Route Optimization For Waste Collection

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1 Introduction

Solid Waste Management (SWM) is considered one of the critical drivers of urban environmental management systems [1].It is generally an exercise to collect the combined waste from households, agricultural, industrial, commercial activity, institutional, and miscellaneous, generated from the living community [2]. India is one of the least urbanized countries in the world, yet urban India produces about 42.0 million tons of municipal solid waste annually, i.e., 1.15 lakh metric tons per day (TPD) [2,3]. These figures are bound to increase in the future, as cities are witnessing extreme demographic transfers, immigration, population growth, and consumption rate, which are the key driving factors for the increase in urban waste. This has become one of the most urgent concerns for local agencies in India. During the last decade, the government has launched various programs e.g., Clean India Mission, Smart Cities, Amruth Cities, and Digital India to improve living standards. Waste management is one of the core infrastructure elements of these missions, which requires empirically driven conclusions to address the SWM related challenges [4].

Solid waste collection is the most integral activity of SWM [2]. However, the waste collection in developing countries like India is very unorganized, primarily due to resource constraints and poor planning of available resource [5]. Collection vehicle route planning (VRP) is the major resource component of a waste collection system, whose planning is often not driven by analytics, resulting in poor collection efficiency [6]. Similar scenarios have been reported across cities of developing countries [7–9]. VRP requires modeling many dynamic components such as path planning, consideration of available resources, spatiotemporal demand patterns, and real-time dynamics of waste volume at collection points and collection vehicles (CV). A plethora of literature addresses subsets of these components in solution development across various cities [10–12]. However, a holistic waste collection system that considers them simultaneously for any region has not been reported in the literature [13]. Hence, the onground implementation of the present approaches are still very limited. This significantly impacts the operation costs and, eventually, the environment [14]. Moreover, the components and their interrelationships are very complex for the resource-constrained societies, and therefore pose new challenges that require the researchers' urgent attention.

To address the challenges stated above, we propose a waste collection framework for cities, with the objective to find the optimal routes for the available CV paths while considering the dynamic variations in the waste information at collection points and also that of the CV. We also discuss the influence of available resources in covering the collection bins, whose dynamic information drives the best path. Finding the best path is formulated as an optimization problem and solved using linear programming. The approach has an advantage over other traditional path planning approaches due to the considerations of field-based activities in the model. Further, the study focuses on resource-constrained societies resulting in a decision making tool that can be scaled and applied universally. Moreover, being dynamic in nature our model can calculate optimal routes, replicating the real-time scenarios. Hence, can help fill the gap a between theory and on ground implementation. The paper has following major contributions:

- Analysis of CV availability in study regions on waste collection, to demonstrate the total coverage.
- Consideration of quantitatively simulated dynamic waste levels for CV and collection bins for realistic outcomes.
- Detailed sensitivity analysis of various parameters affecting selection of the best path.

2 Background

A lot of work has been done in different aspects of waste collection, such as the route optimization, smart bins, segregation, landfill and collection depot location optimization. In recent years the most common topic of work in this area has been Vehicle Routing Problem (VRP). The VRP based studies have mostly addressed the problem of route optimization of collection vehicles for various cases such as landfill and collection sites allocation to minimize distance traveled by collection vehicles [15–17], collection point clustering to increase collection efficiency [18] and calculating the optimal route with a fixed set of collection bins and landfill/depot locations [19–24]. These studies have formulated the problems and solved through various preexisting optimizers. [19, 20, 22, 23, 25, 26]. The biggest drawback of these models remains their static nature hence the route is calculate at once, which does not represent the onground scenario. Some studies have also modeled the some dynamic aspects in the routing to study their impact on fuel consumption [23]. Moreover, various studies have also implemented smart bins to track waste in cities such [7–9, 24, 27, 28]. However, they lack the integration of real world aspects such as changes in routes based various other dynamic factors such as real-time waste status of collection vehicles, and their coordination with other vehicles, hence, are often not implemented in decision making system. Further, most of such works are developed for the cities of developed nations which are not resource constrained, and have less challenges as compared to cities of developing nations.
Waste collection in resource constrained societies comes with the additional challenge of having to allocate insufficient resources to meet the demand. There are many studies that have been implemented on the cities of developing nation such as India that focus on various aspects of waste collection. [10], [11], and [12] have highlighted the dynamism and lack of awareness as the major issues of dynamic waste collection in India. They implemented IoT based bins to plan the collection routes in real time. Their system didnt do an analysis of constraints related to resource availability, along with their coordination. [29] and [30] utilized Geographic Information Systems (GIS) to calculate optimal waste collection routes in the city of Allahabad and Durgapur in India respectively. These studies, however, didn't consider any dynamic considerations. [31] and [25] focused on route optimization in the cities of Onitsha, Ipoh , and Malaysia respectively. [16] focused on optimal bin allocation to maximize the waste collection in the city of Bilaspur, India. These works, however, do not consider any real time data to calculate the optimal routes. Therefore he implementation of dynamic scenarios to suit the requirements of

resource constraint societies still remains an open research problem. The reader can refer to recent reviews by [32–34] for detailed discussion on the works related to optimization of waste collecthttps://www.overleaf.com/project/62ac12790a8159aa6454c027ion and management systems.

3 Problem Definition and Mathematical Formulation

3.1 Problem Definition

The waste vehicle routing problem in dynamic settings is implemented using agent-based modeling approach. A collection vehicle is an individual goal driven agent that implements an optimization module to achieve its goal of routing on a good path. A path is calculated by minimizing the distance traveled and maximizing the waste collected while considering various real-time considerations. We have considered an Indian city to demonstrate its outcomes. To implement the model we have divided the study area in various regions. The region consists of smart collection bins used to collect waste and generally caters to a large area. These bins are assumed to be located on a road network made from edges and bins. We simulated temporally varying waste values (0-100%) for each of these bins; we call them" smart bins". The simulation helped us overcome the requirement of physical sensor placement at these locations. We incorporated the inputs of stakeholder agency in the simulation purpose to keep the simulation values closer to the actual scenarios.

Input
Agent: Waste collection vehicle.
Agents attributes: Waste fill percentage, distance traveled.
Environment: Road network, bins, depot.
Environment attributes: Waste percentage of bins, route length, distance between each bin.
Outcome
Best path for each agent

An agent is initially assigned to a specific region, and it only collects waste from bins from the assigned region through the calculated optimal route. The" route" in our problem corresponds to path of the agent covering these bins and finishing its trip at a fixed depot. A path is made up of non-directional edges, and two or more edges make an "arc". To make the implementation realistic we have applied limits on the total waste that the agents can collect. When the waste from a bin is collected by an agent the waste value of the CV is updated, and the numerical values of the distances are normalized to the same scale as the waste values to avoid any execution bias.
The model is executed after a specific time interval by considering updated bins waste values, CV waste fill status, and CV location to generate a route. The route is updated after every fixed time interval. A priority is being given to a bin based on the distance to that bin from the agents current location and the waste value of bin. This means that a bin with the greater waste value is assigned a higher priority for the same distance value. When the waste from a bin is collected by an agent the waste fill percentage of the CV is updated.

