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. However, the waste collection in India is very unorganized, primarily due to resource constraints and poor planning of available resource [2, 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 by in almost every city in developing countries [2]. VRP requires modeling many components such as path planning, consideration of available resources, spatiotemporal demand patterns, and real-time dynamics of waste volume at collection points and trucks. A plethora of literature addresses subsets of these components in solution development. However, a holistic waste collection system that considers them simultaneously for any region has not been reported in the literature [7]. Hence, the onground implementation of the present approaches are still very limited. This significantly impacts the operation costs and, eventually, the environment [8]. 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 vehicle paths while considering the dynamic variations in the waste information at collection points and also that of the vehicles. 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 with the following major contributions:

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

2 Related Studies:

There has been a decent amount of work done in different aspects of waste collection, such as the costs, route optimization, smart bins, segregation, landfill and collection depot optimal locations. But, by far, the most common topic of work in this area has been VRP and, in recent years, Internet of Things (IoT) enabled smart designs for the waste management systems.

Optimization of vehicle routes is one of the main objectives for this paper. VRP has been previously approached from many directions such as landfill and collection sites allocation to minimize distance traveled by collection vehicles [9–11], collection point clustering to increase collection efficiency [12] and calculating the optimal route with a fixed set of collection nodes and landfill/depot locations [13–18]. The mathematical calculations of the VRP have been solved through pre-existing route optimizer software, such as the ArcGIS Network Analyst [13,14,19], or a formulated single or multi objective functions that calculate the desired routes [16,17]. The biggest drawbacks of these models is that they are predominantly static and calculate the optimal routes once for a set of collection points. Even the papers that do focus somewhat on dynamic methods, they are mostly theoretical and lack the elements necessary for real life application [17]. Some studies have further incorporated smart bins with the VRP to develop a more robust and resource efficient solution to the optimization problem [18,20,21]. These utilize IoT enabled smart bins to keep track of the waste that needs to be collected and reduce redundancy in waste collection runs. Most of these models focus on case studies set in developed nations, which are not constrained in terms of resources.

The application of route optimization models in resource constrained societies is the second of our main objectives. Waste collection in resource constrained societies comes with the additional challenge of having to allocate insufficient resources to meet the demands as much as possible. While not as many as before, there have been papers that focus on this aspect of waste collection [10,19,22–24]. The study in [22] utilizes ArcGIS Network Analyst to calculate optimal waste collection routes in the city of Allahabad. While it does take real life data of collection and landfill sites into consideration for the route calculation, it relies on a pre-existing route optimizer to get the final results. [24] and [19] focus on route optimization in the cities of Onitsha, Nigeria and Ipoh City, Malaysia respectively. The paper [10] focuses on optimal node 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. This is one of the things this paper seeks to address.

There have been many more works done in the field of VRP and the papers mentioned above are in no way exhaustive. They were just meant to be indicative of the general direction of the research done in this field. There are a number of excellent reviews that go into much more detail regarding the other works that address optimization of waste collection and management systems [25–27]. The engineering and construction aspects of the smart bins are outside the scope of this paper, however other works have delved into much more detail on this problem [20, 28].

Our model integrates the concept of smart bins with the optimization algorithm. Smart bins are simply bins that are connected to the internet and provide real time data on how full they are. This data is used by the model to calculate new optimal routes for the collection vehicles after a specified time interval, based on the real-time locations of the vehicles. This paper's main priority is to create a model for route optimization that is suitable for a resource constrained city, yet is general enough to be scaled to fit more developed societies. Moreover, our model works with real time data, capable of adapting to new data and calculating new routes based on changing information, and that information is gained through smart bins. This paper also seeks to keep the simulated data as close the real life situations as possible so that the gap between theory and implementation would be minimal.

3 Problem Definition and Mathematical Formulation

3.1 Problem Definition

We address the problem of developing a vehicle routing model by minimizing the incurred travel cost and maximizing the waste collected by the vehicles 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 which are used to collect waste and generally caters a large areas. These bins as nodes are assumed to be located on a road network made from edges and nodes. We simulated temporally varying waste values for each of these bins, we call them "smart bins". The simulation helped us in overcoming 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.

A collection vehicle is an individual goal driven agent, traversing the simulated environment based on the selected real world location, with the goal being collecting waste from the smart bins while also maintaining efficiency by reducing the distance traveled and maximizing the waste collected. An agent is assigned to a region, and it only collects waste from bins from a specific region through an optimal route. The "route" in our problem corresponds to path of the agent covering these bins and finishing its trip at a depot. The path is made up of non-directional edges. To make the implementation realistic we have applied limits on the total waste that can be collected by the agents. The numerical values of the distances are normalized to the same scale as the waste values to avoid any skewness. The model is executed after a certain time interval by considering bins waste values, vehicle waste fill status, vehicle location, and generates a route which keeps updating with the time. We implemented the smart bins in the route finding process using a priority queues where priority is being given to a bin based on the distance to that bins and the amount of waste value of bin, that is, for the same distance value, the bin with the greater waste value is assigned higher priority. The model stops when either the run is complete or the vehicle is full. A "time slice" here is the route calculation that is done for one time interval, which is repeated multiple times with updated data to get the final route.In other words, a time slice is one iteration of the entire process. The "run" in our problem signifies the whole process of calculating the route for one vehicle, beginning and ending at the depot. A run is the aggregate of multiple time slices over time. The values of the bins can be updated even when the vehicle is moving on an edge and hasn't reached the next node. For such scenarios the model assumes that the vehicle has completed the current edge and considers the next node as the starting point for the new time slice.

