CCL Winter Camp

Adaptive Placement of Aerial Base Stations: A Learning-based Approach

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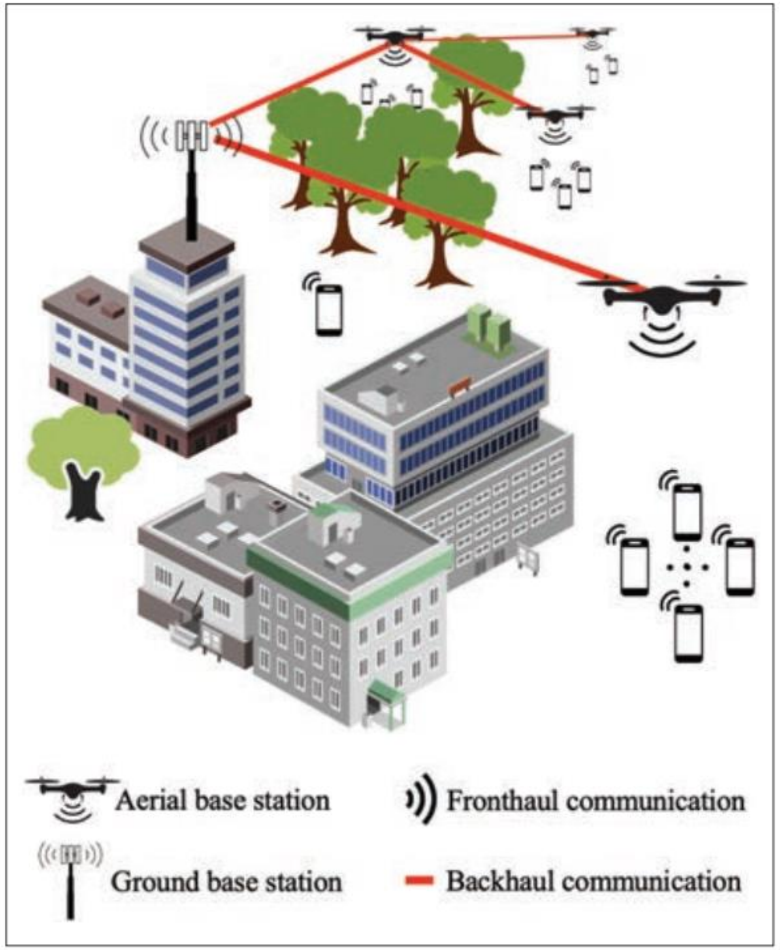
Adaptive Placement of Aerial Base Stations

- **Aerial Base Stations (ABSs):** a promising technology towards high-quality services and ubiquitous coverage
- Potential Use Cases:
  - Remote areas
  - Large open-air events (concerts, carnivals, etc)
  - Natural disaster-effected areas
- Challenge:
  - **Place the ABS dynamically over time** in response to **time-varying network conditions** (e.g., spatial distribution of users)



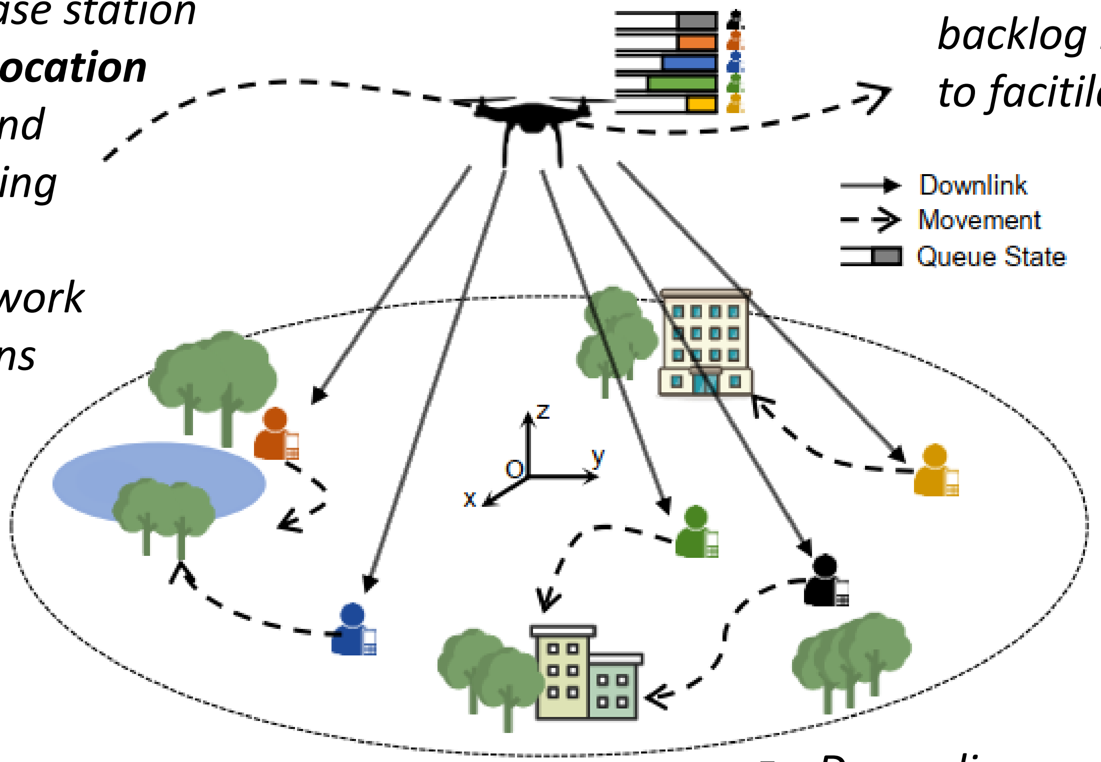
ABSs connect with Ground Terminals (fronthaul connection) and the terrestrial infrastructure (backhaul connection) (P. Q. Viet et al., 2022)

