End-to-end Performance Optimization for Mixed FSO/RF-aided Non-Terrestrial Networks: A DRL Approach

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Outline

I. Introduction

II. System Description

III. MARL for UAV Placement

IV. Simulation Results

V. Conclusion

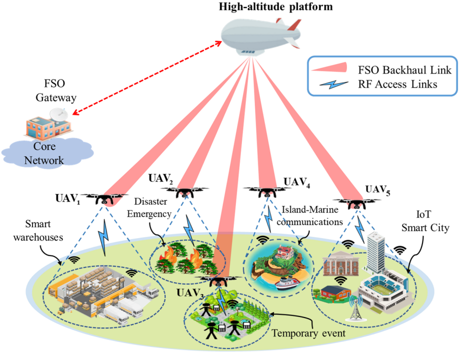
FSO-Based Air-Ground Integrated Networks

- FSO is a line-of-sight technology using infrared frequency bands (187 - 400 THz) for data transmission in space

  ⟹ *Large bandwidth, high-speed connections (∼ hundreds of Gbps or even Tbps)*

  ⟹ *Potential solution for backhaul networks*

- Space networks, employing Unmanned Aerial Vehicle (UAV), and High-Altitude Platform (HAP) as relay/aerial base station (ABS)



⟹ *Low cost, wide coverage, flexible deployment, and strong light-of-sight connectivity*

E.g., SoftBank's HAPS, Airbus's Zephyr S, and Huawei Digital Sky projects

The integration of HAP for FSO backhaul and UAV for last-mile access, forming the FSO-based air-ground integrated network (AGIN), is the promising and pragmatic NTN architecture for the future 6G era.

Critical Issues: End-to-end Dynamic Network

FSO Backhaul links:

- **Atmospheric turbulence:** air pockets with different refractive indexes cause the scintillation effect
- **Pointing error:** misalignment between the center of satellite beam footprint and that of the UAV detector
- **Cloud attenuation:** The liquid water particles in clouds cause the scattering phenomenon
  - Clouds are moving/changing over time

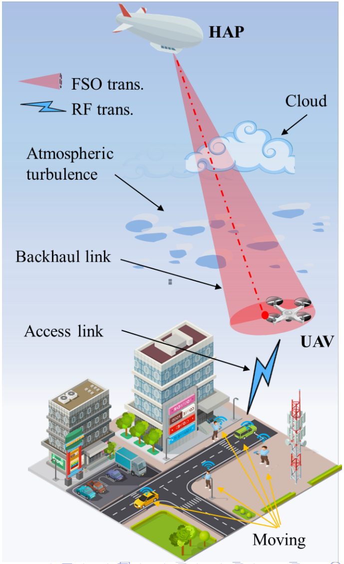
$\Longrightarrow$ *One of the most limiting factors for laser beams*

➡ *Unstable and time-varying channel → Limited capacity of the backhaul link*

Access link:

- Different distributions and the movement of end-users

➡ *Difficulty in the deployment of UAV-mounted BS*



Research Question

How to optimize the end-to-end network performance under the dynamic conditions from both backhaul (e.g., movement of clouds) and last-mile access (movement of end-users) networks?

$\Longrightarrow$ *Find the optimal position of UAV-mounted BS to maximize the end-to-end network performance. An efficient algorithm, indeed, is needed to tackle this critical issue.*

Literature Review

Extensive research endeavors have been conducted to find effective UAV placement algorithms for end-to-end networks comprising FSO backhaul and RF access links[1][2][3][4][5].

- However, the current studies mainly focus on terrestrial networks and ignore the effects of the FSO channel conditions[1][2][3][4][5]
- The current works mainly address the UAV placement problem with static networks[1][2][3][4]

➡ *An efficient algorithm for UAV placement in dynamic air-ground integrated networks is needed*

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[1] S. Liu, H. Dahrouj, and M.-S. Alouini, "Joint user association and beamforming in integrated satellite-haps-ground networks," *IEEE Trans. Veh. Technol.*, vol. 73, no. 4, pp. 5162–5178, 2024.

[2] L. Yu, X. Sun, S. Shao, *et al.*, "Backhaul-aware drone base station placement and resource management for fso-based drone-assisted mobile networks," *IEEE Trans. Netw. Sci. Eng.*, vol. 10, no. 3, pp. 1659–1668, 2023.

[3] S. Zhang and N. Ansari, "3d drone base station placement and resource allocation with fso-based backhaul in hotspots," *IEEE Trans. Veh. Technol.*, vol. 69, no. 3, pp. 3322–3329, 2020.