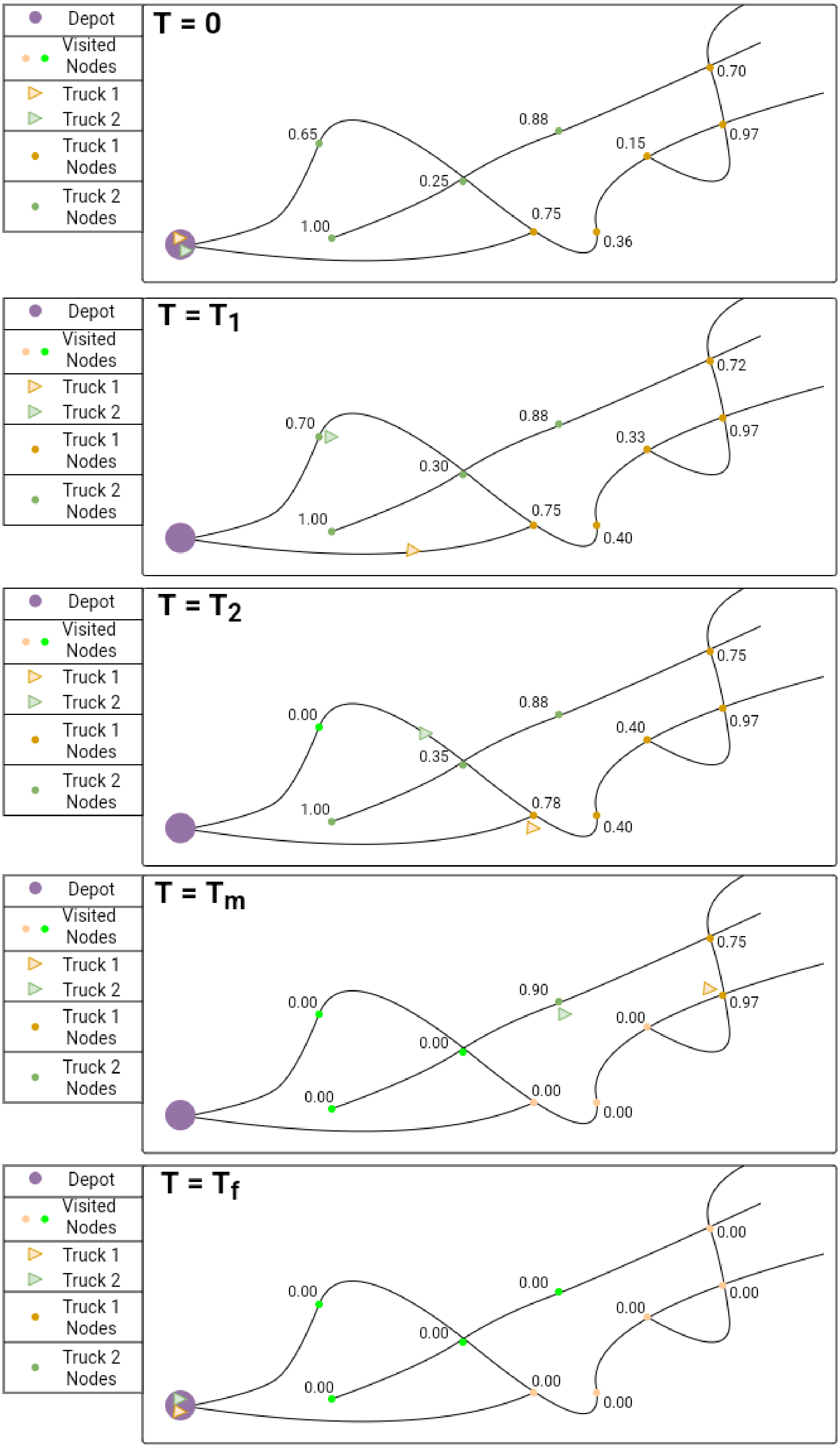


Figure 1: General representation of the process

While running the optimization process, each individual bin is randomly assigned a value between 0 and 1 to denote how full the bin is. This value is updated with each time slice to simulate the real life accumulation of waste in bins. When transferring waste from the bins to the agent, a conversion factor is used to convert the waste amount from the percent fill ratio of the bin to the percent fill ratio of the agent. The agents are programmed to run in parallel, that is, each agent starts its collection run at the same time and continues until they reach full capacity. If an agent, in one time slice, does not visit a node, if there is sufficient capacity remaining, one of the other agents will address that node.

As represented in Figure 1 The agents start at $T = 0$ with the bins present at the nodes having a certain value indicating how full they are. As the trucks move through the route calculated by the model, they collect waste from the bins and and put the visited nodes into a separate list so as to not include them in further route calculations. This continues through different time slices $T = T_1, T_2, T_m$ where the values of bins are updated, and then the agents finally return to the depot node at the final time $T = T_f$

Four 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 is to maximize the waste collected while minimizing the total distance travelled by the vehicles. We formulate the model as a mixed integer linear programming problem and solved it using Gurobi optimizer [29] in polynomial time. Such solvers can solve problems with realistic instance sizes, which was in our case.

