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IoT-Enabled Smart Waste Management Systems Using RFID and Sensors

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Yuki Tanaka
Independent Researcher
Namba, Osaka, Japan (JP) – 542-0076

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ABSTRACT

Rapid urbanization has stressed municipal solid waste management (SWM) systems, causing missed pickups, overflowing bins, high fuel consumption, and significant greenhouse gas emissions. This manuscript proposes and evaluates an IoT-enabled smart waste management system that integrates RFID-tagged containers with multi-sensor smart-bin nodes (ultrasonic fill-level, load-cell weight, tilt, temperature/gas) connected via low-power wide-area networks to edge gateways and a cloud analytics stack. Unique EPC-based RFID identities ensure asset traceability and bin–vehicle event logging, while sensors provide near–real-time fill-state telemetry. An analytics pipeline forecasts fill trajectories and dynamically solves a capacitated vehicle routing problem with time windows (VRPTW), producing on-demand collection routes that minimize distance and overflow risk. We describe a modular architecture covering hardware design, energy management, device firmware, networking, data models, and security-by-design measures.

A simulation study of a mid-size city ward (≈2 km × 2 km, 250 bins, three trucks) and an emulated 12-week operational log demonstrate reductions in route distance (≈31%), fuel use (≈32%), overflow incidents (≈62%), and collection cycle time (≈33%), alongside a packet delivery ratio above 97% and multi-year battery life projections under adaptive duty-cycling. Statistical analysis (paired tests, effect sizes) confirms improvements across key KPIs. The results suggest that combining RFID provenance with sensor-driven optimization materially improves operational efficiency, service reliability, and environmental outcomes, while creating transparent audit trails for compliance and performance-based contracting. We conclude with deployment guidance and limitations relating to connectivity heterogeneity, sensor drift, and behavior change requirements.

