東南大學
SOUTHEAST UNIVERSITY

Benchmarking Dynamic Path Planning Algorithms for Urban Low-Altitude Logistics

Xuanzheng Lin*[1], Runquan Zuo[1], Wenzhuo Li[1], Shuo Xu[1], Dawei Yan[1], Zihao Han[2]

[1]School of Computer Science and Engineering
[2]School of Physics
Southeast University, Nanjing, China

Date：2026.06.18

東南大學
SOUTHEAST UNIVERSITY

目录

01 Abstract

02 Introduction

03 Literature Review

04 Methodology

05 Results & Discussion

06 Conclusion

東南大學
SOUTHEAST UNIVERSITY

PART 01

Abstract

Abstract

Research Context & Objectives

Background

- Urban low-altitude UAV logistics as core of smart-city instant delivery
- Dynamic path planning = key decision module
- Three challenges: 3D airspace, nonlinear energy, stochastic orders

Research Gap

- Two mainstream method families: Heuristic vs RL
- Mechanistic discrepancies under dynamic scenarios
- Existing benchmarks focus on single metrics

Objective & Approach

A systematic comparative evaluation:

- Unified mathematical modeling (3D airspace + nonlinear energy + dynamic order flows)
- Mechanistic analysis (batch global search vs policy-inference online decision)
- Multi-dimensional comparison under diverse dynamic scenarios

Abstract

Approach, Findings & Contribution

APPROACH

① Unified Modeling (3D airspace + nonlinear energy + dynamic orders)

② Mechanistic Analysis (batch global search vs policy-inference online decision)

③ Multi-Dimensional Comparison (path optimality / response latency / energy efficiency / computational overhead)

Findings

Heuristic Algorithms

✓ Global path quality
✓ Energy-aware
✗ Slow convergence
✗ High replan cost

Reinforcement Learning

✓ Low online latency
✓ Strong dynamic adaptability
✗ Generalization & stability risk

CONTRIBUTION

➤ **Hybrid Framework**

Heuristic (global energy-aware init) +
RL (local dynamic replanning & avoidance)

東南大學
SOUTHEAST UNIVERSITY

PART 02

Introduction

Motivation: Urban Low-Altitude UAV Delivery

东南大學
SOUTHEAST UNIVERSITY

01 Growing Attention

- **Last-Mile Logistics Breakthrough**
- Recognized as a highly promising complement to traditional ground-based logistics, addressing congestion and accessibility challenges in urban centers.

02 Key Advantages

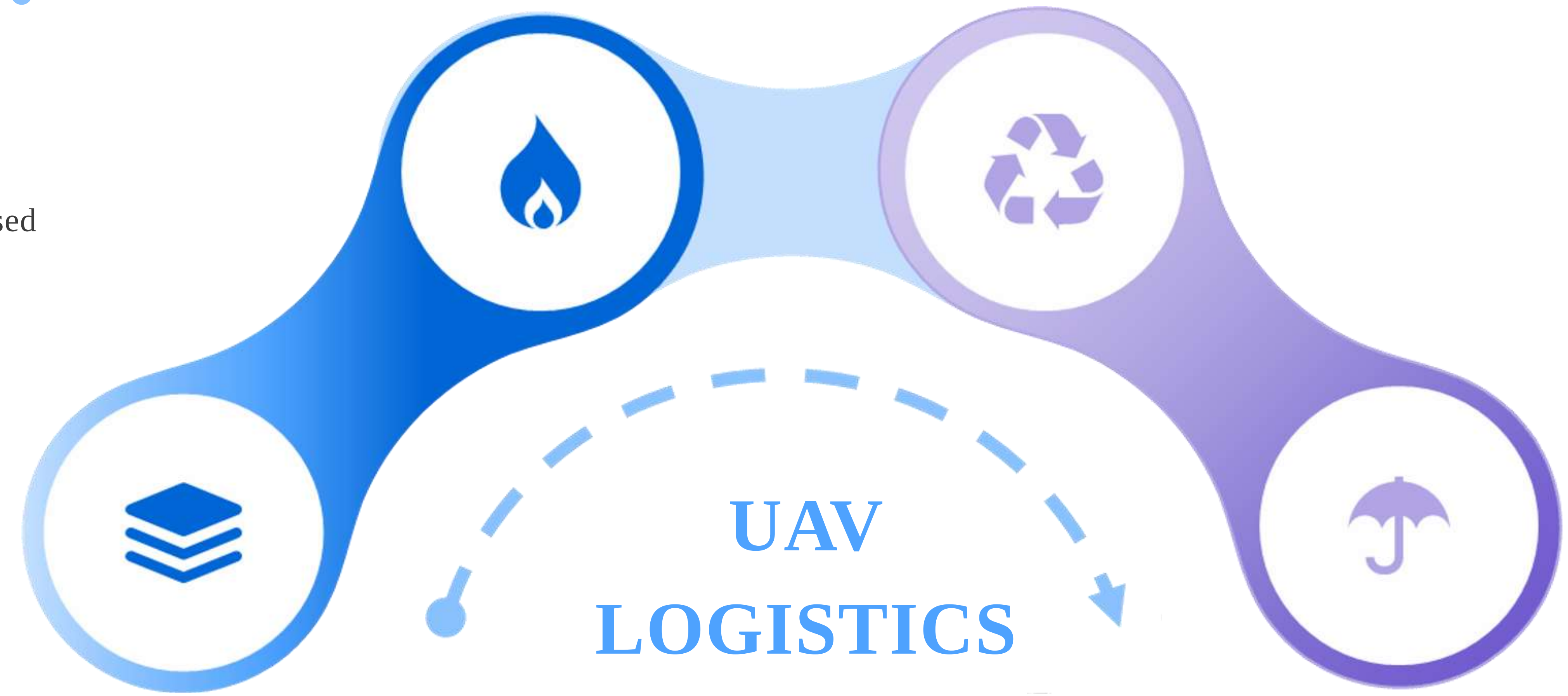
- **Transforming Last-Mile Service**
- Provides rapid delivery speed, flexible access to remote/urban areas, and significantly reduces reliance on ground transportation networks.

03 Early Formalization

- **Conceptual Groundwork**
- Key models like Flying Sidekick TSP and TSP with Drone were proposed to explore hybrid delivery strategies.