In our problem, our two main objectives are:

- Minimize the distance travelled by the collection vehicles
- Maximize the waste collected through the collection run

The following table defines all the variables used for the mathematical formulation: The following table defines all the variables used for the mathematical formulation:

Table 1: The description of variables

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

With this we can formulate our base objective function to be:

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

Here, X_{ij} is a binary variable that can only take the values 0 or 1, based on the fact whether a truck took a route from i to j or not. C_{ij} is the cost, or the distance travelled when moving from i to j. Y_i is another binary variable that indicates if waste from node i has been collected or not. BT is the conversion factor of how much would the waste from a node would fill up a truck collecting it. f_i represents the fill ratio (the percentage of how full the bin is) of the bin, its value being between 0 and 1. 0 meaning it is empty and 1 meaning it is full. The variables w_1 and w_2 are the weights associated with distance travelled and waste collected, respectively, to determine which attribute of waste collection should have the higher priority and by how much. A single instance of the objective function is defined for one vehicle, but for the route optimization involving multiple trucks, multiple instances of the objective function, one for each vehicle, is ran in parallel to simulate simultaneous runs of collection vehicles in real life.

For the weights w_1 and w_2 the following constraint applies:

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

That is, the total sum of w_1 and w_2 will always remain equal to 1. This will be later used to perform the weight analysis in order to get the optimal ratios of the weights for our objective function.

For the objective function to fully represent our problem, we need to add constraints. The subscript 'st' denotes the starting node at the start of another time slice after the given time interval.

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

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

Node 0 is assigned to be the depot, the start and the end point of every collection run. Eq (3) and Eq (4) ensure the looping of the route, with the added caveat that since the calculations are made multiple times per run (called time slices) as new data is obtained, the value of the starting node for each subsequent time slice, after the initial one, changes. Therefore, these new starting nodes have to also be taken into consideration.

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

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

Eq (5) and Eq (6) specify that the nodes that are already visited by the truck in a collection run are not considered again for for further calculations, or in simpler terms, a node that has already been visited is not visited again in the same run.

The variable u_i is a temporary variable that resets to zero at the beginning of each time slice. It represents the percent the the truck is full for each separate calculation. Variable P_t is the variable that stores all the cumulative progress of how full the truck is, in percent, over all the previous and subsequent time slice.

If:

$$X_{ij} = 1$$

then:

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

for:

$$i, j \neq 0$$
$$i, j \neq st$$

This constraint (Eq (7)) ensures that if a truck goes on an arc (an arc being a small portion of the entire collection route) from two consecutive nodes, node i to node j, the amount of waste is continuous, that is, the waste in the truck at node j is the sum of the waste at node i and the waste collected in the route i to j. The value of the waste inside the truck is updated at node j so that there is no discrepancy in the case when a new path has to be calculated with new data.

$$u_i \geq f_i * BT \tag{8}$$
$$\forall i \in N$$

Eq (8) ensures that the amount of waste in a truck after reaching a node must be greater than or equal to the waste it had before that. This makes sure that the truck is actually collecting the waste from that node and not just passing it.

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

Eq (9) ensures that the truck will not collect waste from a node if collecting from that node makes the truck exceed its maximum capacity. Therefore, for the sake of maximizing waste collected, such nodes will not be taken into consideration for further time slices.

$$u_i \leq 100 - P_t \tag{10}$$

$$\forall i \in N$$

This constraint in Eq (10) ensures that for a single time slice in the collection run, the value of how full the truck is does not exceed its capacity. Since P_t stores the cumulative fill percentages of the truck, in any subsequent and previous time slices, the fill percent of the truck should not exceed the sum of the previous fill percentage and the percent filled in the current calculation.

With this, we have formulated our problem and now we can move on to implementing and calculating the solution for our problem

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 114 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) database. OpenStreetMap API was then used to calculate the distance between all nodes, 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 vehicles had to be allocated. To replicate the actual field activities we have considered that a vehicles starts and ends its route at the depot (see Figure) 2)

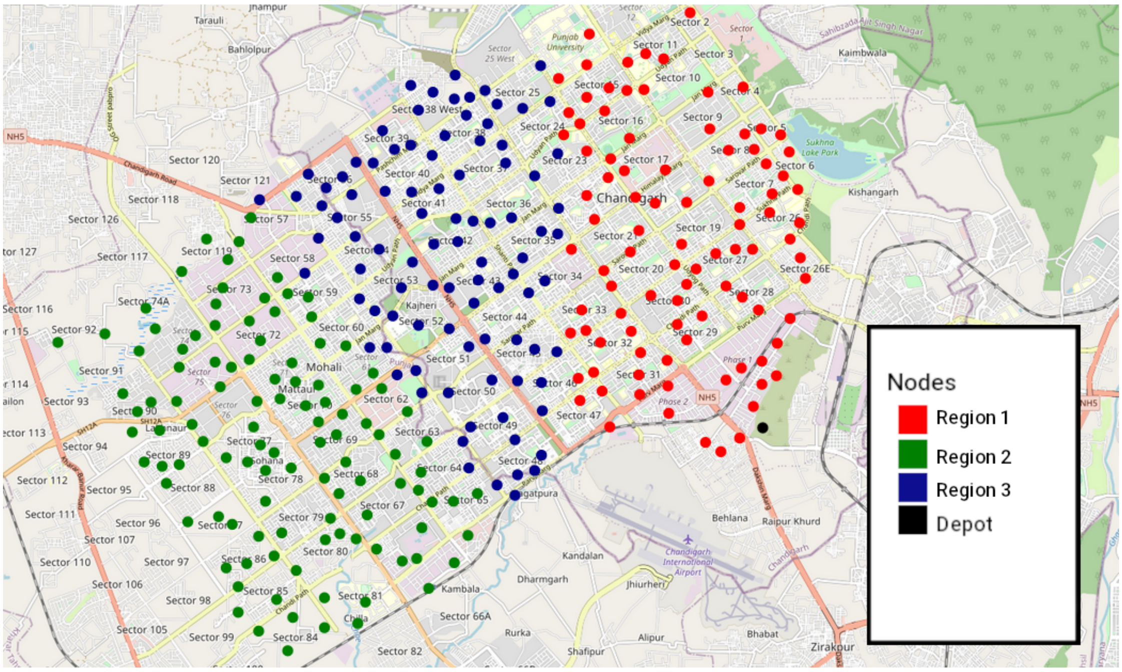


Figure 2: The selected nodes and their clusters

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.

