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A HYBRID ALGORITHM FOR TIME-DEPENDENT CAPACITATED VEHICLE ROUTING PROBLEM OPTIMIZATION

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A B S T R A C T

In the realm of logistic services, the Capacitated Vehicle Routing Problem (CVRP) presents a significant challenge. Recent metaheuristic algorithms have shown promising results in minimizing travel distances for hundreds or thousands of demand points. In this study, we introduce a novel approach that combines the Guided Local Search (GLS) metaheuristic with seed solutions obtained from the cheapest arc method, resulting in rapid optimization and remarkable efficiency. Our GLS-based algorithm is not only competitive with other meta-heuristics but consistently nears the Best-Known Solutions (BKS) for various problem instances. Furthermore, our study includes testing of the proposed algorithm on a variety of benchmark problems, and the results are indeed promising, indicating its potential to revolutionize routing optimization in a wide range of applications. Its efficacy is compellingly demonstrated through a successful case study of Water Sanitation Services Peshawar (WSSP), where we have minimized vehicle travel routes and costs, offering a strong, cost-effective solution with the potential for widespread application and impact.

1. INTRODUCTION

Generally speaking, the vehicle routing problem with time windows (VRPTW) is to select the optimal route while satisfying the requirements of all customers for the time windows (Gayialis et al., 2019). However, whether this arrival time is or is not within a time window is usually defined as a deterministic event (Kim et al., 2015). However, whether this arrival time is or is not within a time window is usually defined as a deterministic event (Arnold & Sörensen, 2019). With the acceleration of urbanization, the per capita motor vehicle ownership of urban population increases year by year, resulting in more and more serious problems such as traffic congestion and the decline of people's life satisfaction (Hannan et al., 2018).

Over the years, researchers have developed numerous approaches to address the complexities of the Vehicle Routing Problem, ranging from traditional heuristic algorithms to more sophisticated meta-heuristic methods (Kyriakakis et al., 2022). Heuristic algorithms are intuitive, easy-to-implement strategies that offer feasible solutions in a reasonable amount of time. One such widely used heuristic algorithm is the Cheapest Arc Method (CAM), which constructs initial routes based on the shortest distances between customers (Kytöjoki et al., 2007). On the other hand, meta-heuristic algorithms, like Guided Local Search, leverage high-level strategies to explore the solution space more effectively and refine the solutions obtained from heuristic approaches (Arnold & Sörensen, 2019).

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The combination of heuristic and meta-heuristic algorithms presents a powerful approach for solving VRP instances efficiently, enabling organizations like WSSP to optimize their vehicle routes, improve operational efficiency, and reduce overall costs. By harnessing the potential of VRP algorithms, WSSP can enhance its services, alleviate financial burdens, and contribute to the sustainable development of Peshawar's urban communities.

Urbanization is on the rise in developing countries, leading to a surge in population growth and an increased concern for negative environmental impacts (Mojtahedi et al., 2021). One of the critical challenges that come with urbanization is the management of household solid waste. Ineffective waste management and weak policies can lead to the degradation of valuable land resources, escalating land prices, and the creation of long-term environmental and human health problems. To address these issues and promote sustainable development, a well-designed and intelligent Solid Waste Collection (SWC) model is essential, considering various factors such as public health principles, legislative requirements, social aspects, economic considerations, and environmental impacts (Mojtahedi et al., 2021).

The SWC model comprises several functional elements, including waste collection, sorting, separation, transfer, and disposal, to address aesthetic, health, economic, energy conservation, and other environmental considerations. Among these elements, waste collection stands out as the most crucial factor in achieving sustainable SWC (Montemanni et al., 2005). Waste collection encompasses a diverse array of services, which include a wide range of operational and logistical tasks, the maintenance of equipment, crew readiness, as well as health and safety protocols (Makan et al., 2011). This sector is also characterized by considerable financial investments and is subject to extensive environmental regulations. Furthermore, consumer awareness and the availability of appropriate waste processing facilities are critical components for the efficient functioning of solid waste collection (SWC) systems (Hannan et al., 2018). Numerous research works have been published on the optimization of objectives in SWC (Qiao et al., 2020). Common optimization objectives include waste collection route optimization by reducing route length, time optimization, waste content, cost optimization, and environmental impacts. To achieve realistic optimization in this field, various constraints have been considered. These constraints may include vehicle capacity, time limitations, and characteristics of collection components, environmental and regulatory constraints, among others (Baldacci et al., 2012).

