

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 calaculations of the VRP has 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 collection bins which are generally used to collect waste from a larger areas using a road network made from edges and nodes. We simulated temporally varying waste values for each of these bins that can be one of the nodes, we call them "smart bins" which are implemented using priority queues based on the distance to that bins and the amount of waste value. 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. The "route" in our problem corresponds to path of the vehicles covering these bins. To make the implementation realistic we have applied limits on the total waste that can be collected by the vehicles. The model is executed after a certain time interval, That considers bins values, current vehicle location during the time interval and generates a route which keeps updating with the time. The model stops until happens repeatedly until either the run is complete or the vehicle is full. The "run" in our problem signifies a collection trip for one vehicle, beginning and ending at the depot. The fact that the values of the bins can updated even when the vehicle is on the move, makes it a realistic case. To implement such conditions the model assumes that the vehicle has completed its current edge and considers the next node as the starting point of the new route calculation.

Three different execution scenarios are demonstrated. The first scenario restricts the available resources, which in our case is the collection vehicles. The second case 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 (<http://www.gurobi.com/>) 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

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

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

Here, X_{ij} is a binary variable that can only take the values 0 or 1, based on the fact if a truck took a route from i to j. 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. N is the set of all nodes, V is the set of all the nodes excluding node 0.

For the weights w_1 and w_2 the following constraint applies:

$$\sum_{i \in N} w_i = 1 \quad (2)$$

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 the calculations after the given time interval.

$$\sum_{j \in N} X_{st,j} = 1 \quad (3)$$

$$\sum_{j \in N} X_{j,st} = 1 \quad (4)$$

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 as new data is obtained, the value of the starting node for each subsequent route calculation, after the initial one, changes. Therefore, these new starting nodes have to also be taken into consideration.

$$\sum_{i \in N} \sum_{j \in V, J \neq i} X_{ji} = 1 \quad (5)$$

$$\sum_{i \in N} \sum_{j \in V, J \neq i} X_{ij} = 1 \quad (6)$$

Eq (5) and Eq (6) specify that the nodes that are already visited by the truck in a collection run is not considered again 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 route calculation. 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 subsequent route calculations.

If:

$$X_{ij} = 1$$

then:

$$u_i + f_j * BT = u_j \quad (7)$$

for:

$$\begin{aligned} \forall i, j \in A \\ i, j \neq 0 \\ i, j \neq st \end{aligned}$$

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.

$$\begin{aligned} u_i \geq f_i * BT \\ \forall i \in N \end{aligned} \quad (8)$$

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.

$$\sum_{i \in N} Y_i f_i * BT \leq 100 \quad (9)$$

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 route calculations

$$\begin{aligned} u_i \leq 100 - P_t \\ \forall i \in N \end{aligned} \quad (10)$$

This constraint in Eq (10) ensures that for a single route calculation 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 route calculation, 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

We have used a set of randomly selected points in the city of Chandigarh as the collection points that the collection vehicles have to travel to. The random bin locations were generated using QGIS function that generates random points inside a polygon, which in our case was the entire city, covering an area of 104.78 Km². Then we divided the points into a certain number of regions, in our case: three, which depend on the number of vehicles that are available for the

job. The regions were assigned by using K-Means Clustering algorithm by allotting the nodes into different clusters (Figure 1)

