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Article

Sustainable Waste Collection Vehicle Routing Problem for COVID-19

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Abstract: COVID-19 pandemic has imposed many threats. One among them is the accumulation of waste in hospitals. Waste should be disposed regularly and safely using sustainable methods. Sustainability is self development with preservation of society and its resources. The main objective of this research is to achieve sustainability in waste collection by minimizing the cost factor. Minimization of sustainable-cost involves minimization of three sub-components – total travel-cost representing economical component, total emission-cost representing environmental component and total driver-allowance-cost representing social component. Most papers under waste collection implement Tabu search algorithm and fail to consider the environmental and social aspects involved. We propose a mathematical model, a novel algorithm called grouping algorithm, a combination of Nearest Neighbor algorithm and Simulated Annealing algorithm to achieve sustainable transportation in waste collection during pandemics. All these algorithms are run on Solomon's and Gehring and Homberger's benchmark dataset. The sustainable-cost obtained from the output routes of the proposed grouping algorithm is found to perform effectively for all the instances with minimized solution. The results are verified using computational techniques such as Integrated Ranking and Relative Percentage Deviation and statistical techniques such as Descriptive Statistics.

Keywords: Sustainable objective; grouping algorithm; nearest neighbor algorithm; simulated annealing algorithm

1 Introduction

Waste materials, obtained from the hospitals, should be properly collected and effectively disposed. The recent pandemic conditions have further emphasized on timely transportation of waste materials such that they do not spread the disease further. The Vehicle Routing Problem (VRP) is a classical Combinatorial Optimization Problem that has many applications such as transportation of hazardous material [1], pharmaceutical distribution [2], food, raw material distribution, school bus routing [3] and scheduling. In this paper, we consider transportation of waste materials from hospitals to various disposal sites based on the type of waste using VRP.

There are many variants in VRP [4] depending on the application and the type of problem to be solved. This study deals with a Single Depot, Heterogeneous Vehicle Routing Problem with Time Windows (SD-HVRPTW).

This study focuses on minimization of distance and sustainable feature for VRPTW. The sustainability is captured by means of summing up the economic, environmental and the social factors. Each factor is calculated as a measure of cost–total travel-cost (Economic), total emission-cost (Environmental) and total Driver-allowance-cost (Social).

The solution approaches to solve VRPTW are classified as exact, greedy heuristics and Meta heuristics. A mathematical model based on [5] is formulated to solve to problem. This study proposes a new algorithm called the grouping algorithm which is used to group locations that are near to each other. This helps in disposal of waste with minimum cost. This algorithm can be combined with the existing greedy heuristic algorithm: Nearest Neighbor Heuristic that considers nearest location as the first point (NNH) and the single point meta-heuristic algorithm, Simulated Annealing. All these algorithms are executed on benchmark datasets. To differentiate the working of algorithms on different sizes of datasets, 56 instances of 100 locations–Solomon's dataset [6] and 60 instances of 1000 locations–Gehring and Homberger's dataset [7] are considered.

The performance of these algorithms is evaluated based on computational and statistical measures. For computational performance, the concepts of Integrated Ranking and Relative Percentage Deviation are considered and the statistical inference is done by means of Descriptive Statistics through which the algorithm that produces the minimized solution is identified.

This paper presents the closely related literature review on the waste collection problem in Section 2. Section 3 presents features and the mathematical model of VRPTW being used. Section 4 discusses the details on the proposed grouping algorithm with Nearest Neighbor and the Simulated Annealing algorithm. In Section 5, the performance evaluations of the proposed algorithms are discussed.

2 Literature Review

The waste collection is a separate category in the study of Vehicle Routing Problem with Time Windows stated by Beltrami et al. [8]. There are many solutions available for Vehicle Routing Problem as it is a NP-Hard problem [9]. The various algorithms used in waste collection transportation model under literature study are listed in Tab. 1.

