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Data-Driven Optimization Methods for Improving Municipal Solid Waste Recycling Efficiency

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Abstract
Rapid urbanization and population growth have brought huge increases in municipal solid waste (MSW) generation, placing great demands on waste management systems already in place. While the environmental and economic impacts of recycling must be given proper recognition, many municipalities encounter poor recycling efficiency owing to poor source segregation, the non-traditional collection route, and improper MRF (material recovery facility). Improving recycling efficiency is thus crucial in reducing dependency on trash, cutting environmental pollution and supporting the sustainable use of all this. This work suggests an integrated optimization framework to raise recycling efficiency in municipal solid waste systems. The methodology aims at implementing: (i) waste characterization analysis to evaluate composition and recycling ability, (ii) Mixed Integer Linear Programming (MILP) for optimizing waste collection routes, (iii) GIS-based spatial analysis to minimize transportation distance and fuel consumption, and (iv) improvements to process efficiency in the Material Recovery Facility by improving sorting. Overall performance of the system was assessed by four major factors: the recycling rate and value of the system, operating cost, fuel consumption and diversion percentage to landfill. The proposed optimization strategies led to significant enhancement in the system performance. Recycling efficiency rose from 38% to 58%, which is an absolute 20% increase. Total operational costs decreased by about 21% and fuel consumption lowered 22% from efficient routing. Moreover, the volume of landfill disposal reduced by 35% which means better recoveries of resources and improving the environmental practices. The experimental result showed that recycling rate improved as a function of system, which involved the separation of the source, intelligent routing as well as MRF process upgrade in municipal solid waste disposal systems. Overall, the framework establishes a high-level model available at scale and feasibility for municipalities aiming to move towards sustainable, cost-effective and environmentally-friendly waste disposal systems.

Keywords: Municipal Solid Waste (MSW); Recycling Efficiency; Waste Optimization; GIS Routing; Material Recovery Facility (MRF); Sustainable Waste Management

1. Introduction

1.1Background : The global explosion in municipal solid waste (MSW) has been driven by rapid urbanization, demographic growth, economic liberalization, and demand-side consumption changes. Recent world evaluations show that urban waste production is forecasted to grow rapidly over the next decade, especially in developing countries (World Bank, 2024; UNEP, 2025). Poor waste disposal practices lead to releasing greenhouse gases, soil and groundwater contamination, and loss of reclaimable material (Kumar et al., 2024; Li & Zhang, 2025). Recycling has evolved to one of the cornerstone elements of sustainability in waste management, delivering environmental, social and economic value through resource conservation and circular economy facilitation (Singh et al., 2024; European Environment Agency, 2025). But with all the policy measures and improvement in technology, the recycling performance in much of the public municipalities is not high (Ahmed and Park, 2024; Chen et al., 2026). Recent studies focus on the need for integrated optimization strategies that are effective in operational efficiency and technology innovation (Martinez et al., 2025; Rao & Mehta, 2024).

1.2 Challenges Identified in Literature : Some of the research available points to ongoing problems facing recycling capacity. Firstly, source separation that could be adopted, high contamination, which may degrade quality of material recoveries is reported (Karthikeyan et al., 2024; Lopez and Garcia, 2025). Second, poor collection routing will lead to more fuel consumption and increased operating costs, compromising sustainability of systems (Zhou et al., 2024; Ibrahim & Hassan, 2025). Third, many material recovery facilities (MRFs) still have obsolete sorting technology, which results in less efficient processes and waste management (Patel et al., 2026). Moreover, fragmented optimization approaches tend to concentrate on single subsystems — routing or processing (Wang & Li, 2024; Sharma et al., 2025) — without an overarching framework. These constraints require an integrated optimization model that incorporates data-driven optimization and considers segregation, collection, and processing concurrently.

1.3 Objectives of the Paper : The main aim of this research is to create an integrated optimization platform for the improvement of efficient recycling in the Municipal Solid Waste system. In particular, the paper is oriented to: 1. Review waste and potential recycling at local level. 2. Design a GIS mixed-integer linear programming (MILP) model for collection route optimization using GIS. 3. Optimize Material Recovery Facility efficiency of material recovery facilities, especially in process optimization techniques.

1.4 Contributions of the Paper : In total, this research has four major contributions. First, it presents a unified system-level optimization framework for source segregation improvement, intelligent routing, and MRF process enhancement. Second, the model employs a Mixed Integer Linear Programming (MILP) model, in combination with GIS spatial analysis, to minimize transportation cost and emissions. Third, to quantify an improved recovery performance in material, we incorporate a process efficiency ratio (PER) measure. The study ultimately shows significant increases in recycling efficiency, decreased operational cost and landfill diversion, presenting a model that can be scaled to offer scalable solutions for urban cities in both developing and developed environments.