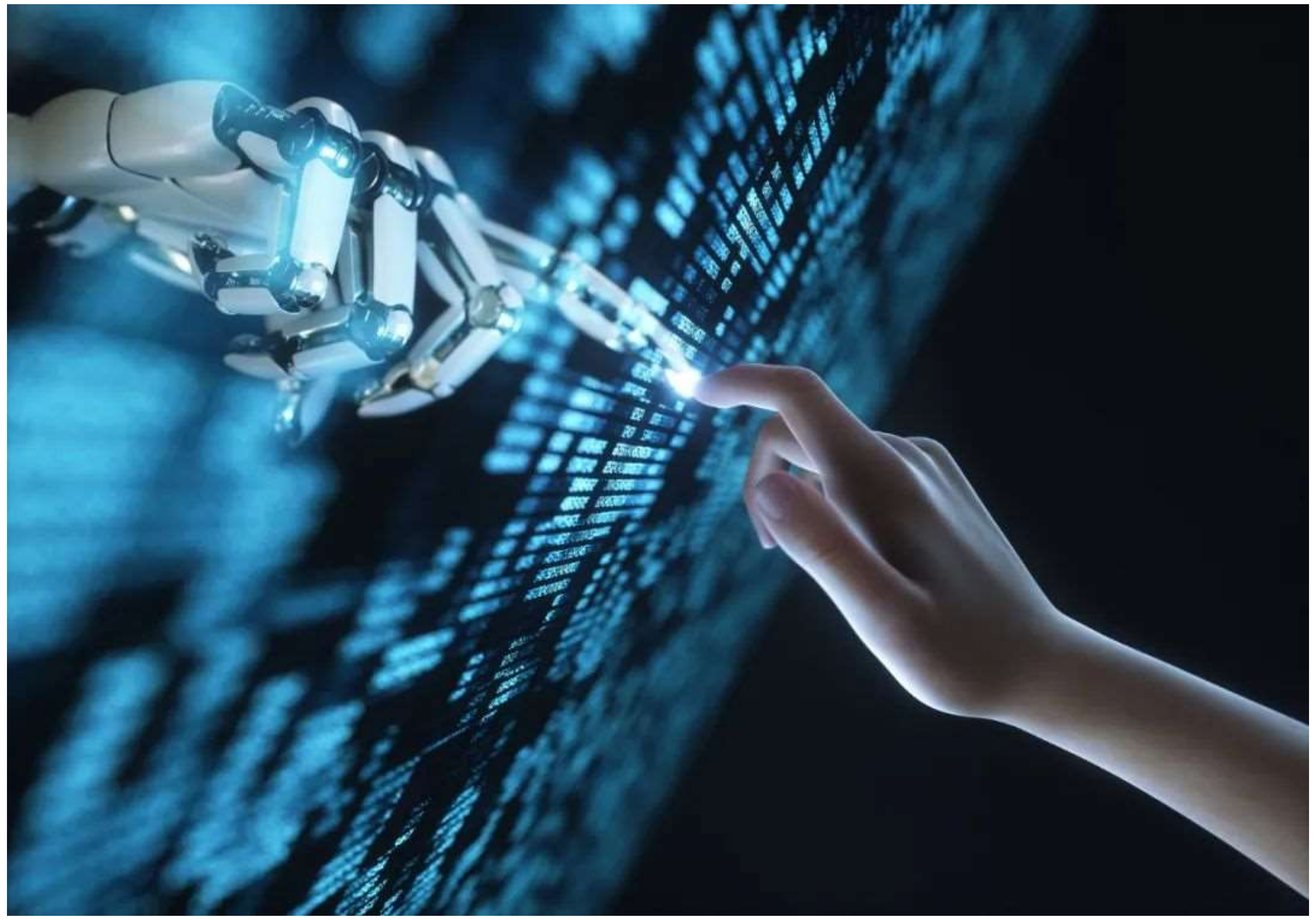
04 Current Limitations

- **Static & 2D Routing Bias**
- Early works focus on truck-drone coordination or static environments, ignoring the complexity of pure UAV operations in dynamic 3D urban airspaces.



The Unique Challenge of Pure UAV Logistics

东南大學
SOUTHEAST UNIVERSITY



Paradigm Shift from 2D to 3D Routing

Pure UAV delivery in dense urban areas is fundamentally distinct from classical ground vehicle routing. It transcends road networks to operate within a complex, unstructured 3D airspace, introducing a new dimension of navigational and operational complexity.

01. COMPLEX 3D AIRSPACE

Operations are constrained by strict altitude limits, mandatory obstacle clearance requirements, and time-varying no-fly zones. Unlike 2D ground routing, UAVs must navigate a continuous, unmarked 3D airspace with dynamic spatial constraints.

02. DYNAMIC & UNCERTAIN

The system must maintain safe inter-UAV separation in real-time, adapt to uncertain and stochastic order arrivals, and optimize the limited battery resources of each drone to balance delivery efficiency and operational safety.

UAV vs. Ground-Vehicle Routing

東南大學 SOUTHEAST UNIVERSITY

Key Differences in Routing Paradigms and Operational Constraints

Spatial Model	Feasible Region	Energy Model	Planning Paradigm
Fixed 2D Road Network	Static & Predefined Boundaries	Proportional to Travel Distance	Static, Offline Route Calculation
Continuous 3D Airspace	Dynamic (No-Fly Zones, Weather & Obstacles)	Nonlinear U-shaped Power-Speed Consumption Curve	Online, Continuous Replanning for Real-Time Adaptation
Navigational Complexity	Environment Uncertainty Challenges	Critical for Endurance & Mission Efficiency	Requires AI/Heuristic Fusion for Optimal Outcomes

Table 1. Comparative Analysis of Core Characteristics in UAV and Ground-Vehicle Routing

Two Existing Algorithmic Paradigms

東南大學
SOUTHEAST UNIVERSITY

01

Metaheuristic Optimization

Core Advantage:
Enables flexible global search capabilities and has been widely applied to complex 3D path planning problems, adapting well to irregular environments.

Key Limitation:
In dynamic environments, repeated solution reconstruction and neighborhood searching lead to significant computational overhead, making real-time responsiveness difficult to achieve.

02

Reinforcement Learning

Core Advantage:
Learns a generalized control policy through offline training, allowing for near-instantaneous decision-making during online execution, which is crucial for time-sensitive tasks.

Key Limitation:
Suffers from limited interpretability, unstable generalization to unseen scenarios, and potential safety hazards when deployed in highly constrained and complex airspace.

03

Future Integration

The next frontier lies in hybridizing the strengths of both paradigms. Combining the global exploration capability of metaheuristics with the fast inference of RL could potentially address the computational cost and safety concerns in dynamic airspace environments.

Research is ongoing to develop adaptive frameworks that leverage offline training for baseline policies and online optimization for fine-grained adjustments.

