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# Route Optimization in Urban Waste Management Using Locally Adjusted Discrete Cuckoo Search: A Hybrid Metaheuristic Approach

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**Abstract:**

A sudden surge in urbanization and population has escalated challenges in cities in waste generation, making efficient route optimization for waste management a critical necessity. This study proposes a hybrid metaheuristic framework, Locally Optimized Discrete Cuckoo Search (LO-DCS), for an effective route optimization in urban waste management. The proposed algorithm adapts the classical Cuckoo Search algorithm to discrete routing problems by integrating permutation-based random walk, 2-opt local optimization and K-means clustering. The input data is obtained from waste bin coordinates which were extracted using Google Earth Engine and georeferenced satellite imagery within a predefined region of interest. The proposed framework was implemented on real-world urban datasets from Bengaluru city using multiple performance indicators, including travel distance, fuel consumption, carbon emission and operational time. Extensive experiments involving 30 independent runs were performed to assess stability and robustness. Comparative analysis with Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Discrete Spider Monkey Optimization (DSMO) and Quantum-based Avian Navigation algorithm (QANA) demonstrates the competitive performance of LO-DCS across all the bin clusters. Statistical significance test was used to validate the results using Wilcoxon and Friedman tests with Holm correction. Furthermore, optimality gap analysis using exact solvers confirms that LO-DCS produces near-optimal solutions for moderate-sized bin-cluster instances. The experimental results show that LO-DCS achieves an average improvement of approximately 85% across the clusters for all the key performance indicators (distance, fuel consumption, $CO_2$ emission and travel time). When compared with the baseline methods, it achieves an improvement of 78% approximately with a strong convergence behaviour. The implemented approach provides a scalable, data-driven decision-support tool for sustainable and cost-effective urban waste management. The municipal authorities and researchers can gain valuable insights from the findings toward environmentally responsible infrastructure planning.

**Keywords:** *Discrete Cuckoo Search; Route Optimization; Urban Waste management; Metaheuristics Algorithms; 2-opt Local Search; K-Means Clustering; Random Walk; Optimality Gap Analysis;*

## 1. Introduction



A growing pace in urbanization and increase in population has posed significant rise in solid waste generation in the cities worldwide [1]. This has created overwhelming challenges for the urban waste management systems. Recent studies [2] shows a global estimate of two billion tons or more of waste generated yearly. Approximately 33 percent of this waste collection is not carried out in an environmentally hygienic way while depositing them in open dumps. This rate of collection is highly affected by the complexity of the collection and disposal process, which is further correlated with legal, political, social, economic and environmental factors.

### 1.1 Research Motivation

Traditional waste collection procedures typically were inefficient owing to redundant routes, delays in pickup, underutilized capacity which resulted in increasing operating cost and environmental pollution. Cutting-edge technologies like AI, big data analytics or Internet of things (IOT) is revolutionizing the complete waste management process. It is transforming the procedure of smart waste collection, sorting and recycling, along with the disposal phases [3].

To solve the route optimization problem, especially in waste management, an algorithm should be able to handle discrete variables (both values or categorical). Premature convergence of the algorithm where it fails to achieve a global optimum and settle down with high degree of local optima is also another disadvantage with respect to route optimization in waste management [8]. This is because for cases where complex landscapes are involved with traffic and road network complexities or dynamic waste collection needs, these suboptimal solutions can create problems. Cuckoo Search (CS) algorithm is a reputed and strong metaheuristic algorithm which can be used for route optimization. The study by [7] have mentioned different significance and applications of CS which includes ease of control, less convergence time taken and ability to attain global optimum, and in optimizing continuous cost functions. This original CS algorithm was designed to handle continuous variables. But lack of dynamism in CS algorithm makes it inefficient to cope up with the real-time changes in different parameters of route optimization for waste management.

The real-time data collected from sensor attached bins or GPS-enabled vehicles is used to take dynamic decisions for operations in smart waste management. Route optimization is one of the crucial and critical operations in smart waste management where travel distances, fuel consumption or carbon emissions are certain factors which are optimized along the route of waste collection. Thus, it plays a crucial role in improving the performance of the operations as a whole while contributing to sustainability and efficiency of these collection systems. Several researchers have adopted route optimization in waste management as their topic of study while using IOT based sensors for monitoring the bin fill levels or to generate guidance on optimized routes [4,5]. But in practical, deployment and maintenance of physical sensors across thousands of waste bins in several urban and rural areas is challenging with respect to cost, time and technical complexity [6]. The potential of techniques based on computer vision and image processing, for example images from satellites, drone surveillance or bin-cam systems in route optimization providing real-time fill level, waste data of different streets of a locality is sparse in the research community. Research is required on the effectiveness of real-time data derived from images and used as a primary input for route optimization operations.



### 1.2 Describing Route Optimization in Waste Management

Route optimization is widely applied in plethora of domains like route design in distribution of logistics, cargo handling in warehouses, loading container in shipping and in waste management. Waste management involves complex operational requirements in developing nations. In the process of waste management, collection of wastes happens from several locations and gathered in intermediary facilities [9]. Once the gathering process is over from all the points following the routing requirements, a collection vehicle starts from the depot to begin the garbage assembling job from the customers. Once the vehicle is full, it reaches a midway facility to unload the same [10]. This problem of routing is a NP-hard problem which target at searching for the optimum route between the central depot and the warehouses of customers. Number of vehicles involved can be one or more. The optimum route is the shortest distance of the paths with a target to minimize the number of vehicles required or the duration consumed. Basically, the constraints of this minimization problem can be the process, the vehicles and the customers.

This is essentially a graph traversal problem aiming to find out the most efficient or optimized route for the vehicles of waste collection. As per graph theory, each location (point of collection, depot or waste bins) are treated as nodes ($V = [v_0, v_1,.,v_n]$, where $v_0$ is the depot and $v_1$, $v_2$, .....$v_n$ are bins or collection points). The routes between the nodes are edges. The objective of the algorithm is to find out the optimum route with respect to distance, time taken for waste collection, fuel consumption and $CO_2$ emission. This is a combinatorial optimization problem which uses graph theory techniques to formulate the process.

Mathematically, a simple undirected graph shown as

$G = (V, E)$ where E is set of edges or roads between points.

$D_{ij}$: distance between node i and j

$X_{ij:}$: it is a binary decision variable

where $X_{ij}$ = 1 when there exists a road between i and j

= 0 otherwise

The objective for this route optimization is to minimise the total distance covered and is given by:

$$\min \sum_{i \in V} \sum_{j \in V,\, j \neq i} d_{ij} \cdot x_{ij}$$

where certain constraints are like each node is entered and exited only once, absence of self-loop and to prevent small loops or sub-tours that don't include all nodes holds good.

