

Sum Rate Maximization in Downlink HAP-RSMA-based THz Systems: A Generative Diffusion Model enabled RL Approach

Insight 

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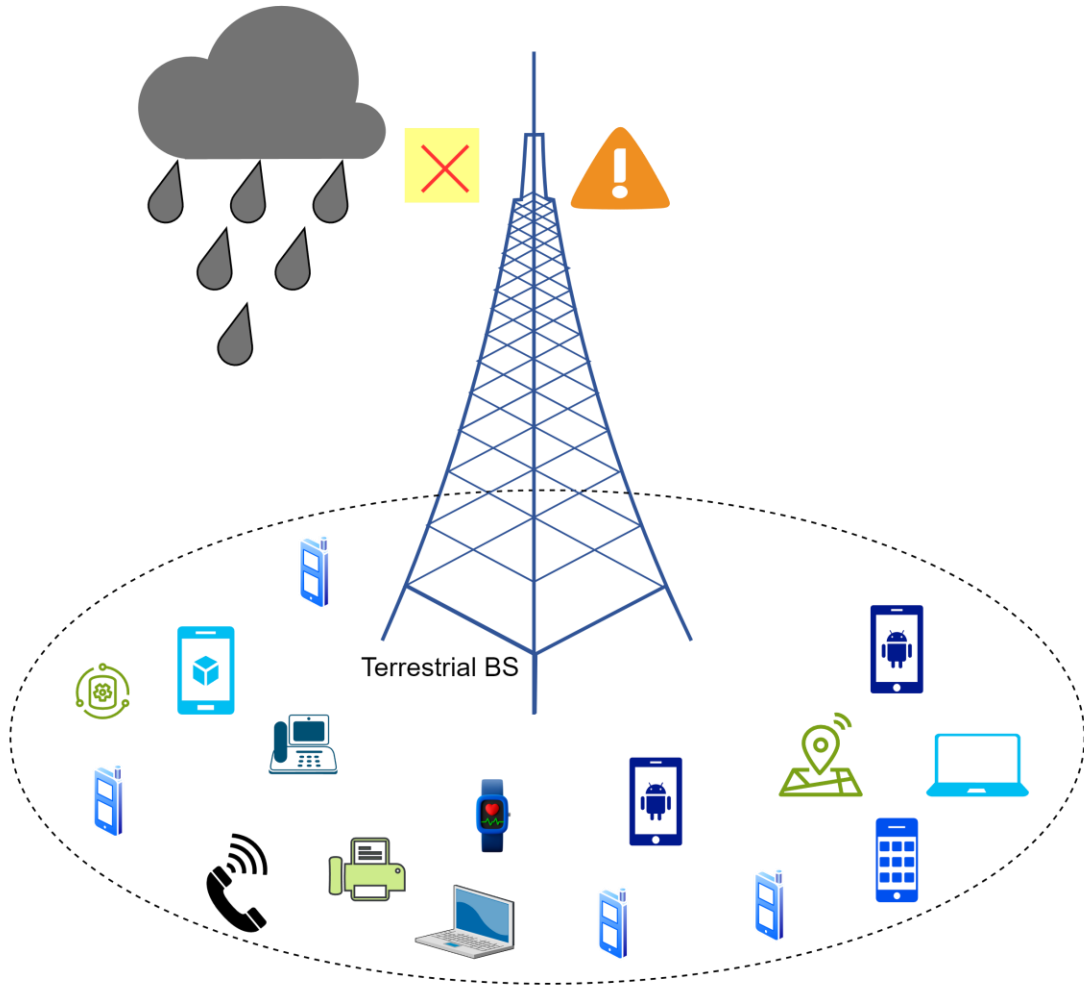
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Problems and Motivations



