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Energy-Efficient UAV Communications with Interference Management: A Deep Reinforcement Learning Framework

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***Abstract*—In this paper, an interference-aware energy-efficient scheme for a network of coexisting aerial-terrestrial cellular users is proposed. In particular, each aerial user aims at achieving a trade-off between maximizing energy efficiency and spectral efficiency while minimizing the incurred interference on the terrestrial users along its path. To provide the solution, we first formulate the energy efficiency problem for UAVs as an optimization problem by considering different key performance indicators (KPIs) for network, coexisting terrestrial users, and UAVs as aerial users. Then, leveraging tools from deep learning, we transform this problem into a deep queue learning problem, and present a learning-powered solution that incorporates the KPIs of interest in the design of the reward function to solve energy efficiency maximization for aerial users while minimizing interference to terrestrial users. A broad set of simulations have been conducted in order to investigate how the altitude of UAVs, and the tolerable level of interference, shape the optimal energy-efficient policy in the network. Simulation results show that the proposed scheme achieves better energy and spectral efficiency for UAV and less interference to terrestrial users incurred from aerial users. The obtained results further provide insights on the benefits of leveraging intelligent energy efficient scheme. For example, a significant increase in energy efficiency of aerial users with respect to increase in their spectral efficiency, while considerable decrease in incurred interference to the terrestrial users is achieved in comparison to the non-learning scheme.**

***Index Terms*—Energy efficiency, unmanned aerial networks (UAV), drone, cellular networks, machine learning, deep reinforcement learning, interference management.**

I. Introduction

Unmanned aerial vehicle (UAV) is an emerging technology which has been effectively applied in different types of use cases such as military, surveillance, and public safety [1]. Among these applications, the use of UAVs in public safety (e.g., fire fighting) has been of particular interest in cellular networks due to its significant flexibility of movement in the three-dimensional (3D) space and low operational cost.

In such UAV systems, live video stream and high-resolution images taken from the area surrounded by fire need to be transmitted with limited UAV onboard battery, thereby posing high uplink data rate and low energy consumption requirements. Furthermore, due to the mobility of UAVs in a 3D space, the probability of experiencing line-of-sight (LoS) propagation to the neighbour base stations (BSs) increases by increasing the altitude. Thus, UAVs' communications are expected to impose significant interference to uplink communications of terrestrial users. Therefore, in order to enable successful deployment of UAV communications in cellular networks, their energy efficiency along with interference management to the terrestrial users should be carefully taken into account.

Energy-efficient designs for UAV communications are significantly different if compared with the terrestrial counterpart [2]. Energy-efficiency maximization in terrestrial communications is mainly for reducing energy consumption and cost. However, that is more critical for UAV communications due to the limited on-board energy. Given the maximum amount of energy that can be carried in an UAV, any improvement in energy efficiency increases the amount of data that can be sent by the UAV before it needs to be recharged. Furthermore, in addition to the energy consumed by signal transmission, UAV systems must provide propulsion power to maintain the UAV up above and ensure its movement, which is usually much higher than the transmission power consumption. One should note that the UAV's propulsion energy consumption directly depends on its flying status consisting of location and velocity which must be considered in an energy-efficient design for UAV communications. Therefore, the legacy energy-efficient frameworks designed for terrestrial networks lose their merit in serving UAV communications due to the 3D space mobility for UAVs and the inherent characteristics of interference in such networks.

The aforementioned challenges have been studied in the literature without a complete consideration of coexisting aerial-terrestrial users. The downlink and uplink interference for coexisting aerial-terrestrial users is investigated in [3] based on empirical observations. In [4], the authors study the coexistence of aerial and terrestrial users in cellular networks and characterize the downlink coverage performance. However, the existing literature [3] [4] does not provide any concrete solution for energy efficiency maximization of aerial users while minimizing the interference challenge for terrestrial users in the context of cellular networks.