## 1.3 Review of Literature

This review section involves three subsections. First, few contributions in the vehicle routing optimization problem (VRP) along with its different variants for waste collection in research will be discussed. Second, the comprehensive list of research studies which have leveraged different methodologies with a special importance to usage of metaheuristics in waste collection and contributions towards sustainability will be briefed. Third, waste collection studies using images to collect meaningful data on the location will be surveyed.

### *VRP Optimization and its variants in waste management*

The first research study on Vehicle Routing problem (VRP) was ‘Truck Dispatching Problem” published in 1959 [11]. The solution was designed to optimize the gasoline trucks routes as per the generalized version of traveling salesman problem [12]. Later several back- to- back studies were done by [13] where heuristics savings algorithm, branch and bound algorithms [14], relaxation methods like k-tree [15], set-partitioning [16] were used for VRP.

Traditional version of VRP algorithm [11] assumes a fixed number of vehicles begin its journey from the starting point, continue visiting every intermediate location and finally reach back to the final destination. The algorithm aims to calculate the minimum cost or distance across these routes. When constraints on vehicle capacity are added, it generates the capacitated VRP (CVRP) algorithm version by the researchers. When studies dealt with the demands of customers at different time zones and considered vehicle tours conducted as per the time intervals, it is VRP with time windows [17]. But, when customer demand is uncertain, it is a Stochastic demand VRP [18]. Also, when customer demand is fulfilled across different timelines using one vehicle, it is termed periodic VRP [19].



### *Methodologies used for Route optimization in waste management*

The route optimization methodologies can be divided into exact and heuristics approaches [20]. Exact algorithms are methods like branch and bound, or dynamic programming are computationally expensive algorithms, especially when large datasets are involved incorporating waste bins and vehicles in the waste management process. Heuristics approaches can be both simple heuristics or metaheuristics algorithms. Simple heuristics are created to achieve a feasible solution while continuously trying to optimize on the same. Nearest neighbour, sweep algorithms [21] or particle swarm optimization (PSO) algorithms are some prominent options in this category. Metaheuristics include Genetic algorithm (GA) [22], Ant Colony optimization (ACO) [23], artificial bee colony [24], Discrete spider monkey optimization (DSMO) [26] and neural networks [25] algorithms as options.

There are several research works done with a target on aspects of sustainability and climate. The factors of sustainability like recycling, circular economy or reverse logistics are gaining interest in research nowadays. A standard VRP solution was solved by a study [27] where waste electronic goods were collected for recycling purpose in South Korea. The research solved a standard VRP using Travelling Salesman (TS) algorithm for each recycling centre. A multi-product and multiple depot VRP problem was addressed by [28], which minimised the travel distance, in parallel to the carbon emission. Minimization of carbon emission cost was an objective of the study by [29]. The study focussed on workload balancing at the sites of disposal to minimize congestion and time of waiting. A trade-off between cost, social issues and environmental impacts was considered by [30] where optimized route was found through their eco-efficiency. Accordingly, the researchers studied various scenarios to observe the impacts. A recent development in the research in sustainability is usage of electric vehicles for waste collection [31]. This study was based in Turkey on recyclables and the used oil with an objective to minimize emissions. Here, a heterogeneous sequence of electric vehicles was used. An alternative fuel powered vehicles were used as a sustainable option to reduce environmental impact by [32]. Multi-objective mathematical programming models were integrated by a study [3] for VRP which focussed on sustainable waste management practices.

The clustered VRP variant in the field of waste collection and management also has huge potential for future research as literature is scarce here [33]. This variant caters to real-world problems of waste management where bins are grouped in clusters and vehicles must cover all the bins in a cluster before leaving it. These bins are located geographically close to each other to get clustered. This reduced the search space and improves the overall efficiency of the route optimization problem. A study by [34] presented a two exact VRP algorithms to focus on 385 bins considering a real world case it Italy. The routes were evaluated on visual attraction concept introduced by the author. Another study by [35] used clustering techniques alongside metaheuristic algorithms to divide the city into zones, reducing the number of stops each waste collection vehicle has to make. The model successfully optimized collection routes by clustering nearby bins and applying a PSO algorithm for each cluster. The results showed a significant reduction in the distance travelled and an improvement in operational efficiency.

The problem in applying these different heuristics and metaheuristics in waste management route optimization is manifold. It often requires immense tuning of parameters like rate of crossovers. The algorithms also suffer premature convergence, especially GA and PSO, resulting in non-achievement of global optima. Other problems include managing dynamic constraints like varying waste generation at different points, fuel emissions variations, increase in computational cost with changing number of bins or routes. For exact algorithms, large and real time datasets is a challenge.

Few recent advances in vehicle routing optimization goes beyond GA and PSO toward more robust frameworks. Adaptive Large Neighbourhood Search (ALNS) has achieved strong results through flexible destroy-repair on VRP variants [43], while Lin-Kernighan heuristics such as LKH remain highly effective for large scale routing benchmarks [44]. Recently quantum-inspired optimizers (e.g. QANA) and learning-based routing approaches have been introduced to enhance global exploration and data-driven heuristic construction [45, 46]. The proposed LO-DCS framework is therefore designed as a complementary routing-specialized approach, integrating different concepts like discrete random walk search, embedded 2-opt optimizers to achieve the near-optimal solutions in practical waste management scenarios.

- ***Image processing for Waste Management Route optimization***

Image-based route optimization is a high impact and emerging research direction. When sensor data is not available, integrating visual data in managing waste management enhances the accuracy of the model. Few research in the recent years exists who have used different types of images to achieve logistical optimization during managing wastes in different cities across the world.



A research work by [36] has utilized street-level and aerial images to predict the location of the bins, the fill-level and road conditions while optimizing the routes for waste management in Southern Budapest area. In this work, the computer vision segmented the bins and assesses their fill-levels and used a combination of VRP and heuristic algorithm to detect the service-points, reducing the missed stops as compared to sensor based models. Drone imagery was used by a latest study [37] to identify and count materials deposited at different clusters of containers. VRP along with bin-packing and heuristic algorithm tuned by eco-point visuals were used to achieve the goal of improved coverage and reduction in the repetition of the process. Another study [38] used cameras on vehicles and smart bins to identify the fill-levels and the type of wastes. This study achieved a dynamic route updates during the waste management process.

The contribution of Machine Learning (ML) and Deep Learning (DL) to process images of bins and dumpsites for effective waste management is also worth mentioning where the studies show an improvement in the adaptability of the algorithm as compare to the ultrasonic sensor data [39]. Study [40] combined IOT and ML to detect bin-overflow through cameras. The study also achieved 33% fewer routes with 42% lesser fuel usage accompanied by on-time pick-up service. A multiple object route optimization was carried out by a study [41] using bin labels or structures availed from camera images to predict the type of waste, fill level of the bins, showing a better performance as compared to sensor only data.