Discussion

東南大學
SOUTHEAST UNIVERSITY

Three Critical Research Gaps in UAM Route Planning

Simplified Spatial Models

Most studies rely on 2D or static airspace models, which fail to accurately capture the complexity of time-varying no-fly zones, dynamic air traffic congestion, and the evolving nature of urban airspace constraints.

Lack of Standardized Direct Comparison

Heuristic algorithms and Reinforcement Learning (RL) methods are rarely evaluated under identical, standardized dynamic conditions, making it difficult to objectively assess their relative performance, robustness, and practical merits for real-world deployment.

Oversimplified Single-Objective Evaluation

The majority of research prioritizes minimizing route length as the sole metric, neglecting critical multi-criteria trade-offs with operational latency, energy consumption, system reliability, and overall flight safety in dense urban environments.

Key Contributions

SOUTHEAST UNIVERSITY 東南大學

Core Innovations in Urban UAV Flight Planning

01

3D Dynamic Benchmark

We introduce a comprehensive benchmark integrating airspace feasibility, time-varying NFZs, nonlinear energy consumption models, and stochastic flight orders for realistic urban UAV operations.

02

Systematic Algorithm Comparison

We perform a head-to-head comparison of ACO, GA, PSO, MAPPO, and our proposed Hybrid framework under identical environmental assumptions to quantify performance gaps and strengths.

03

Hybrid Global-Local Framework

We propose a novel framework combining ACO for global energy-aware initialization, MAPPO for local dynamic replanning, and an embedded safety filter to ensure collision avoidance in dynamic airspaces.

04

Multi-Scenario Robustness Test

We evaluate all methods across Stable, Moderately dynamic, and Highly dynamic urban scenarios, complemented by an ablation study to validate the efficacy of each framework component.

Key Findings & Analysis

東南大學
SOUTHEAST UNIVERSITY

01. No Dominant Paradigm

Our comprehensive analysis reveals that no single algorithmic paradigm can claim superiority across all operational conditions. Each approach exhibits unique strengths and weaknesses that are highly dependent on environmental dynamics and task requirements.

02. Heuristic Performance

Heuristic methods (e.g., ACO) deliver exceptional global path quality and energy efficiency in stable, predictable environments. However, they suffer from slow adaptation and poor reactivity when faced with sudden disturbances or unexpected obstacles in the airspace.

03. RL Performance

Reinforcement Learning techniques (e.g., MAPPO) provide outstanding online responsiveness and real-time decision-making. Yet, their lack of global awareness can lead to instability, oscillations, and increased collision risks in highly congested airspace scenarios.

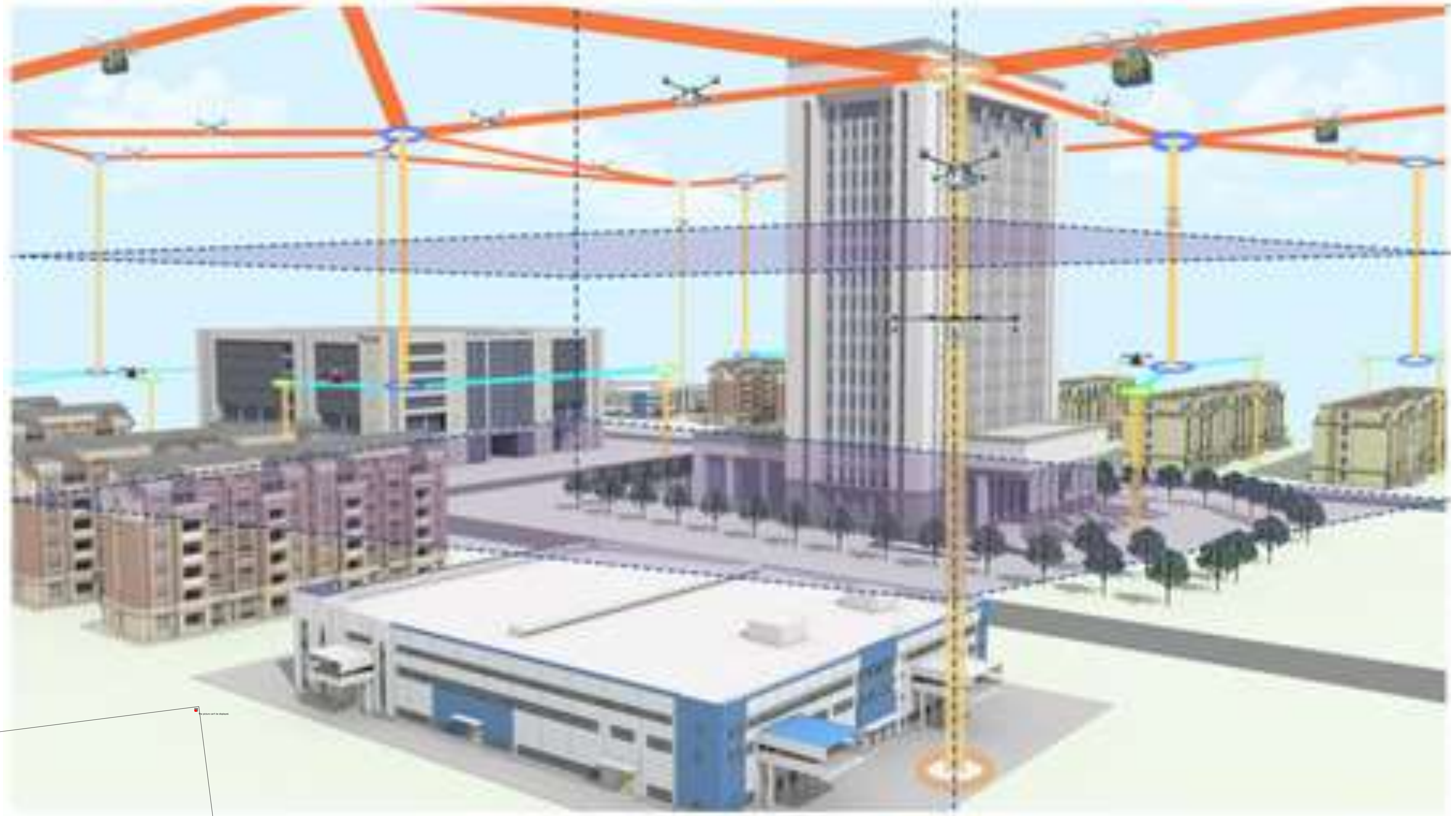
04. Hybrid Superiority

Our proposed Hybrid Framework synergistically combines the strengths of heuristics and RL. It achieves the optimal balance of efficiency, reliability, and safety, demonstrating superior performance in the most challenging, highly dynamic, and congested operational scenarios.

