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Design and Evaluation of a Demand-Responsive IoT–AI Waste Collection Ecosystem for Tier 2 and Tier 3 Indian Cities: Smart Bin Monitoring, Waste Hotspot Mapping, and Dynamic Route Optimisation

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Abstract

Municipal waste-management systems in Tier 2 and Tier 3 Indian cities increasingly incorporate digital monitoring, yet collection remains largely schedule-driven rather than responsive to actual bin demand. This study develops a phased, low-cost IoT–AI architecture that integrates retrofit bin-level sensing, existing GPS-enabled collection fleets, waste-demand analysis, forecasting, and dynamic route optimisation without requiring replacement of existing municipal infrastructure. A city-scale simulator based on the Bareilly road network was used to evaluate demand-responsive collection against fixed-schedule alternatives; physical validation of the ESP32–ToF sensing unit remains pending. Under a baseline scenario of 100 bins and three trucks, demand-responsive collection reduced overflow events by 86% and increased the proportion of waste collected from 78.7% to 97.0%, although this higher service level increased distance travelled and cost per unit collected. Route optimisation independently reduced travel distance by approximately 21–22%. Across 360 simulations, sensing became economically favourable where bin-filling rates were sufficiently heterogeneous and deployment included at least 100 bins, with estimated break-even sensor prices of approximately ₹8,000–₹18,000 compared with a projected field-unit cost of ₹4,758. Hotspot detection required denser coverage, with significant spatial concentrations emerging only at 250 monitored bins. The findings therefore support selective rather than universal sensor deployment. The study contributes an integrated retrofit architecture and identifies the operational conditions under which demand-responsive collection may justify its cost in resource-constrained urban municipalities.

Keywords: smart waste management; Internet of Things; demand-responsive collection; dynamic route optimisation; waste-demand analysis; municipal solid waste; Tier 2 and Tier 3 cities; India

Urban India generates between 130,000 and 150,000 metric tonnes of municipal solid waste (MSW) each day.[1] Generation is far from uniform across cities: in a survey of twenty-eight Indian cities spanning populations from under 50,000 to over five million, daily per-capita generation ranged from 0.19 to 0.99 kilograms. Recent modelling projects that annual MSW generation in urban India could reach 206 to 287 million tonnes under business-as-usual assumptions, and 436 to 711 million tonnes under high-consumption scenarios, by 2050.[2] National processing capacity rose from eighteen per cent in 2014 to seventy per cent in 2021, but the capacity to process waste is not the same as the capacity to collect it responsively.

The regulatory framework governs collection by frequency rather than by need. The Solid Waste Management Rules, 2016 require local authorities to arrange door-to-door collection of segregated waste from all premises, and specify street sweeping daily, on alternate days, or twice a week depending on population density.[3] Swachh Bharat Mission – Urban 2.0 (SBM-U 2.0) simultaneously requires cities to adopt robust information and communication technology (ICT)-enabled governance providing real-time data on operational efficiency, and allocates urban local bodies (ULBs) below one lakh population a fifty per cent central funding share against twenty-five per cent for larger cities.[4] The Ministry of Housing and Urban Affairs (MoHUA) has further restructured Swachh Survekshan into five population categories so that smaller cities are assessed on comparable terms. Policy therefore recognises both that smaller cities face distinct constraints and that digital monitoring is expected of them, yet the collection mandate itself remains schedule-driven.

The consequences of collection that does not track actual fill are documented, though largely in metropolitan settings. A case-comparison study of residents near the Deonar dumping site in Mumbai found respiratory illness in twenty-three per cent of the exposed group against ten per cent of controls, with adjusted odds of 3.06 for respiratory illness and 2.39 for eye infection.[5] Around the Brahmapuram dump yard in Kerala, approximately ninety-four per cent of surveyed residents reported malodour, more often within two kilometres.[6] An analysis of developer offer values within fifteen kilometres of the Uruli Devachi landfill in Pune found that proximity depresses residential property offer values, with the effect

[1] Centre for Science and Environment and NITI Aayog, *Waste-Wise Cities: Best Practices in Municipal Solid Waste Management* (New Delhi: CSE and NITI Aayog, 2021), accessed September 21, 2026, https://niti.gov.in/sites/default/files/2023-02/Waste-Wise-Cities.pdf.

[2] Vinay Yadav et al., "Projected Twelve-Fold Growth in Municipal Solid Waste Generation Calls for Urgent Techno-Policy Intervention across Urban India," *Journal of Industrial Ecology* 30, no. 3 (2026): 987–1001, https://doi.org/10.1007/s44498-026-00067-3.

[3] Ministry of Environment, Forest and Climate Change, *The Solid Waste Management Rules, 2016 (as Amended to Date)*, S.O. 1357(E), April 8, 2016, accessed September 21, 2026, https://cdnbbsr.s3waas.gov.in/s30f46c64b74a6c964c674853a89796c8e/uploads/2024/07/20240710555191345.pdf.

