# Q-러닝 기반 초고밀도 UAV 네트워크 최적화

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# Q- Learning Optimization in UAV Ultra-Dense Networks

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## Abstract

UAV(unmanned aerial vehicle) finds applications in networks focusing on services and use cases such as national defense , providing connectivity during crowded events, UAV traffic management, and internet of things in the sky. Networks face various challenges to ensure dynamic control and safety of drone mobility to deliver these enhanced services. The baseline greedy handover algorithm only ensures the strongest connection between the drone and small cells, so the drone may experience several handovers. Intended for fast environment learning, the machine learning technique such as Q-learning helps the drone to fly with minimum handover cost along with robust connectivity. In this paper, we propose a Q-learning based approach evaluated in three different scenarios. Simulation results demonstrate that the proposed algorithm can effectively minimize the handover cost in a learning environment.

## I. Introduction

In wireless networks, drone's technology has significant impact due to its wide range of applications. Network empowers a new era of internet of everything where a user will be facilitating with high data rate internet speed with ultra-reliable low latency communications (URLLC), enhanced mobile broadband (eMBB) and massive machine type communications (mMTC) [1]. Machine-learning (ML) techniques are anticipated to deliver improved solutions for network performance, channel modeling, resource management, positioning, interference from terrestrial node and path-loss in drone handover performance improvements. ML-algorithms have been proposed as key enablers for decisions making in UAV-based communications i.e., in UAV swarm's scenario, many drone devices required network's resources all together in an optimal manner [2-3].

## II. Proposal

In an ultra-dense small-cell scenario, the coverage area among cells is small and drone may observe frequent handover due to its fast moving. Furthermore, channel fading, and shadowing are also the cause of ping-pongs. According to 3GPP, user equipment and drones are focused on strengthen RSRP and handover happened because of strengthen cell and due to maintaining the best signal strength such unnecessary handover occurred. These unacceptable handovers are mainly caused for delay and lose of packets, so link remain unreliable particularly in the case of mission critical drone use cases [4]. In real-time scenarios, 5G prospective for delivering drones flight trajectory path, tracking, updating the routes but optimized handover still an open issue because the baseline mechanism needs some improvements at the time of handover decision. So, reinforcement learning base solution will help to optimize the existing solution as we will comprise signal strength at some points. The optimized tradeoff between reference signal received power of serving cells and handover occurrence will surely achieve minimum cost for UAV route [5].

## Ⅲ. Implementation

For performance evaluation, we calculate handover ratio as performance metric for every drone trajectory and handover ratio described as proposed scheme to the baseline scheme handovers. The performance evaluation for diverse weight combinations of handover cost and weight for handover cost in the reward function representing the tradeoff between upcoming RSRP values and the quantity of handovers. The handover ratio approaches zero and the number of handovers decreases when the said ratio increases. Simulation of performance based on number of epochs (150) and accumulated reward gained in each epoch. Proposed algorithm converged on the maximum reward for each randomly generated route and demonstrate diverse effect on different parameters. Analytical parameters are set based on exploration and exploitation with greedy algorithm such as $\varepsilon$=0.5, $\alpha$=0.9 and $\gamma$varies from 0.1~0.9.

## Ⅳ. Conclusion

In this work, we proposed a machine learning based algorithm to accomplish strong drone connectivity with less handover cost such that, the drone will not always connect to the strongest cell in a trajectory. We have suggested a robust and flexible way for handover decision using a Q-learning framework under the consideration of trajectory path is provided. The proposed scheme particularly reduces the total number of handovers such as in simulation results, we can see the tradeoff between received signal strength and number of handovers while reference handover scheme always ties to the strongest cell. It is notable contribution for researchers if the testing area is large and flying routes contains a large pool of cells for drone connectivity. At last, prevailing proposed framework studies 2D drone mobility while 3D mobility model will introduce more parameters to help for the efficient handover decision.

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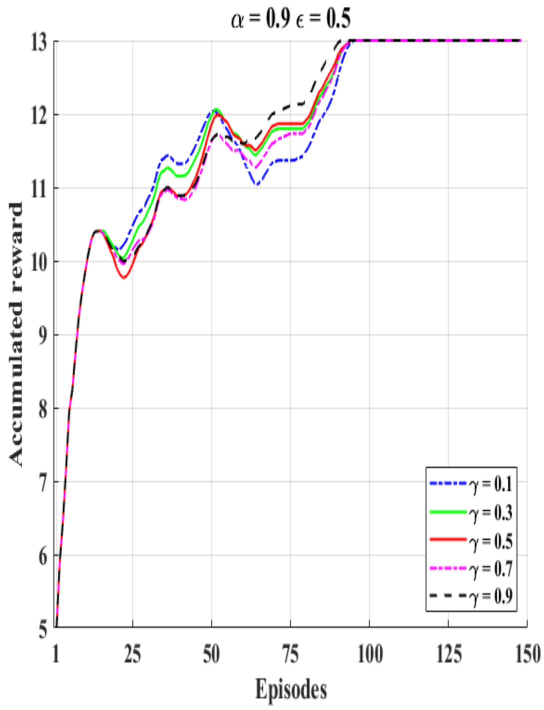


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