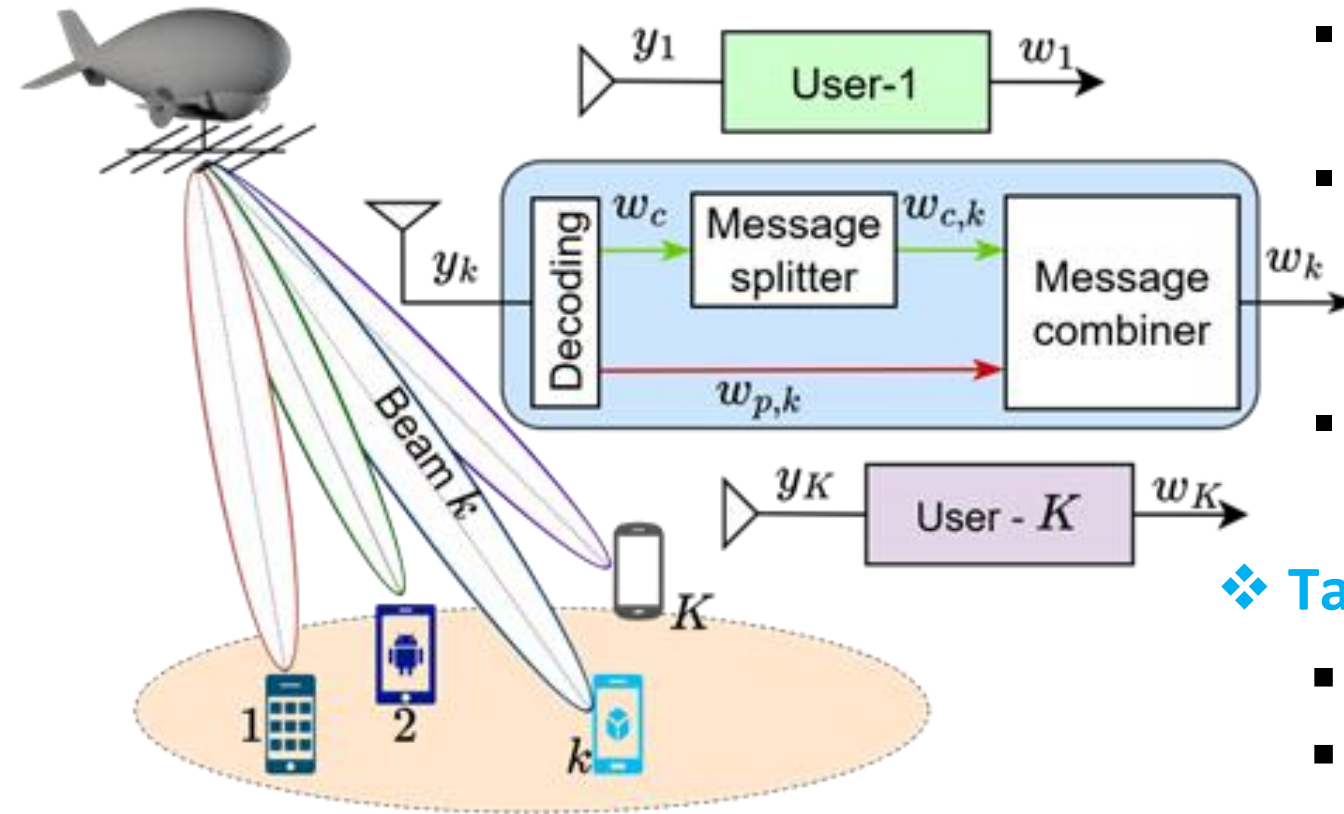
❖ Future networks (6G) are challenging when

- Massive connection with unpredicted rapidly increase IoT devices
- High data rates, low latency communications
- Malfunctioning/overloaded of terrestrial base station
- Effective solutions with the dynamic and uncertainty of network environment

❖ How to solve

- Investigate higher frequency (THz) band
- Expand network coverage by integrating terrestrial wireless with aerial access network
- Investigate multiple access technique
- Apply machine learning-based algorithm

Problem Formulation



$K = \{1, 2, \dots, K\}$ the set of ground users

❖ HAP flies at the center of the network

- Communicate with Ground users (GUs) Rate-Splitting Multiple Access (RSMA) principle [1], [2]
- Resource allocation optimisation
 - Common/private power: p_c, p_p
 - Common rate allocation: c
- Total data rates: $\Gamma_t = R_1 + \dots + R_k + \dots + R_K$

❖ Target

- Ensure services for all users
- Maximize the system throughput in long-term
- Guarantee quality of service of users

[1] B. Clerckx et al., "Multiple Access Techniques for Intelligent and Multifunctional 6G: Tutorial, Survey, and Outlook," Proceedings of the IEEE, vol. 112, no. 7, pp. 832-879, July 2024.