PART 03

Literature Review

From Ground Delivery to UAV Logistics



Urban UAV logistics has become important due to e-commerce and last-mile delivery demand.

Early studies modeled UAV delivery as routing optimization problems. However, many early models still followed ground delivery assumptions.

UAV logistics requires three-dimensional airspace planning, especially *altitude*.

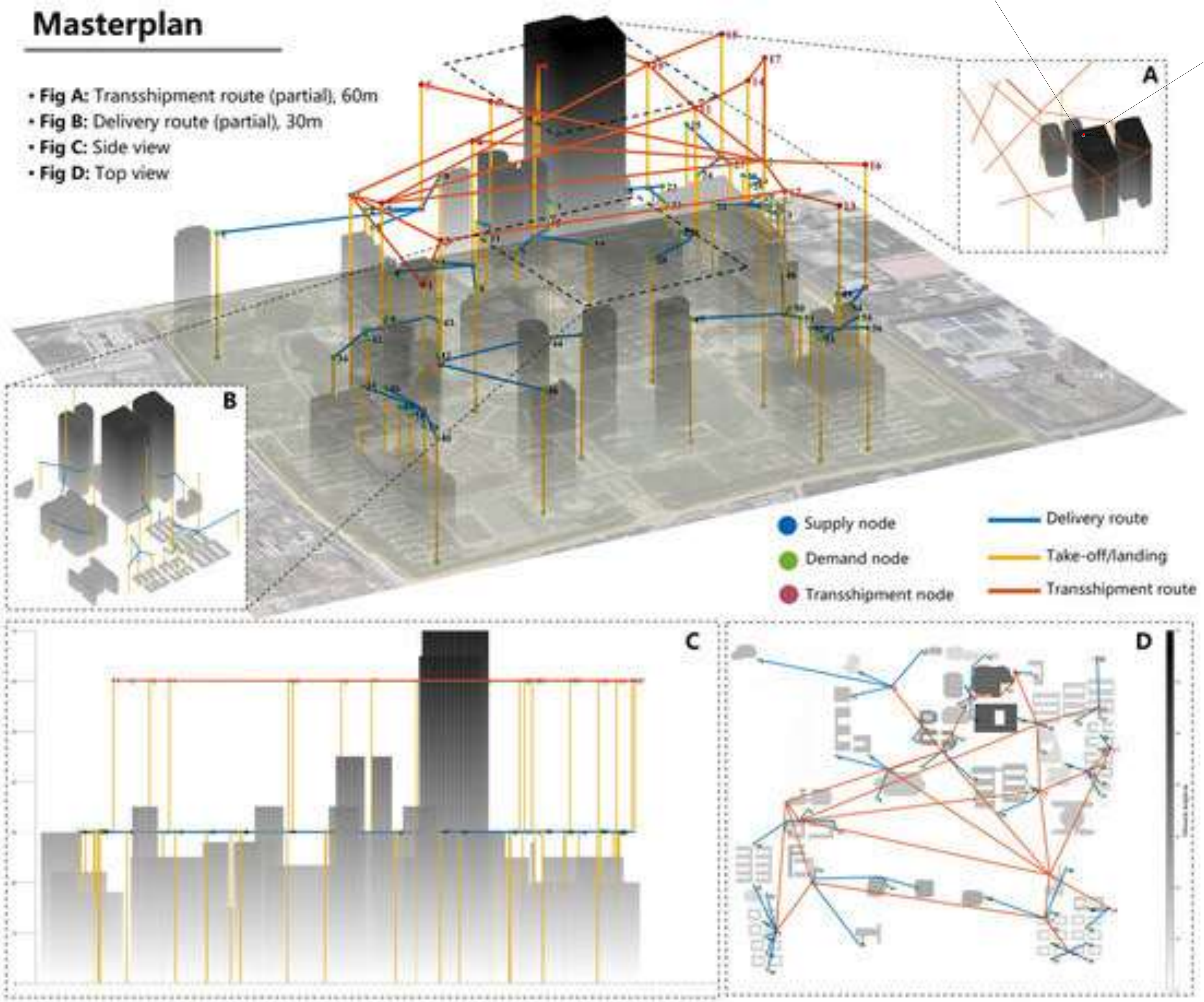
Key Modeling Issues

Airspace modeling: obstacles, temporary restrictions, and no-fly zones.

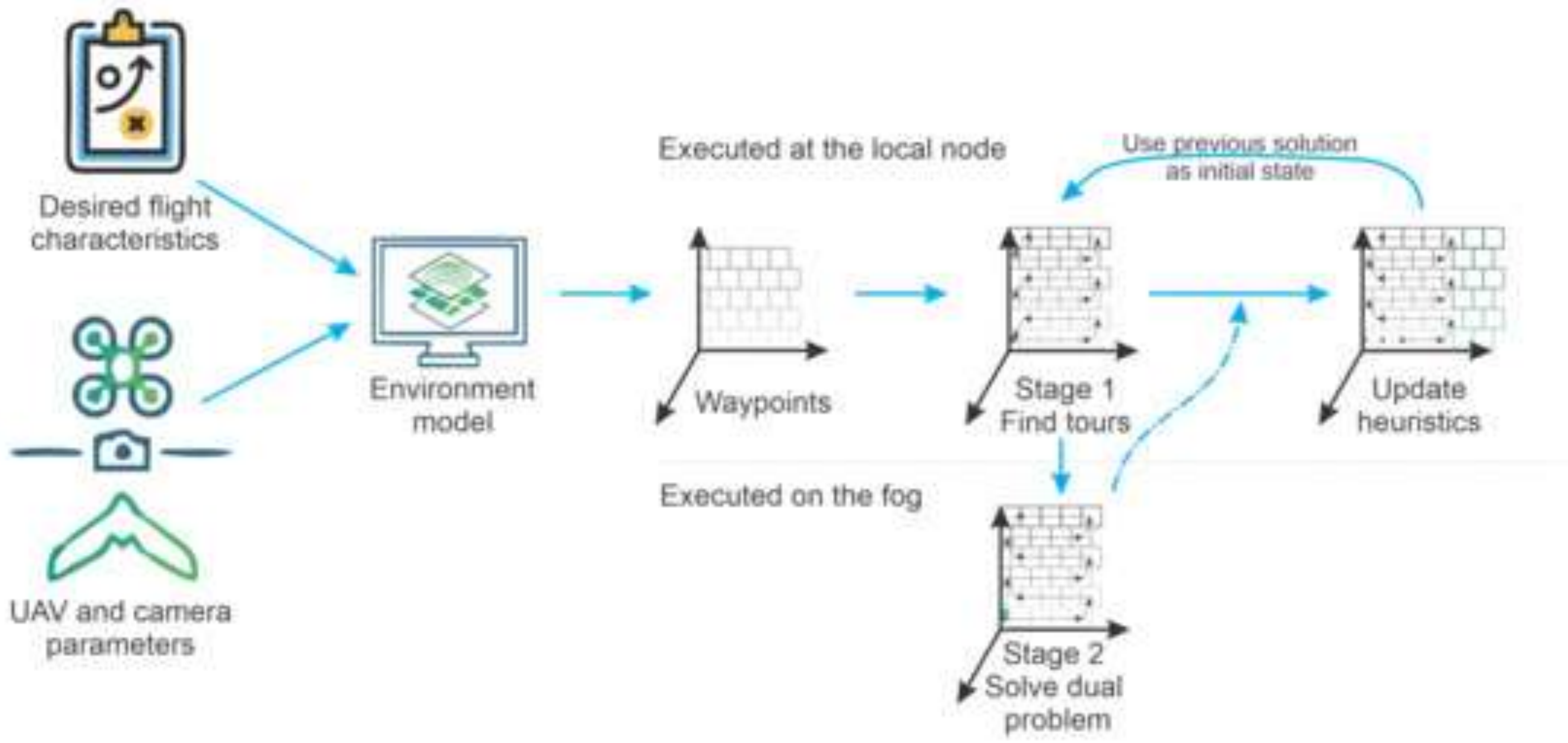
Energy consumption: shortest path may not be the most energy-efficient path.