Globally, there is significant progress in the development of solid waste models. Several SWC models have been reported in the literature, focusing on lowering operating costs, labor hours, collection time, travel distances, and emissions (Baldacci et al., 2012). Various approaches, such as mixed-integer linear programming based exact methods, deterministic, stochastic, probabilistic, and fuzzy approaches, have been applied to establish SWC models (Erdelić & Caric, 2019). In recent years, metaheuristic approaches have gained popularity due to their simplicity, flexibility, and robustness in waste collection optimization. Additionally, the integration of intelligent technologies, such as geographical information systems (GIS), global positioning systems (GPS), remote sensing (RS), radio-frequency identification (RFID), image processing, and intelligent bins with sensors, have been introduced and applied to develop an effective SWC system (Žunić et al., 2018). These advanced technologies not only reduce maintenance costs and travel distances but also save time and reduce carbon emissions (Mojtahedi et al., 2021).

While progress is evident, several crucial issues related to SWC models need to be taken into consideration. SWC operations can vary among countries due to socio-economic factors, population size, financial status, road congestions, air pollution, human labor availability, and the number of collection vehicles (Mojtahedi et al., 2021). The waste collection process may also differ based on the type of buildings, such as residential and commercial areas. Additionally, the development of multiobjective functions and the feasibility of various technologies are considered as significant barriers to execute SWC model operations. Safety and waste disposal are also key issues that must be addressed in the SWC context (Makan et al., 2011). Implementing an optimal SWC system can contribute to multiple SDGs, such as environmental protection, public health preservation, and poverty reduction. Efficient SWC can play a crucial role in achieving SDGs related to responsible consumption and production, renewable energy, prevention of marine pollution, mitigation of greenhouse gas emissions, reduction of hazardous wastes, development of sustainable cities, and economic growth and poverty reduction (Hannan et al., 2020).

2. RELATED WORK

The time-dependent vehicle routing problem (TDVRP) was initially proposed by Malandraki and Dial (1996) to capture the congestion in a traffic network (Mart, Pardalos and Resende, 2018). Other authors constructed a model for time dependent conditions, which lays the foundation of many studies (Zhang et al., 2017). Malandraki and Dial (1996) solved TSP under time dependent conditions by dynamic programming (Salhi &Thompson, 2022). However, all of the above studies disrespect the First-In-First-Out (FIFO) principle, indicating that it is possible that a vehicle departing later arrives earlier. Ichoua et al. (2003) proposed a time-dependent model in which travel speed is a step function and travel time is a piecewise linear function (Bräysy and Gendreau, 2005). Fleischmann et al. (2004) proposed a method to construct time-dependent model in which the travel time was smoothed by a step function. These methods respect the FIFO principle. These two methods are widely used in studies afterwards. Then, Guo et al.

(2020) proposed the conception of path flexibility for TDVRP and solved it by CPLEX (Alsheddy et al., 2018). Çimen and Soysal (2017) extended the conception of TDVRP to stochastic conditions and proposed a heuristic to solve it (Bräysy and Gendreau, 2001). Recent Publication in the field of VRP using different solution methodology are presented in Table 1.

Table. 1. Recent Publication in the field of VRP using different solution methodology.

Author	TWVRP			Depot			Applications		Objectives		Solution Methodology		
	HTW VRP	STW VRP	CVRP	Single	Multi	Waste	Environment	Other	Distance	Cost	GA	ACO	GLS
Osman et al., 2022	✓				✓			✓	✓		✓		
Nura and Abdullah 2022		✓			✓			✓	✓				✓
Tan et al., 2021		✓		✓				✓	✓			✓	
Wu and Gao 2023	✓			✓				✓		✓		✓	
Liang and Luo 2022			✓	✓		✓			✓		✓		
Sukhpal and Kumar 2024		✓		✓		✓			✓			✓	
Li et al., 2023	✓			✓			✓		✓		✓		
Mishchenko et al., 2023	✓				✓		✓		✓				✓
Heng et al., 2023	✓			✓			✓		✓			✓	
Zhang et al., 2023	✓			✓			✓		✓			✓	

3. METHODOLOGY

Proposed Model:
Sets & Symbols:

N=Number of locations +{0} +{n}
Where 0 is depot location and n is set of demand points
D=Set of demand point (d)
A=Set of arcs (d,n)
K= Set of Vehicles [heterogenous vehicles]

Problem Formulation

Let G = (V, A) be a complete graph, where V = [1 ..., n] represents the set of locations, including the depot (location 0) and the waste collection bins (locations 1 to n). The set of arcs, A, contains all possible routes between locations (Toth & Vigo, 2002).

The Capacitated Vehicle Routing Problem (CVRP) with homogeneous fleets can be formulated as follows:

Decision Variables:

Let x_{ij} be a binary decision variable that takes the value 1 if vehicle i travels directly from location j to location k, and 0 otherwise. For every pair of locations $i, j \epsilon v$ and $i \neq j$, x_{ij} satisfies the following constraints (Mart et al., 2018):

$$xij = \begin{cases} 1 \\ 0 \end{cases}$$

$x_{ij} = 1$, if vehicle i travels from location j to location k
$x_{ij} = 0$, otherwise

Objective Function

The objective of the CVRP is to minimize the total distance traveled by the fleet of vehicles. The objective function can be formulated as follows (Salhi & Thompson, 2022):

$$\text{Minimize } \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} d_{ij} \cdot x_{ij}$$

Where d_{ij} represents the distance between locations i and j.