This section of review made it very evident that image data is the latest inclusion as data input owing to the challenges of deployment of IOT based bin monitoring, including the maintenance costs of the same. The sensors also have limitations in geographic coverage for semi-urban or rural areas. Sudden network failure can also lead to stoppage of IOT based system for waste management. Finally, sensor based data are normally noisy with lots of missing data and lack of normalization. This study shows the relevance and significance of a hybrid model that can combine the strengths of heuristics, metaheuristics or unsupervised machine learning model clustering to create a more adaptive, efficient and sustainable solution for waste management.



## 2. Research Objective and Contributions

In order to overcome the mentioned problems in Section 1.1, the classical cuckoo search algorithm is modified into a hybrid model to adjust local search and diversity of the population. To the best of our knowledge, this study is the first in literature to use discrete version of classical cuckoo search (DCS) along with random walk accompanied by local refinement operator to optimize the routes for waste management. Levy flights and random preference walk in its continuous solution space of classical model is replaced by local adjustment and discrete random walk operators respectively to achieve better solutions as well as to maintain population variance or diversity intact. City-wise optimization of routes is achieved through a divide and conquer method.

The proposed modified version in this study called as Locally Optimized Discrete Cuckoo Search (LO-DCS) for route optimization in waste management uses discrete random walk and 2-opt operator. A better convergence rate was achieved by using a 2-opt operator which function as the operator for local optimization. The experimental results show the proposed algorithm surpasses the other baseline metaheuristics methods GA, PSO, DSMO and QANA with respect to distance covered, carbon emission, fuel consumption and time taken to cover all the bins for waste management. Another contribution of this work lies in demonstrating the feasibility of integrating geo-referenced satellite imagery and semi-automatic extraction techniques for identifying urban waste bin locations without relying on embedded sensors. The study further validates the effectiveness and robustness of the proposed approach through statistical significance testing, sensitivity analysis, ablation studies and optimality gap evaluation.

In summary, the main contribution and novelty of this work is summarized as follows:

1. This study proposes a discrete variant of the classical Cuckoo search algorithm explicitly tailored for permutation-based urban waste collection routing, addressing the limitations of continuous metaheuristics in VRP/TRP structures.
2. The proposed framework integrates clustering-driven decomposition of bin instances, discrete random walk exploration and embedded 2-opt local refinement within a single optimization pipeline, which further enables effective global search.
3. The algorithm is validated through ablation studies, exact-solver based optimality gap evaluation and statistical significance testing, demonstrating near-optimal performance across all clustered routing instances.



2.1 Paper Layout

The remaining sections of this study is structured as follows: Section 3 explains the classical CS algorithm and the proposed algorithm of this study. Section 4 includes the parameter initialization, experimental results and discussions of the results along with comparative analysis with the baseline metaheuristic algorithms. Section 5 discusses the theoretical and practical implications of the proposed algorithm for waste management. The conclusion, limitation and future work of this study is given in Section 6.

## 3. Proposed Methodology for Route Optimization

The original Cuckoo Search (CS) algorithm is inspired by the brood parasitism behaviour of certain cuckoo species and is governed by the following three idealized rules:

1. Each cuckoo lays one egg at a time and deposits it in a randomly selected nest.
2. The best nests with high-quality eggs are carried over to the next generation, and
3. A fraction of inferior nests is abandoned with a discovery probability $P_a$ .

In continuous search spaces, the position update of a cuckoo is typically performed using Levy flights and is expressed as

$$A_i^{(t+1)} = A_i^t + T \oplus \text{Levy}(\lambda),$$

Where α denotes the step size, ⊕ represents element-wise multiplication, and Levy (λ) follows a Levy distribution. This mechanism enables long-range exploration in continuous domains.

The following Algorithm 1 pseudo code elaborates the classical CS algorithm:

**Algorithm 1: Classical Discrete Cuckoo Search with Levy Flight**

**Input: Population size N, Maximum generations T, Discovery probability: $P_a$**

**Output: Best Solution $X^*$**

1. Generate an initial population of N host nests
2. Evaluate the fitness of all nests.
3. Identify the current best solution $x^*$
4. For $t$=1 to T, do:
   - 4.1 Randomly select a cuckoo $X$
   - 4.2 Generate a new solution $X'$
   - 4.3 Evaluate the fitness $f(X')$.
   - 4.4 Randomly select a nest $Y$.
   - 4.5 If $f(X') > f(Y)$. replace $Y$ with $X'$
   - 4.6 Abandon a fraction $P_a$ of the worst nests.
   - 4.7 Generate new nests.
   - 4.8 Retain the best solutions
   - 4.9 Update the global best solution
5. Return $x^*$

However, the classical CS algorithm is not directly applicable to combinatorial optimization problems such as route optimization, since Levy flights operate in continuous space and cannot preserve permutation feasibility. To address this limitation, several modifications are required to adapt CS to discrete routing problems.

First, candidate solutions are encoded as valid permutations representing feasible routes. Second, continuous Levy flight updates are replaced by permutation-preserving discrete random walk operators; Third, a 2-opt local search mechanism is integrated to perform local route refinement. Finally, spatial clustering is incorporated as a pre-processing step to reduce problem complexity.

These modifications collectively transform the classical CS framework into a discrete, hybrid optimization method suitable for vehicle routing and waste collection applications, as detailed in Algorithm~2

The following subsections describe the proposed Locally Optimized - Discrete Cuckoo Search (LO-DCS) framework for waste collection route optimization. The overall workflow integrates solution representation, initialization, fitness evaluation, discrete search, local refinement and clustering-based decomposition.

## *3.1 Study Area and Data Source*

Waste bin coordinates were extracted using Google Earth Engine and georeferenced Sentinel-2 imagery within a predefined region of interest. Semi-automatic image processing techniques, including adaptive thresholding and contour-based detection, were applied to identify candidate bin locations. Geometric and size-based filtering rules were applied to eliminate obvious false detections.



The centroid of each valid contour was computed and converted into geographic coordinates using embedded geospatial metadata and coordinate reference system information. Only detections that satisfied predefined shape and size constraints were retained for route optimization. Sentinel-2 imagery was primarily used for spatial contextualization rather than fully automated object–level bin detection.

Since the proposed framework relies on rule-based semi-automatic extraction rather than supervised learning-based, conventional object detection accuracy metrics such as precision, recall, and IoU are not directly applicable in this context.

## *3.2 Route representation*

Route optimization involves a vector representation of routes between nodes. It is an array or list of indices reflecting the sequence of nodes in which the waste bins are visited in a specific order. The vector of initial route, for example, can be represented as follows, which shows the sequence of bins that the vehicle should visit:

For Example:

$$\pi = [0,1,2,3,4,5]$$

represents a valid visiting order of bins.