The execution for any agent terminates when either a run is complete, or the CV is full. The "run" in our problem signifies the process of agents reaching the depot through calculated routes in various time intervals. As the agents execute in parallel, if an agent, in one time interval fails to visit a does not visit a bin because being full, other agent can cater the bin. We also considered the case when bin waste values could update even when the CV is moving on an edge and hasn't reached the next bin. For such scenarios the model assumes that the CV has completed the current edge and considers the next bin as the starting point in the next time interval.

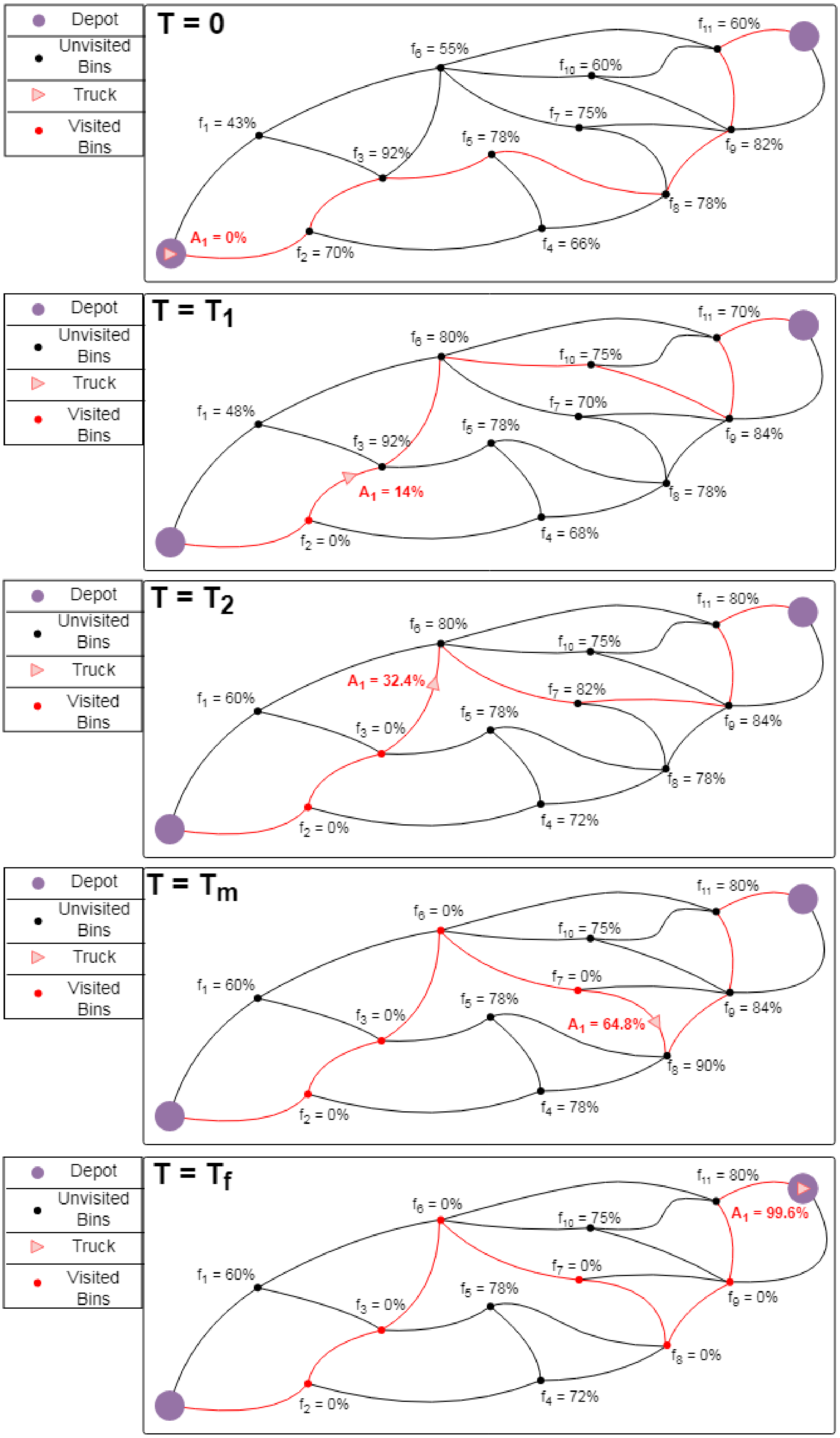


Figure 1: General representation of the dynamism of the process

Figure 1 depicts the discussed problem definition. Figure 1a shows the starting state of the agent at time interval $T = 0$ at depot, and the percentage fill values for various bins, and the agent respectively. Figure 1b-1d illustrate the further time intervals ($T = T_1, T_2, T_m$) and the dynamic changes in the movement of the agent, their updated fill percentages, updates in the bin fill percentage, and updated route after each time intervals i.e., at T1 and T2 the routes are different. Figure 1e depicts the last state at time interval $T = T_f$ when the agent finally returns to the depot.Figure 2 depicts a case of multiple agents moving in parallel while working together to gather the waste in the optimal way.

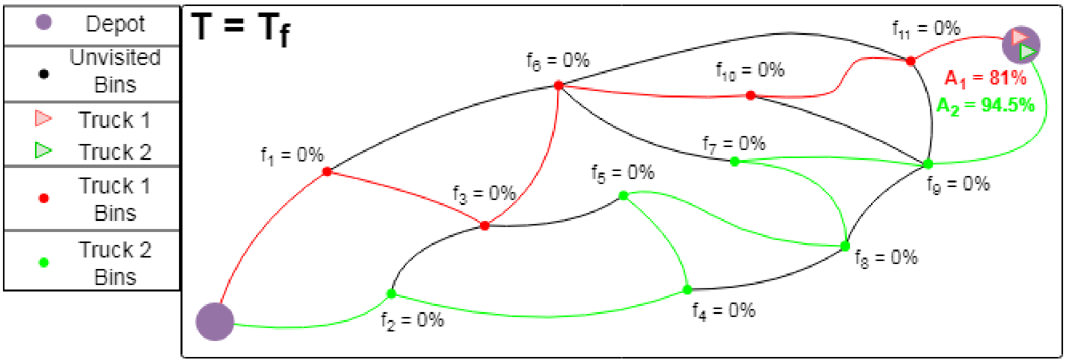


Figure 2: General representation of the process for multiple agents

Three different execution scenarios are demonstrated. The first scenario restricts the available resources, which in our case is the collection vehicles. The second case runs the model without any restriction on available resources and demonstrates the impact of available resources on waste collection, bins covered and distance travelled for each region and accumulated at city scale. Lastly we emphasize the importance of dynamic consideration by comparing the outcome of dynamic model with the static model.