Table 1: Literature review of waste collection with vehicle routing problem with time windows

S. no	Paper	Algorithm	Major objective	Benefit	Gap identified
1	Ombuki-Berman et al. [10]	Genetic algorithm	Multiple trip + lunch break	Crossover operation improves performance	Environmental factors are not considered
2	Runka et al. [11]	Fitness search space	Multiple disposal trip + lunch breaks	Selection of landscapes	Environmental factors are not considered
3	Benjamin [12]	Tabu search	Distance + number of vehicles	Multi depot + homogeneous vehicles	Considers local optimization

(Continued)

Table 1 (continued)

S. no	Paper	Algorithm	Major objective	Benefit	Gap identified
4	Faccio et al. [13]	Simulation	Distance + number of vehicles	Investment, operational and environmental costs are considered	Large datasets are difficult to simulate
5	Benjamin et al. [14]	Tabu search, variable neighborhood search	Choose best disposal facility	Choose best among different types of disposal facilities	Considers local optimization
6	Minh et al. [15]	Memetic algorithm	Minimize travelling time and number of vehicles	Reduces Travel time and the count of vehicles used	The distance between vehicles are not considered
7	Wy et al. [16]	Large neighborhood search based iterative heuristic approach	Disposal of wastes	Huge waste disposal	Cost factor is not considered.
8	Nowakowski et al. [17]	Harmony search algorithm	Cover major collection points	Considers container loading problem	All the locations are not serviced
9	Babaee Tirkolaee et al. [18]	Simulation in CPLEX	Sustainable cost	All components of sustainability	Large datasets are difficult to model
10	Jorge et al. [19]	Simulated annealing + neighborhood search	Shift and route balance	Addresses workload concerns	Cost factor is not considered.

From Tab. 1, it is inferred that servicing most of the locations is also considered as a main objective in some papers. Other major objectives include–travelling time, route balance, cost factors, lunch break for drivers, distance. The algorithms in the literature [13] are limited to servicing only a few locations and end in local optimization.

This study services all the locations even if the problem size is high. Global optimization is addressed to obtain minimized cost. The proposed algorithm works well with scalable data.

3 The Proposed System for Waste Collection During Pandemic

The waste is collected from a single hospital (depot) and is transported to different disposal sites. The number of locations for disposing specific wastes is denoted by n and different types of vehicles by m. Each and every vehicle should start and end at the hospital. Each of these locations should be visited by one of the vehicles. Each vehicle visits a few locations depending on the capacity constraint and the time windows constraint specified. All the ‘n’ locations should be visited but all ‘m’ vehicles need not be used.

Each location including the hospital is defined by the following parameters:

- Customer-number (including hospital as location with number as ‘0’),
- x co-ordinate and y co-ordinate,

- Demand
- Start-time, End-time (denoted as Time Window) and Service-time.

Each vehicle includes the following features:

- Vehicle-number,
- Capacity,
- Mileage per unit of the fuel,
- Total-running-km,
- Age of the vehicle (in months),
- Emission-rate (in g/km), and
- Driver allowance for unit km.

These characteristics vary for each vehicle; and hence the problem comes under the category of heterogeneous fleet of vehicles [20]. The block diagram of the problem is presented in Fig. 1.

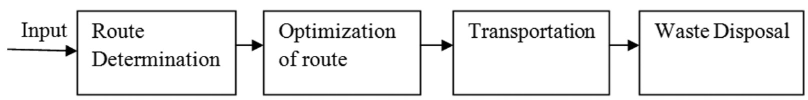

Figure 1: Block diagram of waste collection pandemic model

3.1 Proposed Mathematical Model for Sustainable SD-HVRPTW

The mathematical model generates the best solution for the waste collection pandemic model. The mathematical model is used to obtain the minimized cost when the number of vehicles and locations are limited. When the number of locations and the vehicles increase, the time for obtaining the cost increases exponentially. The sets and indices, Parameters, Variables and the MILP model are presented below:

Sets and Indices:

L – Set of Locations distributed around. L = {0, 1, …, m} where '0' represents the hospital.

V – Set of Vehicles. V = {1, 2, …, n}

Parameters for location:

d_{ij} – Distance (Euclidean distance) between location 'i' and location 'j'.

D_i – Demand of waste that can be dumped in location 'i'

$start_i$ – Start time for location 'i'

end_i – Start time for location 'i'

$service_i$ – Time taken to dump waste in location 'i'

A_i – Arrival time for location 'i'

Parameters for vehicle:

$capacity_k$ – Capacity of vehicle k

$kmpl_k$– Mileage (kilometer per liter) for vehicle k

ER_k-Emission rate (grams per kilometer) for vehicle k

DA_k-Driver-allowance rate (Rs. per liter) for vehicle k. It is an extra allowance that is notionally paid to the driver based on the pollution emitted and the distance travelled by the vehicle.

