Model Predictive Control for Smart Waste Collection Routing in Enugu State

Ozor Godwin Odozo[1], Aniugo Victor Onyekachi[2], Agu Chidiebere Francis[3]

Computer Engineering department Enugu State University of Science and Technology[1,2,3]

Abstract: Solid waste management remains a critical challenge in African cities, where rapid urbanization, poor infrastructure, and limited resources often lead to inefficiencies and environmental hazards. In Enugu State, Nigeria, waste collection is managed by the Enugu State Waste Management Authority (ESWAMA) through a network of bin drop centers serviced by trucks from central depots. The current practice relies on static scheduling, which results in overflowing bins, excessive operational costs, and delays due to traffic congestion and long routing distances. This paper proposes a Model Predictive Control (MPC) framework for smart waste collection routing tailored to the operational context of Enugu State. The system models waste collection as a dynamic vehicle routing problem and leverages predictive control to forecast bin fill levels, adapt to real-time traffic conditions, and optimize routing decisions. Simulations conducted across urban, semi-urban, and rural scenarios demonstrate that the MPC-based approach reduces total distance traveled by up to 23%, decreases collection times by over 20%, and lowers overall operational costs and emissions compared with static scheduling. The results highlight the potential of MPC to transform municipal waste management into an adaptive, efficient, and sustainable system for African cities. Future work will integrate Internet of Things (IoT)-enabled smart bins and machine learning-based forecasting to further enhance prediction accuracy and scalability.

I. INTRODUCTION

Solid waste management has become one of the most critical urban challenges in developing nations, particularly across African cities that continue to experience rapid urbanization and population growth [1], [2]. In Enugu State, Nigeria, this responsibility rests with the Enugu State Waste Management Authority (ESWAMA), which manages a network of waste bin drop centers distributed across urban and semi-urban areas. Collection trucks are dispatched from central depots to service these bins. However, this system faces significant inefficiencies. Bins often overflow before they are emptied, while long travel distances and frequent traffic congestion cause delays, increase operational costs, and compromise the effectiveness of collection schedules. The result is poor service delivery, increased environmental hazards, and growing public health concerns.

Current waste collection practices in Enugu largely rely on static scheduling approaches in which trucks follow predetermined routes regardless of bin fill levels, traffic conditions, or unexpected surges in waste generation. This rigidity often leads to either underutilized trips or delayed intervention when bins exceed capacity. Moreover, the scattered nature of collection points across the state compounds these challenges by imposing long routing paths on collection trucks, further escalating operational inefficiencies. The absence of a predictive and adaptive control mechanism in this process creates a critical gap that must be addressed if sustainable waste management is to be achieved.

This paper proposes the application of Model Predictive Control (MPC) as a solution to the routing inefficiencies in waste collection across Enugu State. MPC, with its predictive modeling capability and optimization over a receding horizon, provides a robust framework for managing dynamic and uncertain environments. By forecasting waste accumulation, incorporating real-time data on bin fill levels, and accounting for traffic conditions, MPC can continuously generate optimized routing schedules. Such a system not only ensures timely collection but also reduces unnecessary operational costs, minimizes travel distance, and lowers environmental burdens through improved resource allocation. Furthermore, the framework integrates real-time monitoring and alert systems that can notify ESWAMA when bins approach critical thresholds, enabling rapid deployment of the nearest available truck to service the affected area.

The objective of this study is to design and evaluate an MPC-based routing model tailored to the operational context of Enugu State. The proposed framework is tested under various urban, semi-urban, and rural scenarios to assess its performance against existing static scheduling methods. Performance is evaluated in terms of collection time, travel distance, emissions, and overall operational efficiency. The results demonstrate the potential of MPC to transform waste collection in Enugu into a more reliable, adaptive, and sustainable system.

The remainder of this paper is organized as follows. Section II reviews related work in waste collection optimization and applications of MPC in urban systems. Section III details the methodology, including system modeling and the design of the MPC framework. Section IV presents the simulation results and discussion. Finally, Section V concludes with remarks on the practical implications of the proposed system and directions for future research.