3.2 Mathematical Formulation

The objective of the model to maximize the waste collected while minimizing the total distance travelled by the CV (see Eq (1)). We formulate the model as a mixed integer linear programming problem and solved it using Gurobi optimizer [35] in polynomial time.

Table1 defines all the variables used in the mathematical formulation.

Table 1: The description of variables

Variables	Description
$i, j \in D$	Bin i and Bin j respectively.
N	Bins for a particular CV excluding depot.
D	Bins for a particular CV including depot.
A	Set of all the arcs formed from a bin i to a bin j for $\forall i, j \in$ V.
$C_{ij} \in \mathbb{R}^+$	Distance cost from a bin i to a bin j for a CV.
$X_{ij} \in \{0, 1\}$	It is a binary variable that is 1 if a CV is travelling between the bin i and bin j.
$Y_i \in \{0, 1\}$	It is a binary variable that is 1 if a CV is visiting bin i.
$u_i \in [0, 100 - P_t]$	The percentage fill of the CV at bin i following given path, for a specific time interval.
$P_t \in [0.0, 100.0]$	Cumulative fill percentage of CV at a time interval t.
$st \in D$	The starting bin of a CV in a new time interval.
$w_1 \in [0.0, 1.0]$	The weight assigned to the distance objective of the objective function
$w_2 \in [0.0, 1.0]$	The weight assigned to the waste amount objective of the objective function
$f_i \in [0.0, 1.0]$	The fill ratio of bin at bin i.
$BT \in \mathbb{R}^+$	The conversion factor for fill of smart bin to fill of CV.

As per Dengel et al [29], one of the most common approaches to handle multi-criteria decision problems is the weighted sum approach. In this approach, the objectives are aggregated prior to the optimization by assigning weights to the objective functions. We followed the similar methodology for solving the model, and the weights (w_1 and w_2 in Eq (1)) were decided after a detailed sensitivity analysis and decision makers preference concerning the objectives.

$$Obj(Maximize) = \sum_{i,j \in A} w_1 X_{ij} C_{ij} - w_2 Y_i f_i * BT \tag{1}$$

Here, X_{ij} is a binary variable whose value is 1 when an edge (i to j) is selected in a route, and 0 otherwise. C_{ij} represents the cost associate with the distance between i and j. The binary variable Y_i is 1 when a bin is served by a collection vehicle, and 0 otherwise. Once a collection vehicle serves a bin and collects the waste (f_i: fill ratio between 0 and 1, where 1 and 0 correspond to full and empty, respectively), the conversion factor "BT" scales the amount in the scale of for the collection vehicle's percentage fill range. The variables w_1 and w_2 are the weights associated with distance travelled and waste collected, respectively. These weights sum up to one which is represented by constraint (2).

$$\sum_{n \in \{1,2\}} w_n = 1 \tag{2}$$

Constraint (3) and constraint(4) ensure that every route deduced after a time interval starts and ends at depot. This also requires updation of starting bin denoted by variable 'st' in Eq

(3).

$$\sum_{j\in N} X_{st,j} = 1; \forall st \in D; j \in N \tag{3}$$

$$\sum_{j\in N} X_{j,0} = 1; \forall j \in N \tag{4}$$

Eq (5) and Eq (6) insure that visited bins are not covered again in the same run.

$$\sum_{i\in N}\sum_{j\in D} X_{ji} = 1; \forall i,j \in A; j \neq i \tag{5}$$

$$\sum_{i\in N}\sum_{j\in D} X_{ij} = 1; \forall i,j \in A; j \neq i \tag{6}$$

The constraint ((7)) ensures that the waste collected by a CV on an arc (collection of one or more edges) is the sum of the waste collected at every bin present on that arc. The value of the waste inside the CV is updated at last bin, which then is used in the calculation of updated path in next time interval. This is achieved using a temporary variable u_i is a temporary variable that resets to zero at the beginning of each time interval. It represents the percent the the CV is full for each time interval. Constraint ((8)) guarantees that the amount of waste in a CV after reaching a bin is greater than or equal to the waste it had before. This constraint helps verify that the CV is actually collecting the waste from the bins in its route without passing it.

$$u_i + f_j * BT = u_j; \forall i,j \in A \tag{7}$$

$$u_i \geq f_i * BT \tag{8}$$

given:

$$i,j \neq 0$$
$$i,j \neq st$$
$$\forall i \in N$$

Constraint ((9)) confirms that the collection will not collect waste from a bin if collecting from that bin makes the CV exceed its maximum capacity. The constraint utilizes the variable P_t, that stores the cumulative values of u_i over all the previous time intervals.

$$\sum_{i\in N} Y_i f_i * BT \leq 100 - P_t \tag{9}$$

Lastly, constraint ((10)) makes sure that at any point of time CV does not exceed its maximum capacity.

$$u_i \leq 100 - P_t \tag{10}$$
$$\forall i \in N$$

4 Case Studies and Empirical Results

4.1 Data Preparation

To prove the effectiveness of the model, we empirically tested the model for the city of Chandigarh in India. The city is located by the foothills of the Shivalik range of the Himalayas in northwest India. It covers an area of approximately 148.95 km^2. It borders the states of Punjab and Haryana. The city is known for being the first planned city of India. The city also has various scattered unplanned built-up patches such as Burail, Nayagaon. The mixed built-up typology was suitable to test the methodology. Hence, the city was found suitable to test the methodology. We generated various waste collection points (location of smart bins) for the city. A total of 300 points were generated randomly using Geographic Information System (GIS) functionalities, with the constraint that the point should fall on the road networks. The road network was extracted from Open Street Map (OSM)[1] database. OpenStreetMap API was then used to calculate the distance between all bins, and generate a distance matrix which was used in the optimization process. We applied K-Means clustering algorithm to cluster these points in a fixed set of clusters (see Figure 1). In this paper we have selected total clusters to be three. The number can be updated based on user requirements. After clustering, region1, region2 and region3 had 95, 111 and 94 points, respectively. The clusters were considered as three regions for which CV had to be allocated. To replicate the actual field activities we have considered that a CV starts and ends its route at the depot (see Figure) 3)