[4] Ministry of Housing and Urban Affairs, *Swachh Bharat Mission – Urban 2.0: Making Cities Garbage Free — Operational Guidelines* (New Delhi: MoHUA, October 2021), accessed September 21, 2026, https://swminfo.in/sbm/Assets/User-manual/SBM-2.0-Guidelines.pdf.

[5] Shri Kant Singh et al., "Open Dumping Site and Health Risks to Proximate Communities in Mumbai, India: A Cross-Sectional Case-Comparison Study," *Clinical Epidemiology and Global Health* 9 (2021): 34–40, https://doi.org/10.1016/j.cegh.2020.06.008.

[6] A. P. Payyappilly, P. Babu, and M. R. Nair, "Distance and Direction Matters: Risk Perception among Residents around a Dump Yard in Kerala, India," *Risk Management and Healthcare Policy* 18 (2025): 65–76, https://doi.org/10.2147/RMHP.S491900.

intensifying closer to the site.[7] Comparable controlled evidence for Tier 2 and Tier 3 cities was not located during this review.

This paper proposes a demand-responsive collection ecosystem developed in three phases. Phase 1 fits low-cost Internet of Things (IoT) sensing units to existing municipal bins, without structural modification, so that the municipality or its contractor is alerted when a bin approaches capacity; units are intended only for bins where overflow recurs. Phase 2 applies fill forecasting, spatial waste-demand (hotspot) analysis and demand-responsive routing, and connects bin data to the Global Positioning System (GPS) tracking already fitted to many municipal collection vehicles, so that no new vehicle hardware is required. Phase 3, autonomous collection, is treated as a conditional roadmap, since fully autonomous refuse trucks do not yet appear to be commercially available.[8] A first prototype, an ESP32 microcontroller with ultrasonic, GPS and Global System for Mobile Communications (GSM) modules installed in a domestic bin, was evaluated only on modelled data. The current version replaces ultrasonic sensing with a time-of-flight (ToF) laser sensor, runs on a battery with a small solar panel, and reports over Wi-Fi during bench and domestic testing, with a cellular module planned for a public-bin trial. The Phase 2 software and a simulator of Bareilly built on the OpenStreetMap (OSM) road network have been developed; the hardware is being assembled, so every result reported here is simulated. Bareilly is the intended case-study site.

The literature reviewed below shows that each component of such a system is individually mature and that the components have rarely been joined. The contribution claimed here is therefore architectural and contextual rather than empirical: an integrated sensing, analysis and routing loop designed for deployment within the operating constraints of Tier 2 and Tier 3 Indian cities, for which no deployed and evaluated system of this kind was found in the literature reviewed.

Literature Review

Smart Waste Monitoring and Demand Prediction

IoT-based fill monitoring is the most mature component of smart waste management. Existing systems combine ultrasonic or related distance sensors with communication modules, power management, and cloud-based reporting. Pardini and colleagues developed a solar-powered unit integrating ultrasonic ranging, load sensing, environmental monitoring, GPS, and GSM,[9] while deployments in Lahore and on university campuses demonstrated that low-cost sensing can achieve high uptime and acceptable measurement accuracy over extended periods.[10]

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[7] Abhijat Arun Abhyankar, Anand Prakash, and Harish Kumar Singla, "Impact of Solid Waste Landfill Proximity on Residential Property Offer Values: A Case Study of Pune," *International Journal of Housing Markets and Analysis* 18, no. 2 (2025): 334–53, https://doi.org/10.1108/IJHMA-08-2023-0109.

[8] National Academies of Sciences, Engineering, and Medicine, "Automated Garbage Collection," chap. 11 in *Automated Applications for Infrastructure Owner-Operator Fleets* (Washington, DC: National Academies Press, 2024), accessed September 21, 2026, https://www.nationalacademies.org/read/27903/chapter/13.

[9] Kellow Pardini et al., "A Smart Waste Management Solution Geared towards Citizens," *Sensors* 20, no. 8 (2020): 2380, https://doi.org/10.3390/s20082380.

[10] Abdullah Addas, Muhammad Nasir Khan, and Fawad Naseer, "Waste Management 2.0: Leveraging Internet of Things for an Efficient and Eco-Friendly Smart City Solution," *PLOS ONE* 19, no. 7 (2024): e0307608, https://doi.org/10.1371/journal.pone.0307608; Reem Alnanih, Lamiaa Elrefaei, and Ayman Al-Ahwal, "Advancing Sustainability through an IoT-Driven Smart Waste Management System with Software Engineering Integration," *Sustainability* 17, no. 21 (2025): 9803, https://doi.org/10.3390/su17219803.