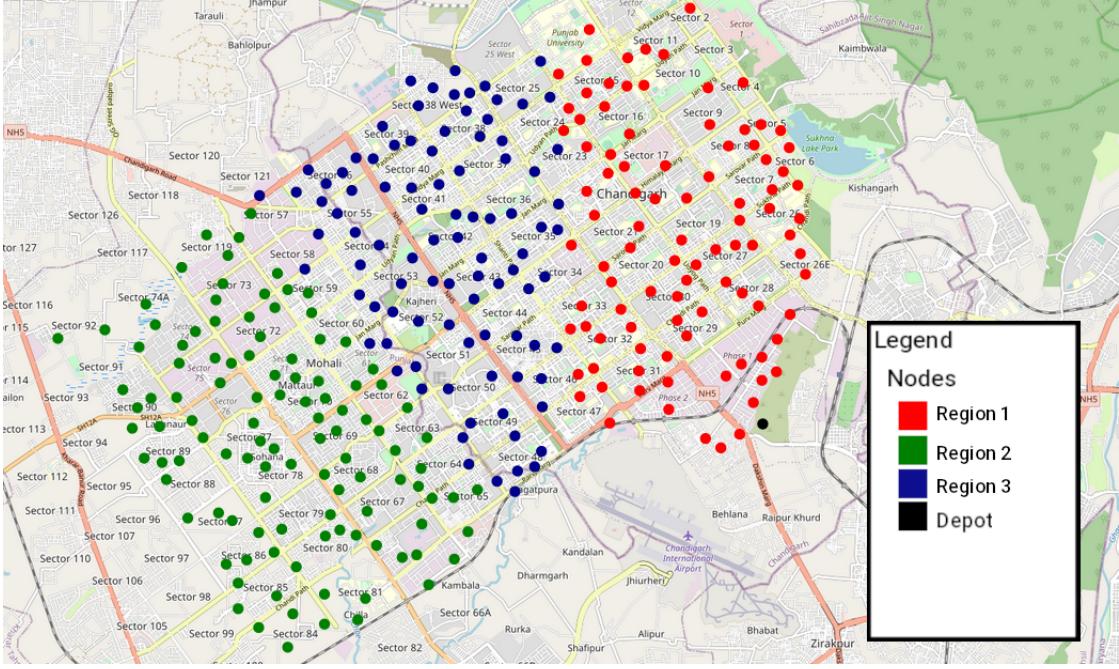


Figure 1: The selected nodes and their clusters

Now, since we are using the concept of smart bins, we also had to simulate their function. 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 will be one of the parameters during the optimization process.

Next, we use OpenStreetMap API to obtain and calculate the distance between all points in the set, subject to the heuristic that all streets are non-directional, meaning all paths measure the same both ways and that a truck assigned to one region will only collect from bins in its own region. The numerical values of the distances are normalized to be in the same scale as the waste so that the algorithm is not skewed by the scale of the quantities itself.

4.2 Execution case studies

Case 1: Weight Analysis

In order to find the best pair of weights that will give us the best results, that is, the minimum value of the objective function, we need to take different weights, plug them into the objective function and plot the resulting graph (Figure 2). It shows the change in the objective function values for the iterated weights. The lowest point of this graph would give us the optimal weight. Since we want the relative importance of the two objectives and the total sum of the weights is equal to one, getting one weight means automatically getting the other.

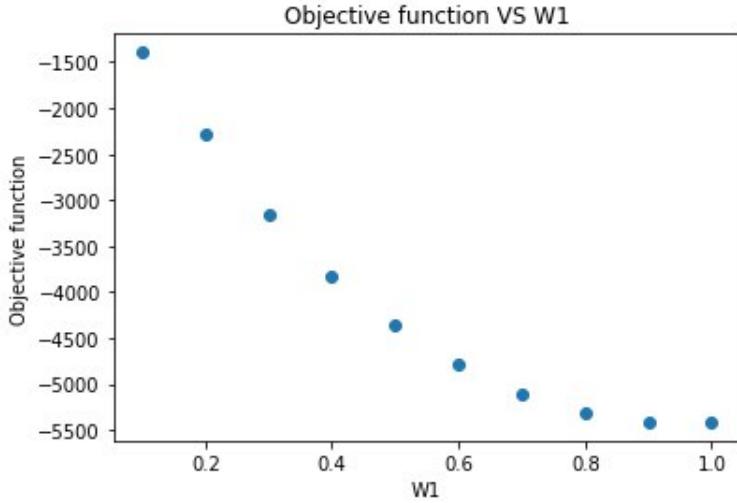


Figure 2: Weight Analysis: Objective function vs w_1

We can see here that for the optimal results, the w_1 should be equal to 0.9 and w_2 equal to 0.1. This means that our optimization procedure should mainly focus on minimizing the distance and to a small extent maximizing the waste collected.