Dynamic demand: new orders arrive during operation.

These factors make continuous replanning necessary.

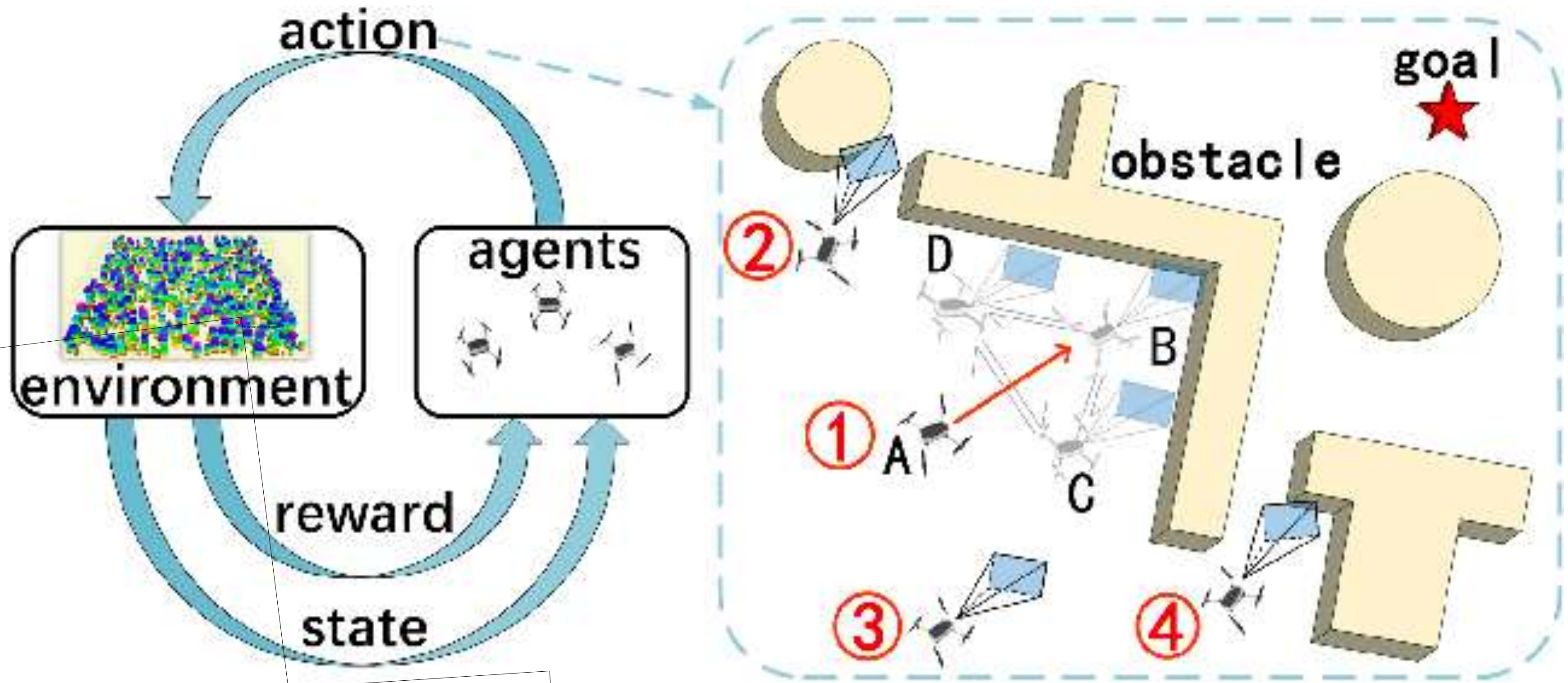


Existing Algorithmic Approaches



Heuristic optimization methods

- Strong global search ability.
- Suitable for stable environments.
- Limited by repeated replanning and high response latency.



Reinforcement learning methods

- Fast online decision-making after training.
- Suitable for dynamic replanning.
- Limited by stability, interpretability, and generalization issues.

Research Gap, Objective, and Question

東南大學
SOUTHEAST UNIVERSITY

Research gap

1. Many studies simplify UAV logistics as static or two-dimensional routing.
2. Few studies compare heuristic methods and reinforcement learning under the same dynamic conditions.
3. Trade-offs among route quality, energy efficiency, latency, and computational cost remain unclear.

Research objective

To build a unified evaluation framework for dynamic UAV path planning.