The principal limitation is measurement reliability under real waste conditions. Ultrasonic sensors are affected by irregular waste surfaces, temperature, and humidity. Maus and colleagues found LiDAR more accurate for volume estimation but too costly for large-scale deployment.[11] Indian work remains dominated by bench-scale prototypes, such as the Arduino-based ultrasonic, GPS, and GSM system developed by Raju and colleagues,[12] with limited evidence of sustained field operation. The challenge is therefore no longer demonstrating that bin fill can be sensed, but doing so reliably and economically at scale.

Forecasting research in India has largely operated at city or aggregate level. Studies in New Delhi, Kolkata, Erode, and Srinagar have applied neural networks, support vector machines, random forests, and related methods to predict waste generation from historical or demographic data.[13] These approaches are useful for long-term planning but are poorly suited to operational collection because they do not identify which individual bins require service. Bin-level forecasting has been demonstrated elsewhere: Ahmed and colleagues used nearly three years of sensor data from thirty-two public bins in Melbourne to predict fullness with high accuracy.[14] Comparable longitudinal bin-level datasets were not identified for Indian cities.

Spatial analysis presents a similar pattern. GIS-based waste planning is well established in India, with studies in Dhanbad, Bilaspur, and Coimbatore using road networks, population density, truck capacity, and other planning variables to optimise bin placement or identify areas vulnerable to waste accumulation.[15] However, demand is typically inferred from population, household counts, or expert-assigned weights rather than observed directly from bin-level waste generation. Spatial statistics such as Getis-Ord Gi* and Moran's I offer a means of identifying statistically significant waste concentrations from measured data, but their use within operational Indian smart-waste systems remains limited.

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[11] T. Maus, N. Zengeler, D. Sänger, and T. Glasmachers, "Volume Determination Challenges in Waste Sorting Facilities: Observations and Strategies," *Sensors* 24, no. 7 (2024): 2114, https://doi.org/10.3390/s24072114.

[12] K. Mallikarjuna Raju et al., "IoT-Based Smart Garbage Monitoring System and Advanced Disciplinary Approach," *E3S Web of Conferences* 507 (2024): 01031, https://doi.org/10.1051/e3sconf/202450701031.

[13] Umang Soni et al., "Forecasting Municipal Solid Waste Generation Using Artificial Intelligence Models — A Case Study in India," *SN Applied Sciences* 1, art. 162 (2019), https://doi.org/10.1007/s42452-018-0157-x; Sk Ajim Ali and Ateeque Ahmad, "Forecasting MSW Generation Using Artificial Neural Network Time Series Model: A Study from Metropolitan City," *SN Applied Sciences* 1, art. 1338 (2019), https://doi.org/10.1007/s42452-019-1382-7; E. B. Priyanka et al., "Prediction of Waste Generation Forecast and Emission Potential on the Erode City Solid Waste Dump Yards Based on Machine Learning Approach," *Scientific Reports* 15, art. 37021 (2025), https://doi.org/10.1038/s41598-025-19288-w, whose figures for population and tonnage are internally inconsistent, so only its model comparison is relied upon; Jasir Mushtaq, Abdul Qayoom Dar, and Naved Ahsan, "Spatial–Temporal Variations and Forecasting Analysis of Municipal Solid Waste in the Mountainous City of North-Western Himalayas," *SN Applied Sciences* 2, art. 1161 (2020), https://doi.org/10.1007/s42452-020-2975-x.

[14] S. Ahmed et al., "Forecasting the Status of Municipal Waste in Smart Bins Using Deep Learning," *International Journal of Environmental Research and Public Health* 19, no. 24 (2022): 16798, https://doi.org/10.3390/ijerph192416798.

[15] D. Khan and S. R. Samadder, "Allocation of Solid Waste Collection Bins and Route Optimisation Using Geographical Information System: A Case Study of Dhanbad City, India," *Waste Management & Research* 34, no. 7 (2016): 666–76, https://doi.org/10.1177/0734242X16649679; Pradeep Rathore, Sarada Prasad Sarmah, and Arti Singh, "Location–Allocation of Bins in Urban Solid Waste Management: A Case Study of Bilaspur City, India," *Environment, Development and Sustainability* 22, no. 4 (2020): 3309–31, https://doi.org/10.1007/s10668-019-00347-y; T. Radhakrishnan et al., "Identifying High-Vulnerable Garbage Accumulation Areas in Coimbatore City, India: An AHP-GIS Approach for Effective Waste Management," *Environmental Science and Pollution Research* 31, no. 14 (2024): 21797–810, https://doi.org/10.1007/s11356-024-32486-9.

Taken together, sensing, forecasting, and spatial analysis are technically established, but they remain only partially connected. The central unresolved issue is how to convert continuously generated bin-level data into actionable municipal intelligence rather than treating monitoring, prediction, and infrastructure planning as separate functions.