Constraints

1. Each demand point must be visited only once
$$\sum^{n}{}_{i=1} x_{ij} = 1, \text{ for } j = 1,2, \dots, n.$$
2. Each vehicle can only visit one location (including the depot) at a time.
$$\sum^{n}{}_{j=1} x_{ij} = 1, \text{ for } i = 1,2, \dots, n.$$

Sub tour elimination

$$\sum_{i,j \epsilon S} x_{i,j} \leq |S| - 1 \qquad \forall S \subseteq \{1 \dots n\}, \; i \epsilon \{1 \dots m\}$$

The total demand served by a vehicle must not exceed its capacity, denoted by Q.

$$\sum_{j}^{1} q_j \cdot x_{ij} \leq Q, \text{ for } i = 1,2, \dots, n.$$

are:

Represents the earliest time at which demand point j can be serviced (start of the time window).

I_j Represents the latest time at which demand point j can be serviced (end of the time window).

s_i Represents the time at which vehicle i arrives at demand point j.

Constraints

The CVRP with time constraints incorporates the following additional constraints

a) Time Window Constraint

The arrival time at each demand point j for each vehicle i should fall within the designated time window

$$e_j \leq s_i \leq l_j + M \cdot (1 - x_{ij}),$$

Where M is a sufficiently large constant. The term $M \cdot (1 - x_{ij})$ ensures that if $x_{ij} = 0$, the arrival time s_i is unrestricted. When $x_{ij} = 1$, the constraint enforces that the arrival time s_i should be between e_j and l_j.

b) Vehicle Departure Time:

The departure time from each waste collection bin j for each vehicle i should be later than the arrival time:

$$s_i \leq t_{ij} \leq s_k + M \cdot (1 - x_{ik}),$$

Where t_{ij} represents the time taken to travel from location j to location k. Similar to the time window constraint, the term $M \cdot (1 - x_{ik})$ allows for unrestricted departure time when $x_{ik} = 0$ (i.e., the vehicle does not travel from location j to k).

The above formulation incorporates time constraints into the CVRP, ensuring that each demand point is serviced within its time window while minimizing the total distance traveled by the fleet of vehicles. By incorporating time windows, the proposed solution will optimize the routes to adhere to specific time constraints,

Solution Approaches:

According to the mathematical model outlined earlier, an algorithm was developed based on arc guided local search. The specific heuristic to solve this CVRP with time window are provided below:

The Cheapest Arc Method (Heuristic)

The Cheapest Arc Method is a classical heuristic algorithm used to construct initial routes for the CVRP. The algorithm aims to connect the demand point in a manner that minimizes the overall cost. It operates by iteratively selecting the cheapest available arc (i.e., the lowest distance or cost) between two demand points until all demand points are connected. This process results in an initial seed solution that serves as a starting point for further optimization (Zadeh, 1973).

The heuristic nature of the Cheapest Arc Method allows for fast and straightforward route construction. While it may not guarantee the optimal solution, it provides a good starting point for more sophisticated metaheuristic approaches like the Guided Local Search.

Following are the stages involved in the Cheapest Arc Method:

1. Initialization: Start with a solution that has no customer nodes assigned to vehicles.
2. Calculate Costs: Compute the cost or distance for every possible arc between the depot and all unassigned customer nodes. Typically, the cost of an arc is proportional to the travelled distance or a combination of distance and other factors, such as time or capacity.
3. Select the Arc with the Lowest Price: Select the arc with the lowest price among all available arcs.
4. Check for Feasibility: Confirm that the selected arc is feasible and meets any constraints, such as capacity or time limitations. Ensure that the addition of the arc does not violate any constraints.
5. Incorporate the selected arc into the current solution by designating the customer node corresponding to the arc to a vehicle.

Repeat steps 3 through 5 until all customer nodes are assigned to a vehicle or until a predefined termination condition is met. This condition may be predicated on achieving a particular solution quality, a maximum number of iterations, or other stopping criteria. Return the final solution generated by designating all customer nodes to vehicles to form optimal routes.

The heuristic nature of the Cheapest Arc Method allows for fast and straightforward route construction. While it may not guarantee the optimal solution, it provides a good starting point for more sophisticated metaheuristic approaches like the Guided Local Search.

