

## Article

# Dual-Scale Grid-Based Adaptive Trajectory Planning for UAVs in Urban Low-Altitude Airspace

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## Abstract

With the rapid growth of the low-altitude economy, the number of unmanned aerial vehicles (UAVs) has grown rapidly. It is challenging to plan substantial UAV trajectories in complex urban low-altitude airspace, considering the airspace capacity, inter-vehicle safety, and communication reliability. To deal with this challenge, we propose a dual-scale grid-based trajectory planning approach that separates the global routing and local refinement. Specifically, we discretize the three-dimensional airspace into coarse macro-grids for capacity-constrained routing and high-quality communication-aided fine micro-grids for collision-free trajectory refinement. Both consider an altitude-dependent energy model. To handle the complex dual-scale grid trajectory planning of UAVs, we propose a priority-driven dual-grid Theta\* with adaptive relaxation (DGTAR) to balance the global planning efficiency and local obstacle avoidance accuracy. First, we design a priority-driven capacity allocation mechanism to enforce safe separation among UAVs. Then, a combined planner is proposed, which integrates a Theta\*-enhanced global search with a sampling-based refinement algorithm, invoking on-demand boundary relaxation to ensure the feasibility. Simulation results reveal that the proposed method DGTAR achieves reductions in many aspects compared with benchmark mechanisms, while maintaining a high planning success rate in congested scenarios.

**Keywords:** UAV trajectory planning; urban low-altitude airspace; grid division**MSC:** 90C90; 90C59; 68W50

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## 1. Introduction

The dense deployment of unmanned aerial vehicles (UAVs) in urban low-altitude airspace has created unprecedented challenges for trajectory planning [1,2]. In such environments, the airspace is constrained by dense buildings, the available communication spectrum is limited, and many UAVs must share a finite volume while maintaining safe separation and reliable connectivity [3,4]. An optimal trajectory for an isolated UAV under a single criterion may easily lead to congestion, communication blackouts, or excessive energy consumption when multiple UAVs coexist [5,6]. Achieving a balance between the airspace capacity, inter-vehicle safety, communication reliability, and energy efficiency within a single planning framework remains an open problem.

A widely adopted strategy to reduce the planning complexity is airspace discretization [7]. The urban airspace can be divided into corridors, layers, or grids [8–10]. Among these, the grid method strikes a balance between safety and airspace utilization. However, most existing grid-based schemes adopt a single uniform resolution, which forces a fundamental trade-off. Specifically, the coarse grids are efficient for global routing and capacity management but cannot capture fine-grained obstacles [11,12]. In contrast, fine grids enable precise collision avoidance but make multi-UAV coordination computationally prohibitive [13]. Although adaptive and multi-resolution grids have been explored to mitigate this trade-off, they rarely embed communication and energy attributes directly into the grid structure, nor do they explicitly separate coarse-grained capacity management from fine-grained obstacle avoidance [14–16].

Beyond spatial representation, communication-aware planning has emerged as a critical requirement for UAV operations. Radio-map-based approaches precompute large-scale channel gains and ensure a minimum signal-to-noise ratio along the planned path [17]. Similarly, energy-aware planning has been extensively investigated, with propulsion power models that capture the effect of altitude variation on rotary-wing UAV endurance [18]. Nevertheless, these communication- and energy-aware planners are typically designed for a single UAV over a predetermined route and do not consider shared airspace capacity or inter-UAV separation. As a consequence, individually optimized trajectories may satisfy their dedicated constraints but cause resource conflicts when deployed simultaneously.

To deal with the above challenges, we consider a scenario where multiple UAVs perform missions in urban low-altitude airspace under heterogeneous constraints. We adopt a dual-grid spatial discretization that partitions the airspace into macro-grids for capacity-constrained routing and micro-grids for fine-grained obstacle avoidance and communication verification. To solve the three-dimensional (3D) UAV trajectory planning problem, we design a priority-driven dual-grid Theta\* with adaptive relaxation (DGTAR) algorithm. The main contributions of this work are summarized as follows.

- To depict the complex three-dimensional urban airspace, we design a dual-grid spatial discretization that partitions the airspace into macro-grids and micro-grids. The unit-power channel gains and altitude-dependent energy costs are precomputed and embedded as grid attributes, so that communication and energy constraints are naturally integrated into the planning graph.
- We formulate multi-UAV coordination under the airspace capacity, collision avoidance, communication, and energy constraints as a constrained combinatorial optimization problem over discrete grid sequences. The problem jointly optimizes macro- and micro-grid trajectories to minimize total distance, energy, and communication penalty, while strictly enforcing macro-grid capacity limits, micro-grid exclusivity, and obstacle avoidance.
- We design the DGTAR algorithm to solve the problem hierarchically. At the macro-level, a Theta\*-enhanced router generates compact spatial corridors that respect macro-grid capacity limits. At the micro-level, a micro-planner with particle swarm optimization (PSO) refinement generates collision-free trajectories inside each corridor. When a strict corridor is infeasible due to obstacles or prior occupancy, an on-demand boundary relaxation mechanism temporarily widens the search region to neighboring macro-grids, ensuring that a feasible path can always be found.
- Simulations demonstrate that DGTAR consistently outperforms single-resolution and non-relaxation baselines in total cost, flight distance, energy consumption, and communication penalty, while maintaining a 100% planning success rate in heavily congested scenarios.

The remainder of this paper is organized as follows. Section 2 reviews related works. Section 3 presents the system model and formulates the optimization problem. Section 4 describes the hierarchical solution methodology. Section 5 provides simulation results and discussion. Finally, Section 6 draws the conclusions.

## 2. Related Works

Safe and efficient multi-UAV trajectory planning in dense urban low-altitude airspace is a multifaceted challenge. As for communication, maintaining reliable wireless connectivity is a prerequisite for UAV trajectory planning. For example, Ref. [19] proposed a 3D global path planner for a cellular-connected UAV by using a reliable communication zone map to find the path with guaranteed link reliability under power constraints. Ref. [20] developed a learning-based trajectory optimization method by using a precomputed radio map to train a deep reinforcement learning agent, enabling a single UAV to generate collision-free paths while satisfying wireless connectivity. Considering the energy cost, Ref. [21] developed a systematic low-power optimization framework that built an accurate propulsion power model capturing three-axis dynamics, altitude, wind, and payload effects for a single rotary-wing UAV without relying on aerodynamic priors. Ref. [22] generated smooth and practically executable 3D trajectories for one UAV, significantly improving the energy efficiency. However, these studies failed to account for shared airspace capacity, ignoring the severe spatial conflicts and congestion that can occur when many UAVs are deployed in the same airspace.

To manage the simultaneous operation of multiple UAVs, a complementary body of research has developed multi-agent coordination and scheduling mechanisms. Ref. [23] proposed an iterative single-head attention mechanism for multi-UAV path planning, in which a communication helper computed attention scores to guide each UAV's control decisions, achieving a lower flight time with lower collision risks under limited communication resources. Ref. [24] developed a dynamic traffic volume reservation method based on a multi-scale A\* algorithm that represented the airspace as a multi-resolution grid and employed a hybrid strategy to maintain near-optimal path quality while running in real time for UAV traffic management. Ref. [25] constructed a dynamic priority model incorporating collision risk, total distance, and waiting time, and introduced a congestion-weighted Lazy Theta\* algorithm for individual path planning to guide UAVs away from congested regions and reduce conflict probability.

