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Multi-Cell Boundary Optimization for UAV-Assisted 5G Networks Using Piecewise Search and Ground-Node Clustering

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Abstract: *In UAV-assisted fifth-generation (5G) networks, Flying Base Stations (FBSs) can dynamically complement terrestrial macro base stations to improve coverage, support flash crowds, and reduce congestion. However, in a multi-cell environment, assigning ground nodes (GNs) to neighboring FBSs solely according to fixed terrestrial cell boundaries can lead to inefficient routing and increased energy consumption. This paper investigates the cell-edge placement problem for two adjacent cells served by two FBSs. The objective is to partition the GNs into two service clusters such that the combined route cost of both FBSs is minimized. The problem is modeled as a clustering-assisted extension of the Multiple Traveling Salesman Problem (MTSP). Three algorithms are considered: a linear boundary-search method, a piecewise boundary-search method, and a combined hierarchical boundary-search framework. Both proposed methods use a Nearest Neighbor plus 2-opt TSP solver to evaluate the route cost induced by each boundary position. Monte Carlo simulations are conducted for uniformly distributed GNs and flash-crowd scenarios with node sizes from 20 to 80. Results show that the piecewise boundary-search method consistently outperforms conventional K-means clustering in terms of mean net travel distance and energy consumption. Under uniform distributions, the optimal boundary remains near the geometric midpoint, while under flash-crowd conditions the optimal boundary shifts significantly toward the congested region to better balance the service burden between the two FBSs. The proposed approach demonstrates the importance of user-distribution-aware cell partitioning in UAV-assisted 5G systems.*

Keywords: UAV, Flying Base Station, 5G, clustering, cell boundary optimization, MTSP, K-means, flash crowd..

I. INTRODUCTION

The growing demand for mobile broadband, IoT connectivity, and reliable low-latency communication has accelerated interest in UAV-assisted 5G networks. UAVs acting as FBSs can provide on-demand aerial coverage where terrestrial infrastructure is overloaded, insufficient, or temporarily unavailable.

While a single-UAV routing problem can be treated as a Traveling Salesman Problem, real deployments often involve multiple neighboring cells and multiple UAVs. In such environments, one of the main challenges is not only how each FBS should move, but also which GNs should be assigned to which FBS.

A fixed geometric cell boundary may be inefficient in practice. For example:

- a GN near the edge of one cell may be easier for the neighboring FBS to serve,
- a flash crowd concentrated in one cell may require asymmetric partitioning,
- forcing one FBS to serve edge nodes far from its efficient route can increase total network cost.

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This motivates cell-edge location optimization, where the service boundary between adjacent cells is adapted according to user distribution rather than kept fixed at the geometric midpoint.

This paper focuses on a two-cell, two-FBS scenario and makes the following contributions:

- formulates GN assignment as a clustering-assisted MTSP-inspired optimization problem,
- proposes a linear boundary-search algorithm,
- extends it to a piecewise boundary-search algorithm,
- compares the proposed approach with K-means clustering,
- evaluates both methods under uniform and flash-crowd GN distributions

II. SYSTEM MODEL

Consider two adjacent terrestrial MBSs separated by distance xxx over a 2D service plane of size x×yx \times yx×y. Two FBSs are deployed, one associated with each MBS. A set of GNs is randomly distributed across the plane.Each GN must be assigned to one of the two FBSs. After assignment, each FBS computes a service trajectory starting from its corresponding MBS, visiting all assigned GNs, and returning to its origin. The route for each FBS is computed using the NN + 2-opt procedure.The objective is to determine a cell boundary that minimizes the combined travel distance of both FBSs:

min (D1+D2)\min \left(D_1 + D_2\right)min(D1+D2)

where D1D_1D1 and D2D_2D2 denote the trajectory lengths of FBS 1 and FBS 2, respectively.

This differs from classical MTSP because each FBS returns to its own depot rather than a common depot.

III. PROPOSED MODEL

3.1 Algorithm 1: Linear Boundary Search

A vertical linear boundary is swept across a restricted search range. For each candidate boundary position:

1. GNs are partitioned into two groups based on which side of the boundary they lie.
2. Each cluster is assigned to the corresponding FBS.
3. The trajectory of each FBS is computed using NN + 2-opt.
4. The combined travel distance is recorded.
5. The optimal linear boundary is the one with minimum net distance.