As per Dengel et al [30], 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. The weights are based on the decision makers preference in order to model the importance of the goal, which in our case is to find minimum path route while maximizing the collected waste.

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 available number of collection vehicles (mv) was considered to be 7, and was considered same for all the regions. The values are selected based on the input of the decision makers. The maximum capacity of a truck (TC) was considered as 1000 Kg, and the maximum capacity of a smart bin (BC) was considered as 100 Kg.

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 vehicle values were varied from one to six and the impact on total distance travelled, total waste collected, and total nodes 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, truck positions in varying time-steps. Table 2 illustrates the cumulative values for the distance and wastes outcomes for all the trucks in each region.

Table 2: Data for the real-time restricted case

Case	Region 1		Region 2		Region 3	
	Waste (Kg)	Distance (Km)	Waste (Kg)	Distance (Km)	Waste (Kg)	Distance (Km)
1 Truck	999.89	39.79	997.36	63.11	999.94	59.22
2 Trucks	1992.68	99.58	1994.29	129.37	1984.23	119.51
3 Trucks	2989.61	142.05	2997.77	195.04	2979.87	180.71
4 Trucks	3989.43	208.59	3986.17	279.63	3977.46	241.80
5 Trucks	4961.06	321.16	4966.69	345.68	4964.88	322.97
6 Trucks	5282.82	362.89	5959.62	433.19	5179.85	373.26