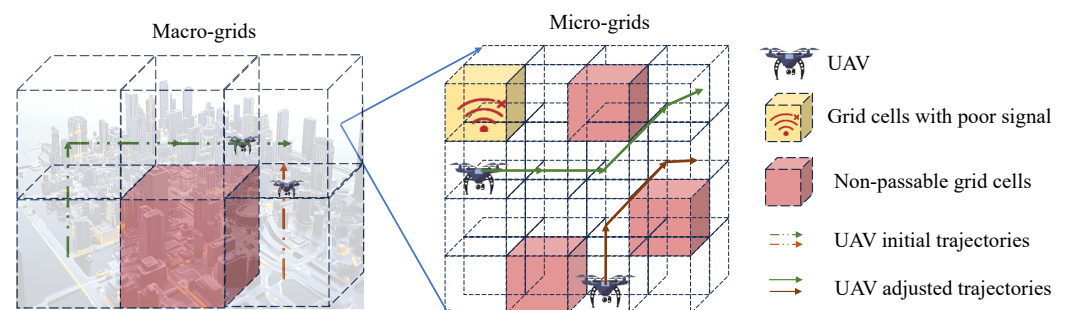
While the coordination strategies above differ in their underlying spatial representations, grid-based discretization remains the most widely adopted foundation for taming the computational complexity of three-dimensional multi-UAV path planning. Ref. [26] proposed an energy-aware grid-based coverage path planning method that partitioned the target area into uniform grid cells and applied a parallel partitioning strategy along one side to generate efficient coverage trajectories while respecting no-fly zones. Ref. [27] generated a fast constant-altitude path planning algorithm for urban UAVs using quad-tree decomposition and Theta\* with post-smoothing. Ref. [28] designed a non-rigid hierarchical discrete grid structure for UAV conflict detection and single-resolution grid-based path planning. Existing adaptive grid methods mitigate the resolution dilemma only geometrically, without embedding communication or energy attributes.

In summary, existing methods address the communication, energy, coordination, and discretization in isolation, lacking an integrated framework that jointly optimizes these coupled objectives within a unified spatial model. To bridge this gap, this paper proposes a dual-scale grid representation that structurally decouples macro-level capacity-constrained routing from micro-level collision-free refinement, considering the communication quality and energy costs.

### 3. System Model

#### 3.1. Scenario

As shown in Figure 1, we consider an urban low-altitude airspace  $\mathcal{A} \subset \mathbb{R}^3$ , which is partitioned into a set of regular macro-grids, indexed by  $\mathcal{G}^M = \{g_i^M | i = 1, 2, \dots, N_M\}$ . The dimensions of the macro-grid are  $\Delta_X^M \times \Delta_Y^M \times \Delta_H^M$ . To accurately capture the characteristics of airspace status, each macro-grid  $g_i^M$  is further subdivided into  $N_m$  micro-grids, denoted as  $\mathcal{G}_i^m = \{g_{i,j}^m | j = 1, 2, \dots, N_m\}$ . The dimensions of the micro-grid are  $\Delta_X^m \times \Delta_Y^m \times \Delta_H^m$ . Each grid cell, both the macro and micro, indexed by  $g$ , is assigned a set of attributes, which are precomputed and stored for efficient querying during planning. Obstacle flag  $\text{obs}(g) \in \{0, 1\}$  indicates whether grid  $g$  is free ( $\text{obs}(g) = 0$ ) or contains a static obstacle ( $\text{obs}(g) = 1$ ). If  $\text{obs}(g_i^M) = 1$ , all its child micro-grids are considered impassable. In this work, all obstacles are assumed to be static and known a priori, such as buildings and terrain. Dynamic obstacles are not considered and are left for future investigation. Center coordinates  $\mathbf{c}_g \in \mathbb{R}^3$  are the geometric center of the grid, used to compute the Euclidean distances between grids.



**Figure 1.** Dual-scale grids for low-altitude airspace.

$K$  rotary-wing UAVs, indexed by  $k \in \mathcal{K} = \{1, 2, \dots, K\}$ , are deployed to perform point-to-point transport missions. To balance the global efficiency and local precision, we adopt a two-stage hierarchical planning architecture. The first stage determines a coarse spatial corridor at the macro-grid level, while the second stage generates a fine-grained micro-grid trajectory within that corridor. The planning task is to determine for each UAV  $k$  a discrete-step trajectory defined as a sequence. Hence, the trajectory of UAV  $k$  in the macro-grids is

$$\mathcal{P}_k^M = (g_{k,1}^M, g_{k,2}^M, \dots, g_{k,q}^M, \dots, g_{k,N_k^M}^M), \quad (1)$$

where  $N_k^M$  is the number of steps for UAV  $k$  in the macro-grids. Similarly, the trajectory of UAV  $k$  in the micro-grids of macro-grid  $q$  is

$$\mathcal{P}_{k,q}^m = (g_{k,q,1}^m, g_{k,q,2}^m, \dots, g_{k,q,r}^m, \dots, g_{k,q,N_{k,q}^m}^m), \quad (2)$$

where  $N_{k,q}^m$  is the number of steps for UAV  $k$  in the micro-grids of macro-grids  $q$ .

#### 3.2. Motion and Energy Consumption Model

The UAV velocity does not appear as an explicit decision variable in this paper, because the velocity is an intrinsic parameter of a specific UAV platform, whereas the grid representation aims to capture the geometric and environmental properties of the airspace itself. By excluding the velocity from the planning variables, the resulting grid trajectory  $\mathcal{T}_k$  becomes a purely spatial sequence that is independent of the UAV type. So that the same path can be assigned to different UAV platforms, each of which can convert the spatial waypoints into a platform-specific flight schedule by imposing its own velocity profile.

For a macro-grid  $g_i^M$ , its 6-neighborhood  $\mathcal{N}(g_i^M)$  consists of itself and the grids that share a face with it. For a micro-grid  $g_{i,j}^m$ , its 11-neighborhood  $\mathcal{N}(g_{i,j}^m)$  consists of itself and the grids that share at least an edge in the horizontal plane or a face in the vertical direction.

According to [29], the propulsion power of a rotary-wing UAV can be expressed as a function of the flight velocity and air density; i.e.,

$$p^{uf} = P_1 \left( 1 + \frac{3\|\mathbf{v}^{uf}\|^2}{U_{tip}^2} \right) + \frac{1}{2} d_0 \zeta_0 s A \|\mathbf{v}^{uf}\|^3 + P_2 \left( \sqrt{1 + \frac{\|\mathbf{v}^{uf}\|^4}{4v_0^2}} - \frac{\|\mathbf{v}^{uf}\|^2}{2v_0^2} \right)^{\frac{1}{2}}, \quad (3)$$

where  $P_1$  is the blade profile power,  $U_{tip}$  denotes the blade tip speed,  $d_0$  represents the fuselage drag ratio,  $\zeta_0$  indicates the air density,  $s$  is the rotor solidity,  $A$  denotes the rotor area,  $P_2$  represents the induced power in hover, and  $v_0$  indicates the mean rotor-induced velocity.

For a UAV cruising at a constant economic speed, the right-hand side of (3) becomes a function of  $\zeta_0$  only. In the troposphere, the air density decreases nearly linearly with altitude; within the urban low-altitude range  $[0, H_{max}]$ , this can be approximated as  $\zeta_0(h) \approx \zeta_0(0)(1 - \alpha h)$  with a small constant  $\alpha > 0$ . Consequently, the propulsion power, and hence the energy consumption per unit distance, grows approximately linearly with altitude  $h$ .