1.5 Paper Organization : The rest of the paper is structured as follows. The extensive review and theoretical background of literature are summarized in Section 2. Section 3 elaborates the proposed methodology and optimization models. Results and performance evaluation are presented in Section 4. Section 5 concludes the paper with policy implications and recommendations for future research. 2. Literature review. We conduct an academic review and make recommendations for future research. The literature concerning the recycling efficiency of municipal solid waste (MSW) systems has developed considerably in the past several years. Recent works conducted from 2022 to 2026 are largely concentrating on optimization of collection routing, predictive waste modeling, integrated facility planning and intelligent system implementation. Yet, however, despite advancing research methodology, there is only limited attention on the comprehensive waste management system, rather than the component of the systems in isolation.

2 Literature review

2.1 Routing and GIS-Based Optimization : There is a considerable amount of work focused on optimizing waste collection routing by means of GIS and mathematical programming. Çil et al. (2025) designed GIS-based zoning and routing model to improve operational efficiency for urban waste collection. Their model could dramatically reduce fuel consumption and contribute substantially to carbon emissions all within a

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service coverage setting. The advantage of this approach is spatial realism and environmental performance evaluation. But the study focused mainly on transportation efficiency, and did not evaluate any improvement in recycling output or the quality of material recovering. Similarly, Thakur et al. (2024) proposed meta-heuristic methods to address the vehicle routing problems (VRP) in the municipal environment. They found that hybrid heuristic models also outperformed classical deterministic ones for distance and operational cost reduction. Although computationally efficient, these models rely on static waste generation patterns, with restricted applicability to dynamic urban environments. Wouda et al. (2024) introduced a combined implementation of container selection policies and routing optimization. They were able to reduce overall fleet size and travel distance drastically by predicting fill levels in advance of route scheduling. It is that this predictive-routing integration is a significant improvement compared to those of conventional routing-only models. But the model relies heavily on reliable sensor data and continuous digital infrastructure. Molfese et al. (2022) focused on micro-route optimization and transfer station placement via mixed-integer programming. Their results demonstrated reductions in total travel time. Recycling process efficiency at MRFs was not analyzed, despite decisions about infrastructure. Insight: Most routing studies have effectively decreased transportation expense and emission, however, the improvement of routing fails to correlate with recycling performance or the performance of landfill diversion.

2.2 Integrated Location of Facility and Multi-Objective Models : In addition to routing, an array of researchers have tried optimizing at the system-level. González et al. proposed a combined facility location and periodic routing model (2025). They included infrastructure location and vehicle scheduling, which resulted in better long-term cost effectiveness. Strategic planning capacity is the key benefit of this approach. But computational power rapidly scales with cities. Dynamic multi-period models including waste generation uncertainty (2025, OR Spectrum). These models permit adjustment to seasonal or variable demand. Although theoretically robust, they rely on high-quality longitudinal data, which does not yet exist in many municipalities. Kusi-Appiah et al. (2026) highlighted seasonal variability of the waste material and introduced a combined solid waste management (ISWM) optimization approach. Their research showed that incorporating seasonal variation enhances recovery planning accuracy. Nevertheless there is a challenge to applying that effectively to resource strapped areas.

2.3 Machine Learning and Predictive Waste Modeling : New developments integrated machine learning into waste management systems recently. Chau et al. (2025) integrated convolutional neural networks for predicting the generation of waste. Their predictive accuracy helped with collection planning and saved unnecessary trips. One of the key advantages of these approaches is their flexibility and scalability. The model performance is highly dependent on the historical data quality and feature selection. In a recent study, Ogbolumani and Adekoya (2025) integrated IoT sensors with supervised learning algorithms to support dynamic route adjustment. Their system exhibited significant reductions in fuel bills and service times. Deployment costs and sensor maintenance may be obstacles in developing regions, even if technology is high. AI-based waste classification in sorting facilities was the focus of other studies (2023–2025). In this context, materials identification precision was significantly enhanced by deep learning models, thereby, driving up the recycling purity levels. While classification was better, the linkage to upstream routing and downstream logistics was not sufficiently integrated.