Adaptive Placement of Aerial Base Stations

- Conventional approaches
  - Utilize spatial distribution of users to place the UAV accordingly
  - Treat users with unbalanced traffic equally
  - Become sub-optimal when the user traffic is highly heterogeneous
    (e.g., users with heavy workloads should be prioritized over those requesting minimal traffic)
- **Our study**
  - Aims at an effective method for **adaptive ABS placement**, by considering not only the **spatial information** but also the **specific network traffic** of each user in optimization
  - Develops a deep reinforcement learning (DRL) method for control of the UAV placement

Modeling of the UAV-aided Communication System

- *A UAV is deployed as an aerial base station*
- ***The UAV updates its horizontal location** according to **users' movement** and **download traffic** while maintaining a static flying altitude*
- *The UAV connect to the core network via nearby terrestrial base stations*



- ***Queues** are maintained at the UAV to backlog incomplete downloads of users to facitilate the placement optimization*

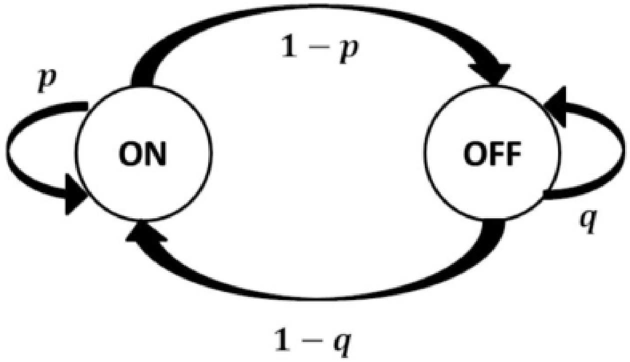
- *Depending on the network condition, the user might need several time slots to fully receive the requested data*

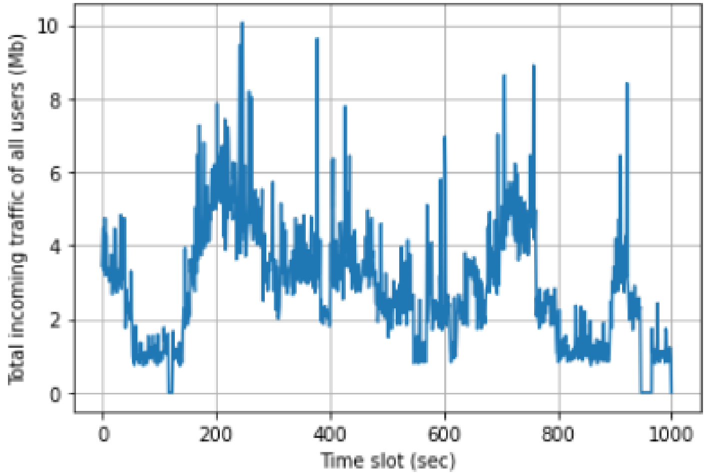
Modeling of the UAV-aided Communication System

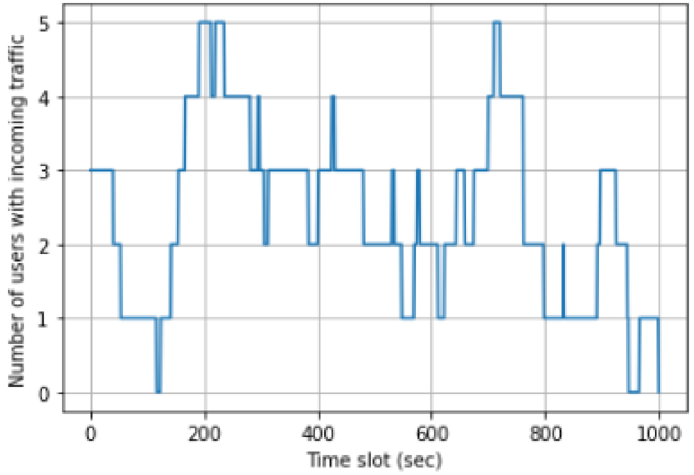
- Modeling of User Traffic:
  ON/OFF Traffic Model (M. Marvi *et al.*, 2019)
  for File Transfer Protocol (FTP) service

TABLE I: Details for ON and OFF states of FTP service [10]

State	Distributions and generated parameters
ON	Pareto distributed file size with mean λ, shape $\alpha = 1.5$, and scale x_m obtained through λ and α.
OFF	Exponentially distributed with mean μ_{OFF} in seconds.

