

# **TRAFFIC-AWARE SINGLE-DRONE DELIVERY ROUTE OPTIMIZATION**

A Project Report Submitted in Partial Fulfillment  
of the Requirements for the Course on Artificial Intelligence

## **Team Delta6**

Barshneyo Chakraborty (B2530075)

Sagnik Chandra (B2530084)

Tamojit Mondal (B2530091)

Ramakrishna Mission Vivekananda Educational  
& Research Institute, Belur

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## Abstract

The rapid growth of autonomous delivery systems has positioned drone-based logistics as a promising solution for last-mile delivery. Traditional route planning methods typically optimize for distance alone, overlooking real-world constraints such as congestion in urban airspace. This project presents a *traffic-aware single-drone delivery route optimization* framework, where travel time is modeled as a function of both Euclidean distance and congestion factors associated with delivery nodes. The routing problem is formulated as a combinatorial optimization problem over permutations of delivery nodes. Two local search algorithms—Deterministic Hill Climbing and Stochastic Hill Climbing—are implemented and compared. Experimental evaluation on a large-scale synthetic dataset demonstrates trade-offs between convergence speed and exploratory capability, providing insights into the suitability of each algorithm under varying traffic conditions.

## **Acknowledgement**

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# **1. Introduction**

## **1.1 Background and Motivation**

With the increasing demand for rapid and contactless delivery services, autonomous drones have emerged as a viable solution for last-mile logistics. Unlike ground vehicles, drones operate in three-dimensional airspace and are not constrained by road networks or traffic signals. However, urban airspace introduces its own form of congestion due to high drone density, regulatory constraints, and environmental factors. Consequently, minimizing travel distance alone is insufficient; instead, minimizing total travel time under traffic-aware conditions becomes essential.

## **1.2 Problem Overview**

This project addresses the problem of determining an optimal closed delivery route for a single drone that must visit a set of delivery nodes exactly once and return to the starting node. The presence of traffic congestion on edges connecting nodes significantly influences traversal time. The resulting problem is closely related to the Traveling Salesman Problem (TSP) but incorporates dynamic edge costs influenced by congestion parameters.

## **1.3 Objectives**

The primary objectives of this project are:

- To formulate a traffic-aware cost model for drone delivery routing.
- To implement deterministic and stochastic hill climbing algorithms for route optimization.
- To analyze and compare the performance of these algorithms in terms of convergence behavior and solution quality.

## 2. Problem Formulation

### 2.1 System Model

Consider a set of  $n$  delivery nodes  $N_0, N_1, \dots, N_{n-1}$  in a two-dimensional plane. The drone starts from a designated depot node  $N_0$ , visits every other node exactly once, and returns to  $N_0$ .

### 2.2 State Space

The state space consists of all possible permutations of the delivery nodes. Each state represents a candidate delivery route. The size of the state space is  $(n - 1)!$ , rendering exhaustive search computationally infeasible for large  $n$ .

### 2.3 Objective Function

The objective is to minimize the total travel time of the route. Let  $d_{ij}$  denote the Euclidean distance between nodes  $N_i$  and  $N_j$ . The total cost of a route is defined as the sum of traffic-adjusted travel times over all consecutive node pairs.

## 3. Traffic-Aware Cost Model

### 3.1 Congestion Factors

Each node  $N_i$  is assigned a congestion factor  $c_i \in [1, 3]$ , where lower values indicate minimal congestion and higher values represent heavy congestion.

### 3.2 Edge Congestion

The congestion factor associated with an edge connecting nodes  $N_i$  and  $N_j$  is defined as the arithmetic mean of their individual congestion factors:

$$c_{ij} = \frac{c_i + c_j}{2}. \quad (3.1)$$

### 3.3 Travel Time Computation

The traffic-adjusted travel time between nodes  $N_i$  and  $N_j$  is given by:

$$t_{ij} = d_{ij} \cdot c_{ij}. \quad (3.2)$$

This formulation ensures that routes passing through highly congested regions incur higher traversal costs.

## 4. Optimization Algorithms

### 4.1 Deterministic Hill Climbing

Deterministic Hill Climbing is a greedy local search algorithm that iteratively improves a candidate solution by selecting the best neighboring state with a lower cost. At each iteration, all neighboring solutions—typically generated via pairwise node swaps—are evaluated. The algorithm terminates when no neighbor offers an improvement.