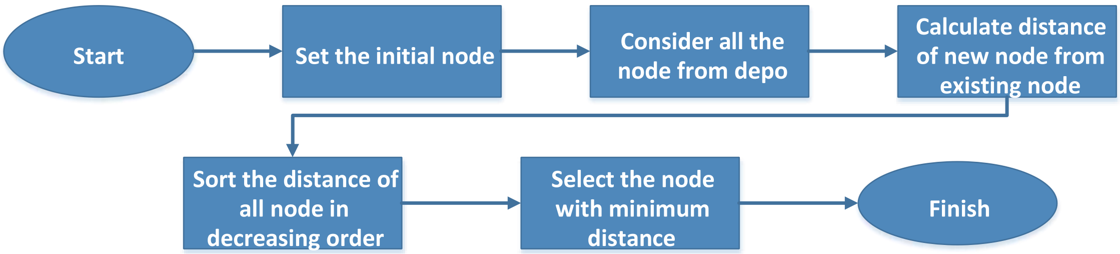


Figure 1. Flow chart of Cheapest Arc Method (CAM)

Guided Local Search (Metaheuristic)

The Guided Local Search (GLS) is a powerful metaheuristic that refines initial solutions obtained from heuristic methods. It systematically explores the solution space by iteratively improving upon the current solution through local search and diversification strategies. GLS introduces guiding mechanisms that bias the search towards more promising regions of the solution space, enhancing its ability to find near-optimal solutions efficiently (Alsheddy et al., 2018).

The GLS operates in two main phases:

a) Exploration: The algorithm conducts local search operations, exploring the neighborhood of the current solution to identify potential improvements. It evaluates nearby solutions by considering objective function values and adherence to problem constraints.

b) Intensification: During this phase, the GLS intensifies the search towards more promising regions. It leverages past experience and knowledge from the initial seed solution, obtained through the Cheapest Arc Method, to guide the search towards better solutions.

By iteratively repeating the exploration and intensification phases, the GLS gradually refines the initial solution, converging towards an improved and near-optimal solution for the CVRP.

The Pseudo code of Guided Local search is shown below.

Algorithm: Guided LocalSearch
Input:a path of all required input parameters
Output:Optimal route for waste collection bin

1. *Initialize SeedSolution <- selectInputFromCAM(lowestCostArc)*
InitializeParameters()
NumberOfIterations <- setNumberOfIterations()
RunningTimeOfAlgorithm <- setRunningTime()
Iteration <- 0
CurrentSolution <- Exploration(SearchForInitialPoint())

2. *While NOT OptimalRoutesGenerated AND within RunningTimeOfAlgorithm DO*

3. *Perform local search to find sub-optimal routes*
SubOptimalRoutes <- LocalSearch(CurrentSolution

4. *SubOptimalRoutes <- Perform 2opt & 3opt (SubOptimalRoutes)*

5. *SubOptimalRoutes <- Neighborhood Search (SubOptimalRoutes)*
OptimalRoutes <- GlobalSearch(SubOptimalRoutes)

6. *If a better solution is found during the search, update the current solution*

7. *If BetterSolutionFound(OptimalRoutes, CurrentSolution)*

8. *Then*
CurrentSolution <- UpdateCurrentSolution(OptimalRoutes)
Finalize and return the optimal solution found
Return CurrentSolution

Integration and Solution Refinement

The Cheapest Arc Method and Guided Local Search are integrated into a coherent solution approach. First, the Cheapest Arc Method constructs initial routes for the waste collection bins, resulting in a feasible seed solution. Next, the Guided Local Search takes over, fine-tuning the initial solution by iteratively optimizing the vehicle routes. During each iteration, the GLS explores neighboring solutions and intensifies the search based on the promising regions identified from the initial seed solution. This iterative process continues until a stopping criterion is met, such as a predefined number of iterations or convergence to a satisfactory solution.

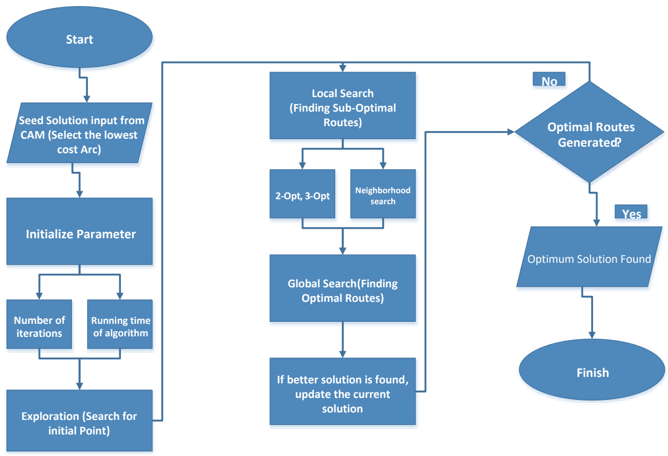


Figure 2. Flow chart of Guided Local Search (GLS)

Computational Testing

The testing phase using benchmark problems is a crucial step in evaluating the efficiency and effectiveness of the chosen algorithm for optimizing vehicle routes. The well-established benchmark instances, namely the Solomon's benchmark, will serve as representative and challenging test cases to assess the algorithm's performance.

