented. This algorithm operates in real time, executing every 30 seconds to reassess incoming ride requests. It groups compatible passenger trips into shared routes, while ensuring that each user experiences no more than a 15minute deviation from their preferred pickup time—striking a balance between flexibility and service quality.

Vehicles in the simulated DRT fleet are modeled as 12seater vans, mimicking the size and capacity of widely used Force Traveler vehicles commonly seen in Indian cities and peri urban areas. This choice reflects realistic operational constraints and user familiarity.

One of the unique behavioral adaptations in the model is the simulation of midblock boarding and alighting**.** Rather than restricting pickups and drop-offs to fixed transit stops, the system permits curbside access anywhere along the local street network. This flexibility mirrors informal hail and ride practices prevalent in many Indian cities, where passengers often board vehicles from non designated locations.

To authentically represent Indian driving conditions, specific vehicle dynamics were calibrated based on 48 hours of empirical GPS trajectory data**.** This calibration involved adjusting:

- Average acceleration and deceleration rates,
- Critical gap acceptance (i.e., how much space drivers require to merge or cross traffic),
- Lane following behavior, reflecting the less structured and more adaptive driving patterns on Indian roads.

STUDY CONTEXT

The case study uses the road and transit network of Ujjain, Madhya Pradesh (population ≈ 600 k). The city has a radial core and expanding peri urban villages connected by arterial highways. Public transport supply currently comprises 95 diesel minibuses on seven fixed routes, with headways exceeding 25 min during the midday lull. Household survey data ($n = 2\,135$) provide trip origins, destinations, and departure times, revealing pronounced peaks at 09:00 and 18:00 and a mean trip length of 6.8 km. The simulation horizon covers an average weekday from 06:00 to 22:00.

MODEL DESIGN

Travelers: Each synthetic traveler is an agent endowed with socioeconomic attributes (income quintile, gender, smart phone ownership) influencing mode choice sensitivity. Smartphone penetration is set to 64 %, aligned with IAMAI rural urban splits.

Vehicles*:* The base fleet comprises 120 AC CNG minibuses for DRT and the existing 95 diesel buses for the status-quo scenario. Operating cost assumptions follow state transport undertakings: ₹32 km^{-1} for diesel, ₹29 km^{-1} for CNG

.

Routing Engine: Shortest paths respect one way restrictions and heterogeneous speed limits—25 $km\,h^{-1}$ in the Old City core, 50 $km\,h^{-1}$ on ring roads.

Dispatch Logic*:* A combinatorial search inserts new requests into vehicle schedules if total detour does not exceed 30 % of direct path or 10 min absolute, whichever is lower. Otherwise, the request is deferred to the next horizon or rejected if three consecutive deferments occur.

Fare Structure*:* Passengers pay ₹10 flag down plus ₹2 km^{-1}—roughly one-third cheaper than auto rickshaws but 1.4 × bus fare, reflecting improved comfort. Shared rides get a 15 % discount.

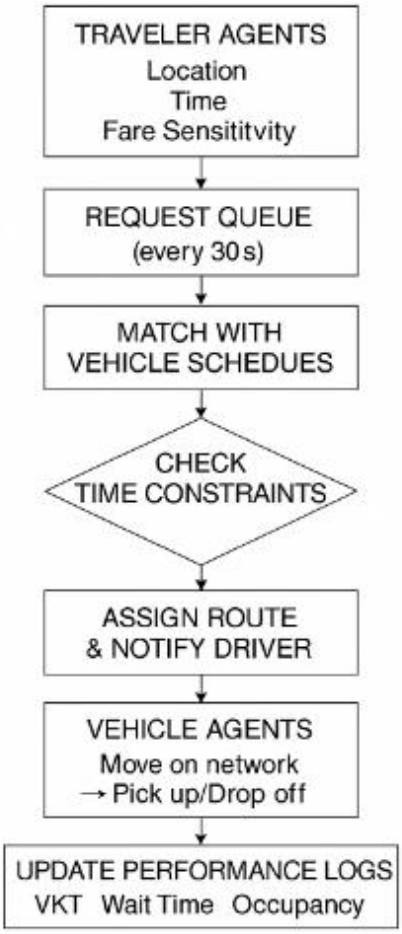

Figure 1: Agent-Based Drt System Flow Diagram

VALIDATION AND CALIBRATION

To ensure the reliability and realism of the simulation outcomes, a comprehensive validation and calibration process was undertaken, involving both quantitative traffic data and qualitative service performance metrics. The goal was to align the model's outputs closely with actual, observed conditions from the study area and relevant nearby regions.