[2] Y. Wu, et al., "Robust Resource Allocation for RSMA Spectrum Sharing Networks," IEEE Transactions on Wireless Communications, vol. 23, no. 11, pp. 16375-16389, Nov. 202.

Problem Formulation (cont.)

❖ Optimization problem

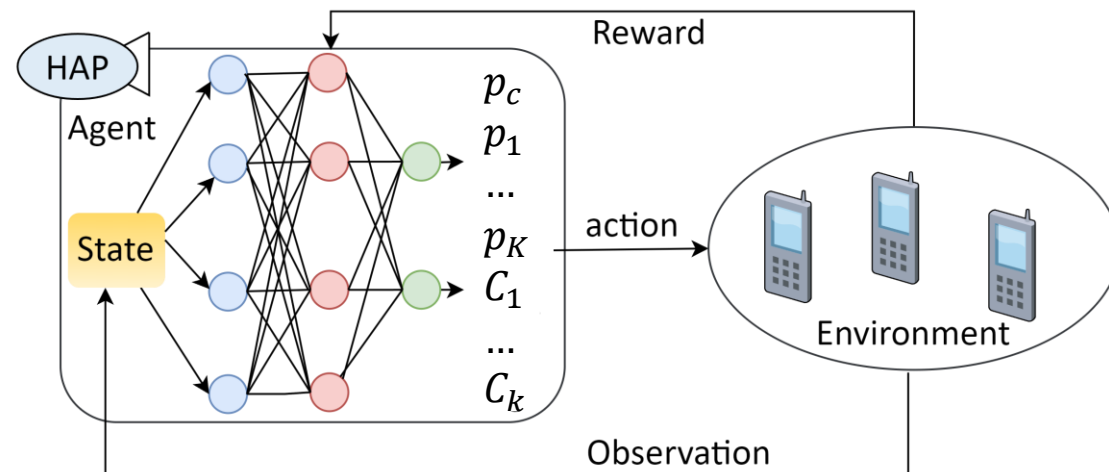
Total data rate of users

$$\begin{aligned} \max_{\mathbf{P}, \mathbf{C}} \quad & E \left(\sum_{t=1}^T \gamma^{t-1} R_t \right), \\ \text{s.t.} \quad & P_{\text{use},t} \leq P_{\text{max}}, \\ & p_{c,t} > 0, p_{k,t} > 0, \forall k, t, \\ & \sum_{i=1}^K C_{k,t} \leq R_{c,t}, \forall t, \\ & C_{k,t} > 0, \forall k, t, \\ & C_{k,t} + R_{p,k,t} \geq R_{\text{min}}, \forall k, t, \\ & p_{c,t} |\mathbf{h}_{k,t}^H|^2 - \sum_{i=1}^K p_{i,t} |\mathbf{h}_{k,t}^H|^2 - \sigma^2 \geq 0, \forall k, t. \end{aligned}$$