#### 4.1.1 Characteristics

- Greedy and deterministic in nature.
- Fast convergence to a local optimum.
- No backtracking or memory of previous states.
- Prone to getting trapped in local minima.

### 4.2 Stochastic Hill Climbing

Stochastic Hill Climbing introduces randomness into the neighbor selection process. Instead of evaluating all neighbors, a randomly selected improving neighbor is accepted based on a probability distribution biased toward higher improvements.

#### 4.2.1 Characteristics

- Enhanced exploration of the state space.
- Reduced computational overhead per iteration.
- Ability to escape shallow local optima.
- Slower and less predictable convergence.

## 5. Experimental Setup

### 5.1 Simulation Parameters

The experimental environment consists of 120 delivery nodes randomly distributed in a plane. Congestion factors are uniformly sampled from the interval [1, 3]. The base airspeed of the drone is set to 50 km/h.

### 5.2 Controlled Randomness

To ensure reproducibility, the random seed is fixed at 46656. This guarantees identical node placements and congestion assignments across multiple experimental runs.

### 5.3 Visualization

Routes and convergence behaviors are visualized using plots generated from the simulation outputs. These visualizations help in understanding algorithm behavior under traffic-aware constraints.

Routes are visualized using directed edges with arrow markers. Color gradients are applied to edges to represent varying congestion levels.

## 6. Results and Analysis

### 6.1 Graphical Outputs and Route Visualizations

This section presents the visual outputs obtained from the simulation runs. The figures included here are directly taken from the program output and illustrate node distributions, optimized routes, and convergence trends for both algorithms.