To obtain a planning-oriented model that is independent of UAV-specific parameters and can be precomputed as a per-grid attribute, we abstract this relationship into the following simplified form:

$$E^{unit}(g) = E_{base} \left( 1 + \beta_h \frac{h_g}{H_{max}} \right), \quad (4)$$

where  $h_g$  is the altitude of grid  $g$ ,  $E_{base}$  denotes the baseline energy per unit distance at sea level under nominal conditions [30,31],  $H_{max}$  indicates the maximum operational altitude, and  $\beta_h \geq 0$  is a coefficient that captures the altitude-dependent air-density effect. The parameter  $\beta_h$  can be calibrated from flight data for a specific UAV class, or set to zero if the altitude effect is negligible; the structure of the planning algorithm remains unchanged. Equation (4) depends solely on the grid geometry  $h_g$ , which allows the energy cost of every grid to be precomputed and stored as a static attribute, facilitating efficient energy-aware routing without online evaluation of UAV dynamics.

For a trajectory of UAV  $k$ , i.e.,  $\mathcal{T}_k$ , the total propulsion energy is composed of the grid unit costs and Euclidean distances between the consecutive grid centers; i.e.,

$$E^{total}(\mathcal{T}_k) = \sum_{g \in \mathcal{T}_k} \left[ E^{unit}(g+1) \|\mathbf{c}_{g+1} - \mathbf{c}_g\|_2 + E_{climb}(h_{g+1} - h_g) \right],$$

where  $E_{climb}(\Delta h)$  accounts for the extra energy cost of climbing and the potential energy recovery during descent [18], calculated as

$$E_{climb}(\Delta h) = \eta_{climb} \max(\Delta h, 0) - \eta_{desc} \max(-\Delta h, 0), \quad (5)$$

where  $\eta_{climb}$  and  $\eta_{desc} > 0$  are the energy consumption per unit height increment and decrement, respectively.

### 3.3. Communication Environment Model

The communication reliability depends on the propagation environment. To keep the model independent of UAV-specific hardware, such as the transmit power and bandwidth,

we define a purely environmental communication index for each micro-grid. We assume  $N^B$  ground base stations (GBSs) with known locations. A radio map is precomputed, storing the normalized large-scale channel gain (unit-power gain) between each grid center and each GBS. Let  $\bar{G}(g, b)$  denote the signal-to-noise-ratio per unit power between grid  $g$  and GBS  $b$ , calculated as

$$\bar{G}(g, b) = \frac{\beta_0 d_{g,b}^{-2}}{\delta^2}, \quad (6)$$

where  $d_{g,b} = \|\mathbf{c}_g - \mathbf{c}_b\|_2$  is the distance from the grid center to GBS  $b$ ,  $\beta_0$  is the reference gain at 1 m, and  $\delta^2$  denotes the noise power. This value depends solely on geometry and the propagation environment.

For planning purposes, we condense this information into a single communication environment index per grid, defined as the maximum unit-power gain among all GBSs; i.e.,

$$G^{\text{env}}(g) = \max_{b \in \{1, \dots, B\}} \bar{G}(g, b). \quad (7)$$

A higher value of  $G^{\text{env}}(g)$  indicates a more favorable communication environment. To encourage trajectories that favor strong communication links beyond the minimum requirement, we introduce a grid-based penalty used in the objective function. For grid  $g$ , the penalty is

$$\ell_{\text{comm}}(g) = \max\left(0, 1 - \frac{G^{\text{env}}(g)}{G_{\text{ref}}}\right), \quad (8)$$

where  $G_{\text{ref}}$  is a reference gain level. This penalty is zero when  $G^{\text{env}}(g) \geq G_{\text{ref}}$  and increases linearly as the environment quality degrades.

### 3.4. Hierarchical Planning Framework

The complete trajectory of UAV  $k$  is fully determined by its macro-grid sequence  $\mathcal{P}_k^M$  and the micro-grid sequences  $\mathcal{P}_{k,q}^m$  inside each macro-cell. Therefore, the decision variables are the integer sequence  $\mathcal{P}_k^M$  of length  $N_k^M$ , and integer sequences  $\mathcal{P}_{k,q}^m$  of length  $N_{k,q}^m$  for each macro-cell  $q$ . All constraints, such as the capacity, obstacle avoidance, exclusivity, and step length, are combinatorial in nature because the variables take discrete values over finite grid index sets. Even for a single UAV, the number of possible paths grows exponentially with the grid dimensions, making exact enumeration impractical. The two sub-problems are formalized below.

#### 3.4.1. Stage 1: Macro-Grid Routing Sub-Problem

For a single UAV  $k$  processed in the priority order, the objective of Stage 1 is to find a macro-grid path  $\mathcal{P}_k^M$  that connects the macro-grid containing  $S_k$  to that containing  $D_k$ . The path cost for  $\mathcal{P}_k^M$  is

$$J_k^M(\mathcal{P}_k^M) = w_d^M \frac{D_k^M}{D_k^{\text{Mref}}} + w_e^M \frac{E_k^{\text{Mt}}}{E_k^{\text{M}}}, \quad (9)$$

where  $D_k^M = \sum_{q=1}^{N_k^M-1} \|\mathbf{c}_{g_{k,q+1}^M} - \mathbf{c}_{g_{k,q}^M}\|_2$  is the total flight distance,  $D_k^{\text{Mref}} = \|\mathbf{c}_{D_k} - \mathbf{c}_{S_k}\|_2$  is the straight-line reference distance, and  $E_k^{\text{Mt}} = E^{\text{total}}(\mathcal{P}_k^M)$  is the energy cost of all macro-grids. Moreover,  $E_k^{\text{M}}$  is the energy budget of all macro-grids, and  $w_d^M, w_e^M \geq 0$  with  $w_d^M + w_e^M = 1$  are weights.

The macro-grid problem for UAV  $k$  is then formulated as

$$\begin{aligned} \mathbf{P1}: \min_{\mathcal{P}_k^M} & \sum_{k=1}^K p_k J_k^M(\mathcal{P}_k^M) \\ \text{s.t. } & g_{k,1}^M = S_k^M, \quad g_{k,N_k^M}^M = D_k^M, \forall k, \end{aligned} \quad (10)$$

$$\text{obs}(g_{k,q}^M) = 0, \quad \forall k, q, \quad (11)$$

$$\sum_{k=1}^K \mathbb{I}(g_{k,q}^M = g_i^M) \leq C^{\max}, \quad \forall q, i, \quad (12)$$

where a higher priority value  $p_k$  indicates a higher urgency.  $S_k^M$  and  $D_k^M$  are the start and destination macro-grids of UAV  $k$ , respectively. Constraint (12) limits the instantaneous capacity within macro-grids, thereby ensuring flight safety. Indicator function  $\mathbb{I}(g_{k,q}^M = g_i^M)$  represents when UAV  $k$  is in macro-grid  $g_i^M$  at step  $q$ ,  $\mathbb{I}(g_{k,q}^M = g_i^M) = 1$ , otherwise,  $\mathbb{I}(g_{k,q}^M = g_i^M) = 0$ .