Search Range

The boundary is evaluated at seven candidate x-coordinates in the interval:

(7x20,13x20)\left(\frac{7x}{20}, \frac{13x}{20}\right)(207x,2013x)

This focuses the search near the central region while allowing adaptation away from the exact midpoint.

Complexity

If the TSP subroutine is O(n2)O(n^2)O(n2) and the number of boundary positions is constant, then the overall complexity remains:

O(n2)O(n^2)O(n2)

3.2 Algorithm 2: Piecewise Boundary Search

To improve over the linear boundary, the second method introduces a three-segment piecewise boundary. Starting from the best linear boundary obtained by Algorithm 1, two internal split points are allowed to vary over a restricted x-coordinate range.

For each candidate pair of split points:

1. A piecewise boundary is formed.
2. GNs are partitioned accordingly.

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3. Two FBS trajectories are computed.
4. The net distance is evaluated.

The optimal piecewise boundary is the one producing the minimum combined route length.

This method provides more flexibility than a simple straight-line division and can better capture asymmetric user distributions.

Complexity

Because the number of candidate split-point combinations is fixed, the complexity also remains:

O(n2)O(n^2)O(n2)

3.3 Algorithm 3: Combined Boundary Search

Algorithm 3 sequentially applies:

1. Algorithm 1 to find the best linear boundary,
2. Algorithm 2 to locally refine it into the best piecewise boundary.

This creates a practical two-stage search process with a single input layer and piecewise-optimized output.

IV. SIMULATION SETUP

Monte Carlo simulation is used because the optimal boundary depends strongly on the random spatial distribution of GNs. A single GN arrangement cannot represent general performance.

Parameters

Parameter	Description	Value
MC	Monte Carlo runs	1000
GNs	Number of ground nodes	20 to 80 in steps of 10
UAV power	Propulsion power	50 W
UAV speed	Velocity	60 m/s
Area	Service area	3 km x 3 km
Distribution 1	Uniform GN distribution	Random
Distribution 2	Flash-crowd distribution	45% nodes in dense strip

Scenarios

Four simulation cases are studied:

Simulation 1: Linear boundary under uniform GN distribution

Simulation 2: Piecewise boundary under uniform GN distribution with K-means comparison

Simulation 3: Linear boundary under flash-crowd distribution

Simulation 4: Piecewise boundary under flash-crowd distribution with K-means comparison

V. RESULTS AND DISCUSSION

5.1 Uniform Distribution: Linear Boundary

Under uniform GN placement, the optimal linear cell boundary is consistently observed near the midpoint at:

x=1.5 kmx = 1.5 \text{ km}x=1.5 km

This is expected due to spatial symmetry between the two cells. The mean combined route length increases with GN count because more nodes require additional travel and hovering.

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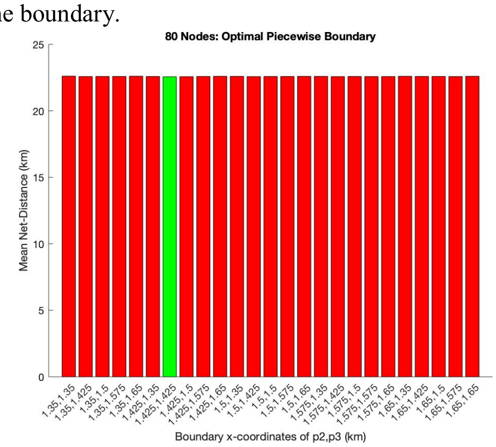
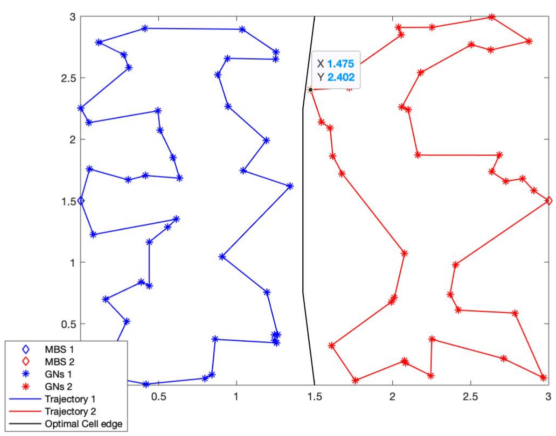
5.2 Uniform Distribution: Piecewise Boundary

The piecewise boundary search produces a small but consistent improvement over the linear boundary. For larger GN counts, the improvement becomes more visible because the increased density creates more opportunities for advantageous reassignment near the boundary.