Now, we have the two cases for which we have solved the objective function for the optimal solution. For the sake of calculations, the maximum capacity of a truck is 1000 Kg of waste, and the maximum capacity of one smart bin is 100 Kg.

Case 2: Real-time, restricted

Restricted here signifies that the resources which, in this case, are the trucks, are restricted and thus not sufficient to cover the demand for them. This is an especially important case for our work because our focus is on resource constrained societies where this is a common scenario.

In this case, the optimal routes will be calculated in real time after a recurring interval of time. We used 1, 2, 3, and 4 trucks per region and compared their performances. The weights, as calculated earlier, for distance minimization is taken as 0.9 and waste collection maximization is taken as 0.1

The following Table 1 summarizes the data obtained from real-time restricted optimization of routes where waste is calculated in kilograms and distance traveled in kilometres.

Table 1: 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	999.98	51.27	998.4	81.19	999.05	52.24
2 Trucks	1995.72	144.47	1976.03	174.03	1981.34	151.07
3 Trucks	2975.73	243.10	2991.24	281.17	2984.48	214.82
4 Trucks	3983.13	170.63	3972.81	251.01	3977.52	210.06

We take away some interesting observations from the above data such as the total distance that is being travelled by the trucks is not increasing by the same factor as the waste collected as we increase the number of trucks. The difference is most pronounced between the cases of 1 to 2 trucks and 2 to 3 trucks where there is an increase of about 150% in the distance corresponding to an increase of a 100% in the waste collected in the 1-2 truck case. But for the same increase in waste collected, the increase in distance travelled is of only about 30% for

2-3 trucks case. This is emphasized even further for regions 2 and 3 where the total distance travelled actually decreases while still having a 100% increase in waste collected (Figure 3).

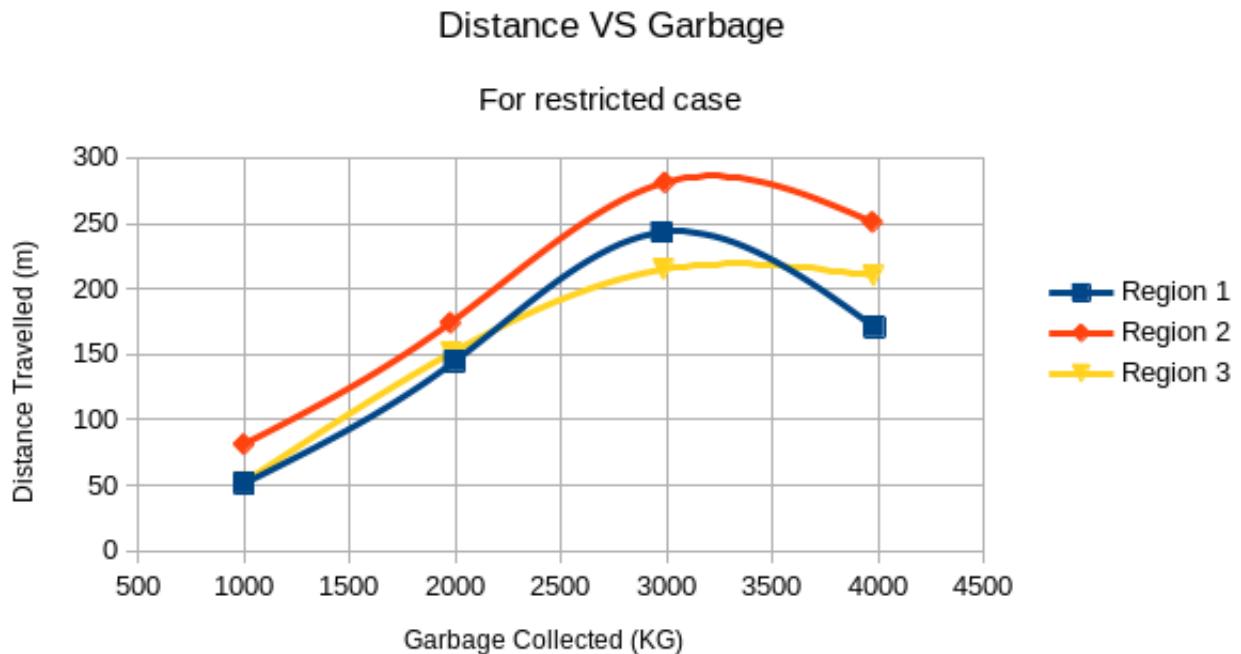


Figure 3: Distance traveled vs waste collected

It is clear from the data that when the resources available and the demand for the said resources are close to each other, the overall allotment of those resources is more efficient. When the resources are constrained, they do not have the freedom to focus on efficiency as much because the first and foremost priority is meeting the demand.

