

# Energy-Efficient Trajectory Optimization of UAV-Based Flying Base Stations in 5G Networks Using Nearest Neighbor and 2-opt Heuristics

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**Abstract:** *The integration of Unmanned Aerial Vehicles (UAVs) as Flying Base Stations (FBSs) has emerged as a promising solution to improve coverage and service flexibility in fifth-generation (5G) wireless networks. UAV-assisted communications are especially useful in scenarios involving temporary traffic surges, infrastructure failure, and underserved regions where terrestrial macro base stations alone are insufficient. However, the limited endurance and onboard energy of rotary-wing UAVs make efficient trajectory planning a critical challenge. This paper formulates the trajectory design problem for an FBS serving distributed ground nodes (GNs) as a Euclidean Traveling Salesman Problem (TSP), where the objective is to minimize total path length and thereby reduce travel-related energy consumption. Since exact TSP methods are computationally impractical for repeated deployment decisions, a heuristic framework combining the Nearest Neighbor (NN) constructive method with 2-opt local search is adopted. The proposed NN-2-opt approach generates an initial feasible tour rapidly and iteratively improves it by edge exchange operations. A detailed analysis of classical TSP solution strategies, including brute-force, Held-Karp, Christofides, Lin-Kernighan, tabu search, and simulated annealing, is presented to justify the selected approach. Simulation-oriented evaluation based on GN sets ranging from 20 to 80 nodes shows that the proposed strategy provides a practical balance between computational efficiency and route quality, making it suitable for real-time or repeated optimization in UAV-assisted 5G systems. The study demonstrates that NN-2-opt is particularly effective when embedded as a subroutine in larger network-level optimization frameworks.*

**Keywords:** UAV, Flying Base Station, 5G, trajectory optimization, Traveling Salesman Problem, 2-opt, Nearest Neighbor, energy efficiency

## I. INTRODUCTION

Fifth-generation wireless networks are expected to support high data rates, low latency, massive connectivity, and reliable service delivery for applications such as smart cities, remote monitoring, public safety, and industrial automation. Although 5G introduces new radio capabilities and dense heterogeneous deployment strategies, coverage limitations remain a major concern, especially in high-frequency bands where propagation losses are severe.

To address these issues, UAV-based Flying Base Stations have gained significant attention. Unlike fixed terrestrial infrastructure, FBSs can be deployed rapidly, repositioned dynamically, and used to extend coverage in overloaded or damaged network regions. Their role is particularly important in disaster recovery, rural connectivity, event-based traffic offloading, and mission-driven Internet of Things (IoT) services.

Despite these advantages, UAV deployment introduces a fundamental challenge: limited onboard energy. Rotary-wing UAVs, which are attractive because of their hovering capability, suffer from constrained flight endurance. As a result,



path planning becomes a central optimization problem. When an FBS must visit multiple ground nodes and return to its origin, the route should be designed to minimize the travel distance and, indirectly, energy expenditure.

This routing problem maps naturally to the Traveling Salesman Problem (TSP). Since TSP is NP-hard, exact solutions become impractical even for moderate problem sizes if repeated optimization is required. Therefore, lightweight heuristics with good empirical performance are preferred.

This paper focuses on the trajectory optimization of a single FBS serving multiple GNs. The main contributions are:

- Formulating FBS trajectory planning as a Euclidean symmetric TSP.
- Reviewing exact, heuristic, and approximation methods relevant to UAV routing.
- Justifying the use of a hybrid Nearest Neighbor + 2-opt heuristic.

Providing a computational discussion that explains why this method is suitable as a subroutine in larger multi-cell optimization problems

## II. RELATED BACKGROUND

### 2.1 UAV-Assisted 5G Networks

UAV-assisted wireless systems complement terrestrial networks by offering flexible aerial coverage. They are useful where ground infrastructure is difficult to deploy or insufficient to support dynamic demand patterns. In 5G, UAVs can assist by:

- extending coverage in weak-signal regions,
- supporting flash-crowd scenarios,
- restoring communication after disasters,
- enabling reliable uplink collection from IoT devices.

### 2.2 Energy Constraints in UAV Communications

The main limitation of UAV-based FBS deployment is energy. Rotary-wing UAVs consume significant propulsion and hovering power. If a UAV follows a poor route, both mission duration and energy usage increase. Therefore, even if communication quality is adequate, inefficient trajectory planning can make deployment infeasible.

### 2.3 TSP in UAV Routing

If one FBS starts from a macro base station, visits all assigned GNs exactly once, and returns to its origin, the trajectory design is equivalent to a TSP. In Euclidean deployment scenarios, edge weights are distances between 2D coordinates of GNs.

## III. PROBLEM FORMULATION

Let the set of nodes be

$$V = \{v_0, v_1, v_2, \dots, v_n\} \quad V = \{v_0, v_1, v_2, \dots, v_n\}$$

where  $v_0$  denotes the depot or MBS location and  $v_1, \dots, v_{n-1}, \dots, v_n$  are the ground nodes to be served.