$Dist_k$-Distance travelled by vehicle k

TC_k-Travel cost for vehicle k

EC_k-Emission cost for vehicle k

DAC_k-Driver allowance cost for vehicle k

General parameters:

CP-Carbon pricing (a constant, penalty that is assumed to be imposed on vehicles based on the emission-rate and the distance travelled by the vehicle)

FC-Fuel cost (a constant, Rs. 70/-per liter)

TTC – Total travel-cost

TEC-Total emission-cost

TDAC-Total Driver-allowance-cost

Variable:

$$X_{ij}^{k} = \left\{ \begin{cases} 1, & \textit{If a vehicle k visits customer i and then visits customer j} \\ 0, & \textit{otherwise} \end{cases} \right\}$$

Objective function:

$$\text{Minimize} \sum_{k=1}^{n} \frac{\mathrm{Dist}_k * FC}{\mathrm{kmpl}_k}, + \sum_{k=1}^{n} \frac{\mathrm{Dist}_k * ER_k}{CP} + \sum_{k=1}^{n} \mathrm{Dist}_k * DA_k, \quad \forall k \in V \tag{1}$$

$$\mathrm{Dist}_k = \sum_{i=0}^{m} \sum_{j=0}^{m} d_{ij} * X_{ij}^{k}, \quad \forall k \in V \tag{2}$$

Subject to

$$\sum_{k=1}^{n} \sum_{i=1}^{m} X_{ii}^{k} = 0, \ \forall k \in V \tag{3}$$

$$\sum_{i=0}^{m} X_{0i}^{k} = 1, \quad \forall k \in V \tag{4}$$

$$\sum_{i=0}^{m} X_{i0}^{k} = 1, \quad \forall k \in V \tag{5}$$

$$\sum_{i=0}^{m} X_{0i}^{k} \le 1, \quad \forall k \in V \tag{6}$$

$$\sum_{k=1}^{n} \sum_{i=1}^{m} X_{ji}^{k} = 1, \quad \forall k \in V \tag{7}$$

$$\mathrm{capacity}_k \ge \sum_{i=1}^{m} \sum_{j=1}^{m} D_j * X_{ij}^{k}, \quad \forall k \in V \tag{8}$$

$$\sum_{i=1}^{m} X_{ij}^{k} = \sum_{i=1}^{m} X_{ji}^{k}, \ i \in C - \{0\}, \ \forall k \in V \tag{9}$$

$$A_i \geq \ start_i, \ \forall i \in L - \{0\} \tag{10}$$

$$A_i + \ service_i \leq end_i, \quad \forall i \in L - \{0\} \tag{11}$$

$$A_i * X_{ji}^{k} + service_i * X_{ji}^{k} \leq A_j * X_{ji}^{k}, \quad \forall i \in L - \{0\}, \ j \in C, \ \forall k \in V \tag{12}$$

Objective function

(1) This equation represents the Sustainable-cost.

(2) This equation is used to calculate the distance travelled by each vehicle which is the sum of Euclidean distance between consecutive locations serviced by the same vehicle.

The various constraints are represented as follows:

(3) For any vehicle, movement from one location to itself is not possible, except the hospital.

(4) All vehicles must start from the hospital.

(5) All vehicles must end at the hospital.

(6) To ensure that every vehicle starts only once from the hospital i.e., there are no multiple travels.

(7) All locations must be visited.

(8) The sum of demands of the locations visited by a vehicle does not exceed its capacity.

(9) Flow conservation Eqs. (10)–(12) These equations are used to ensure that the arrival time of a vehicle for a location must be greater than its start-time, less than its end-time and the arrival time of the next location processed by the same vehicle must be greater than the arrival time of previous location.

4 Proposed Algorithm for SD-HVRPTW

There are many algorithms [21–23] available for Vehicle Routing Problem with Time Windows. The grouping algorithm presented in 4.1 proposes heuristic solution for waste collection during pandemics.

4.1 Grouping Algorithm

The grouping algorithm is presented in the Fig. 2. In this algorithm, we take each and every location and group it with the other location which has the least distance among all the locations present in the dataset. They represent a group and are stored in a separate file. This file is accessed during the execution of other greedy heuristic and meta-heuristic algorithm to allocate locations to vehicles. When a single vehicle services all the locations present in a group, the distance factor is greatly reduced which subsequently leads to the minimization of sustainable-cost.