While some literature has recently investigated the energy-efficient UAVs as mobile BSs/relays [5] [6], the energy efficiency analysis of cellular-connected UAVs remains relatively scarce in this vein [7] [8]. The energy-efficient trajectory design for UAV is investigated in [5]. The authors in [6] jointly optimize the UAV trajectory and transmit power to minimize the outage probability for the UAV relaying network. The work in [7] studied the UAV trajectory optimization problem with some tolerance on the loss of cellular connection, in which disconnected duration does not exceed a given bound. The authors in [8] propose a trajectory optimization scheme in which the time required for a cellular-connected UAV to reach its destination is minimized. In [9], the authors study joint aerial-terrestrial resource management in UAV-assisted mobile networks. To mitigate interference, a learning based approach is proposed in [10]. However, despite being interested, the existing literature [5]- [10] does not provide any concrete solution for optimizing the performance of a cellular network serving both aerial and terrestrial users so that the energy efficiency of aerial network is maximized while minimizing the interference caused on the terrestrial network along UAVs path. In addition, the contributions in the literature rely on optimization scheme in an offline manner that cannot adapt to complexity and dynamicity of a cellular-connected UAV network coexisted with terrestrial network.

The altitude of the UAV has great impact on the energy efficiency as each ascending and descending consume on-board energy of the UAV significantly. Furthermore, as the altitude of the UAVs increases, the signal-to-interference-plus-noise ratio (SINR) for the UAV decreases. This is due to the path-loss which increases as the distance of the UAV from the serving BS increases. On the other hand, higher UAV's altitudes result in a higher average data rate per terrestrial users as the interference level caused from the UAVs on neighboring BSs decreases. Hence, each UAV's altitude must be dynamically adjusted in order to guarantee a minimum achievable data rate for the UAV users while minimizing the severe interference to the terrestrial users.

Hence, each UAV's altitude must be dynamically adjusted in order to guarantee a minimum achievable data rate for the aerial users while minimizing the severe interference to the terrestrial users. Due to the dynamic mobility of the aerial users in 3D space and the altitude dependency in A2G wireless channel, the amount of interference generated by aerial communications is difficult to be predicted. Thus, to continuously adjust flying altitude for drastic interference mitigation becomes too complicated. This brings the need to evolve towards an artificial intelligence (AI) energy efficiency maximization to support more fine-grained aerial-terrestrial user-centric service provision.

The main contribution of this paper is to develop a deep reinforcement learning (DRL) based energy efficiency maximization for aerial users and incurred interference minimization from aerial to terrestrial users for serving this coexisting scenario in 5G cellular networks. We first form the energy efficiency formulation for aerial users as an optimization problem which includes key performance indicators (KPIs) regarding to aerial users coexisted with terrestrial users. Then, we develop a DRL framework to satisfy different KPIs for aerial users while minimizing the interference to the terrestrial users. To the best of our knowledge, utilizing DRL to extract optimal policy for energy efficiency maximization from heterogeneous data which is the case encountered in coexisting aerial-terrestrial users has not been investigated in the literature.

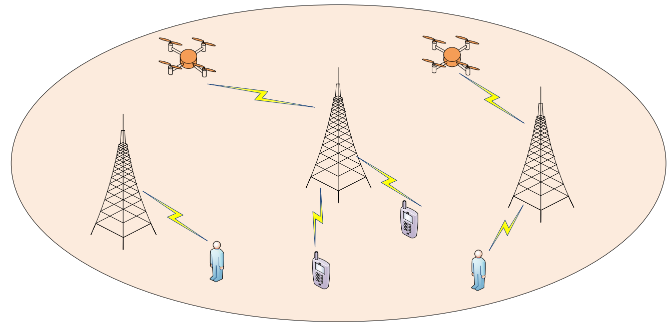

Fig. 1: System model for uplink communications of cellular UAVs coexisting with terrestrial network.

The remainder of this paper is outlined as follows. Section II presents the system model and problem formulation for H-RRM. Section III formulates an optimization problem for energy efficiency maximization of aerial users while minimizing interference to the terrestrial users. Section IV provides the DRL-powered H-RRM algorithm. Simulation results are presented in Section V, followed by the conclusion given in Section VI.