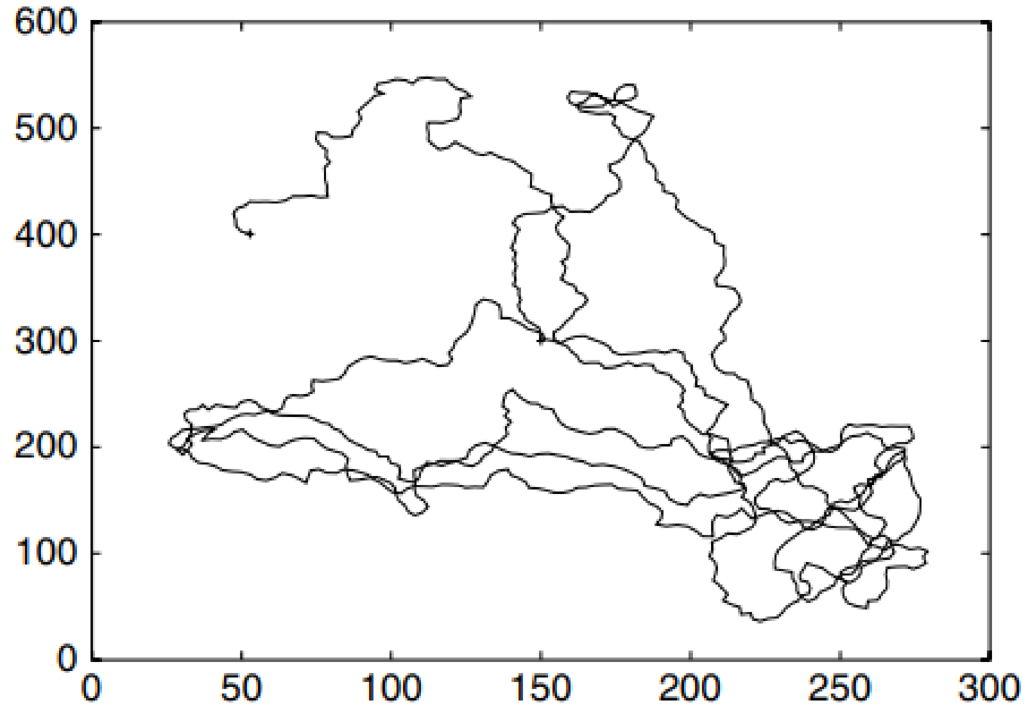






Modeling of the UAV-aided Communication System

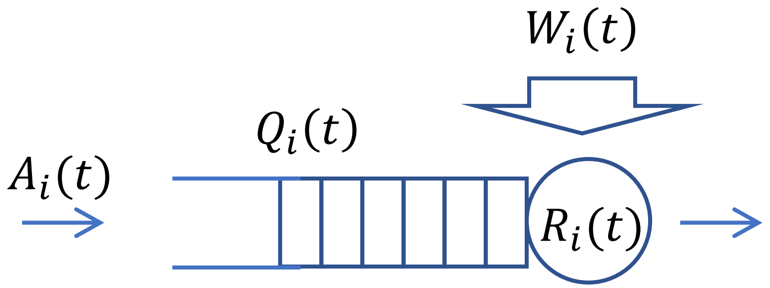
- Modeling of User Movement:
  Gauss-Markov mobility model
  (T. Camp et al., 2002)
- The **velocity** and **movement direction** of one user is **correlated over time** and modeled as a Gauss-Markov stochastic process



Traveling pattern of one user using the Gauss-Markov Mobility Model (T. Camp *et al.*, 2002)

Modeling of the UAV-aided Communication System

- **Download Queue:**



$$Q_i(t+1) = \max\left\{Q_i(t) + A_i(t) - R_i(t)\tau, 0\right\}$$

$Q_i(t+1)$: Queue length for user i at time t+1
$A_i(t)$: newly-requested traffic of user i at time t
$R_i(t)$: Downloading rate (Mbps) of user i at time t, depending on the comm. distance between the user and the ABS at time t
$W_i(t)$: Fluctuation of channel condition (due to user movements)

- **Downlink Throughput:**

The total volume of downloaded files of user i

$$\overline{D}_i = \lim_{T\to\infty} \frac{\boxed{\sum_{t=0}^{T-1} \min\left\{Q_i(t) + A_i(t), R_i(t)\tau\right\}}}{\boxed{\sum_{t=0}^{T-1} \mathbb{1}_i(t)}}$$