Dynamic Collection, Routing and System Integration

Demand-responsive collection has a longer research history than smart-bin hardware itself. Johansson demonstrated in 2006 that sensor-based scheduling across 3,300 recycling containers in Malmö could reduce operating costs, travel distance, and labour compared with fixed collection.[16] Subsequent studies in the Netherlands, Al Ain, and elsewhere have reported similar gains using heuristic and threshold-based routing.[17] Indian research has also examined dynamic routing: Priyadarshi and colleagues reported substantial reductions in travel distance for Chandigarh using agent-based routing, although the underlying fill levels were simulated rather than sensed.[18]

The wider routing literature nevertheless remains dominated by model-based and single-period studies. Relatively few systems combine reliable real-time sensing with multi-period collection planning, and even fewer evaluate that integration under real municipal constraints.[19] The problem is therefore not whether route optimisation is technically possible, but whether it can be linked continuously to changing demand at the bin level.

Evidence from applied deployments further shows that sensing is not universally beneficial. A six-month Lahore pilot reported improvements in route efficiency and fuel consumption, whereas a Valencia pilot found little operational value because bins filled predictably and were already collected daily.[20] This contrast is important: sensing generates value primarily where fixed schedules are poorly aligned with actual demand.

End-to-end integration remains limited, particularly in India. The closest published analogue to the architecture proposed here combines clustering, prediction, and routing in Yenagoa, Nigeria, but remains non-peer-reviewed.[21] Indian studies generally stop earlier. Patil and Gidde proposed an RFID- and GPS-

[16] Ola Johansson, "The Effect of Dynamic Scheduling and Routing in a Solid Waste Management System," *Waste Management* 26, no. 8 (2006): 875–85, https://doi.org/10.1016/j.wasman.2005.09.004.

[17] Martijn Mes, Marco Schutten, and Arturo Pérez Rivera, "Inventory Routing for Dynamic Waste Collection," *Waste Management* 34, no. 9 (2014): 1564–76, https://doi.org/10.1016/j.wasman.2014.05.011; Mohamed Abdallah et al., "Simulation and Optimization of Dynamic Waste Collection Routes," *Waste Management & Research* 37, no. 8 (2019): 793–802, https://doi.org/10.1177/0734242X19833152; M. A. Hannan et al., "Waste Collection Route Optimisation Model for Linking Cost Saving and Emission Reduction to Achieve Sustainable Development Goals," *Sustainable Cities and Society* 62 (2020): 102393, https://doi.org/10.1016/j.scs.2020.102393.

[18] M. Priyadarshi et al., "Dynamic Routing for Efficient Waste Collection in Resource Constrained Societies," *Scientific Reports* 13, art. 2365 (2023), https://doi.org/10.1038/s41598-023-29593-x.

[19] Christina Hess et al., "Waste Collection Routing: A Survey on Problems and Methods," *Central European Journal of Operations Research* 32, no. 2 (2024): 399–434, https://doi.org/10.1007/s10100-023-00892-y.

[20] Addas, Khan, and Naseer, "Waste Management 2.0"; Jerónimo Franco-González et al., "A Pilot Project Using Sensors in the Municipal Solid Waste Collection of a Medium-Sized City," *Resources* 12, no. 9 (2023): 108, https://doi.org/10.3390/resources12090108.

[21] Yolo Bakumor Smith, "GeoWaste: Leveraging GIS and Machine Learning for Urban Waste Management in African Cities" (paper presented at the Tackling Climate Change with Machine Learning workshop, NeurIPS 2025), accessed September 21, 2026, https://ccai-papers.s3.us-east-1.amazonaws.com/neurips2025/111/paper.pdf. Its reported performance figures are unverified and are not relied upon here.

based framework for Pune after extensive fieldwork but did not report implementation,[22] while other South Asian systems remain prototypes, preprints, or weakly evaluated deployments.[23]

Autonomous waste collection sits further downstream. Demonstrations by Volvo, Renova, and the ROAR consortium show that automated driving and robotic bin handling are technically possible,[24] but high costs, uncertain lifecycle economics, and unresolved safety requirements mean full autonomy remains a future extension rather than an immediate operational solution.[25]

Overall, the literature demonstrates that bin-level sensing, demand prediction, spatial analysis, and dynamic routing are individually established, and partially integrated in selected settings. What remains insufficiently addressed is their integration into a low-cost, retrofit operational system suited to the fiscal, infrastructural, and staffing constraints of Tier 2 and Tier 3 Indian cities. The research challenge is therefore one of system integration and deployability, rather than technological novelty at the level of any single component.

Research Gap

Although IoT-based fill-level monitoring, waste-generation prediction, and dynamic route optimisation have each been demonstrated, their integration into a single operational system remains limited. Existing integrated models have largely been evaluated through simulations, small-scale pilots, or in well-resourced municipal settings. In contrast, digital waste-management systems in Tier 2 and Tier 3 Indian cities are used primarily to monitor compliance with predetermined collection schedules rather than to generate demand-responsive collection decisions.

