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

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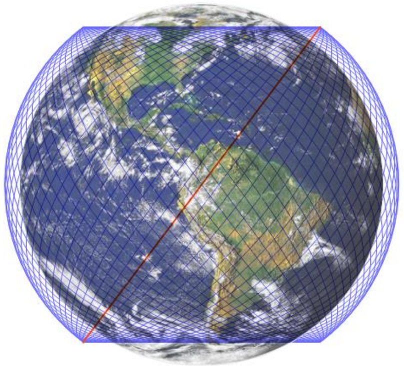
Introduction

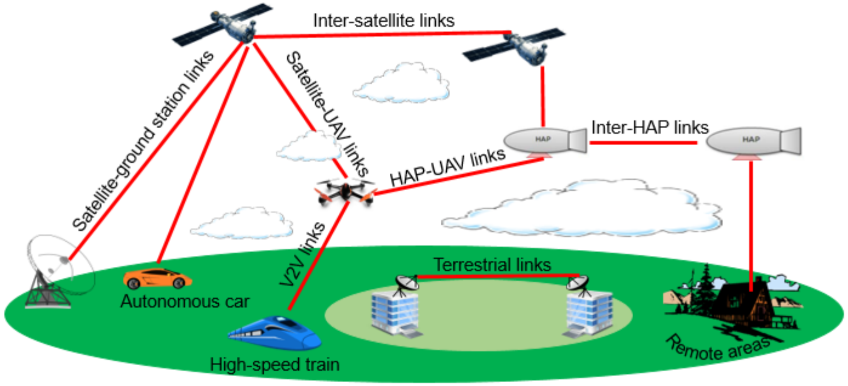
Non-Terrestrial Networks (NTN)

- In recent years, LEO satellites forming constellation networks can provide Internet from space
  - Starlink from SpaceX, Project Kuiper from Amazon, etc.
- High altitude platforms (HAP) (e.g., airships and balloons) can be used as a relay station between satellites/core networks and vehicles/users to extend the system's scalability
  - HAPS project from Softbank
- Unmanned aerial vehicles (UAVs) has recently emerged as an efficient solution for a wide range of applications
  - Delivery services, emergency situations, smart agriculture, and military missions

→ *Thanks to its wide coverage and flexible deployment, the non-terrestrial network, incorporating satellite, HAP, and UAV, can be a promising alternative to the current terrestrial network.*



Demonstration of the Starlink initial phase.
https://en.wikipedia.org/wiki/Starlink