II. System Model

We consider an uplink of cellular mobile network serving coexisting aerial-terrestrial users as shown in Fig. 1. The network consists of a set of base stations (BSs) and the number of aerial users denoted by $\mathcal{M} = \{1, \cdots, M\}$ and $\mathcal{K} = \{1, \cdots, K\}$ respectively. A co-channel deployment is considered, in which BSs operate in a system with a bandwidth $\mathcal{W}$ consisting of $\mathcal{N} = \{1, \cdots, N\}$ radio resource blocks (RRBs). At each decision epoch t, it is of particular important to design the trajectory of the UAV along which it moves towards the targeted locations. We denote the location of the BS by (x_m, y_m, H_m). Furthermore, in each time slot t, let $l_k(t) = (x(t), y(t), z(t))$ be the location of UAV k, and $v_k(t) = (v_x(t), v_y(t), v_z(t))$ be its velocity, with $v(t) = l'(t)$. For the wireless communication requirements for aerial and terrestrial users, the UAV has a minimum and maximum flight altitude h_{min} and h_{max} respectively, and a maximum velocity v_{max}. At each time slot, we decide on the trajectory of the UAV, its speed, target BS to be associated and set of resources for serving each UAV, and the level of transmit power of the UAV.

The air-to-ground (A2G) channel depends on the presence of line-of-sight (LoS) propagation characteristics between the aerial user and BS. The probability of experiencing LoS propagation in communications between aerial user k, at altitude h_k with speed v_k with respect to the lth BS is modeled as [11]. Thus, the average received power of the BS from the UAV is given as follows:

$$P_R(t) = P_T(t)/10^{PL_a(t)/10}, \tag{1}$$

where $P_T(t)$ is the transmission power of the UAV in time slot t, and $PL_a(t)$ is the average path-loss in dB which is denoted as

$$PL_a(t) = Pr_L(t) \times PL_L(t) + Pr_N(t) \times PL_N(t), \tag{2}$$

in which $PL_L(t)$ and $PL_N(t)$ are the LoS and non-line-of-sight (NLoS) path-loss models from the UAV to the BS as given in [11]. $Pr_L(t)$ and $Pr_N(t)$ are the probability of LoS and NLoS connection respectively where $Pr_N(t) = 1 - Pr_L(t)$. The data rate from the UAV to the BS in time slot t is as follows:

$$R_k(t) = W_s|\mathbf{n}_k| \log_2(1 + \frac{P_R(t)}{N_0 + W_s I_{s,k}(t)}), \tag{3}$$

where W_s is the bandwidth of the subcarrier, $\mathbf{n_k}$ the allocated subset of subcarriers for UAV k, N_0 the noise power over each subcarrier, I_s the power density of interference over sth subcarrier, and $P_R(t)$ is the received power of the BS from the UAV.

III. Energy-Efficient UAV Communications with Interference Management

In this section, we first introduce the energy consumption of the UAV, and then formulate the energy efficiency (EE) maximization problem in which the minimum data rate requirements of aerial users are satisfied while minimizing interference to the terrestrial users.

A. Energy Consumption

The total energy consumption includes the UAV's uplink transmissions and its mechanical movements given as:

$$EC_k(t) = E_{P,k}(t) + E_{W,k}(t) \tag{4}$$

where $E_{P,k}(t) = \frac{1}{2}m_k v_k^2(t)$ denotes the energy consumption for movement control, and $E_{W,k}(t) = (\eta P_k(t) + P_c)\tau$ indicates the energy consumption for wireless transmission. The parameter m_k is the mass of the k-th UAV, P_k is the transmit power, P_c the circuit power, η the inverse of power amplifier efficiency, and τ is the length of a time slot. Afterward, we wish to maximize the bits-per-Joule, as a metric for EE as follows.

$$EE(t) = \frac{b(t)}{E_P(t) + E_W(t)}, \tag{5}$$

where $b(t)$ is the amount of information data to be transmitted by a UAV user.