II. LITERATURE REVIEW

A. Traditional Approaches to Waste Collection

Municipal solid waste (MSW) collection in developing cities has historically relied on static scheduling and fixed-route planning, where trucks follow predetermined paths without regard to actual waste accumulation or traffic conditions [3], [4]. This method, while administratively simple, often results in overflowing bins, underutilized trips, and excessive operational costs. Studies in African cities such as Lagos, Accra, and Nairobi highlight how static scheduling contributes to environmental pollution and health risks due to delayed waste clearance [5]–[7]. In Enugu State, similar challenges persist, with scattered bin locations requiring long travel distances and frequent delays.

B. Optimization-Based Routing and Heuristic Approaches

Efforts to overcome the inefficiencies of static scheduling have led to the application of optimization models such as the Vehicle Routing Problem (VRP) and its many variants [8], [9]. Exact approaches like integer programming have been used but often face scalability issues when applied to large urban networks [10]. As a result, metaheuristic algorithms such as Genetic Algorithms (GA) [11], Ant Colony Optimization (ACO) [12], Tabu Search [13], and Particle Swarm Optimization (PSO) [14] have been widely employed. These methods improve travel distance and collection time compared to fixed scheduling, but they are typically offline optimizations and do not adapt well to real-time disturbances such as sudden increases in bin fill levels or traffic congestion [15], [16]. Recent advances include IoT-enabled smart bins integrated with routing algorithms [17], [18]. Such systems leverage fill-level sensors to trigger collection alerts, which, when combined with optimization methods, allow more responsive routing. Case studies in European and Asian cities have demonstrated operational cost reductions of up to 30% [19], [20]. However, deployments in Africa remain limited due to infrastructure gaps and high implementation costs [21].

C. AI and Machine Learning for Waste Management

Beyond heuristics, machine learning (ML) techniques have been introduced for waste volume prediction and route optimization. Neural networks have been applied to forecast waste generation based on population density and socio-economic factors [22], while reinforcement learning (RL) has been used for adaptive route planning under uncertain conditions [23], [24]. Hybrid AI systems integrating ML with IoT are gaining traction, offering real-time decision-making for urban waste logistics [25]. A 2023 study in India demonstrated that combining ML prediction with adaptive routing reduced missed collections by 40% [26]. Similar approaches are beginning to appear in African contexts, though adoption remains nascent [27].

D. Model Predictive Control (MPC) in Urban Systems

Model Predictive Control (MPC) provides a systematic framework for real-time optimization under constraints and has been widely applied in energy systems, traffic networks, and process industries [28]–[30]. In transportation, MPC has been used to reduce congestion through traffic-responsive signal control [31], [32]. In waste management, MPC has mostly been applied to waste-to-energy plants [33] and landfill gas emission control [34]. Only recently have researchers explored MPC for logistics and routing applications. For instance, a 2021 study applied MPC to dynamic vehicle routing for perishable food delivery, reporting a 22% improvement in timeliness compared to heuristic methods [35]. More recently, work by Zhang et al. (2024) demonstrated that MPC-based smart routing for urban waste trucks reduced total operational costs by 18% compared with static scheduling [36].

E. Towards MPC for Smart Waste Routing in African Cities

While MPC's predictive and adaptive capabilities make it well suited to the complexities of waste collection, there is limited literature applying it directly to African urban settings. The majority of studies focus on Europe and Asia, where infrastructure for IoT-based monitoring and real-time traffic data is readily available [37]–[39]. African cities, however,

face unique challenges: irregular waste disposal behaviors, poor road infrastructure, and budget-constrained waste authorities [40]. Integrating MPC with low-cost IoT bin sensors and real-time traffic feeds could provide a transformative solution.