[4] D. Wu, X. Sun, and N. Ansari, "An fso-based drone assisted mobile access network for emergency communications," *IEEE Trans. Netw. Sci. Eng.*, vol. 7, no. 3, pp. 1597–1606, 2020.

[5] Y. Guan, S. Zou, H. Peng, *et al.*, "Cooperative uav trajectory design for disaster area emergency communications: A multiagent ppo method," *IEEE Internet Things J.*, vol. PP, pp. 1–1, Jan. 2023. DOI: `10.1109/JIOT.2023.3320796`.

Goals of the Study

1. We deploy an optimization framework leveraging multi-agent reinforcement learning (MARL) to address the UAV placement problem in the end-to-end AGIN network
   - The framework accounts for the dual constraints of both backhaul and access links
   - The dynamic conditions include the mobility of end-users and the movement of clouds
   - The algorithm seeks to determine the optimal UAV positions to maximize end-to-end throughput while adapting to the continuously changing network conditions
2. We conduct extensive simulations to validate the effectiveness of the framework
   - The results reveal that the trained agents can adapt to the dynamic nature of network environment and maintain high throughput performance

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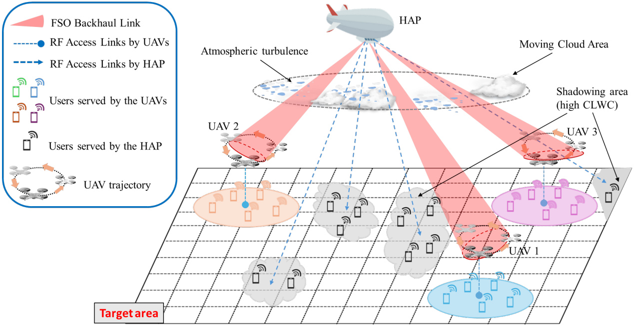
System Model (1)



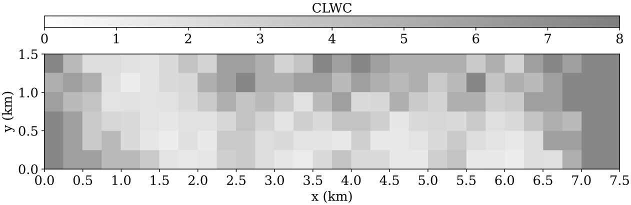
One HAP and multiple UAVs are deployed to provide internet connection to rural/remote areas or temporary events. The service duration is divided into T equal time slots. The end-to-end network scenario includes 2 main transmission links:

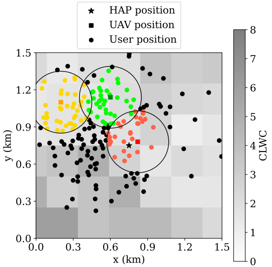
1. **Backhaul links:** from HAP to M UAVs → FSO transmission
2. **Access links:** from HAP and M UAVs to N users → RF transmission

System Model (2)

We consider a target area of 1.5 km x 1.5 km

- **Users**:
  - N mobile users (MU) are normally distributed with a random mean and a standard deviation of 300m
  - A part of users follow the Gauss-Markov mobility model
- **Cloud model:**
  - We consider a 7.5 km × 1.5 km cloud with heterogeneous CLWC[1]
  - The cloud moves to the west with a velocity of 8 m/s





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[1] CLWC (cloud liquid water content) - a measure of the total liquid water contained in a cloud in a vertical column of the atmosphere (the less, the better)

Problem Formulation (1)

- Link association:
  - We consider a greedy approach that assigns the user to either the HAP or one of the UAVs that provides the strongest signal.
  - Let $\alpha_{n,i,t} \in \{0,1\}$ and $\beta_{n,t} \in \{0,1\}$ be binary indicate whether user n is associated with the i-th UAV or the HAP. The constraint is formulated as

$$\sum_{i=1}^{M} \alpha_{n,i,t} + \beta_{n,i,t} = 1$$

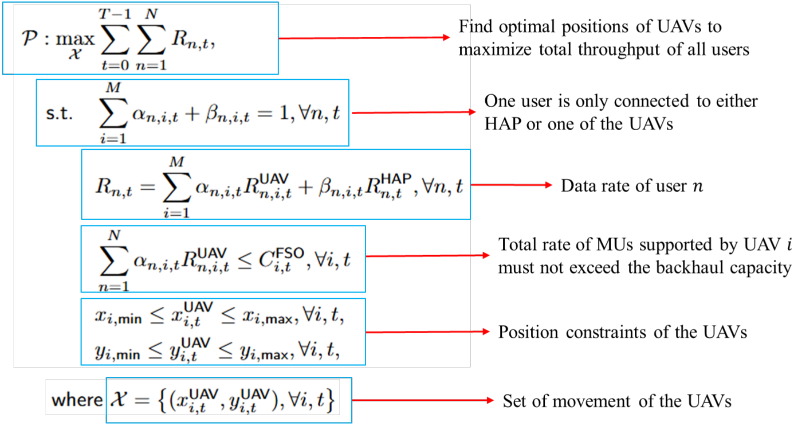
  - The data rate of user n at time slot t is given as