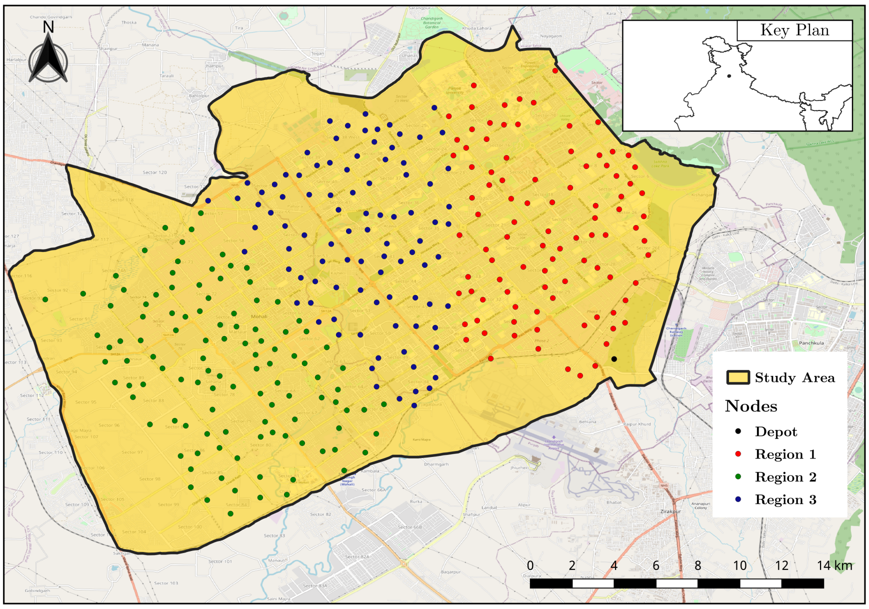


Figure 3: The selected bins and their clusters

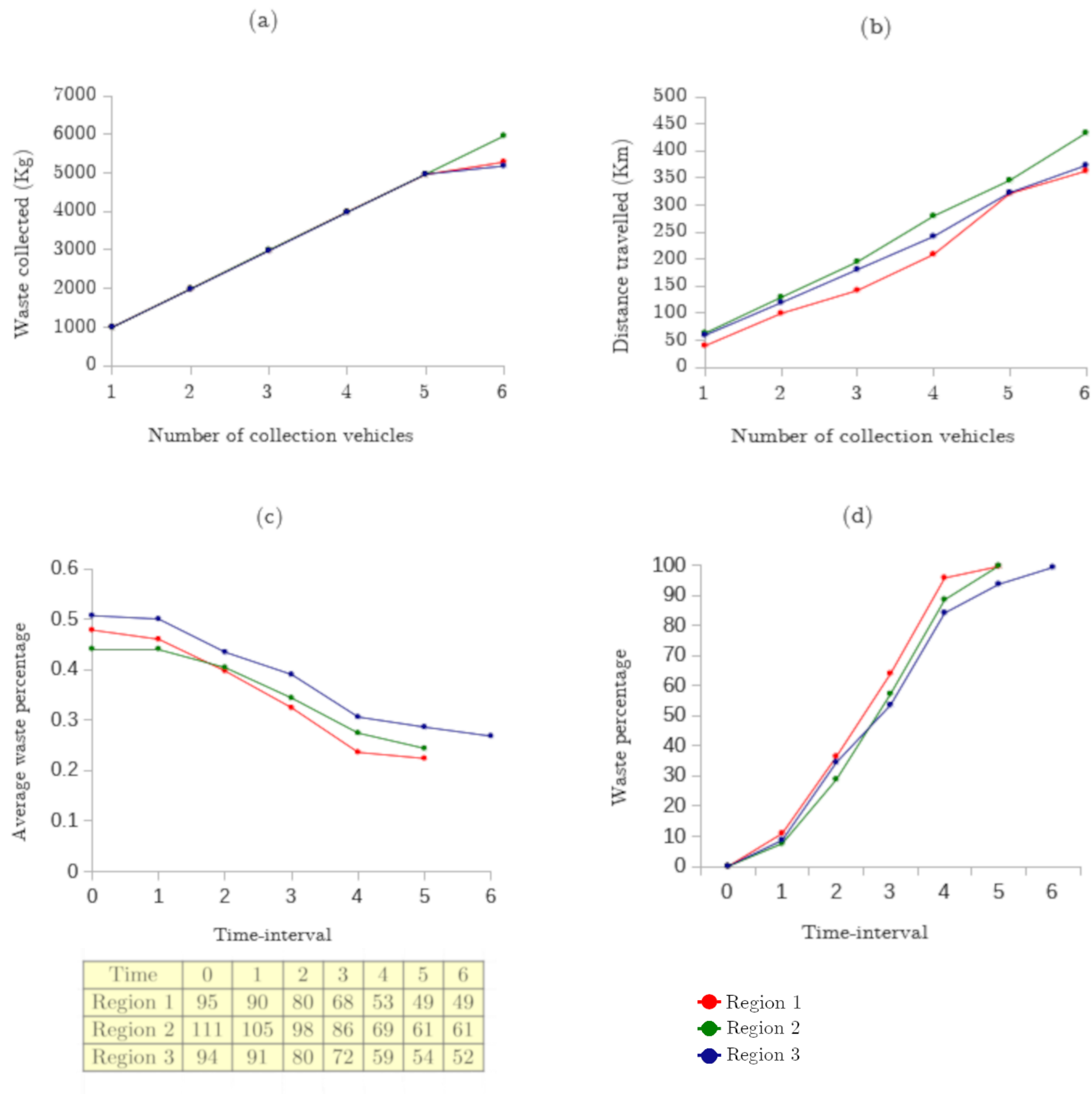
4.2 Execution case studies

Experiments were carried out on a AMD A6-9220 processor which runs at 2.5GHz and utilizes 8 GB RAM. The model was implemented in Python 3.10.5 and solved with Gurobi optimizer version Gurobi 9.5.1. A total of four scenarios were implemented and the minimum and maximum solving time was around 67.0618 s having total variable count: 7041 and total constraint count: 7075 for the maximum case. The suggestion of the decision makers (Municipal Corporation Chandigarh) was to provide equal preference to find minimum distance routes and maximizing the waste collection. Hence, we assigned w_1 and w_2 to be 0.5 to execute the scenarios. This means that our optimization model gives equal importance to minimizing the distance and maximizing the waste collected. To highlight the important of weights a detailed sensitivity analysis of weights on outcomes is discussed later in a subsection. The maximum capacity of a CV (TC) was considered as 1000 Kg, and the maximum capacity of a smart bin (BC) was considered as 100 Kg.