The principal gap, therefore, lies in developing an integrated system suited to the fiscal, staffing, and infrastructural constraints of these cities. This study addresses that gap through a phased, low-cost IoT–AI architecture that retrofits existing bins, prioritises sensing at recurrent overflow locations, and integrates bin-level data with existing GPS-enabled collection systems. It combines sensing, spatial waste-demand analysis, predictive collection, and dynamic route optimisation, while also evaluating the conditions under which such a system can justify its deployment cost. Its contribution is an integrated architecture designed for implementation within existing municipal waste infrastructure, rather than a claim of large-scale deployment.

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[22] Sangram C. Patil and Milind R. Gidde, "RFID and IoT Enabled Framework to Make Pune City an Eco-Friendly Smart City," *Nature Environment and Pollution Technology* 22, no. 2 (2023): 553–63, https://doi.org/10.46488/NEPT.2023.v22i02.002.

[23] Laboni Paul, Rahul Deb Mohalder, and Kazi Masudul Alam, "An IoT Based Smart Waste Management System for the Municipality or City Corporations," arXiv preprint arXiv:2411.09710 (2024), https://arxiv.org/abs/2411.09710, a preprint that has not undergone peer review; D. Jagadeesh, Santhebennur Jayappa Veeresh, and N. D. Hitesh, "Integrated Municipal Solid Waste Management in a Tier-II Indian Smart City: A Case Study of Davanagere," *International Journal of Environment and Climate Change* 16, no. 8 (2026): 520–37, https://doi.org/10.9734/ijecc/2026/v16i85592, whose publisher's standards have been questioned and whose figures are not treated as verified.

[24] Volvo Group, "Volvo Pioneers Autonomous, Self-Driving Refuse Truck in the Urban Environment," press release, May 17, 2017, accessed September 21, 2026, https://www.volvogroup.com/en/news-and-media/news/2017/may/news-2561936.html; Penn State Engineering, "Penn State Researchers Help Develop Robot-Based Refuse Collection," Thomas D. Larson Pennsylvania Transportation Institute, September 21, 2015, accessed September 21, 2026, https://www.larson.psu.edu/news-archive/penn-state-researchers-help-develop-robot-based-refuse-collection.aspx.

[25] B. Amante García et al., "Robots in Waste Management," *Detritus* 29 (2024): 179–90, https://doi.org/10.31025/2611-4135/2024.19430; National Academies, "Automated Garbage Collection."

Research Question

The primary research question of this paper is as follows: How can a low-cost retrofit IoT–AI architecture enable demand-responsive municipal waste collection in Tier 2 and Tier 3 Indian cities?

This is examined through two subsidiary questions:

RQ1. How reliably can a low-cost ESP32–ToF sensing system generate actionable bin-level data on fill status and spatial waste demand?

RQ2. Under what operational and cost conditions can integrating this data with existing GPS-enabled collection fleets improve routing efficiency and collection performance relative to fixed-schedule systems?

Case Study: Prototype

Design Objectives

Each objective follows from a gap in Section 3. Low unit cost and retrofitting onto existing bins respond to the failure of expensive, imported smart bins and to ULB budgets. Using the GPS tracking already on collection vehicles avoids new vehicle hardware. Alerts reach existing supervisors through a web dashboard, so no new posts are needed. Sensors are placed only where overflow recurs, because sensing pays where filling is irregular. Finally, every unit generates the bin-level data that forecasting needs and that these cities lack.

Architecture

In Phase 1, a sensing unit on each selected bin measures fill level every fifteen minutes and sends it to a central platform. In Phase 2, the platform registers each device with its own key, stores readings, raises alerts, forecasts when each bin will fill, maps hotspots and plans routes that start from each truck's current GPS position. Because fleet data were not available, a simulated GPS feed modelled on typical vehicle-tracking fields stands in for a city's feed; it is not an official ICCC format. Phase 3 remains conditional. Built so far: the unit's design and firmware, the platform and dashboard, and the simulator. Proposed: the cellular field unit, deployment with a ULB, ICCC integration and Phase 3.

Two Prototypes and the Market

The first prototype (v1) used ultrasonic ranging, a GPS module and GSM in a domestic bin. The second (v2) replaces all three: a ToF sensor measures fill, location is recorded once at installation from the installer's phone, and readings travel over Wi-Fi, with a 4G Long-Term Evolution (LTE) module planned for field use. Table 5.1 compares both with what is available. Commercial retrofit sensors such as Sensoneo's mount on existing bins with screws, clamps or rails and report over LoRaWAN, Sigfox, Narrowband IoT (NB-IoT) or LTE for Machines (LTE-M), but publish no price.[26] Indian purpose-built bins (Section 3) were costly and did not deliver usable data.