$$R_{n,t} = \sum_{i=1}^{M} \alpha_{n,i,t} R_{n,i,t}^{\text{UAV}} + \beta_{n,i,t} R_{n,t}^{\text{HAP}},$$

where $R_{n,i,t}^{\text{UAV}}$ and $R_{n,t}^{\text{HAP}}$ denote the data rates provided by the UAV i and the HAP, respectively.

Problem Formulation (2)

- Problem formulation
  - We aim to maximize the cumulative data rate of users by optimizing the UAV positions. The optimization problem can be formulated as



$$\mathcal{P}: \max_{\mathcal{X}} \sum_{t=0}^{T-1} \sum_{n=1}^{N} R_{n,t},$$

Find optimal positions of UAVs to maximize total throughput of all users

$$\text{s.t.} \quad \sum_{i=1}^{M} \alpha_{n,i,t} + \beta_{n,i,t} = 1, \forall n, t$$

One user is only connected to either HAP or one of the UAVs

$$R_{n,t} = \sum_{i=1}^{M} \alpha_{n,i,t} R_{n,i,t}^{\text{UAV}} + \beta_{n,i,t} R_{n,t}^{\text{HAP}}, \forall n, t$$

Data rate of user n

$$\sum_{n=1}^{N} \alpha_{n,i,t} R_{n,i,t}^{\text{UAV}} \leq C_{i,t}^{\text{FSO}}, \forall i, t$$

Total rate of MUs supported by UAV i must not exceed the backhaul capacity

$$x_{i,\text{min}} \leq x_{i,t}^{\text{UAV}} \leq x_{i,\text{max}}, \forall i, t,$$
$$y_{i,\text{min}} \leq y_{i,t}^{\text{UAV}} \leq y_{i,\text{max}}, \forall i, t,$$

Position constraints of the UAVs

$$\text{where } \mathcal{X} = \{(x_{i,t}^{\text{UAV}}, y_{i,t}^{\text{UAV}}), \forall i, t\}$$

Set of movement of the UAVs

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Multi-agent Reinforcement Learning (MARL)

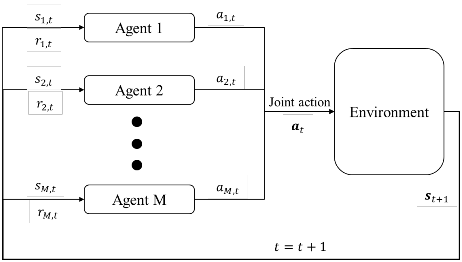

Figure: Diagram of the agent-environment interaction loop in MARL

- **RL:** a process in which an agent learns to make decisions *through trial and error*
- The problem is often modeled mathematically as *a Markov decision process (MDP)*, where the agents interact with the environment based on a particular policy
- At time step t, each agent observes its current observation $s_{i,t}$ and chooses an action $a_{i,t}$ from the action space. The combination of all actions from the agents is called a joint action. The environment then returns the new observation $s_{i,t+1}$ and reward/punishment $r_{i,t}$ for each agent.
- The algorithm aims to *maximize the cumulative received rewards*

Markov Decision Process (MDP)

Considered state, action, and reward function of UAV i:

- **Observation** $s_{i,t}$: the current location of the UAV, the locations of other UAVs, the heatmap of users (currently supported by that UAV or HAP), and the cloud heatmap of the area
- **Action** $a_{i,t}$: move (1)-north, (2)-west, (3)-south, (4)-east, (5)-remain stationary
- **Reward function**: we consider individual and teamwork (global) rewards to encourage collaboration among agents
  - *Global reward:*

$$r_t^{\text{glob}} = \begin{cases} c_1 \sum_{i=1}^{M} \sqrt{R_{i,t}^{\text{UAV}} \times C_{i,t}^{\text{FSO}}}, & R_{i,t}^{\text{UAV}} \geq R_i^{\text{thres}}, \forall i, \\ c_1 \sum_{i=1}^{M} \sqrt{R_{i,t}^{\text{UAV}} \times C_{i,t}^{\text{FSO}}} - 1, & \text{otherwise}, \end{cases}$$

where

c_1: normalization factor

$R_{i,t}^{\text{UAV}}$: Data rate provided to users by UAV i

$C_{i,t}^{\text{FSO}}$: FSO backhaul capacity of UAV i

R_i^{thres}: Data rate threshold of UAV i

Markov Decision Process (MDP)