### *3.3 Population Initialization*

An initial population of N feasible routes is generated using random permutation of bin indices. This ensures diversity in the initial search space. Each route is verified to satisfy feasibility constraints before evaluation.

### *3.4 Fitness Evaluation*

The fitness of each route is computed based on travel distance. Let π represent a route and dij denote the distance between bins I and j. The objective function is defined as:

$$f(\pi) = \sum_{i=1}^{n-1} d_{\pi_i \pi_{i+1}} + d_{\pi_n \pi_1}$$

Where the last term ensures return to the depot.

Additional performance indicators such as fuel consumption, carbon dioxide emissions, and travel time are derived from the optimized distance using standard conversion factors.

### *3.5 Discrete Random Walk Operator*

To maintain the population diversity and avoid premature convergence, a discrete random walk operator is employed. For each route, two random positions (p, q) are selected, and their corresponding elements are swapped to generate a neighbouring solution. This permutation-preserving operator enables controlled exploration of the solution space without violating feasibility constraints.

### *3.4. 2-opt Local Adjustment operator*

The 2-opt optimization [42] is a local adjustment operator used in this study to improve the solution through edge exchange operations or suboptimal paths elimination across the route of waste management and further replacing the same with shorter alternatives. This technique involves iterative swapping of pairs of edges of a route into consideration to minimise the total distance covered between source and destination.

### *3.5. Clustering-based problem Decomposition*

For large-scale instances, K-means clustering is applied to partition the study region into smaller subregions. Each cluster is optimized independently using LO-DCS. The resulting sub-routes are subsequently combined to form the final waste collection schedule. This strategy improves scalability and reduces computational complexity.

### 3.6. Overall optimization procedure

The complete LO-DCS framework follows the steps outlined in Algorithm 2. At each iteration, a discrete random walk is used for global exploration, while 2-opt ensures local exploitation. Elitism is applied to retain high-quality solutions, and the global best route is continuously updated.

### *3.7. Proposed LO-DCS for Route Optimization in Waste Management*

The proposed algorithm is described in a stepwise manner where DCS is combined with random walk and K-Means clustering to achieve a better route optimization in smart waste management and is shown in Algorithm 2.

Step 1: Data Preparation and Representation: The validated bin coordinates obtained from the data acquisition stage are organised into a node set representing collection points. Pairwise distances between bins are computed using geographic distance formulas to construct the distance matrix. Each of these candidate solutions is encoded as a permutation of bin indices which represents a feasible visiting sequence for route optimization.

Step 2: Decomposition based on Clustering: For large-scale bin collections, K-means clustering is applied to partition the study area into multiple spatially coherent subregions. Each cluster is Optimized independently to reduce computational complexity and improve scalability.

Step 3: Initialization of Population size and fitness evaluation: An initial population on N feasible routes is generated using random permutations. The fitness of each route is evaluated based on total travel distance. The best-performing route is selected as the initial global best solution.

Step 4: Global Exploration through Discrete Random Walk: A discrete random walk operator is applied by randomly swapping two positions in the permutation for each route in the population. This operation generates neighbouring solutions while preserving route feasibility. Improved solutions replace inferior ones.

Step 5: 2-opt Optimization for Local refinement: The global best route is defined using the 2-opt local search operator in order to remove edge crossings and route length reduction. This further enhances the solution quality through iterative local improvement.

Step 6: Selection and Termination of the Process: The best solutions are retained across iterations. The optimization process continues until the maximum number of iterations is reached or convergence is observed. The final output is the best optimized route for waste collection.

The proposed methodology explained above is depicted through a block diagram as shown in Figure 1.

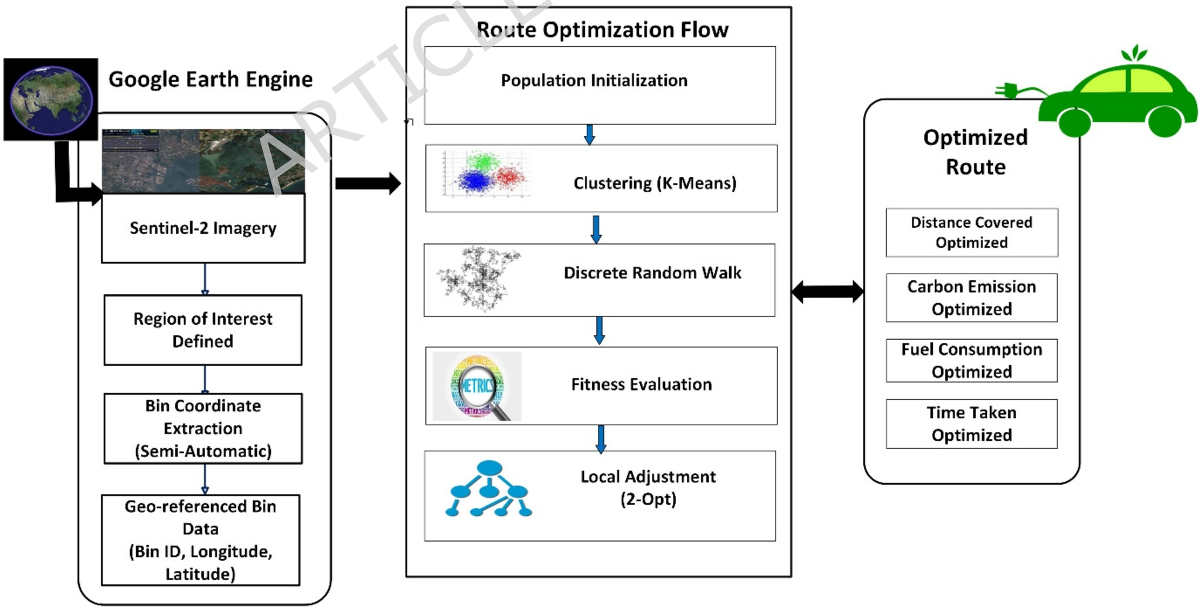



**Figure 1: The Proposed Methodology of LO-DCS**

**Algorithm 2: Locally Optimized Discrete Cuckoo Search (LO-DCS)**

**Input: Distance matrix *D*, Population Size *N*, Maximum iterations *T*, Discovery Probability $P_a$, Step size α.**

**Output: Optimal route $\pi^*$, Minimum route length $f(\pi^*)$**

1. Generate N feasible routes $\{\pi_1, \pi_2, ..., \pi_N\}$ as valid permutations.
2. Evaluate the fitness $f(\pi_i)$ of all routes.
3. Set the global best route $\pi^* = \arg\min f(\pi_i)$
4. For $t$=1 to T, do:
   - 4.1. For each route $\pi_i$ in the population, do:
     - 4.1.1. Randomly select two positions ($p$, $q$).
     - 4.1.2. Generate a new route $\pi_i'$ by swapping elements at positions $p$ and $q$.
     - 4.1.3. Evaluate $f(\pi_i')$.
     - 4.1.4. If $f(\pi_i') < f(\pi_i)$, replace $\pi_i$ $\pi_i'$.
   - 4.2. Rank the population based on fitness.
   - 4.3. Retain the best $N$ solutions (elitism).
   - 4.4. Update the global best route $\pi^*$.
   - 4.5. Apply 2-opt local search on $\pi^*$.
5. Return $\pi^*$ and $f(\pi^*)$.