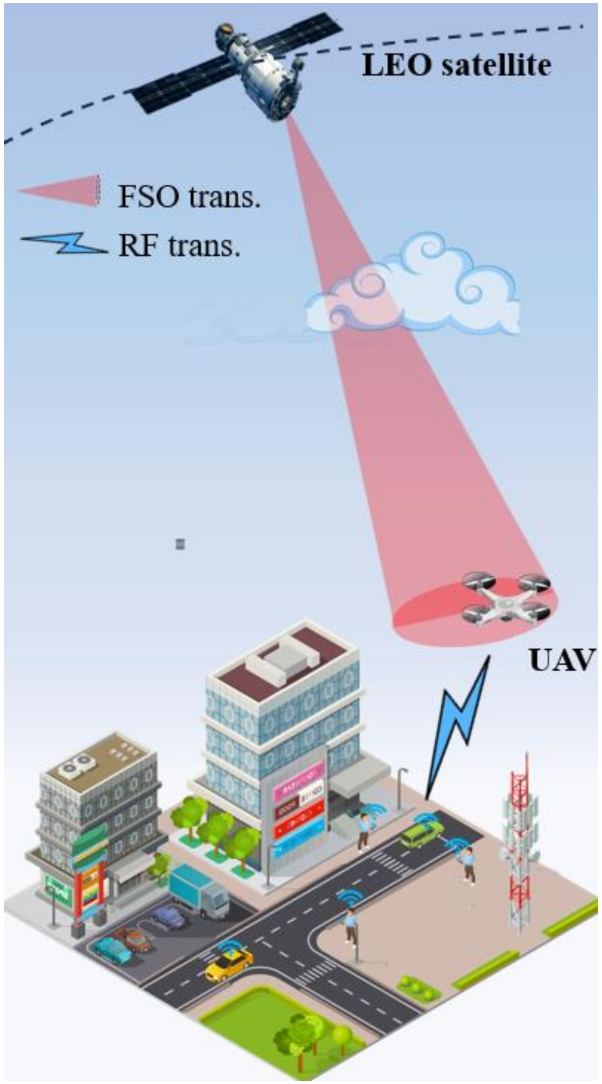


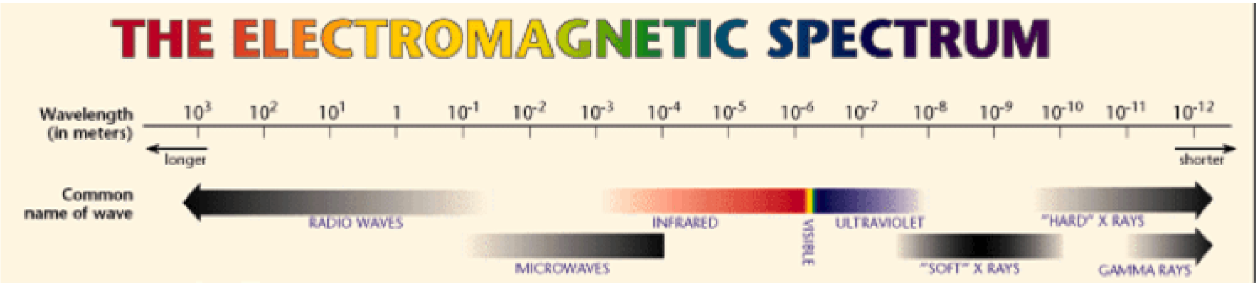
The space-air-ground integrated networks

Free-space Optics (FSO)

- Recently, free-space optics (FSO) is envisioned as a ***promising candidate for backhaul networks***
- FSO is a ***line-of-sight*** technology using ***infrared frequency bands (187 – 400 THz)***
  - Large bandwidth
  - Extremely high-speed connections (~ Gbps or even Tbps)
  - Immunity to electromagnetic interference

➔ *NTN architecture, leveraging FSO backhaul and UAV for radio frequency (RF) last-mile access, is a promising solution for the future 6G era.*





Electromagnetic spectrum

Literature Review

- Current studies usually consider the backhaul and access networks **separately**.
  - **FSO backhaul networks** (satellite-to-UAV [1], Satellite-HAP-UAV [2]): channel modeling, cross-layer design, and mitigation techniques to reduce the atmospheric impact
  - **RF access networks** (UAV to end users): ***optimal placement/dynamic trajectory*** of the UAV to deal with the users' distribution/movement [3-5]

[1]. L. Qu, G. Xu, Z. Zeng, N. Zhang and Q. Zhang, "UAV-Assisted RF/FSO Relay System for Space-Air-Ground Integrated Network: A Performance Analysis," in IEEE Transactions on Wireless Communications, vol. 21, no. 8, pp. 6211-6225, Aug. 2022

[2]. H. D. Le, H. D. Nguyen, C. T. Nguyen and A. T. Pham, "FSO-Based Space-Air-Ground Integrated Vehicular Networks: Cooperative HARQ With Rate Adaptation," in IEEE Transactions on Aerospace and Electronic Systems, vol. 59, no. 4, pp. 4076-4091, Aug. 2023

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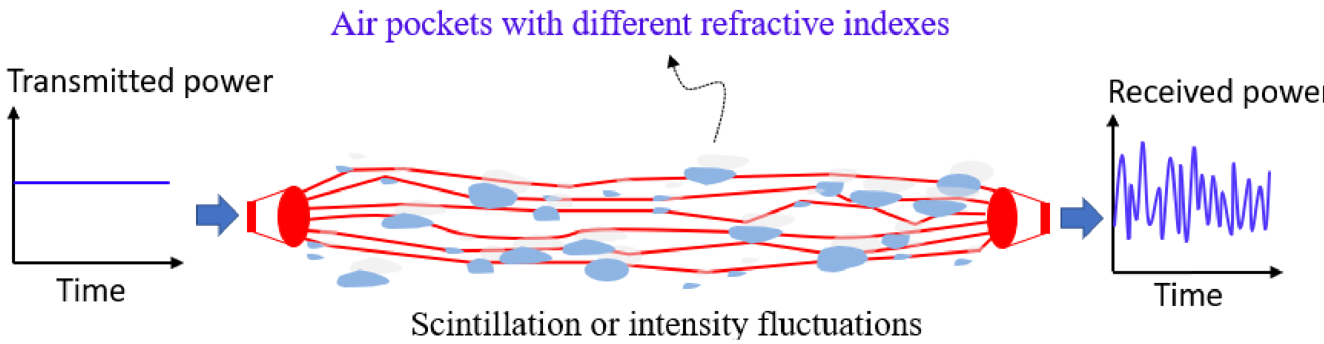
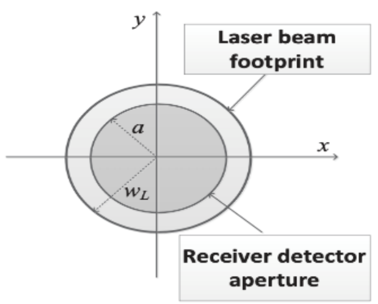
Problem Statement (1)

