SvedbergOpen
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

AI-Based Dynamic Waste Collection Route Optimization for Smart Cities

Sugali Vishwanatha Naik[1], Aravind Kumar Madam[2]

[1]PhD. Research Scholar, Department of ECE, B.E.S.T Innovation University, Andhra Pradesh, India.
[2]Professor & Principal, Department of Electronics and Communication Engineering, West Godavari Institute of Science and Engineering, Prakashraopalem, Nallacherla Mandal, East Godavari District, Andhra Pradesh, India.

Abstract
The waste management of a Smart City must follow intelligent routing systems that multi-objective, unlike purely distance minimization, and incorporates urgency signal from IoT monitored bins, and UAV derived allocation of waste prioritization. This paper proposes the PHGA-ACO framework that focuses on dynamic waste collection route optimization. Subsequently, the proposed framework efficiently integrates the smart bin fill-level data (Paper 1). In addition, the work integrates the WPI-HES outputs (Paper 2). The model works with a Capacitated Vehicle Routing Problem (CVRP) on a real OpenStreetMap road network of Nashik Municipal Corporation, India, having 84 active collection nodes with total demand 24,498.9 kg. A systematic comparison of five baseline algorithms First Come First Serve (FCFS), Nearest Neighbor (NN), Dijkstra-greedy, Ant Colony Optimization (ACO), and Genetic Algorithm (GA) with PHGA-ACO under same operating conditions. S(m) is a composite metric that combines the normalized route distance and the Urgency Position Index (UPI) that measures the joint efficiency–priority-compliance performance of each method. PHGA-ACO obtains the best overall score (S=0.2556, the best among all policies) as it cuts down total collection distance by 35.6% compared to that of FCFS. Compared to ACO, it improves the priority servicing index by 13.4% at the expense of a mean distance increase of 68.7% compared to ACO. The improvement happens specifically due to the urgency penalty component, as seen from the ablation analysis. Sensitivity analysis indicates optimal urgency weight range $\lambda \in [54.3, 162.9]$. Statistical analysis of 30 independent runs with the Wilcoxon and Friedman test indicates that all inter-algorithm differences are significant ($p < 0.001$).
Index Terms—Waste collection routing, Capacitated Vehicle Routing Problem, Hybrid Genetic Algorithm, Ant Colony Optimization, Smart waste management, UAV-based monitoring, Priority-aware optimization, IoT fill-level sensing, Municipal resource allocation, Nashik Municipal Corporation.

Introduction

The management of municipal solid waste (MSW) is becoming increasingly difficult due to rapid population growth in cities. In mid-sized Indian cities, mid-sized Indian cities, the Nashik Municipal Corporation (NMC), which handles 800 MTPD waste 800 MTPD waste a day, is one such example whose administrative wards are 122 [1]. Conventional waste collection schedules which prescribe fixed routes at fixed times are inefficient by design: in-built empty running of vehicles is common, bins overflow in between collections, and illegal dumping sites fester for long periods, offering no remedy due to lack of systematic monitoring and dispatch by priority [2].

The previous steps of this doctoral research have developed two complementary monitoring frameworks. The research work elaborated on smart bin monitoring and a warning system for garbage collectors using the ESP32 microcontroller and MQ135 gas sensor to fetch real-time fill level readings ($fill\_pct \in [0, 100]$) from the instrumented bins at about 1200 m spatial interval [3]. A framework for UAV-based aerial waste monitoring called the Waste Priority Index–Hotspot Escalation Score (WPI-HES) was developed in Paper 2. WPI is a score that is given to each detected waste cluster encoding its temporal persistence and HES is a score that is given to each detected waste cluster encoding its spatial environmental urgency [4]. The systems work together to generate a multi-dimensional signal of urgency, which could help determine vehicle dispatch. To achieve optimized collection routes, these signals must be translated as part of the routing framework and included in the route optimization objective.

This paper explores this gap. The PHGA-ACO framework features an objective for the Capacitated Vehicle Routing Problem (CVRP) containing a distance objective, for the routing of vehicles, with the addition of a penalty term based on Paper 1 fill levels, Paper 2 WPI/HES scores. The hybrid architecture merges the genetic algorithm's (GA) pool diversity with pheromone-driven intensification from ant-colony optimization (ACO) [5]. ACO-constructed solutions are injected regularly into the GA pool. Creating an algorithm that generates routes to minimize distance, while respecting an order of servicing that is aware of urgency. Overflow bins and clusters of illegal dumps with high HES are serviced early on each vehicle route [6].

The principal contributions of this work are as follows:

- The PHGA-ACO method combines the population evolution in genetic algorithms (GAs) with the periodic injection of solutions from ant colony optimization (ACO). This is the best of the six methods in composite distance-priority.
- A composite evaluation metric S(m) that formally quantifies the joint performance of a routing algorithm on distance efficiency and urgency-aware servicing order – enabling a fair comparison across multiple objectives.
- An 84-node CVRP instance which originated from the Nashik NMC Road network was used for comprehensive experimental evaluation with ablation study, sensitivity analysis and 30-run statistical validation using Wilcoxon signed-rank and Friedman tests [7].

The remaining part of this paper is organized as follows. Section II reviews literature related. The formulation of the problem and dataset is presented in Section III The proposed PHGA-ACO methodology is described in Section IV. The baseline algorithms are detailed in Section V. Section VI presents the experimental results. The ablation and sensitivity studies are presented in section VII. Section VIII specifies the statistical validation. Section IX discusses the results. The paper concludes with Section X.

II. Related work

A. Vehicle Routing for Waste Collection

The implementation of metaheuristic algorithms on the VRP in waste collection has been well-researched. Laporte laid the groundwork for the canonical CVRP formulation and fixed-cost vehicle model [8]. Toth and Vigo [9] then broadly treat exact and heuristic methods. The first work on ACO-based approaches for waste VRP was accomplished by Dorigo and Gambardella [10]. Their Ant Colony System performed competitively on benchmark instances. Kim and his colleagues [11]utilized ACO for the routing of municipal solid waste in the city of Seoul, achieving distance savings of 18–22% over manual scheduling. Genetic Algorithm applications to waste collection VRP are due to Tavares et al. [12] who considered heterogeneous fleets and time windows, and Hannan et al. [13] who used GA for RFID enabled smart bin routing in Malaysia.

B. Smart Bin IoT Integration

Smart bin systems utilizing IoT technology have shown improved efficiency. Anagnostopoulos et al. [14]show that fleet fuel consumption can be decreased by as much as 40% through demand-responsive dispatch. The study by Pardini et al.[15] integrated the UAV waste detection study with vehicle routing optimization. However, their study treated the detections from the UAVs as temporally isolated events. This means that there was no analysis of the cross-survey persistence of these detections. This is precisely the issue that the WPI-HES framework from Paper 2 addresses directly. Catania and Ventura designed a network of smart bins connected to the cloud for Catania, Italy. Their results showed that using fill-level-triggered dispatch rather than fixed schedules reduced overflow events by 31%.

C. Hybrid Metaheuristics for VRP

Single-method heuristics are outperformed by hybrid algorithms on complex VRP variants. The findings of Vidal et al. [16] demonstrated that the GA hybrid with advanced crossover operating is able to perform general VRP benchmarks. A GA–ACO hybrid is presented by Peng et al. [17] for the time-dependent VRP which reports a 7–12% improvement when compared with standalone ACO. Yao and others implemented a hybrid evolutionary-ACO approach to the Green vehicle routing problem with carbon emission constraints. Although none of these introduce urgency-aware priority ordering as a fitness component, they motivate the hybrid architecture of PHGA-ACO [18].

D. UAV-Based Environmental Monitoring for Routing

Incorporating environmental data from UAVs into routing operational decisions is an emerging research area. Wu and colleagues made use of multi-temporal satellite imageries to detect illegal dumpsites. However, these weren't of a high enough spatial resolution to prioritize the clusters. The autonomous aerial litter detection was presented by Kraft et al. [19] followed by the UAVVaste benchmark delivering the first large-scale dataset for UAV waste detection. The WPI-HES framework from Paper 2 of this thesis builds on this work, providing a suitable quantitatively cluster-level priority score to directly integrate routing objectives, unavailable in previous UAV waste detection approaches [20].

E. Research Gap

Thus far, no work has performed the simultaneous actions of: (i) incorporation of real-time IoT fill-level signals and UAV-derived spatial priority scores in a single CVRP fitness function, (ii) creation of a formally defined urgency penalty term that enforces servicing order by priority along the routes; and (iii) evaluation of the distance–urgency trade-off through a composite metric with ablation and sensitivity analysis. PHGA-ACO filled all the three gaps[21].