Considered state, action, and reward function:

- **Reward function**:
  - *Local reward:*

$$r_{i,t}^{\text{local}} = \begin{cases} c_2\sqrt{R_{i,t}^{\text{UAV}} \times C_{i,t}^{\text{FSO}}} - n_{\text{c},i}p, & R_{i,t}^{\text{UAV}} \geq R_i^{\text{thres}}, \\ c_2\sqrt{R_{i,t}^{\text{UAV}} \times C_{i,t}^{\text{FSO}}} - n_{\text{c},i}p - 1, & \text{otherwise}, \end{cases}$$

where

c_2: normalization factor

$n_{c,i}p$: penalty term for overlapping coverage among UAVs

$\Longrightarrow$ *The combined reward for the i-th UAV:*

$$r_{i,t} = wr_t^{\text{glob}} + (1-w)r_{i,t}^{\text{local}},$$

where w is the weight ratio between global and local reward

UAV Placement Algorithm

Algorithm MARL-based UAV Placement Algorithm

```
for each UAV $i$ do
    Initialize the replay buffer $D_i$ with capacity $C_i$
    Initialize the $Q_i$ network with random weights $\boldsymbol{\theta_i}$
    Initialize the target $\hat{Q}_i$ network with weights $\hat{\boldsymbol{\theta}}_i = \boldsymbol{\theta}_i$
end for
for each episode do
    Initialize/Reset the network environment
    for each time slot $t$ do
        for each UAV $i$ do
            Obtain the observation $\boldsymbol{s}_{i,t}$ from the environment
            Obtain action $a_{i,t}$ according to the $\epsilon$-greedy policy
            Execute $a_{i,t}$ and perform link association
        end for
        Update the environment
        for each UAV $i$ do
            Observe reward $r_{i,t}$ and next state $\boldsymbol{s}_{i,t+1}$
            Store transition $(\boldsymbol{s}_{i,t}, a_{i,t}, r_{i,t}, \boldsymbol{s}_{i,t+1})$ in replay buffer $D_i$
            Sample a random minibatch of transitions from $D_i$
            Obtain the target Q-value $y_{i,t}$
            Perform a gradient descent step with respect to $\boldsymbol{\theta}_i$
            Reset $\hat{Q}_i = Q_i$ every fixed number of steps
        end for
    end for
end for
```

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System Parameters

Name	Value
FSO Backhaul Links	
FSO transmit power	6 dBm
FSO bandwidth	3 GHz
HAP altitude	20 km
CLWC range	0.5 - 7.5 mg/m^3
RF Access Links	
HAP transmit power	35 dBm
UAV transmit power	25 dBm
Total RF bandwidth	600 MHz
UAV altitude	250 m
UAV coverage	250 m
RL Model	
DRL framework	DQN
Learning rate	0.001
Discount factor	0.99
Time slot duration	1 s
Total time slot	300 (training), 900 (testing)
Scale factor	$c_1 = 5.56 \times 10^{-10}$, $c_2 = 1.67 \times 10^{-9}$
Data rate threshold	0.6 Gbps
Weight ratio	0.35

Deployed Models

For comparison, we employ two benchmark algorithms:

1. **Multi-agent reinforcement learning without consideration of clouds (MARLwC):**
    - The agents do not have any information related to the status of clouds
      → *observation spaces do not include the current CLWC heatmap*
2. **Single-agent reinforcement learning (SARL):**
    - Each UAV is controlled by a DQN agent and makes the movement decision independently without collaboration with other UAVs
      → *positions of other UAVs are not included in the observation space, and the reward function only takes into account local rewards*

Episode Return

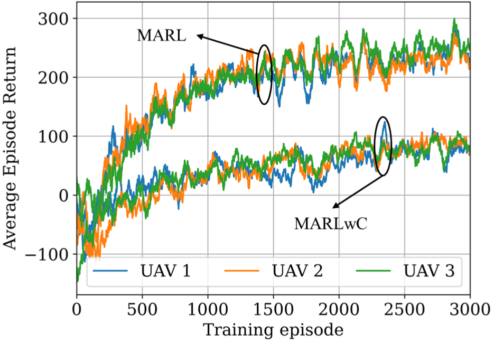


Figure: Average episode reward versus training episodes.