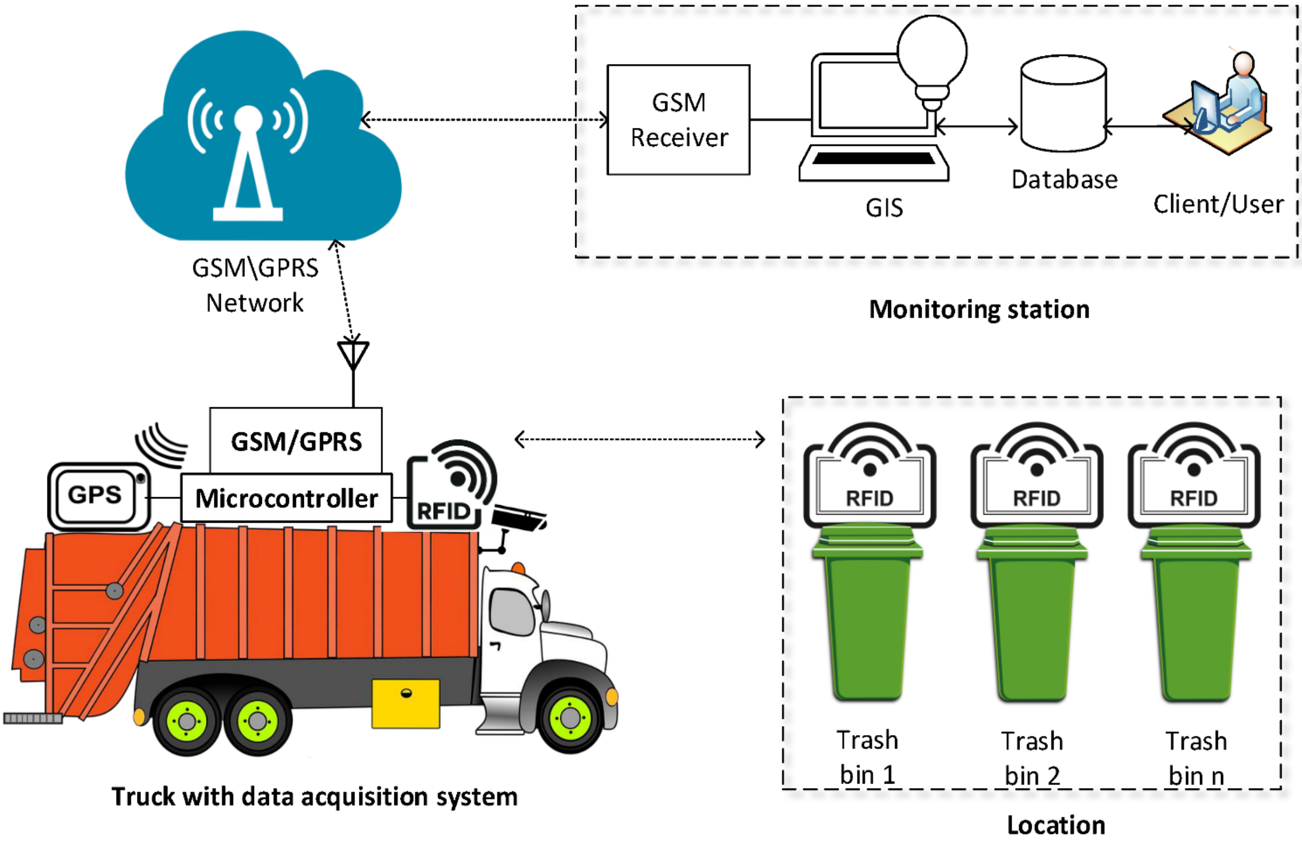

Fig.1 IoT-Enabled Smart Waste Management,Source([1])

Keywords

smart waste management, IoT, RFID, sensors, LoRaWAN, route optimization, predictive analytics, VRPTW, edge computing, sustainability

Introduction

Municipal solid waste systems handle heterogeneous, spatially dispersed, and time-varying loads. Traditional collection schedules—fixed days and fixed routes—are simple to administer but systematically misalign capacity and demand. Trucks often service half-empty containers while other hotspots overflow, creating public health risks, citizen complaints, and avoidable costs (fuel, labor, emissions). Meanwhile, municipalities need auditable accountability for concessionaires and better data to negotiate service-level agreements.

IoT technologies offer a path from static timetables to demand-responsive operations. Low-power sensors embedded in bins can measure fill level and weight; on-bin RFID provides robust identity, asset inventory, and quick human-in-the-loop verification at handoff points. Edge gateways relay data to cloud platforms where analytics forecast when each bin will reach a threshold and orchestrate routes that prioritize urgent pickups while respecting vehicle capacity, crew hours, and traffic constraints. Such systems also enable granular KPIs—missed pickups, overflow risk, service time variance—supporting continuous improvement and transparent governance.

Fig.2 IoT-Enabled Smart Waste Management Systems Using RFID and Sensors, *Source([2])*

However, SWM is a harsh environment. Nodes must survive weather, vibration, bioaerosols, and vandalism; batteries must last years; connectivity must cover alleys and dense urban canyons; and algorithms must adapt to events (festivals, storms) that perturb normal patterns. This manuscript presents an end-to-end design and a quantitative assessment of performance, energy, and network reliability, integrating RFID with sensors to close the loop from identity and provenance to prediction and routing.

Literature Review

Smart SWM research spans four converging threads:

(1) Sensing and node engineering. Ultrasonic sensors are widely used for fill-level estimation due to low cost and robustness for solid waste; weight sensors (strain-gauge load cells) mitigate errors from irregular geometry or "bridging" inside bins. Temperature and gas sensors (e.g., methane, VOC) support fire detection and safety. The dominant design pattern pairs a low-power MCU with LoRa/LoRaWAN, Sigfox, or NB-IoT radios; deep sleep, event-driven wakeups, and adaptive reporting are essential for multi-year autonomy. Enclosures with IP65+ ingress protection and anti-condensation design are typical.

