End-to-end Performance Optimization for Mixed FSO/RF-aided Vertical Networks: A ML Approach

Tinh Nguyen

Computer Communications Lab.,
The University of Aizu

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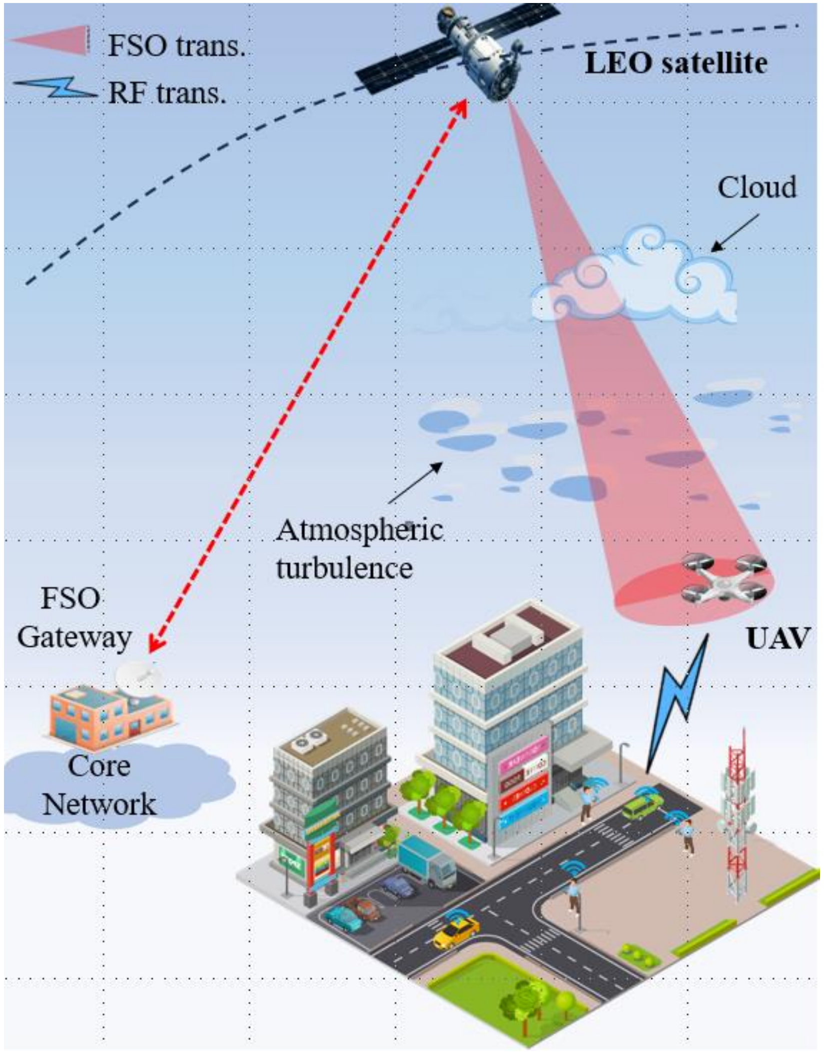
Introduction

Aerospace integrated network

- Recently, ***free-space optics (FSO)*** is envisioned as a promising candidate for backhaul networks thanks to its ***extremely high-speed connection***
- ***Aerospace integrated network***, incorporating satellites, HAP, and UAV, can guarantee ***seamless and ubiquitous access services***, especially in remote, hotspot, or emergency areas.

→ The aerospace integrated network jointly comprised of the UAV access and LEO satellite/HAP backhaul is a promising framework for future 6G networks.



Literature Review

- Some major papers that consider both access and FSO-based backhaul links

Ref.	Year	Journal	Title
1	2020	Trans. Netw. Sci. Eng.	An FSO-Based Drone Assisted Mobile Access Network for Emergency Communications
2	2021	Trans. Veh. Technol.	Latency Aware 3D Placement and User Association in Drone-Assisted Heterogeneous Networks With FSO-Based Backhaul
3	2023	Trans. Wireless Commun.	Backhaul-Aware Drone Base Station Placement and Resource Management for FSO-Based Drone-Assisted Mobile Networks
4	2022	Trans. Veh. Technol.	Spectral-Efficient Network Design for High-Altitude Platform Station Networks with Mixed RF/FSO Systems
5	2023	Internet Things J.	Cooperative UAV Trajectory Design for Disaster Area Emergency Communications: A Multi-Agent PPO Method
6	2023	Photon. J.	Outage Probability Analysis and Joint Optimization for UAV-aided FSO/RF Systems with Nonlinear Power Amplifiers