Optimal Piecewise Cell Edge Location after 1,000 Instances



Optimal Piecewise Cell Edge for 80 GNs - Instance 1 Trajectory Representation

Representative results show that:

- the best piecewise boundary slightly perturbs the central vertical line,
- the improvement in mean distance is around 10 to 20 meters in several cases,
- the method consistently performs better than K-means clustering.

5.3 Comparison with K-means

K-means is more flexible geometrically, but it optimizes clusters based on centroid proximity rather than FBS route cost. As a result:

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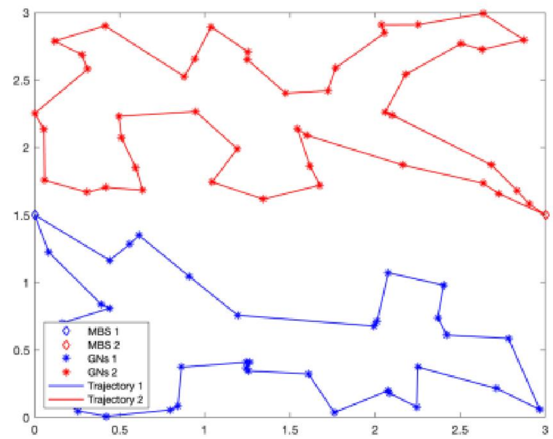
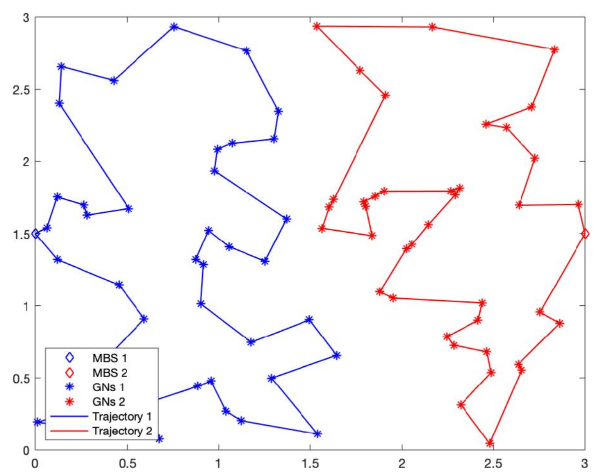
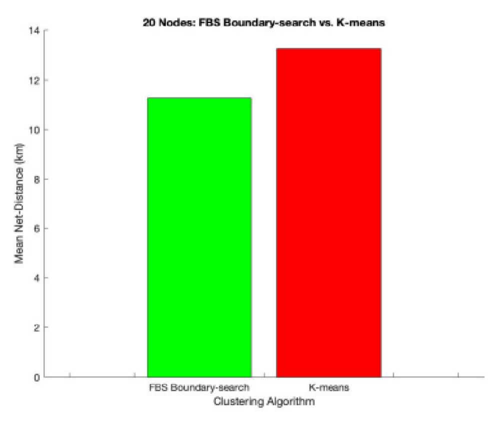


K-means clustering of 80 GNs at Instance 1



K-means clustering of 80 GNs at Instance 10



Comparison of Algorithm 2 and K-means Clustering - Mean Net Distance

- K-means does not necessarily minimize combined trajectory length,

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- the proposed piecewise boundary method yields lower mean net distance,
- both FBSs consume less energy when using the proposed method.

This confirms that route-aware clustering is more appropriate than pure geometric clustering in this application.

5.4 Flash-Crowd Scenario

When 45% of GNs are concentrated in a dense strip, the optimal boundary shifts strongly toward the congested region. This allows one FBS to focus on the flash crowd while the other serves scattered nodes in the remaining space.

Key observations include:

- the optimal linear boundary moves away from the midpoint,
- the piecewise boundary further improves performance,
- for very sparse total node counts, it may even become preferable to let one FBS dominate service while the second has minimal workload,
- the proposed method significantly outperforms K-means in mean route distance.

This shows that fixed terrestrial boundaries are unsuitable in highly non-uniform demand conditions.