The total active time (for downloading) of user i

$1_i(t) = 1$ if in time slot t, there exist some files that have been requested but not yet downloaded by user i (i.e., $Q_i(t) + A_i(t) > 0$), and vice versa

Problem Formulation and Transformation

Problem Formulation:

$$\mathbf{P}: \max_{\mathbf{p}_s} \quad \sum_{i\in\mathbb{N}} \overline{D}_i \tag{6a}$$

$$\text{s.t.} \quad \lim_{T\to\infty} \frac{1}{T} \sum_{t\in\mathbb{T}} \sum_{i\in\mathbb{N}} \mathbb{E}\left[Q_i(t)\right] < \infty, \tag{6b}$$

$$\|\mathbf{p}_s(t+1) - \mathbf{p}_s(t)\| \le v_{\max}\tau, \forall t \in \mathbb{T}, \tag{6c}$$

$$\mathbf{p}_s(0) = \mathbf{0}; -R \le x_s(t), y_s(t) \le R, \forall t \in \mathbb{T}, \tag{6d}$$

(The original multi-stage stochastic optimization)

(6a) Maximizes the long-term download throughput experienced by all users

(6b) Ensures all download queues are *strongly stable* (M. J. Neely, 2010)

(6c) Constraint on the UAV’s maximum horizontal speed

(6d) Enforces the UAV to fly in the designated area

Transfomed Problem:

- To maximize the long-term throughput while ensuring queue stability, we maximize the upper bound of the Lyapunov drift-minus-reward as

$$\mathbf{P'}: \max_{\mathbf{p}_s(t)} \quad -\sum_{i\in\mathbb{N}} \Big[\left(Q_i(t) + A_i(t)\right) R_i(t)\tau + V \min\left\{Q_i(t) + A_i(t), R_i(t)\tau\right\} \Big] \tag{9a}$$

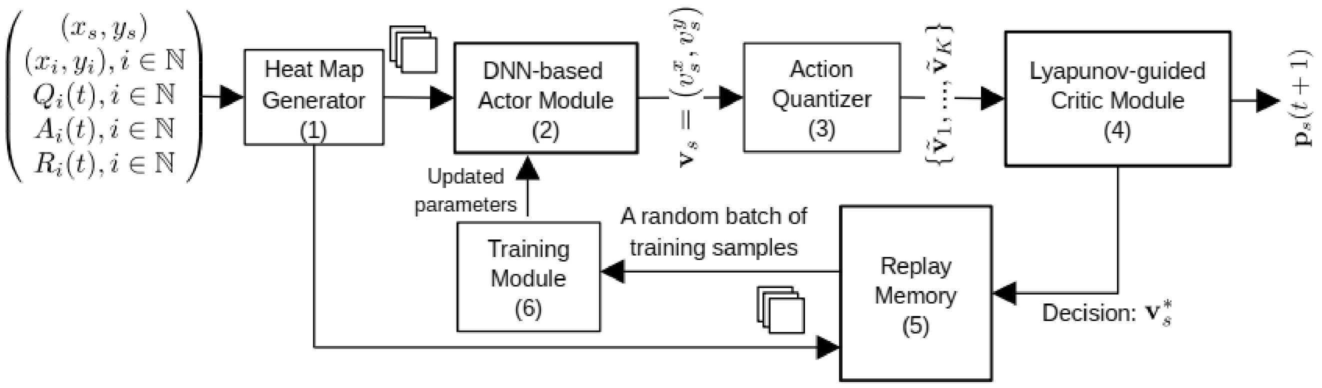
$$\text{s.t.} \quad (6c), (6d)$$

(The transformed per-time slot optimization)