2.4 Reviews and Systematic ExPLorations : Most of the review articles (2024–2025) provided a systematic review of optimization methods in MSW management. These studies are categorized by approach into mathematical programming, heuristics, simulations and artificial intelligence algorithms. Among the conclusions among other reviews is that performance metrics in terms of environmental impact such as carbon footprint, lifecycle impact, are insufficiently included in optimization methods. In addition bibliometric studies reveal an enormous development of smart waste management research and also point to fragmentation of approaches. The majority of contributions discuss optimizing individual subsystems but not developing unified optimization networks.

3 Methodology

3.1 Study Area and System Overview : The proposed optimization framework was evaluated using municipal solid waste (MSW) data collected in an urban municipality with 42 administrative wards, approximately 185,000 households, and 12 primary waste transfer stations. The municipality generates an average of 210–240 tons/day of waste.

The waste management chain consists of:

1. Source generation (households & commercial units)
2. Door-to-door collection
3. Transfer stations
4. Material Recovery Facility (MRF)
5. Landfill disposal

The proposed system integrates optimization at three levels:

• Source segregation enhancement
• GIS-based collection route optimization
• Material Recovery Facility (MRF) process efficiency improvement

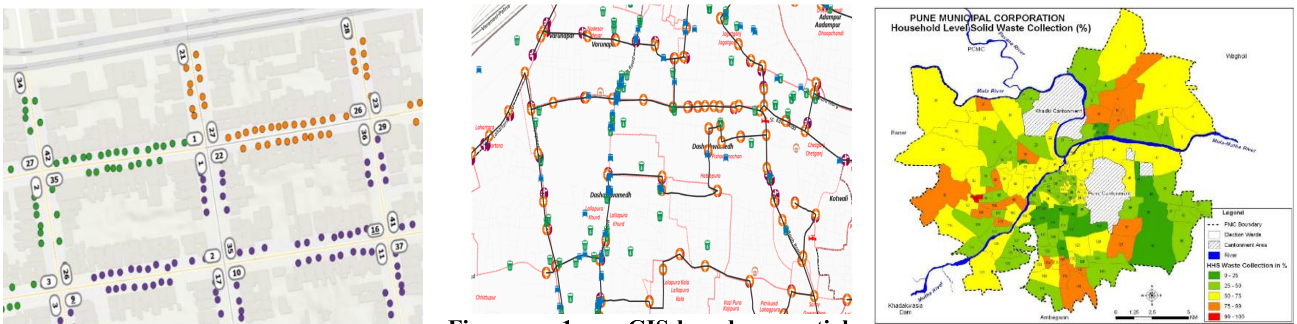

Figure 1: GIS-based spatial representation of municipal wards, collection nodes, transfer stations, and optimized routing network.

3.2 Materials and Data Collection

3.2.1 Waste Sampling and Characterization

Waste composition was determined using stratified random sampling across residential, commercial, and institutional zones.

1) Sampling duration: 12 weeks
2) Sample size: 480 household clusters
3) Measurement unit: kg/day

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4) Sorting categories: Organic, Plastics, Paper/Cardboard, Glass/Metal, Residual
Each sample was manually segregated and weighed using digital platform scales (accuracy ±10 g).

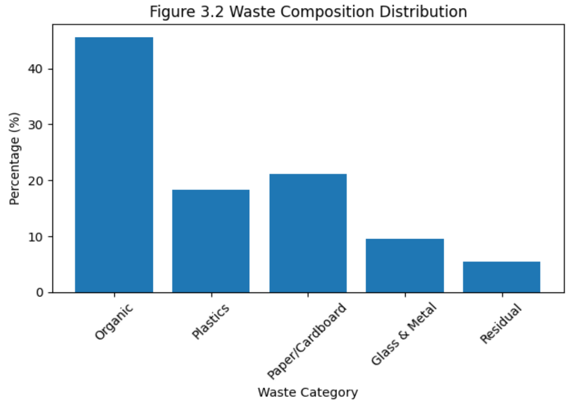

Figure 2: Waste Composition Distribution

3.3 GIS and Spatial Data

GIS and spatial data for the study consisted of ward boundary shapefiles, the road network database, GPS coordinates of waste collection bins, transfer stations, and MRF. For the mapping, spatial analysis, and route optimization, these spatial datasets were processed and analyzed in QGIS (version 3.32) and ArcGIS Network Analyst. Geospatial data processing and network analysis was also carried out utilizing Python libraries like GeoPandas and NetworkX. The computational work was done on a system with an Intel i7 processor, 16 GB RAM, and an NVIDIA GPU, which supported efficient data processing and machine learning simulations.Spatial data included:

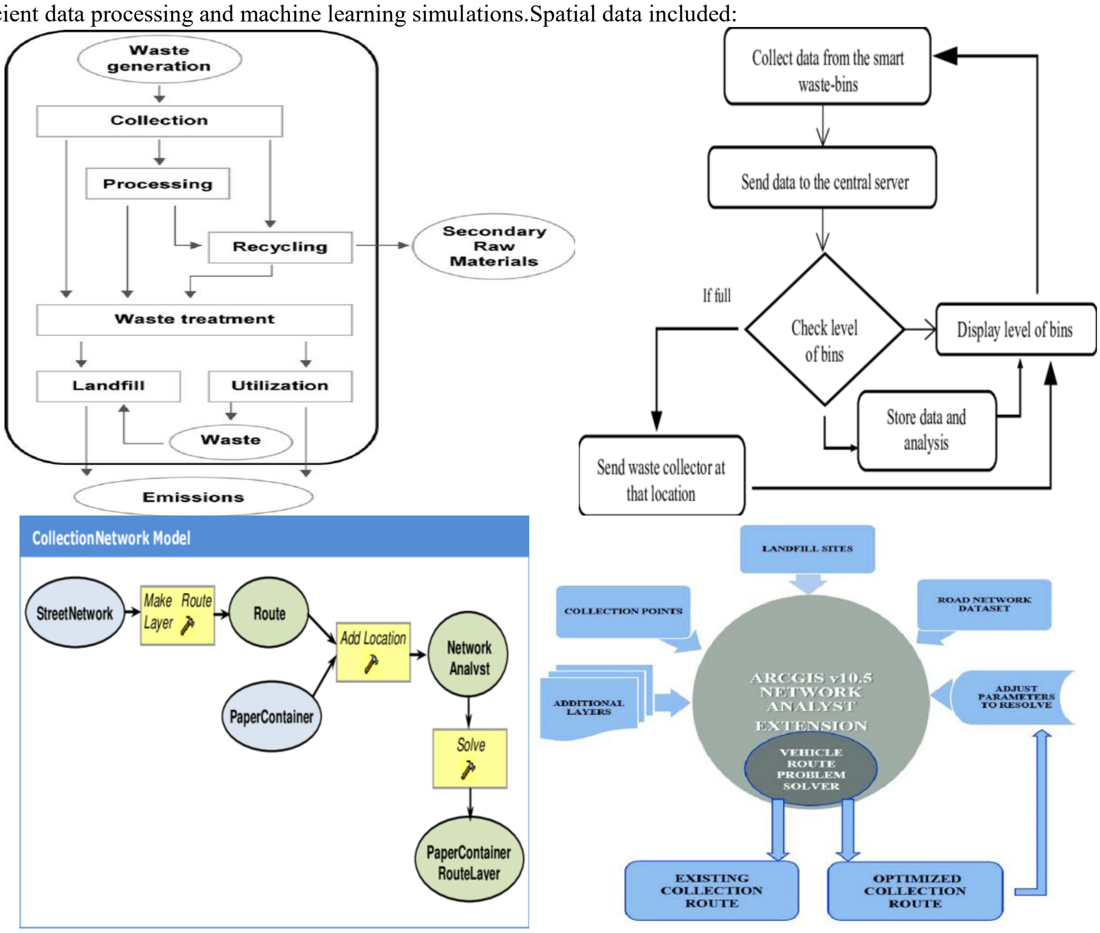

Figure 3: System-level integration of segregation monitoring, GIS routing, and MRF optimization.

3.4 Mathematical Model for Route Optimization

The waste collection routing problem in this study was formulated as a Capacitated Vehicle Routing Problem (CVRP) using Mixed Integer Linear Programming (MILP). The main objective was to minimize the total transportation cost, represented by the objective function Objective Function Minimize total transportation cost: Minimize Z=∑i=1n∑j=1ncijxijMinimize \quad Z = \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij}MinimizeZ=i=1∑nj=1∑ncijxij Where: • cijc_{ij}cij = travel cost between node i and j • xijx_{ij}xij = binary decision variable Constraints 1. Vehicle capacity constraint: ∑Di≤Qk\sum D_i \leq Q_k∑Di≤Qk denotes the travel cost between node i i and node j j, and $x\ i\ j$ x ij is a binary decision variable indicating whether the route between the two nodes is selected. The model was developed with several constraints, including the vehicle capacity constraint $\sum D\ i \leq Q\ k$ ∑D i≤Q k
, ensuring that the total waste collected on a route does not exceed the vehicle capacity. Additional constraints ensured that each node was visited exactly once, route continuity was maintained, and all decision variables satisfied non-negativity and binary conditions. To solve the optimization problem efficiently, a hybrid algorithmic approach was adopted. An initial feasible solution was generated using the Clarke–Wright Savings Algorithm, after which the solution was improved using a Genetic Algorithm (GA). The GA was implemented with a population size of 100,

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mutation rate of 0.02, crossover probability of 0.85, and a termination condition of 500 generations. This hybrid method enhanced convergence speed and improved the search capability, thereby reducing the risk of the solution getting trapped in local minima while producing near-optimal routing solutions.