Table 5.1. The two prototypes compared with market options

	v1	v2	Commercial retrofit sensor	Indian purpose-built bins
Sensing	Ultrasonic	ToF, four zones	Ultrasonic	Ultrasonic, or never supplied

[26] Sensoneo, "Ultrasonic Bin Sensor," accessed October 26, 2026, https://www.sensoneo.com/products/ultrasonic-bin-sensor/. This is a vendor's product page, cited only to show that commercial retrofit sensors exist.

Location	GPS module	Set at installation	Not stated	Not reported
Network	GSM	Wi-Fi; 4G LTE planned	LoRaWAN, Sigfox, NB-IoT, LTE-M	Not reported
Unit cost	Not recorded	₹2,141 (₹4,758 field)	Not published	≈₹40 crore scheme
Status	Domestic bin, modelled data	Software built; hardware in assembly	On sale	Removed or unevaluated

Hardware and the Switch to ToF Sensing

v2 is built around an ESP32 microcontroller and a VL53L1X ToF laser sensor (Table 5.2). Ultrasonic sensing was dropped because its readings are distorted by irregular waste surfaces, temperature and humidity.[27] Maus and colleagues' objection that LiDAR is too costly applies to scanning and long-range units; the VL53L1X is a short-range ToF sensor costing ₹865 against ₹345 for a common waterproof ultrasonic sensor from the same supplier. The premium of about ₹520 is real, the sensor being forty per cent of the unit cost, but small in absolute terms. Any single distance reading can be fooled by a bag or stick standing above the waste, so the firmware reads the sensor as four zones, reports their median, and flags a suspected obstruction when one or two zones read much closer than the rest. Deep, open-top bins in direct sun are beyond this sensor's reliable range; a LiDAR unit costing ₹5,326 would be needed there, reintroducing the cost problem.

Table 5.2. Bill of materials, v2 domestic-test unit

Component	**₹**
ESP32 DevKit V1 (replacement price)	445
VL53L1X ToF sensor	865
18650 lithium-ion cell and holder	189
Charger with protection; 3.3 V converter	364
70 × 70 mm solar panel	59
IP65 enclosure and cable glands	219
Unit cost	2,141
Field unit (branded cell, fuse, temperature cut-off, 4G modem)	4,758

Source: author's bill of materials; Robocraze and Robu.in listings including goods and services tax, checked October 17, 2026. The final enclosure will be 3D-printed; its cost is not yet known.

Communications and Power

Wi-Fi is enough for bench and domestic tests. The 4G modem (₹1,899) was chosen for the public-bin trial because it works on ordinary prepaid SIM cards, at a recurring cost of about ₹200 a month. At city scale the choice remains open: a field comparison reported battery lives of 3.0 years for LoRaWAN, 7.2 for NB-IoT and 6.8 for LTE-M, and roughly one thousand devices per LoRaWAN gateway, which the city would have to install and run.[28] The unit sleeps between readings. From component datasheets, the

[27] Maus et al., "Volume Determination Challenges."

[28] Dmitrijs Orlovs et al., "LPWAN Technologies for IoT: Real-World Deployment Performance and Practical Comparison," *IoT* 6, no. 4 (2025): 77, https://doi.org/10.3390/iot6040077.

unmodified board is predicted to use about 104 mAh a day at fifteen-minute Wi-Fi reporting, about twenty-six days per charge without sunlight, and about 9.1 mAh a day once its power indicator and on-board regulator are disconnected. These are predictions; measured values are pending (Table 5.4).

Data Flow, Alerts and Phase 2 Software

Each reading is sent with the device's key; readings taken while the network is down are stored for up to twenty-four hours and sent later with their original times. The platform raises five alerts: fill threshold (eighty per cent by default), forecast to reach it within six hours, low battery, a silent device and a suspected obstruction. Forecasting starts from a robust straight-line fill rate and blends in each bin's hour-of-day pattern once a day of history exists, reporting an earliest–latest range. Hotspots are mapped with the Getis-Ord Gi* statistic on observed fill rates, with a false discovery rate (FDR) correction, so the map updates from live readings rather than fixed inputs. Routes are planned as a capacitated vehicle routing problem (CVRP) with Google OR-Tools on road distances: bins likely to overflow before the next decision must be visited, and others are added only when the detour is cheaper than a later trip. Plans are revised at 06:00 and 10:00.

Simulator and Test Method

The simulator uses the OSM road network within six kilometres of OSM's central point for Bareilly (11,361 junctions). Bin numbers, fleet, waste generation, wages, fuel price, depot and disposal site are assumptions, not facts about Bareilly; only the road network is real. Each run covers fourteen days in fifteen-minute steps, discards two warm-up days and fixes its random seeds. The fixed-schedule baseline uses the same route optimiser, so differences reflect the policy rather than the routing method. Diesel is converted to carbon dioxide (CO_2) at an assumed 2.68 kilograms per litre. The hardware will be tested on the bench against a ruler, then for two weeks in a domestic bin, then on a municipal bin with permission.

