Note: Demonstrating Analytics in a Low-Tech Context–Truck-Routing for Solid-Waste Collection in an Indian Metropolis

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Abstract: This paper describes an approach to introducing analytics through various algorithms and applications to users in a low-tech environment as a first step toward understanding such a context. The South Delhi Municipal Corporation (SDMC) of New Delhi, India, have partitioned their collection points into “wards” or clusters, each served by a dedicated truck depot and manually routing trucks for solid waste collection within each ward, with the waste from all wards going to a single landfill. To demonstrate analytics in tactical planning, we implemented the nearest neighbor algorithm mimicking the manual process to provide the baseline cost. Thus, we presented two very different vehicle routing algorithms: (1) a simple but fast revised nearest neighbor algorithm that decreased the baseline total routing cost by 1.57% and (2) an optimal but time-intensive algorithm using a mixed-integer-linear programming model, which decreased the total cost by 4.05%. To demonstrate strategic planning, we tested the efficacy of the cluster structure of collection points by comparing its total routing cost (using the revised nearest neighbor algorithm) to that of other partitions obtained with Minimum Spanning Tree (MST) and K-medoids clustering. The existing wards provided a lower waste pickup cost than the alternative clusters we created, showing SDMC that their existing ward structure was sound.

Keywords: Hierarchical method, vehicle routing problem, municipal solid waste collection, Mixed-Integer Linear Programming (MILP), India.

1. Introduction

There is always a need for real-life contexts with hitherto undiscussed practical considerations, especially in environments such as these that are decidedly low-tech as regards the use of computers and analytics. Gorman (2021) notes that the contextual aspects of any optimization project are crucial, identifying contextual factors that may complicate or impact the modeling process. Comprehending the context is necessary to fully grasp the problem, find an appropriate solution, and implement it successfully. Failing to consider the context creates a disconnect between algorithms in the research literature and practice. As optimization-based analytics takes off in corporate and other sophisticated environments, we wish to consider low-tech environments that currently do not even use computers. Therefore, *this paper seeks to present the context of a low-tech environment and demonstrate the use of analytics as a starting point*.

One low-tech environment is solid waste collection in developing countries. In 2007, the urban proportion of the global population exceeded the rural proportion, and that trend has continued since. The growing urban population also means high waste-generation rates in urban areas (Hoornweg et al., 2012; Kookana et al., 2020; UN, 2019) with correspondingly high waste-collection costs (Erdinç et al., 2019), especially in populated developing countries (Huang & Lin, 2015). For instance, in a typical Indian city, waste collection and related transportation costs amount to 60-85% of the municipal budget (Khan et al., 2022; Tirkolaee, 2019) because of high operating costs for maintenance, processing labor, and fuel (Wu et al., 2020). Thus, even minor improvements in cost reduction can provide significant savings to municipalities (Cattaruzza et al., 2017). Moreover, the improved waste collection helps reduce greenhouse gas (GHG) emissions and land pollution (Ferronato & Torretta, 2019; Hannan et al., 2020). Much research has been reported in the literature on the waste collection problem, generally using a variation of the vehicle routing problem (VRP) for vehicles starting from a source, covering all the points (nodes) to pick up waste, and ending at a landfill (Badran & El-Haggar, 2006; Beliën et al., 2014; Han & Cueto, 2015; Li et al., 2008; Tung & Pinnoi, 2000).

This paper's particular setting of choice is the solid waste collection by the South Delhi Municipal Corporation (SDMC) in New Delhi, India. The central zone of the South Delhi Municipal Corporation (SDMC) covers over 100 square kilometers, with an estimated 2021 population of 1.7 million (DDSIL, 2022). The area is divided into *wards*, each ward being a cluster of collection points, each served by a dedicated depot from where trucks leave for waste collection and eventually return at the end of the day. There is a single landfill-and-processing center for all five wards to compost biodegradable waste, incinerate high-calorific waste, and dump the rest into the landfill (Sharma, 2022). The waste collection runs from 8 am to 6 pm every day of the week. There are nine trucks at each of the five depots, so 45 trucks in total. Each truck has a capacity of 15 cubic meters to pick up solid waste. There are 288 collection points across all the wards in four capacity-based categories: (1) fixed compact transfer stations (bins where garbage is collected and hydraulically operated through a compressor to reduce the volume of the waste), (2) open sites (open corners where waste is dumped), (3) waste collection bins, and (4) *dhalaos*, which are large three-walled concrete structures for garbage collection. The trucks must cover all the collection points in a single shift and return to their depots daily. Currently, these trucks are routed manually, with each truck effectively picking up the waste from the nearest available point on its way to the landfill.

In this setting, the municipality or its contractors *can* use computer-based analytics for operational and strategic planning, so the two areas we picked for the demonstration were:

(1) Operational planning, demonstrating how computers could provide better routes within each ward to route trucks and pick up waste from collection points, and
(2) Strategic planning, evaluating whether the existing ward structure needs to be modified to lower costs.

While "analytics" refers to the umbrella term that includes AI/ML, statistics, data science, and other methods, we focus on optimization and optimization-oriented heuristic algorithms.

For operational planning, we implemented the nearest neighbor algorithm mimicking the manual process to provide the baseline cost. In doing so, we demonstrated two algorithms for the vehicle routing problem (VRP) at extreme ends of the spectrum of speed and solution quality. The first was a simple but fast heuristic, a revised nearest neighbor (RNN) algorithm that decreased the baseline total routing cost by 1.57%. The second was an optimal but extremely time-intensive algorithm using a mixed-integer-linear programming (MILP) model, which lowered the total cost by 4.05%. To reduce the problem size for MILP for a speedier solution, we further partitioned each ward into sub-wards using the K-medoid clustering method.