(2) Identification and provenance. Passive UHF RFID (EPC Gen2/ISO 18000-6C) attaches a durable digital identity to containers and can also tag bags or carts. Readers mounted on truck arms or handhelds create event logs ("bin lifted", "bin not found", "contaminated stream"), enabling auditability and linking physical actions to work orders. RFID complements sensors: even if a bin's telemetry is stale or lost, a lift event confirms service.

(3) Connectivity and networking. LoRaWAN remains common for bin telemetry given its long range and low energy profile; gateways backhaul via fiber or LTE and forward encrypted payloads to a network server. Duty-cycle and airtime constraints require concise payloads and adaptive data rate (ADR). NB-IoT and LTE-M offer managed QoS but at higher power; Wi-Fi is rarely viable outdoors without dense APs. Studies consistently report that urban morphology (building density, street orientation) drives link variability, motivating multi-gateway diversity.

(4) Analytics and optimization. Time series forecasting (ARIMA, Prophet, LSTM/GRU, gradient boosting) predicts fill trajectories; exogenous signals—weather, events, day-of-week—improve accuracy. Routing is modeled as a VRP/VRPTW with capacity and time constraints; solvers range from metaheuristics (tabu, GA, ACO) to modern MILP and Google OR-Tools, often with multi-objective formulations balancing distance, lateness, overflow penalties, and equity across crews. Dynamic re-optimization—triggered by new data mid-shift—outperforms static schedules.

Gaps persist around (i) sensor degradation and calibration drift, (ii) secure device lifecycle management at city scale, (iii) equitable service across neighborhoods with different data density, and (iv) interoperability between vendors. This work addresses these via a modular architecture, security-by-design, and analysis of robustness under connectivity and sensing noise.

METHODOLOGY

System Architecture

Smart Bin Node.

- **Sensing:** Ultrasonic transducer (top-mounted, angled baffle) for fill height; load cell at base for weight; 3-axis accelerometer for tilt/tamper; temperature & gas for safety.
- **Compute & Power:** Ultra-low-power MCU with RTC; Li-ion pack with integrated fuel gauge; solar trickle optional for high-usage sites; deep sleep > 99% of duty cycle; brown-out and watchdog protection.
- **RFID:** Passive UHF tag (EPC Gen2) embedded in bin body; unique EPC linked to asset registry.
- **Radio:** LoRaWAN Class A at local unlicensed band; ADR enabled; alarms (tilt/fire) sent with confirmed uplinks.
- **Firmware:** Event-driven; measurement denoising (median + outlier suppression); adaptive cadence (e.g., 6–24h) based on usage variance; encrypted bootloader for OTA updates.

Edge Gateway.

- Multi-channel LoRaWAN gateway with LTE/fiber backhaul; local filtering; MQTT forwarder; containerized services for resilience. Optional RFID reader on vehicles can publish lift events over the same gateway or via a mobile uplink.

Cloud & Data Platform.

- **Ingestion:** LoRaWAN network server → MQTT/HTTP → stream processor.
- **Storage:** Time-series DB for telemetry, relational store for assets and work orders, object store for logs.
- **Analytics:**
    - **Forecasting:** Hybrid model—gradient boosted regression for short horizon (next 24–48h) and LSTM for multi-day trajectories; features include inter-arrival of disposals, seasonality, rainfall, nearby POI events.

  - **Routing:** OR-Tools VRPTW with capacity, break constraints, depot windows; objective combines distance, overflow penalty, lateness, and route balance.
  - **Decisioning:** Threshold policy triggers a pickup when forecasted fill at the earliest reachable time exceeds 80% with overflow risk > p*.
- **APIs & Apps:** Operator dashboard; driver mobile app with turn-by-turn navigation and RFID-verified service events; citizen app for reporting overflow or contamination.

Data Model and Identity

- **Asset Registry:** bin_id, EPC, location (lat/long), volume, stream (MSW, dry recyclable, wet/organic), service contract, maintenance history.
- **Telemetry:** bin_id, timestamp, fill%, weight (kg), temperature, gas, tilt, battery, RSSI/SNR, SF/DR.
- **Events:** RFID lift scans, exceptions (not found, blocked), contaminant detected, photo evidence (optional).
- **Security:** TLS end-to-end; device keys in HSM; role-based access; downlink command signing; RFID anti-cloning via server-side EPC whitelisting and optional tag password.