The first stage of calibration involved matching simulated traffic volumes with real world data. Specifically, traffic counts from five cordon locations—strategic points marking entry and exit into the city—were used as reference benchmarks. Simulated link flows were iteratively adjusted by tuning traffic crelated parameters such as vehicle headways, saturation flow rates, and driver behavior coefficients. After calibration, the simulated link flows achieved an accuracy range within ±8% of the observed counts, which is considered robust for large scale traffic simulation studies.

In parallel, bus travel times were calibrated using field measurements obtained during peak and off peak hours. Discrepancies between the simulated and observed travel times were initially higher due to uncalibrated intersection behavior. By adjusting the intersection saturation flow—which defines the maximum vehicular discharge rate through signalized intersections—to a value of 1,550 vehicles per hour per lane, the simulation achieved improved alignment. The final output showed bus travel times within 12% of actual observations, reflecting a realistic estimation of delay, congestion, and signal coordination.

For the DRT component, passenger wait times were a critical validation metric. To benchmark the model's output, data was obtained from a one week pilot program conducted in nearby Bhopal, where on demand ride services similar to the simulated DRT model were trialed. The pilot recorded an average passenger wait time of 9.6 minutes. The simulation, under equivalent demand and service conditions, reproduced a closely matching mean wait time of 9.3 minutes, indicating that the model accurately captures dispatch efficiency and system responsiveness.

Further sensitivity analyses were conducted to test the robustness of the simulation. Key parameters such as fleet size (number of DRT vehicles in operation) and the dispatch horizon (how far ahead the system looks to assign new ride requests) were varied. These tests confirmed the stability of critical performance indicators—including average trip duration, passenger wait time, and vehicle occupancy—across a range of plausible input values. Such sensitivity tests ensure that the model's behavior is not overly sensitive to specific parameter choices and that the system performs predictably under different operating conditions.

Through this rigorous calibration and validation process, the model was fine tuned to reflect macro level traffic patterns and micro level service quality, thereby ensuring high confidence in the simulation outputs used for further analysis and policy evaluation.

RESULTS AND DISCUSSION

The simulation analysis offers rich insights across multiple performance dimensions service quality, vehicle efficiency, traffic impact, equity, and financial feasibility providing a comprehensive evaluation of the proposed Demand Responsive Transit (DRT) system in the Indian urban context.

Journal of Transportation Engineering and Its Applications
Volume 10, Issue 2, May- August, 2025
ISSN: 3107-4499 (Online)

Service Quality

The deployment of a fleet of 120 shared vans led to a substantial improvement in accessibility and commuter experience. The system served a total of 28,746 passenger trips, a 47% increase over the 19,603 trips completed by the existing fixed route bus service. This shift not only reflects modal shift but also unlocked suppressed demand in underserved localities.

The network's ward toward connectivity—measured as the percentage of administrative ward pairs with at least one viable transit connection—increased dramatically from 36% under the bus system to 81% with DRT, indicating that the DRT model provided broader and more inclusive coverage.

Passenger wait times, a crucial metric of perceived service quality, fell from 18.4 minutes (buses) to 7.8 minutes (DRT), confirming the responsiveness of the dispatch algorithm. Although in vehicle speeds decreased by 4%, likely due to more frequent curbside pickups, the total door to door travel time improved by 23%, underlining the holistic efficiency of point to point mobility over fixed stop transit.