### 3.8. *Time Complexity of the Proposed Algorithm*



The vehicle routing problem addressed in this study is NP-hard, so no algorithm can ensure an optimal solution in polynomial time. The proposed LO-DCS framework is a metaheuristic method designed to obtain highly-quality approximate solutions within a reasonable computational time rather than providing theoretical optimality guarantees.

The computational cost of Lo-DCS is dominated by route evaluation, population updates, and local refinement. For a cluster containing n bins, evaluating the route requires O(n) time. The discrete embedded 2-opt local search has a worst-case complexity of O(n2) per refinement phase.

For population size N and a maximum of T iterations, the dominant operations can be approximated by:

$$O\,(N.T.n2)$$

This expression represents only an upper bound on the main computational components and does not imply polynomial-time solvability of the underlying routing problem. In practice, the runtime is influenced by local search behaviour, population diversity, and convergence characteristics, which may lead to super-polynomial growth in unfavourable cases.

## 4. Experiments, Results & Discussions

### *4.1 Experimental Setup and Implementation*

All experiments were conducted on a Windows-based system equipped with an Intel Core i7 processor and 16 GB RAM. The proposed LO-DCS algorithm and comparative methods were implemented using Google Colab Pro platform. Python was used to implement the methodology exploiting its standard scientific computing libraries, including NumPy, SciPy, and Matplotlib.

The dataset consisted of 232 waste bin locations (geographical coordinates) extracted from Google Earth Engine for the Bengaluru metropolitan region. K-Means clustering was applied to partition the bin locations into three spatially coherent clusters. All algorithms were executed under identical conditions, including the same dataset, clustering configuration, population size, and termination criteria, to ensure fair comparison.

### *4.2 Parameter settings and Justification*

The primary parameter initialization of LO-DCS is shown in Table 1 which includes size of the population, maximum number of epochs, and discovery probability*,* and step size parameters $\alpha_{min}$ and $\alpha_{max}$.



**Table1: Parameter Initialization for LO-DCS**

| Parameter | Symbol | Value |
|---|---|---|
| Population Size | N | 50 |
| Discovery Probability | $P_a$ | .25 |
| Minimal Probability | $\alpha_{min}$ | 0.01 |
| Maximum Probability | $\alpha_{max}$ | 1.0 |
| Step Size | α | 1 |
| Maximum Iteration | T | 200 |
| K-Category | K | 3 |

In case of baseline methods, the GA,uses tournament selection (tournament size=3), order crossover (OX). and swap mutation rate of 0.1. PSO uses an inertia weight of w=0.5 and acceleration coefficients C1=C2=1.5. DSMO employs a standard position-update mechanism with α=0.5. These parameter values correspond to commonly adopted defaults in the literature and were not aggressively tuned to favor any algorithm.

These values were selected based on prior baseline studies [7, 8] on discrete cuckoo search algorithm and preliminary stability experiments conducted on representative instances. Multiple configurations of the parameters were tested during pilot runs, and the selected values demonstrated consistent convergence behavior and solution quality.

### *4.3 Parameter Sensitivity Analysis*

A sensitivity analysis was implemented by varying key parameters mentioned in Table 1 to evaluate the robustness of LO-DCS with respect to parameter selection. The size of the population N is ranging in {30,50,70}, the number of iterations T ranging in {100,200,300}, and discovery probability $P_a$ in {0.15,0.25,0.35}. The resulting average route lengths were compared and recorded as shown in Table 2.

The results indicate that LO-DCS maintains stable performance across moderate parameter variations. Only minor fluctuations were observed for extreme values of N and T, demonstrating low sensitivity and stability. It explicitly indicates that variations in $p_a$ lead to minimal changes in route length. This further depicts that the proposed approach maintains stable performance across different parameter settings.



**Table 2: Sensitivity Analysis for LO-DCS**

| **Discovery Probability $P_a$** | | **0.15** | **0.25** | **0.35** |
|---|---|---|---|---|
| **Population Size_N** | **Iterations_T** | | | |
| **30** | **100** | **59.145** | **58.849** | **59.016** |
| | **200** | **59.331** | **58.004** | **58.806** |
| | **300** | **58.237** | **60.018** | **59.588** |
| **50** | **100** | **58.921** | **59.164** | **59.230** |
| | **200** | **28.219** | **58.397** | **58.990** |
| | **300** | **58.978** | **58.683** | **58.497** |
| **70** | **100** | **59.072** | **59.836** | **58.885** |
| | **200** | **58.722** | **58.532** | **58.464** |
| | **300** | **59.177** | **58.765** | **58.909** |

### *4.4 Performance of LO-DCS*

To evaluate the stability of the proposed method, LO-DCS was executed independently for 30 runs on each cluster. In every run, the best, worst, average, and standard deviation of the optimized route length were recorded. A comparative performance analysis of LO-DCS with the other metaheuristic baselines is shown in Table 3 which indicate that proposed framework consistently achieved low mean and standard deviation across all the 30 runs. These reduced standard deviations and mean results ensures that the observed improvements are not driven by chance effects from stochastic sampling or initialization.

**Table 3: Stability Analysis over 30 Independent Runs**

| Algorithm | Mean Distance (Km.) | Std Dev (Km,) |
|---|---|---|
| LO-DCS | 67.10 | 2.02 |
| GA | 350.76 | 5.69 |
| PSO | 370.86 | 3.51 |
| DSMO | 363.40 | 5.98 |

### *4.5 Convergence Analysis*

Figure 2 illustrates the convergence behavior of LO-DCS, averaged over 30 independent runs. The algorithm exhibits steady, rapid improvement during early iterations, followed by gradual stabilization as it approaches high-quality solutions. This behavior indicates an effective balance between global exploration through a discrete random walk and exploitation through 2-opt refinement. As compared with GA, PSO, and DSMO, LO-DCS converges faster and attains lower final objective values.