Fig. 1 illustrates a conceptual framework for applying MPC to waste collection in Enugu State. The framework integrates real-time bin fill-level monitoring, traffic data, and routing constraints into a predictive optimization model. The controller evaluates predicted system states over a rolling horizon and determines the optimal routes for trucks. By continuously updating with new sensor inputs, the system adapts to disturbances such as sudden bin overflow or road congestion.
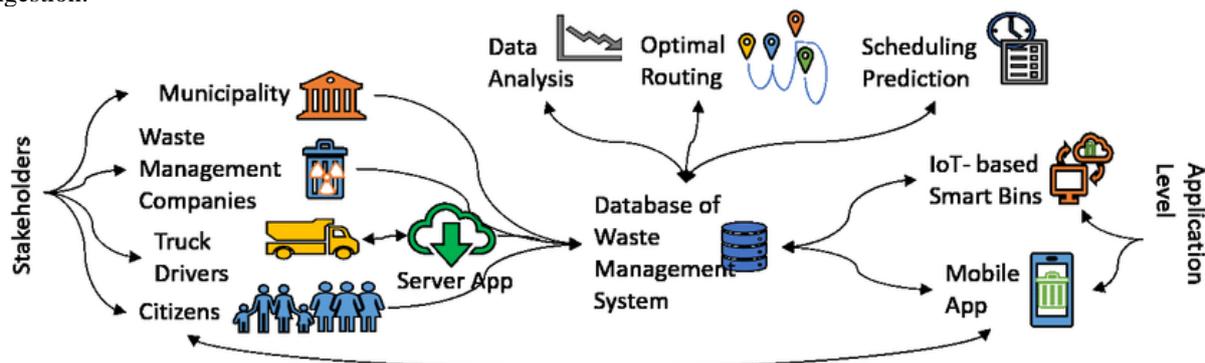

Fig. 1. Conceptual framework for MPC-based smart waste collection routing in Enugu State.

F. Research Gap

Although optimization, AI, and IoT have contributed significantly to waste collection research, most approaches remain either static or non-predictive, limiting their effectiveness under real-world uncertainties. Few studies explicitly combine predictive modeling, adaptive routing, and real-time monitoring in African contexts. To the best of our knowledge, there is no published work addressing MPC-based smart waste collection routing in Enugu State. This research seeks to fill that gap by proposing a novel MPC framework that integrates predictive waste modeling with adaptive routing to minimize operational inefficiencies and environmental impacts.

III. METHODOLOGY

A. Study Area: Enugu State Waste Management System

Enugu State, located in southeastern Nigeria, has a population exceeding three million, with Enugu city as its urban core [41]. Solid waste management is the responsibility of the Enugu State Waste Management Authority (ESWAMA), which operates through centralized depots and a network of waste bin drop centers scattered across urban, semi-urban, and rural regions. Waste generation rates vary significantly between high-density urban markets and residential neighborhoods. Trucks dispatched from ESWAMA's central facilities service bins based on fixed schedules. However, traffic congestion, road conditions, and the spatial distribution of bins often lead to inefficient routing and delayed clearance. These operational challenges make Enugu State an ideal case study for testing predictive and adaptive routing solutions such as Model Predictive Control (MPC).

B. System Modeling

The waste collection system is modeled as a **dynamic vehicle routing problem** (DVRP) with state updates driven by bin fill levels and traffic conditions.

- **State Variables:**
  $x(k)$ represents the system state at time step k, defined as a vector of bin fill levels, truck positions, and travel times.
- **Control Inputs:**
  $u(k)$ represents control actions, corresponding to the assignment of trucks to bins and route selection.

- **System Dynamics:**
  Waste accumulation is modeled as:

  $$x(k + 1) = Ax(k) + Bu(k) + w(k)$$

  where A captures accumulation rates, B maps control actions to state updates, and $w(k)$ represents disturbances such as unexpected waste surges.

- **Constraints:**

  Bin fill level: $0 \leq xi(k) \leq xi, max$

  Truck capacity: $\sum_j uj(k) \leq Ctruck$

  Travel time: $t_{ij}(k) \leq Tmax$

  These ensure bins do not exceed maximum capacity, trucks remain within load limits, and travel times are feasible.