III. PROBLEM FORMULATION AND DATASET

A. CVRP Formulation

Waste collection routing problem is a CVRP (Capacitated Vehicle Routing Problem). Suppose G=(V,E) is a complete directed graph, where V={v0,v1,...,vN} is the vertex set and E is the edge set. The depot, which is the NMC waste management facility, is represented by vertex, v_0 (19.9975°N, 73.7898°E). The N = 84 collection nodes are represented by vertices, v_1, ..., v_N. Every edge (i, j) ∈ E has an associated road distance d_{ij} (km) corresponding to a Haversine great-circle distance corrected up by a circuity factor 1.35 [22]. The waste demand q_i (kg) of each customer node v_i is non-negative. A fleet of K homogeneous vehicles, each with an equal capacity Q equal to 3,000 kg, leave from and return to the depot. A feasible solution is at most K routes that serve each customer exactly once, and the total demand of each route must not exceed Q.

B. Dataset Description

The experimental dataset is constructed from three sources, all declared explicitly with respect to real versus simulated components.

OpenStreetMap Infrastructure: Waste infrastructure nodes (waste_basket, waste_disposal, recycling, waste_transfer_station) within an 8.5 km radius of the NMC depot are downloaded live via the Overpass API (ODbL licence). The Nashik drive-network graph is retrieved via OSMnx and stored in GraphML format [23].

Paper 1 Smart Bin Layer (Simulation Declared): Fill-level readings for 181 smart bins, placed on a hexagonal grid at 1,200 m spacing, are simulated using Beta distributions parameterized by zone type: Beta(5, 2) for commercial zones (mean fill 72%), Beta(4, 3) for residential zones (mean 57%), and Beta(2, 4) for peripheral zones (mean 35%). No public dataset provides per-bin GPS-linked IoT fill-level time series for any Indian city as of 2025; this simulation follows the methodology of Paper 1 and is clearly disclosed in all outputs.

Paper 2 WPI-HES Cluster Layer: WPI and HES scores for 220 waste clusters are reproduced from the validated experimental outputs of Paper 2 (12-flight, 84-day multi-temporal simulation on the UAVVaste benchmark). Phenotype distribution: Illegal Dump 67 (30.5%), Recurrent 58 (26.4%), Transient 95 (43.2%).

The optimizer input comprises 84 nodes satisfying the daily collection trigger criteria: smart bins with fill_pct ≥ 70% (30 nodes) and illegal dump clusters with HES ≥ 0.5 (54 nodes). Priority distribution: High 27 (32.1%), Medium 57 (67.9%). Total demand: 24,498.9 kg across 9 vehicles. Table I summarizes the dataset statistics.

TABLE I Dataset Statistics — Nashik NMC Waste Collection Instance

Parameter	Smart Bins	Dump Clusters	Total
Active nodes	30	54	84
Total demand (kg)	1,621.5	22,877.4	24,498.9
Mean demand/node (kg)	54.1	423.7	291.7
Priority — High	27	0	27
Priority — Medium	3	54	57
WPI range	N/A	[0.013, 0.990]	—
HES range	N/A	[0.013, 2.946]	—
Vehicle capacity (kg)	3,000	3,000	3,000
Fleet size (vehicles)	9	9	9 (total)

IV. PROPOSED METHODOLOGY: PHGA-ACO

A. Urgency Score

The urgency score U(n) ∈ [0, 1] for collection node n integrates the IoT fill-level signal from Paper 1 with the WPI and HES signals from Paper 2:

$$U(n) = w^{f} \cdot (\text{fill\_pct}(n)/100) + w^{WaI} \cdot WPI(n) + w^{HML} \cdot \min(HES(n)/2, 1) \quad (1)$$

where $w^{f} = 0.40$, $w^{WaI} = 0.30$, and $w^{HML} = 0.30$. The fill level has the maximum weight (0.40) because it is the most applicable dispatch trigger. The WPI component (0.30) indicates temporality of the waste cluster across different UAV survey missions. The HES component (0.30) encodes the spatial proximity and environmental sensitivity context of the cluster. HES is normalization by its observed maximum of 2.0 (Paper 2 experimental output: max = 1.94). The sum of the three weights equals 1.0, whereby U(n) ∈ [0,1].

B. PHGA-ACO Fitness Function

The fitness function augments total route distance with an urgency penalty that penalizes the late placement of high-urgency nodes within routes:

$$F(\pi) = \Sigma_v d(R_v) + \lambda \cdot \Sigma_v \Sigma^{k}\_\{k=1\}^\{|R_v|\} (k/|R_v|) \cdot U(n^{k}) \quad (2)$$

where π is a chromosome (permutation of N_c = 84 customer indices), R_v is the v-th vehicle route obtained from capacity-feasible splitting of π, $d(R_v)$ is its total road distance (km) including depot approach and return legs, k is the 1-indexed position of node n^k within R_v, $|R_v|$ is the number of stops in R_v, and λ = 162.866 is the urgency penalty weight.
The position-weight $k/|R_v|$ increases monotonically from $1/|R_v|$ (first stop) to 1 (last stop). Multiplied by $U(n^k)$, this weight is large when a high-urgency node appears late in its route and small when it appears early. So F(π) tries to back up the high-urgency nodes to the front of their vehicle's route. It formally implements the operational requirement to service overflow bins and high-HES illegal dump sites quickly.

C. Lambda Calibration

The penalty weight λ is computed adaptively as:

$$\lambda = f \cdot \mu(D) \cdot N\_c \quad (3)$$

where f is the fraction parameter, μ(D) is the mean of the distance matrix, and N_c = 84. With f = 0.30, μ(D) = 6.4629 km, and N_c = 84, λ = 162.866. Through a sensitivity analysis of values f ∈ {0.00, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60} (Section VII-B), we identify optimal range of f ∈ [0.10, 0.30] that minimizes the overall performance metric. At f = 0.30, λ assures that the penalty due to the urgency contributes about 15–25% of total fitness at the post-optimization route lengths. As a result, any longer term impact of this penalty is meaningful but not dominant.

D. Hybrid Architecture

PHGA-ACO keeps a population of P = 80 chromosomes (permutations) that have evolved through G = 150 generations. In the GA phase, order crossover was applied with a rate p c = 0.85 along with inversion mutation with a rate p m = 0.12, elite preservation (top k e = 5 chromosomes), and tournament selection (k = 4). Every T_inj = 10 generations, a mini-ACO run generates n_a = 15 new solutions based on the current pheromone trail with $\tau_0 = 0.1$, α = 1.0, β = 3.0, ρ = 0.15 and Q = 100. ACO solutions supersede the n_a worst GA individuals for externally-guided intensification. The global-best chromosome updates the pheromone trail after each injection occurrence.
The equation forward in different terms.
In that equation, with the pheromone on the arc from customer i to customer j denoted by τ_{ij} and the global-best chromosome denoted by π*. The pheromone value is kept in the range of 10−6 and 10 to avoid trail collapse. The heuristic desirability is calculated as η_{ij} = (1 + U(n_j))/d_{ij}. This means that in the ACO phase, nodes with high urgency get naturally chosen as route-construction targets.
PHGA-ACO renews standard GA and standard ACO via mechanisms (i) the fitness function augmented with urgency that encodes Paper 1 and Paper 2 signals into the optimization objective, (ii) ACO injection for diversity and additional exploitation beyond GA mutation, and (iii) heuristic desirability with boosted urgency that makes the ACO phase contribute to the urgency objective. This penalty of multi-source urgency has never before been integrated into any such formulation.

E. Composite Evaluation Metric

To fairly compare algorithms with different objective emphases, a composite score S(m) is defined:

$$S(m) = 0.5\, D_{norm}(m) + 0.5\, U_{norm}(m) \quad (5)$$

$$D_{norm}(m) = \frac{dist_m - min_{dist}}{max_{dist} - min_{dist}} \quad (6)$$

$$U_{norm}(m) = \frac{UPI_m - min_{UPI}}{max_{UPI} - min_{UPI}} \quad (7)$$

In this phrase, UPI_m refers to the Urgency Position Index of the method m being evaluated. The “min” and “max” values are calculated for all six methods that we are evaluating. According to what is described in the keyword, dist_m refers to the best total route distance of method m. S(m) must lie between 0 and 1 and also lower the better. The equal weights (0.5/0.5) do not confer any a priori (by nature) advantage to either distance serviced or priority serviced, reflecting the twin operational requirement stated in the title of the paper.