B. Problem Formulation

Given the status of aerial users at time t, $S_k(t)$, $\forall k \in \mathcal{K}$, as well as the available RRBs at each BS, i.e. $N_m(t)$, $\forall m \in \mathcal{M}$, the problem is to find the best serving BS, set of allocated resource blocks $\mathbf{X}(m,n,t,k)$, level of transmit power $\mathbf{P}_k(t)$, $\forall k,n,m$, and UAV's optimal altitude $\mathbf{H}_k(t)$ in order to satisfy the data rate requirements of aerial users with a minimum amount of allocated radio resources for aerial users and minimum interference on terrestrial users. Then, at decision epoch t, we need to solve the following optimization problem for the k-th node in order to maximize energy efficiency for the UAV and maximize their spectral efficiency while minimizing interference to the terrestrial users:

$$\max_{\left[\mathbf{X}(t),\mathbf{P}(t),\mathbf{H}(t),\mathbf{M}(t)\right]} \frac{\xi_1 b(t)}{E_P(t)+E_W(t)} + \frac{\xi_2 b(t)}{X(m,n,t,k)} + \frac{\xi_3}{1+Int(t)}$$

subject to: (6)

$$\begin{aligned}
&\mathrm{C}_1)\ R_k(t) \geq R_k^{min},\\
&\mathrm{C}_2)\ Int_k(t) \leq Int_k^{max},\\
&\mathrm{C}_3)\ H_{min} \leq H(t) \leq H_{max},\\
&\mathrm{C}_4)\ v(t) \leq v_{max},\\
&\mathrm{C}_5)\ \sum\nolimits_{m\in\mathcal{M}} \sum\nolimits_{n\in\mathcal{N}_l(t)} P_k(t)x(m,n,t,k) \leq P_k^{\max},\ \forall k,\\
&\mathrm{C}_6)\ \sum\nolimits_{k\in\mathcal{K}}^{K} x(m,n,t,k)=1,\ \forall k,\\
&\mathrm{C}_7)\ \sum\nolimits_{m\in\mathcal{M}} \sum\nolimits_{n\in\mathcal{N}_m(t)} x(m,n,t,k)=1,\ \forall m_1 \neq m_2,\ \forall t,n,
\end{aligned}$$

in which, C_1 is the minimum data rate requirement for every individual UAV user, C_2 stands for the interference threshold on the terrestrial user, C_3 indicates that the UAV's altitude should be bounded, C_4 is the threshold for the UAV's speed, C_5 stands for the maximum allowable transmit power, C_6 assures that each RRB in each cell is allocated to at most one user, and finally C_7 assures that each aerial user receives service from one cell only.

It is obvious that (6) is a highly-complex non-convex optimization problem as it includes several objective parameters that they should be optimized. Furthermore, due to high mobility of a UAV network coexisted with terrestrial network, acquiring the solution for the aforementioned optimization problem in each time instant would be a challenging task. In addition, the type of traffic generated varies from one time instant to another which makes the amount of interference hard to predict. Thus, due to the strong dynamics in high mobility aerial networks, making the solution adaptive to the changes in the environment is favorable. Therefore, we consider a centralized approach in which BSs are connected to each other and all of them are connected to a central entity, named as controller, with designed interfaces. The controller has full knowledge of the current state of the network and it can be able to communicate with all BSs at all time. We propose a centralized approach that learns for each UAV k its transmission power level, the set of radio resource blocks, association vector, and altitude along its path in an autonomous and online manner. Based on these motivations, we transform the energy efficiency maximization problem to a deep queue network (DQN) problem.

IV. The Deep Queue Learning-Powered Solution

In this section, the framework on DQN for energy efficiency maximization and spectral efficiency maximization in aerial network while minimizing the interference from aerial to terrestrial users is introduced. Furthermore, the key parts in DQN framework are presented in detail and algorithm to train the DQN is shown as the proposed solution.

The architecture of the proposed DQN used for maximizing energy efficiency of aerial communications is as follows:

1) Input Layer: In our model, the state of aerial user k at time t, $S_k(t)$ represents a set of features which characterizes the action in relation to the network including the Euclidean distance from UAV k to its serving BS, the path-loss measurements to neighbor BSs, interference measurements, current serving BS, available radio resource blocks (RRBs), speed, and buffer queue size of aerial users. This state space is fed to the DQN.

2) Hidden Layer: We consider a dense network including five hidden layers. Layer one to layer five consist of 512, 256, 128, 64, and 32 neurons respectively in which their activation function is the rectified linear unit (ReLU).