For strategic planning, we sought an estimate for the daily running costs to compare the existing ward structure with other possible clusters of collection points. We used our previously developed revised nearest neighbor heuristic to create truck routes for any collection points in each ward using three different types of clusters of collection points–the existing ward structure and the clusters obtained from the Minimum Spanning Tree (MST) and K-medoids clustering. The results with multiple random variations on the distance matrix indicate that the existing ward structure provides a lower cost for waste collection than the cluster structures obtained from the K-medoid and MST methods, indicating that the current ward structure is sound.

We contribute to the overlap of the OR modeling practice literature (Murphy, 2005abc; Gorman, 2021; Sharkey et al., 2022) with the multi-vehicle routing literature by showing how to introduce analytics and OR modeling in a low-tech context of solid waste management that is currently functioning without computers. We have described the challenges of an actual situation – namely, solid waste management in a developing country – and demonstrated the application of OR methods by applying both simple heuristics and optimal algorithms. Moreover, we show both an operational use of analytics with routing and a strategic use, evaluating the ward structure of waste collection points. Our paper thus offers a practical approach for demonstrating the introduction of analytics in low-tech environments with a spectrum of techniques, from speedy less-sophisticated methods to slower but optimal approaches for operational and strategic applications.

The rest of the paper is structured as follows: Section 2 presents some pertinent literature to position our article and some specifics of the waste collection context in South Delhi. Then section 3 shows the tactical planning demonstrating two truck routing algorithms, while Section 4 explains strategic planning by evaluating the ward structure. Finally, Section 5 discusses managerial implications and possible research extensions.

2. Context

The organizational context and its associated complications significantly impact decision-making processes and outcomes. For instance, resource-intensive modeling techniques entailing sophisticated simulation models or complex optimization algorithms may not be feasible in resource-constrained organizations. In such cases, simpler or heuristic-based models that require fewer resources may be more suitable. Moreover, Gorman (2021) lists ten contextual factors that impact the success of implementation: (1) organization, (2) decision-making processes, (3) measures and key performance indicators, (4) rational and irrational biases, (5) decision horizon and interval, (6) data availability, accuracy, fidelity, and latency, (7) legacy and other computer systems, (8) organizational and individual risk tolerance, (9) clarity of model and method, and (10) implementability and sustainability of the approach. Several waste management research studies also emphasize that the modeling approaches employed are influenced by the specific context in which they are applied.

Our interest is in the highly constrained residential and commercial waste collection in highly urban environments in developing countries with (1) low-tech organization, (2) decentralized decision-making, (3) no apparent measures or KPIs, although cost is the primary driver, (4) unknown biases, (5) short decision horizon, (6) data is available (via Google maps, etc.) but not used, (7) no computers, (8) unknown risk tolerance, (9) no explicit models although nearest neighbor is a good proxy, and (10) unclear implementability and sustainability. As such, the first step in such an environment would be to demonstrate the range of things analytics can do to elicit information from the organization. In this case, we targeted the range of applications: the (daily or even hourly) tactical vehicle routing problem and the (annual) strategic problem of determining the structural boundaries for waste collection when contracts are given out. Beliën et al. (2014) provide an extensive literature review on the waste management problem, while Han & Ponce-Cueto (2015) present vehicle routing for the waste-collection problem, whether residential, commercial, or construction. We refer the reader to Gour and Singh (2023) for a review of the broad solid waste management literature focused on India. Indeed, many papers on solid waste collection are set in developing countries (**Table 1**).

Table 1: A sampling of papers showing the diversity of approaches for municipal solid waste collection in developing countries.

Paper	Reference	Area	VRP-based algorithmic approach	Strategic planning (Structure)	Tactical planning) (Static routes)
A smart framework for municipal solid waste collection management: A case study in Greater Cairo Region	Alsobky et al. (2023)	Greater Cairo, Egypt		■	■
Municipal solid waste management challenges in developing countries – Kenyan case study	Henry et al. (2006)	Kenya			
Solid waste collection systems in developing urban areas of South Africa: An overview and case study	Smith (2016)	Winterveld, Bophuthatswana, South Africa			
An engineering approach to solid waste collection system: Ibadan North as case study	Ayininuola & Muibi (2008)	Ibadan North, Nigeria			
Appraisal of solid waste collection following private sector involvement in Dar es Salaam, Tanzania	Kaseva & Mbuligwe (2005)	Dar es Salaam City, Tanzania			
Truck scheduling for solid waste collection in the City of Porto Alegre, Brazil	Li et al. (2008)	Porto Alegre, Brazil	■		■
Optimal location and proximity distance of municipal solid waste collection bin using GIS: A case study of Coimbatore City	Nithya et al. (2012)	Coimbatore, India		■	
Municipal solid waste collection routes optimized with ARC GIS Network Analyst	Bhambulkar, (2011)	Nagpur, India	■		■
A multi-stage optimization approach for sustainable municipal solid waste collection systems in urban areas of Asia's newly industrialized countries	Mondal et al., (2019)	Bangalore, India		■	■
Sustainable multi-trip periodic redesign-routing model for municipal solid waste collection network: The case study of Tehran	Mahdavi et al., (2022)	Tehran, Iran	■		■
A multi-compartment capacitated arc routing problem with intermediate facilities for solid waste collection using hybrid adaptive large neighborhood search and whale algorithm	Mofid-Nakhaee & Barzinpour, (2019)	Tehran, Iran	■		■