The Solomon's benchmark features 200 customers and is widely used in the vehicle routing field due to its complexity and realism. The algorithm will be executed on this benchmark to evaluate its ability to handle moderately-sized problem instances. The evaluation will focus on key performance metrics, such as solution quality (measured by total distance traveled or total cost), computational time required to find solutions, and the algorithm's scalability in handling larger problem instances.

Through the evaluation of the algorithm across various benchmark instances, a comprehensive understanding of its strengths and weaknesses will be acquired. Discrepancies between the solutions obtained and optimal solutions will serve as indicators, directing potential enhancements to augment the algorithm's precision and efficiency. This iterative testing and improvement process is instrumental in refining the algorithm, ensuring superior performance in practical computational scenarios, specifically within the area of waste collection for real world case study analysis.

Experimental Results

Ant Colony Optimization appears to be the least effective in this benchmark testing. While ACO is a powerful algorithm for certain problems, its performance on the Solomon's benchmark instances may be limited due to the complex nature of the vehicle routing problem. The algorithm's probabilistic nature and use of pheromone-based exploration may result in less competitive solutions and slower convergence towards near-optimal solutions. Additionally, its scalability may be more limited compared to the other algorithms, struggling to handle larger benchmark instances efficiently.

The results of the benchmark testing provide valuable insights into the performance of different algorithms for optimizing vehicle routes in waste collection, using the Solomon's benchmark instances (Table 2). Based on the obtained results, the Guided Local Search (GLS) emerges as the best performer, followed by Simulated Annealing (SA), while Ant Colony Optimization (ACO) appears to be the least effective in this particular context.

Table 2. Chart of Algorithm Performance on Solomon's Benchmark Instances

Algorithm	Average Solution Quality	Computational Time	Scalability
Guided Local Search	Best	Fast	Good
Simulated Annealing	Second Best	Moderate	Moderate
Ant Colony Optimization	Worst	Slow	Limited

The results obtained from this benchmark testing will aid in making informed decisions regarding algorithm selection for vehicle routing optimization in real-world waste management scenarios. The best-performing algorithm, Guided Local Search, can be further applied and fine-tuned for Water and Sanitation Services Peshawar (WSSP) to optimize their waste collection routes effectively and efficiently, leading to reduced operational costs and improved waste management services.

Gehring & Homberger Benchmark

Simulated annealing vs ant colony optimization for 200, 400 and 800 customers are presented in Table 3, Table 4 and Table 5 retrospectively.

For 200 Customers

Table 3. Simulated Annealing vs Ant Colony Optimization for 200 customers

	Distance	Vehicles	Distance	Vehicles
r1_2_1	4903.41	20	6484.5	42
r1_2_2	4249.27	19	5949.2	36
r1_2_3	3852.92	19	5522.11	30
r1_2_4	3446.42	18	5105.4	25
r1_2_5	4484.1	19	6070.8	39
r1_2_6	3972.42	19	5618.2	33
r1_2-7	3536.5	19	4760.04	24
r1_2_8	3471.92	18	4329.73	22
r1_2_9	4062.52	19	6027.2	36
r1_2_10	3917.65	18	4834.6	26

Optimization for 200 customers

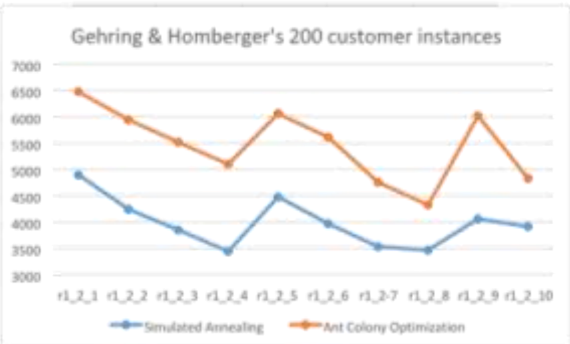


Figure 3. Gehring & Homberger's 200 customer instances

Gehring & Homberger's fo 200, 4000 and 800 customer instances are presented at Figure 3, Figure 4 and Figure 5 retrospectively.