- It is challenging but necessary to investigate the ***end-to-end network performance*** incorporating ***FSO backhaul and RF access links for NTN***
  - ***End-to-end dynamic environment:***
    - **Users' movement** of access networks
    - **Time-varying channel conditions** of backhaul networks
- Access link: *users' movement*
- Backhaul link: *time-varying channel conditions*
  - ***Atmospheric turbulence:*** air pockets with different refractive indexes cause the scintillation effect

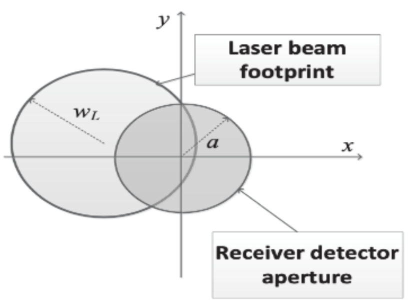


Problem Statement (2)

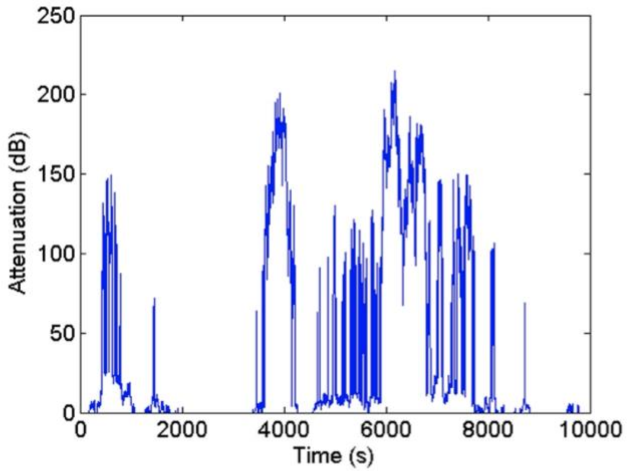
- Backhaul link:
  - ***Pointing error:*** misalignment between the center of the laser beam footprint and that of the UAV detector



(a) Without pointing error [7]



(b) With pointing error [7]



Cloud attenuation in Milan, Italy in 2017 [8]

  - ***Cloud attenuation:*** the liquid water particles in clouds cause the scattering phenomenon

    → *One of the most limiting factors for laser beams*

Goals of the Study

- GOAL: find the **optimal placement of the UAV** to **optimize the end-to-end throughput performance**
  - We consider the **movement of users** (access link) and **the moving clouds** (backhaul link) as the **dynamic factors** of the network
  - We implement **Deep Reinforcement Learning (DRL)** as an effective approach to handle the real-time UAV placement for the end-to-end dynamic network

System Description

System Model (1)

Application: to provide the internet connection to **rural/remote areas** or **temporary events** where **ground base stations are unavailable**