### 6.1.1 Test Case : Deterministic Hill Climbing - Node Positions and Route

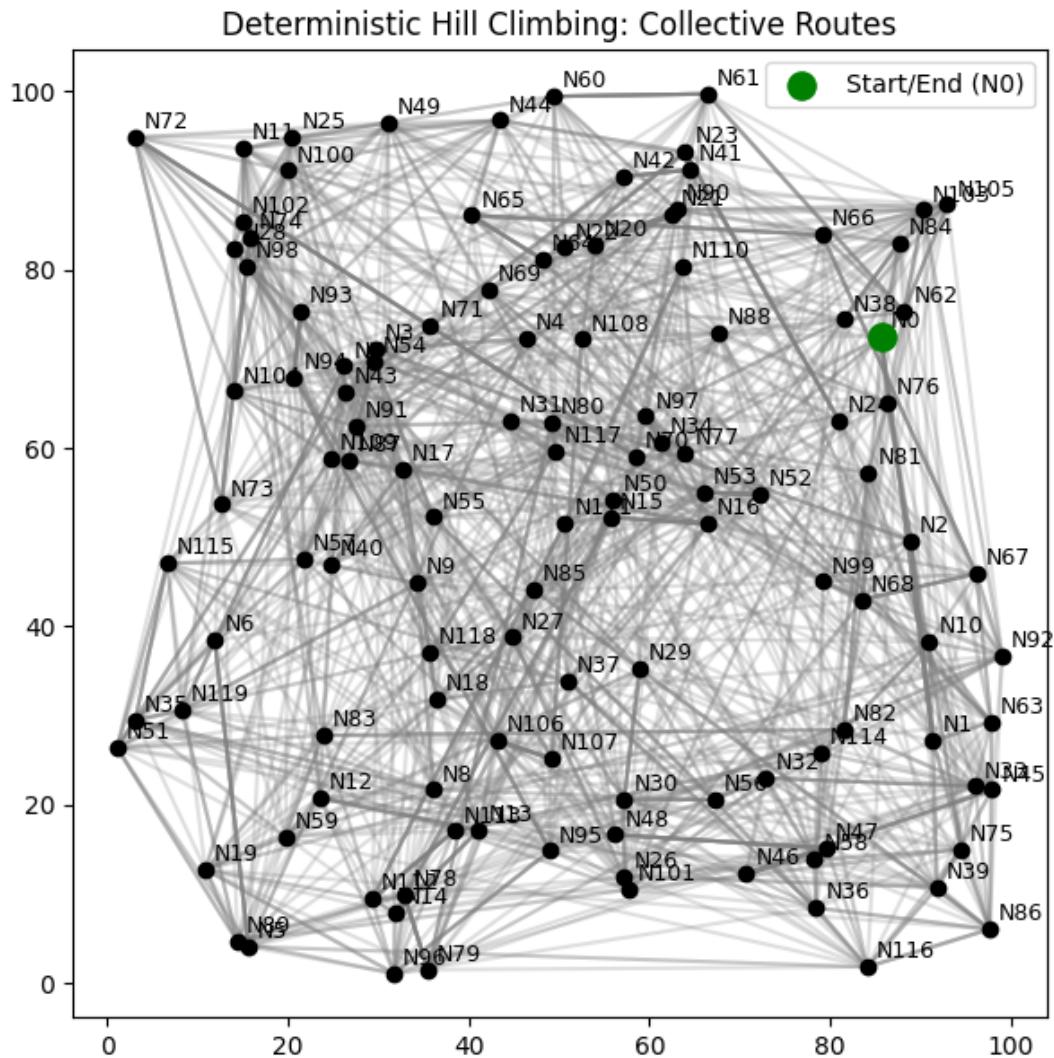


Figure 6.1: Collective delivery route obtained using Deterministic Hill Climbing.

### 6.1.2 Test Case : Stochastic Hill Climbing - Node Positions and Route

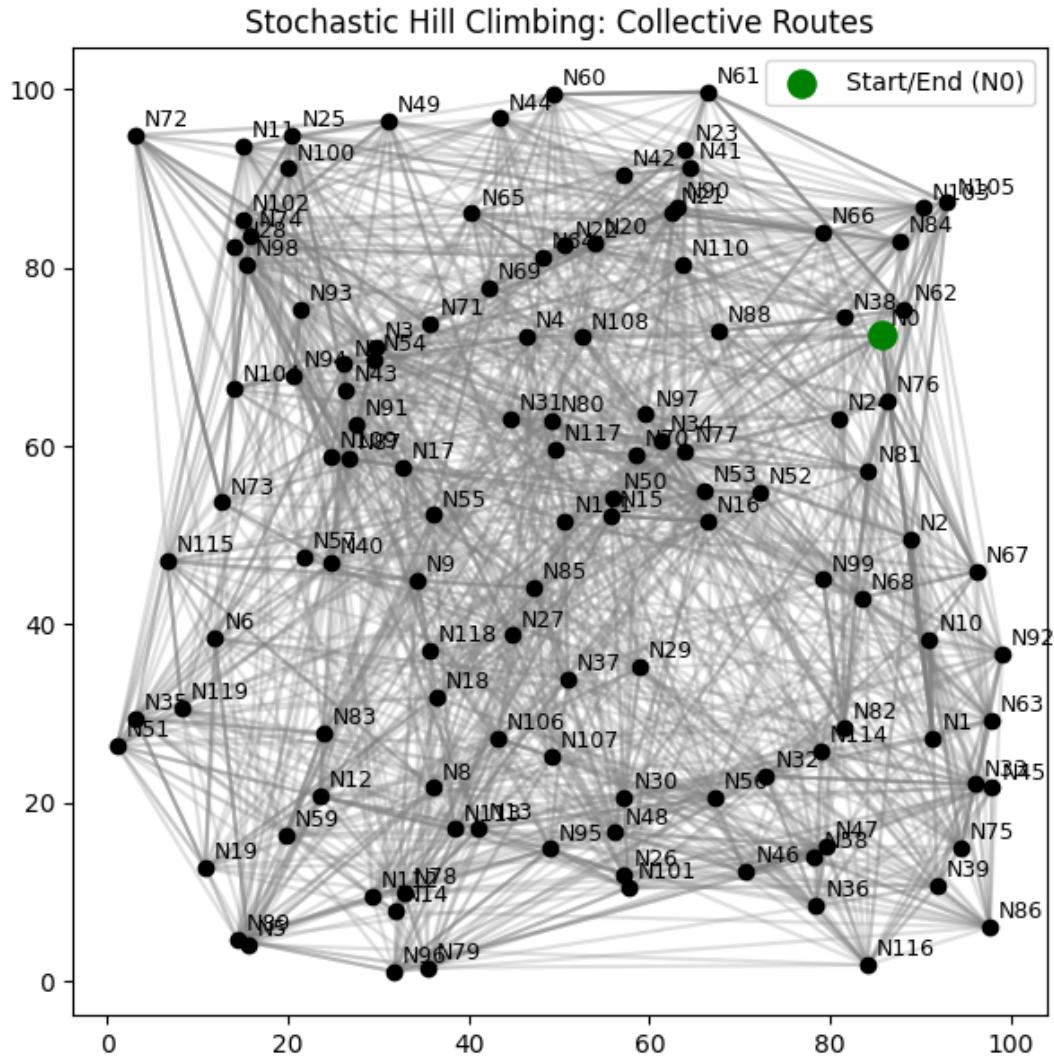


Figure 6.2: Collective delivery route obtained using Stochastic Hill Climbing. Increased exploration of the state space is evident.