For 400 customers

Table 4. Simulated Annealing vs Ant Colony for 400 customers

	Distance	Vehicles	Distance	Vehicles
r_1_4_1	10942.96	41	16743.5	87
r_1_4_2	9869.84	38	15226	68
r_1_4_3	8992.26	37	13372.06	56
r_1_4_4	8282.02	36	11142.27	42
r_1_4_5	10222.52	37	15858.5	75
r_1_4_6	9289.88	37	1473	65
r_1_4_7	9089.53	36	12685	52
r_1_4_8	8690.53	36	11081	41
r_1_4_9	9763	37	13666	59
r_1_4_10	9286.08	37	13083	55

Figure 4. Gehring & Homberger's 400 customer instances

For 800 customers

Table 5. Simulated Annealing vs Ant Colony for 800 customers

	Distance	Vehicles	Distance	Vehicles
r1_8_1	39005	81	39015	80
r1_8_2	37410	74	37068.48	74
r1_8_3	34549.82	73	34893	73
r1_8_4	32200	72	32329	81
r1_8_5	39130	73	38436	74
r1_8_6	36394	72	36563	73
r1_8_7	34556	72	36563	73
r1_8_8	31332	72	31332	72
r1_8_9	37721	73	37648	73
r1_8_10	37300	72	36264	73

Figure 5. Gehring & Homberger's 800 customer instances

4. CASE STUDY

Case Study Area and Data Collection:

A real-world case study is considered to validate the effectiveness of our proposed algorithm. The case study area is chosen to be Zone D of Water and Sanitation Services Peshawar (WSSP) in Peshawar, Pakistan for real-time investigation of their waste collection routing issues. The objective is to optimize the routes of their fleet of vehicles to efficiently collect waste from 109 bins located in Zone D. To achieve this, data was collected by visiting the locations, including offices to obtain information on the number of vehicles, their capacities, and the locations of bins. The data was initially in a large and unorganized format, but after data cleaning, it became suitable for analysis and optimization.

In the operational domain denoted as Zone D, the heterogenous vehicular fleet is employed by the WSSP namely:

- Compactors, characterized by a volumetric capacity of 6m^3.
- Suzuki vehicles, possessing a volumetric capacity of 3m^3.
- Bike loaders, distinguished by a volumetric capacity of 2m^3.

The pivotal function of each vehicle type revolves around the collection of waste emanating from a cumulative total of 109 bins strategically positioned within Zone D. The inherent capacities of these vehicles assume a paramount role in delineating the scope of bins that can be effectively serviced during a singular operational excursion.

There are two types of bins in Zone D

- Arm roll containers with a capacity of $2m^3$
- Small containers with a capacity of $0.8m^3$

It is crucial to note that each type of bin has specific capacity requirements. Therefore, careful consideration is essential when assigning these bins to vehicles for waste collection. Our proposed algorithm aims to guarantee the compatibility between selected bins and the capacities of the designated vehicles tasked with their service. For instance, a vehicle with a 2m^3 capacity (e.g., bike loaders) should be allocated to collect waste exclusively from arm roll containers (2m^3) and small containers (0.8m^3) that do not surpass its capacity during a single operational trip.

In the context of waste collection optimization, the algorithm must consider various factors. Given that vehicles possess different capacities and can collect from multiple bins in a single trip, the algorithm's primary objective is to optimize route planning. This optimization aims to maximize collection efficiency while respecting vehicle capacities.

Another critical aspect involves balancing the distribution of loads among vehicles to prevent overloading or underutilization. This contributes to an overall improvement in waste collection processes.

Additionally, adherence to time constraints specified by the municipal waste authority is imperative. Waste collection operations are permitted within the time window of 8:00 AM to 4:00 PM, as directed by regulatory guidelines. Integrating this temporal constraint into the vehicle routing problem ensures that waste collection activities align with operational hours. This not only enhances the efficiency of waste management but also ensures compliance with municipal waste authority regulations, thereby fostering a seamless and effective waste collection process**.** Result Analysis:

On the basis of proposed local guided search model was implemented on (computer details) with the following algorithm parameters (show table of parameters). Table 6 shows the optimal route generation for 109 bins.

Optimal Route Generation

Table 6. Optimum route generation

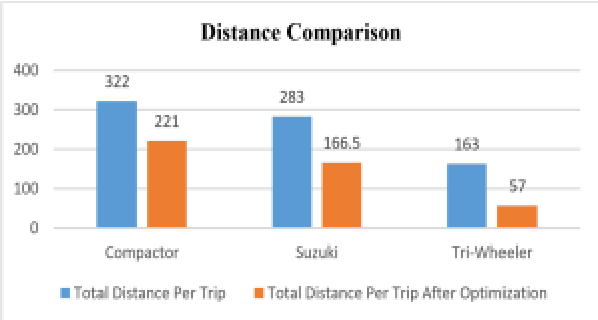
Optimal Route (Node Representation)	Total Route Distance (Km)	Total Route Load (m^3)
Route 0 [0, 64, 59, 62, 110]	15.981	6.0
Route 1 [0, 56, 42, 43, 110]	13.516	6.0
Route 2 [0, 50, 90, 48, 81, 110]	13.546	5.6
Route 3 [0, 63, 58, 60, 110]	17.596	6.0
Route 4 [0, 52, 51, 53, 110]	12.364	6.0
Route 5 [0, 85, 84, 93, 55, 94, 102, 110]	14.334	6.0
Route 6 [0, 2, 65, 44, 110]	7.648	6.0