Motivations

- These current works mainly focus on the access network with terrestrial backhaul links
  - The channel conditions of the backhaul links are usually ignored
- For vertical FSO links, it is necessary to investigate the channel conditions on the end-to-end performance
  - FSO channel conditions, e.g., atmospheric turbulence, cloud, and pointing error conditions, have a considerable impact on the link capacity
  - Limited backhaul capacity directly affects the end-to-end performance

➔ ***Goal of the study:*** *optimize the end-to-end network performance for mixed FSO/RF-aided vertical networks considering the constraints of both links*

System Description

System Model

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

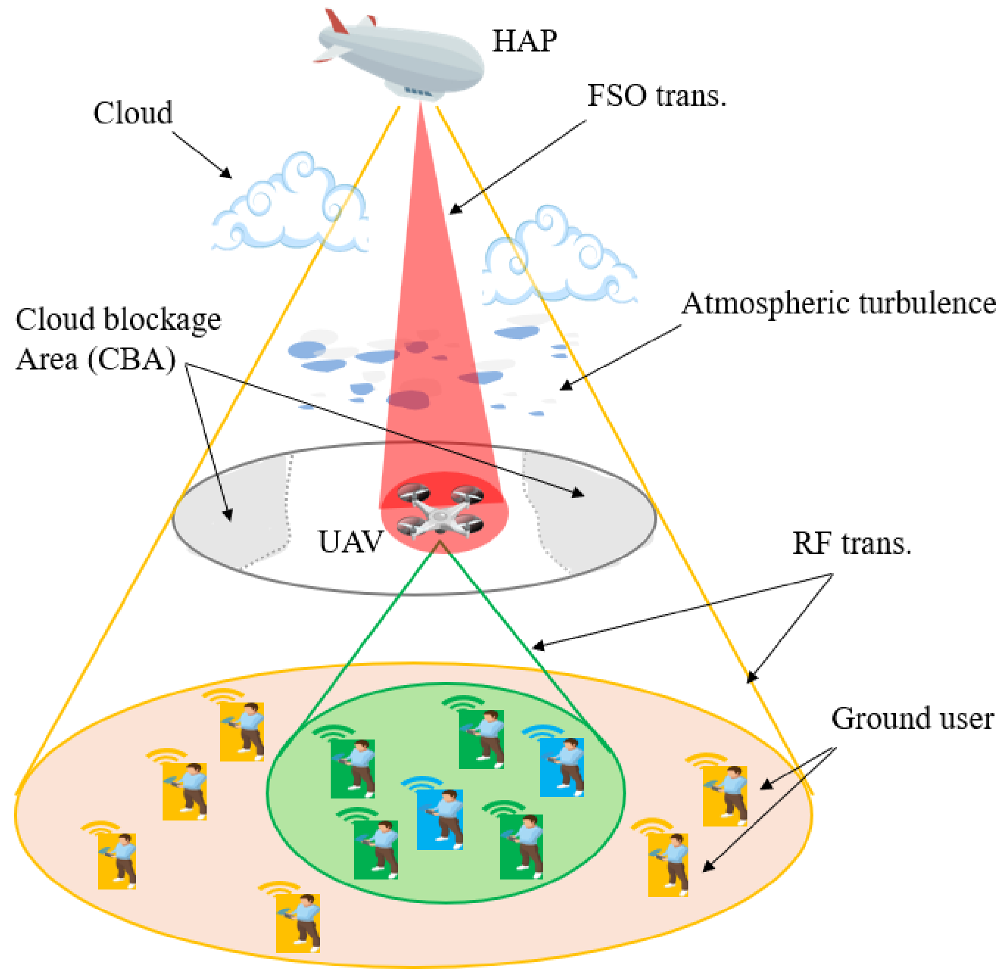
The end-to-end network scenario includes 2 main transmission links

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*



Critical Issues

- Backhaul link:
  - ***Cloud attenuation:*** the liquid water particles in clouds cause the scattering phenomenon. Due to LoS characteristic of FSO link, the *projection of clouds* creates *cloud-blockage areas (CBA)* on the UAV's horizontal plane
  - ***Atmospheric turbulence:*** air pockets with different refractive indexes cause the scintillation effect
  - ***Pointing error:*** misalignment between the centers of the beam footprint and the UAV detector