### 6.1.3 Test Case : Convergence Rate Comparison

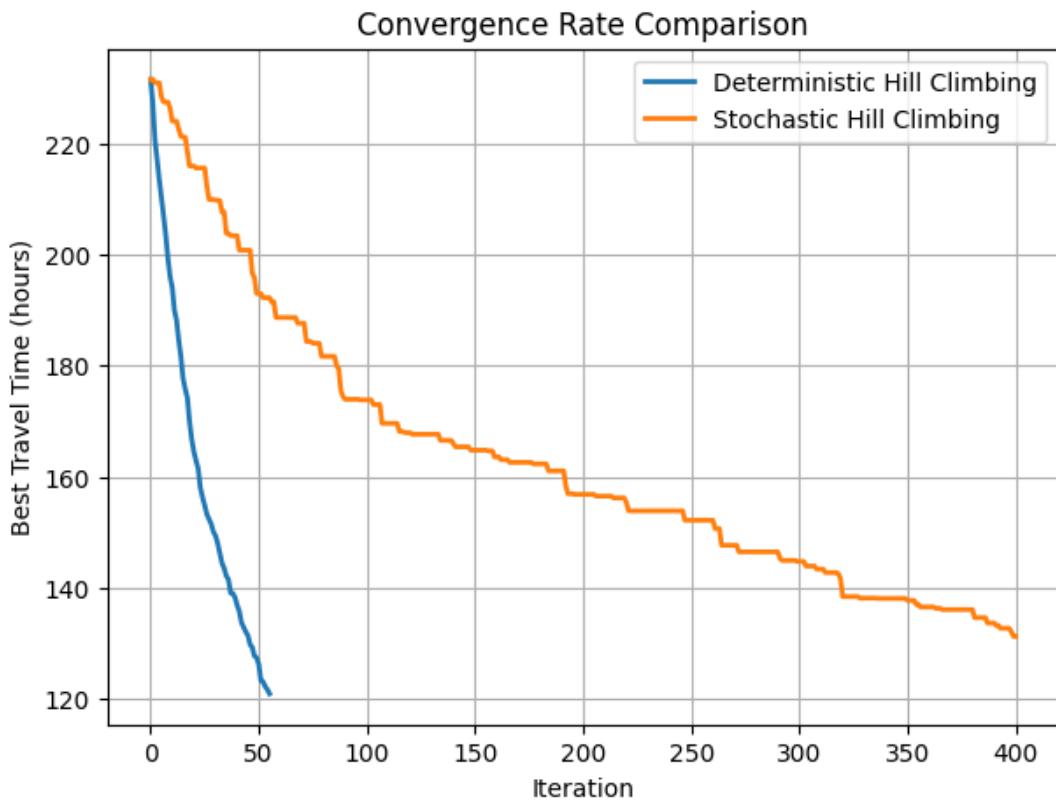


Figure 6.3: Convergence behavior of Deterministic vs. Stochastic Hill Climbing over 400 iterations.