We can see that

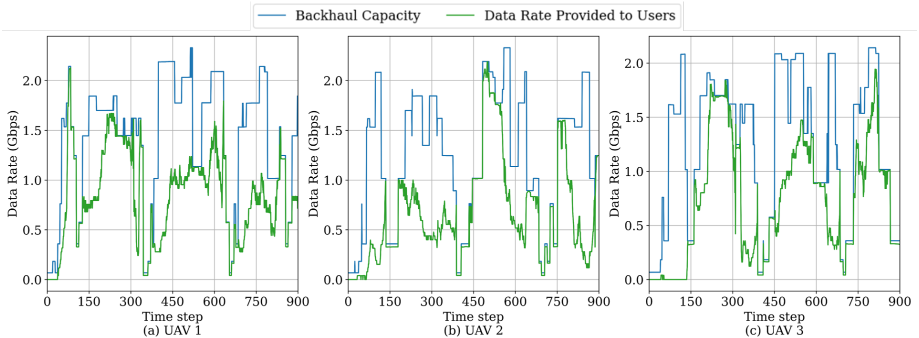
- The episode reward for each UAV gradually increases and converges after about 1500 episodes

⟹ *All agents are learning from the environment and making more efficient decisions to achieve higher returns.*

- MARL model gains significantly higher returns than MARLwC model.

⟹ *The MARL model can adapt well to the changing cloud conditions*

Backhaul Capacity vs. Data Rate



(a) UAV 1
(b) UAV 2
(c) UAV 3

Figure: Backhaul capacity and data rate provided to users using MARL algorithm.

- The trained MARL can maintain a high and stable backhaul capacity
- Also, the data rate delivered to users closely follows the upper bound dictated by the available FSO backhaul capacity

⟹ *The MARL algorithm successfully optimizes UAV positioning to mitigate moving cloud conditions and adapt to user distribution/mobility*

Total data rate of users (1)

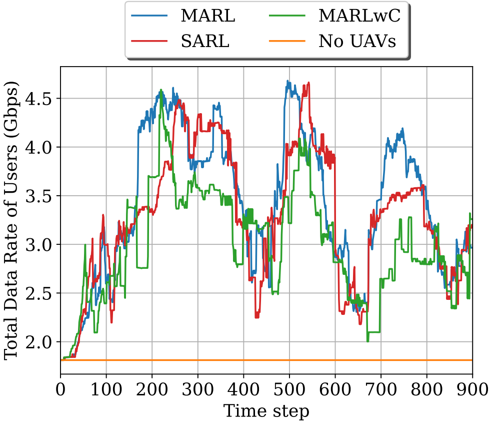


Figure: Total data rate of users over one test episode.

$\Longrightarrow$ The proposed MARL approach consistently achieves the highest overall performance while SARL follows closely behind. In contrast, the MARLwC algorithm exhibits the lowest overall throughput

$\Longrightarrow$ The deployment of UAVs as aerial base stations leads to a substantial increase in the total data rate delivered to users

Total data rate of users (2)

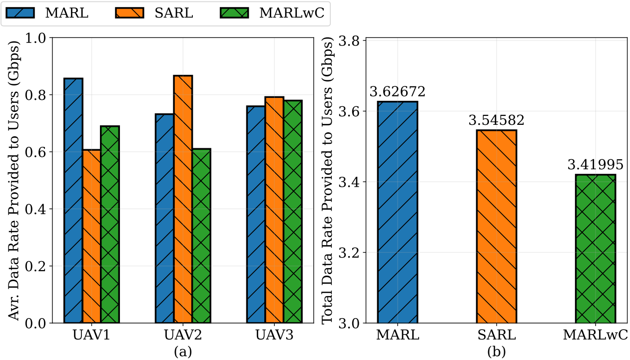


Figure: (a) Average data rate provided to users by each UAV; (b) Total data rate of users. (The results are taken across 100 test episodes).

- The data rate trends vary across each UAV. However, the MARL provides the most stable performance
- In total, the MARL algorithm can greatly enhance network performance, resulting in significant gaps with other algorithms

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Conclusion

1. This thesis introduced an optimization framework leveraging MARL to address the UAV placement problem to optimize the end-to-end throughput of users in dynamic air-gorund integrated networks

2. Remarkable observations from the results:
    - The trained agents can adapt to the dynamic nature of network environment and maintain high throughput performance
    - The proposed algorithm performs significant gaps with other baseline algorithms, which highlights the collaboration and environmental awareness in optimizing network performance