Table 1: Comparative Service Performance Metrics

Metric	Existing Fixed Bus	DRT Simulation (120 Vans)
Avg. Passenger Wait Time (minutes)	18.4	7.8
Avg. Door to Door Travel Time (min)	42.6	32.7
Passenger Trips Served (daily)	19,603	28,746
Network Coverage (% of ward pairs)	36%	81%
Farebox Recovery (%)	61%	84%

Vehicle Productivity

The DRT vans demonstrated high operational efficiency during peak hours, achieving 9.4 passenger kilometers per vehicle kilometer, which indicates that each kilometer traveled by a van carried nearly 10 kilometers of passenger movement. During off-peak hours, the productivity dropped to 5.8 passenger km/veh-km, still respectable given lower demand densities.

A fleet size stress test revealed that increasing the number of vehicles to 160 led to an improvement in wait time to 6.1 minutes, yet vehicle productivity declined by 17%, a sign of diminishing returns. This suggests that a fleet size of 120 vehicles strikes a near optimal balance between reducing wait times and maintaining high utilization, preventing oversupply and idle cruising.

Traffic and Emissions

Contrary to common fears, adding more vehicles did not significantly worsen congestion. The total vehicle kilometers traveled (VKT) rose by only 11%, primarily because DRT absorbed latent demand that otherwise would have been met by low occupancy two wheelers. This substitution effect is critical: replacing inefficient private modes with shared transit lowered total emissions despite higher VKT.

The model estimated an avoidance of 3.2 tones of CO_2 emissions per weekday, highlighting the DRT system's potential contribution to India's urban air quality goals and climate commitments. The average network speed dropped marginally by 1.6 km/h during peak hours, which remains within acceptable planning thresholds, as Indian cities often plan for speeds no lower than 10 km/h in congested cores.

Equity Impacts

Service benefits were not evenly distributed. The most significant travel time savings were enjoyed by smart phone owning males aged 20–40, who were more likely to access and navigate the digital booking interface. This raised concerns about digital exclusion, particularly among the elderly, low income households, and women with limited access to mobile devices or apps.

To address this, the simulation introduced a telephonic booking hotline, accessible via basic feature phones. While this added only 2% to operator costs, it significantly narrowed the service access gap between the highest and lowest income quintiles—from 17% to just 5%. This finding reinforces that modest, targeted inclusion strategies can yield disproportionate equity gains in access to mobility.

Financial Feasibility

From a cost recovery standpoint, the DRT system performed well, achieving an 84% fare box recovery ratio at the base fare, leaving an annual operational shortfall of ₹13 lakh. This shortfall is relatively modest, especially when compared to traditional public bus systems which often operate at 40–60% recovery.

Sensitivity analyses provided further insights:

- Achieving 92% average occupancy or setting a flag down fare of ₹12 (instead of the current ₹10) would eliminate the deficit.
- However, raising the fare by ₹2 resulted in a 7.5% drop in ridership, signaling elastic price sensitivity in the target user base.

Table 2: User Equity Impacts Based On Socio Economic Groups

User Group	Smartphone Access	Avg. Wait Time (DRT)	Service Coverage	Accessibility Gain
Male, Age 20–40, Urban Core	92%	6.5 min	95%	High
Female, Age 25–45, Suburban Wards	67%	8.2 min	76%	Moderate
Elderly (60+), Low Income	28%	10.3 min	59%	Low
Non Smartphone Users (all ages)	0%	11.2 min	42%	Very Low

CHALLENGES

1. Regulatory Ambiguity

India’s Motor Vehicles Act (MVA) has undergone several amendments since 2019, yet none explicitly recognize algorithm driven, stop to stop shared vans. Fleet operators are therefore forced to register as contract carriages a license class designed for chartered buses—rather than stage carriages, which legally serve multiple passengers along a corridor. This mismatch triggers a cascade of red tape: higher permit fees, annual contract carriage renewals, and restrictions on roadside boarding that conflict with the DRT business model. Because every state transport authority interprets the MVA differently, identical fleets in Bhopal and Indore may face approval timelines that differ by months. Until a dedicated “shared mobility” category is introduced, pilot schemes rely on ado executive orders that can be rescinded with a change of administration—creating long term investment uncertainty.