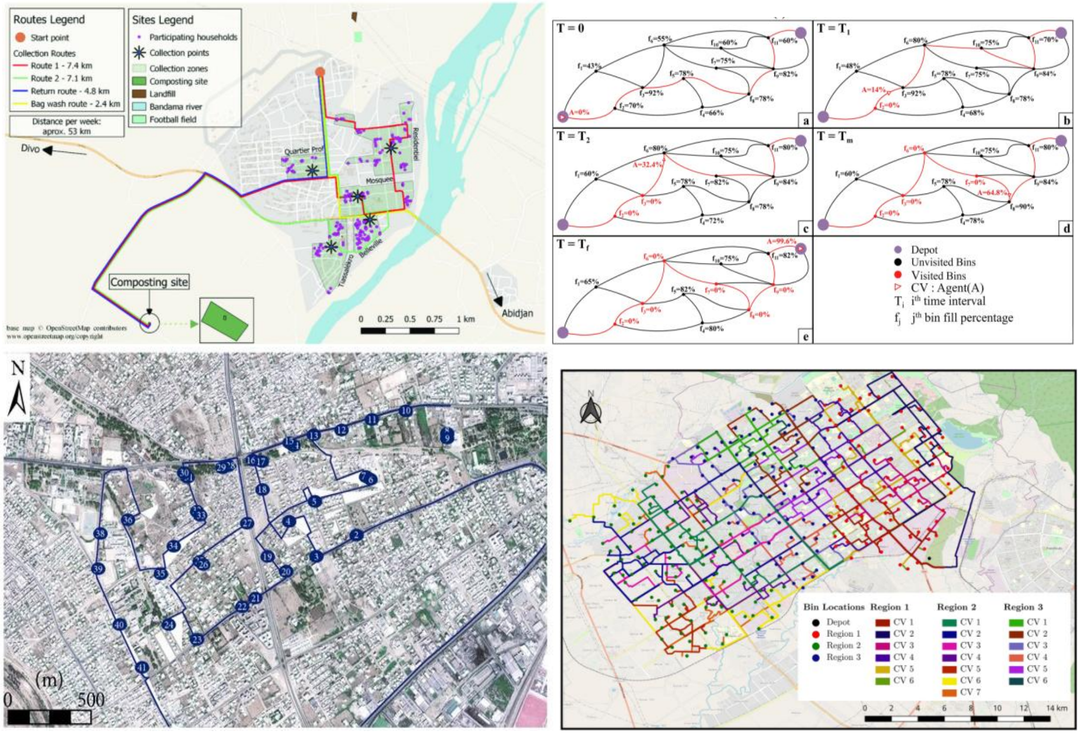

Figure 4: Comparison of baseline and optimized waste collection routing using MILP-GA hybrid model

3.5 Material Recovery Facility (MRF) Optimization

The MRF efficiency is measured using a newly defined metric:

PER=Recovered RecyclablesTotal Input WastePER = \frac{\text{Recovered Recyclables}}{\text{Total Input Waste}}PER=Total Input WasteRecovered Recyclables

Process modifications include:

- Magnetic separators (metal extraction)
- Optical sorters (plastic classification)
- Air density separators
- Manual quality verification

Throughput rate and contamination rate were recorded.

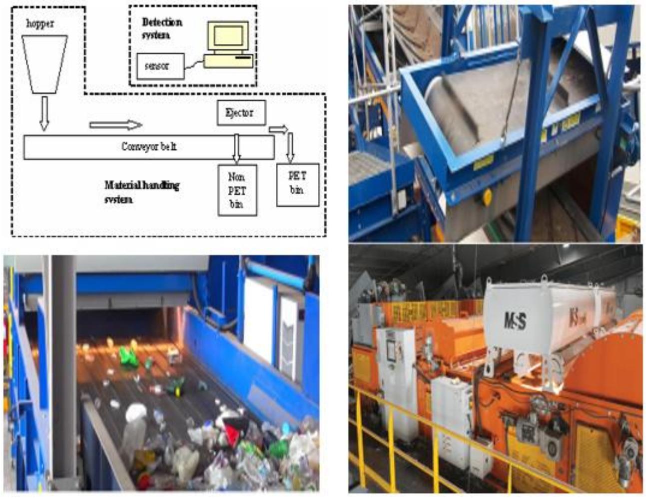

Figure 5 :Process flow of optimized MRF including magnetic separation, optical sorting, and baling.