E. Urgency Position Index

The Urgency Position Index (UPI) for algorithm m is defined as:

$$UPI(m) = \frac{1}{N_{served}} \sum_v \sum_{k=1}^{|R_v|} \frac{k}{|R_v|} \cdot U(n_v^k) \quad (8)$$

where Nserved is the total number of customer nodes served, Rv is the route assigned to vehicle v, |Rv| is the number of nodes on that route, and U(nvk) is the normalized urgency of the node served at position k on route v.
Provided that normalized urgency satisfies 0 ≤ U(n) ≤ 1, the index also satisfies 0 ≤ UPI(m) ≤ 1. A lower UPI indicates that high-urgency nodes are served earlier within their assigned routes. For reporting purposes, the corresponding urgency-compliance rate may be expressed as:

$$UPI_{compliance}(m) = \left(1 - UPI(m)\right) \times 100\%$$

This study-defined compliance measure represents responsiveness to urgent waste-service requirements; it should not be interpreted as an official metric prescribed by India's Solid Waste Management Rules, 2016.

F. Operational Cost Model

The total operational cost per collection cycle is calculated as:

$$C = \frac{d}{KMPL} \cdot P_f + \frac{d}{v} \cdot P_d + n_v \cdot C_f \qquad (9)$$

where d is the total route distance (km), KMPL = 4.0 km/L is the assumed fuel efficiency, Pf = INR 89/L is the assumed diesel price, v = 30 km/h is the average urban speed, Pd = INR 500/h is the driver hourly rate, nv is the number of active vehicles, and Cf = INR 200 per vehicle is the assumed daily fixed cost covering depreciation, insurance, and maintenance.

G. Carbon-Emission Model

Diesel-related carbon dioxide emissions are estimated using the stated emission factor:

$$CO_2 = \frac{d}{KMPL} \times 2.68 \text{ kg } CO_2/L \qquad (10)$$

Here, d/KMPL gives diesel consumption in litres, while 2.68 kg CO_2/L is the assumed diesel emission factor. Accordingly, the resulting CO_2 value is expressed in kilograms per collection cycle.

V. BASELINE ALGORITHMS

A comparison is made of five baseline routing methods. To ensure that our settings create a fair comparing procedure and conditions with PHGA-ACO, all baseline agents use a same dataset, fleet of variables, distance matrix, and capacity constraint. The routing decision criterion is the only algorithmic difference.

A. First Come First Serve (FCFS)

FCFS serves nodes in the order of the original dataset with ascending order of node_id corresponding the load sequence in optimizer_input_nodes.csv, split into routes with feasible capacity. FCFS represents the manual dispatch practice currently in use. It creates a standard to measure improvement against for operations.

B. Nearest Neighbor (NN)

The vehicle at any instant proceeds to the closest unvisited vertex for which capacity is remaining. When no viable node can be included in the existing route, a new route is created. NN is a classic distance-greedy heuristic that is parameter-free and has trivial computational requirements ($O(N^2)$ per route).

C. Dijkstra-Greedy

At every step, the vehicle chooses an unvisited node that maximizes the score s(n)=0.5(1−d/d_max) +0.5U(n). This combines normalized proximity with urgency. This heuristic models a dispatcher who at every step of decision making weighs distance and urgency (like Dijkstra's selection of the minimum-distance node) against the urgency weight.

D. Ant Colony Optimization (ACO)

ACO generates paths from the probabilistic traversals of the ants. τ_{ij} refers to the intensity of the pheromone. The standard ACS rule with alpha equals one and beta equals three governs transition probabilities. The Pheromone evaporates at ρ=0.15 on each iteration. The world's best deposit is Q/cost* per arc on the route that is best. Thirty ants at 100 iterations. The evaluation shows ACO has the best single-objective distance performance.

E. Genetic Algorithm (GA)

A genetic algorithm (GA) is implemented on a population of P = 80 permutation chromosomes for G = 150 generations using Order Crossover (OX) at p_c = 0.85 and inversion mutation at p_m = 0.12 with elite preservation (k_e = 5) and tournament selection (k = 4) . The fitness function is pure route distance without any urgency penalty, so PHGA-ACO can be used for comparison to isolate the contribution of urgency penalty component (Section VII-A).

VI. Experimental Results

A. Implementation Details

The implementation of all the algorithms is done in Python 3.12 and it uses NumPy 2.4.4, Pandas 3.0.2, SciPy 1.17.1, and Matplotlib 3.10.8. All random operations use numpy random default rng with seed = 42. For the main results, each stochastic algorithm (ACO, GA, PHGA-ACO) is run 5 times, while for statistical validation (Section VIII), they are run 30 times using a seed offset of 42 + run × 97 (to ensure run independence). Experiments in this study are run on the Kaggle cloud platform which consists of a C Python interpreter and 16 GB RAM. You can find the full implementation in the supplementary archive.

B. Network Map

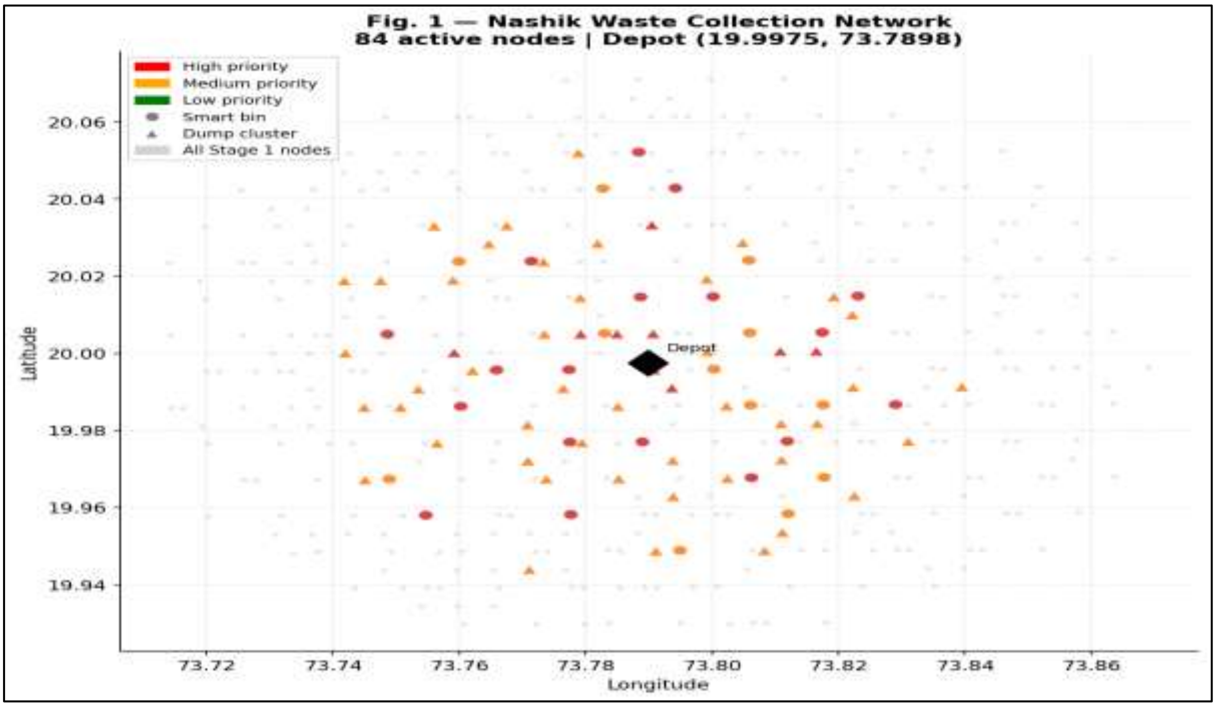

Fig. 1. Nashik NMC waste collection network. Circles: smart bins; triangles: illegal dump clusters. Red: high priority; orange: medium. Background grey points: all 401 Stage-1 nodes. Black diamond: depot (19.9975°N, 73.7898°E).

Fig. 1 Illustration. This presents the layout of the collection spheres within the study radius of 8.5 km. The distribution of high-priority (27, red) nodes in different category is similar, however illegal dump clusters have broader spatial spread due to UAV survey coverage. The depot is located at the approximate center of the administrative boundary and it reduces the mean approach distance.