[1] https://www.openstreetmap.org/

Case 1: Restriction on Resources

To highlight the importance of strategical usage of available resources in resource constraint societies, we applied restrictions on the available collection vehicles. The CV values were varied from one to six and the impact on total distance travelled, total waste collected, and total bins covered was studied for each region, and eventually for the city. The routes were calculated while considering the temporal dynamics of bin and waste level, CV positions in varying time-steps.



Time	0	1	2	3	4	5	6
Region 1	95	90	80	68	53	49	49
Region 2	111	105	98	86	69	61	61
Region 3	94	91	80	72	59	54	52

Figure 4: Analysis of real-time restricted case

A significant impact of available CV on collected waste was observed. The increase in collected waste for different number of CV per region varied almost linearly w.r.t the total distance traveled (Figure 4). The increase in distance and collected waste is a direct result of having more CV running at the same time. For region1 and region3, a sharp drop in the waste collected was observed after five CV. Which means almost all the smart bins for these regions were catered by these CV. On the other hand region2 still required more resources to cater the demand. This is more evident by Table 2, which details the case of 6 CV per region to determine whether it is sufficient to satisfy the waste collection demand of regions and the city. It can be observed that all bins for regions 1 and 3 were covered by utilizing 6 CV, while only 85% of the bins for region2 were covered by the six CV. This is primarily because the value of waste for the bins in this regions was higher due to region2 having more bins than region1 and region3.

Table 2: Data for 6 CV per region

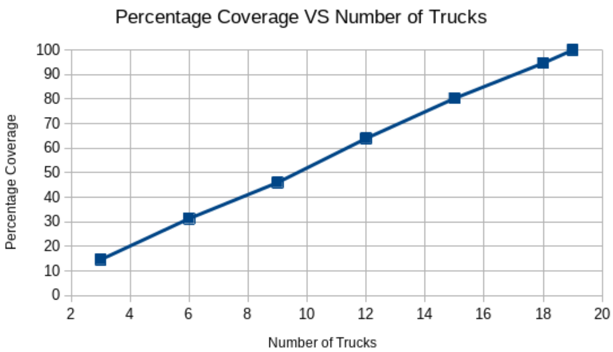
Region	CV	Waste (Kg)	Distance (Km)	Waste/Distance	Percent collected
Region 1	CV 1	999.07	38.53	25.93	14.74%
	CV 2	990.67	47.20	20.99	13.68%
	CV 3	994.66	43.57	22.83	15.79%
	CV 4	998.21	72.55	13.76	20.00%
	CV 5	977.66	121.86	8.02	24.21%
	CV 6	322.56	39.19	8.23	11.58%
				Total:	**100%**
Region 2	CV 1	999.71	62.64	15.96	12.61%
	CV 2	993.32	71.67	13.86	12.61%
	CV 3	985.38	56.82	17.34	14.41%
	CV 4	991.47	78.51	12.63	13.51%
	CV 5	990.43	64.48	15.36	13.51%
	CV 6	999.31	99.06	10.09	18.92%
				Total:	**85.5856%**
Region 3	CV 1	999.68	48.07	20.80	15.96%
	CV 2	998.71	55.13	18.12	15.96%
	CV 3	991.22	50.32	19.70	14.89%
	CV 4	998.88	74.83	13.35	21.28%
	CV 5	955.92	87.04	10.98	23.40%
	CV 6	235.45	57.88	4.07	8.51%
				Total:	**100%**

Case 2: Real-time, unrestricted

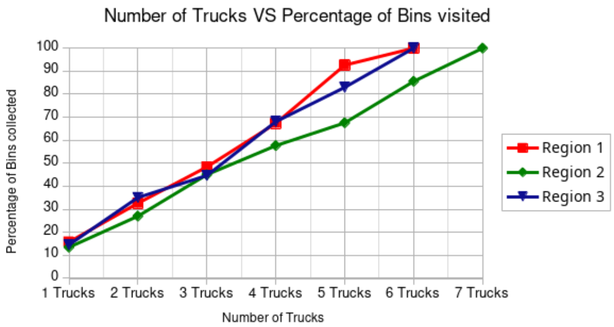
Often the decision makers want to derive the requirement of resources that could cater to the whole demand. To achieve that, we relaxed the constraint on available resources to deduce the the total resource requirement for achieving 100% bin visits, with high waste. In the previous case it was established that six CV would cater to all the bins for region1 and region3. We extended the experiment for region2 by increasing the available CV till we achieved 100% bin coverage. It was observed that region2 was fully covered by seven CV (see Table 3). Hence, given the existing bins, the city requirements can can be fulfilled by 19 CV (see Figure 5a). Figure 6 shows the calculated routes for each CV of regions to depot.It can be noted that (see Figure 5b) for region2, the rise in the percentage coverage of bins is less than the other two. This is primarily because region 2 is larger than region 1 and 3, and contains more bins. This can be confirmed as the waste that is collected for equal number of CV are similar to all regions.

Table 3: Data for unrestricted resources

Region	CV	Waste (Kg)	Distance (Km)	Waste/Distance	Percent collected
Region 1	CV 1	999.07	38.53	25.93	14.74%
	CV 2	990.67	47.20	20.99	13.68%
	CV 3	994.66	43.57	22.83	15.79%
	CV 4	998.21	72.55	13.76	20.00%
	CV 5	977.66	121.86	8.02	24.21%
	CV 6	322.56	39.19	8.23	11.58%
	Total:	**5282.82**	**362.89**	-	**100%**
Region 2	CV 1	999.69	60.89	16.42	12.61
	CV 2	992.96	70.29	14.13	13.51%
	CV 3	988.65	65.86	15.01	11.71%
	CV 4	997.20	68.30	14.60	15.32%
	CV 5	983.61	73.17	13.44	15.32%
	CV 6	934.99	94.22	9.92	14.41%
	CV 7	740.36	111.69	6.63	17.12%
	Total:	**6637.42**	**544.42**	-	**100%**
Region 3	CV 1	999.68	48.07	20.80	15.96%
	CV 2	998.71	55.13	18.12	15.96%
	CV 3	991.22	50.32	19.70	14.89%
	CV 4	998.88	74.83	13.35	21.28%
	CV 5	955.92	87.04	10.98	23.40%
	CV 6	235.45	57.88	4.07	8.51%
	Total:	**5179.85**	**373.26**	-	**100%**