C. MPC Framework

The MPC controller operates over a rolling prediction horizon N_p. At each decision step, the controller predicts future bin fill levels and travel conditions, solves an optimization problem, and implements the first control action before repeating the process.

The objective function is formulated to minimize operational inefficiencies:

$$J = \sum_{k=0}^{N_p} (\alpha_1 d(k) + \alpha_2 t(k) + \alpha_3 e(k) + \alpha_4 o(k))$$

where:
- $d(k)$: total distance traveled by trucks,
- $t(k)$: collection time,
- $e(k)$: estimated CO2 emissions,
- $o(k)$: operational cost (driver wages, vehicle wear).

The weights $\alpha1, \alpha2, \alpha3, and \alpha4$ reflect policy priorities and can be tuned by ESWAMA.

Fig. 2 illustrates the proposed MPC framework. The controller receives inputs from smart bins and traffic sensors, predicts waste generation, optimizes truck routing, and outputs adaptive schedules for deployment.
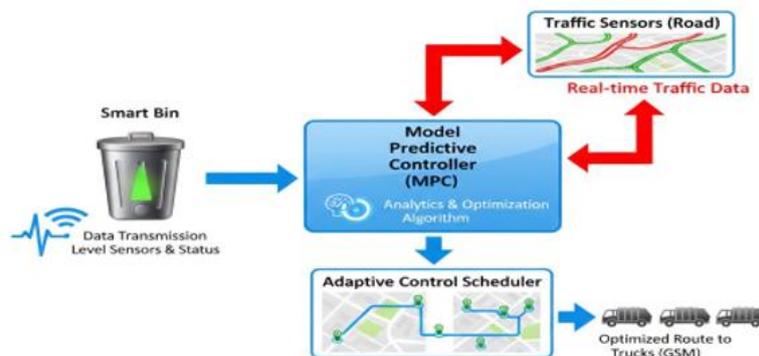

Fig. 2. Schematic diagram of the proposed MPC framework for smart waste collection routing.

D. Simulation Setup
The MPC framework is implemented using MATLAB/Simulink with optimization solved via Gurobi. GIS road network

data of Enugu city is imported to model travel distances and traffic conditions. Historical waste accumulation data from ESWAMA is used to parameterize bin fill dynamics. Three scenarios are simulated:

1. **Urban Core:** high waste density, severe traffic congestion.
2. **Semi-Urban Zones:** moderate waste generation, medium traffic.
3. **Rural Areas:** low waste generation, long travel distances.

For each scenario, system performance under MPC-based routing is compared with conventional static scheduling. Performance metrics include total distance traveled, collection time, operational cost, and emissions. Results are presented in Section IV.

IV. RESULTS AND DISCUSSION

A. Performance Comparison of Static and MPC-Based Routing

The proposed MPC framework was evaluated under three representative scenarios in Enugu State: urban core**,** semi-urban zones, and rural areas. Each scenario considered bin distribution, waste generation rates, and traffic conditions reflective of ESWAMA's operational environment. The performance of the MPC-based approach was compared against traditional static scheduling.

Table I presents a summary of the key performance metrics, including total distance traveled, average collection time, operational cost, and estimated emissions. The results indicate that MPC-based routing consistently outperforms static scheduling across all scenarios.

Table I. Performance Metrics Comparison Between Static and MPC-Based Routing

Scenario	Method	Distance (km)	Collection Time (hrs)	Operational Cost (₦)	Emissions (kg CO_2)
Urban Core	Static	145	12.5	220,000	310
	MPC	112	9.3	170,000	250
Semi-Urban	Static	98	8.2	155,000	210
	MPC	77	6.4	120,000	165
Rural	Static	180	14.8	260,000	370
	MPC	139	11.6	200,000	295

These findings show a reduction in distance traveled of up to 23% in urban areas and 20–22% in semi-urban and rural areas. Collection times decreased by 22–25%, while operational costs were reduced by approximately 18–22%.