### 6.1.4 Test Case : Best travel time for Deterministic Hill Climbing

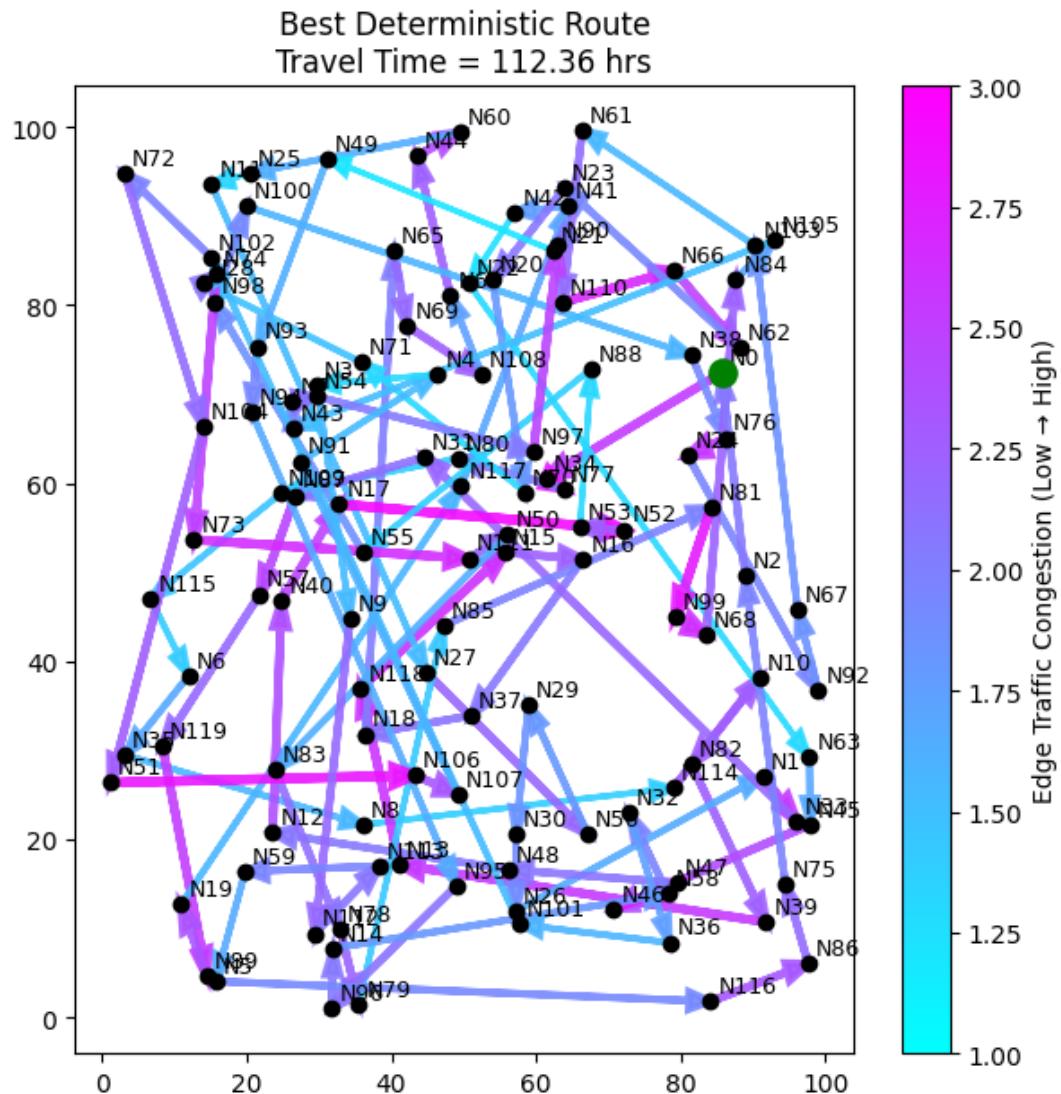


Figure 6.4: Best travel time taken by Deterministic Hill Climbing.