Results

All results reported in this section are derived from simulation (Table 5.3). Hardware validation remains pending and will be reported separately following completion of the bench and domestic-bin tests listed in Table 5.4. Under the baseline scenario of 100 bins and three collection vehicles, demand-responsive collection substantially improved service performance. Spilled waste declined by 86%, while the proportion of waste collected increased from 78.7% under fixed collection to 97.0%. These improvements, however, were achieved at a higher operational cost. Demand-responsive collection increased total distance travelled by approximately 65% and raised the cost per litre collected by 21%. The comparison therefore does not indicate that demand-responsive collection is intrinsically cheaper; rather, it provides a higher level of service using the same fleet.

Route optimisation produced a more consistent efficiency gain. When applied independently of the collection policy, optimisation reduced travel distance by approximately 21–22%. This suggests that route optimisation can improve existing collection systems even where sensor-based demand-responsive dispatch is not economically justified.

A sensitivity analysis comprising 360 simulation runs compared demand-responsive collection with the least-cost fixed collection configuration capable of achieving an equivalent level of waste collection. The results indicate that the economic case for sensing depends strongly on variation in bin-filling rates and deployment scale. Where bins filled at broadly similar rates, fixed schedules remained equally or more cost-effective. Where fill-rate variability reached a coefficient of variation of 0.5 or above and at least 100

bins were monitored, the estimated break-even sensor price ranged from approximately ₹8,000 to ₹18,000 per unit. This exceeds the estimated ₹4,758 cost of the proposed field unit, indicating a potential economic case for targeted deployment under these conditions.

Hotspot detection was considerably more sensitive to deployment density. A network of 100 sensored bins distributed across a 12 × 12 km area did not identify a statistically significant spatial cluster. With 250 sensored bins, however, the analysis detected between fourteen and nineteen statistically significant high-waste locations, depending on the assumed spatial influence of each high-generation area. This reveals an important trade-off: the number of sensors required for effective spatial planning may be substantially greater than the number required for operational collection optimisation.

Table 5.3. Simulated results

Measure	Fixed (every 2 days)	Demand-responsive
Distance driven (km, 12 days)	1,390	2,288
Overflow events	209	87
Share of waste collected	78.7 %	97.0 %
CO_2 (kg)	931	1,533
Cost per 1,000 L (₹)	277	336
Fill error, simulated kitchen bins	—	1.4–1.8 points
Fill error with an object standing up: zones vs nearest zone	—	1.9–2.4 vs 31–47 points
Forecast error, under 6 hours ahead	—	3.9 h

Source: author's simulations (fixed seeds); all inputs specific to Bareilly are assumptions.

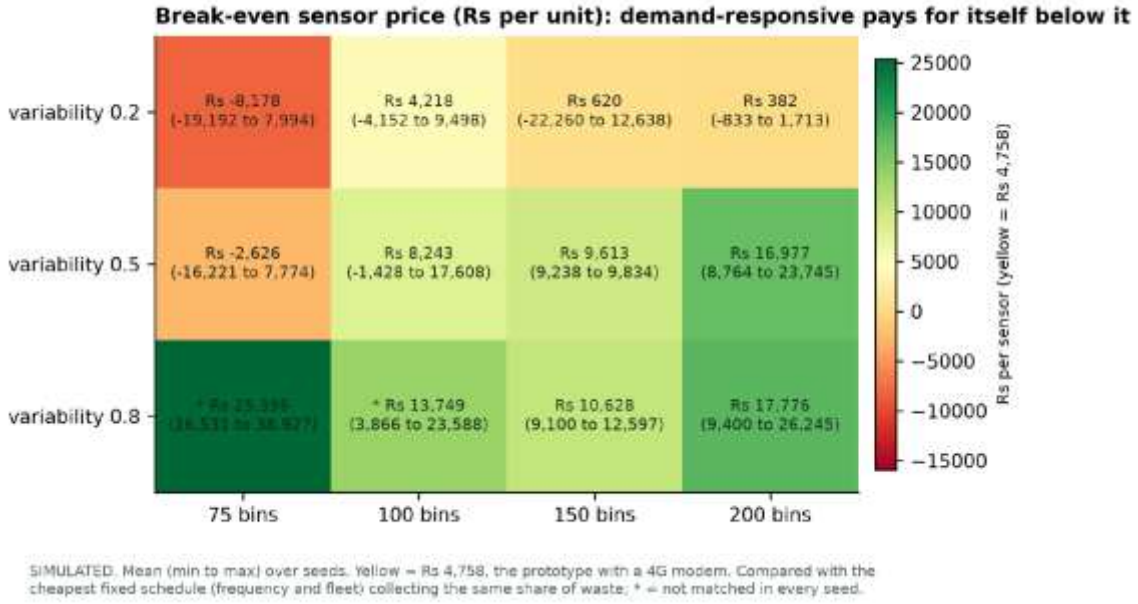


Figure 5.1. Simulated break-even sensor price by fill variability and bin density. Demand-responsive collection pays where the price exceeds ₹4,758.