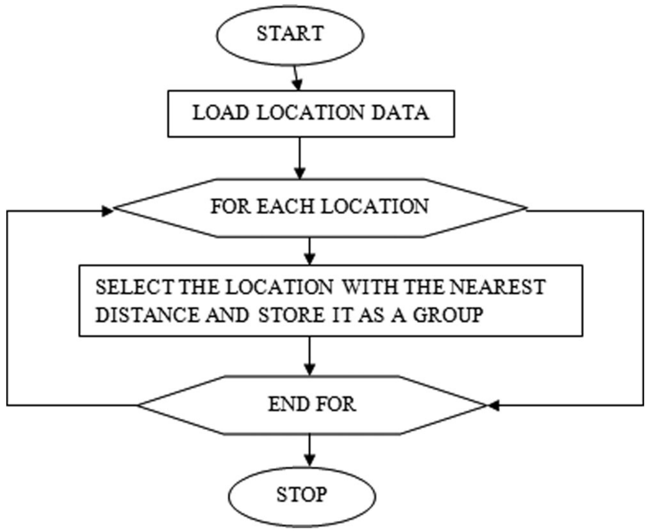

Figure 2: Flowchart for grouping algorithm

4.2 Proposed Grouping Nearest Neighbor Algorithm (G-NNH)

The pseudo code for the proposed G-NNH algorithm is given in Fig. 3. The Nearest Neighbor algorithm was proposed by Solomon [24]. It is also used in last mile deliveries [25]. In the NNH algorithm, for every vehicle, one location is selected based on the distance from the hospital and added to the route. Consequent locations are added to the same route which has the minimal distance from the last location serviced by the vehicle. The process is repeated until all the locations are serviced [26].

Step 1: Load the location, vehicle and grouping data
Step 2: Calculate inter-distance matrix
Step 3: REPEAT until all locations are visited
Step 4: Select vehicle based on the *kmpl*$_k$, *ER*$_k$ *and capacity*$_k$
Step 5: If vehicle k is new
Step 6: Create partial-route with the first point as hospital
Step 7: else
Step 8: Select location where *distance = min{distance(location, last-location of k)}*
Step 9: *If location U group(location) satisfy capacity and time constraints*
Step 10: *route = route U {location, group(location)}*
END LOOP
Step 11: Add the hospital as the last point for each vehicle
Step 12: Calculate sustainable-cost

Figure 3: Grouping-Nearest Neighbor Heuristic (G-NNH) algorithm

In G-NNH algorithm, when a location is serviced by a particular vehicle, the other location belonging to group of the original location will also be serviced by the same vehicle. This leads to the reduction of distance travelled by all the vehicles and subsequently, the sustainable-cost.

4.3 Proposed Grouping Simulated Annealing (G-SA) Algorithm

Even though there are many meta-heuristic algorithms like Variable Neighborhood Search [27], we are using Simulated Annealing algorithm introduced by Kirkpatrick et al. [28] which is a single point meta-heuristic approach. Simulated Annealing algorithm is used for complex problems and is used to achieve global optimization instead of local optimization [29]. In this study, solution obtained from NNH and

G-NNH is given one at a time as initial solution to the proposed SA and its variant-G-SA, respectively. The pseudo code of the proposed variant of SA is presented in Fig. 4.

```
Step 1:  Let new-sus-cost = sus-cost of current-solution
Step 2:  Let temp = initial-temp
Step 3:  REPEAT
Step 4:          REPEAT Max_no_of_Iteration times
Step 5:                  Generate N(S) using swap (ri, cm,group(cm), rj, cn, group(cn))
Step 6:                  Calculate new-sus-cost
Step 7:                  if (new-sus-cost<sus-cost)or(exp((sus-cost–new-sus-cost)/temp) in [0,1]) then
Step 8:                          current-solution = N(S); sus-cost = new-sus-cost
                         end-if
         END LOOP
Step 9:          temp = temp - cooling-factor
 UNTIL temp > final-temp
```

Figure 4: Pseudo code for G-SA

The Simulated Annealing algorithm (SA) takes the output route from NNH algorithm as the initial input. A swap operation is carried out between locations of two different locations. After swap, if the objective value is minimized, the swapped route becomes the new solution. The same process is repeated based on the parameters.