  → *Limit the capacity of the backhaul link*

- Access link:
  - Dynamic network: GUs move over time → *time-varying network topology*

→ ***Problem:*** *find the optimal position of the UAV to maximize the total throughput of GUs under the constraints of the limited capacity of backhaul link and dynamic network of access links*

Problem Formulation

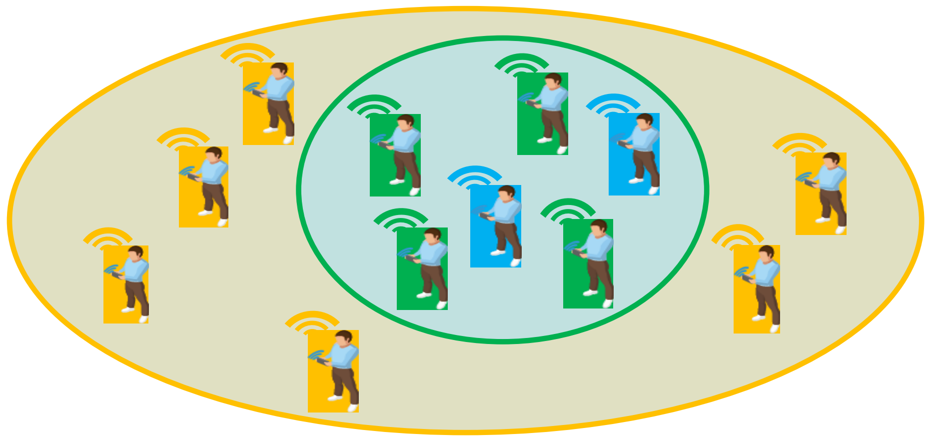
Users supported by UAV → **Group U_1**

Users in the coverage of UAV but supported by HAP → **Group U_2**

Other users supported by HAP → **Group U_3**

UAV coverage

HAP coverage



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

$$\mathscr{P}: \quad \max_{(x,y,z)} \sum_{u \in U} R_u$$

→ Find 3D position of UAV to maximize total rate of all GUs

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

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

$$C_2: \quad (x, y) \notin \text{CBA}$$

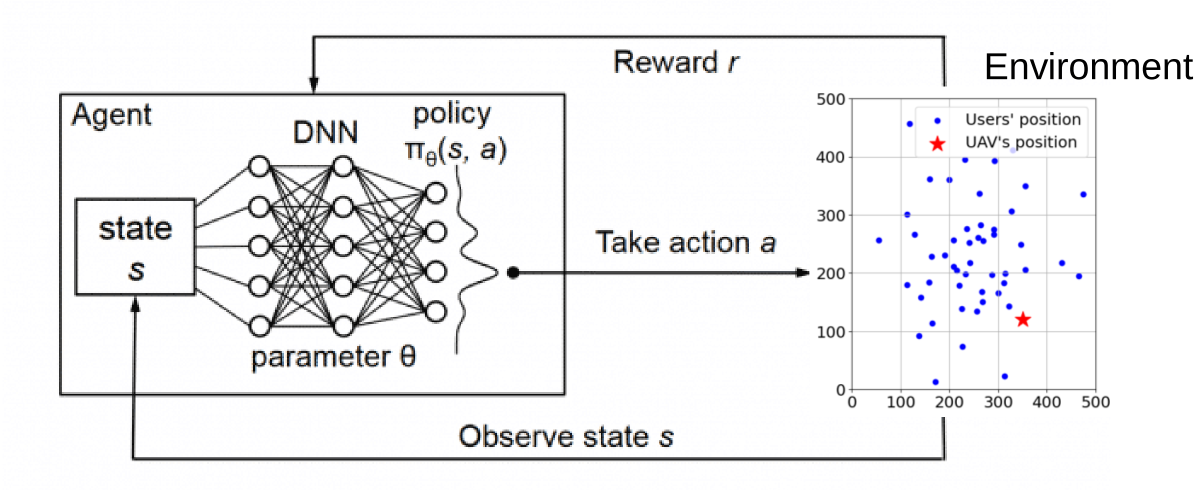
→ UAV avoids the cloud blockage areas

$$C_3: \quad (x_{\min}, y_{\min}, z_{\min}) \leq (x, y, z) \leq (x_{\max}, y_{\max}, z_{\max})$$