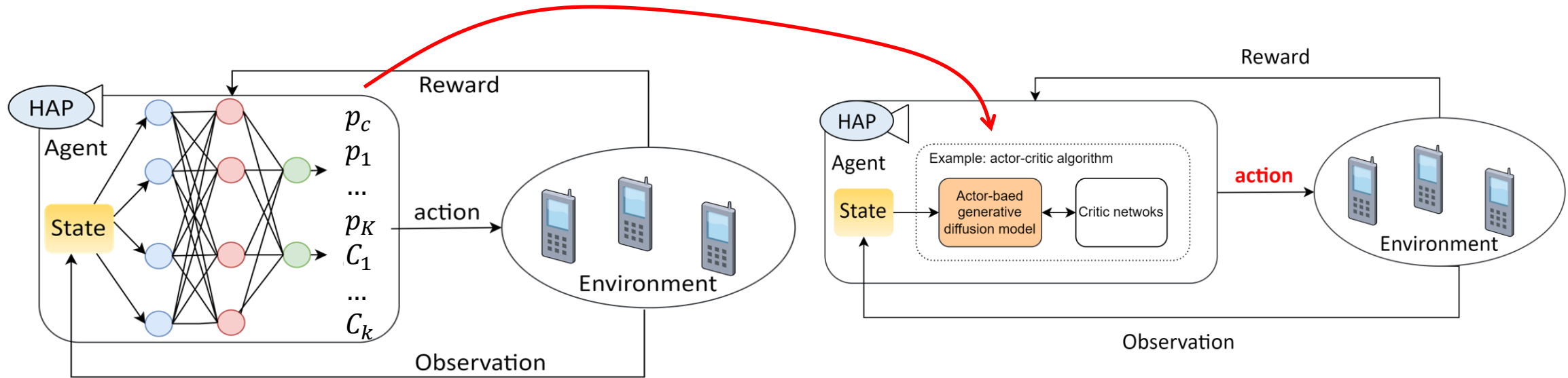
Resource Constraints

❖ Deep reinforcement learning

- Integrated of Deep learning and Reinforcement learning



Generative Diffusion Model-Enabled DRL



(a): Example of DRL

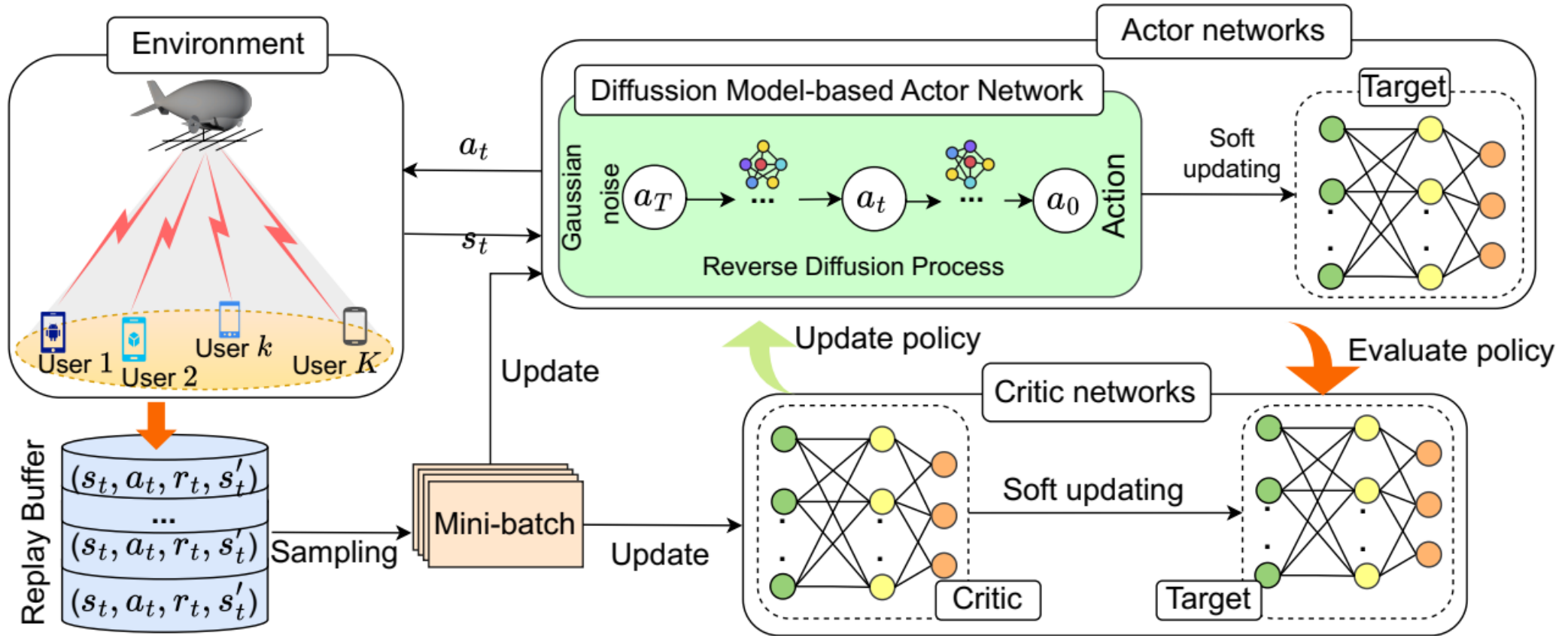
(b): Example of DRL-based generative diffusion model