We observe the case of 4 trucks per region to determine whether it is sufficient to satisfy the waste collection demand of the city. Table 3 summarizes the data obtained from running the algorithm with this setup.

Table 2: Data for 4 trucks per region

Region	Truck	Waste (Kg)	Distance (Km)	Waste/Distance	Percent collected
Region 1	Truck 1	998.8048	30.52	32.72	16.8421%
	Truck 2	999.28	49.81	20.1	14.7368%
	Truck 3	999.09	31.72	31.4	18.9474%
	Truck 4	985.96	58.57	16.83	18.9474%
				Total:	69.47%
Region 2	Truck 1	998.82	64.74	15.43	14.4144%
	Truck 2	992.05	42.71	23.23	13.5135%
	Truck 3	991.81	64.76	15.32	18.018%
	Truck 4	990.12	78.80	12.57	18.018%
				Total:	63.9639%
Region 3	Truck 1	999.32	37.57	26.60	15.9574%
	Truck 2	989.50	57.30	17.27	14.8936%
	Truck 3	997.948	39.26	25.42	14.8936%
	Truck 4	990.7538	75.96	13.04	20.2128%
				Total:	65.9574%

We can infer from the above data that the number of trucks falls just short of being able to satisfactorily cover most of the city's bins. It is only able to cover, on an average, 70% of the total number of bins that need to be collected.

Case 3: Real-time, unrestricted

In this case, we want to see the results of route optimization if the resources were not constrained and there were enough, in our case, trucks to cover the waste collection demands at a satisfactory level. From the previous case, we saw that 4 trucks per region fell just short of being enough, so for this case, we raised the number of trucks to 5 per region. Table 3 summarizes the data obtained from this case.

Table 3: Data for 5 trucks per region

Region	Truck	Waste (Kg)	Distance (Km)	Waste/Distance	Percent collected
Region 1	Truck 1	998.37	27.39	36.45	17.8947
	Truck 2	999.66	39.19	25.51	15.7895%
	Truck 3	997.94	49.22	20.28	16.8421%
	Truck 4	996.54	48.59	20.51	22.1053%
	Truck 5	996.94	106.85	9.33	26.3158%
Total:		4989.45	271.24	-	98.9474%
Region 2	Truck 1	994.87	54.85	18.14	12.6126
	Truck 2	994.63	67.35	14.77	13.5135%
	Truck 3	998.21	54.87	18.19	12.6126%
	Truck 4	999.51	96.53	10.35	17.1171%
	Truck 5	999.43	45.39	22.02	17.1171%
Total:		4986.65	318.99	-	72.9729%
Region 3	Truck 1	998.95	37.27	26.80	14.89
	Truck 2	999.23	56.54	17.68	15.9574%
	Truck 3	992.91	55.05	18.04	18.0851%
	Truck 4	999.70	50.32	19.87	25.5319%
	Truck 5	907.36	109.96	8.25	25.5319%
Total:		4892.15	309.14	-	99.9999%