In the proposed G-SA, the input is the output route obtained from G-NNH. For the swap operation, in addition to the location, the other locations that belong to a particular group are also swapped. The terminologies in Fig. 4 are as follows:

- Current-solution first refers to the output route obtained from G-NNH.
- Swap (ri, cm, group(cm), rj, cn, group (cn)) exchanges location 'cm' and group location of 'cm' from route 'ri' to location 'cn' and its group location from route 'rj' and vice-versa.
- N(S) indicates the feasible Neighborhood solution
- New-sus-cost denotes the sustainable-cost of solution after swapping.

Based on the analysis and the simulation output done on the dataset C1-10-1 for the parameters mentioned in [30–33], the following values are set for G-SA based on [33] for faster convergence:

- Initial Temperature (T0): 100
- Number of iterations (Max_no_of_Iteration): 300
- Cooling-factor (alpha): 0.9
- Final Temperature (TF): 0.001

The Nearest Neighbor algorithm selects the nearest location from the list of available locations and adds them to the route. This leads to increase in time for calculating routes and the possibility of two nearest locations being serviced by two different vehicles. Adding grouping algorithm greatly reduces these two disadvantages. Similarly, in the simulated annealing when locations between two different routes are swapped, their corresponding neighbors are also swapped decreasing the distances travelled by the corresponding vehicles.

5 Performance Evaluation

To understand the performance and to evaluate the algorithms performance, a series of computational experiments are conducted. For those experiments, we need (i) Parameters, and (ii) Performance measures.

5.1 Parameters

In this study, the distance, total travel-cost, total emission-cost, total driver-allowance-cost, sustainable-cost obtained from the NNH, G-NNH, SA, G-SA algorithms are considered for evaluation.

5.2 Performance Measures

The empirical performance measure – Integrated Rank and Relative Performance Deviation (RPD) are used to assess the performance of algorithms. In addition, we consider the statistical measure–Descriptive Statistics. The performance measure considered is as follows:

Integrated RANK (IRANK): IRANK was introduced by Mathirajan et al. [34]. The formula used to calculate the IRANK is given in Eq. (13). It ensures the consistency of performance across all the instances for all the algorithms considered.

$$\mathrm{IRANK\ (A)} = \frac{\sum_{\mathrm{I=1}}^{\mathrm{MaxRank}}[\mathrm{N(I,\ A)} * \mathrm{I}]}{\sum_{\mathrm{I=1}}^{\mathrm{MaxRank}}\mathrm{N(I,\ A)}} \tag{13}$$

where

IRANK (A): Integrated RANK for Algorithm ‘A’

A: Algorithm, I: Rank

N(I, A): Number of times the solution of the algorithm ‘A’ is in RANK ‘I’ over 56 or 60 or 116 instances for benchmark datasets separately.

MaxRank: Maximum rank possible [This is equal to number of algorithms]

Relative Percentage Deviation (RPD): This is one of the standard performance measures for best case analysis given by Rardin et al. [35]. The formulae to compute relative percentage deviation with respect to the Estimated Optimal Solution (EOS) is given in Eq. (14).

$$\mathrm{RPD} \ = \frac{(\mathrm{SOA} - \mathrm{EOS})}{\mathrm{EOS}} \times 100 \tag{14}$$

where

SOA: Value obtained pertaining to corresponding algorithm for each of the instance.

EOS: Smallest value obtained among the 4 algorithms for each instance. If number of algorithms > = 7, EOS = 0.63*n + 1.

From the value of RPD, ARPD (Average RPD) and MRPD (Maximum RPD) is calculated for each of the instance using the Eqs. (15) and (16) respectively.

$$ARPD = \frac{sum\ o\ RPD\ of\ \ all\ instances}{Total\ number\ of\ \ instance} \tag{15}$$

$$MRPD = Maximum(RPD\ of\ \ all\ instances\ for\ a\ particular\ algorithm) \tag{16}$$

5.3 Result Analysis

All the algorithms are implemented in C Programming on a computer: Intel® Core™ i5-4590 CPU @ 3.30 GHz with RAM: 4.00 GB.