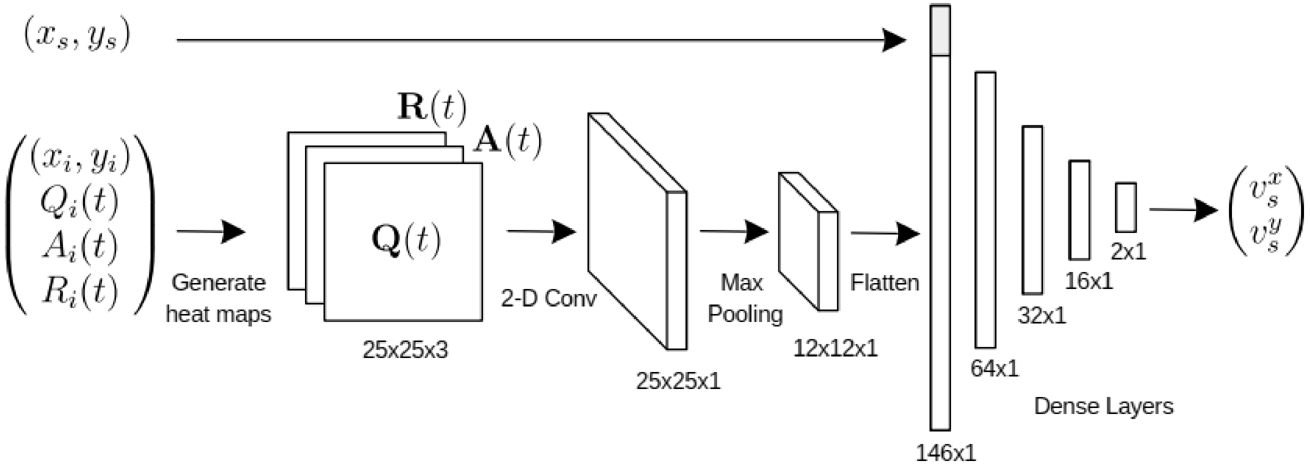
- V is the importance factor of maximizing the throughput to ensuring queue stability
- Online optimization:
  (9a) only takes the current network situation as the input. Future knowledge of user movement and traffic arrival is not required.

Deep Reinforcement Learning Framework

- Input:
  - The UAV's location
  - User's statistics (location, queue length, and traffic arrival)
- Output:
  - The UAV's velocity on the x- and y-axis → the travel distance and movement direction



(a) Schematic of the proposed DRL-based method



(b) Details of the DNN-based actor module

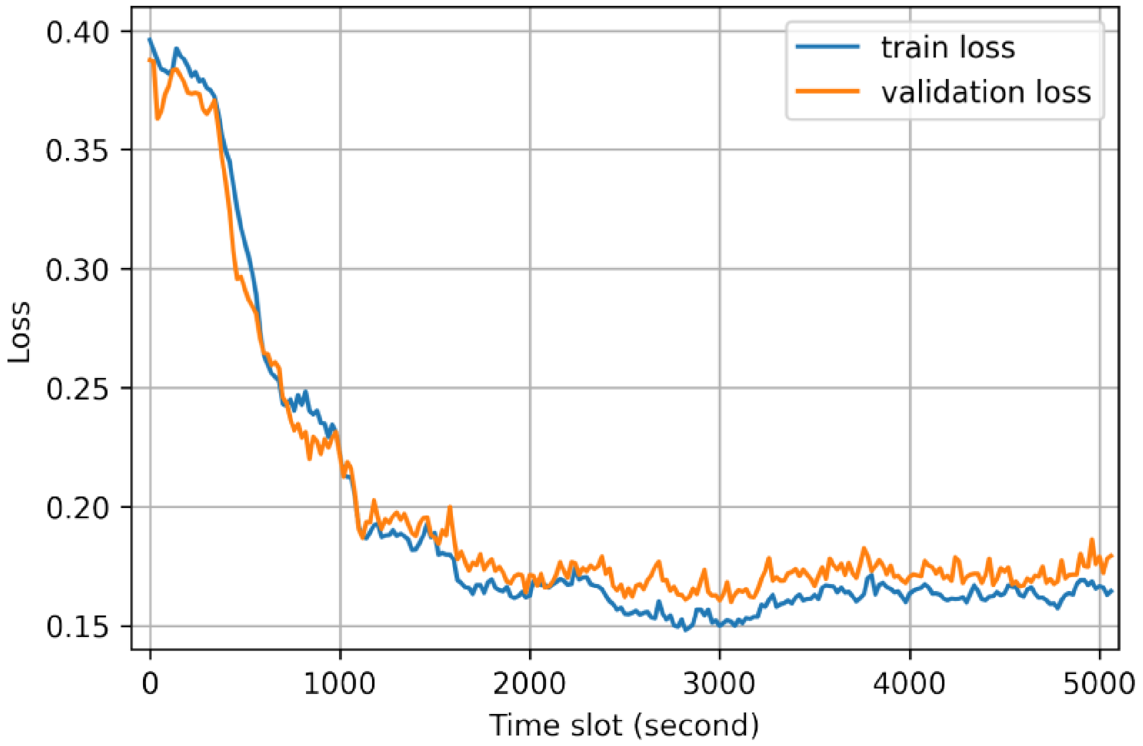
Simulation Setup

Simulation Parameter	Value
Number of users	5
The UAV's coverage area	500m x 500m
The grid size of heat maps	20m x 20m
Average movement speed of the user	1.5 m/s
Maximum horizontal speed of the UAV	5 m/s
Traffic arrival rate during the ON state	1.2 Mbps
Traffic state duration (ON/OFF)	100 s
Time slot length	1 s
Learning rate	0.001

Benchmarking schemes:

1. **Fixed at the center**: The UAV is stationary at the area's center, denoted as point O
2. **Centroid of all users**: The UAV moves toward the centroid of all users during the process