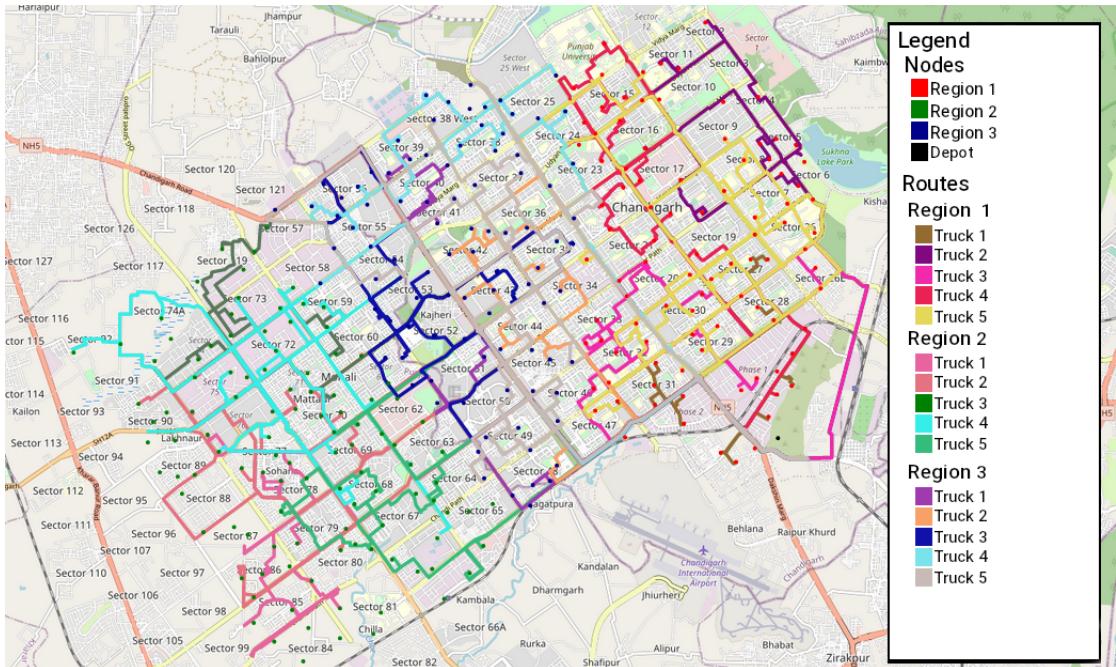


Figure 4: Realtime Unrestricted

From this data, we can easily observe that with 5 trucks per city region, around 90% of the city's bins get covered, and with a similar procedure, more trucks can be added for even more efficient collection. While the total distance is increased, it is a direct result of having more trucks running at the same time, and since most of the bins are being collected, some trucks need to traverse outlying regions to cover the remaining bins. This is visualised in Figure 4 where we have plotted the optimized routes dictated by the objective function.

Case 4: Impact of the number of trucks on total bin coverage.

As expected from our previous cases, increasing the number of trucks available per region leads to a more thorough collection of waste as shown in Table 4 and represented graphically in Figure 5. Compared to case 2, where the number of trucks per region was varied from 1 through 4, we can see a clear rise in the coverage of bins as we increase the number of trucks, concluding in the last and our best case of 5 trucks. Having more trucks at your disposal is a matter of resources, and for a resource constrained region, their availability of trucks may not be sufficient for the amount of waste generated which will, unless overcome by alternate methods such as multiple collection runs per vehicle, will lead to subpar waste collection, as shown by the data. However, those alternate methods are beyond the scope of the current work.

Table 4: Bins coverage in percent based on number of trucks per region

Region	Number of trucks				
	1 Truck	2 Truck	3 Truck	4 Truck	5 Truck
Region 1	11.5789%	41.0526%	60.0001%	69.4737%	98.9474%
Region 2	9.9099%	32.4324%	52.2522%	63.9636%	72.9728%
Region 3	11.7021%	42.5532%	58.5107%	65.9574%	99.9999%