(a) For the entire city



(b) Region-wise

Figure 5: Effect of number of CVs on bin coverage

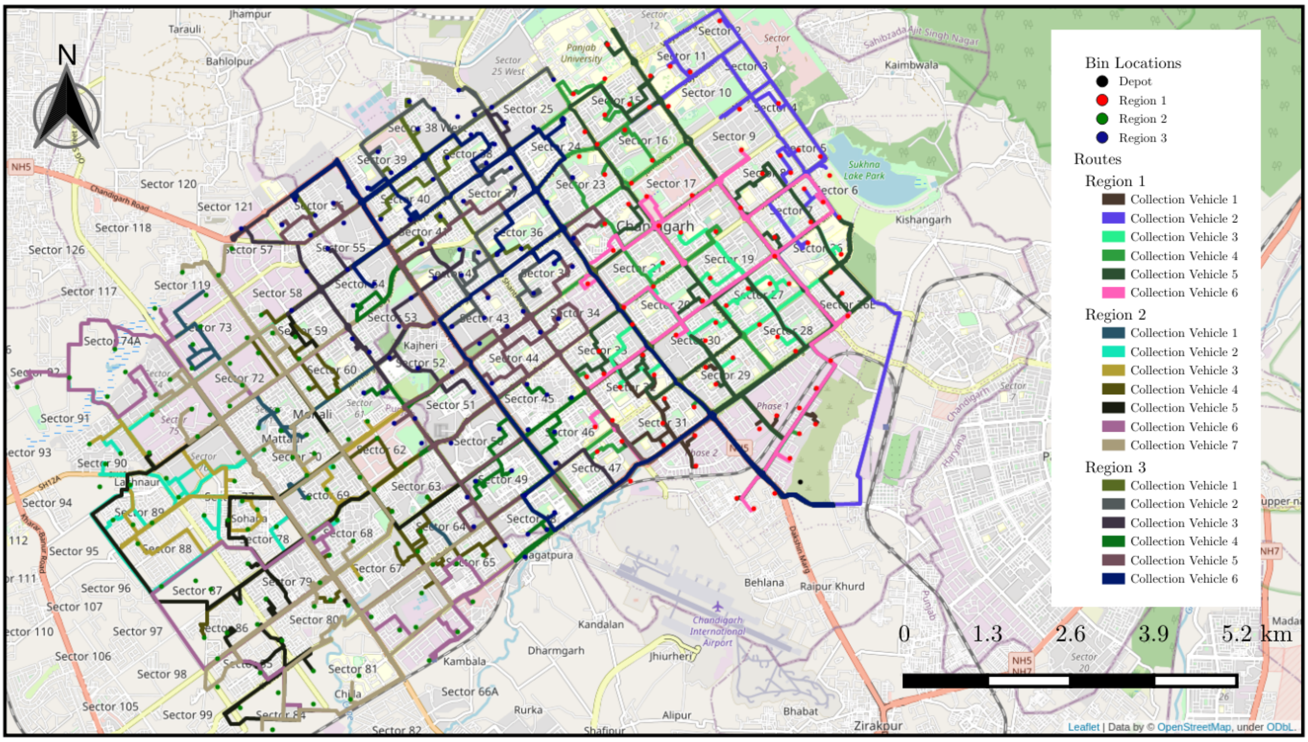


Figure 6: Realtime Unrestricted

Case 3: Comparison of real-time with static route calculation

Our base case of route calculation considers real time dynamics of waste (bin, CV) and CV's current position in real time. However, the existing collection system of the city is static. Hence, we compared the real-time route calculation model with static by modifying the eq (10) where the constraint will simply be less than 100, as shown in (11). In equation (3) and Eq (4), instead of *st*, the beginning bins will always be 0 ((12)(13)).

$$u_i \leq 100 \tag{11}$$

$$\sum_{j \in N} X_{0,j} = 1; \forall j \in N \tag{12}$$

$$\sum_{j \in N} X_{j,0} = 1; \forall j \in N \tag{13}$$

The above constraints when implemented results in a fixed optimal route which doesn't change with the time. We executed the dynamic and static models for 3 CV per region, for a total of 9 CV. The comparison is represented in Table 4

Table 4: Comparison of static and real-time optimization performance

Case	Waste (Kg)	Distance (Km)	Percent Covered
Static	8996.88	798.13	40.33%
Real-Time	8967.25	517.8	46.00%

The routes (Figure 7 and Figure 8) show the routes obtained for static and dynamic case for 9 CV. The outcomes demonstrate the consideration of dynamic variables on the routes which are different than the static model.