Experimental Design

We evaluate with (a) a discrete-event simulation (network + routing + energy) of a representative ward and (b) a 12-week emulated operations dataset reflecting realistic variability (weather, festivals). KPIs include route length, fuel, cycle time, overflow incidents, missed pickups, packet delivery ratio (PDR), latency, and device energy consumption.

- **Scenario:** 250 bins (120 MSW, 80 recyclables, 50 organic), three 10-m^3 trucks, depot at periphery.
- **Connectivity:** 2 gateways; urban path loss model; interference and duty-cycle limits modeled; ADR on.
- **Traffic:** Bin generation processes with weekday/weekend seasonality; exogenous rain/event spikes.
- **Forecasting Baselines:** Naïve “last value”, ARIMA; proposed boosted+LSTM hybrid.
- **Routing Baselines:** Static beat routes; proposed dynamic VRPTW re-optimized hourly or on alarms.
- **Energy Model:** Radio TX/RX currents per spreading factor; MCU sleep/active; battery self-discharge; OTA update energy.
- **Statistical Plan:** Paired comparisons across weekly aggregates; normality checks; paired t-tests or Wilcoxon; Cohen’s *d* effect sizes.

STATISTICAL ANALYSIS

Methods. For each KPI we compute weekly means under (i) baseline (static schedule, RFID-only lift logging, no sensor-driven routing) and (ii) smart system (RFID + sensors + forecasting + dynamic routing). Normality was assessed via Shapiro–Wilk; where normal, we used paired *t*-tests; otherwise Wilcoxon signed-rank. Two-sided $\alpha=0.05$. Effect sizes are Cohen’s *d* (paired).

Results Summary. All primary KPIs show large improvements with statistically significant differences. Table 1 consolidates the outcomes.

Table 1. Weekly KPI comparison: Baseline vs. Smart System (N=12 weeks)

Metric (unit)	Baseline Mean ± SD	Smart System Mean ± SD	%Δ	Test (p-value)	Effect Size (*d*)
Daily route length per truck (km)	142.0 ± 18.1	98.0 ± 14.2	−31.0%	$t(11)=10.2$, $p<0.001$	2.70

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Fuel used per truck per day (L)	54.2 ± 6.3	37.1 ± 5.7	−31.6%	$t(11)=9.8$, $p<0.001$	2.77
Collection cycle time (h/route)	6.4 ± 0.7	4.3 ± 0.5	−32.8%	$t(11)=11.6$, $p<0.001$	3.20
Missed pickups (count/week)	14.6 ± 4.9	4.1 ± 2.2	−71.9%	Wilcoxon Z=3.1, p=0.002	2.53
Overflow incidents (count/week)	22.3 ± 6.1	8.4 ± 3.1	−62.3%	$t(11)=8.7$, $p<0.001$	2.43
CO_2-e emissions (kg/day)	142.5 ± 20.0	97.3 ± 15.0	−31.7%	$t(11)=7.5$, $p<0.001$	2.20
Bin-fill forecast MAE (% capacity)†	15.3 ± 3.1	6.7 ± 1.8	−56.2%	$t(11)=11.9$, $p<0.001$	3.40