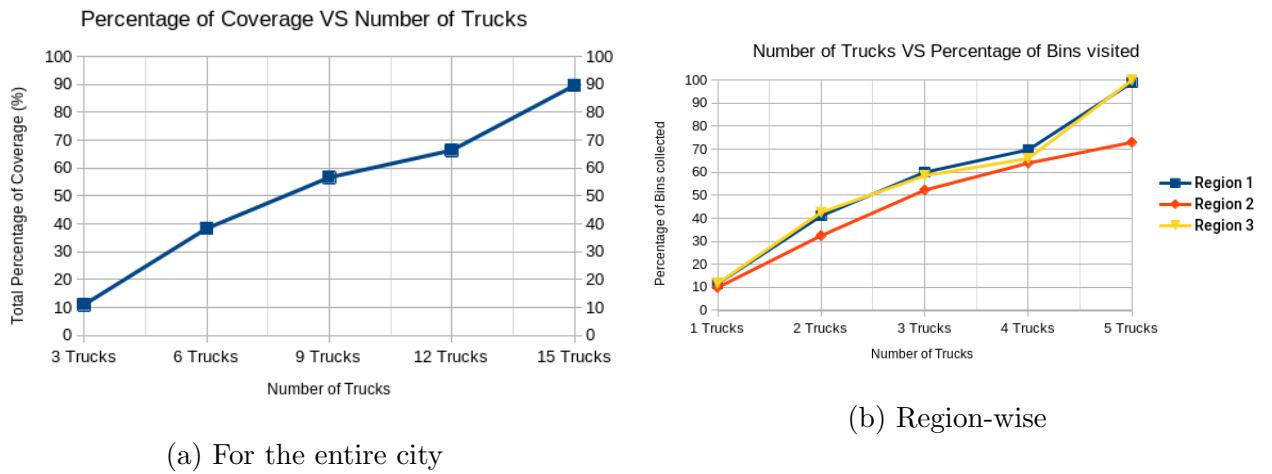


Figure 5: Effect of number of trucks on bin coverage

We visualized the bin coverage data in two separate figures to help see the effects from two different perspectives. In order to give a better idea of the bigger picture that is true for the entire city, Figure 5a shows the coverage of the total number of bins, regardless of regions, against the number total number of trucks available for collection. For a more detailed look of the effects of the number of trucks on bin coverage, especially after a more granular level, like regions, we have added Figure 5b.

We can observe that for region 2, the total coverage doesn't have the same rise in as compared to regions 1 and 3. It is because, region 2 is larger than region 1 and 3, and contains more nodes. Thus, the observation is explained by the fact that in order to have the same coverage with a higher number of nodes, it would need a larger number of trucks as well. And since, we have taken a uniform number of trucks per regions, as a result, the coverage in region 2 is slightly less than the other regions.

Case 5: Comparison of real-time with static route calculation

While our main method of route calculation works in real time by getting new fill values from the smart bins throughout the collection run and calculates new best routes based on the truck's current position in real time, there is another, more simpler method that trades off the reliability and adaptability of the real-time method for faster computational time and slightly more efficient routes. That is the static route calculation method and we get it by relaxing and modifying a few constraints mentioned earlier. In Eq (10) the constraint will be just less than 100. In Eq (3) and Eq (4) instead of s_t , the beginning nodes will always be 0. This results in one single route calculation at the beginning of the run that gives us the best route with the data available at that time, but does not consider any new data after that.

To compare the two methods, for the sake of simplicity, we will use the 1 truck per region case from case 2 and compare it to the static method by applying it to the same 1 truck per region case. 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	2999.32	112.25	13.96%
Real-Time	2999.16	168.30	11.00%

Figure 6 and Figure 7 are the plots of the routes calculated by the static and the real-time optimization methods respectively.