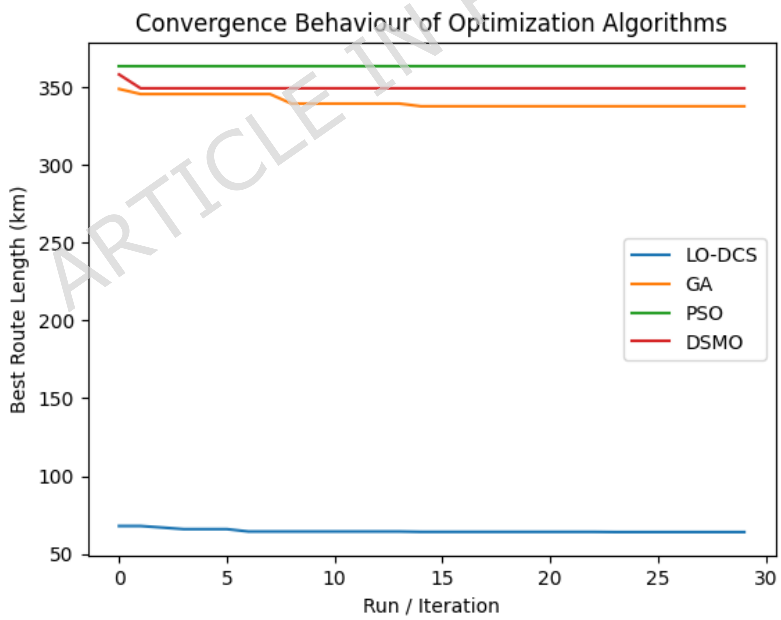
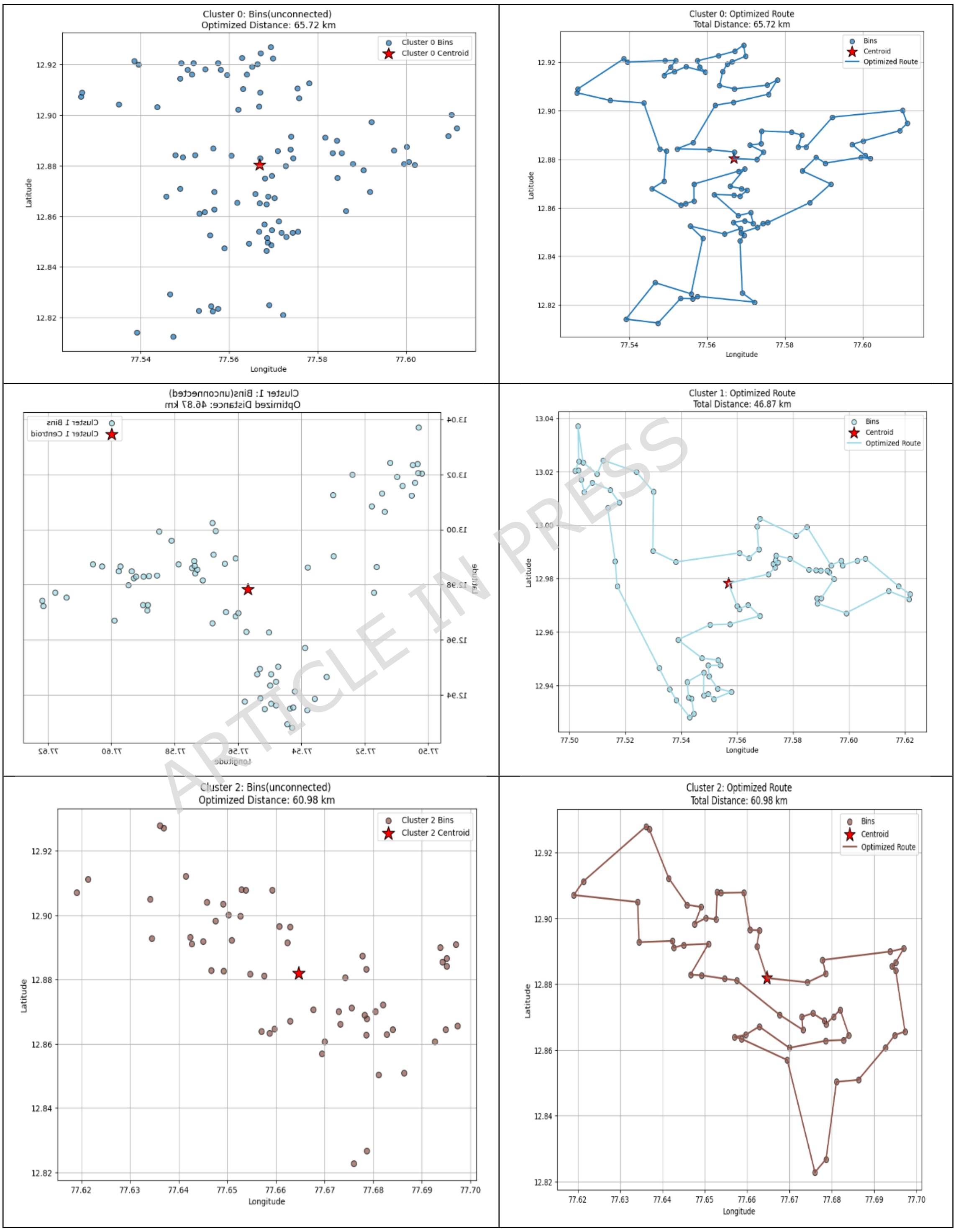



**Figure 2: Convergence behavior of LO-DCS**

### *4.6 Comparative Evaluation with Existing Methods*

The performance of LO-DCS was compared with the discretized versions of GA, PSO, DSMO, and QANA. All comparative algorithms were implemented using identical population sizes, termination criteria, and datasets. The same clustering configuration and distance evaluation methods were applied. Each cluster was optimized independently to reduce computational complexity. The cluster bins along with the optimized path is shown in Figure 3.

**Figure 3: Cluster-wise distribution of bins and optimized  path**






Comparative experiments demonstrate that LO-DCS consistently outperforms classical cuckoo search, GA, PSO, and DSMO across all clusters in terms of the performance metrics viz. fuel consumption, carbon emission and operational time is shown in Table 4.