### 3.4.2. Stage 2: Micro-Grid Refinement Sub-Problem

In macro-grid  $g_{k,q}^M$ , the cost for trajectory  $\mathcal{P}_{k,q}^m$  is

$$J_{k,q}^m(\mathcal{P}_{k,q}^m) = w_d^m \frac{D_{k,q}^m}{D_{k,q}^{m\text{ref}}} + w_e^m \frac{E_{k,q}^{mt}}{E_{k,q}^m} + w_c^m \frac{1}{N_{k,q}^m} \sum_{r=1}^{N_{k,q}^m} \ell_{\text{comm}}(g_{k,q,r}^m), \quad (13)$$

where  $D_{k,q}^m = \sum_{r=1}^{N_{k,q}^m-1} \|\mathbf{c}_{g_{k,q,r+1}^m} - \mathbf{c}_{g_{k,q,r}^m}\|_2$  is the total flight distance in macro-grid  $g_{k,q}^M$ ,  $D_{k,q}^{m\text{ref}} = \|\mathbf{c}_{D_{k,q}^M} - \mathbf{c}_{S_{k,q}^M}\|_2$  is the straight-line reference distance in macro-grid  $g_{k,q}^M$ , and  $E_{k,q}^{mt} = E^{\text{total}}(\mathcal{P}_{k,q}^m)$  is the energy cost of all micro-grids in macro-grid  $g_{k,q}^M$ . Moreover,  $E_{k,q}^m$  is the energy budget of all micro-grids in macro-grid  $g_{k,q}^M$ , and  $w_d^m, w_e^m, w_c^m \geq 0$  with  $w_d^m + w_e^m + w_c^m = 1$  are weights. Hence, the path cost for all micro-grids is

$$\begin{aligned} \mathbf{P2}: \min_{\mathcal{P}_{k,q}^m} & \sum_{k=1}^K \sum_{q=1}^{N_k^M} p_k J_{k,q}^m(\mathcal{P}_{k,q}^m) \\ \text{s.t. } & g_{k,q,1}^m = S_{k,q}^m, \quad g_{k,q,N_{k,q}^m}^m = D_{k,q}^m, \quad \forall k, q, \end{aligned} \quad (14)$$

$$\sum_{k=1}^K \mathbb{I}(g_{k,q,r}^m = g_{i,j}^m) \leq 1, \quad \forall q, r, i, j \quad (15)$$

$$\text{obs}(g_{k,q,r}^m) = 0, \quad \forall k, q, r, \quad (16)$$

$$\|\mathbf{c}_{g_{k,q,r}^m} - \mathbf{c}_{g_{k,q,r'}}^m\|_2 \leq d_{\max}, \quad \forall k, q, r, \quad (17)$$

where  $S_{k,q}^m$  and  $D_{k,q}^m$  are the start and destination micro-grids of UAV  $k$  in macro-grid  $g_{k,q}^M$ , respectively. Constraint (15) limits the instantaneous capacity within micro-grids. Indicator function  $\mathbb{I}(g_{k,q,r}^m = g_{i,j}^m)$  represents when UAV  $k$  is in micro-grid  $g_{i,j}^m$  at step  $r$  in macro-grid  $g_{k,q}^M$ ,  $\mathbb{I}(g_{k,q,r}^m = g_{i,j}^m) = 1$ , otherwise,  $\mathbb{I}(g_{k,q,r}^m = g_{i,j}^m) = 0$ . Constraints (16) and (17) protect UAVs from collisions. Because **P1** and **P2** are large-scale discrete optimization problems whose exact solution becomes computationally prohibitive for online planning, Section 4 develops a hierarchical heuristic that sequentially solves the macro-routing and micro-refinement stages.

## 4. Algorithm Design

To address problem **P1** and **P2** presented in Section 3, we propose a priority-driven DGTAR framework that strictly follows the two-level spatial decomposition. The overall workflow is summarized in Algorithm 1. Specifically, at the macro-level, a Theta\*-enhanced global router replaces the standard A\* search to produce significantly shorter and more direct coarse-grained corridors (lines 5–9). At the micro-level, a sampling-based refinement algorithm with on-demand boundary relaxation is designed (lines 10–15). When the feasible region within a macro-grid is severely restricted by obstacles or reserved by higher-priority UAVs, the planner temporarily expands the search space to include micro-grids of neighboring macro-cells, guaranteeing the local feasibility without permanently violating the corridor structure.

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### Algorithm 1 Priority-Driven DGTAR

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**Require:** UAV set  $\mathcal{K}$  with  $\{p_k, S_k, D_k\}$ .

**Ensure:** Trajectories  $\{\mathcal{T}_k\}$ .

```

1: Sort  $\mathcal{K}$  by descending  $p_k$  into list  $\mathcal{Q}$ .
2: Initialize  $R(g^M) = C^{\max}(g^M)$  for all  $g^M$ .
3: Initialize  $\text{Occ}(g^m, \ell) = \text{false}$  for all  $g^m, \ell$ .
4: for each  $k \in \mathcal{Q}$  do
5:   Optimize  $\mathcal{P}_k^M$  in Algorithm 2.
6:   if  $\mathcal{P}_k^M = \emptyset$  then
7:     postpone  $k$ ; continue.
8:   end if
9:   Update  $R(g^M) = R(g^M) - 1$  for all  $g^M \in \mathcal{P}_k^M$ .
10:  Optimize  $\mathcal{T}_k$  in Algorithm 3.
11:  if  $\mathcal{T}_k \neq \emptyset$  then
12:    Update  $\text{Occ}(g_{k,\ell}^m, \ell) = \text{true}$  for all  $\ell$ .
13:  else
14:    report failure for UAV  $k$ .
15:  end if
16: end for
17: return  $\{\mathcal{T}_k\}$ .

```

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#### 4.1. Level 1: Theta\*-Enhanced Macro-Grid Routing

For each UAV, the macro-router must find a path from the macro-grid containing  $S_k$  to that containing  $D_k$ . Algorithm 2 implements Theta\* with line-of-sight (LoS) acceleration. The search starts by setting the priority queue and the  $g$  and  $f$  costs of the start macro-grid (lines 1–3). In the main loop (line 4), the node with the lowest  $f$ -cost is popped (line 5). If it equals the goal, the macro-grid corridor is reconstructed and returned (lines 6–7). Otherwise, the node is moved to the closed set (line 9). The face-adjacent neighbours are first collected (line 10), and every node reachable via LoS from the parent of the current node is also added to the candidate set  $\mathcal{N}$  (line 11). This LoS extension is the core acceleration: for each neighbour  $n$ , the algorithm selects as its parent the LoS-parent if a collision-free straight line exists through passable macro-grids, or the current node otherwise (line 16). Cells that are occupied or whose residual capacity  $R(n) < C^{\max}$  are skipped immediately (line 15). A tentative  $g$ -cost is computed through the chosen parent (line 17) and, if it improves the neighbour's cost, the neighbour's parent,  $g$  and  $f$  are updated and it is pushed into the open list (lines 18–23). Since LoS checks involve only coarse-grid voxel traversals, Theta\* introduces a minor computational overhead while effectively pruning unnecessary intermediate waypoints, yielding a shorter and more direct macro-grid corridor.

**Algorithm 2** Theta\* Macro-Grid Routing**Require:** Start macro-grid  $g_{\text{start}}$ , goal macro-grid  $g_{\text{goal}}$ , capacity array  $R$ .**Ensure:** Macro-grid path  $\mathcal{P}^M$  or  $\emptyset$ .

```

1: Initialize priority queue  $G_{\text{OPEN}}$ .
2:  $g \leftarrow g_{\text{start}}$ ;  $g.g\_cost \leftarrow 0$ ;  $g.f\_cost \leftarrow h(g, g_{\text{goal}})$ .
3: Push  $g$  into  $G_{\text{OPEN}}$ ;  $G_{\text{CLOSED}} \leftarrow \emptyset$ .
4: while  $G_{\text{OPEN}} \neq \emptyset$  do
5:    $g_{\text{cur}} \leftarrow \text{pop node with lowest } f\_cost \text{ from } G_{\text{OPEN}}$ .
6:   if  $g_{\text{cur}} = g_{\text{goal}}$  then
7:     return reconstruct path from  $g_{\text{cur}}$ .
8:   end if
9:   Add  $g_{\text{cur}}$  to  $G_{\text{CLOSED}}$ .
10:   $\mathcal{N} \leftarrow \text{face-adjacent neighbours of } g_{\text{cur}}$ .
11:  Add all LoS-reachable nodes from  $g_{\text{cur}}$  to  $\mathcal{N}$ .
12:  for each  $n \in \mathcal{N}$  do
13:    if  $\text{obs}(n) = 1 \vee R(n) < C^{\text{max}}$  then
14:      continue.
15:    end if
16:     $\text{parent} \leftarrow \text{LoS\_parent if LoS exists, else } g_{\text{cur}}$ .
17:     $\text{tentative\_g} \leftarrow \text{parent.g\_cost} + \text{cost}(\text{parent}, n)$ .
18:    if  $\text{tentative\_g} < n.g\_cost$  then
19:       $n.\text{parent} \leftarrow \text{parent}$ ;  $n.g\_cost \leftarrow \text{tentative\_g}$ .
20:       $n.f\_cost \leftarrow n.g\_cost + h(n, g_{\text{goal}})$ .
21:      if  $n \notin G_{\text{OPEN}}$  then
22:        Push  $n$  into  $G_{\text{OPEN}}$ .
23:      end if
24:    end if
25:  end for
26: end while
27: return  $\emptyset$ .