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

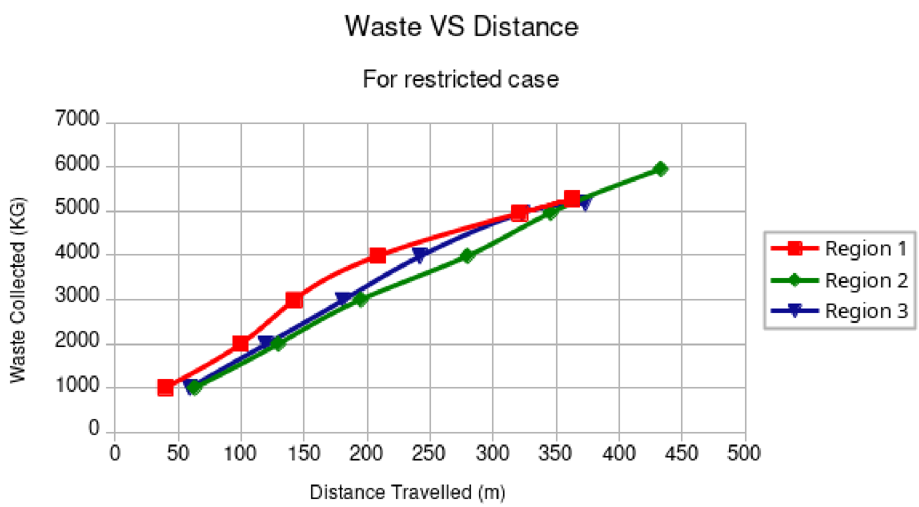


Figure 3: Distance traveled vs waste collected

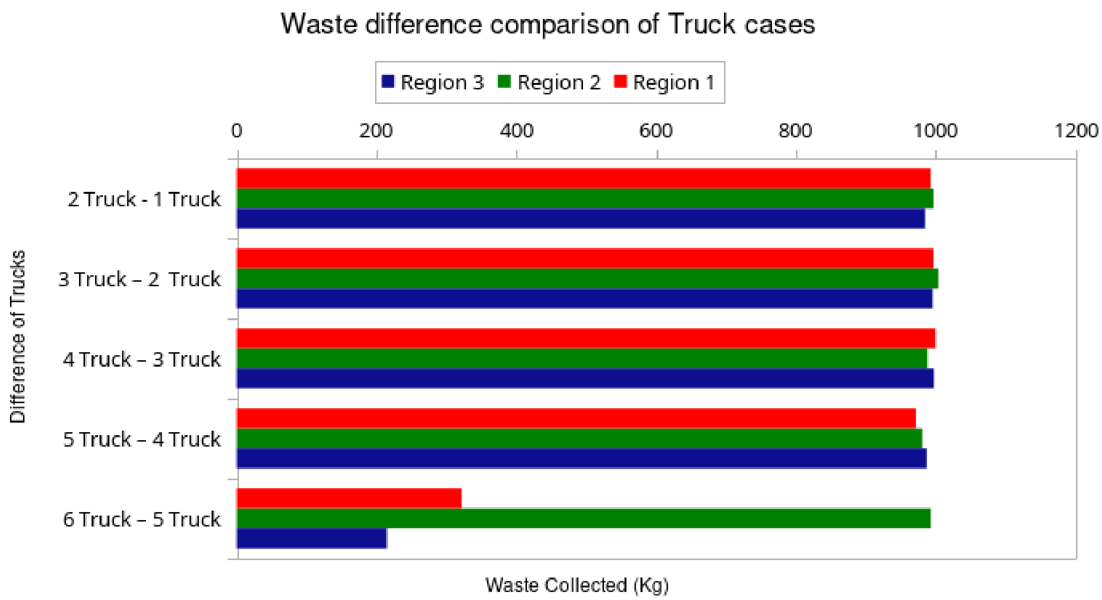


Figure 4: Difference in waste between cases

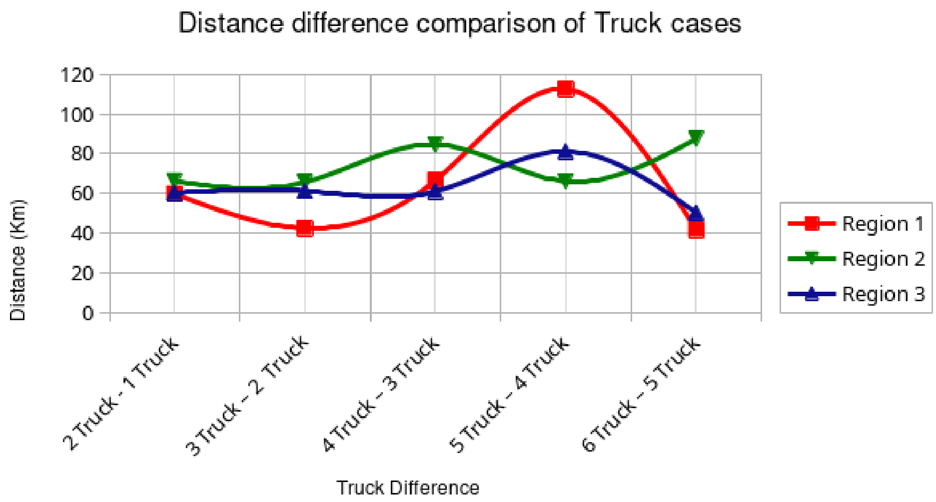


Figure 5: Difference in distance between cases

As observed in Figure 4, the difference of the increase of waste collected for the cases of different number of trucks per region is linear, that is, the difference remains more or less the same. This also appears to be true for the case of distance (Figure 5), which has slight deviations from a completely linear trend, but the deviations occur for both sides of the graph, making the deviations effectively inconsequential.

Table 3: Data for 6 trucks per region

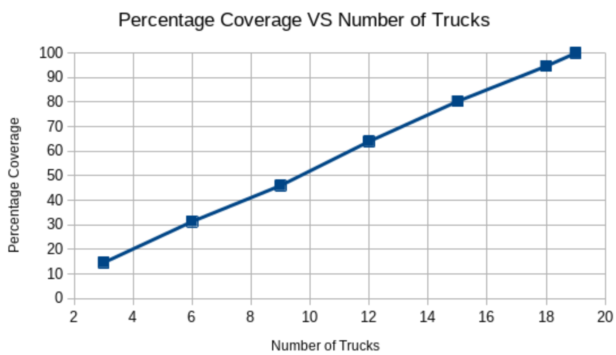
Region	Truck	Waste (Kg)	Distance (Km)	Waste/Distance	Percent collected
Region 1	Truck 1	999.07	38.53	25.93	14.7368%
	Truck 2	990.67	47.20	20.99	13.6842%
	Truck 3	994.66	43.57	22.83	15.7895%
	Truck 4	998.21	72.55	13.76	20.0000%
	Truck 5	977.66	121.86	8.02	24.2105%
	Truck 6	322.56	39.19	8.23	11.5789%
				Total:	**100%**
Region 2	Truck 1	999.71	62.64	15.96	12.6126%
	Truck 2	993.32	71.67	13.86	12.6126%
	Truck 3	985.38	56.82	17.34	14.4144%
	Truck 4	991.47	78.51	12.63	13.5135%
	Truck 5	990.43	64.48	15.36	13.5135%
	Truck 6	999.31	99.06	10.09	18.9189%
				Total:	**85.5856%**
Region 3	Truck 1	999.68	48.07	20.80	15.9574%
	Truck 2	998.71	55.13	18.12	15.9574%
	Truck 3	991.22	50.32	19.70	14.8936%
	Truck 4	998.88	74.83	13.35	21.2766%
	Truck 5	955.92	87.04	10.98	23.4043%
	Truck 6	235.45	57.88	4.07	8.5106%
				Total:	**100%**

Case 2: Real-time, unrestricted

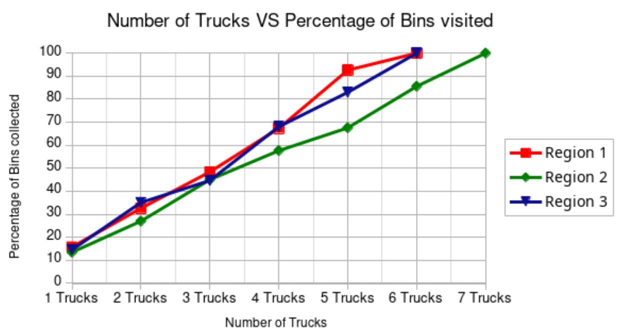
Often the decision makers want to derive the requirement of resources that could cater to the whole demand. To achieve that, we relaxed the constraint on available resources to deduce the the total resource requirement for achieving 100% bin visits, with high waste. In the previous case it was established that six trucks would cater to all the bins for region1 and region3. We extended the experiment for region2 by increasing the available trucks till we achieved 100% bin coverage. It was observed that region2 was fully covered by seven trucks (see Table 4). Hence, given the existing bins, the city requirements can can be fulfilled by 19 trucks (see Figure 6a). Figure 7 shows the calculated routes for each trucks of regions to depot.It can be noted that (see Figure 6b) 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 nodes. This can be confirmed as the waste that is collected for equal number of trucks are similar to all regions.