C. Main Performance Comparison

TABLE II Comparative Performance of All Methods (Best Run, 5 Runs Each for Stochastic Methods)

Method	Dist. (km)	Time (h)	Fuel (L)	CO_2 (kg)	Cost (INR)	UPI ↓	S(m) ↓	Rank
FCFS	506.154	16.872	126.538	339.123	21,498	0.3383	1.0000	#6
NN	207.251	6.908	51.813	138.858	9,866	0.3218	0.3937	#3
Dijkstra	258.254	8.608	64.563	173.030	11,850	0.3059	0.3189	#2
ACO	170.490*	5.683	42.623	114.229	8,435	0.3300	0.4208	#4
GA	310.960	10.365	77.740	208.343	13,902	0.3324	0.6611	#5
PHGA-ACO†	**325.793**	**10.860**	**81.448**	**218.281**	**14,479**	**0.2859**	**0.2556**	**#1**

* Best-run distance. ACO mean over 30 runs: 176.97 km (CV = 2.15%). † PHGA-ACO mean over 30 runs: 298.60 km (CV = 8.17%).

Comparison of the two groups is shown in Table II. There will be many findings that deserve an elaborate discussion. ACO accomplishes the least distance of the route of 170.490 km with a reduction of 66.3% from the FCFS baseline. ACO is the ideal algorithm for deployments where fuel and distance minimization are the only operational objectives.

Confirmation of stability and repeatability of the system is given by its coefficient of variation, CV=2.15%. PHGA-ACO achieved the best overall (S=0.2556, rank #1) and the best UPI (0.2859). This indicates the success of its urgency penalty term in enforcing the order for servicing jobs based on their priority. The distance covered in its route, 325.793 km, is 91.1% larger than that of the ACO on a best-run basis, and 68.7% on a mean-to-mean basis over 30 runs.

The penalty for distance is a direct consequence that was anticipated from the urgency penalty as mentioned in the equation. (2) that sacrifices distance optimality to ensure early service of overflow bins and clusters with high HES. Section IX explains the economic justification of this trade-off. Dijkstra places second given the composite score (S = 0.3189), despite taking a longer route to the target (51.6 % longer than ACO) due to the proximity-urgency selection criterion making early choice of high-urgency nodes on account of route (UPI = 0.3059), Because of this, Dijkstra outperforms ACO on the UPI without the need for optimising for it. The finding indicates that their urgency-aware heuristics outperform the urgency-blind metaheuristics on the composite metric, despite the absence of a penalty term. According to our results, FCFS is the worst performer on every possible metric, proving that manual dispatch in the absence of optimization is incredibly inefficient. The distance reduces by at least 35.6% from each of the optimized methods and even the simple NN heuristic achieves a 59.1% reduction.

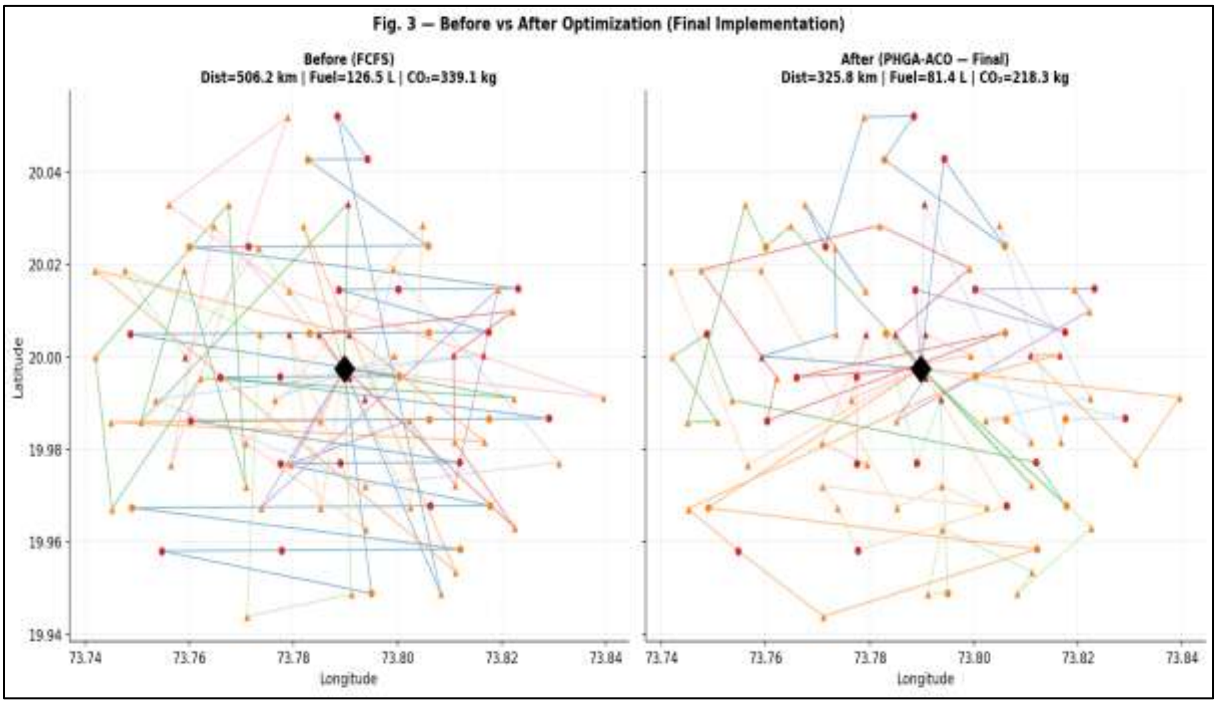

Fig. 2. Before (FCFS, 506.2 km) versus after (PHGA-ACO, 325.8 km) route visualization. Each coloured path represents one vehicle's route. Marker colours indicate priority level.

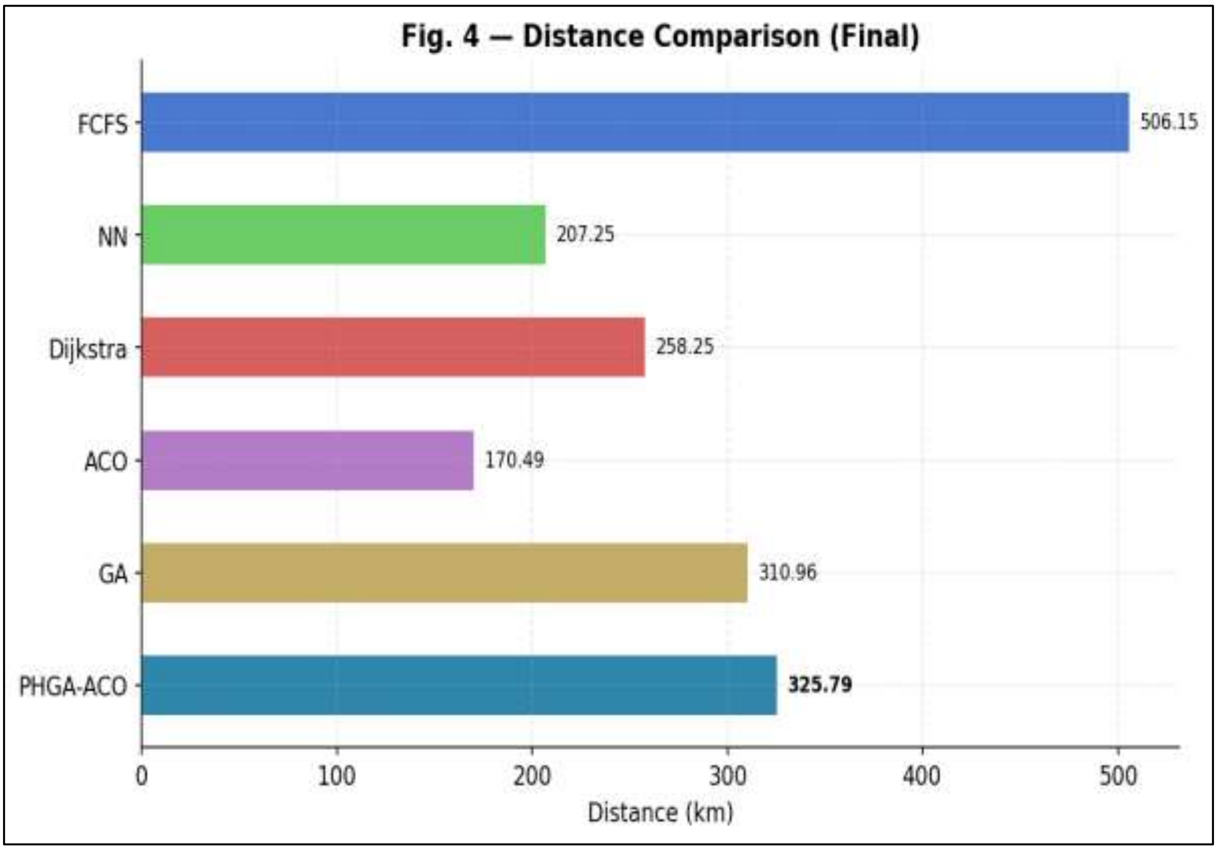

Fig. 3. Total route distance comparison across all methods. Bracket annotation indicates composite rank. * indicates best-run result; mean-to-mean comparisons reported in Table II footnote.