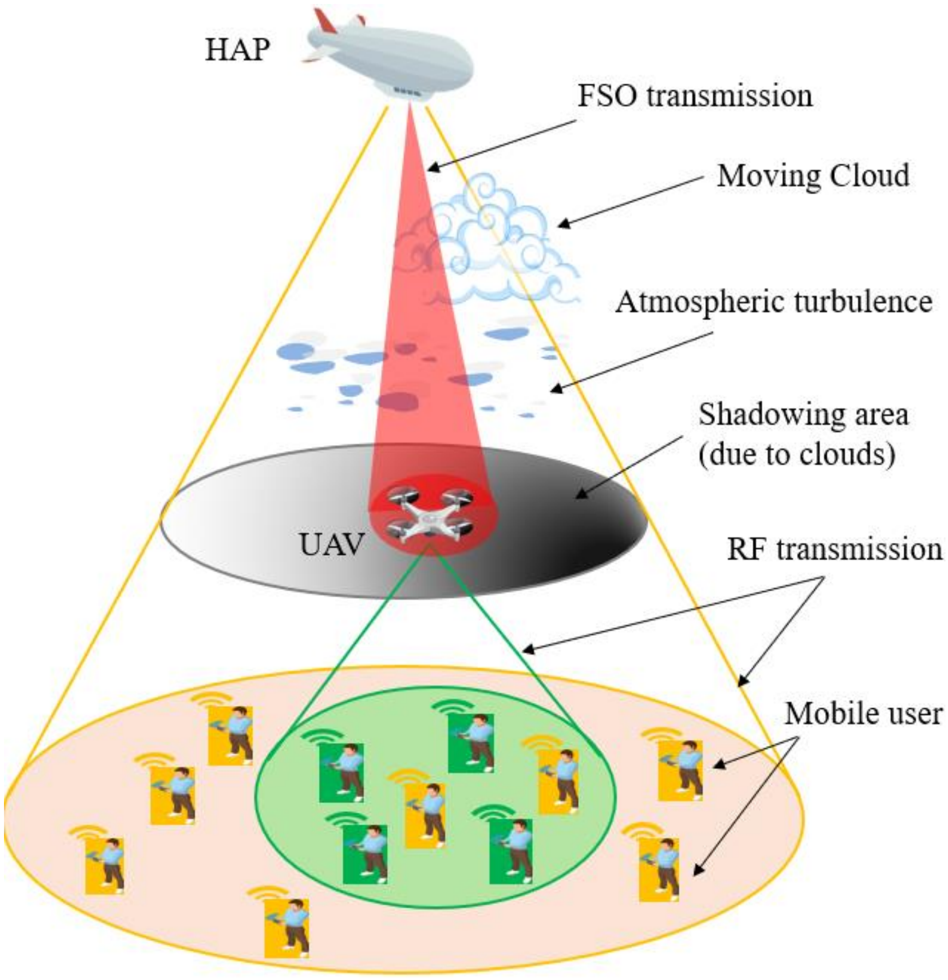
The end-to-end network scenario includes 2 main transmission links:

1. **Backhaul link:** from HAP to UAV

→ *FSO transmission is used for high-speed connection*

2. **Access link:** from UAV to GU and HAP to GU

→ *RF transmission is used*

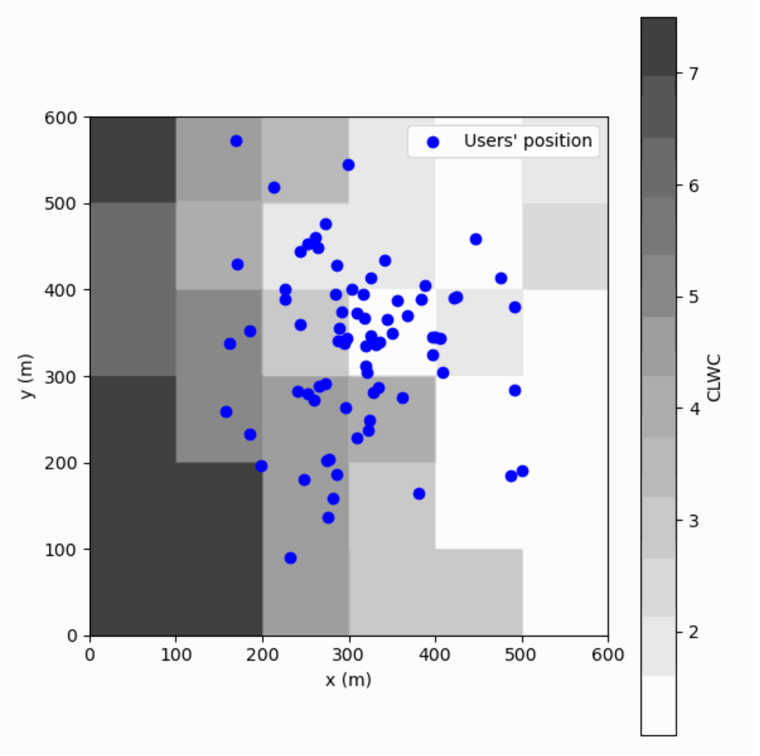


System Model (2)