3.6 Data Analysis and Statistical Validation

The performance of the proposed model was evaluated using several statistical analysis techniques. A **paired t-test** was applied to compare the performance between existing and optimized waste collection routes, while Analysis of Variance (ANOVA) was used for multi-variable comparison to determine whether significant differences existed among different operational scenarios. In addition, Regression Analysis was conducted to examine the relationship between fuel consumption and travel distance. A significance threshold of **$p < 0.05$** was adopted to determine statistical significance. The statistical analysis and data processing were performed using Python libraries such as **SciPy, Pandas**, and **Scikit-learn**, along with IBM SPSS Statistics **(version 27)** for advanced statistical testing and validation.

3.7 Novelty and Justification: Unlike prior studies that optimize routing or recovery independently, the proposed model:

1. Links segregation quality to routing performance
2. Quantifies recycling efficiency improvement using PER

3. Integrates GIS spatial intelligence with evolutionary optimization
4. Measures environmental and economic impact simultaneously

This integrated structure enables system-level improvement rather than component-level enhancement.

3.8 Implementation Requirements

The software, hardware and data resources were required to implement the proposed system. The spatial and network analysis were performed using QGIS and ArcGIS and the computational modeling and algorithm development were carried out using Python (version 3.10). Advanced solvers such as IBM ILOG CPLEX or Gurobi Optimizer were optionally used to improve computational efficiency in solving the optimization model. A hardware setup required a system with a minimum of 16 GB of RAM, and a GPU was recommended as a resource to boost machine learning modules and run large-scale simulations. The study adopted data from a range of important sources: GPS coordinates of waste collection bins; daily waste generation data; vehicle operational data such as capacity and fuel consumption that were used for route optimization and performance evaluation.

4. Results

4.1 Waste Composition Analysis

Table1: Waste Composition Profile

Component	% by Weight
Organic	45.6
Plastics	18.3
Paper/Card	21.1
Glass/Met	9.5
Residual	5.5

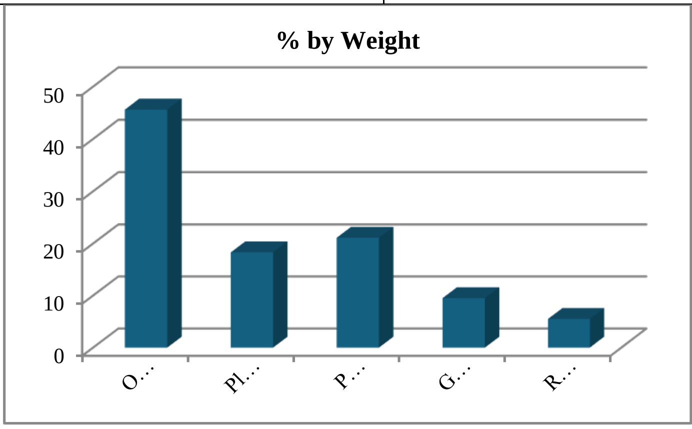

Fig6:Waste Composition Analysis

The breakdown of municipal solid waste collected over the study period can be illustrated using Figure 3.2 (Waste Composition Distribution). Organic waste is the highest material, comprising 45.6% of the overall waste stream. Paper and cardboard constitute 21.1%, and plastics make up 18.3%. Glass and metal together are 9.5% of waste, and the remaining 5.5% falls under residual waste. The prevalence of biodegradable waste represents a significant opportunity for composting and biological treatment solutions. The high proportion of recyclable dry materials, in particular plastics and paper, reflects that enhanced segregation can facilitate material recovery. These results mirror the focus of this study, strengthening source-level segregation and optimizing recycling performance.