Route 7 [0, 70, 80, 77, 86, 38, 83, 110]	17.149	6.0
Route 8 [0, 46, 47, 54, 110]	10.995	6.0
Route 9 [0, 109, 97, 87, 91, 92, 40, 110]	12.492	6.0
Route 10 [0, 88, 96, 45, 49, 110]	8.74	5.6
Route 11 [0, 39, 36, 35, 110]	12.436	6.0
Route 12 [0, 15, 57, 61, 110]	14.747	6.0
Route 13 [0, 69, 23, 19, 110]	10.631	6.0
Route 14 [0, 20, 14, 13, 110]	10.95	6.0
Route 15 [0, 22, 41, 16, 110]	10.394	6.0
Route 16 [0, 37, 33, 34, 110]	10.828	6.0
Route 17 [0, 4, 5, 3, 110]	7.134	6.0
Route 18 [0, 71, 67, 110]	14.526	2.8
Route 19 [0, 73, 1, 110]	18.22	2.8
Route 20 [0, 74, 29, 110]	9.322	2.8
Route 21 [0, 32, 98, 110]	7.18	2.8
Route 22 [0, 72, 21, 110]	13.453	2.8
Route 23 [0, 66, 79, 110]	8.995	2.8
Route 24 [0, 75, 17, 110]	9.986	2.8
Route 25 [0, 26, 105, 110]	9.478	2.8
Route 26 [0, 27, 76, 110]	9.805	2.8
Route 27 [0, 25, 78, 110]	9.249	2.8
Route 28 [0, 18, 101, 110]	9.38	2.8
Route 29 [0, 68, 100, 110]	7.188	2.8
Route 30 [0, 107, 28, 110]	7.663	2.8
Route 31 [0, 89, 7, 110]	6.903	2.8
Route 32 [0, 103, 106, 104, 110]	9.548	2.4
Route 33 [0, 6, 95, 110]	6.872	2.8
Route 34 [0, 24, 99, 110]	8.747	2.8
Route 35 [0, 82, 108, 110]	6.726	1.6
Route 36 [0, 10, 110]	7.031	2.0
Route 37 [0, 31, 110]	7.295	2.0
Route 38 [0, 11, 110]	7.093	2.0
Route 39 [0, 9, 110]	6.547	2.0
Route 40 [0, 12, 110]	6.508	2.0
Route 41 [0, 8, 110]	6.245	2.0
Route 42 [0, 30, 110]	8.892	2.0
Total Vehicles = 43	Total Distance = 444.333	Total Load = 170

Table 7. Service time calculation

Point	ai	bi	Demand	Service Time
0	8:00	12:00	2m3	46
1	8:00	13:30	2m3	60
2	8:00	16:00	2m3	51
3	8:00	12:00	2m3	60
4	8:00	13:30	2m3	56
5	8:00	16:00	2m3	51
6	8:00	12:00	2m3	47
7	8:00	13:30	2m3	51
8	8:00	16:00	2m3	46
9	8:00	12:00	2m3	60
10	8:00	13:30	2m3	53
11	8:00	16:00	2m3	56
12	8:00	12:00	2m3	59
13	8:00	13:30	2m3	57
14	8:00	16:00	2m3	60
15	8:00	12:00	2m3	46
16	8:00	13:30	2m3	57
17	8:00	16:00	2m3	48
18	8:00	12:00	2m3	58
19	8:00	13:30	2m3	52
20	8:00	16:00	2m3	45
21	8:00	12:00	2m3	52
22	8:00	13:30	2m3	58
23	8:00	16:00	2m3	49
24	8:00	12:00	2m3	60
25	8:00	13:30	2m3	48
26	8:00	16:00	2m3	48
27	8:00	12:00	2m3	47
28	8:00	13:30	2m3	49
29	8:00	16:00	2m3	53
30	8:00	12:00	2m3	54
31	8:00	13:30	2m3	60
32	8:00	16:00	2m3	53
33	8:00	12:00	2m3	60
34	8:00	13:30	2m3	60
35	8:00	16:00	2m3	45
36	8:00	12:00	2m3	47
37	8:00	13:30	2m3	46
38	8:00	16:00	2m3	52