Table 4: Data for unrestricted resources

Region	Truck	Waste (Kg)	Distance (Km)	Waste/Distance	Percent collected
Region 1	Truck 1	999.07	38.53	25.93	14.7368%
	Truck 2	990.67	47.20	20.99	13.6842%
	Truck 3	994.66	43.57	22.83	15.7895%
	Truck 4	998.21	72.55	13.76	20.0000%
	Truck 5	977.66	121.86	8.02	24.2105%
	Truck 6	322.56	39.19	8.23	11.5789%
	Total:	**5282.82**	**362.89**	-	**100%**
Region 2	Truck 1	999.69	60.89	16.42	12.6126
	Truck 2	992.96	70.29	14.13	13.5135%
	Truck 3	988.65	65.86	15.01	11.7117%
	Truck 4	997.20	68.30	14.60	15.3153%
	Truck 5	983.61	73.17	13.44	15.3153%
	Truck 6	934.99	94.22	9.92	14.4144%
	Truck 7	740.36	111.69	6.63	17.1171%
	Total:	**6637.42**	**544.42**	-	**100%**
Region 3	Truck 1	999.68	48.07	20.80	15.9574%
	Truck 2	998.71	55.13	18.12	15.9574%
	Truck 3	991.22	50.32	19.70	14.8936%
	Truck 4	998.88	74.83	13.35	21.2766%
	Truck 5	955.92	87.04	10.98	23.4043%
	Truck 6	235.45	57.88	4.07	8.5106%
	Total:	**5179.85**	**373.26**	-	**100%**



(a) For the entire city



(b) Region-wise

Figure 6: Effect of number of trucks on bin coverage

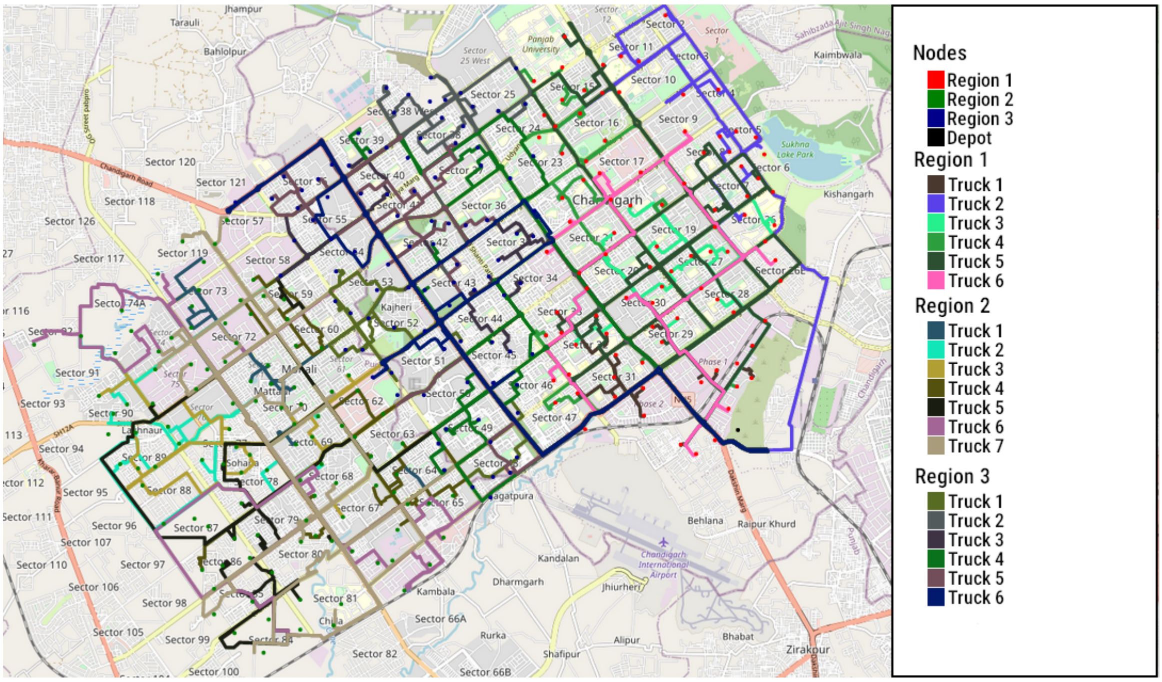


Figure 7: Realtime Unrestricted

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

Our base case of route calculation considers real time dynamics of waste (bin, truck) and truck'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 nodes 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 trucks per region, for a total of 9 trucks. The comparison is represented in Table 5

Table 5: 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 8 and Figure 9) show the routes obtained for static and dynamic case for 9 trucks. The outcomes demonstrate the consideration of dynamic variables on the routes which are different than the static model.