The Euclidean distance between nodes  $v_i$  and  $v_j$  is

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

The objective is to find a Hamiltonian cycle of minimum total cost:

$$\min \sum_{i < j} d_{ij} x_{ij} \quad \min \sum_{i < j} d_{ij} x_{ij}$$

subject to standard TSP constraints:

Each selected edge variable satisfies

$$x_{ij} \in \{0, 1\} \quad x_{ij} \in \{0, 1\}$$

Each vertex has degree 2:

$$\sum_i x_{ik} + \sum_j x_{kj} = 2, \forall k \in V \quad \sum_i x_{ik} + \sum_j x_{kj} = 2, \forall k \in V$$

Subtours are eliminated for all proper subsets  $S \subset V$ .



The optimization objective is to reduce total travel distance, which directly supports lower propulsion-related energy consumption and improved UAV endurance.

#### IV. METHODOLOGY

##### 4.1 Why Exact Methods Are Not Preferred

Exact TSP methods such as brute-force enumeration, branch-and-bound, and dynamic programming can produce optimal solutions, but their computational cost grows rapidly with the number of nodes. Since UAV deployment decisions may need to be recomputed repeatedly across many simulation runs or real-time network states, exact methods are not practical in this setting.

##### 4.2 Candidate Heuristics

Several classical heuristics and approximation methods were considered:

Algorithm	Typical quality	Complexity
Greedy	Moderate	$O(n^2 \log n)$
Christofides	Good	$O(n^3)$
2-opt	very good	$\Theta(n^2)$ per improvement search
3-opt	better than 2-opt	$\Theta(n^3)$
Lin-Kernighan	Excellent	higher practical cost
Tabu Search	very good	$O(n^3)$
SA/GA/ACO	Competitive	parameter-sensitive

For the present problem, the desired method should be:

- computationally light,
- simple to implement,
- robust for repeated runs,
- suitable for embedding in a higher-level optimization framework.

##### 4.3 Proposed NN + 2-opt Hybrid

The proposed method uses two phases:

- Nearest Neighbor (NN): quickly builds an initial feasible tour.
- 2-opt local search: iteratively improves the tour by replacing crossing edges with shorter alternatives.

###### Phase 1: Nearest Neighbor

Starting from the MBS, the UAV repeatedly visits the nearest unvisited GN until all GNs are included, then returns to the depot.

###### Phase 2: 2-opt Improvement

Given the initial tour, 2-opt checks whether swapping two edges reduces total route length. If an improvement exists, the tour is updated. This continues until no further improving swap is possible.



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**Algorithm 1** 2-opt NN

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**Input:** 1. (n points) 2. (xy coordinates of points) 3. (Starting NN tour)

**Output:** 1. Tour between n points

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1 Evaluate the distance matrix
2 Define the NN tour
3 for i = 1 : n - 2 do
4   for j = i + 2 : n do
5     evaluate total length  $d_1$  of two edges
6     evaluate total length  $d_2$  of two edges when edges are swapped according to a 2-opt move
7      $d_2 < d_1$  implement edge swap
8   end
9 end

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#### 4.5 Complexity

NN construction:  $O(n^2)O(n^2)O(n^2)$

2-opt improvement search:  $O(n^2)O(n^2)O(n^2)$  per pass

Thus, the hybrid approach remains computationally manageable and is well suited for repeated optimization over moderate problem sizes.

#### 4.6. System and Evaluation Setting

The studied environment consists of a 2D Euclidean space with an MBS acting as depot and a set of GNs distributed across the service region. The UAV is assumed to be a rotary-wing platform with constrained energy and hovering capability.

The route quality is evaluated mainly in terms of:

- total path length,
- suitability for energy-efficient service delivery,
- practical computational time.

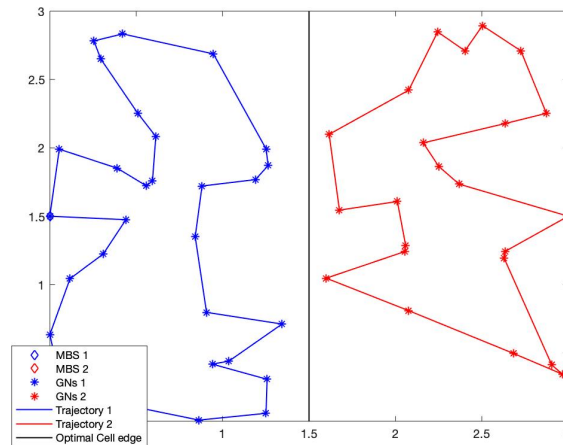
The work particularly targets GN sizes between 20 and 80 nodes, which are realistic in clustered service scenarios and repeated Monte Carlo evaluation.