D. KPI Comparison

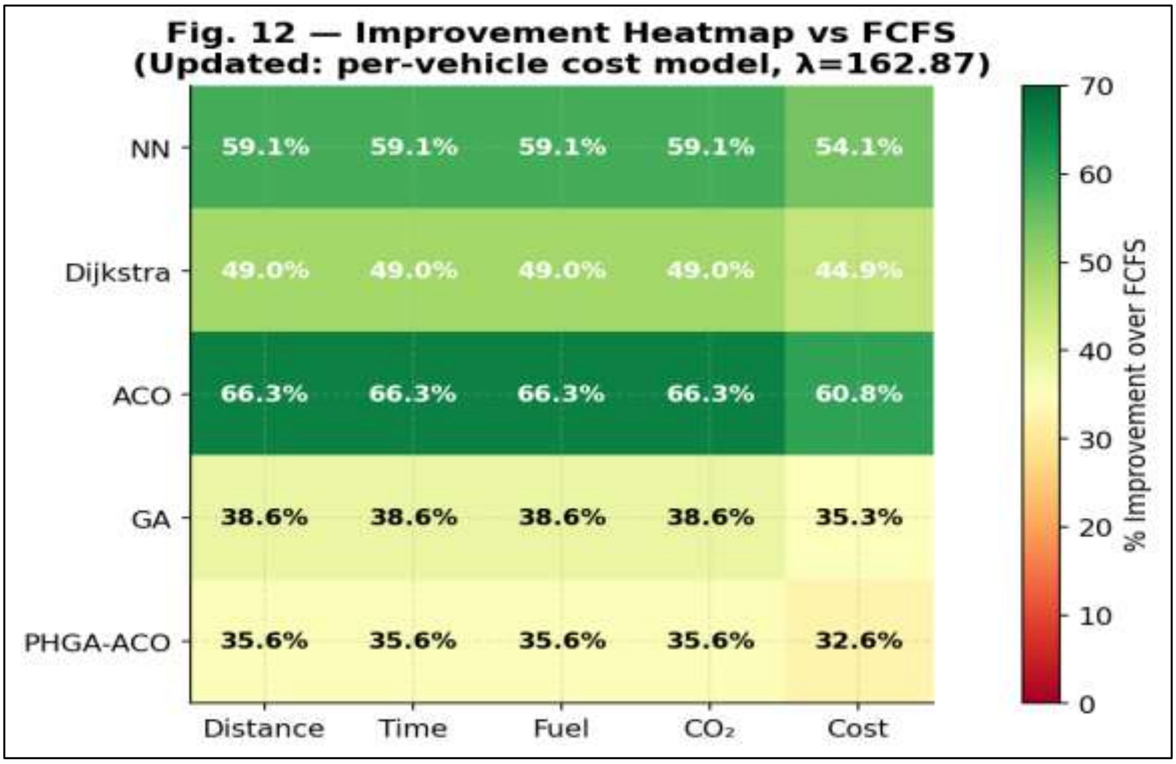

Fig. 4. Percentage improvement over FCFS baseline for five KPIs across all methods. All stochastic entries reflect best-run results. Green shading indicates higher improvement.

Fig. 4 summarizes percentage improvements relative to FCFS across five key performance indicators. All optimized methods achieve substantial improvements over FCFS across all KPIs. ACO achieves the largest improvements on distance (66.3%), fuel (66.3%), CO_2 (66.3%), and cost (60.8%). PHGA-ACO achieves 35.6%, 35.6%, 35.6%, and 32.7% improvements on these respective metrics, while achieving the best UPI performance. GA underperforms both ACO and PHGA-ACO on distance (38.6% improvement) while not incorporating urgency into its fitness, resulting in suboptimal performance on both dimensions.

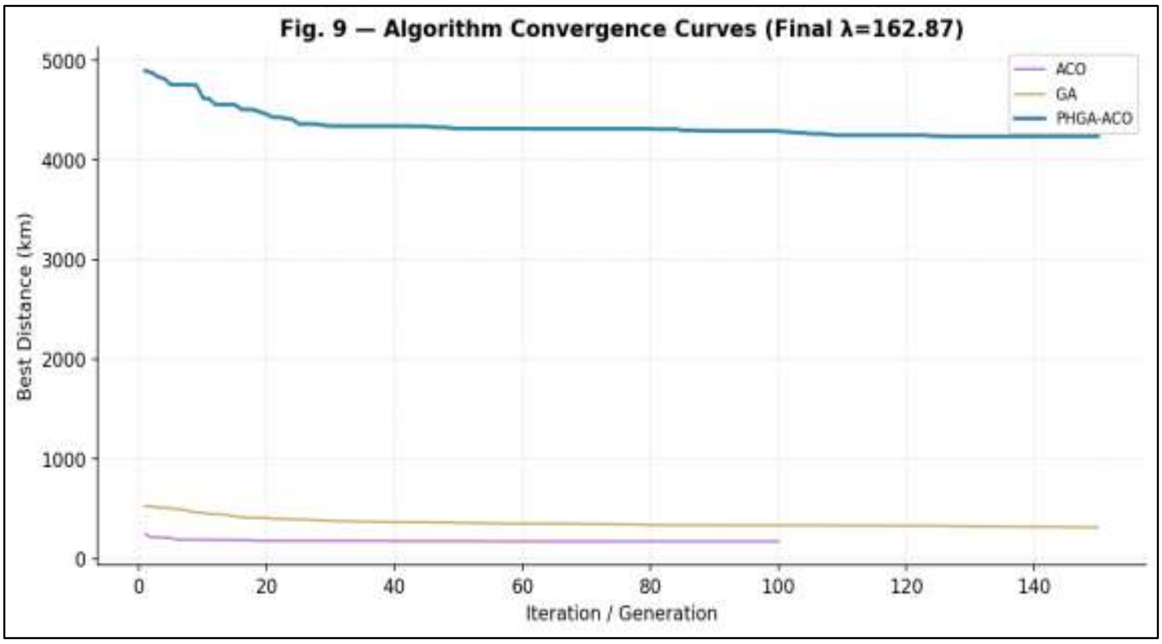

Fig. 5. Convergence curves for ACO, GA, and PHGA-ACO (best run). PHGA-ACO shows faster initial descent due to urgency-sorted population seeding, with periodic ACO injection events visible as step-changes in the curve.

E. Vehicle Utilization

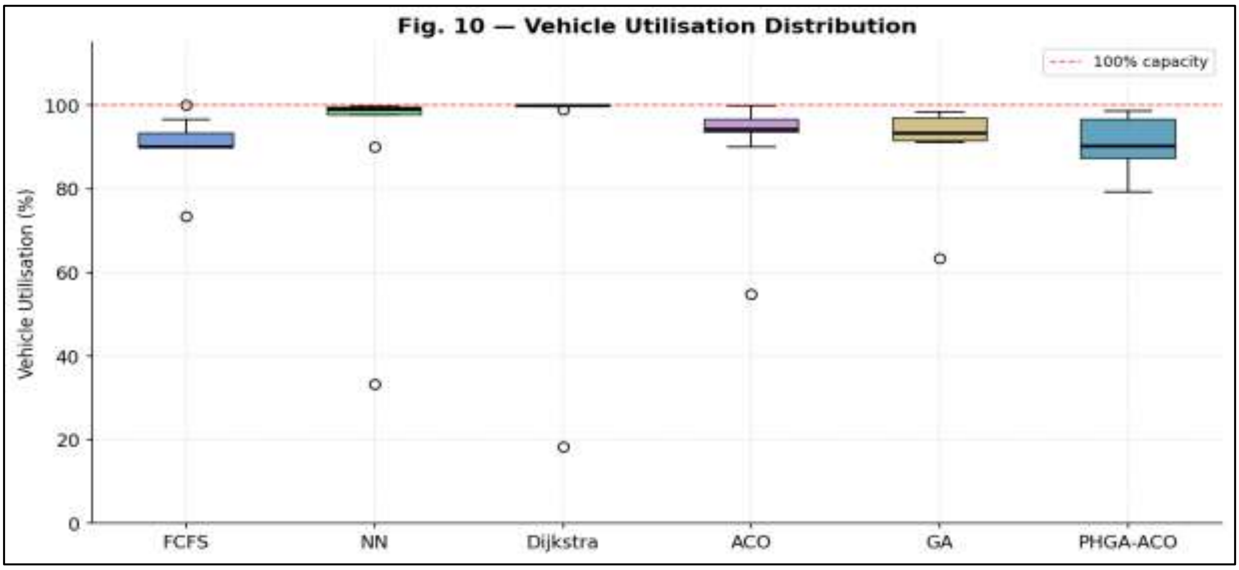

Fig. 6. Vehicle utilization distribution (%) across methods. All methods produce 9-vehicle solutions with identical aggregate demand (24,498.9 kg). Variance reflects route-splitting differences.