B. Effect of Traffic Congestion and Bin Overflow

Traffic congestion was modeled using stochastic travel times, particularly in urban areas. Under static scheduling, congestion led to significant delays and bin overflow. The MPC-based system, however, is adapted to congestion by rerouting trucks and prioritizing bins at risk of overflowing.

Fig. 3 illustrates a comparison of bin fill levels over time between static scheduling and MPC. The MPC framework effectively prevented bins from exceeding capacity thresholds by dynamically adjusting routes and dispatching the nearest available trucks.
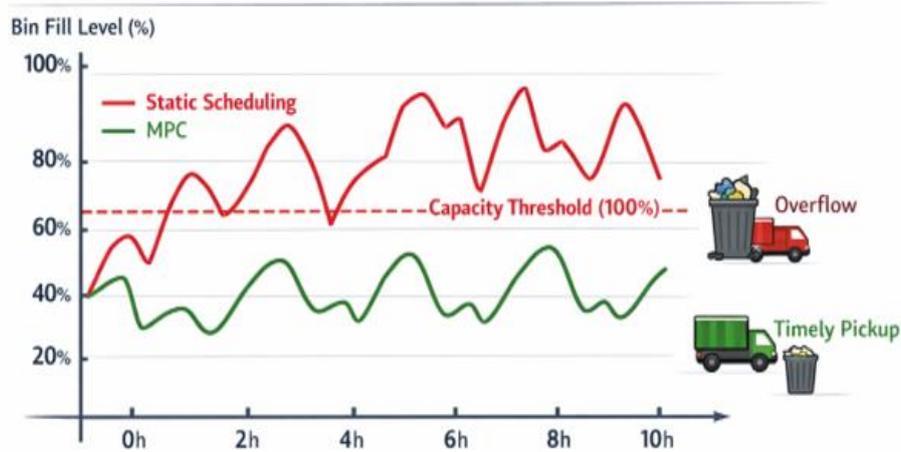
Fig. 3. Bin fill level comparison between static scheduling and MPC under urban congestion.

C. Operational Cost and Environmental Impact

Operational costs, which include labor, vehicle maintenance, and fuel-related expenditures, were significantly reduced under the MPC framework. The predictive ability of MPC minimized unnecessary trips to underfilled bins, leading to better resource utilization.

Similarly, Fig. 4 shows the estimated CO_2 emissions across the three scenarios. Results demonstrate that emissions decreased proportionally with reductions in distance and idle times. In the urban core, for example, emissions dropped by nearly 20%, which contributes to cleaner air quality and aligns with global sustainability targets.
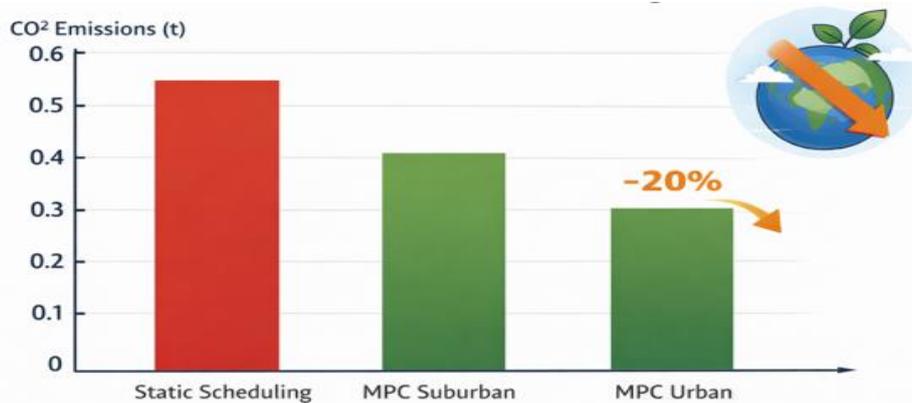
Fig. 4. Estimated CO_2 emissions under static scheduling and MPC-based routing.