We consider an area of $600 \times 600\ m^2$

- Users
  - The users are normally distributed with the standard deviation of 100m. The mean is randomly chosen in the whole area
  - A part of users follow the Gauss-Markov mobility model, while others stay unchanged
- Cloud model
  - We consider moving cloud with heterogeneous clwc*
  - The cloud moves to the west with a velocity of 4 m/s

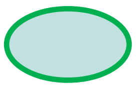
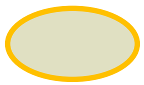
** : clwc (cloud liquid water content) - a measure of the total liquid water contained in a cloud in a vertical column of atmosphere (the less, the better)*

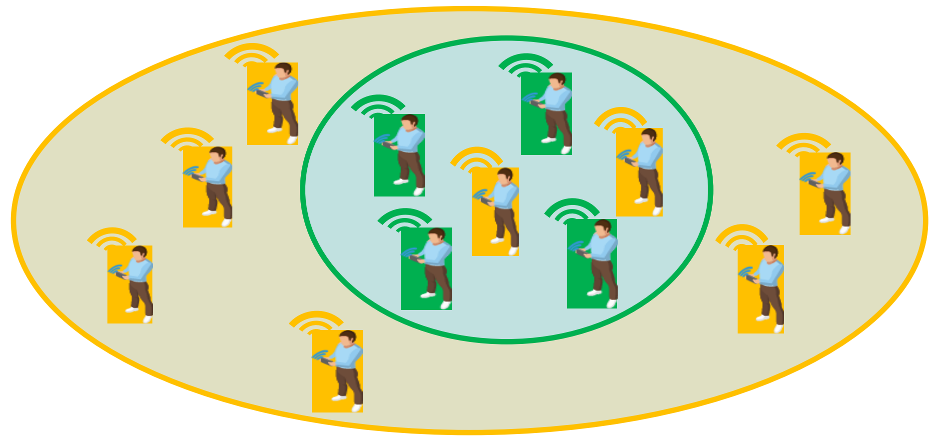


Problem Formulation

 Users supported by UAV → **Group U_1**

 Users supported by HAP → **Group U_2**

 UAV coverage  HAP coverage



- The optimization problem ($\mathcal{P}$) is formulated as

$$\mathscr{P}: \quad \max_{(x_t, y_t)} \sum_{t=0}^{T-1} \sum_{u \in U} R_u(t)$$

Find optimal position of UAV to maximize total rate of all GUs

$$\text{s.t.} \quad C_1: \quad \sum_{u_1 \in U_1} R_{u_1}(t) \leq R_{\mathrm{FSO}}(t)$$

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

$$C_2: R_{\mathrm{FSO}}(t) = f\left(M_c(t)\right)$$

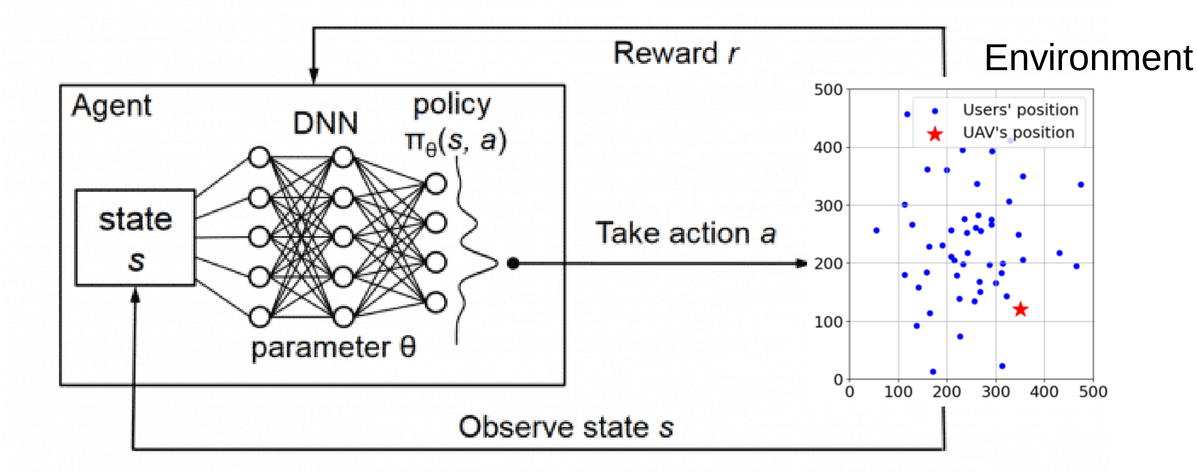
FSO capacity depends on the current clwc of clouds

$$C_3: \quad (x_{\min}, y_{\min}) \leq (x_t, y_t) \leq (x_{\max}, y_{\max})$$

Position constraints of the UAV

DRL for UAV Deployment

DRL Algorithm



- DRL Algorithm:
  - DRL: 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 agent interacts with the environment based on a particular policy
  - At time step t, the agent *chooses an action* a_t from the action space. It then *receives a reward/punishment* r_t from the environment and then *updates its current state* s_t
  - The algorithm aims to ***maximize the cumulative received rewards***