This paper		South Delhi, India	■	■	■

In a typical waste collection problem, a vehicle starts from the depot, visits several collection points, dumps waste at a disposal site whenever it gets full, continues for the shift time, and ends at the depot at the end of the shift (e.g., Huang et al., 2021). A functional variant will have multiple vehicles, sources (vehicle depots), trips, and disposal sites. Generally, the objective function minimizes the total transportation cost or travel time. For the SDMC, the trucks are initially located at the depots and move sequentially from one collection point to another. After filling capacity, they go to the disposal site to unload and start their next trip toward the waiting collection points if they still have waste to pick up. Finally, they return to the depot to conclude their service tour at the end of the day **(Figure 1)**.

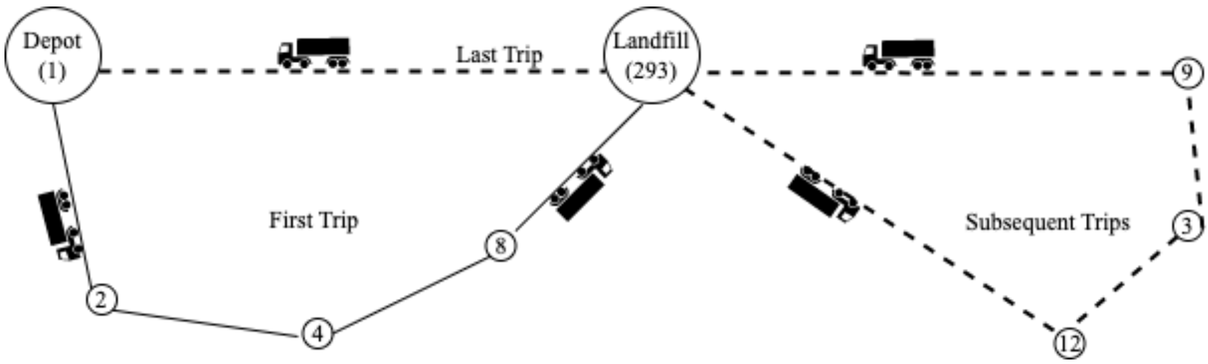

Figure 1: A pictorial view of the waste-collection process

The location of all the depots, collection points, and disposal site(s) is known. The ward structure, i.e., partitioning all the collection points, is also known. Each collection point must be served by exactly one truck. Waste collected at each stop is known beforehand and assumed to be constant. The capacity of each truck is known. The travel time between any two nodes is known, and for our demonstration, we assume this time is constant, not changing with the time of day. Fixed and variable costs for the trucks are known and assumed constant. We assume the same time and cost of a route for all garbage trucks suggesting no high-cost or priority route or time-dependent changes for our demonstration.

In our context of South Delhi municipality, the operations staff at the SDMC provided the location of each of the 294 nodes in hardcopy. We plotted these on Google Maps (**Figure 2**) and obtained the inter-node distances by running a Python script through a programming interface, *distance.ai*, for distances between the collection points, depots, and the landfill as a 294x294 distance matrix. We checked the data for consistency. For instance, if any collection point is inaccessible, we place it on a nearby access road. The distance between any two nodes is the shortest drivable distance between them.

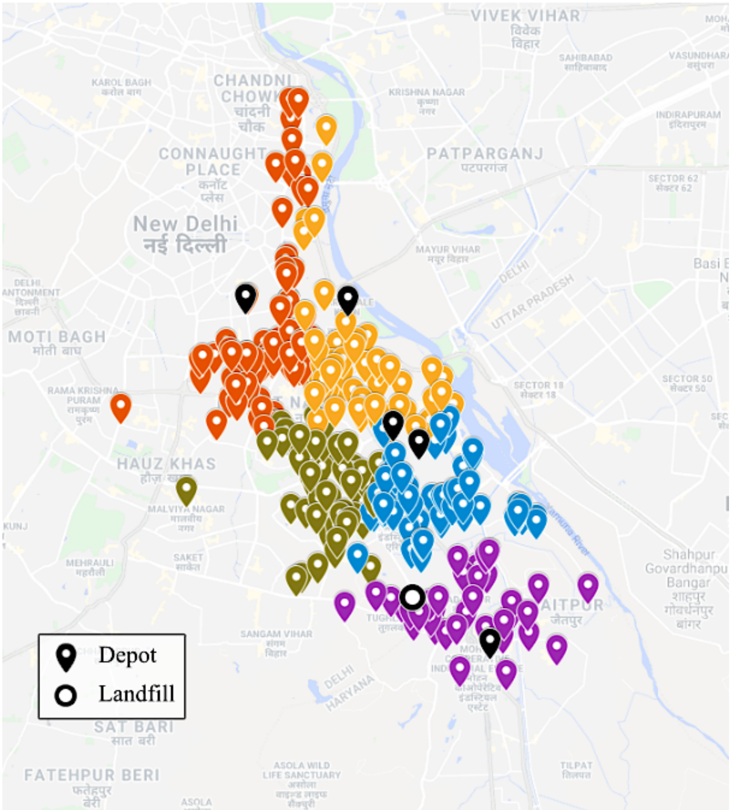

Figure 2: The current ward structure for the central zone of the SDMC with a single landfill and five depots, one each for the five wards that are a partition of the collection points (the wards are shown in different colors)

The SDMC also provided us with all the data on quantities handled by each collection point, the capacity of garbage trucks, and operational costs (**Table 2**).