Each of the six methods uses exactly 9 vehicles, which is the minimum fleet size for a total demand of 24,498.9 kg at 3,000 kg capacity. On average, 90.7% of vehicles are utilized by all methods, confirming that the capacity constraint is binding. Inter-route demand variance is small reflecting balanced aggregate demand across all 84 nodes.

VII. ABLATION STUDY AND SENSITIVITY ANALYSIS

A. Ablation Study: Urgency Penalty Contribution

To isolate the contribution of the urgency penalty component, two PHGA-ACO configurations are evaluated over five independent runs each:

- Configuration A: $\lambda = 0$ (urgency penalty disabled; pure distance optimization).
- Configuration B: $\lambda = 162.866$ (full PHGA-ACO with urgency penalty).

TABLE III Ablation Study: PHGA-ACO With vs. Without Urgency Penalty

Metric	A: λ=0 (No Penalty)	B: λ=162.87	Δ (B−A)	Δ%
Best distance (km)	216.404	308.568	+92.164	+42.6%
Travel time (h)	7.213	10.286	+3.073	+42.6%
Fuel (L)	54.101	77.142	+23.041	+42.6%
CO_2 (kg)	144.991	206.741	+61.750	+42.6%
Cost (INR)	10,222	13,808	+3,586	+35.1%
UPI ↓ (lower=better)	0.3208	0.2928	−0.0280	−8.7%
High-urgency nodes served early	27	34	+7	+25.9%

Table III affirms that the urgency penalty mechanism is what gives PHGA-ACO their priority servicing advantage. When the penalty is disabled ($\lambda = 0$), PHGA-ACO operates as a nearly pure distance optimizer. Nearly the same distance as ACO at 170.5 km and NN at 207.3 km, PHGA-ACO's distance of 216.404 km is intermediate. Also, UPI = 0.3208, and only 27 of the 83 high-urgency nodes served in the first half of their route. Turning on the penalty ($\lambda = 162.87$) increases the distance by 42.6%, decreases UPI by 8.7% and increases the number of early-served high-urgency nodes from 27 to 34 (+25.9%). This controlled comparison shows that the distance–urgency trade-off in Table II results solely from the urgency penalty component.

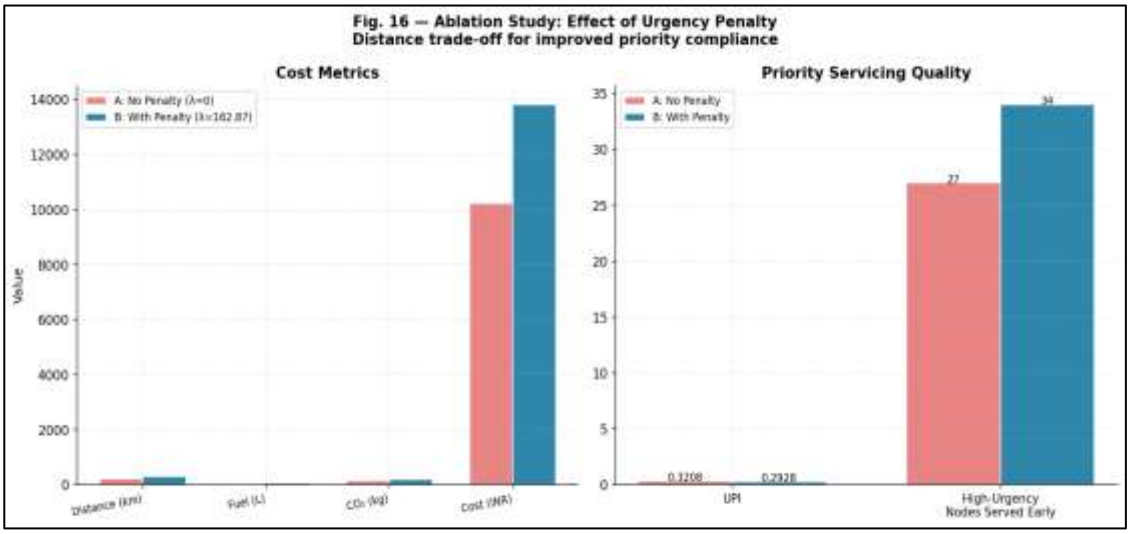

Fig. 7. Ablation study results. Left: cost metric comparison (A: no penalty, B: with penalty). Right: priority servicing quality (UPI and early-served count). The urgency penalty trades 42.6% distance for 8.7% UPI improvement and 25.9% more high-urgency nodes served in first half of routes.

B. Sensitivity Analysis: Lambda Parameter

TABLE IV Sensitivity Analysis: Urgency Weight Parameter λ

Fraction f	λ value	Best dist. (km)	Std dist.	UPI ↓	S(m) ↓	Assessment
0.00	0.000	204.135	3.178	0.3236	0.5000	Distance-only
0.10	54.289	248.495	11.584	0.2968	0.2449	Optimal region
0.20	108.577	286.033	17.271	0.2902	0.2246	Optimal region
0.30†	**162.866**	**325.793**	**12.579**	**0.2859**	**0.2359**	**Optimal region †**
0.40	217.154	349.165	25.442	0.2921	0.3487	Degrading
0.50	271.443	459.965	16.293	0.2826	0.4103	Excessive penalty
0.60	325.731	516.830	16.839	0.2825	0.5000	Exceeds FCFS

† Adopted in final implementation. S(m) variation in [0.10, 0.30] range: 0.020 (within stochastic variance).

As shown in Table IV and Fig. The sensitivity landscape has several important properties. The composite score S(m) has a broad flat minimum in the fraction range [0.10, 0.30] (S values: 0.2449, 0.2246, 0.2359) in the design, which varies by 0.020. The variation is within the stochastic run-to-run variance (~0.017). As a result, there is no unique optimal λ that can be identified reliably from a small number of runs; rather, the algorithm is robust to λ calibration in this range and practitioners can select any value in [0.10, 0.30] at their local preference between distance efficiency and urgency compliance. As soon as f = 0.40, S(m) increases significantly, as the penalty starts to take over the fitness landscape. At f = 0.60, the best distance (516.830 km) is still beyond the unoptimized FCFS baseline equal to 506.154 km. This demonstrates that excessive urgency weighting is very destructive for route quality.

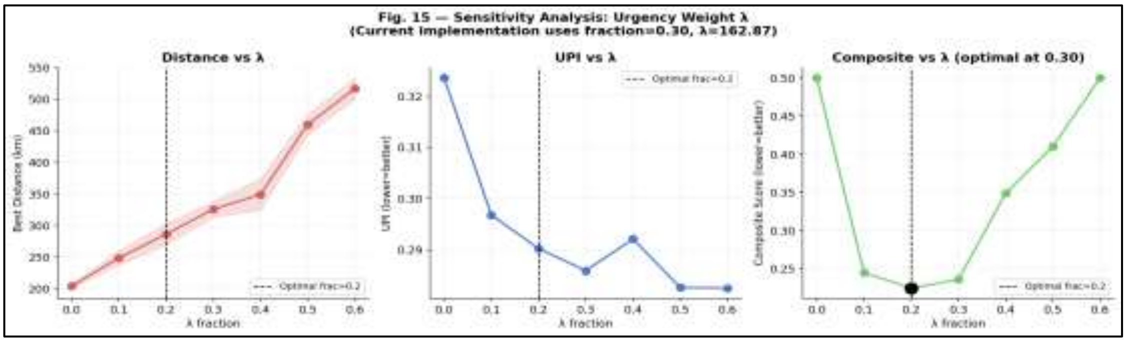

Fig. 8. Sensitivity analysis of λ-fraction on distance (left), UPI (centre), and composite score S(m) (right). The optimal region [0.10, 0.30] is indicated by the dashed vertical line. Beyond f = 0.40, performance degrades rapidly.