Markov Decision Process (MDP)

- Considered state, action, and reward:
  - **State $\boldsymbol{s}_t$:** the coordinates of UAV, users, and clwc grid
  - **Action a_t:** move ***(1)-north, (2)-west, (3)-south, (4)-east, (5)-remain stationary***
  - **Reward:** $$r(\boldsymbol{s}_t, a_t) = \begin{cases} r_t, & R_{U_1}(t) \geq R_{\text{thres}}, \\ 1 - r_t, & \text{otherwise}, \end{cases}$$
    - $r_t = \alpha\sqrt{R_{U_1}(t) \times R_{FSO}(t)}$
    - α: normalization factor
    - $R_{U_1}(t) = \sum_{\{u1 \in U_1\}} R_{u_1}(t)$: total users' rate provided by the UAV at time step *t*
    - $R_{FSO}(t)$: backhaul capacity at time step *t*
    - R_{thres}: data rate threshold

System Parameters

FSO backhaul link

Parameter	Value
FSO transmit power	6 dBm
FSO bandwidth	3 GHz
Optical wavelength	1.55 μm
HAP divergence angle	1 mrad

RF access links

Parameter	Value
Transmit power (HAP)	35 dBm
Transmit power (UAV)	25 dBm
Total bandwidth	300 MHz
Carrier frequency	2 GHz

DRL model

Parameter	Value	Parameter	Value
DRL framework	DQN	Time slot duration	1s
Learning rate	0.001	Total time slot	900
Discount factor	0.99	Scale factor	2e-9
Epsilon-greedy parameters ($\epsilon_{\max}, \epsilon_{\min}, \Delta\epsilon$)	0.99, 0.01, 0.01	Data rate threshold	0.4 Gbps

Episode Reward

- As we can see, the episode reward gradually increases and converges after about 1200 episodes

→ *The agent is learning from the environment and making more efficient decisions to achieve higher returns.*

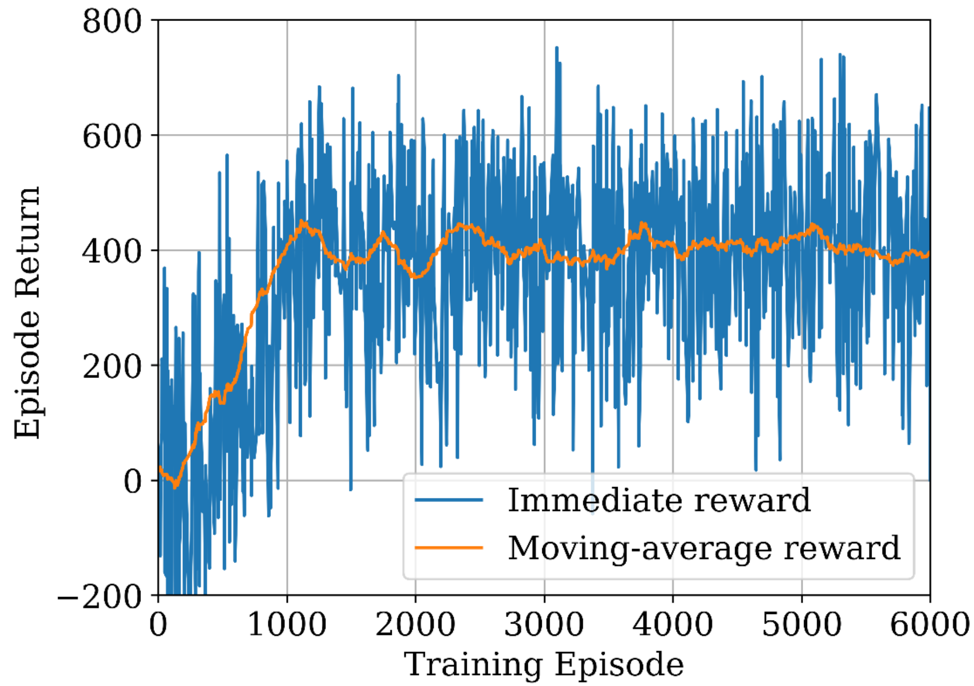


Fig. Episode reward vs. number of episode

Path of Movement

- The figure demonstrates the movement of the trained agent in a test environment
  - The test environment was set up randomly
  - The agent was not trained during the test