Table 2: Input parameters

Item	**Symbol**	**Value**	**Source**
Number of depots	G	5	SDMC
Location of depots		0, 1, 2, 3, 4	Google Maps
Number of landfills	L	1	SDMC
Location of landfills		293	Google Maps

Number of collections points	N	288	SDMC
Collection points			
Capacity of -- *dhalao*	q	7 m³	SDMC
-- Open sites		5 m³	SDMC
-- FCTS		10 m³	SDMC
-- dustbins		4 m³	SDMC
Max. number of trucks available across all wards	I	56	SDMC
Distance matrix with 294 nodes		294×294	Distance.ai
The average capacity of a truck container	Q	15 m³	SDMC

With this data, we first tackled the tactical planning problem of route planning (Section 3) and then the strategic planning problem of evaluating the ward structure (Section 4).

3. Improved Routes within a Ward using the Vehicle Routing Problem

We interviewed the operations staff at the SDMC to understand how they designed the truck routes and understood that their routing effectively follows a greedy algorithm, the *nearest neighbor algorithm*, that starts from the source, then moves to the nearest collection point based on the length of the edge (here, distance traveled), repeating this step until the truck is full and then directing it to the disposal site. Next, we mimicked their approach into a Python 3.7 program with the nearest neighbor algorithm to provide a *baseline* transportation cost.

With a baseline cost in hand, our first objective was to demonstrate how computers would help find routes with transportation costs that would be lower than the baseline. For the problem at hand, we took the approach of a vehicle routing problem (VRP) (Breakers et al., 2016; Toth & Vigo, 2014). As the VRP is an NP-hard optimization problem, the computation time for finding an optimal solution increases exponentially with the size of the problem. The search for solutions requiring an acceptable computation time for practical-sized problems has motivated researchers to investigate other approaches despite computers getting faster (Ramos et al., 2014; Yousefikhoshbakht & Khorram, 2012). These approaches–heuristics, metaheuristics, or hierarchical methods–produce acceptable results in a reasonable time rather than optimal ones that take an unacceptably large amount of time (Comert et al., 2017; Dondo & Cerdá, 2006). We take the hierarchical approach, dividing the problem into smaller sub-problems or levels and then using exact methods to find the (near) optimal solution for each sub-problem or level.

We took the hierarchical approach, noting that the SDMC area is already divided into five *wards*, each with its dedicated depot and contractor responsible for waste collection. So, we can divide the overall problem into five smaller ones corresponding to the wards. Then, we applied the ward-by-ward approach to two extreme methods we developed: (1) a revised nearest neighbor algorithm (RNN) as a quick heuristic and (2) a MILP-based approach, for which we took the idea further, dividing each *ward* into sub-wards and then applying the exact optimal method to each.

The RNN algorithm entailed tweaking the nearest neighbor algorithm by attempting swaps of collection nodes across any pair of tours to lower the total cost, giving us a slight improvement over the baseline for which we used the nearest neighbor algorithm. The MILP-based approach fits into the class of hierarchical algorithms called *cluster-first-route-second* (CFRS) approaches (Qi et al., 2012), and we describe the model in §3.1, some additional constraints in §3.2, the hierarchical approach with sub-wards §3.3, and results from both algorithms in §3.4.

3.1 A MILP Formulation of the VRP

We formulate this problem as a MILP model with variables and parameters (**Table 3**). The objective function (1) minimizes the total transportation cost with the *fixed cost* of operating a garbage truck (such as the salary of the drivers and maintenance cost) and the *variable cost* of the distance traveled by truck. The model itself has twenty constraints that capture operational and flow conservation requirements (**Table 4**).

Table 3: Sets, indices, variables, and parameters

Sets and Indices	$I = set\ of\ the\ trucks\ at\ a\ garage\ (1,2, \ldots, \mathrm{I})$ $M = set\ of\ number\ of\ trips\ (1,2, \ldots, \mathrm{M})$ $G = set\ of\ depots\ (1,2, \ldots, \mathrm{G})$ $N = set\ of\ collection\ points\ (1,2, \ldots, \mathrm{M})$ $L = set\ of\ landfill\ sites\ (\mathrm{G + N + 1, \ldots G + N + L})$ $i = vehicle\ index\ (i \in I)$ $j, k = indices\ of\ nodes\ (j, k \in G \cup N \cup L)$ $m = index\ for\ the\ trip\ (m \in M)$ $g = index\ of\ the\ depots\ (g \in G)$ $l = index\ of\ the\ landfills\ (l \in L)$
Parameters	$\mathrm{B} = total\ number\ of\ trucks\ currently\ being\ used$ $\mathrm{M} = maximum\ number\ of\ trips\ a\ truck\ can\ take\ (heuristics)$ $q_g = 0;\ (quantity\ of\ waste\ at\ depots)$ $q_l = 0;\ (quantity\ of\ waste\ at\ landfills)$ $q_k = quantity\ of\ waste\ at\ k^{th}\ collection\ point$ $d_{j,k} = distance\ between\ j^{th}\ and\ k^{th}\ collection\ point$ $t_{j,k} = travel\ time\ between\ j^{th}\ and\ k^{th}\ collection\ point$ $F_{i,g} = capapcity\ of\ i^{th}\ truck\ from\ g^{th}\ depot$ $C_f = fixed\ cost\ of\ running\ a\ truck$ $C_v = variable\ cost\ of\ running\ per\ km$ $T_{i,g} = maximum\ shift\ time\ for\ i^{th}\ truck\ from\ g^{th}\ depot$
Decision Variables	$x_{i,g,m} = \begin{cases} 1, if\ i^{th}\ truck\ from\ g^{th}\ garage\ is\ operational\ on\ m^{th}\ trip \\ 0, otherwise \end{cases}$ $(defined\ for\ i\ \in I;\ g\ \in\ G;\ m\ \in\ M)$