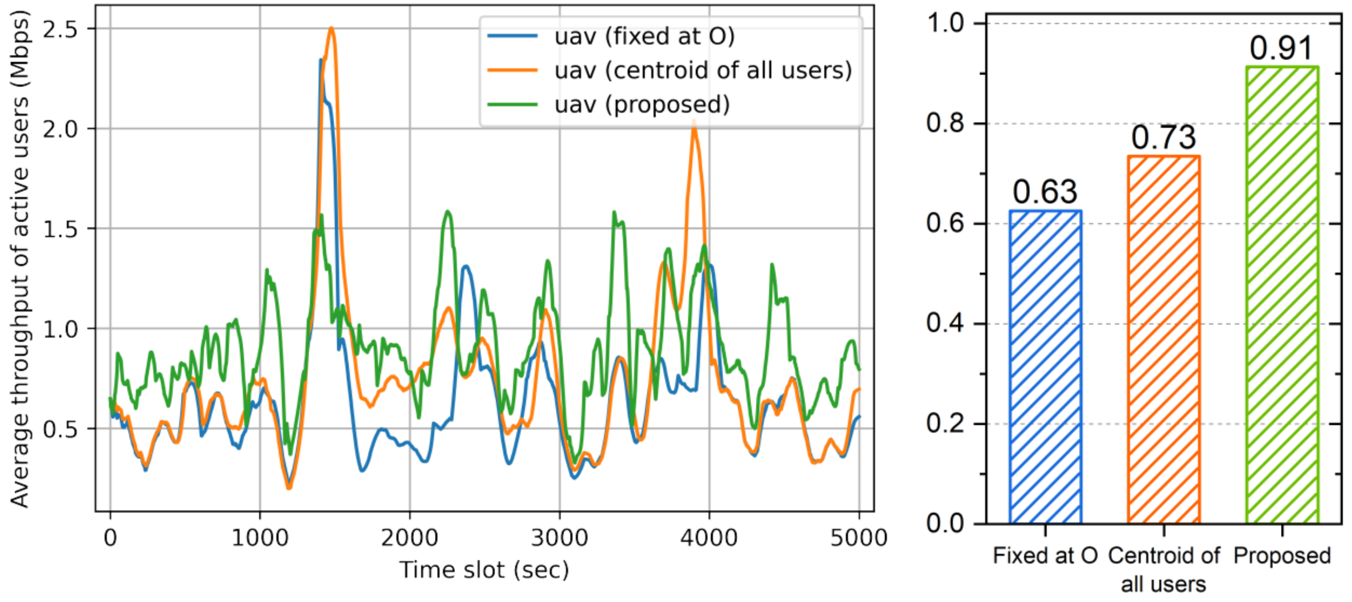
Numerical Results: DNN Training

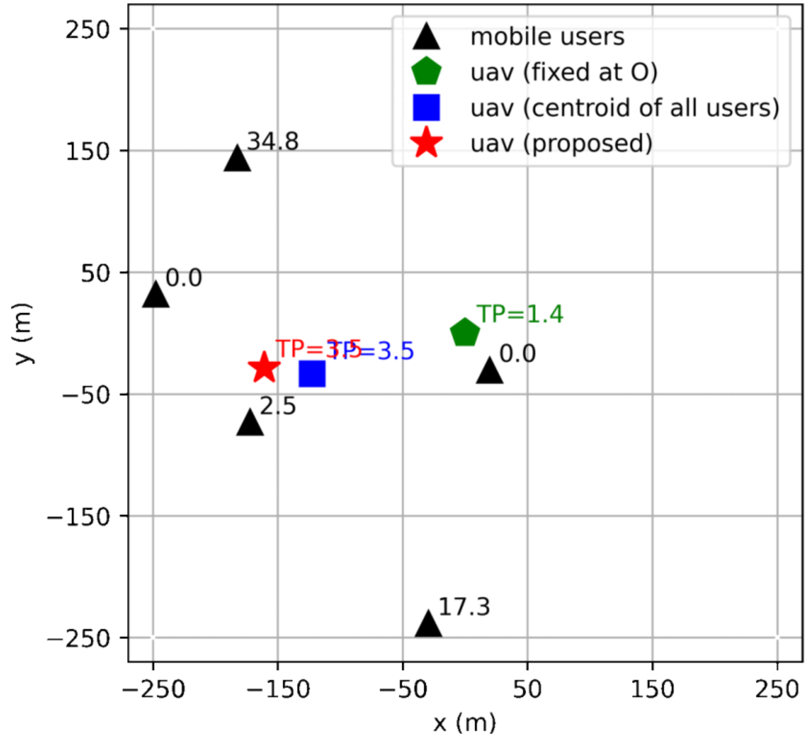


Training and validation loss of the DNN

- The DNN gradually outputs better movement decisions for the UAV through training
- The convergence trend is clear after 2000 time slots