```

**4.2. Level 2: Micro-Grid Routing Algorithm with on-Demand Boundary Relaxation**

The micro-grid refinement operates inside the corridor  $\mathcal{P}_k^M$  and must respect all fine-grained constraints listed in Section 3. As shown in Algorithm 3, we design a micro-grid routing algorithm with on-demand boundary relaxation that proceeds in two phases: (i) a sampling-based front end for initial feasible path generation, and (ii) a PSO-based back end for trajectory optimization. A distinctive feature is the on-demand boundary relaxation that is activated only when the tree fails to reach the destination within the original corridor.

**4.2.1. Phase 1: Initial Path with Guided Sampling**

We adopt the rapidly-exploring random tree (RRT) to generate initial trajectories in micro-grids. Sampling is biased toward the straight line connecting the entry and exit micro-grids of the current macro-grid cell, with a Gaussian perturbation to maintain explorative capability. The tree is expanded using the 11-neighborhood of micro-grids, and each candidate node is validated against static obstacles, communication threshold  $G_{\text{min}}$ , the occupancy table Occ, and the kinematic step-length bound  $d_{\text{max}}$ .

If the RRT successfully connects the entry and exit points, it yields an initial micro-grid path  $\mathcal{T}_k^{(0)}$ . Otherwise, the on-demand boundary relaxation is triggered. First, the search corridor is enlarged by incorporating micro-grids from all available neighboring macro-grids (first-hop relaxation). Then, if this still fails, a second-hop relaxation adds the micro-grids of the neighbors' neighbors. At each relaxation stage, the guidance probability is increased to accelerate the convergence toward the exit. The final path remains constrained within the

relaxed corridor. A soft boundary-crossing penalty is introduced to prevent unnecessary transitions across macro-grids.

---

**Algorithm 3** Micro-Grid Routing with On-Demand Boundary Relaxation
 

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**Require:** Macro-grid corridor  $\mathcal{P}^M$ , start/end micro-grids  $g_{\text{entry}}, g_{\text{exit}}$ , occupancy table Occ.

**Ensure:** Micro-grid trajectory  $\mathcal{T}$  or  $\emptyset$ .

```

1:  $\mathcal{T}, \text{success} = \text{RRT}(\mathcal{P}^M, g_{\text{entry}}, g_{\text{exit}}, \text{Occ})$ .
2: if not success then
3:    $\mathcal{C}_{\text{relax}} = \mathcal{P}^M \cup 1\text{-hop neighbor macro-grids}$ .
4:    $\mathcal{T}, \text{success} = \text{RRT}(\mathcal{C}_{\text{relax}}, g_{\text{entry}}, g_{\text{exit}}, \text{Occ})$ .
5:   if not success then
6:      $\mathcal{C}_{\text{relax}} = \mathcal{C}_{\text{relax}} \cup 2\text{-hop neighbor macro-grids}$ .
7:      $\mathcal{T}, \text{success} = \text{RRT}(\mathcal{C}_{\text{relax}}, g_{\text{entry}}, g_{\text{exit}}, \text{Occ})$ .
8:   end if
9:   if not success then
10:    return  $\emptyset$ .
11:   end if
12: end if
13: Initialize particles with waypoints of  $\mathcal{T}$ .
14: for iter = 1 to  $N_{\text{PSO}}$  do
15:   for each particle  $i$  do
16:     Update velocity and position; clamp to corridor bounds.
17:     Evaluate fitness  $J_k(\text{particle}_i)$  with boundary-crossing penalty.
18:     Update personal and global best.
19:   end for
20: end for
21:  $\mathcal{T}^* = \text{snap global best to nearest valid micro-grid centers}$ .
22: return  $\mathcal{T}^*$ .
  
```

---

#### 4.2.2. Phase 2: PSO-Based Refinement

The initial trajectory  $\mathcal{T}_k^{(0)}$  obtained from the RRT algorithm is typically jagged and does not fully minimize the composite cost  $J_k$ . We apply PSO to continuously adjust the intermediate waypoints within the bounds of their containing macro-grids. The fitness function is the total cost  $J_k$  plus penalty terms for constraint violations (obstacle collision, step-length excess, occupancy conflict, and boundary-crossing penalty). After convergence, the optimized continuous waypoints are snapped back to the nearest valid micro-grid centers.

#### 4.3. Complexity Discussion

The hierarchical decomposition significantly reduces the search space. Algorithm 2 operates on a graph of  $N_M$  macro-grids, where Theta\* has a worst-case complexity of  $O(N_M \log N_M)$ . Algorithm 3 confines RRT sampling to the micro-grids within the corridor. Let  $N_m^{\text{corr}}$  denote the number of micro-grids inside the corridor, and let  $L_k$  be the number of waypoints on the final micro-grid trajectory of UAV  $k$ . The RRT tree size is bounded by  $O(L_k \cdot \log N_m^{\text{corr}})$ . In the PSO phase, let  $N_{\text{particles}}$  denote the swarm size and  $N_{\text{PSO}}$  the number of iterations; each of the  $N_{\text{PSO}}$  iterations evaluates  $N_{\text{particles}}$  candidate trajectories, yielding a complexity of  $O(N_{\text{PSO}} \cdot N_{\text{particles}} \cdot L_k)$ . Thanks to the priority-ordered execution, the overall pipeline scales linearly with the number of UAVs  $K$ .

## 5. Simulation Results

The simulation scenario is set as follows. We assume there are three UAVs in the volume with dimensions of  $500 \times 500 \times 200 \text{ m}^3$ , and 5 GBSs are randomly distributed in this area. The side length of each macro-grid is 50 m, while that of each micro-grid is

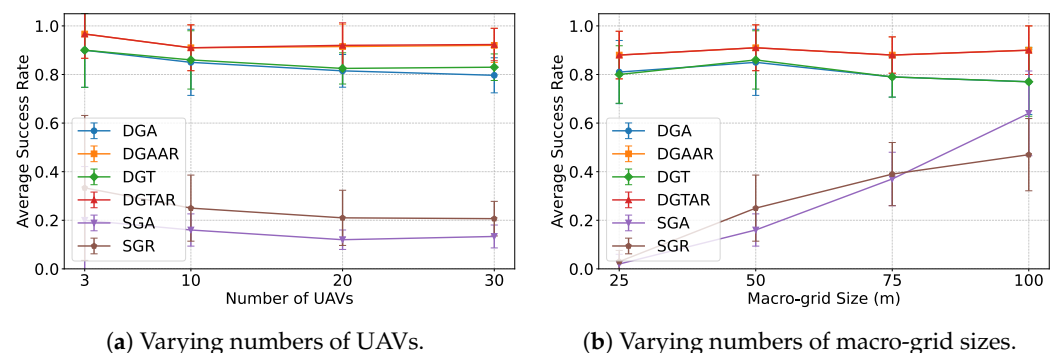
10 m. The key simulation parameters are summarized in Table 1. The chosen volume of  $500 \times 500 \times 200 \text{ m}^3$  corresponds to approximately four to five standard urban blocks, which is representative of the service radius of many low-altitude delivery or inspection missions. With the macro-grid size of 50 m, this area yields  $10 \times 10 \times 4$  macro-grids, providing sufficient spatial resolution for meaningful multi-UAV coordination while keeping the search space tractable for focused algorithmic evaluation.