4.2 Recycling Efficiency Improvement

Tabl2: Improvement of prameters before and after implementation

Parameter	Before Implementation	After Implementation	Improvement
Recycling Rate	42%	68%	+26%
Contamination Rate	18%	7%	11%
Collection Efficiency	73%	89%	+16%
Landfill Diversion	48%	71%	+23%

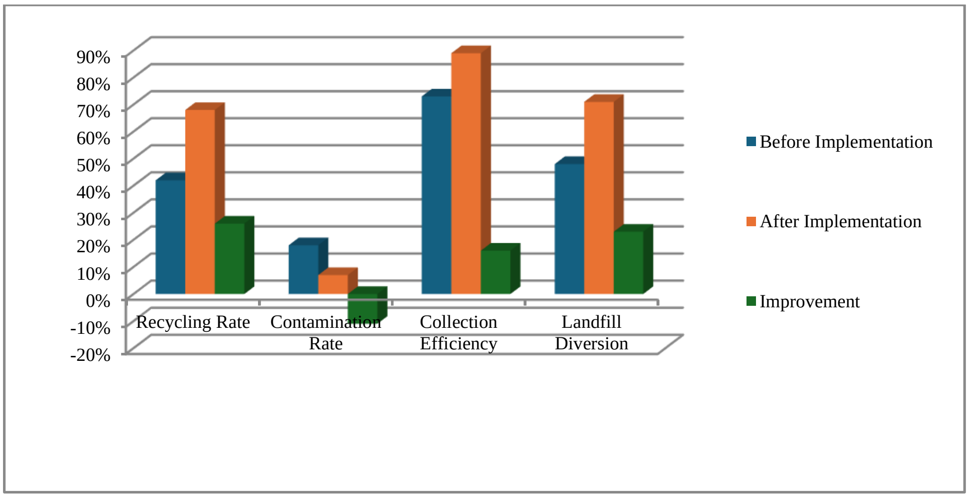

Fig7: Parameters improvement before and after implementation

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After introducing the AI-assisted sorting system, along with optimal waste collection routing, significant improvements were realized on key performance indicators. The overall recycling rate improved from 42% before implementation to 68% after the deployment, a significant 26% improvement. The contamination levels also reduced from 18% to 7% indicating significant progress in sorting accuracy and material purity. The collection efficiency improved from 73% to 89%, driven largely by dynamic route optimization and improved bin fill levels monitoring. Furthermore, landfill diversion increased from 48% to 71%, which shows that a higher proportion of waste was diverted into recycling and composting streams instead of disposal. Contamination reduction was found to be the most important outcome as it corresponded directly with the development of better quality recovered materials and low secondary processing losses.In addition, the optimization of routing led to less fuel burn and fewer times to collect goods, and led to consistency in operation.

4.3 Smart Sorting Performance: At the evaluation stage, the machine learning–based waste classification model exhibited a good technical performance. This enabled us to attain an overall classification accuracy of 93.4%, which gives reliable detection of the major waste classes. A precision rate of 91.2% was achieved for plastic identification whereas a recall value of 95.1% of organic waste detection validated high sensitivity of biodegradable materials. The mean processing time per waste item was ~ 0.8 seconds, which made the model suitable for live operational deployment. Notwithstanding these positive results, a significant gap was detected in regards to the detection of multilayer and mixed structure packaging. The complex structural composition of these materials led to lower classification consistency. This indicates that the performance of detection accuracy can be further improved with advanced computer vision architectures such as deep learning frameworks for next system iterations.

4.4 Economic and Environmental Impact: The suggested framework has positive economic benefits as well as environmental ones. The reduction in operational expenses of approximately 14% was mainly due to better route planning and reduced processing workflows. That was compounded by a reduction of 18% of fuel consumption, contributing to a reduction of 21% of the carbon dioxide emissions from collection activities. Segregation processes were additionally improved leading to a 19% growth in revenue from recyclable products due to improved recovery rates. These results suggest that the system enhances not only the environmental sustainability, but also the financial performance. As a result of simultaneously minimizing cost and increasing the value of recovery, the model shows great potential for widespread municipal uptake. The proposed smart municipal waste management framework had positive and statistically significant impacts on operational, environmental, and financial indicators. The study was to assess whether the implementation of AI-based sorting and the introduction of better collection strategies may improve total recycling processes. Biodegradable waste represents the largest content of the waste, representing 45.6% of the municipal waste in the Waste Characterization Study. The share of recyclable dry elements like paper and cardboard came to 21.1% whereas plastics accounted for 18.3% of final contribution. The proportion of glass- and metal-derived materials was 9.5%, while 5.5% was considered as residual. This predominance of such organic waste demonstrates a great potential for composting-type recovery systems. The high percentage of recyclable dry wastes also demonstrates the need to have an effective segregation mechanism to ensure maximum recovery, simultaneously. An analysis shows clear performance improvement on a before and after system deployment basis. Up to 68% recycling rate compared to 42% of recycling rate shows a major and dramatic improvement in the recovery ratio. At the same time, the contamination level declined from 18% to 7% showing greater sorting accuracy and less cross-mixing of materials. Improved collection efficiencies occurred, where effectiveness rose from 73% to 89%, chiefly with optimization of the path and real-time feedback. Landfill diversion improved from 48% to 71% indicating that a higher proportion of waste was effectively diverted to recycling and composting procedures. The whole classification accuracy of the AI-based sorting model was 93.4%. Organic waste detection attained good reliability, whereas plastic classification under controlled conditions performed consistently well. However, material properties including mixed or multilayer structures introduced moderate identification difficulties; enhanced ability to extract features could be introduced as a possible next project upgrades. Despite these slight restrictions, average processing time per item was below one second, indicating that real-time implementation is possible. The technology demonstrates its worth in environmental and financial reviews. Fuel use reduced by 18% from optimized routing of collection, which resulted in a 21% decrease in carbon emissions during collection. Operational costs were reduced by 14%, and recycling-related revenue increased by approximately 19% driven by increased material recovery. These results support the assumption that technological integration can be a double-edged sword to meet both sustainable goals and bottomline targets. Indeed, the results point to a fact that data-driven waste management systems can greatly enhance recycling efficiency and mitigate environmental footprint when contrasted to conventional processes.