Two types of benchmark datasets are considered:

- 56 instances of 100 location Solomon's benchmark dataset
- 60 instances of 1000 location Gehring and Homberger's benchmark dataset

A sample data of customers is presented in Tab. 2. These benchmark datasets are chosen because they have been used in many papers available in literature from 1987 to 2021 to represent different applications of Vehicle Routing Problem [36].

Table 2: A sample data format for location details from Solomon's dataset

Customer-identification	x-coordinate	y-coordinate	Demand	Start-time	End-time	Service-time
0	35	35	0	0	1000	0
1	41	49	10	707	848	10
2	35	17	7	143	282	10
3	55	45	13	527	584	10
4	55	20	19	678	801	10
5	15	30	26	34	209	10

The data for the vehicles are generated as the benchmark instances are designed only for homogeneous vehicles and our problem considers a heterogeneous fleet of vehicles. The characteristics of the vehicle are generated based on the classification scheme in Tab. 3 and the sample is presented in Tab. 4. The capacity of the vehicles is 50, 56 and 60 (capacity of normal buses and vans on Indian roads) with a probability of 0.2, 0.3 and 0.5. A total of 800 vehicles are generated to accommodate 1000 locations.

Table 3: A classification schema for the vehicle data

Classification based on the number of kilometers run by the vehicle in 1 year	Vehicle-mileage range (in kmpl)	Emission-rate (in g/km)	Driver-allowance-rate (in Rs. per km)
≤5000	[4, 6]	[515, 524]	10
5001–10000	[3, 4]	[525, 534]	12
>10000	[1, 3]	[534, 540]	14

Table 4: A sample format of the vehicle-data

Vehicle-identification	Vehicle-capacity	Vehicle-mileage	Total-running-kilometer	Vehicle-age	Emission-rate	Driver-allowance-rate
1	60	4	13577	146	518	10
2	50	2	30050	2	535	14
3	56	5	505	124	521	10
4	60	5	8946	103	515	10
5	60	6	20836	158	520	10

5.3.1 NNH vs. G-NNH

Both the Greedy algorithms – NNH and G-NNH are evaluated using IRANK as in Tab. 5 and their mean, median are compared in Tab. 6.

Table 5: Integrated rank for the greedy algorithms for the various parameters

Dataset	Distance		Total travel-cost		Total emission-cost		Total driver-allowance-cost		Sustainable-cost	
	NNH	G-NNH	NNH	G-NNH	NNH	G-NNH	NNH	G-NNH	NNH	G-NNH
Solomon's	2	**1**	2	**1**	2	**1**	2	**1**	2	**1**
Gehring and Homberger's	2	**1**	2	**1**	2	**1**	2	**1**	2	**1**
Overall	2	**1**	2	**1**	2	**1**	2	**1**	2	**1**

Table 6: Mean and median for the greedy algorithms for the various parameters

Dataset		Solomon's dataset		Gehring and Homberger's dataset		Overall	
Algorithm		NNH	G-NNH	NNH	G-NNH	NNH	G-NNH
Distance	Mean	4860.05	**2990.18**	244550.44	**180720.40**	128837.80	**94919.6**
	Median	5112.64	**3060.46**	244318.84	**184045.93**	222309.20	**165195.2**
Total travel-time	Mean	92450.61	**52901.40**	4434329.12	**3229375.01**	2338250.00	**1695905**
	Median	92255.52	**57073.64**	4404923.75	**3286708.97**	4052909.00	**2919892**
Total emission-cost	Mean	2538.41	**1562.05**	127730.38	**94388.27**	67292.88	**49575.61**
	Median	2669.21	**1600.30**	127600.04	**96121.68**	116117.90	**86254.4**
Total driver-allowance-cost	Mean	52297.52	**32296.41**	2596622.77	**1917591.28**	1368328.00	**1007449**
	Median	54918.88	**33189.83**	2590944.61	**1951950.64**	2360451.00	**1747053**
Sustainable-cost	Mean	147286.54	**86759.86**	7158682.26	**5241354.56**	3773871.00	**2752930**
	Median	149853.15	**91847.58**	7115434.91	**5326824.94**	6531258.00	**4753199**

Inference: In Tab. 5, the values of Integrated RANK for all the parameters are presented. Integrated Rank is a measure that is used to check the consistency of a parameter across different kinds of instances. The ranking for Grouping-NNH is 1 which leads to the minimized value obtained. From Tab. 6, even the mean and median values are lower for all the parameters irrespective of the datasets. It further insists that the G-NNH algorithm gives 26% more efficient minimized solution than NNH for distance, 28% for total travel-cost, 26% for total emission-cost and total driver-allowance-cost and 27% for sustainable-cost.