$$y_{i,g,m,j,k} = \begin{cases} 1, if\ i^{th}\ truck\ from\ g^{th}\ garage\ goes\ from\ j\ to\ k\ in\ its\ m^{th} trip \\ 0, otherwise \end{cases}$$

$$(defined\ for\ i \in I;\ g \in G;\ j \in G \cup N \cup L;\ k \in G \cup N \cup L)$$

Minimize

$$\sum_{g=1}^{G} \sum_{i=1}^{I} C_f * x_{i,g,1} + \sum_{i=1}^{I} \sum_{g=1}^{G} \sum_{m=1}^{M} \sum_{j \in G \cup N \cup L} \sum_{k \in N \cup L} C_v * d_{j,k} . y_{i,g,m,j,k} \sum_{i=1}^{I} \sum_{g=1}^{G} \sum_{m=2}^{M} \sum_{j \in L} C_v * d_{j,g} . y_{i,g,m,j,g} \quad (1)$$

Subject to:

$$\sum_{g=1}^{G} \sum_{i=1}^{I} x_{i,g,1} \leq \mathrm{B} \quad (2)$$

$$y_{i,g,m,j,k} \leq x_{i,g,m}\ \forall i,g,j,k,m \quad (3)$$

$$\sum_{g=1}^{G} \sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{j \in G \cup N \cup L} y_{i,g,m,j,k} = 1 \quad \forall\ k \in N \quad (4)$$

$$\sum_{j \in G \cup N \cup L} \sum_{k \in N \cup L} y_{i,g,m,j,k} . \frac{q_j + q_k}{2} \leq F_{i,g} \quad \forall i,g,m \quad (5)$$

$$\sum_{j \in N} y_{i,g,m,j,k} \leq x_{i,g,m} \quad \forall i,g,m \in M, k \in N \quad (6)$$

$$\sum_{j \in N} y_{i,g,m,j,k} \leq x_{i,g,m} \quad \forall i,g,m \in M, k \in L \quad (7)$$

$$\sum_{j \in N} \sum_{k \in L} y_{i,g,m,j,k} \leq x_{i,g,m}\ \forall i,g,m \quad (8)$$

$$\sum_{j \in L} \sum_{k \in N \cup \{g\}} y_{i,g,m,j,k} = x_{i,g,m}\ \forall i,g,m \quad (9)$$

$$x_{i,g,m} \geq x_{i,g,m+1}\ \forall i,g,m \quad (10)$$

$$x_{i,g,m+1} \leq 1 - \sum_{j \in L} y_{i,g,m,j,g} \quad \forall i,g,m \quad (11)$$

$$\sum_{j \in L} \sum_{k \in G} y_{i,g,m,j,k} = 0\ \forall i,g,m,k \neq g \quad (12)$$

$$\sum_{j \in L} \sum_{m=2}^{M} y_{i,g,m,j,g} = x_{i,g,m} \quad \forall i,g \quad (13)$$

$$\sum_{j \in G} \sum_{k \in G \cup N \cup L} y_{i,g,m,j,k} = 0 \quad \forall i,g,m\ j \neq g \quad (14)$$

$$y_{i,g,1,j,k} = 0 \quad \forall i,g,j \in L; k \in N \quad (15)$$

$$\sum_{k \in N} y_{i,g,1,g,k} = x_{ig1} \quad \forall i,g \quad (16)$$

$$\sum_{k \in N \cup L} y_{i,g,1,j,k} = y_{i,g,1g,j} \quad \forall\ i,g\ ,j\ \in N \quad (17)$$

$$\sum_{k \in N \cup L} y_{i,g,1,j,k} = \sum_{k \in N \cup G} y_{i,g,1,k,j} \quad \forall j \in N, \quad \forall i,g \quad (18)$$

$$\sum_{k \in G \cup N} y_{i,g,m+1,j,k} = \sum_{k \in N} y_{i,g,m,k,j} \quad \forall j \in L\ \ \forall i,g,m \quad (19)$$

$$\sum_{k \in N \cup L} y_{i,g,m,j,k} = \sum_{k \in N \cup L} y_{i,g,m,k,j} \quad \forall j \in N\ \ \forall i,g \quad (20)$$

$$\sum_{m=1}^{M} \sum_{j \in G \cup N \cup L} \sum_{k \in G \cup N \cup L} y_{i,g,m,j,k} * t_{j,k} \leq T_{i,g}\ \forall i,g \quad (21)$$

Table 4: Explanation for each constraint

Constraint	Explanation
2	Trucks used for the routing are less than or equal to trucks available
3	Trucks used in their first and subsequent trips should be operational
4	All the collection points are served only once
5	The total amount of waste that a truck carries in a trip is less than the truck's capacity.
6,7 8	Only one truck visits a stop or landfill from a stop A truck can go to only one landfill from a stop
9	The rest of the trip's starting point is a landfill
10	The subsequent trips could happen if the previous trip ended
11	The penultimate trip happens at the landfill.
12	Each truck reaches its own depot
13 14	Across all trips, only one trip ends at the depot Each truck leaves from its own depot
15	No truck can leave from landfill in its first trip
16-20	Connectivity constraints that maintain the integrity of a route and ensure that every truck entering a node is also leaving that node
21	The total travel time for a given truck from depot to landfill should be less than the maximum shift time