❖ Limitations of existing DRL approaches

- High computational requirements, especially for problems with large state or action spaces
- Deviating learned policy distribution from the true data distribution due to struggling to capture deeper data features

➔ Generative diffusion models thanks to superior feature learning capabilities

Generative Diffusion Model-Enabled DRL

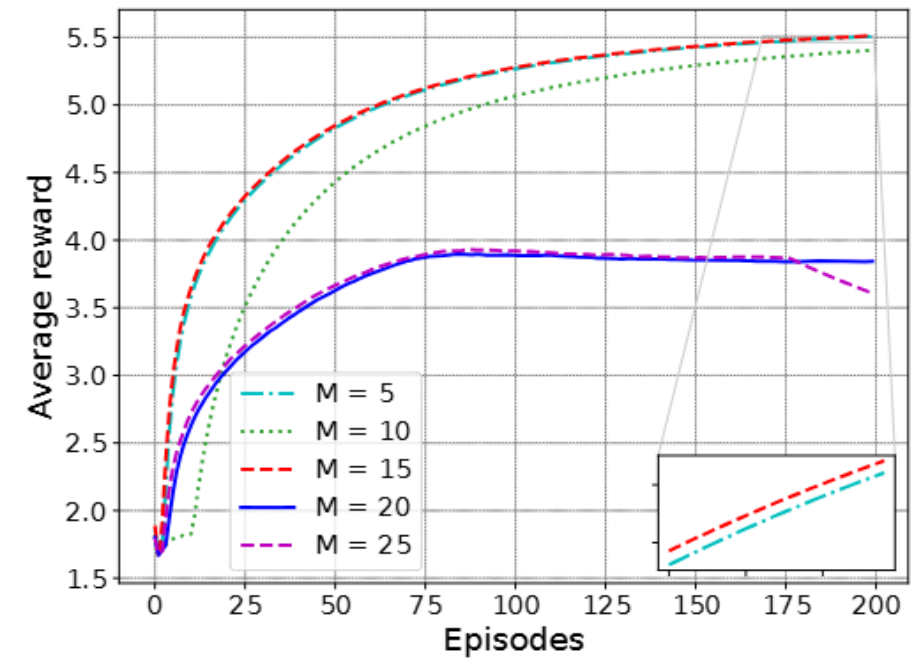
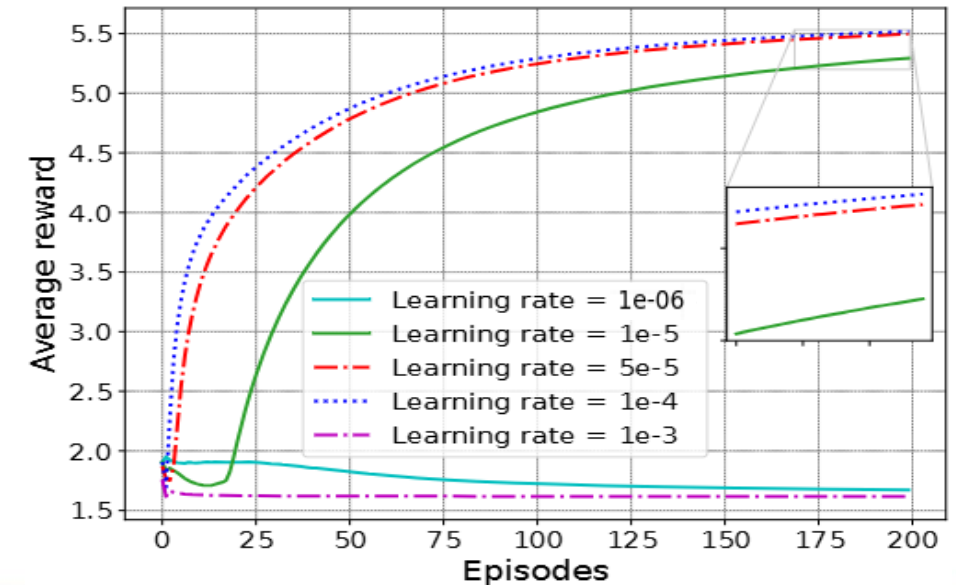