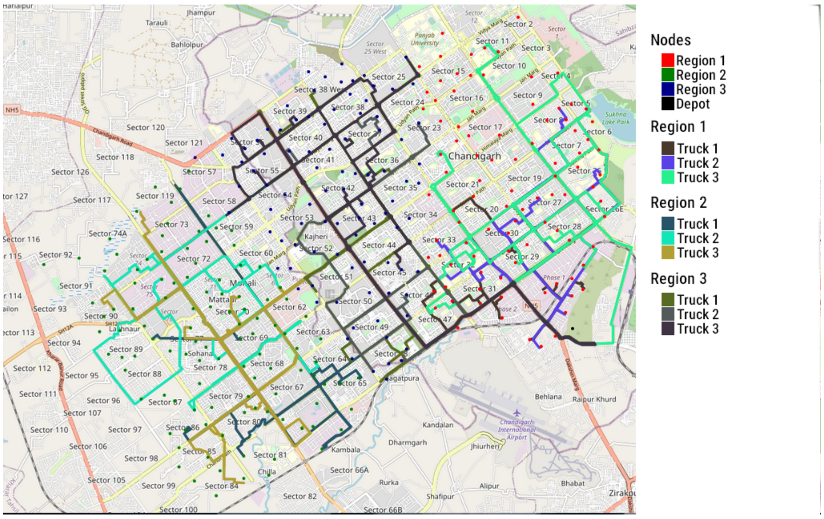


Figure 7: Routes for 3 CV per region as calculated by static optimization

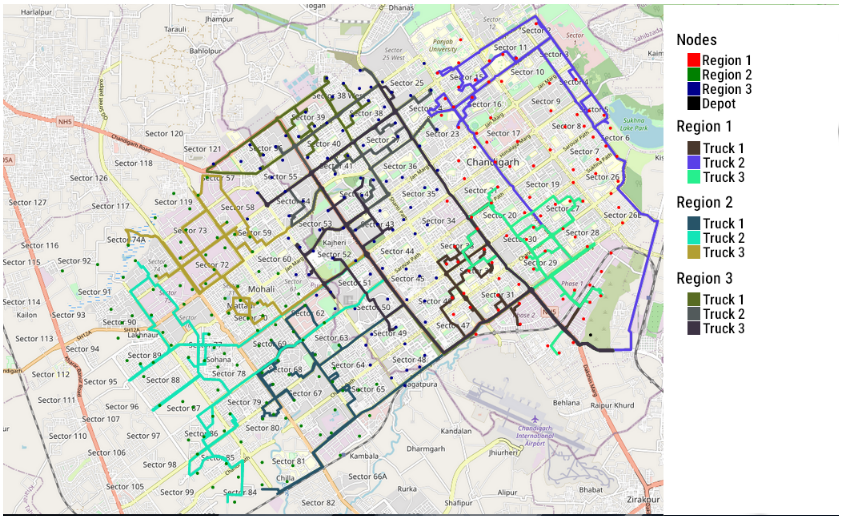
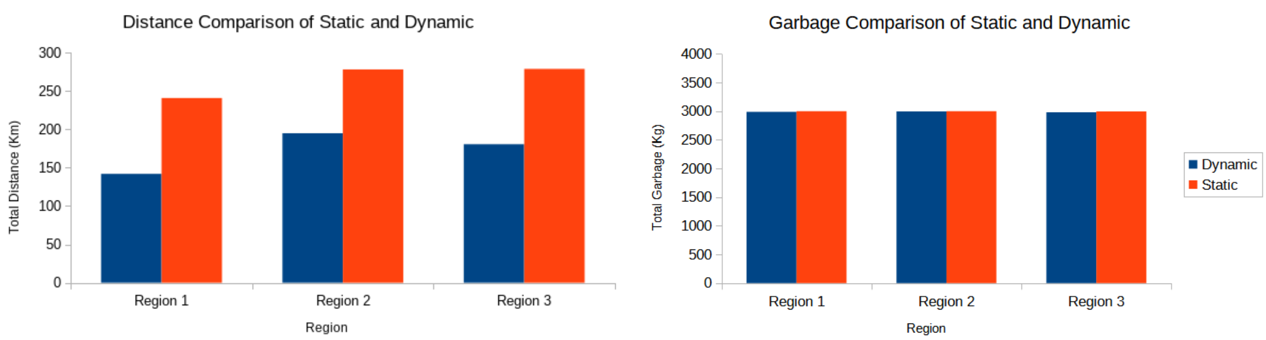


Figure 8: Routes for 3 CV per region as calculated by real-time optimization



(a) Distance comparison

(b) Waste comparison

Figure 9: Comparison between static and real-time models

We used the case of 3 CV per region in order to achieve a suitable middle ground, providing enough complexity to the problem for the two models to be fully utilized and compared while also maintaining the resource constrained aspect of the problem. We observe that the weight of the waste collected is nearly the same for both cases but the distance travelled by the CV in the real-time case is significantly less than the static case. This further emphasizes the efficiency of the real-time method over the static method.

This makes real-time optimization the superior model in terms of both efficiency and features. In the static model, there is no accounting for new data. The initial route is the only route that is calculated. This, consequently, also makes it unreliable. Real-time model, on the other hand, accounts for new data and creates new optimal routes taking it into consideration, making it very adaptable and robust. Since real-time is just a modified and iterated version of the static model, the difference in computational power required between the two methods is not large.

Therefore, for real life applications, real-time model is the preferred method as it is able to deal with non-deterministic events that are synonymous with ground use and adapt to them, giving an uninterrupted and reliable service, while also providing greatly efficient results.

5 Discussion

The collection of waste is a highly visible and important municipal service that involves large expenditures. Waste collection problems are, however, one of the most difficult operational problems to solve, as it involves a lot of complex dynamic activities. Without modeling these activities a solution often have limited on-ground implementation. Our objective in this paper addresses these challenges by simultaneously modeling the dynamic changes in waste values of bin and CV to dynamically update the routes for maximizing the collected waste while covering less distance. Moreover, the consideration of dynamic bin values replicates the realistic scenario. A very few research has coupled such variations with the dynamically varying routes based on the model objective. The outcomes of various experiments prove that our methodology outperforms the existing static method of waste collection. Our model was able to collect almost similar amount of waste in significantly less travelled distance. This can have direct implications on the carbon footprint and eventually on developing sustainable societies.

Another important aspect of a sustainable system that this study addresses is strategic planning of the available resources. As a general theory a lot of resources can solve the problem. However, this can be a challenge for a resource constrained society, as the resources are limited and their availability may not be sufficient for the amount of waste generated. A way to address this can be using alternate methods such as multiple collection runs per CV. However, this will have time limitations and can also lead to subpar waste collection, considering the dynamics of wastes. The outcomes of the model execution show that using a reasonably less number of collection CV a large area can be catered with good efficiency. Further, the performed sensitivity analysis of various objective weights as a decision making tool can help planners preempt the collection scenarios, which makes this system highly relevant to city managers. Unlike the currently implemented systems with limited dynamic considerations, our solution:

- is capable of calculating optimal paths based on the dynamic updates (real-time fill levels of smart bins, priority to bins based on fill values, CV position and its fill levels) that generally happen in real-time.
- significantly improves the performance of waste collection system in terms of distance travelled and waste collected.
- reduces the distance overheads by removing the need to visit redundant bins.
- being generic can be implemented to any city across the globe by updating the specific objectives and constraints.

- addresses the challenges of decision makers concerning a system that could be implemented in the realistic environment. Our approach of modeling the problem as linear programming model makes it ideal for integrating it with a real-time system.

The paper put forwards following major policy suggestions that can be implemented to to support the vision of creating smart sustainable cities:

- Inclusion of waste collection system in climate resilience plan: Climate resilience based urban planning is at the centre of major decision-making systems. Waste collection involves trips of collection vehicles, which adds to carbon emission. Strategic routing of available CV can not only benefit the economic aspects but can also help reduce the carbon emissions. To achieve this the government can include the waste collection system with the climate resilience plan of the city. The methodology proposed in this research can serve as an important component of such systems.