3.2 Sub-Tour Elimination Constraints and Exogeneous Heuristic

A sub-tour is a closed loop among some collection points, where none is a depot or a disposal site. To eliminate such a loop, we added the Miller–Tucker–Zemlin (MTZ) sub-tour elimination constraint (SEC) to the formulation (Bektaş & Gouveia, 2014). The (MTZ) formulation has $O(n^2)$ extra variables and constraints with n nodes as opposed to other approaches for which the number of additional constraints increases exponentially with n (Bazrafshan et al., 2021).

The structure of the MTZ constraints we develop in equations (22-25) is different from the previously used structure (Sawik, 2020; Sundar et al., 2016.; Yuan et al., 2020) as we solve a multi-trip problem. Since the MTZ SECs can be computationally challenging, we used various settings (in CPLEX). For instance, "Emphasis-Memory" is set to 1 to optimize the working memory. To yield competitive upper and lower bounds with smaller gaps, "MIP-Emphasis" is set to 2, emphasizing optimality over feasibility in MILP solving.

$z_{i,g,m,j} = \{Rank\ of\ i^{th}\ truck\ from\ g^{th}\ garage\ on\ m^{th}\ trip\ from\ j^{th}\ point$

$S = total\ number\ of\ nodes$

$$z_{i,g,1,g} = x_{ig1} \quad \forall i, g \tag{22}$$

$$z_{i,g,1,j} \geq z_{i,g,1,k} + 1 - S(1 - y_{i,g,1,k,j}) \quad \forall i, g, m\ j \in N \cup L, k \in G \cup N\ j \neq k \tag{23}$$

$$z_{i,g,m,j} = x_{igm} \quad \forall i, g, m > 1, j \in L \tag{24}$$

$$z_{i,g,m,j} \geq z_{i,g,m,k} + 1 - S(1 - y_{i,g,m,k,j}) \quad \forall i, g, m > 1, j \in G \cup N, k \in N \cup L\ j \neq k \tag{25}$$

The following heuristic determines M, the maximum number of trips allowed for a vehicle.

1. Identify the farthest collection point from a disposal site
2. Compute the travel time (t_m) associated with the distance between the collection point and the disposal site
3. Compute the maximum number of collection points (c) a vehicle can visit in a trip
4. Compute the loading (t_l) and unloading (t_u) time at the collection points and the disposal sites, respectively

The maximum number of trips by a vehicle then is $M = T/(t_m + ct_l + t_u)$, where T is the total shift time.

3.3 Partitioning the Wards Further

Despite modifying the default CPLEX settings, we could not solve this problem optimally for any ward, even in 72 hours of computation time on a Windows 2019 server machine with 64 RAM. However, we did obtain solutions for the wards as a whole after running the model for much longer, as we mention later in §3.4. Therefore, we created sub-clusters within each primary cluster (*ward*) using the K-medoid method using the algorithm below. Then, we split up each ward into sub-wards, and noted that each sub-ward took 12 hours.

Initialize variable $\tau = 12\ hours$

$\boldsymbol{if}\ computation\ time\ \geq\ \tau$

Apply K-medoid clustering algorithm with k=2

Choose two random nodes as medoids (a and b)

Initialize min_diff = 100

Loop over all the nodes

Choose the medoids that generate the least difference between the size of the clusters

c = abs(len(clusters[a]) – len(clusters[b]))

if (c<min_diff)

a=a* and b= b* (a* and b* are the medoids for the most balanced clusters)

Solve for each sub-cluster and ***check*** τ again

The average computation time for the exact routing problem using the MILP model within each sub-cluster is then reduced to the manageable figure of approximately 10-12 hours on average (50-60 hours for the whole ward, if run sequentially) because of the fewer nodes and trucks in the sub-cluster. Of course, we can run the models in this hierarchical approach for all the sub-cluster in a ward (and all wards) in parallel, as even laptops have processors with multiple cores.

3.4 Results for Truck Routing

We compared the total transportation cost across all five wards for: (1) the existing manual method with the nearest neighbor algorithm (baseline), (2) the revised nearest neighbor (RNN) heuristic for routing for the entire ward, and (3) the method using MILP in a hierarchical approach using the K-medoid method for creating sub-clusters within each ward (H-MILP). The results show we can reduce the cost with improved routing across the entire SDMC zone comprising all five wards. The RNN algorithm we propose with the existing wards can result in a percentage savings of 1.57%, a savings of Rs 3.9mn (US$51,000) for the year. The HMILP would lead to an annual savings of 4.05%, or INR10mn (US$ 1,32,000) (**Table 5**).

Table 5: Results from different solution methods

Model / Parameters	Baseline approach	Revised nearest neighbor on the full ward (RNN)	MILP model for each sub-cluster in a ward using K-medoid sub-clusters (HMILP)
Daily running cost (INR = Indian rupees)	INR 679287.70	INR 668615.70	INR 651738.90
Daily absolute savings over baseline	-	INR 10672.00	INR 27548.80
Percentage savings over baseline (%)	-	1.57%	4.05%
Average solution time for each ward	2 minutes	2 minutes	50-60 hours (with sub-clusters run sequentially)

As mentioned before, we ran the MILP-based exact method for each ward as a whole by letting the computer run for several days. With an 8% optimality gap, we obtained 5.51% in cost savings over the baseline, a saving of INR13mn (US$ 159,000), but the method was impractical as it took 20-30 days to reach optimality. Overall, even a very basic heuristic like the RNN can give decent solutions quickly, so there is scope to improve the solution quality or use it without modification in a real-time context to obtain further savings.