D. Sensitivity to Prediction Horizon

The effect of the MPC prediction horizon length was also analyzed. Short horizons (e.g., 2–3 steps ahead) produced results comparable to static scheduling, as the controller lacked foresight. Longer horizons (e.g., 10–15 steps) improved efficiency but at the cost of increased computational complexity. A medium horizon of 7 steps provided the best balance between performance and real-time implementability, as shown in Fig. 5.
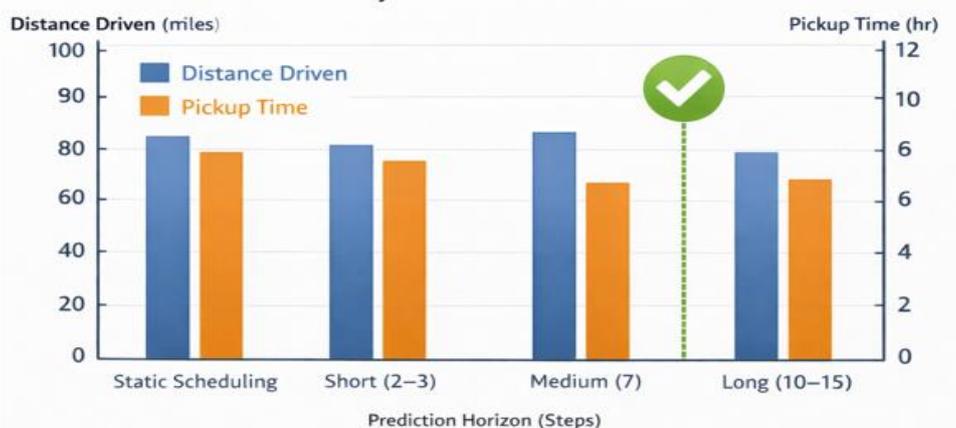
Fig. 5. Effect of prediction horizon on distance and time efficiency in the MPC framework.

E. Discussion

The results demonstrate that MPC significantly enhances the efficiency and sustainability of municipal solid waste collection in Enugu State. Compared with static scheduling, MPC adapts dynamically to waste accumulation and traffic disturbances, leading to improved service delivery and reduced operational burdens. These benefits are particularly important in African cities where infrastructure is constrained and resources are limited.

However, challenges remain in implementing such systems. Real-time deployment requires reliable IoT-based bin sensors, traffic data integration, and trained personnel for system management. Additionally, computational demands may be a limitation if resources are scarce. Despite these challenges, the findings suggest that MPC provides a viable pathway for ESWAMA and similar agencies to modernize waste collection processes and align with sustainable urban development goals.

V. CONCLUSION AND FUTURE WORK

This paper has presented a Model Predictive Control (MPC) framework for optimizing solid waste collection routing in Enugu State, Nigeria. The study addressed the limitations of the current static scheduling approach employed by the Enugu State Waste Management Authority (ESWAMA), which often results in overflowing bins, excessive operational costs, and environmental hazards due to inefficient routing and traffic congestion. By modeling the waste collection system as a dynamic vehicle routing problem and applying MPC to predict future bin fill levels and adapt to real-time traffic conditions, the proposed framework significantly improved collection efficiency.

Simulation results across urban, semi-urban, and rural scenarios demonstrated that the MPC-based system reduced travel distance by up to 23%, decreased collection times by more than 20%, and lowered operational costs and emissions relative to static scheduling. The adaptive nature of MPC ensured timely interventions by prioritizing bins at risk of overflowing and dispatching the nearest available trucks. These improvements are especially relevant for resource-constrained urban centers such as Enugu, where waste management agencies must balance service delivery with cost efficiency.