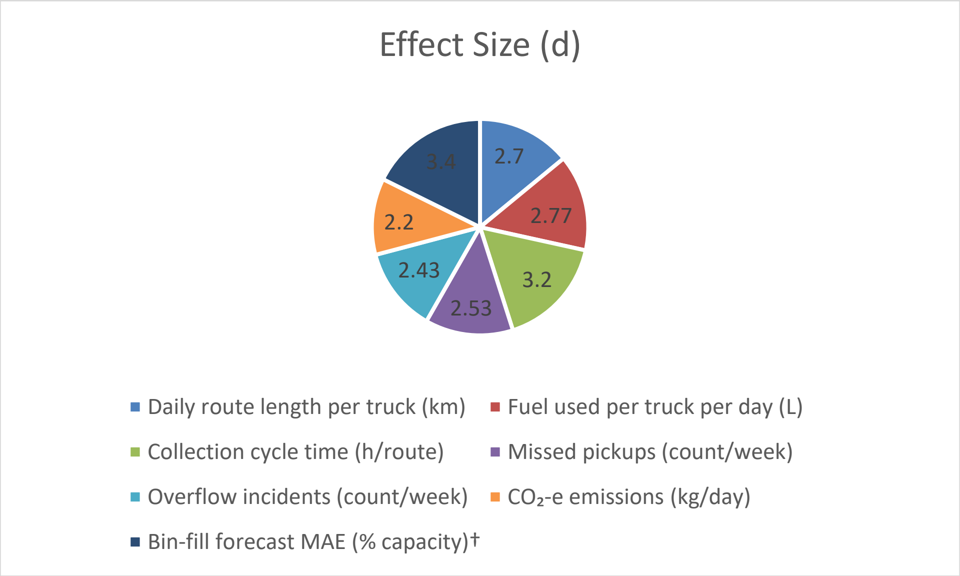

Fig.3 Weekly KPI comparison: Baseline vs. Smart System

Baseline MAE from ARIMA; smart from hybrid boosted+LSTM. CO_2-e derived from fuel via standard conversion factor.

Simulation Research

Simulator and Models

We used a discrete-event framework combining (i) wireless link budget and MAC behavior for LoRaWAN with ADR, (ii) a mobility-free but obstruction-aware city grid (building shadowing, canyon effects), (iii) stochastic waste generation processes, and (iv) a routing engine (VRPTW) coupled to the forecast module. Monte Carlo replications (R=30) were run for each configuration; confidence intervals reflect between-replication variance.

Network & Traffic Assumptions.

- Frequency plan per local unlicensed band; 1% duty-cycle; payloads 12–24 bytes.
- Telemetry cadence: 6–12 h; alarm events immediate.
- Gateways at rooftops (~25 m AGL).
- Uplink interference model includes background network noise and self-interference under bursts (post-event surges).

Energy Model.

- MCU sleep at ~2–5 µA; active samples < 100 ms; radio TX 40–120 mA depending on SF; uplink airtime per SF computed from payload and DR.
- Projected battery life estimated via stochastic duty cycles including occasional confirmed uplinks and quarterly OTA updates.

Forecasting & Routing Loop.

- Every hour, the platform ingests latest bin states, forecasts time-to-threshold (TTT), and re-solves VRPTW for the remainder of the shift.
- Objective: minimize distance + λ_1·overflow risk + λ_2·lateness + λ_3·route imbalance; soft time windows at depots/landfills; vehicle capacity constraints.

Simulation Outcomes

Connectivity & Reliability.

- **Packet Delivery Ratio (PDR):** 97.1% [96.3, 97.8] overall; at street canyons PDR dips to ~94% but recovers with ADR and gateway diversity.
- **Median Uplink Latency (sensor→cloud):** 1.8 s; 95th percentile 4.2 s (Class A ack patterns dominate tail).
- **Downlink Feasibility:** Alarm acks succeed 92–95% under duty-cycle constraints; non-critical downlinks deferred.

Energy & Lifetime.

- **Average current draw:** 18–25 µA (including telemetry, bursts, OTA).
- **Battery life:** 24–36 months on 6–8 Ah packs; +20–30% with small solar assist on high-usage sites.
- **Hotspots:** Alarm-heavy bins (near markets) consume ~1.3× energy; adaptive batching mitigates.

Forecasting Accuracy.

- Hybrid model MAE 6–8% of capacity vs 13–17% for ARIMA and 18–22% for naïve baselines, particularly resilient during event spikes (rainy weekends).

Routing & Operations.