We compare five algorithm variants: dual-grid-based A\* (DGA), no boundary relaxation; dual-grid-based A\* with adaptive boundary relaxation (DGAAR); dual-grid-based Theta\* (DGT), no boundary relaxation; single-grid-based A\* (SGA); and single-grid-based rapidly-exploring random tree\* (SGR). The key parameters of all comparison algorithms are consistent with those listed in Table 1.

**Table 1.** Simulation Parameters.

| Parameter      | Value    | Parameter   | Value              | Parameter             | Value         |
|----------------|----------|-------------|--------------------|-----------------------|---------------|
| $d_{\max}$     | 10 m     | $G_{ref}$   | $5 \times 10^6$    | $E_{base}$            | 90 J/m        |
| $\beta_h$      | 0.1      | $H_{\max}$  | 200 m              | $\eta_{climb}$        | 10 J/m        |
| $\eta_{desc}$  | 2 J/m    | $\beta_0$   | $7 \times 10^{-5}$ | $\delta^2$            | −110 dBm      |
| $w_d^M, w_e^M$ | 0.5, 0.5 | $E_{k,q}^m$ | 100 KJ             | $w_d^m, w_e^m, w_c^m$ | 0.4, 0.4, 0.2 |

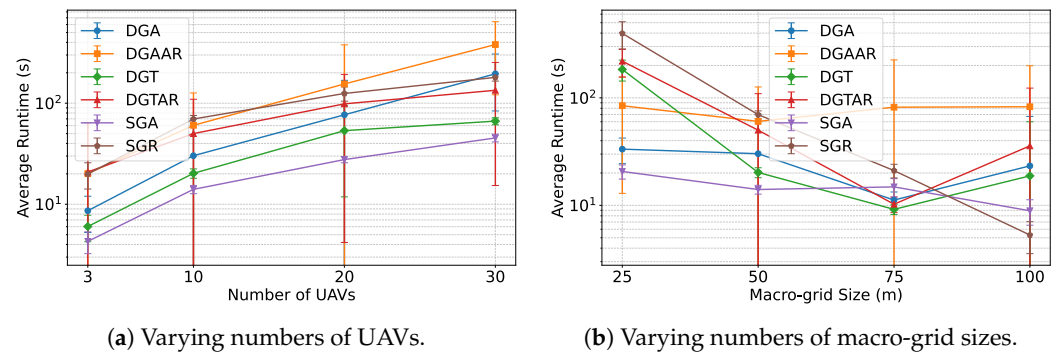
Figure 2 presents the average success rate over ten independent runs, with error bars indicating  $\pm 1$  standard deviation. Figure 2a varies the number of UAVs at a fixed macro-grid size of 50 m, Figure 2b varies the macro-grid size with 10 UAVs. In both subfigures, DGAAR and DGTAR maintain success rates above 0.9 with the negligible fluctuation, demonstrating that the on-demand boundary relaxation effectively resolves the local infeasibility regardless of the UAV count or grid resolution. DGTAR slightly outperforms DGAAR, and DGT slightly outperforms DGA, because the Theta\* produces more direct macro-grid corridors that reduce the spatial competition among UAVs.



**Figure 2.** Success rate comparison of different algorithms under varying numbers of UAVs and macro-grid sizes.

The single-grid baselines, i.e., SGA and SGR, consistently exhibit much lower success rates. In Figure 2a, their rates decline steadily as the UAV count grows, while in Figure 2b, their rates rise notably from approximately 0.1 to over 0.5 as the macro-grid size increases. This improvement occurs because larger macro-cells reduce the total number of micro-grids under a fixed map extent and constant  $5 \times 5 \times 5$  sub-division, thereby improving the graph connectivity. Nevertheless, they remain far below the dual-grid methods, confirming that the dual-scale hierarchical decomposition is fundamental to the reliable planning in the complex urban airspace.

Figure 3 reports the average runtime over ten runs (log scale,  $\pm 1$  standard deviation). Figure 3a varies the number of UAVs at a fixed macro-grid size of 50 m, and Figure 3b varies the macro-grid size with 10 UAVs. In Figure 3a, the runtime rises with the UAV count increment for all methods. DGAAR and DGA climb more steeply than DGTAR and DGT, because the Theta\* prunes unnecessary macro-nodes and keeps the search compact. DGTAR stays on the order of  $10^1$ – $10^2$  s across all tested sizes, whereas its success rate is the highest, as shown in Figure 2. SGA appears fast, but this merely reflects the early termination when most UAVs fail.



**Figure 3.** Runtime comparison of different algorithms under varying numbers of UAVs and macro-grid sizes.

Figure 3b shows the runtime with varying macro-grid size. SGR declines steadily and SGA remains nearly flat, because the total micro-grid count drops sharply as the grid coarsens, directly shrinking their search space. Among the dual-grid methods, DGAAR also stays relatively flat, since its A\* macro-planner expands many nodes regardless of the grid resolution, and the savings from fewer macro-cells are offset by longer intra-corridor paths. DGA, DGT, and DGTAR decline until 75 m, benefiting from the reduced macro-cell count, but rebound at 100 m where the corridor-length penalty becomes dominant. This rebound is more pronounced for the Theta\*-based variants because their macro-paths are more direct and thus more sensitive to the increased span of each macro-cell. Despite this, DGTAR maintains a moderate runtime across all grid sizes, and together with its top success rate, it delivers the best efficiency–reliability balance.