4. Evaluating the Ward Structure

The other question for the SDMC was whether the ward structure could be improved. Recall that the zone is partitioned into five *wards*. As the RNN gave decent solutions, we used it to compare the running costs of clusters of collection points obtained using different methods with the existing ward structure. The two methods we used for clustering nodes were:

1) *K-medoid*: It is based on a greedy algorithm and is insensitive to outliers (Arora et al., 2016). It attempts to minimize the distance between nodes classed in a cluster and a point titled as the cluster's center or medoid (k). In this case, the medoids are the location of the depots (k=5). The algorithm assigns collection points to a cluster so that they are nearer to the depot in the cluster and further from the other depots.
2) *Minimum Spanning Tree (MST):* The MST takes any undirected, connected, and weighted graph and finds a tree sub-graph with all the nodes but only those arcs that minimize the total length of the edges. The edge length, in our cases, is the inter-node distance (Pop, 2020).

Perturbing the distance matrix: To get a more convincing result than that obtained from a single run, we perturbed the distance matrix by multiplying each cell that is not on the diagonal with $(1 + x/10)$ where $x \in [0,1]$ is a random number generated each time. We thus generated 20 randomly perturbed distance matrices. Besides, we have the original distance matrix and its symmetric equivalent, replacing each distance with the average of to-and-fro distances between the two nodes. Then, we applied our RNN algorithm for each clustering method to obtain tours and their total transportation cost, ranking the three clustering methods (including the existing ward structure) by lower transportation cost for each distance matrix in turn (**Table 6**).

Table 6: Transportation costs obtained for tours generated for the existing ward structure and that generated with MST and K-Medoids for the 22 instances of the distance matrix, and the rank of the clustering method based on the lower transportation cost for each instance

Distance matrix	**Total transportation cost by clustering method**			**Rank among clustering methods by lower total transport. cost**		
	Existing wards	*MST*	*K-medoid*	*Existing wards*	*MST*	*K-medoid*
Distance_1	679737.62	694218.76	689754.19	1	3	2
Distance_2	678189.95	679476.93	691032.43	1	2	3
Distance_3	692901.47	692722.77	692326.69	3	2	1
Distance_4	691183.08	690052.70	690526.69	3	1	2
Distance_5	676939.29	693197.43	692540.23	1	3	2
Distance_6	690370.54	692353.32	693145.98	1	2	2
Distance_7	689877.38	692221.22	690718.34	1	3	3
Distance_8	676909.80	679425.59	689508.52	1	2	2
Distance_9	680129.61	690483.20	689801.51	1	3	3
Distance_10	688668.58	694507.52	689032.85	1	3	2
Distance_11	676746.27	692437.75	692324.70	1	3	2
Distance_12	676746.27	689922.58	688022.66	1	3	2
Distance_13	679442.83	690314.05	690600.61	1	2	2
Distance_14	681288.50	692471.56	691833.72	1	3	3
Distance_15	678555.00	691084.18	690216.10	1	3	2
Distance_16	689571.77	690695.63	691924.99	1	2	3
Distance_17	692435.12	692097.52	689337.90	3	2	1
Distance_18	691441.33	691500.89	691414.95	2	3	1
Distance_19	676440.16	691237.47	687686.77	1	3	2
Distance_20	679945.07	692329.67	692752.08	1	2	3
Original	668615.70	679907.00	681762.60	1	2	3
Symmetric	681810.30	673985.40	682130.50	2	1	3
Modal rank	-	-	-	**1**	**3**	**2**

Then we used the nonparametric Wilcoxon matched-pair signed-rank test in Stata SE 17 to compare the existing ward structure with either partition obtained using the MST and K-medoids. The null hypothesis is that the median of the differences is zero, without any assumptions about the distributions (unlike the parametric t-test or z-test) (Ramachandran & Tsokos, 2015). The null hypothesis amounts to the true proportion of positive (negative) signs, with the differences being 0.5. The exact p-values are 0.0002 and 0001 for the existing structure versus the MST and K-medoids, respectively, showing we can reject the null hypothesis in either case, even at a 0.0001 level.

Alternatively, with the equivalent test in R language, the value of the test statistic of the Wilcoxon test (W) for the existing ward structure versus MST is 21 and versus K-medoids is 19, both of which are significantly smaller than the critical value of 75 for the statistic (W_c) at $N = 22$ ($p < 0.05$). Also, the modal ranks show that the existing ward structure has a lower cost than the K-medoids clustering of collection points. In turn, the K-medoid clustering has a lower cost than the clusters created by the MST (**Table 6**).

5. Conclusion

This paper demonstrates using analytics in a low-tech environment, using an optimization-based improvement approach for a currently manual process of planning truck routes for an urban solid-waste-collection system in the South Delhi region of Delhi, India. The current route planning process is a manual method, effectively the nearest neighbor method, to pick up waste from collection points. The municipality wanted to know how computers and analytics could help them. We suggested improved route planning and evaluating the existing ward structure.