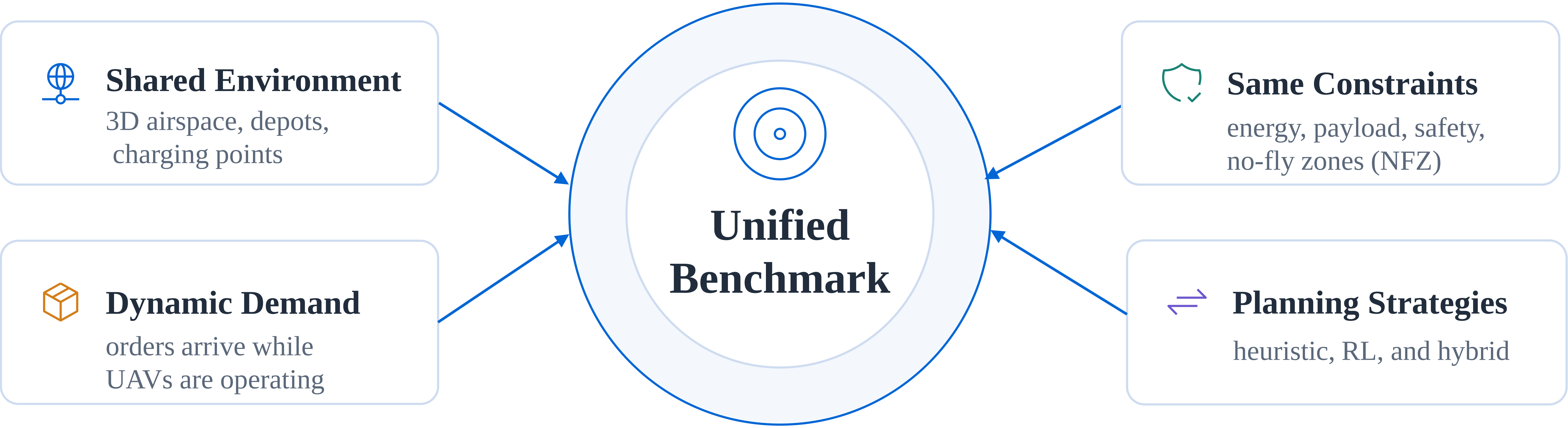
Research question

How do different algorithms balance route quality, energy efficiency, response latency, and computational overhead in urban low-altitude UAV logistics?

PART 04

Methodology

Methodological Core: A Fair Benchmark



All algorithms face the same low-altitude environment, energy and safety constraints, dynamic orders, and evaluation metrics.

Linking Modeling, Planning and Evaluation

東南大學
SOUTHEAST UNIVERSITY

Shared System State

standardized inputs

- Feasible airspace
- Fleet state and energy
- Dynamic orders

inputs

Planning Layer

Heuristic Search
ACO, GA, PSO route repair

RL Policy
fast local decisions

Hybrid Global-Local
global prior plus adaptation

decisions

Execution and Metrics

Feasibility gate
battery, payload, altitude, NFZs

- Executed route/action
- Recorded metrics

Common objective function

Shared System State

Airspace Feasibility

$$\square(t) = \square \ \square \left(\square_{\text{static}} \cup \square_{\text{dynamic}}(t) \cup \square(t)\right)$$

- **W** **full urban low-altitude space**
- **O** **static and dynamic restrictions**
- **Z(t)** **time-varying no-fly zones**

Fleet State

$$x_k(t) = [p_k(t), v_k(t), b_k(t), m_k(t)]$$

position **velocity**

battery **payload**

The planner must exactly know both where a UAV is and how much capacity it still has.

Energy Model

$$E_k = \int_{t_s}^{t_e} P(\| v_k(t) \|) dt$$

Power is battery use per moment. Energy is power accumulated over the flight.

Distance is an inadequate proxy for cost. We instead calculate energy as the integral of power over time.

Dynamic Demand

orders appear during operation

$$\Pr\{N(t+\Delta) - N(t) = k\} = \frac{(\lambda\Delta)^k e^{-\lambda\Delta}}{k!}$$

$$o_i = (r_i, \ell_i, q_i, [a_i, b_i], h_i, w_i)$$

Denote release time,delivery location, payload demand, time window, service duration and priority.

Provide a common and realistic state representation for all planning algorithms.

Objective Function

One score combines efficiency, service quality, reliability, safety and responsiveness.

$$\min_{\pi} \mathbb{E}\left[\sum_{k\in\mathcal{K}} E_k + \alpha_T \sum_{i\in\mathcal{S}} \max(T_i^{\text{start}} - b_i, 0) + \alpha_M N_{\text{missed}} + \alpha_C N_{\text{viol}} + \alpha_R N_{\text{replan}} \right]$$

Energy

Energy used by all UAV routes

Delay

Penalty when service starts after a window

Missed

Orders that cannot be served in the horizon

Violations

Safety, airspace, or separation breaches

Replans

Response cost under frequent disruption

The optimization chooses the policy with the lowest expected operational cost rather than only consider shortest path.

Three Planning Mechanisms

東南大學
SOUTHEAST UNIVERSITY

Same airspace, same fleet state, same order stream, same objective function

Heuristic Search

How it decides

Search and repair routes through ACO · GA · PSO style operators.

Strength high-quality global routes

Risk respond slowly under frequent changes

RL Policy

How it decides

Use a learned MAPPO-style policy for fast local action selection.

Strength online response speed

Risk needs filtering for safety

Hybrid Global-Local

How it decides

Use a global route prior, then adapt locally with safety masks.

Strength quality plus adaptation

Risk more design complexity

Only the decision mechanism changes, all problem assumptions remain the same.

Replanning and the Same Workflow

Initialize
airspace, fleet,
depots, orders

Event Trigger
new orders
NFZ updates
route infeasibility

Replanning
route repair,
policy action,
or hybrid update

Feasibility Gate
battery, payload,
altitude, separation,
no-fly zones

Metrics
route length, energy use,
latency, violations

PART 05

Results & Discussion

Results

SOUTHEAST UNIVERSITY

Core Findings：

Heuristic methods

Strong route quality and energy efficiency in stable conditions, but slower replanning under frequent changes.

MAPPO

Very low online latency across scenarios, but weaker energy, reliability, and safety balance than Hybrid.

Hybrid method

Best overall balance under highly dynamic conditions by combining global planning and local replanning.

Results

東南大學 SOUTHEAST UNIVERSITY

high dynamics require balanced performance.

Hybrid overall result

In the highly dynamic scenario: 11.98 km/order, 233.8 Wh/order, 90.2% success, and 3.1 violations.

Latency comparison

Hybrid reduces ACO latency from 22.90 s to 1.73 s, a 92.4% reduction, while keeping stronger safety than MAPPO.

Result meaning

The result confirms that shortest path alone is not enough; response speed, energy, reliability, and safety must be evaluated together.

Results

SOUTHEAST UNIVERSITY

each Hybrid component matters.

Energy-aware cost

Removing it raises energy use from 233.8 to 245.4 Wh/order.