### 6.1.5 Test Case : Best travel time for Stochastic Hill Climbing

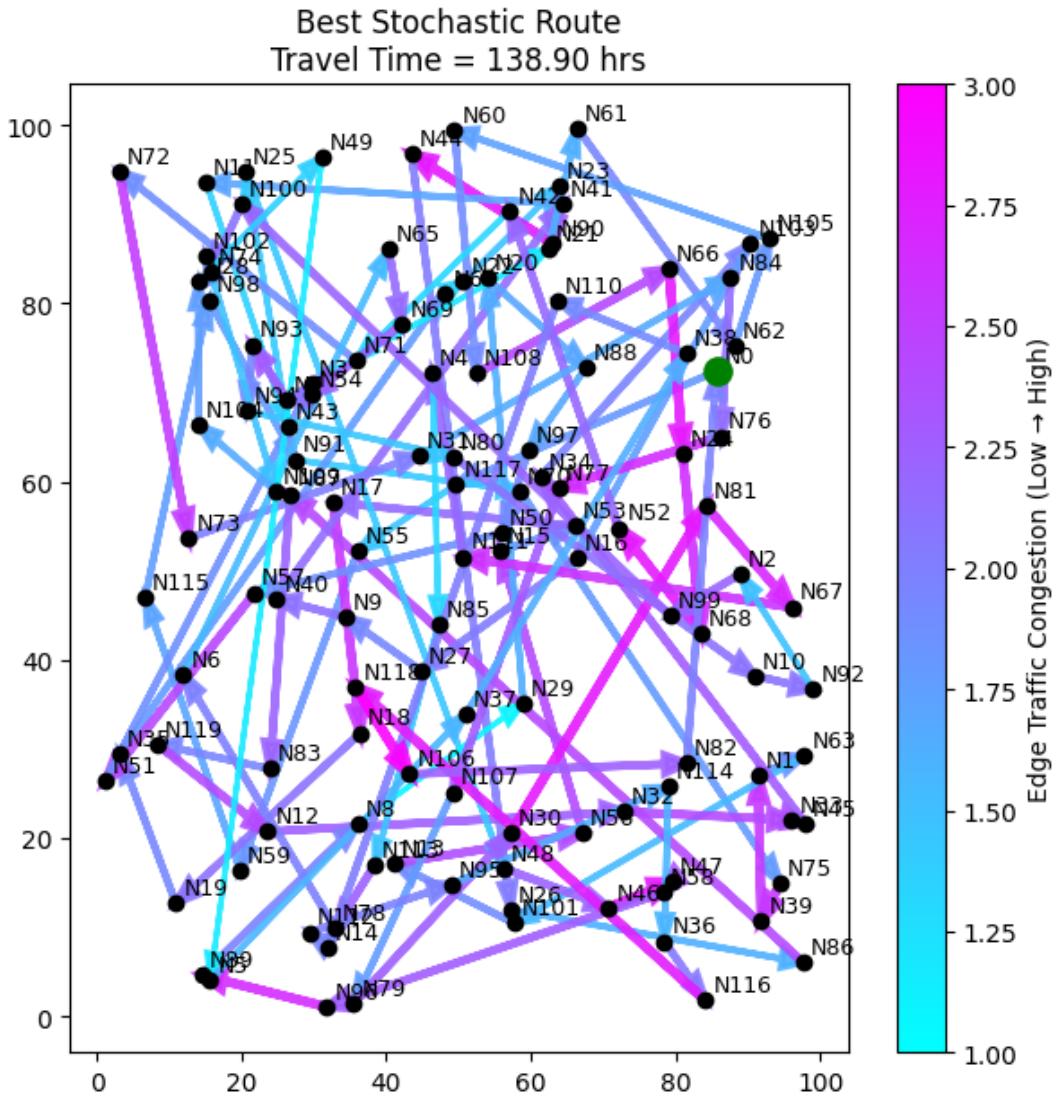


Figure 6.5: Best travel time taken by Stochastic Hill Climbing.

## 6.2 Deterministic Hill Climbing Results

Figure 6.4 shows the optimized route obtained using deterministic hill climbing. A representative test run achieved a total travel time of 112.36 hours. The algorithm converged rapidly but demonstrated sensitivity to initial route configuration.

A representative test run using deterministic hill climbing achieved a total travel time of 112.36 hours. The algorithm converged rapidly but exhibited sensitivity to initial conditions.

### 6.3 Stochastic Hill Climbing Results

Figure 6.5 illustrates the route produced by stochastic hill climbing. In a representative run, the total travel time was 138.90 hours. Although suboptimal in this instance, the algorithm explored a wider variety of routes, increasing robustness.

In contrast, stochastic hill climbing produced a solution with a travel time of 138.90 hours in a sample run. While less optimal in this instance, the algorithm explored a broader range of routes.

### 6.4 Convergence Comparison

The convergence trends shown in Figure 6.3 highlight the faster convergence of deterministic hill climbing compared to the more gradual but exploratory nature of stochastic hill climbing.

Empirical results indicate that deterministic hill climbing converges faster, whereas stochastic hill climbing provides better exploration of the search space. The optimal algorithm varies depending on traffic distribution and node geometry.

## **7. Future Scope**

### **7.1 Multi-Drone Extension**

The framework can be extended to a multi-drone delivery system by partitioning nodes into clusters based on spatial proximity. Each cluster can be serviced by a dedicated drone.

### **7.2 Altitude-Based Traffic Management**

As a continuation of the previous application, to mitigate congestion, drones can operate within predefined altitude bands. Each class of drone is assigned a unique altitude range, ensuring vertical separation and reduced interference.

## **8. Conclusion**

This project demonstrates that incorporating traffic awareness significantly enhances the realism of drone delivery route optimization models. Local search techniques such as hill climbing offer computationally efficient solutions, with clear trade-offs between exploitation and exploration. The study highlights the importance of contextual factors such as congestion and spatial distribution in determining algorithmic performance.

## Bibliography

- [1] Stuart Russell and Peter Norvig, *Artificial Intelligence: A Modern Approach*, Pearson Education.