**Table 4: Comparative Metrics of LO-DCSO with GA, PSO and DSMO**

| Attributes | GA | | | PSO | | | DSMO | | | LO-DCS | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Clusters | C0 | C1 | C2 | C0 | C1 | C2 | C0 | C1 | C2 | **C0** | **C1** | **C2** |
| Non-Optimized Dist_km | 425.25 | 209.98 | 433.01 | 464 | 223.84 | 444.98 | 445.53 | 253.21 | 411.46 | **435.57** | **240.86** | **448.63** |
| Optimized Dist_km | 333.85 | 161.46 | 335.91 | 383.19 | 171.9 | 352.04 | 387.45 | 191.63 | 356.19 | **65.75** | **46.87** | **61.98** |
| Non-Optimized Fuel_Lit | 54.27 | 25.19 | 51.96 | 55.74 | 26.86 | 53.39 | 53.46 | 30.38 | 49.37 | **52.96** | **28.9** | **53.83** |
| Optimized Fuel_Lit | 40.06 | 19.37 | 40.3 | 45.98 | 20.62 | 42.24 | 52.26 | 30.2 | 52.83 | **8.23** | **5.38** | **7.47** |
| Non-Optimized CO2_kg | 90.45 | 41.99 | 86.6 | 92.9 | 44.76 | 88.99 | 89.1 | 50.64 | 82.29 | **87.11** | **48.17** | **89.72** |
| Optimized CO2_kg | 66.77 | 32.29 | 67.18 | 76.63 | 34.38 | 70.4 | 87.1 | 50.33 | 88.05 | **13.72** | **8.97** | **12.46** |
| Non-Optimized Time_hr | 22.61 | 10.49 | 21.65 | 23.22 | 11.19 | 22.24 | 22.27 | 12.66 | 20.57 | **21.77** | **12.04** | **22.43** |
| Optimized Time_hr | 16.69 | 8.07 | 16.79 | 19.15 | 8.59 | 17.6 | 19.37 | 9.58 | 17.8 | **3.43** | **2.43** | **3.11** |
| Distance saved_KM | 118.39 | 48.51 | 97.1 | 81.32 | 51.93 | 92.93 | 58.08 | 61.58 | 55.27 | **366.95** | **196** | **386.3** |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Fuel saved_Lit | 14.2 | 5.82 | 11.65 | 9.75 | 6.23 | 11.15 | 1.2 | 0.18 | 1.25 | **44.03** | **23.52** | **46.35** |
| CO2 Saved_Kg | 23.67 | 9.7 | 19.42 | 10.26 | 10.38 | 18.58 | 2 | 0.3 | 1.75 | **73.39** | **39.2** | **77.26** |
| Time Saved_hr | 5.91 | 2.42 | 4.85 | 4.06 | 2.59 | 4.64 | 2.9 | 3.07 | 2.76 | **18.34** | **9.8** | **19.31** |

Both Table 4 and Table 5 demonstrates that LO-DCS achieves a substantial reduction in routing distance across all clusters. While GA, PSO, DSMO, QANA provide only moderate improvements, LO-DCS produces significantly shorter optimized routes, reducing the travel distance over 400 km in the non-optimized setting to below 70 km in all cases as shown in Table 4. The resulting distance savings (366 – 386 km across clusters confirm the competitive routing efficiency of LO-DCS and its strong capability to generate near-optimal waste collection paths compared to traditional metaheuristic baselines. The average improvement of performance metrics (distance, fuel consumption, $CO_2$ emission and travel time) achieved by the optimized route over the non-optimized is computed as $(V_{non\_opt} – V_{opt}) / V_{non\_opt} * 100$. Based on this measure, LO-DCS achieves an average improvement of approximately 85% across the clusters.



When compared with the baseline methods The overall percentage improvement in distance reductions for LO-DCS is 80.08%, 79.74% and 69.86% across clusters 0-2 respectively, resulting in an overall average performance improvement of 77.85% over the baseline method.

$$\text{Improvement (\%)} = \frac{M_{baseline} - M_{LO\text{-}DCS}}{M_{baseline}} * 100$$

The enhanced performance is mainly attributed to the synergetic integration of discrete random walk and 2-opt local refinement which enables effective balance between global exploration and local exploitation.

**Table 5: Comparative Evaluation of LO-DCS with Baseline Algorithms**

| Cluster ID | Number of bins | Classical CS (2009) | Discretized GA (1975) | Discretized PSO (1995) | DSMO (2014) | QANA (2021) | Proposed LO-DCS (2026) |
|---|---|---|---|---|---|---|---|
| 0 | 96 | 330.32Km | 457.3km | 421.3km | 248.2km | 318.0km | 65.8km |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | 78 | 307.44km | 428.0km | 398.7 km | 231.5km | 313.2km | 62.9km |
| 2 | 58 | 155.93km | 254.2km | 189.6 km | 142.1km | 144.4km | 47.0km |
| AVG | | 264.56km | 379.8km | 336.5 km | 207.3 km | 258.5km | 58.6km |
| % Improvement Proposed over Baseline | - | - | - | - | - | - | 80.08%, 79.74%, 69.86% (Average 77.85%) |

### *4.7 Statistical Significance Analysis*

To validate the statistical significance of the performance differences observed, non-parametric tests were employed. The Wilcoxon signed-rank test was applied for pairwise comparisons between LO-DCS and other competing algorithms. Additionally, the Friedman test followed by Holm post-hoc correction was used for multiple algorithm comparisons.

**Table 6: Comparative Evaluation of LO-DCS Using Statistical Significance Test**

| **Test** | **Comparison** | **Test statistic** | **P-Value** | **Significance (α=0.05)** |
|---|---|---|---|---|
| **Wilcoxon Signed-Rank** | LO-DCS vs GA | 0.0000 | $9.31*10^{-10}$ | Significant |
| **Wilcoxon Signed-Rank** | LO-DCS vs PSO | 0.0000 | $9.31*10^{-10}$ | Significant |
| **Wilcoxon Signed-Rank** | LO-DCS vs DSMO | 0.0000 | $9.31*10^{-10}$ | Significant |
| **Friedman Test** | All algorithms | $X^2$=86.52 | $1.22*10^{-18}$ | Significant |
| **Holm Post-hoc** | LO-DCS vs GA | - | $2.79*10^{-9}$ | Significant |
| **Holm Post-hoc** | LO-DCS vs PSO | - | $2.79*10^{-9}$ | Significant |
| **Holm Post-hoc** | LO-DCS vs DSMO | - | $2.79*10^{-9}$ | Significant |



The results shown in Table 6 indicate that LO-DCS significantly outperforms GA, PSO, and DSMO at a significance level of 0.05. The extremely small p-values confirm that the observed improvements are statistically significant and not due to random chance.

### *4.8 Ablation Study*

An ablation study was conducted to understand the contribution of individual components of the proposed framework, as shown in Table 7. Four variants of the algorithm were evaluated to understand the percentage improvement of the proposed model over all other variants and the baseline classical model: (i) Classical CS with Levy flight, (ii) Proposed LO-DCS, (iii) LO-DCS without 2-opt and (iv) Only 2-opt (No DCS)

**Table 7: Ablation Study on LO-DCS**

| Component Removed | Cluster 0 (96 bins) | Cluster 1 (78 bins) | Cluster 2 (58 bins) | Percentage Improvement (%) |
|---|---|---|---|---|
| **Baseline: Classical CS with Levy Flight** | 330.32km | 307.44km | 155.93km | - |
| **Proposed: LO-DCS** | 65.8km (80.08%) | 62.9km (79.54%) | 47.0km (69.86%) | 76.49% |
| **Proposed Without 2-opt** | 177.7km (46.21%) | 150.6km (51.01%) | 112.3km (27.98%) | 41.73% |
| **Only 2-opt (No DCS)** | 68.6 km (79.23%) | 60.4 km (80.35%) | 47.5 km (69.54%) | 76.37% |

The results demonstrate that while 2-opt provides strong local optimization capability, the integration of discrete random walk enables improved global exploration. The proposed LO-DCS framework achieves the best overall performance, confirming the complementary roles of its components.