Numerical Results: Downlink Throughput



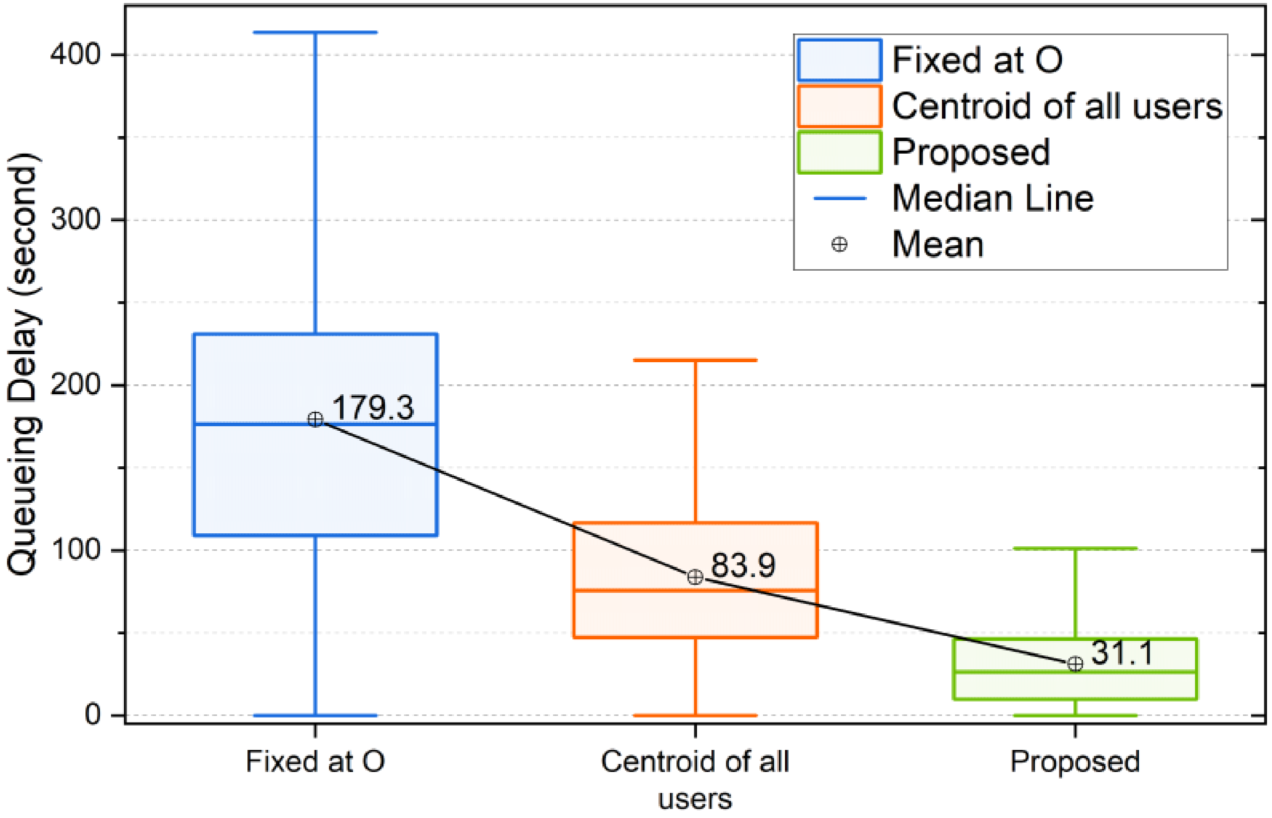


(Left) Download throughput of active users over time, rolling average with an interval of 120 s
(Right) All-time average of one user's download throughput, arrival rate = 1.2 Mbps

Locations of the UAV and users over time

- *Numbers next to user markers denote the user's requested data in Mb*
- *Annotations of colored markers (e.g., TP=3.6) indicate the download speed (Mbps) provided by corresponding UAVs*