Using the nearest neighbor routing as a proxy for the current manual process, we implemented two algorithms on the opposite ends of the spectrum for speed and optimality to demonstrate the tradeoff between solution quality and computation time for the first question. The first algorithm was a revised version of the nearest neighbor algorithm giving a slight improvement of 1.57% in solution quality over the baseline. The second algorithm used an optimal MILP-based approach, first by using the K-medoid method to partition the nodes within each ward further and then by solving each sub-ward optimally, resulting in a 4.05% improvement. Thus, we demonstrated the range of solutions SDMC could expect regarding solution quality and computation time, paving the way for developing more sophisticated approaches. For the second question, we were able to show that the existing ward structure was better than other partitions we tried, giving SDMC the confidence that they need not make changes there and that they could use analytics to answer strategic questions.

5.1 Managerial Implications

Despite the attractions of new technology, including analytics, low-tech environments are naturally cautious, perhaps even skeptical, in understanding the costs and benefits of tactical and strategic (structural) planning. A demonstration like ours can help municipalities focus on getting higher benefits at lower costs and ignore areas that are working fine.

For the SDMC's strategic problem, we showed that they do not need to change the ward structure as the benefits of making any changes are not obvious. At the same time, the costs of any changes are high due to contractual relations with the different contractors for each ward. For their tactical problem, we demonstrated that even the simplest route planning method could give better routes than their existing method. Moreover, the algorithm can be run in minutes, even on a slow computer, allowing it to be run several times a day as conditions change due to road closure or other conditions.

More generally, the critical managerial implication is the design of such demonstrations of analytics in a low-tech context can focus on (a) the speed vs. solution quality tradeoff so that the organization can decide what it wants and (b) a range of applications to that the organization can decide which application could be adopted first (**Table 7**). Such a demonstration can be a foray into a context where we know little about the ten contextual dimensions Gorman (2021) has outlined.

Table 7: An approach for demonstrating analytics in a low-tech environment, exemplified here by the solid waste collection context.

<table>
<tr><td></td><td></td><th colspan="2">Demonstrate speed vs solution quality tradeoff</th></tr>
<tr><td></td><td></td><th>Fast solution</th><th>Optimal solution</th></tr>
<tr><th rowspan="2">Demonstrate a range of applications</th><th>Tactical planning</th><td>Revised nearest neighbor algorithm</td><td>Vehicle route planning using MILP modeling</td></tr>
<tr><th>Strategic planning</th><td>Evaluation of wards with different clustering methods (K-medoids, MST) using the revised nearest neighbor method for route planning</td><td>Did not attempt – need a fast route planning algorithm</td></tr>
</table>

5.2 Research Implications

Our efforts here were to develop a "proof-of-concept" demonstrating what is possible with analytics in a low-tech context rather than implementing an operational system. Assuming that an analytics approach is being adopted, there are several opportunities to extend this paper on both the theoretical and practical fronts:

(1) *More operational constraints*: We must consider precedence relationships among the various collection points as some residential collection points tend to fill up earlier in the day than commercial ones. Further, the travel times in routes change during the day based on known traffic patterns. For instance, schools and offices have peak crowding in specific time windows. Avoiding pickups during those times is highly desirable, and the models must be tuned to capture such requirements.

(2) *Strategic location choices*: At a more strategic design level, we need to consider the location of collection points and possibly the depots and disposal sites. Using ideas from the facility location models and geospatial analysis, we can determine better locations for placement collection centers

and landfills. Such models can also account for location-specific environmental or hygiene factors, thus connecting health and waste management systems. Moreover, as we go from simply dumping waste to sorting and recycling waste, the location of sites for these activities would also have to be considered within the same strategic location problem.

(3) *Real-time routing algorithms*: For an operational setting, we need to determine what to emphasize– the heuristics or the optimization–in a heuristic-optimization framework when there are unplanned or disruptive changes in distances and time between nodes in real time. For example, would it be better to keep running the revised nearest neighbour algorithm (or a more sophisticated version) with the latest distances and times obtained from Google Maps, or would it be better to create (near) optimal static routes with overnight computer runs and then tweak these in real-time as data change during the day? Moreover, there are existing algorithms that could be both efficient and exact. We refer the reader to the Han & Ponte-Cueoto (2015) review on waste collection and the Braekers et al. (2016) review on algorithms for vehicle routing.

(4) *Machine learning*: Besides an operations research approach, machine learning (ML) could be explored independently or with optimization models for the solid waste process. Xia et al. (2022) review machine learning algorithms in (a) waste generation prediction, (b) waste collection and transportation (including route optimization), and (c) waste treatment and disposal. Andeobu et al. (2022) also review AI/ML applications for solid waste management. However, ML approaches require a huge amount of high-quality data that may not be available in this low-tech environment of developing countries. Indeed, creating synthetic data may provide another research opportunity.

(5) *Increasing the scope from collection to management*: Our paper focuses on solid waste collection to disposal at a landfill. Given that the world is urbanizing, particularly in developing countries, and people are producing more waste, there is an urgent need to consider not just collection and disposal but also recycling at different stages; incineration; anaerobic digestion to produce fuel or even electricity (e.g., Naveenkumar 2023); and simply reducing the waste produced (e.g., Khan et al., 2022). Kurniawan et al. (2022) describe the need and approach to reducing, reusing, and recycling solid waste using digitalization in urban China.

We hope our paper will trigger further research on practical-sized problems of waste collection that large cities face, particularly in developing countries. More than that, we hope that our overall approach of tackling both the operational and strategic aspects using a variety of algorithms will be beneficial in low-tech contexts when considering the adoption of analytics.

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