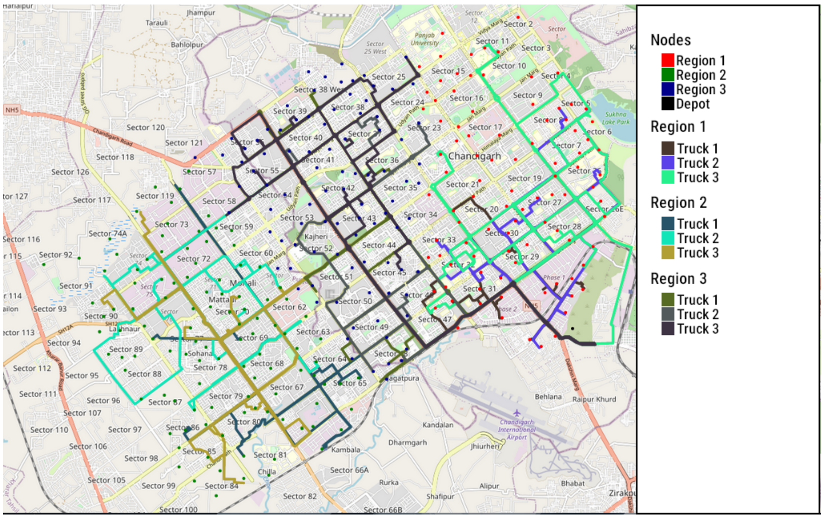


Figure 8: Routes for 3 truck per region as calculated by static optimization

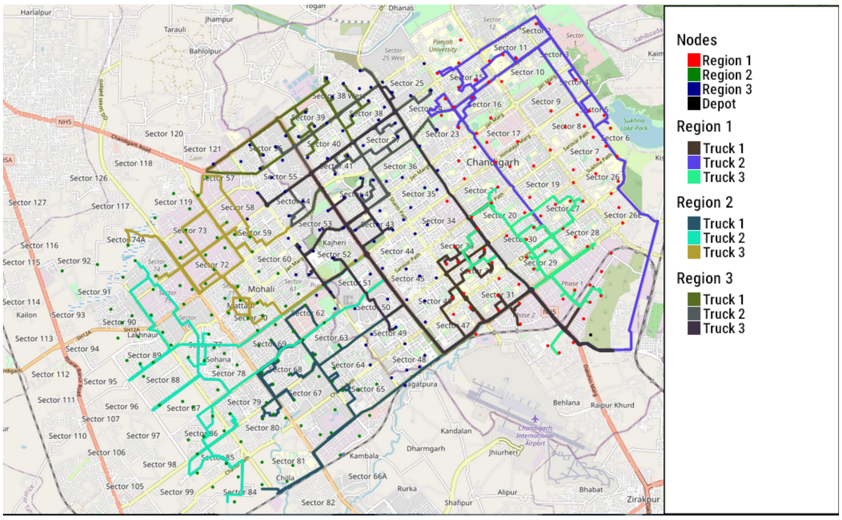
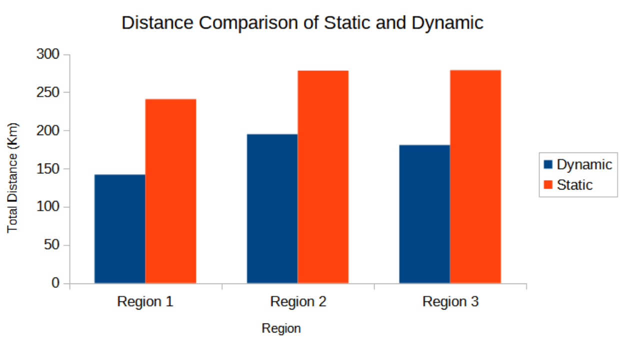
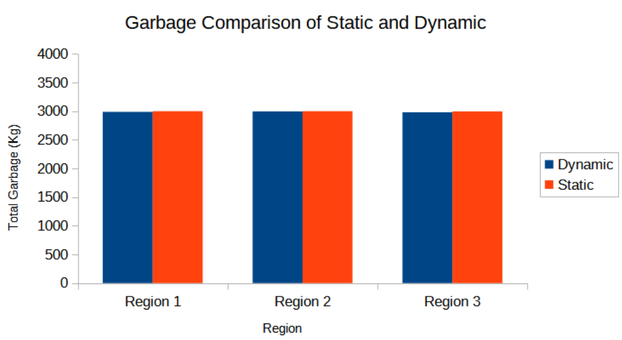


Figure 9: Routes for 3 truck per region as calculated by real-time optimization



(a) Distance comparison



(b) Waste comparison

Figure 10: Comparison between static and real-time models

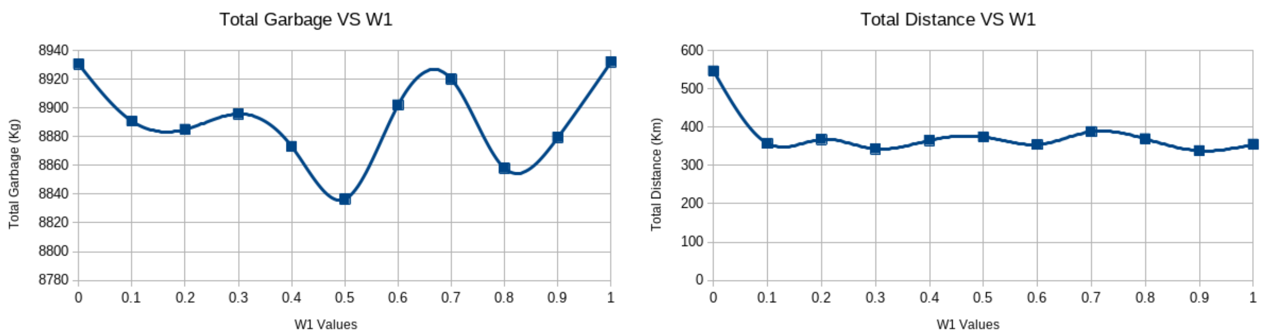
We used the case of 3 vehicles per region in order to achieve a suitable middle ground, providing enough complexity to the problem for the two models to be fully utilized and compared while also maintaining the resource constrained aspect of the problem. We observe that the weight of the waste collected is nearly the same for both cases but the distance travelled by the trucks 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.