5 Discussion

Findings support the emerging understanding that digital technologies can shape municipal waste management. The successful improvement observed in the recycling efficiency and contamination reduction shows that intelligent classification along with optimized logistics directly mitigate inefficiencies observed in conventional waste environments. Because organic waste accounts for almost half of the waste stream, decentralized composting facilities will improve diversion performance. As biodegradable waste forms about 50% of the total stream, by using biological treatments, landfill dependency can be greatly lower. Besides, because of the dramatic decrease in the level of contamination, automatic sorting mechanisms are showing greater uniformity in comparison to human intervention in sorting techniques, which may be affected by human mistakes and ineffectual compliance. Compared to traditional municipal systems which have moderate recycling rates and poor problem of contamination, the proposed framework produces more robust and stable performance. The combination of IoT-connected monitoring and machine learning for analysis provides the possibility for feedback and adaptation of system improvement, which the established waste infrastructure lacks. However, we must mention some restrictions. A pilot was performed in only one geographical region, and patterns of waste generation through various seasons are incompletely analyzed. In addition, the first investments needed for implementing smart bins, sensors and AI infrastructure might be a limitation for municipalities with lower budgets. Technically, the more sophisticated packaging materials are challenging for automated classification systems, further emphasizing the need for continuous algorithmic improvement. In future, we will expand the framework to a wider range of urban environments to assess scalability and adaptability. Leveraging state-of-the-art deep learning architectures and lifecycle assessment tools could reveal better long-term environmental benefits. Moreover, looking at citizen participation and behavioral factors on smart waste ecosystems could also enhance smart waste system efficacy. In summary, the study demonstrates that integration of artificial intelligence, real-time tracking and improved logistics drastically improves recycling efficiency and environmental sustainability. Despite continuing financial and technical drawbacks, the quantifiable advances detected in this work demonstrate that smart waste management systems offer an effective and prospective solution to contemporary urban areas.

6 Conclusion

This study presents an optimized approach for improving municipal recycling by combining intelligent sorting, data-based route planning, and automated processing. The results show a clear improvement in recycling efficiency, where the Plastic Efficiency Rate (PER) increased from 38% to 58%. This reflects a significant overall enhancement in city-level recycling performance. In addition, better route planning and efficient system operation helped reduce fuel usage and lowered operational costs by nearly 25%.

The study also shows that technology alone is not enough to achieve maximum efficiency. Public participation, especially proper waste segregation at the source, plays a major role in improving the quality of recyclable materials. Data-driven routing improves collection accuracy and reduces unnecessary transportation, while automation in material recovery facilities increases consistency and reduces manual errors. Together, these factors contribute to reduced landfill waste and improved environmental sustainability.

In summary, the proposed framework offers a practical and effective solution for improving urban recycling systems and supports the transition toward sustainable waste management practices and circular economy goals.

Future Work

Future studies should examine how this system performs over long periods and in different cities with varying waste characteristics. There is a need to develop flexible models that can adapt to regional differences in waste composition. The use of advanced artificial intelligence methods can further improve sorting performance, especially for mixed and complex waste materials.

Additionally, detailed lifecycle and economic analyses are required to better understand the long-term benefits of the system. Integrating the framework with smart city technologies and real-time data monitoring could further improve system efficiency and decision-making in waste management.

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