→ The UAV tends to move to the area that gathers many users and has low clwc

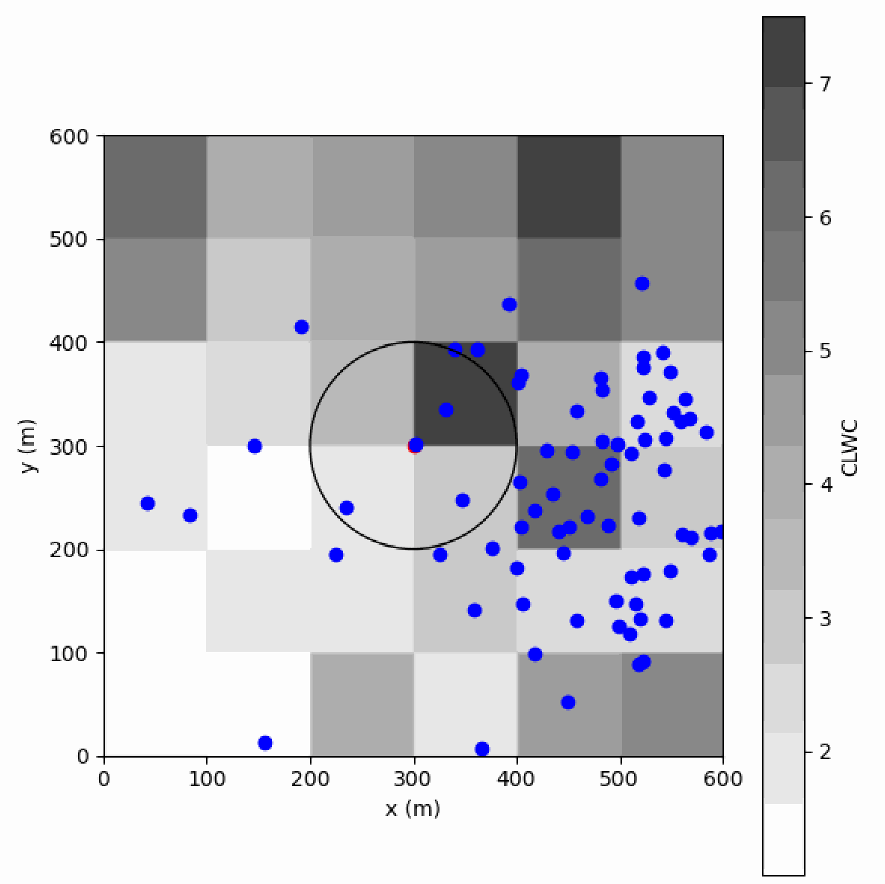


Fig. Behavior of the trained agent in the test environment

Total Users' Data Rate

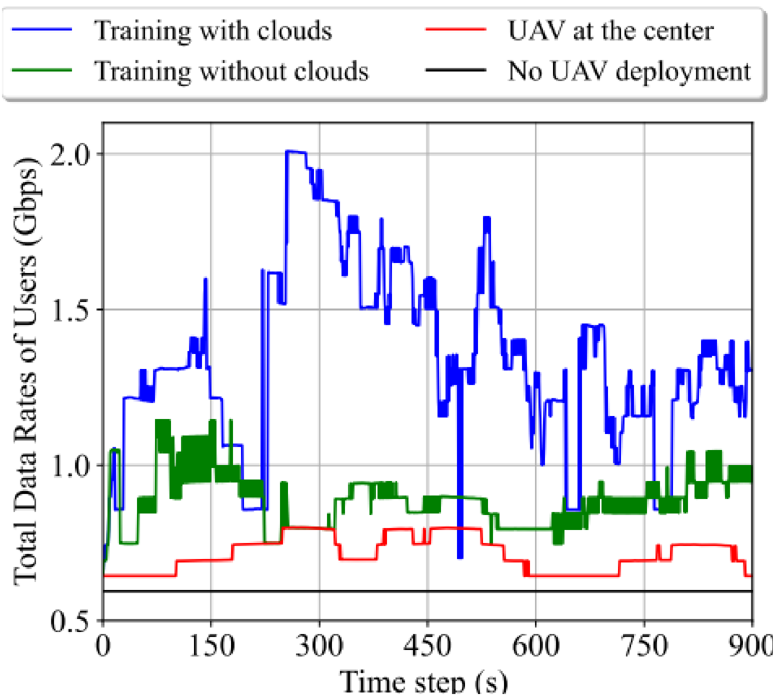


Fig. Total users' rate over time (1 episode)