### V. RESULTS AND DISCUSSION

The comparative discussion in the dissertation indicates that constructive heuristics alone, such as NN, Greedy, or Christofides, are not sufficient if used without improvement. Their tours remain relatively far from the best-known lower bounds. However, a simple constructive solution becomes much more valuable when followed by a fast improvement heuristic.

Among the improvement heuristics, 2-opt, 3-opt, and Lin-Kernighan (LK) are the strongest candidates. Although LK often gives better final tour quality, it requires higher runtime and implementation complexity. Since the trajectory solver in this work is intended to operate as a subroutine within a broader boundary optimization framework, speed is a dominant requirement.





The findings support the following conclusions:

- NN is a suitable initializer because it generates reasonably structured tours quickly.
- 2-opt substantially improves the NN solution while keeping runtime low.
- The resulting NN-2-opt hybrid offers the most practical trade-off for moderate-sized UAV routing problems.
- For repeated optimization inside larger algorithms, 2-opt is more useful than 3-opt or LK despite slightly lower route quality.

This makes the proposed approach particularly appropriate for UAV-assisted 5G applications where responsiveness matters as much as route optimality

## VI. CONCLUSION

This paper addressed the trajectory optimization of a UAV-based Flying Base Station in 5G wireless networks. The problem was formulated as a Euclidean Traveling Salesman Problem, with the objective of minimizing total route length and supporting energy-efficient deployment. After examining exact and heuristic TSP methods, a hybrid Nearest Neighbor + 2-opt strategy was selected due to its favorable balance between computational simplicity and route quality. The study shows that the proposed method is well suited for moderate GN sizes and repeated optimization tasks. Its main strength lies not only in good standalone performance, but also in its compatibility with larger optimization frameworks for multi-cell UAV-assisted networking.

Future work may extend this model by incorporating:

- communication-aware trajectory design,
- altitude optimization,
- joint hover-point and route optimization,
- time-varying GN demand,
- multi-UAV cooperative routing.

## REFERENCES

- [1]. Adnan Aijaz, Mischa Dohler, A Hamid Aghvami, Vasilis Friderikos, and Magnus Frodigh. Realizing the tactile internet: Haptic communications over next generation 5g cellular networks. *IEEE Wireless Communications*, 24(2):82–89, 2016.
- [2]. Mohammed A Alhanjouri and Belal Alfarra. Ant colony versus genetic algorithm based on travelling salesman problem. *Ant colony versus genetic algorithm based on travelling salesman problem*, 2(3), 2013.
- [3]. Daniel-Ioan Curiac. Towards wireless sensor, actuator and robot networks: Conceptual framework, challenges and perspectives. *Journal of Network and Computer Applications*, 63:14–23, 2016.
- [4]. George Dantzig, Ray Fulkerson, and Selmer Johnson. Solution of a large-scale traveling- salesman problem. *Journal of the operations research society of America*, 2(4):393–410, 1954.



- [5]. Harpreet S Dhillon, Howard Huang, and Harish Viswanathan. Wide-area wireless communication challenges for the internet of things. *IEEE Communications Magazine*, 55(2):168–174, 2017.
- [6]. Matthias Englert, Heiko Röglin, and Berthold Vocking. Worst case and probabilistic analysis of the 2-opt algorithm for the tsp. In *SODA*, pages 1295–1304. Citeseer, 2007.
- [7]. Michael Held and Richard M Karp. The traveling-salesman problem and minimum spanning trees. *Operations Research*, 18(6):1138–1162, 1970.
- [8]. Ekram Hossain, Mehdi Rasti, Hina Tabassum, and Amr Abdelnasser. Evolution toward 5g multi-tier cellular wireless networks: An interference management perspective. *IEEE Wireless Communications*, 21(3):118–127, 2014.
- [9]. David S Johnson and Lyle A McGeoch. The traveling salesman problem: A case study in local optimization. *Local search in combinatorial optimization*, 1(1):215–310, 1997.
- [10]. Michael Jünger, Gerhard Reinelt, and Giovanni Rinaldi. The traveling salesman problem. *Handbooks in operations research and management science*, 7:225–330, 1995.
- [11]. Christian Nilsson. Heuristics for the traveling salesman problem. 01 2003.
- [12]. Qingqing Wu, Yong Zeng, and Rui Zhang. Joint trajectory and communication design for multi-uav enabled wireless networks. *IEEE Transactions on Wireless Communications*, 17(3):2109–2121, 2018.
- [13]. Yong Zeng, Jie Xu, and Rui Zhang. Energy minimization for wireless communication with rotary-wing uav. *IEEE Transactions on Wireless Communications*, 18(4):2329–2345, 2019.
- [14]. Pei-Yuan Zhou and Keith CC Chan. A model-based multivariate time series clustering algorithm. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 805–817. Springer, 2014.