The findings provide several practical implications for ESWAMA and similar agencies across Africa. First, the integration of MPC with smart bin monitoring and traffic data can transform waste collection into a predictive, demand-driven service rather than a reactive, fixed-schedule operation. Second, reductions in operational costs and emissions contribute to both financial sustainability and environmental protection, aligning with Sustainable Development Goals (SDGs) related to health, clean cities, and climate action. Third, the flexibility of MPC allows for policy-driven prioritization, enabling waste authorities to balance cost savings, service coverage, and environmental considerations.

Future research will extend this work in several directions. The integration of IoT-enabled smart bins and low-cost sensor networks will be pursued to provide real-time monitoring of bin fill levels. Machine learning techniques could be coupled with MPC to improve prediction accuracy for waste generation patterns, especially during seasonal or event-driven surges. In addition, studies will focus on scaling the framework to multi-city systems across Nigeria and other African countries, incorporating economic, infrastructural, and cultural variations. Finally, real-world pilot implementations with

ESWAMA are necessary to validate the feasibility of the system under practical constraints such as limited computational resources, incomplete traffic data, and varying compliance levels among residents.

REFERENCES

[1].   United Nations Human Settlements Programme (UN-Habitat), *Solid Waste Management in the World's Cities: Water and Sanitation in the World's Cities 2010*. London, U.K.: Earthscan, 2010.

[2].   World Bank, *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050*. Washington, DC, USA: World Bank Publications, 2018.

[3].   S. Tchobanoglous, H. Theisen, and S. Vigil, *Integrated Solid Waste Management: Engineering Principles and Management Issues*. McGraw-Hill, 1993.

[4].   A. O. Awomeso, O. O. Adebayo, and G. N. Taiwo, "Waste management practices in developing countries: A review," *Waste Manag. Res.*, vol. 28, no. 9, pp. 833–840, 2010.

[5].   K. Wilson et al., "Challenges and opportunities in MSW management in Africa," *Waste Manag.*, vol. 29, no. 2, pp. 929–938, 2009.

[6].   O. Katusiimeh, D. Mol, and L. Burger, "Solid waste management in urban areas of Uganda," *Habitat Int.*, vol. 41, pp. 41–49, 2014.

[7].   E. N. Sulemana and S. Darko, "Municipal solid waste collection challenges in Accra," *J. Environ. Urbanization Africa*, vol. 5, no. 1, pp. 15–29, 2020.

[8].   G. B. Dantzig and J. H. Ramser, "The truck dispatching problem," *Manage. Sci.*, vol. 6, no. 1, pp. 80–91, 1959.

[9].   P. Toth and D. Vigo, *Vehicle Routing: Problems, Methods, and Applications*, 2nd ed. SIAM, 2014.

[10]. A. C. Friesz et al., "Dynamic vehicle routing with real-time traffic updates," *Transport. Sci.*, vol. 49, no. 3, pp. 543–564, 2015.

[11]. K. Karadimas and P. Loumos, "Genetic algorithms in waste collection routing," *Eur. J. Oper. Res.*, vol. 87, no. 2, pp. 508–520, 2009.

[12]. L. H. Chen and C. S. Ting, "Ant colony optimization for waste collection," *Comput. Oper. Res.*, vol. 30, no. 8, pp. 1131–1146, 2012.

[13]. R. K. Ahuja, T. L. Magnanti, and J. B. Orlin, *Network Flows: Theory, Algorithms, and Applications*. Prentice-Hall, 2014.

[14]. S. Omrani and H. K. Singh, "Particle swarm optimization in municipal waste logistics," *Int. J. Ind. Eng. Comput.*, vol. 11, pp. 223–236, 2020.

[15]. T. Oyegoke and G. D. Agunwamba, "Solid waste routing in Lagos metropolis," *Niger. J. Technol.*, vol. 38, no. 1, pp. 200–207, 2019.

[16]. M. A. Al-Salem et al., "Waste logistics optimization in GCC cities," *Waste Manag.*, vol. 119, pp. 330–343, 2021.

[17]. M. Longhi et al., "Smart bins: IoT-based waste monitoring," *IEEE Access*, vol. 7, pp. 77518–77540, 2019.