Action mask

Removing it increases safety violations from 3.1 to 7.8 per 100 orders.

Immigrant repair

Removing it lowers success from 90.2% to 87.9%, showing weaker adaptation to dynamic changes.

Discussion

东南大学
SOUTHEAST UNIVERSITY

Discussion Roadmap:

01

Principal findings

02

Interpretation of findings

03

Interpretation in context of literature

04

Implications and limitations

Discussion

東南大學
SOUTHEAST UNIVERSITY

Principal Findings:

Heuristic	RL	Hybrid
Stable	**Fast**	**Best fit**
global route quality	frequent updates	high dynamics

Hybrid combines energy-aware global optimization, rapid local adaptation, and explicit safety filtering.

Discussion

東南大學
SOUTHEAST UNIVERSITY

Interpretation of Findings: stable setting shows the speed-quality trade-off.

Route length gap
+0.07 km
Hybrid vs ACO, stable

Energy gap
+1.3 Wh
Hybrid vs ACO, stable

Latency reduction
85.3%
Hybrid vs ACO, stable

Safety result
0.6
violations per 100 orders

Stable scenario	Length	Energy	Latency	Success	Violations
ACO	8.42	162.8	8.60	96.4%	0.8
MAPPO	8.94	174.5	0.38	94.9%	1.4
Hybrid	8.49	164.1	1.26	96.9%	0.6

Table 1. Comparative results under stable scenario

Discussion

Interpretation of Findings: repeated global search drives latency.

Frequent order arrivals and no-fly-zone updates force heuristic methods to rebuild routes repeatedly.

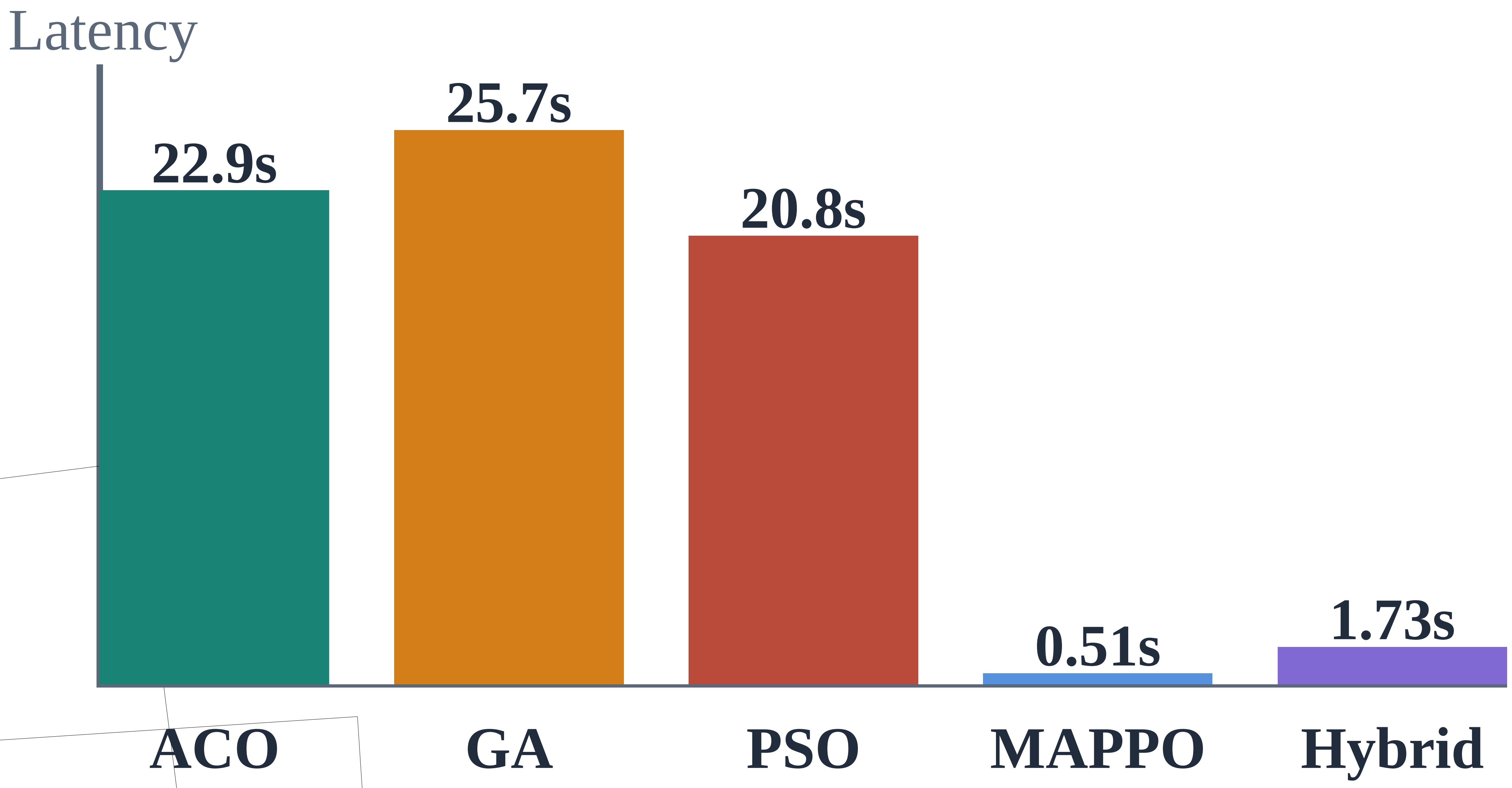


Figure 1. Comparative latency under highly dynamic scenarios

Hybrid shows why responsiveness matters when the environment changes frequently.

Reduction vs ACO: 92.4%

Discussion

Interpretation of Findings: replanning behavior changes energy use.

In high dynamics, energy reflects detours, route invalidation, and local adaptation, not distance alone.