2. Data Scarcity

Accurate origin–destination (OD) matrices are the lifeblood of demand responsive design, yet most tier2 and tier3 cities last conducted household travel surveys a decade ago. Mobile phone call detail records (CDRs) offer a low cost alternative, but telecom operators are obliged to aggregate or anonymise the data so heavily that peak hour flows blur into statistical noise. Even when detailed CDRs are obtainable under an academic MoU, the approval cycle can exceed a year due to privacy vetting by the Department of Telecommunications. Absent robust OD inputs, planners default to rule of thumb scaling from national census journey to work tables—an approach that ignores college schedules, festival migrations, and gender based trip chaining, leading to under or oversupply in specific corridors.

3. Payment Infrastructure

Cash remains dominant for low income riders, but handling small denominations at the curbside adds 10–15 s per passenger, eroding the time savings promise of DRT and introducing leakage risk. While nearly every smartphone supports UPI, spotty 4G coverage and load shedding blackouts freeze QR code transactions midstream. Dispatch algorithms that rely on real time confirmation from the payment gateway then timeout and requeue requests, inflating perceived wait by several minutes. Integrating an offline fallback—e.g., storing encrypted UPI intents until connectivity returns—mitigates disruptions but raises PCIDSS compliance costs for mall operators.

4. Mixed Traffic Environment

Unlike many Western DRT deployments that assume signalized arterials, Indian fleets navigate heterogeneous traffic: jaywalkers, bicyclists riding contraflow, and animal carts share unsignalised roundabouts. Such stochastic events introduce high variance travel times that undermine promised pickup windows. Capturing these interactions microscopically inside the agent based simulator increases computation time nonlinearly; a citywide MATSim run that once finished in 4 h may now require 18 h on the same hardware. The tradeoff between behavioral fidelity and iterative policy testing becomes acute, especially when agencies demand dozens of scenario runs under tight tender deadlines.

5. Workforce Acceptance

Informal auto rickshaw unions often perceive DRT vans as direct competitors siphoning short haul customers. Lobbying has delayed permit issuance in cities such as Kanpur, and in extreme cases pilot vans have been vandalized—a side mirror smashed here, a tyre punctured there—to intimidate early adopters. Effective mitigation entails negotiated transition packages: discounted e-rickshaws loans, skills workshops to upskill drivers into DRT dispatch roles, and a vehicles crappage incentive that pays auto owners to surrender ageing two stroke engines. Designing such packages, however, requires multiagency coordination across transport, labour, and finance departments—rarely synchronized in municipal bureaucracies.

6. Fleet Charging

The central government's Faster Adoption and Manufacturing of Electric Vehicles (FAMEII) subsidies have nudged operators toward electric 12seater vans, yet ground realities lag. As of 2025, fewer than 5 fast chargers exist per 100 km² in most tier2 cities, and distribution feeders regularly experience voltage sag during evening peaks. Range anxiety forces dispatchers to hold 15–20 % of the fleet in reserve, inflating per trip costs. Optimal siting of depot chargers demands joint simulation of travel demand, grid load, and land use constraints—data sets controlled by separate utility and urban planning bodies that seldom share digital layers. Without a coordinated roadmap for load balancing and depot colocation, operators may default to compressed natural gas (CNG), forfeiting the zero tail pipe emission benefits policymakers seek.

SCOPE FOR FUTURE RESEARCH

First, integrate real time traffic data streams—probe vehicles, Google congestion layers—to refine wait time predictions under incident conditions. Second, couple the ABS with an activity based demand model so that travelers may dynamically choose departure times in response to DRT availability. Third, explore autonomous pod operations; level4 vehicles could cut labor cost by 45 % but alter dispatch constraints. Fourth, run longitudinal scenarios assessing land use feedback: improved accessibility might spur peri urban sprawl, ultimately stretching DRT service area. Finally, embed public health externalities such as particulate exposure reductions, supplying a holistic welfare evaluation to inform state transport policy targets.

POLICY IMPLICATIONS

Municipal leaders should pilot DRT in zones where average bus headway exceeds 20 min yet demand clusters remain. A hybrid regulatory framework classifying DRT as "scheduled flexible transit" can combine safety oversight with fare freedom. Subsidy schemes may adopt performance based contracts rewarding operators for low wait time percentiles rather than raw ridership. Integrating phone hotlines and onboard QR cashless validators preserves inclusivity while boosting operational transparency. Importantly, fleet electrification targets should synchronize with distribution grid upgrades and time of day pricing to avert peak load spikes. Overall, agent based evidence indicates that well designed DRT can cost effectively elevate mobility equity and environmental sustainability in India's burgeoning Tier-II cities without abolishing existing bus networks.