[18]. S. Iqbal and H. Al-Hussein, "IoT and AI integration in smart waste systems," *Sensors*, vol. 22, no. 6, p. 2325, 2022.

[19]. A. Al Mamun et al., "IoT-driven waste management in Singapore," *J. Clean. Prod.*, vol. 312, p. 127719, 2021.

[20]. N. Akhtar et al., "AI-enabled solid waste systems," *Sustainability*, vol. 13, no. 12, p. 6705, 2021.

[21]. J. K. Mensah and A. Larbi, "Barriers to smart waste adoption in Sub-Saharan Africa," *Afr. Dev. Rev.*, vol. 34, no. 3, pp. 347–361, 2022.

[22]. R. Kumar et al., "Predictive modeling of waste using neural networks," *Expert Syst. Appl.*, vol. 140, p. 112906, 2020.

[23]. X. Li et al., "Reinforcement learning for vehicle routing under uncertainty," *Transp. Res. C*, vol. 126, p. 103107, 2021.

[24]. Y. Sun et al., "Deep reinforcement learning for real-time waste collection," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 4, pp. 3457–3468, 2022.

[25]. J. Huang et al., "IoT-ML frameworks in waste management," *IEEE Internet Things J.*, vol. 10, no. 3, pp. 1892–1905, 2023.

[26]. V. Raj et al., "AI-enhanced waste collection in urban India," *Waste Manag.*, vol. 161, pp. 45–56, 2023.

[27]. A. Adewumi et al., "Towards AI adoption for municipal waste in Nigeria," *Niger. J. Eng.*, vol. 30, no. 2, pp. 77–88, 2024.

[28]. J. B. Rawlings and D. Q. Mayne, *Model Predictive Control: Theory and Design*. Nob Hill, 2009.

[29]. F. Borrelli, A. Bemporad, and M. Morari, *Predictive Control for Linear and Hybrid Systems*. Cambridge Univ. Press, 2017.

[30]. S. Qin and T. Badgwell, "Survey of MPC applications," *Control Eng. Pract.*, vol. 11, no. 7, pp. 733–764, 2019.

[31]. J. R. Aslam et al., "MPC for traffic-responsive signal control," *Transp. Res. C*, vol. 109, pp. 308–329, 2019.

[32]. M. Gholami and H. Ahmadi, "Adaptive MPC for smart transportation," *IEEE Trans. Control Syst. Technol.*, vol. 30, no. 5, pp. 2098–2109, 2022.

[33]. L. Huang et al., "MPC in waste-to-energy plants," *Appl. Energy*, vol. 253, p. 113531, 2019.

[34]. B. Xue et al., "MPC for landfill gas management," *J. Environ. Eng.*, vol. 149, no. 4, p. 04023018, 2023.

[35]. P. Singh et al., "Dynamic MPC routing for perishable goods," *Int. J. Prod. Econ.*, vol. 239, p. 108205, 2021.

[36]. Y. Zhang et al., "MPC-enabled smart routing for urban waste," *IEEE Access*, vol. 12, pp. 67510–67525, 2024.

[37]. D. Rossi et al., "Integrating MPC and IoT for urban logistics," *Sustain. Cities Soc.*, vol. 65, p. 102614, 2021.

[38]. H. Park and C. Lee, "Smart routing with predictive control in Seoul," *Sensors*, vol. 23, no. 2, p. 789, 2023.

[39]. M. K. Abedin et al., "Resilient routing for urban waste logistics," *IEEE Trans. Syst. Man Cybern.*, vol. 55, no. 2, pp. 287–298, 2025.

[40]. J. Okoro et al., "Waste management infrastructure challenges in Nigeria," *Afr. J. Sustain. Eng.*, vol. 12, no. 1, pp. 12–23, 2024

[41]. National Bureau of Statistics, "Demographic and health survey: Enugu State population statistics," Abuja, Nigeria, 2022.