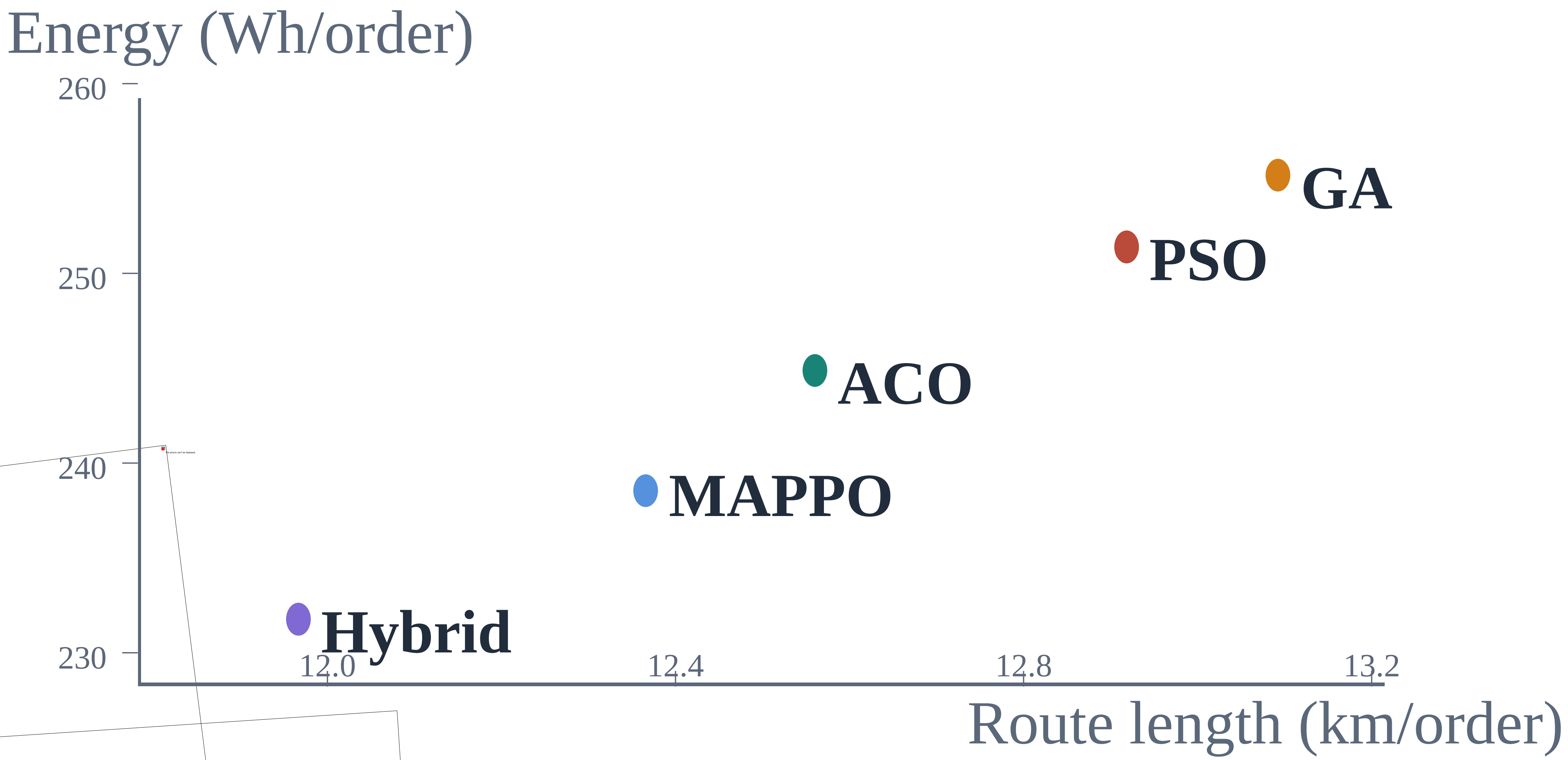


Figure 2. Comparative route length and energy under highly dynamic scenarios

Why Hybrid saves energy

ACO supplies energy-aware global initialization.

MAPPO supplies fast local adjustment under fragmented airspace.

Energy-aware initialization helps reduce repeated invalidation and unnecessary detours.

Discussion

東南大學
SOUTHEAST UNIVERSITY

Interpretation in Context of Literature:

Literature issue	Typical limitation	Paper response	Result interpretation
Simplified airspace	Static or 2D models	Dynamic 3D benchmark	Hybrid’s advantage is meaningful under changing constraints, not only in static routing.
Separated paradigms	Heuristic and RL methods are often evaluated separately	Same environment and metrics	Results show that global search and policy inference are complementary.
Single-objective focus	Route length dominates evaluation	Latency, energy, reliability, safety	The main contribution is operational balance, not improvement on one metric alone.

Table 2. Literature-review gaps and present results interpretation

Discussion

東南大學
SOUTHEAST UNIVERSITY

Implications and Limitations: dynamic deployment requires validation.

UTM implication

Planning systems should update feasible airspace as a spatio-temporal object.

Logistics implication

Operators should not optimize only for the shortest route; delay, hovering, reliability, and safety also matter.

Limitations

Simulation excludes wind, communication delay, localization error, sensor uncertainty, and traffic-control interactions.

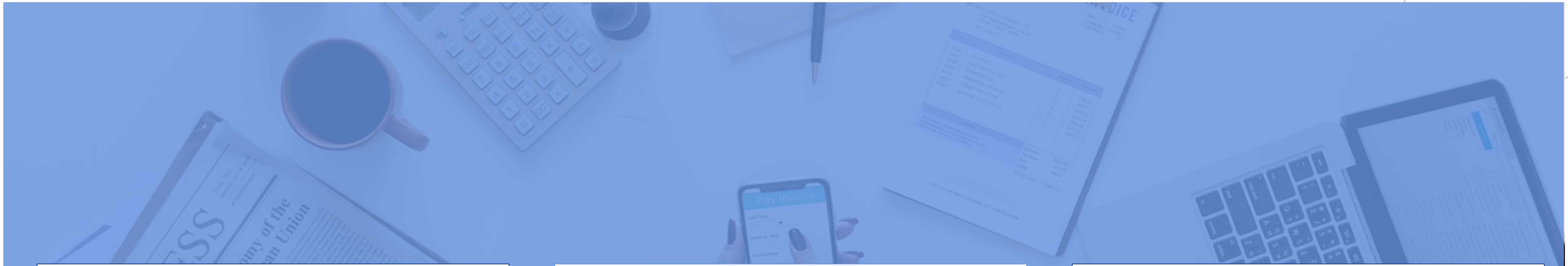
東南大學
SOUTHEAST UNIVERSITY

PART 06

Conclusion

Conclusion

東南大學
SOUTHEAST UNIVERSITY



01 FINDINGS

•Heuristic: Quality at a Cost

•RL: Speed with Caution

•Shortest Path ≠ Energy-Optimal Path

•Hybrid Framework: Heuristic (global energy-aware init) + RL (local dynamic replanning)

02 LIMITATIONS

•Simulation fidelity gap

•Energy model simplifications

•Method sensitivity (reward, params)

03 FUTURE WORK

•Transfer learning + domain randomization

•UAV + charging stations + ground hubs synergy

•High-fidelity sim or real-world pilot test

Thank you for your attention！

Date：2026.06.18