3) Output Layer: The output layer includes the number of neuron equals to the action space size with linear activation function. The actions specific taken for aerial user k at time t, $A_k(t)$, are represented by allocated set of RRBs, transmit power, altitude, and associated BS in a way that to maximize the reward function. Our reward function takes into account the KPIs including maximizing energy efficiency and their spectral efficiency, and also minimize the interference from aerial users to terrestrial users. In order to reach this objective, we define a reward function for aerial user k at time t as follows.

$$r_k(t) = \sum_{t=1}^{T} \eta_e EE(t) + \sum_{t=1}^{T} \frac{\eta_s b(t)}{X(m,n,t,k)} + \sum_{t=1}^{T} \frac{\eta_f}{1+Int(t)}, \tag{7}$$

where η_1, η_2, and η_3 are weights determined from the relative importance of the energy efficiency and spectral efficiency of aerial users, and the interference incurred from aerial to terrestrial users in the target application. All the weights have been normalized, to prevent dealing with a dominant factor. Furthermore, we note that the coefficients are normalized, to prevent dealing with a dominant factor.

To cope with the large dimensionality of EE optimization problem, we develop deep queue network (DQN) framework in intelligent decision making of EE maximization for aerial communications. DQN framework directly learns a function $Q(s, a, \omega)$ parameterized by a set of parameters ω that are optimized through minimizing a mismatch between the current

Algorithm 1: Deep queue learning for energy efficiency maximization of aerial users coexisting with terrestrial users

Initialize: DQN weights, i=1;
for *the number of training iteration* **do**
  while *aerial user is inside of service area* **do**
    Input: state of aerial user;
    Step 1: Action selection;
    A random action is selected to the aerial user k with probability ϵ;
    Otherwise, an action is selected by $\max_{a\in\mathcal{A}} Q(s, a; w)$;
    Step 2: Location, cell association, transmit power, and altitude update;
    Controller updates the location, cell association, transmit power, and altitude of aerial user k based on the selected action;
    Step 3: Reward computation;
    The controller calculates the reward values for each aerial user based on (7);
    if *s is not in the action space* **then**
      $y = r_t$;
    else
      $y = r_t + \beta \max_{a\in\mathcal{A}} Q(s, a; w)$;
    Step 4: train DQN weights, ω;
    Train DQN weights to minimize the loss function (8);
    if *reward* $>$ *reward$_{max}$* **then**
      The policy is set;
    else
      Repeat

Q-value $Q(s, a)$ and the target Q-value namely loss function on state-action space:

$$Loss(w) = \sum_{s_t\in\mathcal{S}, a_t\in\mathcal{A}} (y - Q(s_t, a_t; w))^2, \tag{8}$$

where

$$y = r_t + \beta \max_{a\in\mathcal{A}} Q(s_t, a; w). \tag{9}$$

where r_t and β are the corresponding reward and discount factor respectively.

The probability of an action selection is random at the beginning and gradually is improved with the update of the weights of DQN through the minimizing the loss function. The output of this layer results in selection of optimal action for the DQN scheme. A summary of the proposed solution is given in Algorithm 1.

V. Performance Evaluation

We consider a service area of 500×500 m^2 including three macro BSs serving both aerial and terrestrial users. Our focus is on uplink service to aerial users, flying with speed v, while they are crossing the service area. The simulator has been developed in Python, and implements the DQN-powered EE maximization, as well as a baseline scheme. In the baseline scheme, RSS is used at each radio subframe equal to 1msec, according to the amount of data to be transmitted, the minimum RRBs are determined in the RSS scheme. Furthermore, at each radio frame, if the received power from the target BS is 7dB stronger than the serving BS, the aerial

TABLE I: Parameters for performance evaluation.

Parameters	**Values**
Service area	500×500 m^2
BSs' positions in meter	$(50, 100)$; $(200, 400)$; $(450, 50)$
Available RRBs for aerial user (per TTI)	Random, up to 4×180 KHz
BSs antenna height, carrier frequency	25 m, 2 GHz
Packet arrival rate and size at the buffer of aerial user	0.3 Hz; 2 Kbits
Handover control packet size	$4\times$ 1Kbits
Max transmit power over each carrier	0.2 Watt
Aerial user's maximum speed	20 m/sec