→ Position constraints of the UAV

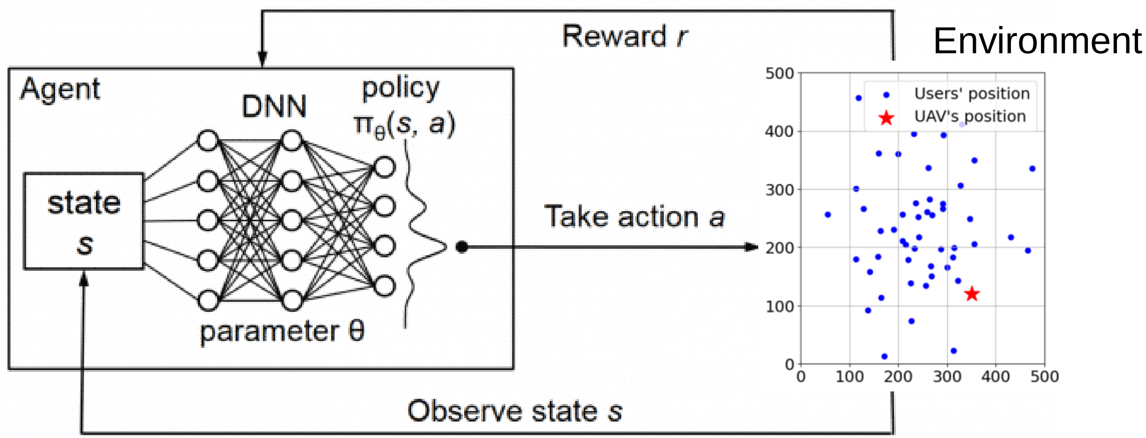
RL for UAV Deployment

RL Algorithm



- RL Algorithm:
  - The agent (i.e., UAV) 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* from the environment and then *updates its current state*
  - The algorithm aims to ***maximize the cumulative received rewards***

RL Algorithm



- Considered state, action, and reward:
  - **State:** the coordinates of UAV and users
  - **Action:** move ***(1)-north, (2)-west, (3)-south, (4)-east, (5)-remain stationary*** (the altitude will be considered later)
  - **Reward:**

    +1 if $R_{\text{tot}}(t+1) > R_{\text{tot}}(t)$

    -1 if $R_{\text{tot}}(t+1) < R_{\text{tot}}(t)$

    -0.1 if $R_{\text{tot}}(t+1) = R_{\text{tot}}(t)$

    ($R_{\text{tot}}(t)$: the total users' data rate at time t)

System Parameters

- RL Framework: Q-Learning
  - The considered area ($500 \times 500\ m^2$) is divided into a 50×50 grid
  - There are 5 available actions

Parameter	Value
Number of GUs	100
UAV's covered radius	100 m
Learning rate	0.01
Discount factor	0.9
Decaying epsilon-greedy parameters ($\epsilon_{\text{max}}, \epsilon_{\text{min}}, \Delta\epsilon$)	0.99, 0.01, 0.01
Number of episodes	2000
Number of iterations per episode	250

Episode Reward

- As we can see, the episode reward gradually increases and converges after about 200 episodes
- This means that the agent forms a better movement policy over time