5.3.2 SA vs. G-SA

The simulated annealing algorithm and the corresponding grouping variant are measured using Integrated Rank in the Tab. 7 and their mean and median are compared and presented in the Tab. 8.

Table 7: Integrated Rank for the SA and G-SA for various parameters

Dataset	Distance		Total travel-cost		Total emission-cost		Total driver-allowance-cost		Sustainable-cost	
	SA	G-SA	SA	G-SA	SA	G-SA	SA	G-SA	SA	G-SA
Solomon's	2	**1**	2	**1**	2	**1**	2	**1**	2	**1**
Gehring and Homberger's	2	**1**	2	**1**	2	**1**	2	**1**	2	**1**
Overall	2	**1**	2	**1**	2	**1**	2	**1**	2	**1**

Table 8: Mean and median using single point meta-heuristic algorithms for the various parameters

Dataset		Solomon's dataset		Gehring and Homberger's dataset		Overall	
Algorithm		SA	G-SA	SA	G-SA	SA	G-SA
Distance	Mean	4759.4	**2980.0**	242331.9	**180491.7**	127641.7	**94796.41**
	Median	4877.6	**3061.5**	241265.8	**183784.1**	221104.5	**165056.8**
Total travel-time	Mean	89272.2	**52443.7**	4372585	**3216562**	2304779	**1689057**
	Median	88292.9	**54876.2**	4319283	**3269373**	3976080	**2903140**
Total emission-cost	Mean	2485.3	**1556.5**	126561.8	**94263.3**	66662.8	**49508.3**
	Median	2545.5	**1600.6**	126010.7	**95981.5**	115486.8	**86173.36**
Total driver-allowance-cost	Mean	51090.9	**32146.4**	2570854	**1914029**	1354417	**1005534**
	Median	52141.6	**33150.9**	2558896	**1950891**	2345210	**1744033**
Sustainable-cost	Mean	142848.4	**86146.6**	7070000	**5224854**	3725858	**2744099**
	Median	143625	**89819.0**	6997180	**5308432**	6462531	**4733347**

Inference: Based on Tab. 7, the values of Integrated RANK for all the parameters are the least for Grouping-SA which leads to the minimized value obtained. From Tab. 8, the mean and median values indicate the corresponding values obtained in all the instances. Their values are lower for all the parameters irrespective of the number of locations in each instance. Based on this Tab. 8, the mean of G-SA algorithm are 26% more efficient in terms of distance, 27% in total travel-cost, 26% in total emission-cost and total driver-allowance-cost and 26% for sustainable-cost than SA algorithm for all the instances.

5.3.3 NNH, G-NNH, SA and G-SA

The comparison of all the four algorithms – NNH, G-NNH, SA, and G-SA in terms of Average Relative Percentage Deviation and Maximum Relative Percentage Deviation using Eqs. (15) and (16) are shown in Tab. 9 and the mean and median comparisons are presented in Fig. 5.

Table 9: Average Relative Percentage Deviation (ARPD) and Maximum Relative Percentage Deviation (MRPD) for the various parameters

Algorithm	ARPD for sustainable-cost			MRPD for sustainable-cost		
	Solomon's dataset	Gehring and Homberger's dataset	Overall	Solomon's dataset	Gehring and Homberger's dataset	Overall
NNH	71.34	37.46	54.40	109.40	73.13	109.40
G-NNH	0.71	0.35	0.53	8.84	1.23	8.84
SA-NNH	66.22	35.77	51.00	109.39	72.19	109.39
G-SA-NNH	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