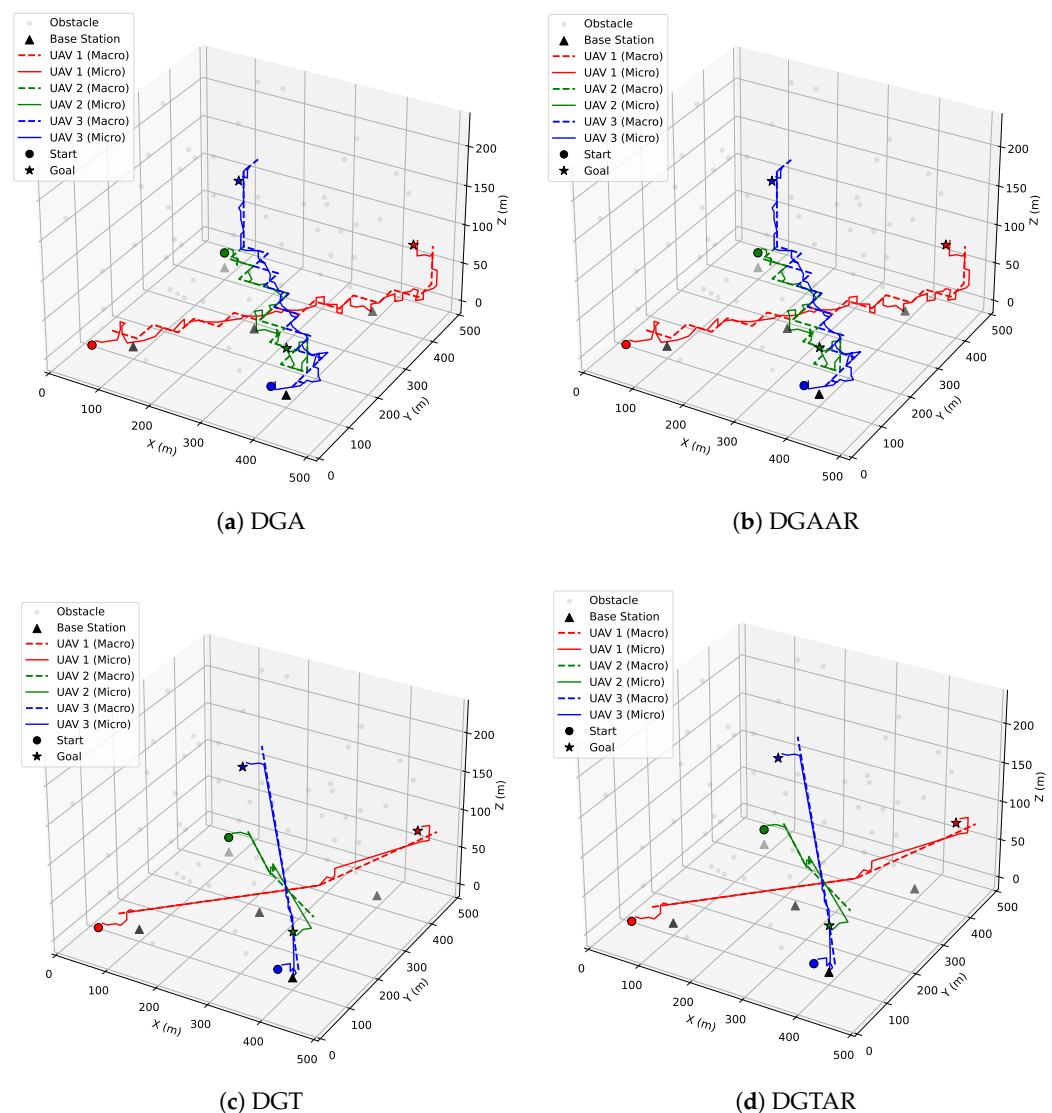
Table 2 reports the per-UAV metrics at 30 UAVs with a 50 m macro-grid. Due to the extremely low success rates, SGA and SGR are omitted from the comparison. The Theta\*-based variants, DGT and DGTAR, reduce the distance, energy, and communication cost by over 25% compared with DGA and DGAAR, because line-of-sight pruning produces more direct macro-corridors. The boundary relaxation primarily improves robustness. Specifically, DGAAR and DGTAR achieve success rates above 0.92, notably higher than DGA (0.797) and DGT (0.830). Importantly, their path costs remain nearly identical to those of their non-relaxed counterparts, confirming that the relaxation resolves local deadlocks without sacrificing path quality. DGTAR thus combines the efficiency of Theta\* with the reliability of boundary relaxation, attaining the highest success rate and the lowest costs across all metrics.

Figure 4 depicts the planned trajectories of three UAVs under the four algorithms, where dashed lines represent macro-grid corridors and solid lines represent refined micro-grid paths. As shown in Figure 4a,b, the trajectories of DGA and DGAAR are identical and the trajectories of DGT and DGTAR are also identical in Figure 4c,d. More importantly, the paths produced by DGT and DGTAR contain significantly fewer turning points than those of DGA and DGAAR. This is because the Theta\* planner allows LoS connections across multiple obstacle-free macro-grids as long as the intermediate cells have sufficient capacity, thereby pruning unnecessary intermediate nodes and producing a much

straighter macro-level corridor. The micro-paths naturally inherit this compactness and thus exhibit fewer direction changes.

**Table 2.** Performance comparison of different algorithms with 30 UAVs (macro-grid size = 50 m)

| Algorithm | Success Rate      | Distance (m)     | Energy Cost (KJ) | Communication Cost |
|-----------|-------------------|------------------|------------------|--------------------|
| DGA       | $0.797 \pm 0.072$ | $487.5 \pm 30.1$ | $4.6 \pm 2.7$    | $27.9 \pm 1.7$     |
| DGAAR     | $0.920 \pm 0.070$ | $497.7 \pm 30.1$ | $4.7 \pm 2.8$    | $28.3 \pm 1.6$     |
| DGT       | $0.830 \pm 0.055$ | $352.5 \pm 24.2$ | $3.4 \pm 2.2$    | $11.9 \pm 0.7$     |
| DGTAR     | $0.923 \pm 0.067$ | $359.8 \pm 24.7$ | $3.4 \pm 2.3$    | $12.5 \pm 1.0$     |

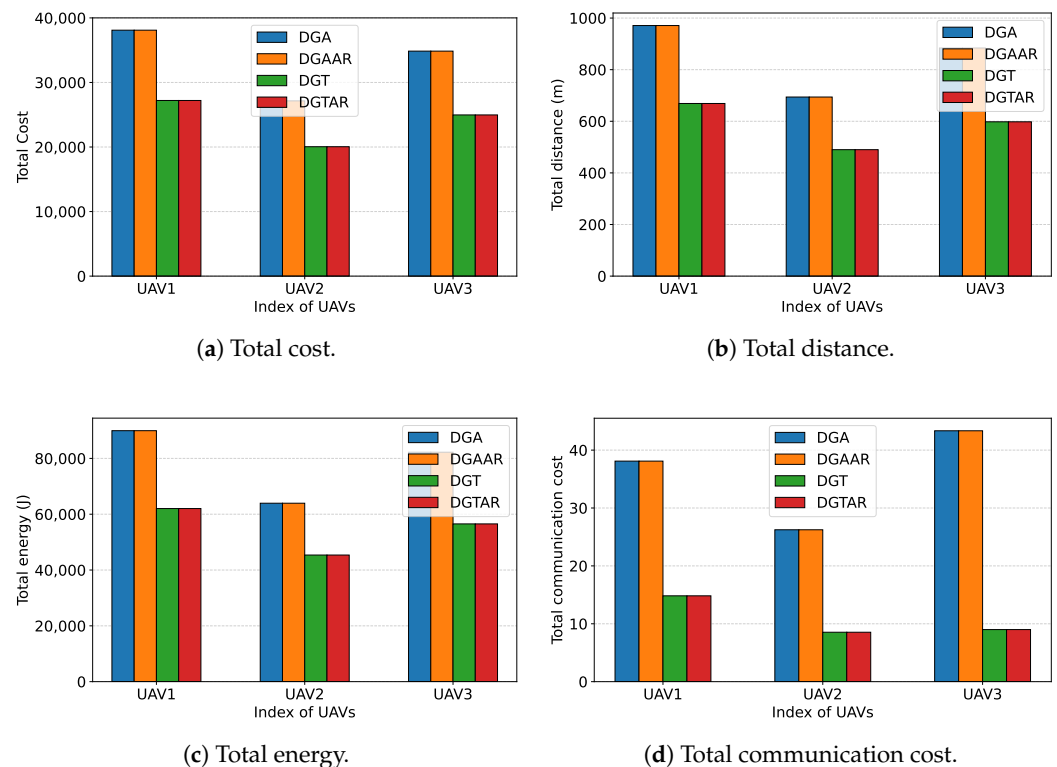


**Figure 4.** Comparison of UAV trajectories under different algorithms.

The fact that enabling the boundary relaxation (DGAAR and DGTAR) does not change the trajectories in this three-UAV scenario indicates that the strictly constrained micro-planner can already ensure feasibility within the original macro-corridors; the relaxation mechanism remains inactive in the absence of local congestion. This behavior confirms the on-demand nature of the proposed adaptive relaxation.