Sensitivity Analysis of Weights

In order to depict the effect of selected objective function weights on the waste (11a) collected and the distance travelled by the collection trucks (11b), we performed a detailed sensitivity analysis. The Figures indicate that weights had highly non linear influence on the total distance travelled collected than the garbage collected. We normalized the distance and garbage collected values for their comparison (see 12). From the graph it can be observed that the weight combinations such as W1=0.9,W2=0.1; W1=0.4,W2=0.6 can be reasonably good for maximizing the collection of waste at minimum distance cost (W1=0.9,W2=0.1). The outcome is also inline with our selected weights. The analysis as a decision making tool can help in selecting the best weights for desired scenarios.



(a) Waste vs w_1 (b) Distance vs w_1

Figure 11: Effect of weight on waste and distance for 3 trucks per region

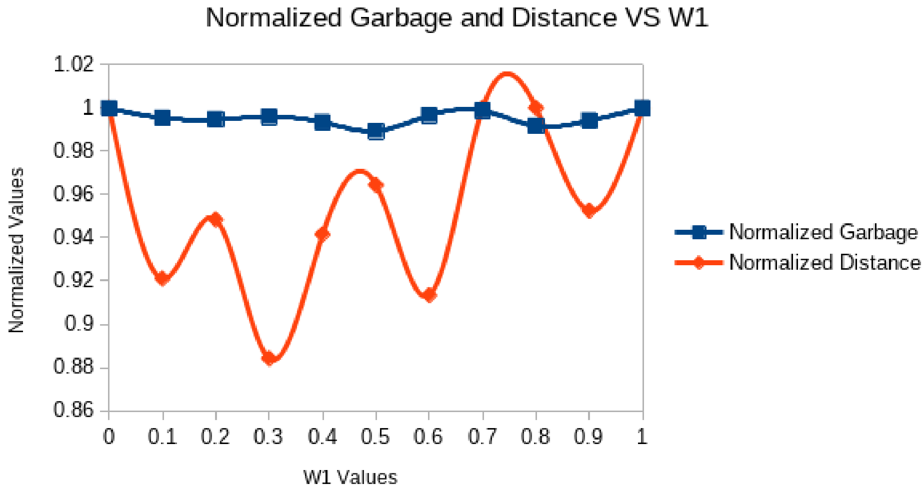


Figure 12: Normalized weight sensitivity graph

One of the most noticeable observations that can be derived from the sensitivity analysis is the changes in the distance and waste as the weights are varied. The behaviour seems anomalous at first glance, but it can be explained by the fact that the weights do not directly affect the waste collected and distance travelled. The weights only directly affect the objective function and the new routes that are calculated by it, as a result, affect the distance and waste values. Therefore, as the weights are changed, the calculated routes change. Since the paths in real life are not continuous, that is, they do not have paths of every possible length, the distance travelled and similarly, the waste collected values vary significantly as the weights vary.

However, we must keep in mind that this does not mean that the paths calculated are unideal. The calculated routes are still the best possible routes following all of the specified requirements and constraints.

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 truck 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 vehicle. 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 trucks 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, vehicle 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 nodes.

- 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 vehicles 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 vehicles 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. [31]

- 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 vehicle 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

There has been a noticeable lack of work in real-time optimization of VRP compared to standard static optimization. This paper fills that gap by designing a flexible real-time route optimization model that accepts and adapts to constantly updating data to provide optimal routes. This makes the model excellent for real world applications as it can take care of unseen circumstances and automatically adapt to them with little modification. The routes formed by real-time optimization have also been shown to be much more efficient when compared to static optimization models, reducing the distance travelled by around 35% for the same amount of waste collected (Table 5).

The paper also fills the relatively niche research gap of VRP applications in resource constrained societies and developing countries. It achieves that goal by creating and testing the model for the city of Chandigarh, India. Chandigarh, being a relatively well planned city, still has many unplanned regions, This allowed us to test the effects of our model for both a developing as well as developed city. This enabled the model to deal with the challenges of a resource constrained society, while also being able to be scaled for a developed region. The paper also focuses on the policy application side of this problem. The sensitivity analysis allows decision makers to decide on the best compromise that is possible for limited resources and the unrestricted case details the minimum amount of resources that are needed to cover the whole region.

Scopes for future development may focus on improving upon our works by integrating more detailed street data like street signs, one-way roads and using the additional parameters as factors to provide a more street accurate route tailored for a specific region. Further integration of real time data such as accidents, construction work etc. in route calculations to provide a more robust and exception friendly model may also be considered for further works.

Future forays into this field may also focus on the effects different sets of weights may have on the results of the objective function for more granular levels of resource constraint. In our current work, we have focused solely on the best weights for one specific case and sensitivity analysis for resource constrained case. So further research can be done to find a more concrete relationship between weights, results and resource availability. In our current method of real time route calculation, our algorithm does not consider the route already travelled when calculating the new routes for new data. This leads to some degree of inefficiency in the optimization process and is also a viable topic for further work in this field.

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