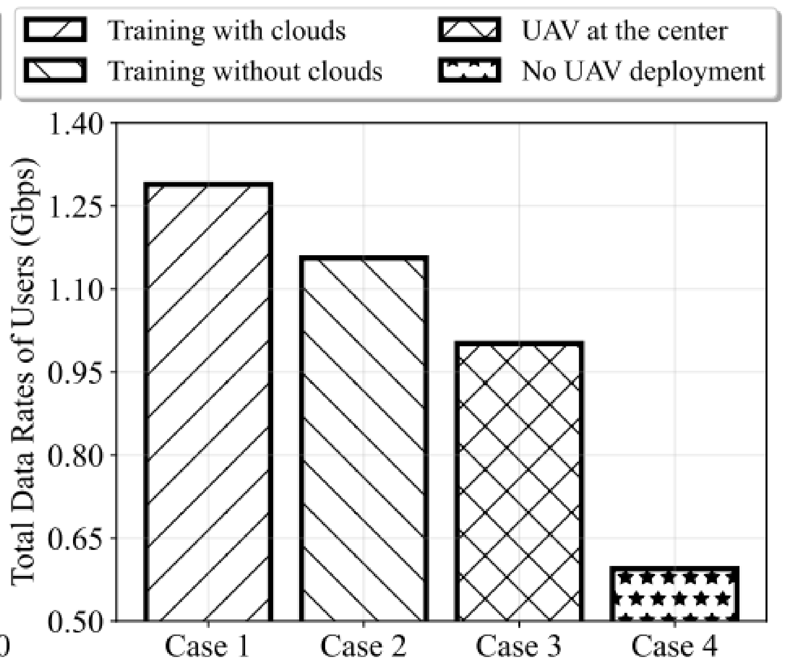


Fig. Average total user's rate over 100 test episodes

- I consider other system scenarios, including *training the UAV without considering the moving clouds*, *fixing the UAV at the center of the area*, and *no UAV deployment*
- As can be seen, our trained agent offers the highest performance and can maintain a relatively high data rate over time

→ *The trained agent can move efficiently, leading to significant gaps compared to other scenarios.*

Conclusion & Future Direction

- We have demonstrated an optimization framework that utilized DQN for the UAV placement problem to maximize the end-to-end throughput performance
  - The simulation results confirmed that the UAV can learn well from the dynamic environment and move efficiently to attain high throughput performance.
- Current status:
  - We have deeply investigated the FSO backhaul links for satellite-to-UAV and HAP-to-UAV networks, as reported in [9] and [10]
  - The current results of this work have been accepted for publication in an IEEE International Conference [11]
- Future direction: several potential extensions of the current work
  - ***Satellite-to-ground network:*** The movement of the satellite along its orbit can make the network more dynamic
  - ***Multi-UAV network:*** Multi-agent DRL can be used in this case

[9]. **Tinh V. Nguyen**, Hoang D. Le, and Anh T. Pham, "Adaptive Rate/Power Control with ML-based Channel Prediction for Optical Satellite Systems," IEEE Transactions on Aerospace and Electronic Systems, May 2024.

[10]. Hoang D. Le, **Tinh V. Nguyen**, Vuong V. Mai, and Anh T. Pham, "Resource Allocation for FSO-Based Multi-UAV Backhauling Over F Channels With Imperfect CSI," IEEE Transactions on Vehicular Technology. (**In revision**)

[11]. **Tinh V. Nguyen**, Hoang D. Le, Vuong Mai, Swaminathan R., and Anh T. Pham, "Deep Reinforcement Learning for UAV Placement over Mixed FSO/RF-Based Non-terrestrial Networks," IEEE VTS Asia Pacific Wireless Communications Symposium (APWCS), Singapore, Singapore, Aug. 2024.

Thank you for your listening!

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