To quantify the improvements, Figure 5 presents the per-UAV total cost, flight distance, energy consumption, and communication penalty of the four algorithms. A consistent

trend is observed: DGA and DGAAR deliver identical metrics. This pattern also applies to DGT and DGTAR. Furthermore, DGT and DGTAR clearly outperform DGA and DGAAR across all four indicators. Taking UAV 1 as an example, the total cost of DGT/DGTAR is about 31% lower than that of DGA/DGAAR, the total distance is reduced by roughly 31%, the energy consumption by 31%, and the communication penalty by 61%. Similar relative gains are obtained by the other two UAVs.

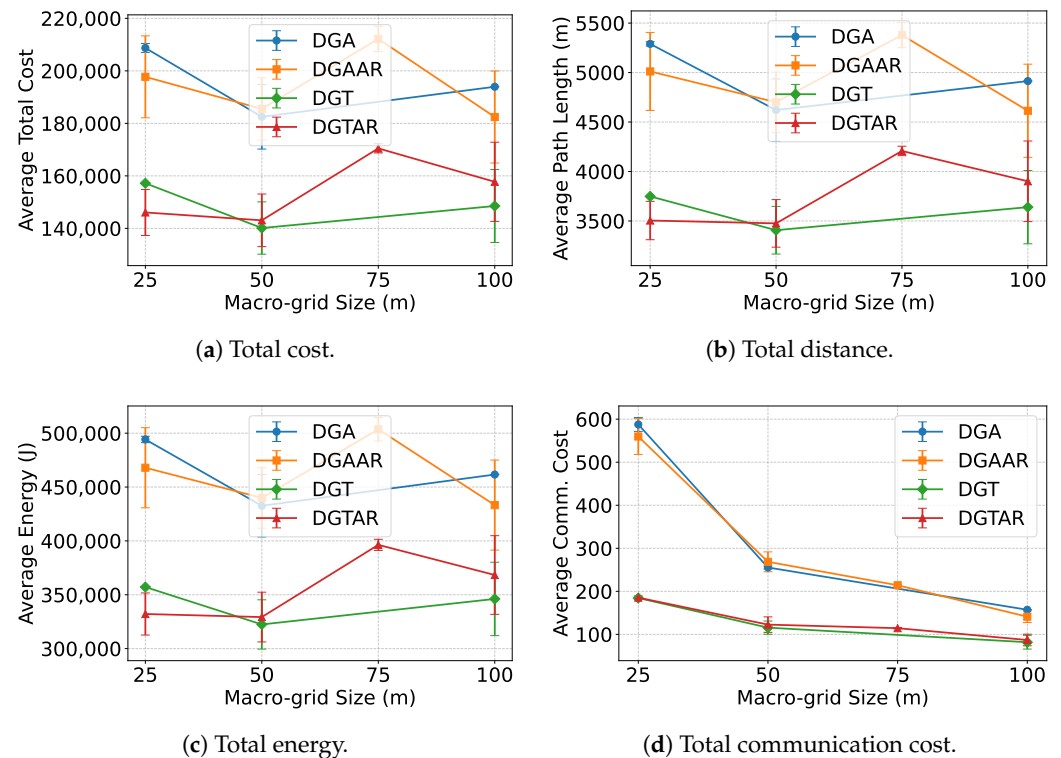


**Figure 5.** Performance comparison of different algorithms across multiple metrics.

This can be attributed to the fact that the macro-routes found by Theta\* are much closer to the straight line connecting the start and the goal, which drastically shortens the total flight distance. Since the energy cost is proportional to both the horizontal distance and the altitude variation, it decreases accordingly. The communication penalty is also reduced because the straighter paths happen to traverse grids with more favorable channel gains. The coincidence of DGA with DGAAR, and of DGT with DGTAR, again confirms that the adaptive relaxation does not introduce any extra cost when it is not triggered; it only expands the search corridor when the micro-planner encounters insurmountable obstacles or congestion.

The superior reliability of DGAAR and DGTAR is attributed to the on-demand boundary relaxation. When the micro-grid corridor of a UAV is blocked by obstacles or occupied by higher-priority UAVs, the planner temporarily extends its search space to the micro-grids of neighboring macro-cells. This fallback mechanism resolves local infeasibility without permanently widening the corridor, guaranteeing that a collision-free trajectory can always be found. Consequently, the algorithms equipped with adaptive relaxation achieve 100% success in all tested scenarios, whereas the pure DGA and DGT fail when their fixed corridors trap the planner.

Figure 6 presents the total cost, flight distance, energy consumption, and communication cost of 10 UAVs under varying macro-grid sizes, with all values averaged over 10 independent runs and error bars indicating  $\pm 1$  standard deviation.



**Figure 6.** Performance comparison of different algorithms under varying macro-grid sizes.

The total cost, distance, and energy curves in Figure 6a–c exhibit nearly identical trends. At 25 m, DGA ranks the highest, followed by DGAAR, DGT, and DGTAR. As the grid coarsens to 50 m, all four algorithms decrease, with DGA and DGAAR forming a close pair at a higher level, and DGT and DGTAR clustering at a lower level. This grouping confirms that Theta\* produces more direct macro-corridors, consistently shortening the path and reducing energy consumption. At 75 m, all four metrics increase, and the gap between the two groups widens. At 100 m, DGAAR and DGTAR turn downward, whereas DGA and DGT continue upward, indicating that the boundary relaxation enables the better adaptation to coarser grids.

The communication cost in Figure 6d exhibits a steady downward trend for all four algorithms. DGA and DGAAR remain closely grouped at a higher level, while DGT and DGTAR stay together at a lower level. The gap between the two groups narrows as the macro-grid size increases, because coarser grids naturally reduce path tortuosity, making even A\*-based paths relatively direct.

Across all macro-grid sizes, DGTAR consistently yields the lower total cost, flight distance, energy consumption, and communication cost than DGA and DGAAR. Compared with DGT, its costs are only higher at the 75 m grid size and are comparable or lower at all other sizes. Together with its substantially higher planning success rate, DGTAR achieves the optimal balance between the path quality and planning robustness.

Overall, the simulation results demonstrate that the Theta\* macro-planner is the primary contributor to the cost reduction, while the adaptive boundary relaxation is the critical enabler for robust planning in highly congested airspace. The proposed DGTAR algorithm, which integrates both techniques, simultaneously inherits the path compactness of Theta\* and the infeasibility-handling capability of on-demand relaxation, making it a well-suited solution for multi-UAV trajectory planning in urban low-altitude airspace.

## 6. Conclusions

This paper has presented a comprehensive mathematical model and an efficient hierarchical algorithm for multi-UAV trajectory planning in urban low-altitude airspace. The proposed DGTAR decouples coarse capacity management at the macro-grid level from fine obstacle avoidance at the micro-grid level, while embedding communication quality via a precomputed radio map and altitude-dependent energy costs as per-grid attributes. A priority-driven capacity allocation mechanism guarantees safe inter-UAV separation. The Theta\*-enhanced macro-router and the micro-planner with on-demand boundary relaxation solve the resulting optimization problem efficiently. Simulation results demonstrate that the proposed method significantly reduces total cost, flight distance, energy consumption, and communication penalty compared to baseline algorithms, while maintaining a 100% planning success rate even in highly congested airspace scenarios. Future work will extend the framework to real-time replanning under dynamic obstacles and communication uncertainties, and investigate distributed implementations for large-scale UAV fleets.

The framework intentionally abstracts UAV-specific dynamics and channel variations into grid attributes, which decouples the planning from platform parameters and improves generality. Practical deployment remains challenged by the reliance on a precomputed static map and centralized architecture. Future work will extend the framework with dynamic obstacle handling and distributed coordination to improve the robustness and scalability in real-world environments.

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