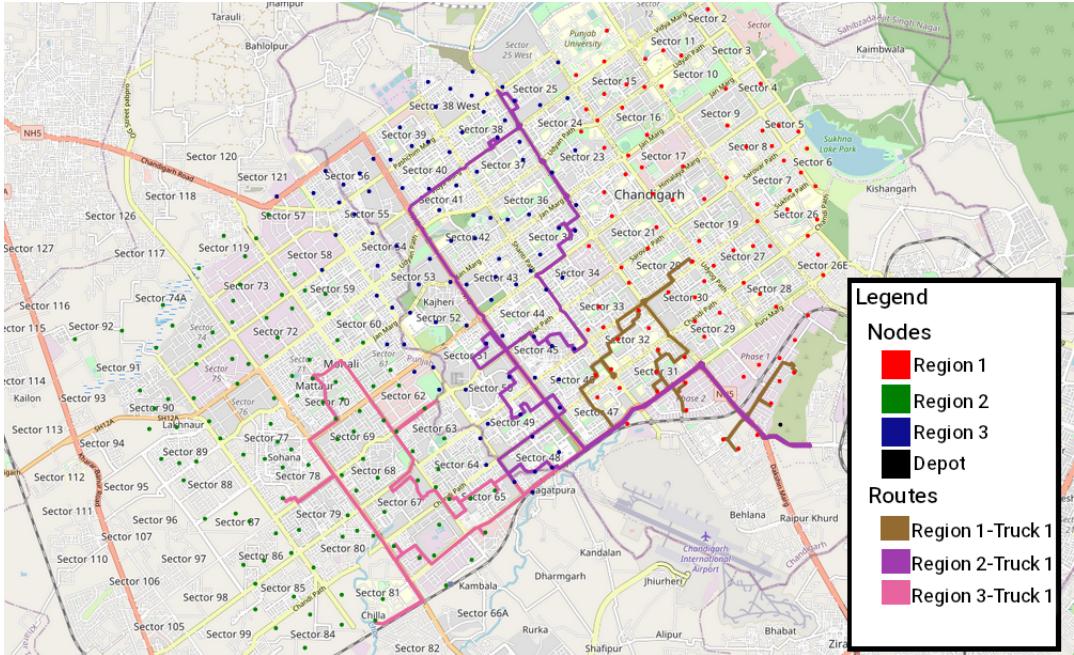


Figure 6: Routes for 1 truck per region as calculated by static optimization

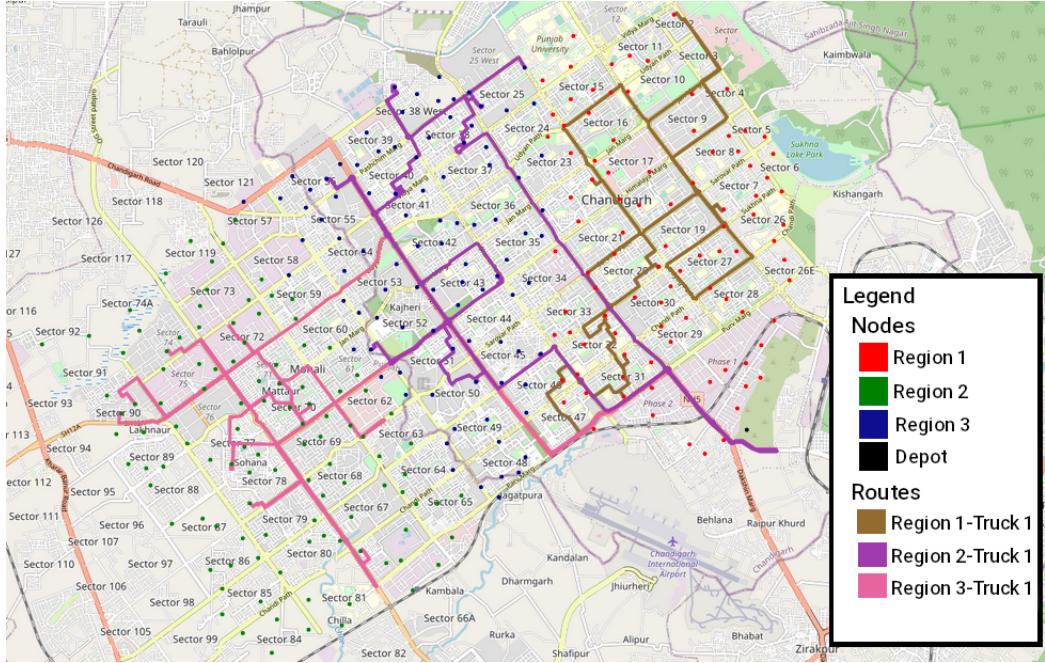


Figure 7: Routes for 1 truck per region as calculated by real-time optimization

We observe that the weight of the waste collected is nearly the same but the distance travelled by the trucks is smaller in the static case. This can be easily explained by the fact that, in essence, real-time method is just the static method applied repeatedly after certain intervals of time. Therefore, static gives one optimal route for the currently available data, but real-time has to do that each time the data is updated. It has to calculate new routes multiple times, even when the vehicle is already traversing the previous optimal route, and it also has to take the current position of the vehicle into consideration. This makes it inherently slightly more inefficient compared to the static method.