Numerical Results: Queueing Delay

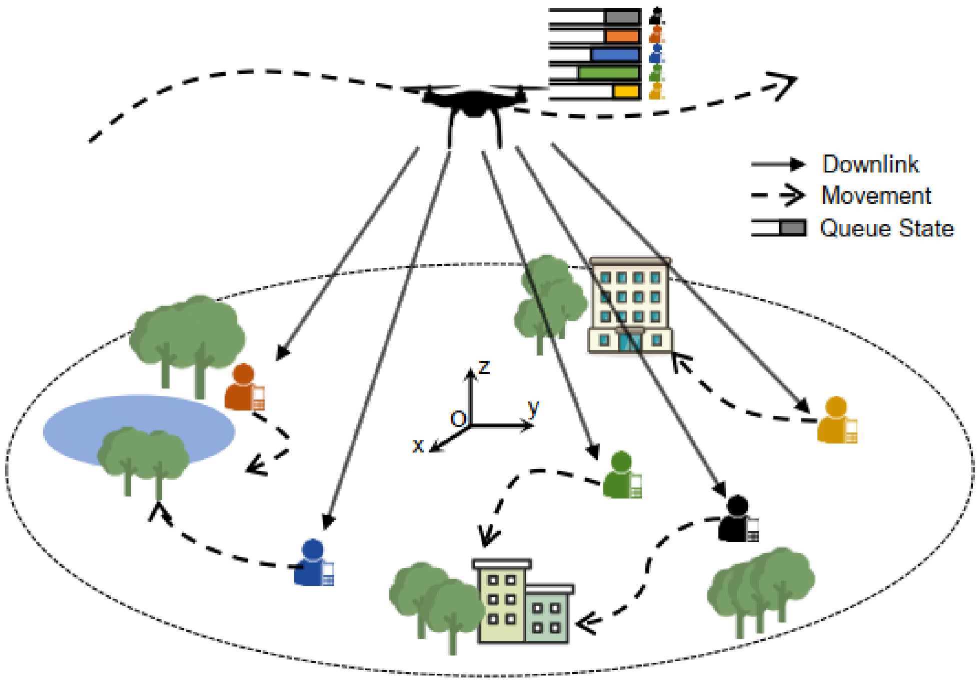


Queueing delay experienced by users;
Number inside the boxes denote the mean values

The average delay experienced by users of the proposed method is just 17.3% and 37.1% of the two benchmarks, Fixed at O and Centroid of all users, respectively

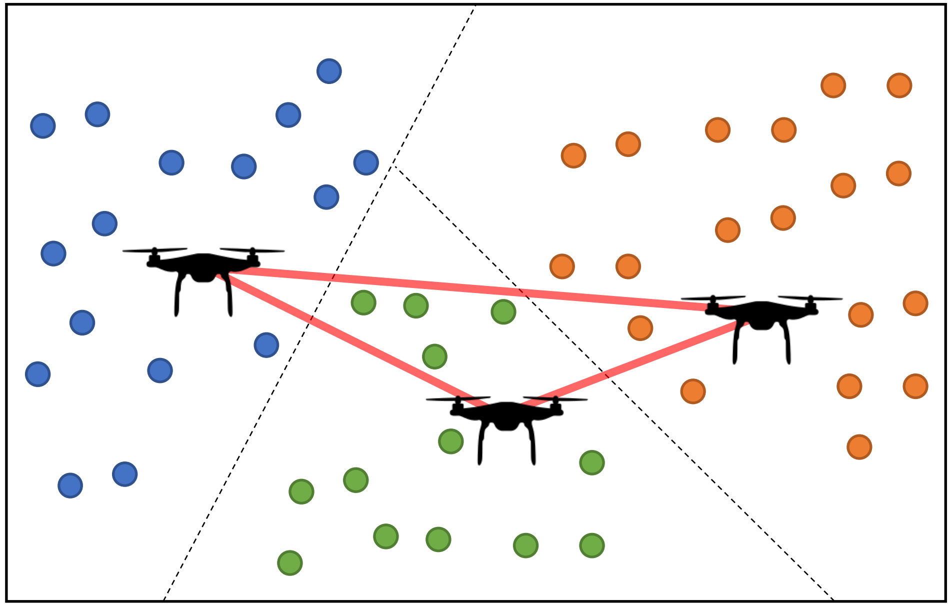
Simplified Points in the current research

- While there is a constraint about the UAV's maximum velocity, the UAV's **propulsion energy** was obmitted
- A small network was considered with **a few users** and **a single UAV**
- The rotary-wing UAV has strict requirements on the size, weight, and power (SWaP)
  → The coverage area of one UAV is limited
  → **Co-operation of multiple UAVs**
- Only the **downlink traffic** was considered



The considered UAV-aided communication system

Future Work



*A large network with many mobile users and several UAVs, **considering both uplink and downlink with mixed traffic***

Maximize	Long-term Throughput (**QoE-oriented**)
Subject to	Maximum horizontal speed of the UAV
	Queues are strongly stable
	The UAVs operate within the target area
	Long-term propulsion energy $\leq$ E_avg
	d_min $\leq$ **Distance between two UAVs** $\leq$ d_max
	Instanteneous Channel capacity of one user $\geq$ C_min

Optimization variables:

- User Clustering
- UAV Placement

Conclusions

- The research aims at an effective method for **adaptive ABS placement,** by considering not only the **spatial information** but also the **specific network traffic** of each user in optimization
- We develop a deep reinforcement learning (DRL) framework that directly maps the network situation to the UAV movement using three heat maps of user's statistics (the queue length, newly-requested traffic, and channel condition)
- Simulation results reveal a great potential of DRL in flight control of the UAV in future research

References

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- T. Camp, J. Boleng, and V. Davies, "A survey of mobility models for ad hoc network research," *Wirel. Commun. Mob. Comput.*, vol. 2, no. 5, pp. 483–502, Aug. 2002.

Thank you for your attention