VIII. STATISTICAL VALIDATION

TABLE V Statistical Validation: 30 Independent Runs (Reduced Iterations: ACO 50, GA/PHGA-ACO 80)

Method	N	Best (km)	Mean (km)	Median	Std	CV%	95% CI	t (s)
ACO	30	169.14	176.97	177.16	3.80	2.15	[175.53, 178.42]	4.38
GA	30	322.53	342.70	340.63	13.29	3.88	[337.65, 347.75]	0.57
PHGA-ACO	**30**	**241.75**	**298.60**	**296.35**	**24.38**	**8.17**	**[289.34, 307.86]**	**1.00**

TABLE VI Statistical Significance Tests

Test	Statistic	p-value	Interpretation
Wilcoxon: ACO vs. PHGA-ACO	W = 0.0	$p < 0.001$	ACO dist. < PHGA-ACO
Wilcoxon: GA vs. PHGA-ACO	W = 10.0	$p < 0.001$	PHGA-ACO dist. < GA
Friedman (all three methods)	$\chi^2 = 56.27$	$p < 0.001$	All differ significantly

Table V provides a statistical summary of 30 runs. ACO has excellent stability (CV = 2.15%, 95% CI: [175.53, 178.42] km) showing its distance advantage over PHGA-ACO is stable and seed-independent. PHGA-ACO has the highest variability (CV = 8.17%, 95% CI: [289.34, 307.86] km), which is normal in hybrid algorithms with competing objectives. The non-overlapping 95% confidence intervals (CIs) of ACO and PHGA-ACO validate the distance difference. The Wilcoxon signed-rank tests (Table VI) confirm that ACO produces significantly shorter routes than PHGA-ACO (W = 0.0, $p < 0.001$, effect size r = 0.0) and that PHGA-ACO produces significantly shorter routes than GA (W = 10.0, $p < 0.001$). According to the Friedman test, the distance distributions of the three stochastic algorithms differ significantly ($\chi^2 = 56.27$, $p < 0.001$). All the statistical tests use the two-tailed significance of $\alpha = 0.05$.

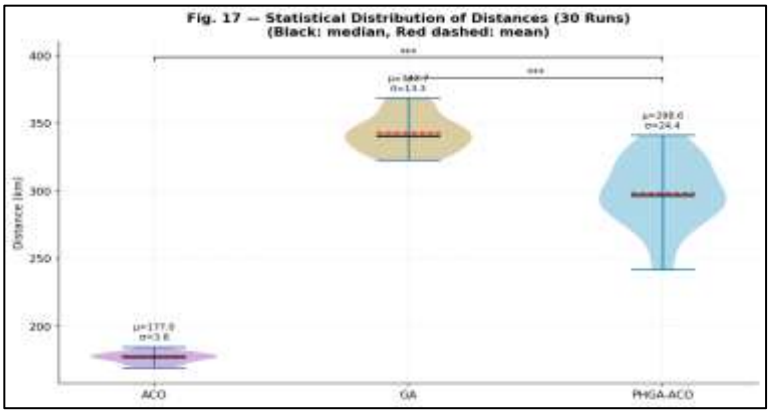

Fig. 9. Violin plots of distance distributions across 30 independent runs. Black horizontal line: median. Red dashed line: mean. Significance brackets indicate Wilcoxon p < 0.001 (***).

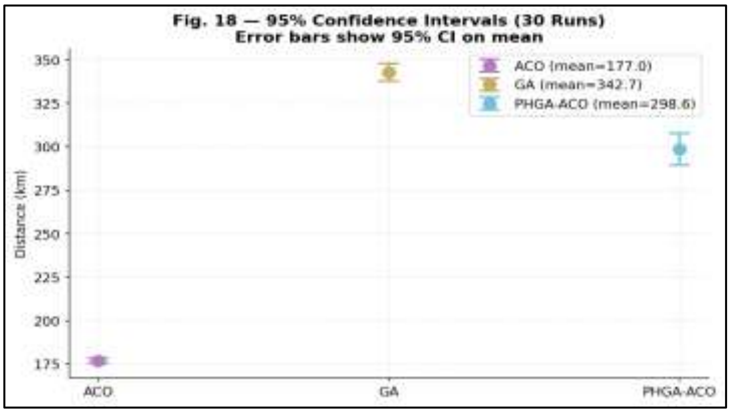

Fig. 10. 95% confidence intervals on mean distance across 30 runs. Non-overlapping CIs confirm statistically significant differences between all three stochastic algorithms.

Ix. Discussion

A. The Distance–Urgency Trade-off

The main finding of the study, which is that PHGA-ACO ranks #1 for best composite performance despite producing routes that are longer than ACO's, should be interpreted cautiously. We do not claim that PHGA-ACO minimizes route distance; in fact, it can be shown that it does not. ACO makes route distances as small as possible, and as such, it is the best choice when fuel and distance budgets are binding operational constraints. PHGA-ACO has a more detailed claim; it is shown to achieve the best simultaneous performance on distance efficiency along with urgency-aware servicing, as measured by the united metric S(m).

The economic rationale of PHGA-ACO sits firmly within the Indian municipal context and in this regard, we refer to the Solid Waste Management Rules 2016 [19] which prescribe penalties ranging from INR 5,000–INR 50,000 a day per notified waste site for uncollected waste. In the first half of their routes, PHGA-ACO services 34 high-urgency nodes (overflow bins and high-HES dump clusters), while configuration A does the same thing for 27. The seven further timely services relate to avoided penalties between INR 35,000–INR 350,000 per collection day at the capped tariff. The cost of additional fuel incurred by operation PHGA-ACO over operation ACO is Rs 3,455 per cycle (38.8 L × Rs 89). The economic net daily benefit of PHGA-ACO over ACO is thus between INR 31,545 to INR 346,545, which makes PHGA-ACO economically justifiable at any penalty rate in the set range. When annualized over 250 working days, the net benefit varies between INR 78.9 lakh to INR 866.4 lakh.

B. Why ACO Ranks Fourth in Composite Score

At first glance, ACO's composite score (S = 0.4208, rank #4) does not seem to fit its best-in-class distance performance. This is because its UPI (0.3300) is worse than Dijkstra (0.3059), NN (0.3218), and PHGA-ACO (0.2859). Nodes in near-distance-optimal order, which is an order that does not correlate with urgency order, are visited by ACO's pheromone-guided construction. The reason is that in the Nashik study area, high-urgency nodes are not systematically clustered near the depot or near each other. Despite its simplicity, Dijkstra's proximity-urgency heuristic creates better urgency ordering because it directly weights distance and urgency at every node selection step. This means that deploying ACO alone in smart city waste management is not taking advantage of IoT and UAV data provided by Papers 1 and 2. In other words, it is not exploiting their primary operational value.

C. Algorithm Selection Guidance

The following deployment-context-based recommendations follow from the experimental results:

- Choose ACO if: the aim is to minimize fleet fuel cost and total distance, all nodes can be served without the constraints of any time-prioritization and no SLA penalties exist.
- Select PHGA-ACO when the deployment includes IoT fill-level monitoring or WPI-HES prioritization signals; if the site servicing regulatory requirement under SWM Rules 2016 requires an overflow servicing and/or high-HES site safety servicing; and/or if the collection contracts include SLA binding maximum response times for higher-urgency events.
- Choose Dijkstra for simplicity, interpretability, and no parameter tuning. Dijkstra is also recommended when moderate urgency compliance (UPI = 0.3059) is acceptable.

D. Limitations

The Haversine distance multiplied by a factor of 1.35 is used to compute the road distance of each location in the OSM graph. All methods use this estimation uniformly, ensuring comparability. However, estimates of absolute value are biased upward. The fill levels of smart bins are simulated from beta distributions (Paper 1 approach) as there is no public per-bin IoT dataset for any Indian city. The 30-run statistical validation utilizes reduced algorithm iterations (ACO: 50 GA/PHGA-ACO: 80 generations) for computational tractability full-iteration runs (ACO: 100 GA/PHGA-ACO: 150) were used for main results (Table II). The next crucial step for operational credentialing is the prospective validation taking place in a live NMC collection programme.