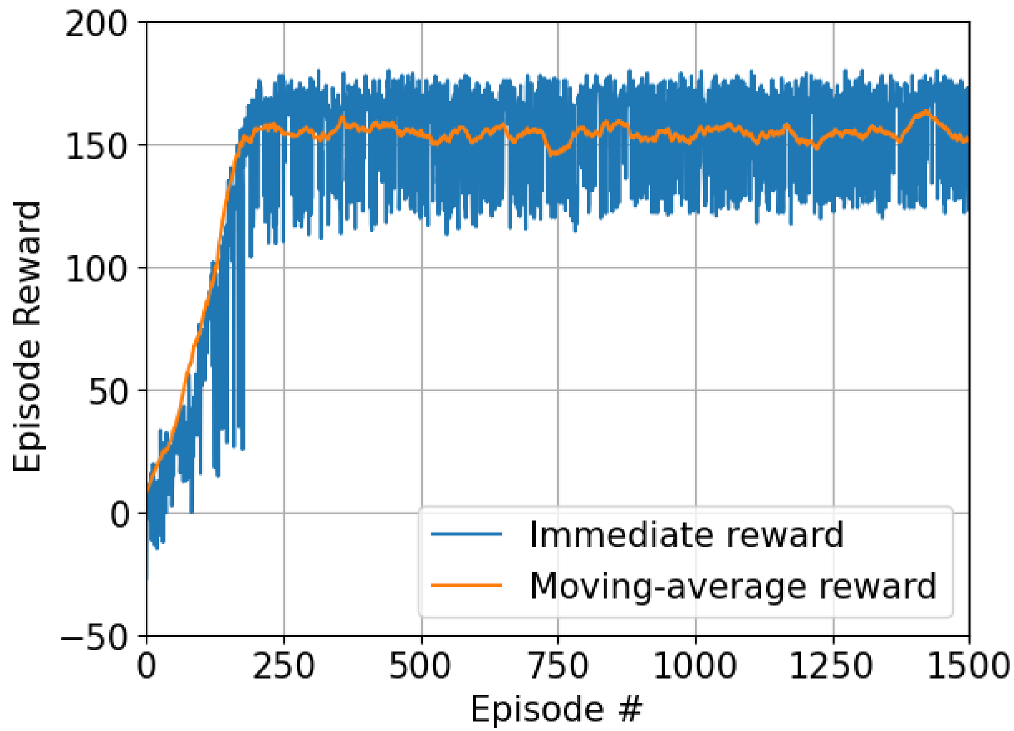


Fig. Episode reward vs. number of episode

Path of Movement

- The figure demonstrates the movement of the trained agent in a test environment
  - The test environment was set up randomly but had the same distribution as the trained environment
  - The agent was not trained during the test

→ We can see that the UAV tends to move to the center of the area, where more users are currently located

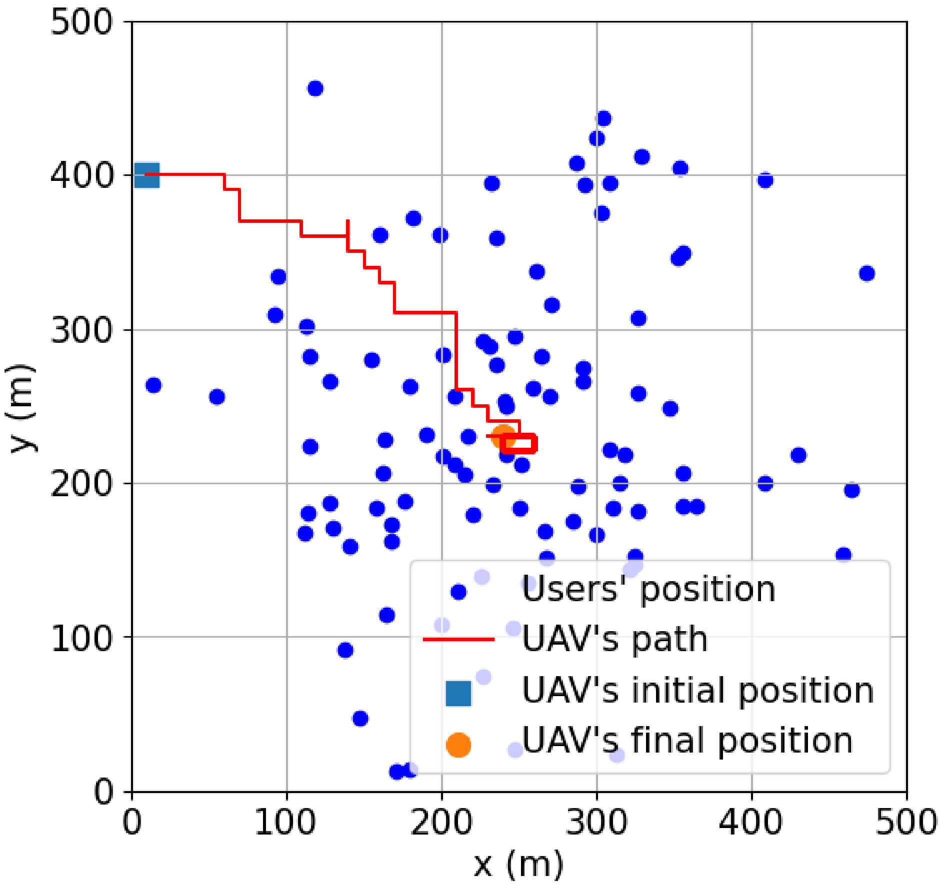


Fig. Behavior of the trained agent in the test environment

Thank you for your listening!