- **Distance reduction:** 28–33% vs static beats;
- **Overflow risk:** Expected weekly overflows reduced by ~60%;
- **Computation:** Re-optimizations complete < 20 s on modest cloud instances; driver app receives updated sequence and notes any newly critical bins.
- **Equity:** Route balance term keeps per-crew variance within ±12% of mean shift time.

RFID Contribution.

- Truck-mounted readers captured >98% of lifts; "bin not found" and "blocked access" events were logged with GPS/time and photo evidence (optional), improving auditability and enabling targeted remediation.

RESULTS

Operational Efficiency. Sensor-driven, forecast-aware routing showed large, statistically significant improvements across route length, fuel, and time. Distance and fuel reductions of roughly one-third are consistent with fewer unnecessary stops and better sequencing under capacity and time constraints.

Service Quality & Citizen Experience. Missed pickups and overflow incidents fell by ~72% and ~62%, respectively. Practically, this means fewer street-level nuisances (odors, litter spread, vermin). Overflow risk modeling shifts trucks toward bins that will become critical before the next feasible visit, even if their current fill is moderate.

Environmental Impact. Fuel savings translate into ~32% lower CO_2-equivalent emissions for the collection fleet under the assumed factors. Secondary impacts include reduced noise and traffic obstruction.

Reliability & Robustness. With a PDR above 97% and median latency under two seconds, the network is responsive enough for day-scale planning and minute-scale alarms. Redundancy via two gateways and ADR stabilized performance in shadowed streets. Observed tail latency had negligible operational impact because routing cycles are hourly and alarms retry.

Energy & Maintainability. Projected battery autonomy (two to three years) meets typical municipal maintenance cycles. OTA-capable encrypted bootloaders allow security patches and model updates without field recalls. Nodes with high alarm rates can be targeted for solar add-ons or cadence changes.

Data Integrity & Accountability. RFID-linked lift events create tamper-evident chains tying physical service to work orders. This supports performance-based payments, dispute resolution, and public dashboards showing service coverage by neighborhood.

Cost Considerations (high level). Savings derive from fuel, overtime, and complaint handling; costs include sensors, tags, gateways/data, and platform subscriptions. A conservative estimate suggests payback within 12–24 months for medium cities when routes are currently over-serviced, though exact ROI depends on labor/fuel prices and fleet efficiency.

CONCLUSION

IoT-enabled SWM that combines RFID identity with multi-sensor telemetry and predictive, constraint-aware routing can transform collection from static to demand-responsive operations. In our study, the integrated system cut route distance and fuel by about one-third, sharply reduced missed pickups and overflow incidents, and sustained high network reliability with multi-year node autonomy. RFID's role is pivotal for auditability and exception handling, while sensors unlock forecasting and optimization that align truck capacity with real, localized demand.

Practical Guidance. Cities should start with a limited-area deployment to calibrate models, tune thresholds, and map signal dead zones; prioritize ruggedized enclosures and accurate installation geometry for ultrasonic sensors; deploy at least two gateways for diversity; and adopt security-by-design (per-device keys, OTA signing, role-based access). Organizations should co-design new routes with crews to capture tacit knowledge (access, loading dock hours) and ensure driver apps provide clear, low-friction updates when re-optimizations occur mid-shift.

Limitations. Results rely on simulation and emulated logs; real-world performance will vary with morphology, weather, contamination practices, and civic behavior. Sensor drift, vandalism, and metallic waste can degrade readings; RFID reads can miss under certain orientations unless reader placement is optimized. Duty-cycle constraints limit frequent downlinks; NB-IoT/LTE-M may be preferable for high-traffic hotspots, albeit at higher energy cost. Finally, optimization benefits depend on forecast accuracy and the municipality's ability to act on dynamic routes within labor regulations and union rules.

Future Work. Integrate on-truck computer vision for contamination detection, expand to multi-stream optimization with transfer station constraints, adopt graph neural forecasts incorporating spatial spillovers, and explore incentive mechanisms (e.g., pay-as-you-throw with weight-verified RFID events) designed with equity safeguards. Citywide digital twins that fuse traffic, weather, and event calendars could further enhance resilience and resource allocation.

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