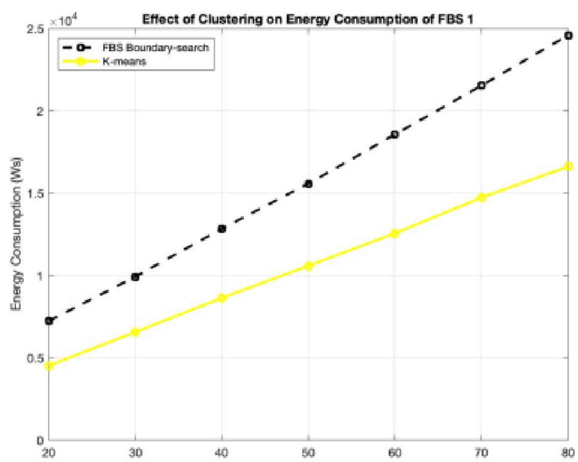
The results lead to several important insights.

First, cell-edge placement should depend on user distribution, not only on the terrestrial geometry. A static midpoint boundary is reasonable only under near-uniform conditions.

Second, piecewise boundaries are more effective than linear boundaries because they allow local refinement near dense clusters or near-edge nodes.

Third, K-means is not ideal for this problem. Although it is widely used for clustering, it does not account for the closed-loop routing cost of each FBS. In contrast, the proposed boundary-search framework evaluates the true operational objective.

Fourth, the proposed method remains computationally practical because the boundary candidate set is bounded and the embedded TSP solver is polynomial-time.



Effect of Clustering on Energy Consumption of FBS 1 after 1,000 Instances

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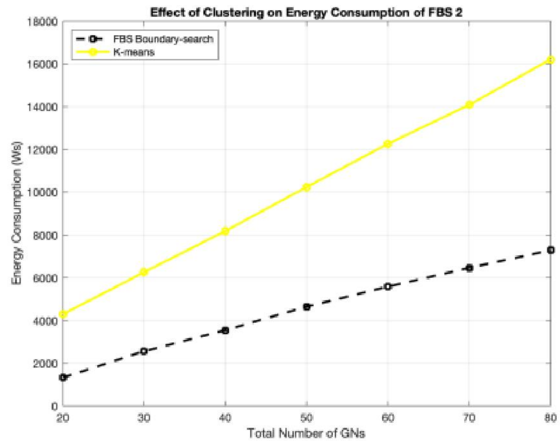

Effect of Clustering on Energy Consumption of FBS 2 after 1,000 Instances

GNs	20	30	40	50	60	70	80
Algorithm 2							
(1) (x_1, x_2)(km)	(2.1,2.1)	(1.425,1.35)	(1.2,1.275)	(1.125,1.125)	(1.05,1.125)	(1.05,1.12 5)	(1.125,1 .
(2) μ_p(km)	11.26	13.34	14.81	16.09	17.19	18.21	19.23
(3) $\mu_l - \mu_p$(m)	30	0	30	10	10	50	50
(4) σ_1(km)	0.0222	0.0148	0.0258	0.0218	0.0291	0.0529	0.0522
(5) σ_2(km)	1.6593	1.3884	1.1829	1.1579	1.0798	1.1011	1.0966
K-means Clustering							
(6) μ_k(km)	13.26	15.14	16.56	17.88	18.89	19.93	20.86
(7) σ_k(km)	1.5594	1.3610	1.1455	1.0719	0.9776	0.9601	0.9053 hei

Simulation Summary of Results

VI. CONCLUSION

This paper investigated boundary optimization for two-FBS deployment in UAV-assisted 5G networks. The problem was formulated as a clustering-driven extension of the MTSP in which the assignment of GNs to neighboring FBSs is determined by minimizing the combined route cost.

A linear boundary-search algorithm and a refined piecewise boundary-search algorithm were proposed. Simulation results under both uniform and flash-crowd distributions showed that the proposed approach consistently outperforms K-means clustering in terms of mean net travel distance and energy usage.

The study highlights a central design principle for UAV-assisted wireless systems: efficient routing requires adaptive partitioning of service regions.

Future work may extend this framework by:

- allowing angled or curved boundaries,

- optimizing more than two cells,
- incorporating communication rate and SINR constraints,
- considering altitude and hovering-point selection jointly,
- Supporting dynamic online re-partitioning in time-varying traffic environments.

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