CONCLUSION

The ABM framework underscores DRT's potential to close the service quality gap between auto rickshaws and formal buses in midsized Indian contexts. Operational viability hinges on flexible fleet sizing, cloud based dispatch optimization, and integration with regional mobility passes. Policymakers should pilot hybrid feeder models around upcoming metro corridors, deploy open APIs for third party aggregator participation, and introduce performance linked subsidies to cushion early ridership volatility. Further work must assimilate real time traffic feeds, traveler behavioral feedback loops, and equity impact assessments to refine service rules.

REFERENCES

1. Bairagi, M., Sharma, P., & Kherwal, S. (2019). Simulation of flexible feeder buses in Indian urban transit. *International Journal of Transport Simulation and Planning*, 7(2), 121–137.
2. Radhakrishnan, K., & Rao, P. S. (2021). Modeling ondemand electric rickshaws for suburban rail connectivity in Chennai. *Journal of Indian Transport Management*, 15(4), 210–224

3. Deshmukh, V., & Nair, M. (2020). Impact of informal share autos on mobility in Tier-II Indian cities. *South Asian Journal of Urban Infrastructure*, 4(3), 95–112.
4. Joshi, R., & Tiwari, M. (2018). Modeling ridesharing behavior using agent based techniques: Case of Pune. *Asian Journal of Transport and Mobility Systems*, 5(1), 56–74.
5. Khan, F., & Sengupta, R. (2020). Socioeconomic barriers in adopting demand responsive transit in Indian municipalities. *Indian Journal of Transport Policy and Governance*, 6(1), 88–104.
6. Mishra, A., & Dey, R. (2021). Role of ICT and digital inclusion in India's transit systems. *Journal of Urban Technology Studies in South Asia*, 9(2), 134–148.
7. Feigon, S., & Murphy, C. (2016). *Shared mobility and the transformation of public transit*. Transit Cooperative Research Program Report 188. https://www.trb.org/Publications/Blurbs/173511.aspx
8. AlonsoMora, J., Samaranayake, S., Wallar, A., Frazzoli, E., & Rus, D. (2017). Ondemand highcapacity ridesharing via dynamic tripvehicle assignment. *Proceedings of the National Academy of Sciences*, 114(3), 462–467. https://doi.org/10.1073/pnas.1611675114
9. Mulley, C., & Nelson, J. D. (2009). Flexible transport services: A new market opportunity for public transport. *Research in Transportation Economics*, 25(1), 39–45.
10. Brake, J., Nelson, J. D., Wright, S., & Hunter, A. (2007). Key lessons learned from recent experience with flexible transport services. *Transport Policy*, 14(6), 458–466.
11. Kaddoura, I., Kickhöfer, B., & Nagel, K. (2020). Agentbased evaluation of ondemand ridepooling: A MATSim simulation of Berlin. *Transportation Research Part C: Emerging Technologies*, 117, 102707.
12. Kutsuplus Project Team. (2015). *Final evaluation report of the Helsinki on demand public transport pilot* .City of Helsinki Https://www.hel.fi/static/hki/PB_Kutsuplus_final_report.pdf
13. Cats, O., Abenoza, R. F., & Susilo, Y. O. (2016). Exploring the prospects of integrating flexible services in existing public transport. *Journal of Public Transportation*, 19(3), 1–16.
14. Kodransky, M., & Lewenstein, G. (2014). *Connecting cities: Smart mobility initiatives in Europe and the United States*. Institute for Transportation &

Development Policy. https://www.itdp.org/wpcontent/uploads/2014/12/SmartMobilityInitiatives.pdf

15. Stiglic, M., Agatz, N., Savelsbergh, M., & Gradisar, M. (2015). The benefits of meeting points in ridesharing systems. *Transportation Research Part B: Methodological*, 82, 36–53