- Action: $a_t = \{p_{c,t}, p_{1,t} \dots, p_{K,t}, C_{1,t}, \dots, C_{K,t}\}$
- State: $s_t = \{h_{1,t}, \dots, h_{K,t}, R_{c,1,t-1}, \dots, R_{c,K,t-1}, R_{p,1,t-1}, \dots, R_{p,K,t-1}\}$
- Reward: $r_t = \Gamma_t$ or $\Gamma_t - \text{penalty}$ (violated constraints)

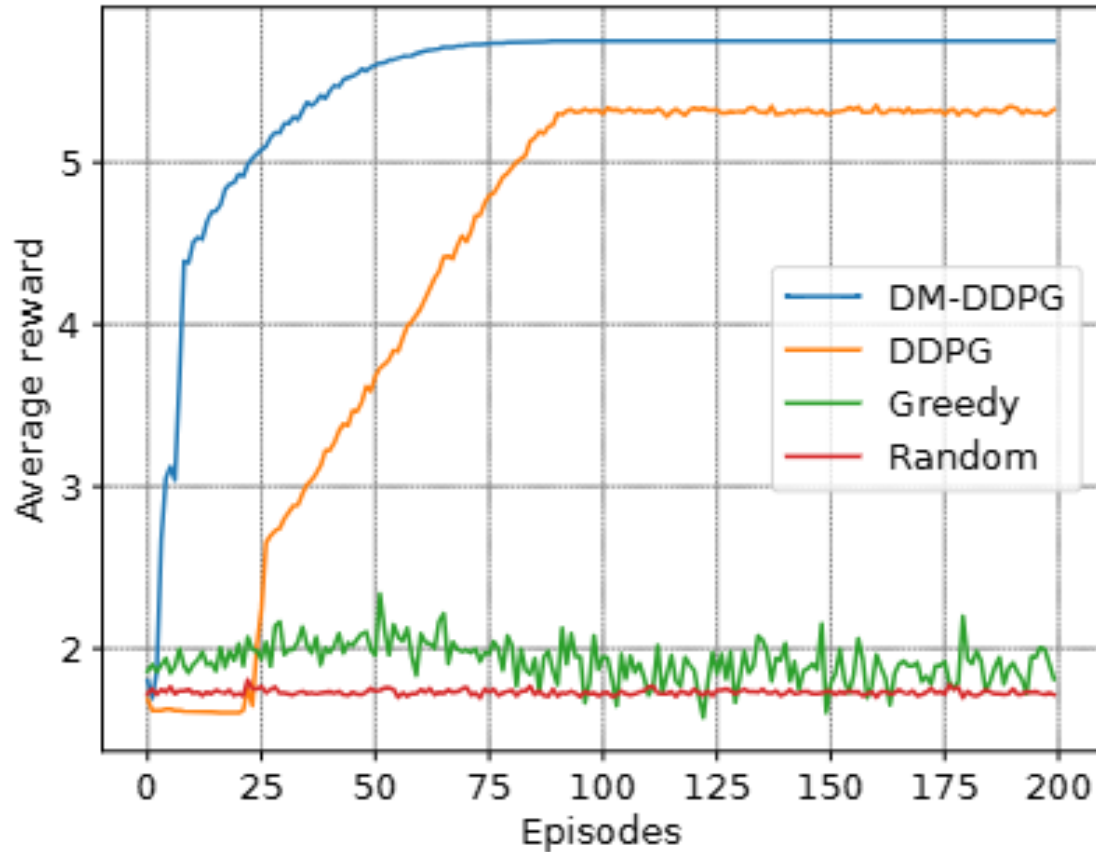
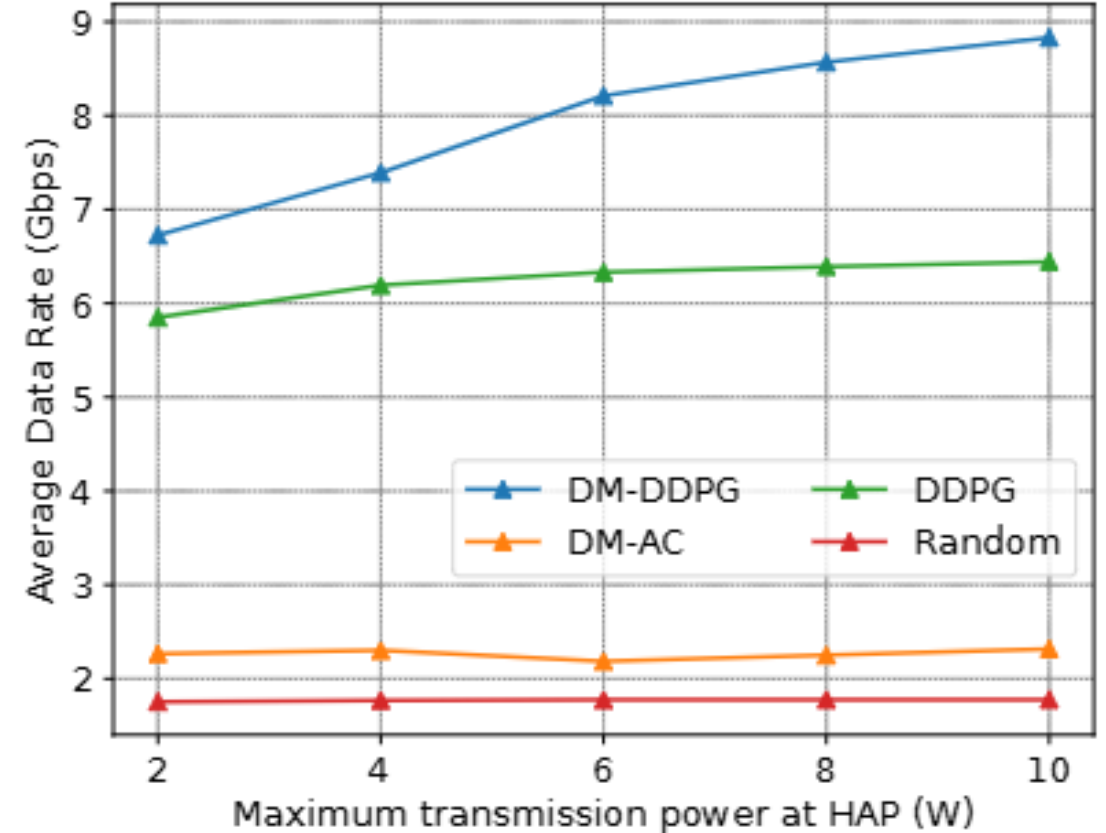
Simulation Results

❖ Network settings

Parameter	Value
Maximum transmit power of the HAP $P_{\max}$	30 dBm
Antenna gains $G_{\text{tx}}, G_{\text{rx}}$	32, 25 dBi
Noise power spectrum density σ^2	-174 dBm/Hz
The operating frequency f	140 GHz
Molecular absorption coefficient ς_{abs}	0.5 dB/km
The minimum data rate $R_{\min}$	0.001 bps/Hz
Number of episodes T	200
Number of time steps of each episode E	200
Discount factor γ	0.99
Soft-updating coefficient τ	0.005
Replay buffer R	10000
Batch size B	64
Learning rate of the actor network	10^{-4}
Learning rate of the critic network	10^{-3}
Denoising steps for the DM M	5



Simulation Results



❖ Observations:

- The proposed approaches saturates in reasonable time
- The proposed algorithm consistently outperforms other benchmarks

Conclusion & Future Works

- Address the non-convex nature of communication problem
- Improve the quality of service as well as solving the long-term maximization system throughput with uncertainties environment
- Demonstrate the proposed approach outperforms other baselines

❖ Future works

- Investigate multi-agent aerial access network
- Investigate the effect of others factors into the network capabilities, such as base station placement, propagation indices



Thank you

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