39	8:00	12:00	2m3	53
40	8:00	13:30	2m3	60
41	8:00	16:00	2m3	50
42	8:00	12:00	2m3	53
43	8:00	13:30	2m3	52
44	8:00	16:00	2m3	57
45	8:00	12:00	2m3	54
46	8:00	13:30	2m3	58
47	8:00	16:00	2m3	50
48	8:00	12:00	2m3	52
49	8:00	13:30	2m3	59
50	8:00	16:00	2m3	46
51	8:00	12:00	2m3	52
52	8:00	13:30	2m3	49
53	8:00	16:00	2m3	46
54	8:00	12:00	2m3	50
55	8:00	13:30	2m3	53
56	8:00	16:00	2m3	60
57	8:00	12:00	2m3	49
58	8:00	13:30	2m3	46
59	8:00	16:00	2m3	56
60	8:00	12:00	2m3	56
61	8:00	13:30	2m3	45
62	8:00	16:00	2m3	52
63	8:00	12:00	2m3	54
64	8:00	13:30	2m3	51
65	8:00	16:00	2m3	59
66	8:00	12:00	2m3	53
67	8:00	13:30	2m3	51
68	8:00	16:00	2m3	58
69	8:00	12:00	0.8m3	44
70	8:00	13:30	0.8m3	36
71	8:00	16:00	0.8m3	43
72	8:00	12:00	0.8m3	45
73	8:00	13:30	0.8m3	43
74	8:00	16:00	0.8m3	45
75	8:00	12:00	0.8m3	35
76	8:00	13:30	0.8m3	41
77	8:00	16:00	0.8m3	43
78	8:00	12:00	0.8m3	41
79	8:00	13:30	0.8m3	39
80	8:00	16:00	0.8m3	41
81	8:00	12:00	0.8m3	44
82	8:00	13:30	0.8m3	42
83	8:00	16:00	0.8m3	42
84	8:00	12:00	0.8m3	42
85	8:00	13:30	0.8m3	39
86	8:00	16:00	0.8m3	39
87	8:00	12:00	0.8m3	36
88	8:00	13:30	0.8m3	39
89	8:00	16:00	0.8m3	39
90	8:00	12:00	0.8m3	45
91	8:00	13:30	0.8m3	44
92	8:00	16:00	0.8m3	45
93	8:00	12:00	0.8m3	41
94	8:00	13:30	0.8m3	38
95	8:00	16:00	0.8m3	38
96	8:00	12:00	0.8m3	38
97	8:00	13:30	0.8m3	38
98	8:00	16:00	0.8m3	43
99	8:00	12:00	0.8m3	35
100	8:00	13:30	0.8m3	40
101	8:00	16:00	0.8m3	42
102	8:00	12:00	0.8m3	45
103	8:00	13:30	0.8m3	45
104	8:00	16:00	0.8m3	35
105	8:00	12:00	0.8m3	43
106	8:00	13:30	0.8m3	44
107	8:00	16:00	0.8m3	39
108	8:00	12:00	0.8m3	37
109	8:00	13:30	0.8m3	45
110	8:00	16:00	0.8m3	40



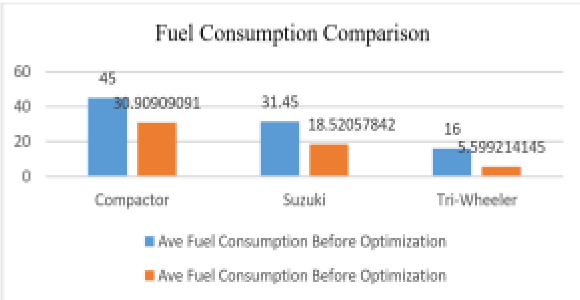


Figure 6. Distance and Fuel comparison

Service time calculation is presented on Table 7 and Distance and Fuel comparison at Figure 6.

5. CONCLUSION

The primary objective of our research was to develop a practical solution to address the challenges faced by Water and Sanitation Services Peshawar (WSSP) in optimizing their waste collection routes. By implementing the Cheapest Arc Method as the heuristic and the Guided Local Search as the metaheuristic, we successfully optimized the vehicle routes, minimizing the total travel distance from 768 km to 445 km. This reduction of approximately 42% in per trip distance traveled signifies a remarkable improvement in the waste collection process.

Furthermore, our optimization efforts have demonstrated the efficiency of the algorithm in allocating resources effectively. Specifically, we observed a 31% reduction in the distance traveled by compactors, a 41% reduction in the distance traveled by Suzuki vehicles, and an impressive 65% reduction in the distance traveled by bike loaders. This optimized resource allocation ensures that each type of vehicle is utilized optimally, leading to cost savings, reduced fuel consumption, and minimized wear and tear on the fleet. The success of our research extends beyond just route optimization. By minimizing travel distances, our solution also contributes to a greener and more sustainable waste management system, significantly reducing the carbon footprint associated with waste collection activities.

In conclusion, our research contributes a practical and effective solution for optimizing waste collection vehicle routes, making significant strides towards improving waste management services in Zone D of Peshawar. We are confident that the outcomes of this research will play a vital role in enhancing waste management practices, resource utilization, and sustainability efforts, ultimately benefiting the health and well-being of the urban community as a whole

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