This makes static optimization superior but only theoretically, because when applied in the real world, static has a lot of disadvantages that real-time solves, such as the adaptability. In the static case, there is no accounting for new data. The initial route is the only route. This, consequently, also makes it unreliable. Real-time method, on the other hand, accounts for new data and creates new optimal routes taking it into consideration, making it very adaptable and reliable. Since real-time is just a modified and iterated version of the static method, the difference in computational power required between the two methods is not large.

Therefore, for real life applications, real-time method is the superior method as it is able to deal with non-deterministic events that are common for ground use and adapt to them, giving an uninterrupted and reliable result.

5 Discussion and Policy Suggestions

One of the most noticeable observations that can be derived from the results is the weights attached to the two objectives in the objective function. In this case, the distance traveled was computed to be the main factor which must be considered when solving the objective function for the optimal solution. The waste collected appears to be almost completely irrelevant in this case. While this may look like an anomaly, this is solely due to the fact that this is a resource constrained operation. The trucks have to continue their runs until they are full. Therefore, in the end, the amount of waste collected will always be equal to the maximum capacity, hence rendering maximizing the waste collected objective irrelevant.

However, we must keep in mind that this will not always be the case. In a case where the resources, that is, the trucks are more than sufficient to cover the demand, the weight for the objective to maximize waste collected will be greater. The more is the resource greater than the requirement, the greater the weight of that objective will be.

We also observe that the distance travelled in the case of real-time optimization is greater than that of static one. It is due to the fact the optimal routes are calculated multiple times with different starting points based on the truck's current location. This makes the resultant route slightly more inefficient when compared to the initial calculation. This is an unavoidable effect of recalculating the routes and not a problem with the algorithm as the path that is already been travelled is not considered by the newly calculated route, hence the resultant route is longer than the initial optimal route

We have selected the city of Chandigarh as the base location for paper because while it is our goal to focus on resource constrained regions for route optimization for waste collection, we also want to make it general enough so that with a few tweaks, the same method can also be scaled to be used for more developed regions and cities. Chandigarh was found to be the most suitable choice as it is the perfect blend of the two goals that we have: it is a well-planned city and still retains some of the characteristics of a developing nation.

Our program, once the initial setup of the nodes and the distance between two nodes is done, can efficiently and quickly calculate the optimal route that should be followed by a collection vehicle, whether once per run or in real time. Unlike the currently used systems that are either controlled manually or use general GPS systems to do their collection runs, our process is capable of:

- Vastly improved performance in terms of distance travelled
- Smart bins further reduce the distance travelled by removing the need to visit redundant nodes
- We have used linear programming which is a simple yet novel approach to this problem and it is not too mathematically complex
- Our program is able to calculate new paths according to new data in real-time which is much more flexible than the systems currently being used in most places
- We also calculated the effects of resource availability on the overall performance and can further suggest the minimum amount of resources that would be sufficient for the operation.

For real world application of this method, the suggested policy would be to first use the software to calculate the current capabilities of the resources that are available, then apply the algorithm to utilize those resources, namely trucks, to their maximum potential and efficiency. If needed, how much more resources are needed to sufficiently cover the city in question can also be calculated by the software, and the results can be used as data for the requisition request of more resources.

6 Conclusion

We have achieved most of our core goals of optimizing waste collection with a focus on resource constrained societies. We were able to devise a method to use the available resources as efficiently as possible and at the same time ensure that the method also remains viable in more developed regions if scaled accordingly. Yet there still were things that we were not able to implement in our current endeavour.

In our process, we divide the total number of nodes into specific clusters depending upon the resources that we have. These clusters are called regions and in the current version, vehicles assigned to each cluster are completely independent of the points in another cluster, and will not collect from a node from another cluster even when it is more efficient to do so.

These can be taken as goals for future forays into this field to overcome the current limitations of our work. 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.

Future works may also focus on the effects different sets of weights may have on the results of the objective function for different granular levels of resource constraint. In our current work, we have focused solely on the best weights for one specific 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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