- Implementation of smart bins for community or regions: Door-to-door collection of waste is not practiced in majority of city/town. The issue is even more challenging in dense urban regions with narrow lanes where accessibility of CV can be limited. However, smart bins for various unorganised and organized built-up regions can address the challenge. Smart bins with sensors that send fill details can help in prioritising them leading to better collection and routing strategies on the similar lines to our method. The information of waste type automatically sensed using smart sensors can further benefit the waste segregation which is an another major challenge in waste management. [36]

- On-board computation: Future smart cities are going to be developed using modern technologies as its backbone. Technology can immensely benefit waste collection by implementing numerous technologies in everyday collection practices. One of these valuable pieces of equipment is the on-board computation. The routing module proposed in the study integrated with Global Navigation Satellite Systems (GNSS) can be implemented in on-board computer for generating routes . Not only can the driver follow his route on the system, but can also communicate with the office notifying them of any important information. Benefits that increase driver efficiency are:
  - Track routes in real-time
    * relief driver can run route without any prior knowledge of it, which can reduce unnecessary time and cost.
    * the generated trip data can further be used to update the routing model based on the future requirements.
    * brings accountability to the system as stakeholders (decision makers, citizen) can track the CV and plan accordingly. Moreover, the decision makers can quantify the effectiveness of the collection process.
  - Integration with billing systems with smart bins
    * by integrating the billing system in the routing software with smart bins, customers can for charged for extra collection thus not missing additional revenue.
    * customers can also be charged for not segregating waste at the collection point, which can address the segregation process challenges, and will help bring accountability in the system.

6 Conclusion

Waste collection is one of the most important components of waste management process, comprising various interlinked components such as smart bins, dynamic routing, smart collection vehicles and their coordination. The existing research either is focused on static models or lack the integration of these components with realistic objectives. This paper with the aim to fill this gap implements a flexible real-time route optimization model that accepts and adapts to constantly updating data to provide optimal routes while maximizing the collected waste and minimizing the distance travelled by each CV implemented in an ABM environment. This makes the model suitable for onground implementations as it can take care of unseen circumstances and automatically adapt to them. The model was executed for the city of Chandigarh and it was found that the dynamic routes can reduce the distance travelled by around 35% for the same amount of waste collected suing existing static methods.Various execution cases to support waste collection process in resource constrained societies show the effectiveness of model in identifying the required resources to satisfy the demand in dynamic environments.

The outcomes as a planning tool can help taking decisions concerning the compromises for limited resources and its impact on waste collection and extra distance travelled to fulfill the demand. One of the limitations of the study is non-consideration of a bin by any other CV even if the bin was not full when visited. This can be addressed by relaxing the constraint,and its impact on outcomes can be examined. We have considered simulated smart bins to test of models, which can be replaced by IoT enabled smart bins in real environments. Further integration of real time data of accidents, construction work etc., can provide more accurate routes.

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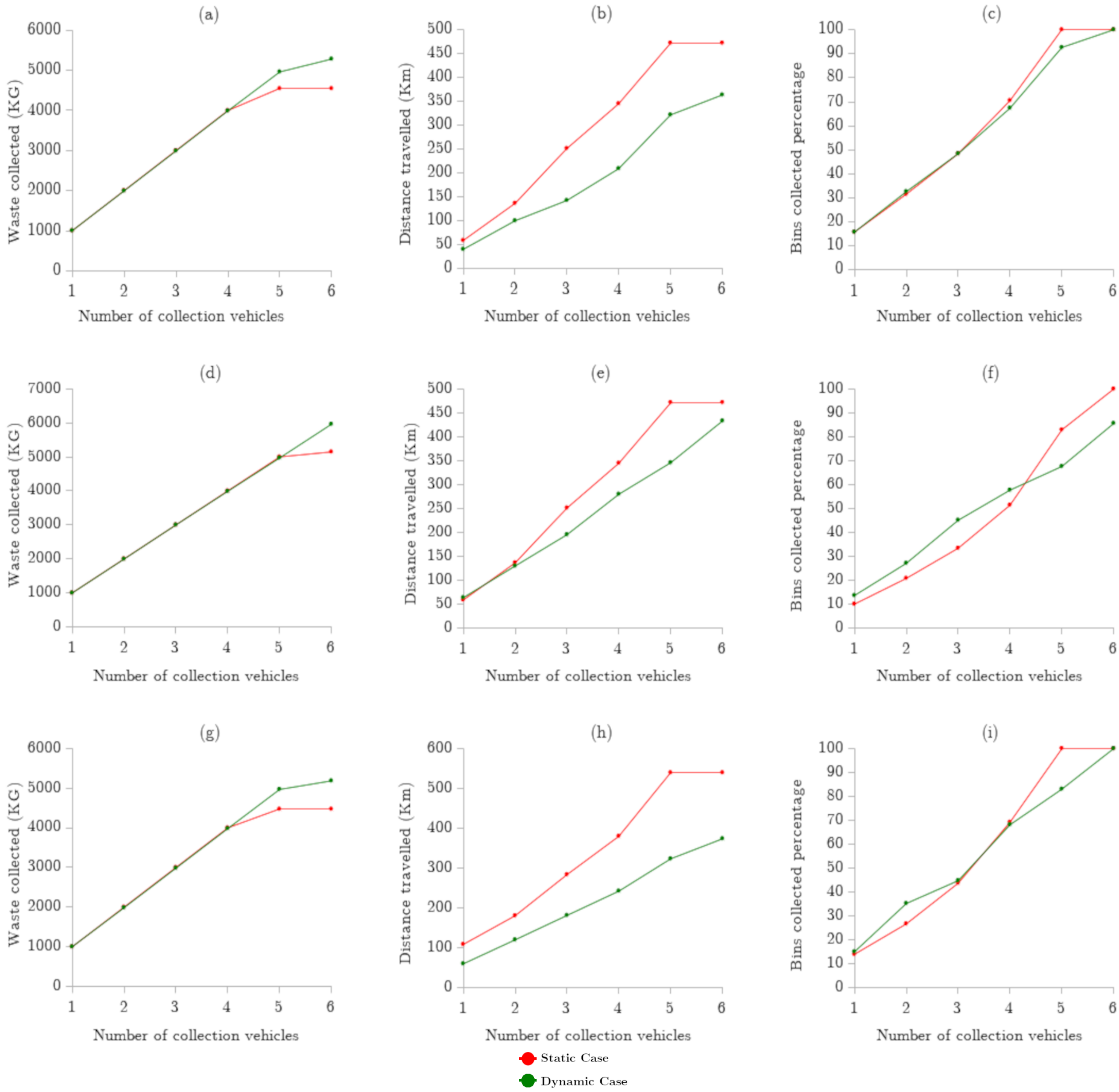
(a)
Waste collected (KG)
Number of collection vehicles
(b)
Distance travelled (Km)
Number of collection vehicles
(c)
Bins collected percentage
Number of collection vehicles
(d)
Waste collected (KG)
Number of collection vehicles
(e)
Distance travelled (Km)
Number of collection vehicles
(f)
Bins collected percentage
Number of collection vehicles
(g)
Waste collected (KG)
Number of collection vehicles
(h)
Distance travelled (Km)
Number of collection vehicles
(i)
Bins collected percentage
Number of collection vehicles
Static Case
Dynamic Case