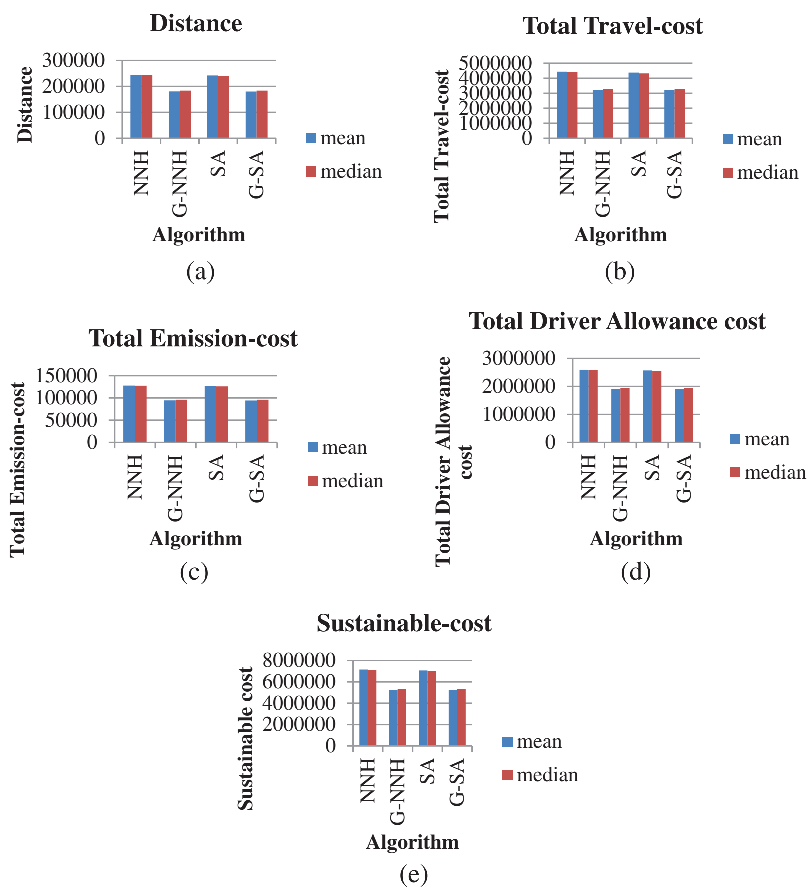

Figure 5: Comparison of mean and median obtained from NNH, G-NNH, SA, G-SA algorithms for different parameters, (a) Distance, (b) Total Travel-cost, (c) Total Emission-cost, (d) Total Driver Allowance cost, (e) Sustainable cost

Average Relative Percentage Deviation is the average value of RPD obtained from all the instances. The RPD considers the least value of the sustainable cost as the Estimated Optimal Solution as the number of algorithms considered is less than 7. MRPD is the maximum value obtained in all the instances for all the parameters. From Tab. 9, even though the ARPD and MRPD seem closer to each other, the single point variant of the meta-heuristic algorithm–G-SA produces the least value in all the three types of datasets. This means that the least sustainable-cost obtained from the G-NNH algorithm is further minimized by the Grouping variant SA. From the Fig. 5a represents the mean and median for total distance, Fig. 5b represents for total travel-cost, Fig. 5c represents for total emission-cost, Fig. 5d for total driver-allowance-cost and Fig. 5e for sustainable-cost. For all the parameters, the new algorithm–Grouping, when combined with Simulated Annealing algorithm gives the least value for all the benchmark instances. In terms of efficiency, for distance, G-SA is 26.42%, 0.13%, 25.73% more efficient than NNH, G-NNH and SA algorithms respectively. For total travel-cost, G-SA is 27.76%, 0.40%, 26.72% more efficient, for total emission-cost, 26.43%, 0.14% and 25.73%, for total driver-allowance-cost, 26.51%, 0.19% and 25.76%, and for sustainable cost, 27.29%, 0.32% and 26.35% more efficient than NNH, G-NNH and SA algorithms respectively.

6 Conclusion and Future Work

Pandemic has a significant influence on us both financially and physically. The economic component is important in addition to disposing waste timely and efficiently by preserving the environment and taking care of co-workers. The proposed novel algorithm has greatly reduced the distance travelled by the vehicles, total travel-cost, total emission-cost, total driver-allowance-cost and hence, sustainable cost. The Grouping algorithm combined with Simulated Annealing algorithm helps to reduce the parameters involved to a great extent irrespective of the number of waste disposal sites available.

The scope of this study can be further improved by inserting the concept of grouping algorithm to collect waste from multiple hospitals and disposing them altogether and hence reducing the cost further. In addition, various other meta-heuristic algorithms such as Tabu Search, Ant colony Optimization can be applied along with the proposed algorithm – grouping to obtain minimized sustainable-cost.

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