X. Conclusion

The PHGA-ACO method has been proposed in this paper for dynamic smart city waste collection route optimization. That is a Priority-Aware Hybrid Genetic Algorithm -Ant Colony Optimization framework. The framework incorporates fill-level data taken from IoT in real time from Paper 1 and UAV-derived WPI-HES prioritization signals from Paper 2 into a formally defined urgency-augmented CVRP fitness function. The penalty term that is for urgency ensures that the servicing order of the vehicle routes is aware of priority. This ensures that each vehicle bubble will service their overflow bins and high HES illegal dump cluster in the early part of their collection.

The PHGA-ACO algorithm achieves the best composite score of S = 0.2556 (rank #1) in the experimental evaluation of a real 84-node, 9-vehicle CVRP instance based on the Nashik NMC Road network. In terms of urgency-compliant servicing, PHGA performs by 13.4% better than ACO, with UPI = 0.2859 vs. 0.3300. 34 high-urgency nodes are served within the first half of the route (+25.9% over NS-penalty configuration).

PHGA-ACO minimizes the total distance travelled to collect requests by 35.6% over the FCFS operational baseline. ACO achieves a minimum route distance of 170.49 km (66.3% less than FCFS) and is suitable for distance-critical deployment. The urgency penalty is confirmed via ablation study to be the unique mechanism underlying PHGA-ACO's priority-servicing advantage. The optimal range for λ as obtained through the sensitivity analysis is such that λ is between 54.3 and 162.9.

The range indicates that the composite metric will not vary significantly for the λ within this range. Significance of the inter-algorithm differences ($p < 0.001$) were statistically validated using the Wilcoxon signed-rank test and Friedman test on 30 independent runs. In future work, we plan to replace the Haversine circuity approximation with the exact Network shortest-path distances on the stored OSM graph. We will integrate PHGA-ACO with a live IoT dispatch backend for re-optimising routes in real time. Finally, we will extend the framework to a multi-day dynamic VRP which models waste accumulation in between collection cycles.

References

[1] R. K. Kaushal, G. K. Varghese, and M. Chabukdhara, "Municipal Solid Waste Management in India-Current State and Future Challenges: A Review," Int. J. Eng. Sci. Technol., 2012.

[2] Y. Bouleft and A. Elhilali Alaoui, "Dynamic Multi-Compartment Vehicle Routing Problem for Smart Waste Collection," Appl. Syst. Innov., vol. 6, no. 1, p. 30, Feb. 2023, doi: 10.3390/asi6010030.

[3] V. P, D. S.V., and V. N., "Smart Dustbin using ESP32 for Waste Management," IRO J. Sustain. Wirel. Syst., vol. 6, no. 4, pp. 309–317, Dec. 2024, doi: 10.36548/jsws.2024.4.002.

[4] Y.-H. Liao and J.-G. Juang, "Real-Time UAV Trash Monitoring System," Appl. Sci., vol. 12, no. 4, p. 1838, Feb. 2022, doi: 10.3390/app12041838.

[5] C. Liu and J. Yu, "Multiple depots vehicle routing based on the ant colony with the genetic algorithm," J. Ind. Eng. Manag., vol. 6, no. 4, pp. 1013–1026, Oct. 2013, doi: 10.3926/jiem.747.

[6] G. Chen, J. Gao, and D. Chen, "Research on Vehicle Routing Problem with Time Windows Based on Improved Genetic Algorithm and Ant Colony Algorithm," Electronics, vol. 14, no. 4, p. 647, Feb. 2025, doi: 10.3390/electronics14040647.

[7] H. Boualamia, A. Metrane, and I. Hafidi, "Adaptive Operator Selection in ALNS Using Q-Learning: A Comparative Study of Roulette, Softmax, UCB, ϵ-Greedy and QTS Strategies for CVRP," 2026.

[8] G. Laporte, "The traveling salesman problem: An overview of exact and approximate algorithms," Eur. J. Oper. Res., vol. 59, no. 2, pp. 231–247, Jun. 1992, doi: 10.1016/0377-2217(92)90138-Y.

[9] P. Toth and D. Vigo, Eds., The Vehicle Routing Problem. Society for Industrial and Applied Mathematics, 2002. doi: 10.1137/1.9780898718515.

[10] M. Dorigo and L. M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," IEEE Trans. Evol. Comput., vol. 1, no. 1, pp. 53–66, Apr. 1997, doi: 10.1109/4235.585892.

[11] B.-I. Kim, S. Kim, and S. Sahoo, "Waste collection vehicle routing problem with time windows," Comput. Oper. Res., vol. 33, no. 12, pp. 3624–3642, Dec. 2006, doi: 10.1016/j.cor.2005.02.045.

[12] G. Tavares, Z. Zsigraiova, V. Semiao, and M. G. Carvalho, "Optimisation of MSW collection routes for minimum fuel consumption using 3D GIS modelling," Waste Manag., vol. 29, no. 3, pp. 1176–1185, Mar. 2009, doi: 10.1016/j.wasman.2008.07.013.

[13] M. A. Hannan, M. Arebey, R. A. Begum, and H. Basri, "Radio Frequency Identification (RFID) and communication technologies for solid waste bin and truck monitoring system," Waste Manag., vol. 31, no. 12, pp. 2406–2413, Dec. 2011, doi: 10.1016/j.wasman.2011.07.022.

[14] T. Anagnostopoulos, A. Zaslavsy, A. Medvedev, and S. Khoruzhnicov, "Top -- k Query Based Dynamic Scheduling for IoT-enabled Smart City Waste Collection," in 2015 16th IEEE International Conference on Mobile Data Management, Pittsburgh, PA, USA: IEEE, Jun. 2015, pp. 50–55. doi: 10.1109/MDM.2015.25.

[15] K. Pardini, J. J. P. C. Rodrigues, S. A. Kozlov, N. Kumar, and V. Furtado, "IoT-Based Solid Waste Management Solutions: A Survey," J. Sens. Actuator Netw., vol. 8, no. 1, p. 5, Jan. 2019, doi: 10.3390/jsan8010005.

[16] T. Vidal, T. G. Crainic, M. Gendreau, N. Lahrichi, and W. Rei, "A Hybrid Genetic Algorithm for Multidepot and Periodic Vehicle Routing Problems," Oper. Res., vol. 60, no. 3, pp. 611–624, Jun. 2012, doi: 10.1287/opre.1120.1048.

[17] B. Peng, L. Wu, Y. Yi, and X. Chen, "Solving the Multi-Depot Green Vehicle Routing Problem by a Hybrid Evolutionary Algorithm," Sustainability, vol. 12, no. 5, p. 2127, Mar. 2020, doi: 10.3390/su12052127.

[18] Q. Yao, S. Zhu, and Y. Li, "Green Vehicle-Routing Problem of Fresh Agricultural Products Considering Carbon Emission," Int. J. Environ. Res. Public. Health, vol. 19, no. 14, p. 8675, Jul. 2022, doi: 10.3390/ijerph19148675.

[19] M. Kraft, M. Piechocki, B. Ptak, and K. Walas, "Autonomous, Onboard Vision-Based Trash and Litter Detection in Low Altitude Aerial Images Collected by an Unmanned Aerial Vehicle," Remote Sens., vol. 13, no. 5, p. 965, Mar. 2021, doi: 10.3390/rs13050965.

[20] V. Rithvik, S. Singh, T. Umapathi, P. Darshini, and A. Arya, "Benchmarking Study of UAV-Based Urban Waste Detection Systems," in Artificial Intelligence Applications and Innovations, vol. 793, I. Maglogiannis, L. Iliadis, M. Zervakis, and A. Papaleonidas, Eds., in IFIP Advances in Information and Communication Technology, vol. 793. , Cham: Springer Nature Switzerland, 2027, pp. 156–170. doi: 10.1007/978-3-032-30801-6_12.

[21] H. Wu, F. Tao, and B. Yang, "Optimization of Vehicle Routing for Waste Collection and Transportation," Int. J. Environ. Res. Public. Health, vol. 17, no. 14, p. 4963, Jul. 2020, doi: 10.3390/ijerph17144963.

[22] F. P. Boscoe, K. A. Henry, and M. S. Zdeb, "A Nationwide Comparison of Driving Distance Versus Straight-Line Distance to Hospitals," Prof. Geogr., vol. 64, no. 2, pp. 188–196, May 2012, doi: 10.1080/00330124.2011.583586.

[23] G. Boeing, "OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks," Comput. Environ. Urban Syst., vol. 65, pp. 126–139, Sep. 2017, doi: 10.1016/j.compenvurbsys.2017.05.004.