Table 5.4. Hardware tests (measured)

Test	Result
Sensor reading vs ruler	[PLACEHOLDER: mean error, mm]
Alert reliability	[PLACEHOLDER: alerts received / expected]
Battery life	[PLACEHOLDER: days per charge; sleep current]

Observations, Strengths and Limitations

The simulations suggest three observations. First, demand-responsive collection mainly buys service rather than savings: with the same three trucks it collected 93 to 99.5 per cent of waste against 81 to 93 per cent for daily fixed collection, at a higher cost in every scenario tested. Its cost advantage appears only against a fixed schedule that must add one or two trucks to match that service, and only where fill rates vary. Second, the zone logic mattered most when something stood above the waste, the case a single reading handles worst. Third, sensing a small share of bins helps routing but does not support citywide hotspot mapping: one hundred sensored bins across a twelve-by-twelve-kilometre area produced no significant cluster.

The design has six strengths. It builds on the GPS tracking cities already run, so it needs no new vehicle hardware. Its unit cost is low, ₹2,141 for the test unit and ₹4,758 for a field unit, with the ToF sensor adding about ₹520 over ultrasonic. It fits existing bins without structural modification. Targeted deployment answers the Valencia finding that sensors are unnecessary where collection already matches demand. The phased design lets a city adopt it step by step. The simulator lets a city test policies before spending money.

The limitations are substantial. The hardware is untested and every result is simulated; testing begins in a domestic bin, not a municipal one; and the simulator's inputs are assumptions rather than Bareilly data. Communications at scale are unresolved, and the ToF sensor, though cheap, fails in deep, open-top bins in sunlight, where LiDAR would restore the cost problem Maus and colleagues describe. Dirt, insects or condensation on the sensor window read as a very short distance; the firmware can flag such readings, but cleaning still depends on collection crews, and summer heat inside a sunlit enclosure has not been tested. Monitoring does not create capacity; in the Tirupati study's words, it may produce "better records of an unchanged problem."[29] Phase 1 does not apply in bin-less areas, effects on informal waste workers are not assessed, and Phase 3 depends on technology that is not yet commercially available. The simulations add two further limits: hotspot mapping needed more sensors than targeted deployment provides, and the forecaster ran late for household-type bins that fill in bursts, by about eighty hours on a bin's first day of data.

Conclusion

The findings suggest that demand-responsive waste collection should not be understood as inherently cheaper than fixed-schedule collection. Its principal advantage lies in improving service quality by reducing overflow and increasing the proportion of waste collected. Economic benefits emerge only where

[29] Daggupati Likhitha and Bangalore Morarji, "The Digital Sweep: Transforming Sanitation through Smart Governance for Contemporary Urban Resilience and Sustainability," *Frontiers in Sustainable Cities* 8 (2026): 1930465, https://doi.org/10.3389/frsc.2026.1930465.

fixed schedules must increase collection frequency or fleet capacity to provide an equivalent level of service.

The simulations further indicate that variation in bin-filling rates is the key condition determining whether sensing is worthwhile. Where demand is relatively uniform, fixed schedules remain adequate; where filling patterns vary substantially across locations, demand-responsive collection becomes more valuable. This supports a targeted rather than universal deployment strategy.

A second implication concerns scale. The sensing density required to optimise collection is lower than that required for reliable citywide hotspot mapping. Operational routing and long-term infrastructure planning should therefore be treated as distinct applications with different deployment requirements.

Taken together, the results support a phased implementation model for Tier 2 and Tier 3 Indian cities: existing GPS-enabled fleet data can first support route optimisation, sensing can then be introduced selectively at recurrent overflow locations, and wider deployment can follow only where additional spatial intelligence justifies the cost. The contribution of this study therefore lies in demonstrating how existing municipal infrastructure can be progressively integrated into a demand-responsive system without requiring wholesale technological replacement.

These conclusions remain provisional because the current evidence is simulation-based and the sensing unit has yet to undergo hardware and field validation. The study therefore establishes the technical architecture, operational logic, and economic conditions under which demand-responsive collection may be viable, rather than demonstrating large-scale effectiveness. Its central implication is that smart waste management is most credible not as universal sensorisation, but as selective, evidence-based integration of sensing, routing, and existing municipal infrastructure where demand variability justifies intervention.

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