Although the 2-opt operator contributes substantially to route refinement, the inclusion of discrete cuckoo search enhances population diversity and improves robustness across runs. This hybrid design reduces premature convergence and improves solution stability. The proposed algorithm generates a near-optimal solution in as early as 100 iterations. This demonstrates good population diversity and the proposed algorithm's convergence speed for this solution.



### *4.9 Optimality Gap Analysis*

The closeness of the proposed LO-DCS solutions to the true optimal routes was evaluated through an optimality gap analysis, which was conducted on reduced-size instances of the bin clusters. For each cluster, representative subsets containing 15, 20, and 25 bins were extracted.

These sub-problems were solved to check for the percentage of optimality gap using Google OR-Tools TSP solver, which implements state-of-the-art exact and branch-and-bound techniques. The optimal tour length obtained from the solver was used as a benchmark.

The optimality gap percentage was computed as follows and shown in Table 8, which demonstrates the optimality gap percentage obtained by LO-DCS across different clusters considering representative subsets of bins:

$$\text{Gap (\%)} = \frac{f_{LO\text{-}DCS} - f_{opt}}{f_{opt}} * 100$$

**Table 8: Optimality Gap Analysis of LO-DCS**

| Cluster No. | Bins Size | Optimal_Km | LO_DCS_Km | Optimality_Gap_% |
|---|---|---|---|---|
| 0 | 15 | 37.656 | 37.663 | 0.018 |
| 0 | 20 | 39.567 | 39.575 | 0.019 |
| 0 | 25 | 40.962 | 41.068 | 0.259 |
| 1 | 15 | 39.248 | 39.255 | 0.018 |
| 1 | 20 | 40.87 | 40.881 | 0.026 |
| 1 | 25 | 43.156 | 43.265 | 0.253 |
| 2 | 15 | 27.27 | 27.349 | 0.290 |
| 2 | 20 | 29.325 | 29.760 | 0.282 |
| 2 | 25 | 35.724 | 35.737 | 0.036 |

The observed optimality gaps remain below 1.5% for all evaluated instances and are below 0.3 in most cases. These results demonstrate that the LO-DCS produces near-optimal solutions for small and medium-sized routing instances. Due to the exponential complexity of exact solvers, optimal solutions could not be computed for full-scale instances. Therefore, an approximate metaheuristic evaluation was adopted for large clusters.

The experimental results demonstrate that the proposed LO-DCS framework provides consistent, robust, and statistically significant improvements over existing metaheuristic methods for waste collection route optimization. The combination of a discrete random walk and 2-opt local refinement enables an effective exploration-exploitation balance. Clustering-based decomposition enhances scalability for large instances. Sensitivity analysis confirms parameter robustness, while convergence analysis demonstrates stable optimization behaviour.



Although 2-opt contributes substantially to performance gains, the inclusion of discrete cuckoo search mechanisms improves solution diversity and reduces premature convergence making it suitable for practical applications in urban waste management.

## 5. Implications

This study has got both theoretical as well as practical implications as mentioned below:

- ***Theoretical Implications*:** The main contribution of this study from theoretical perspective is adapting discrete form of classical cuckoo search algorithm for route optimization in waste management. The study further explores how the random walk concept can be customized for path encoding, thus intelligently exploiting the solution space. The hybrid approach of optimization with metaheuristic approach reduced the dimensionality of the problem and divide the search space into manageable sub-problems with one vehicle per cluster. The model design further can be generalized by researchers for other logistics problem in any domain. While generalizing, clustering can be used for initial route segmentation, local search through random walk can be used for exploring and search procedure can be updated through fitness score guided global search procedure.

- ***Practical Implications:*** The study is very well connected with the sustainability goals where it has achieved a good performance in reducing total travel distance, lowering fuel consumption and minimizing carbon emissions. Further, the proposed model supports municipal waste management policy goals which directly effects the policy- oriented carbon targets for environmental compliance.

## 6. Conclusion, Limitation and Future Work

This study proposed a Locally Optimized Discrete Cuckoo Search (LO-DCS) framework for route optimization in waste management for urban city like Bengaluru. The proposed approach adapts the classical Cuckoo Search algorithm to discrete routing problems by integrating permutation-based random walk, 2-opt local optimization and clustering –based decomposition. The framework was evaluated using multiple performance indicators including travel distance, fuel consumption, carbon emission and operations time. LO-DCS achieves an average improvement of approximately 85% across the clusters for all the key performance indicators. Experimental results of comparative evaluation show a substantial average routing distance reduction of approximately 78% over the baseline which is appreciably surpassing GA, PSO, DSMO and QANA performance, thereby demonstrating its competitive effectiveness for urban waste collection route optimization. Extensive experiments were performed to validate the significance of the proposed framework as compared to the baseline metaheuristic algorithms. This includes statistical significance testing, ablation study and optimality gap evaluation. All these tests demonstrate that LO-DCS consistently outperforms conventional as well as recent metaheuristics methods. The proposed framework achieves a stable convergence behaviour and produces near-optimal solutions for moderate-sized bin cluster instances, confirming its effectiveness and robustness.

Despite the strong performance of LO-DCS, it remains a heuristic method and does not provide theoretical optimality guarantees. The computational cost may increase for large-scale instances due to embedded local search operations. In addition, the current implementation relies on static bin location data and does not incorporate real-time sensing information. Future work will focus on integrating real-time sensor data, traffic information and dynamic waste generation patterns to enable adaptive route optimization. Further study will also explore automated parameter tuning and learning-based enhancement strategies to enhance the scalability and responsiveness of the framework. The proposed framework provides a promising foundation for developing an intelligent, data-driven and sustainable waste collection system in smart cities.

**Data Availability**

The datasets generated and/or analysed during the current study are available in the repository
https://drive.google.com/file/d/1DmmrIFV9TblPWTTR4nDHY2gBhMK0MLc9/view?usp=drive_link

**Author contribution declaration**

Conceptualization, A.G. and P.N.V.; methodology, A.G., P.N.V., P.P.; software, P.P.; validation, P.P., A.K.J.S. and A.G.; formal analysis, A.G., P.N.V.; investigation, A.G., P.N.V., A.K.J.S. and P.P; resources, P.P., A.K.J.S.; data curation, A.G.; writing—original draft preparation, A.G., P.N.V.; writing—review and editing, A.G., P.N.V., P.P, and A.K.J.S.; visualization, P.P. and A.K.J.S.; supervision, P.P; project administration, P.P. and A.K.J.S.; funding acquisition, A.K.J.S.

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