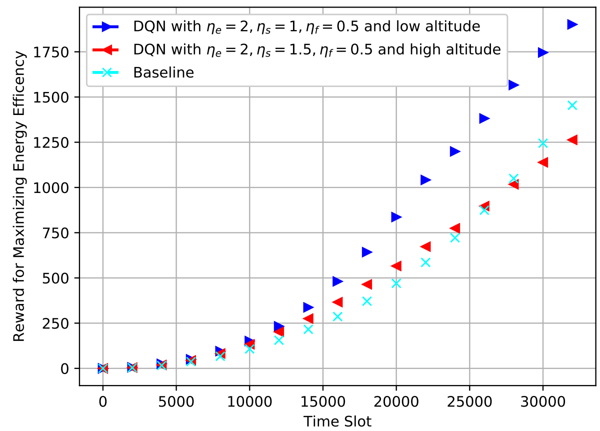

Fig. 2: Reward for maximizing energy efficiency of aerial users. One further can observe the impact of changing the altitude of aerial user in the reward function.

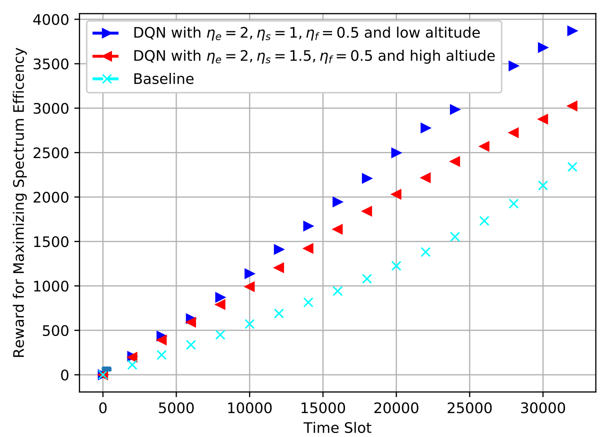

Fig. 3: Reward for maximizing spectral efficiency of aerial users. One further can observe the impact of changing the altitude of aerial user in the reward function.

user is handed over to the target BS. In the DQN, at each radio subframe, serving BS, the best set of radio resource blocks (RRBs), the respective transmit power over them, and altitude are decided by the DQN management entity. The simulation parameters can be found in Table I.

The KPIs of interest in serving aerial-terrestrial users are the energy efficiency and spectral efficiency for aerial users and incurred interference to terrestrial communications from aerial communications. In the DQL scheme, we consider a weighted sum of standardized values of maximizing energy efficiency as well as spectral efficiency, and minimizing interference as the reward function, where the weight of energy efficiency, spectral efficiency, and incurred interference are shown by η_e, η_s, and η_f respectively.

The performance impacts of altitude in energy efficiency and spectral efficiency for aerial users, and incurred interference to terrestrial users are demonstrated in the Fig. 2, Fig. 3, and Fig. 4 respectively. In the Fig. 2, one observes that by decreasing altitude, the achieved energy efficiency for aerial users is increased significantly. Furthermore, the Fig. 3 demonstrates that by decreasing the altitude, the spectral efficiency for aerial users increases. However, the Fig. 4 shows that decreasing the altitude of aerial users incurs more interference to the terrestrial users. This is mainly due to the decrease in the distance of the UAVs from their corresponding serving BSs, which attenuates the path-loss effect. However this decrease in altitude is coming at the cost of incurring some interference to the terrestrial users as indicated in Fig. 4. Furthermore, numerical results demonstrate that the DQN framework outperforms baseline scheme in terms of energy and spectral efficiency maximization for aerial communications while minimizing interference to the terrestrial networks.

VI. Conclusion

In this paper, we propose an interference-aware energy-efficient scheme that allows cellular-connected aerial users to minimize the interference they incur on terrestrial users while maximizing their energy efficiency as well as spectral efficiency. The major challenges consist of the maximizing energy efficiency for aerial users while minimizing interference from aerial users on uplink communications of coexisting terrestrial users. We demonstrate that these challenges are coupled in conflicting ways, in which an improvement in one potentially deteriorates the other one. Therefore, we first formulate the energy efficiency problem for aerial users as an optimization problem by considering KPIs requirements for aerial users (i.e., energy efficiency, spectral efficiency) and terrestrial users (i.e., interference). Then, we transform the energy efficiency problem to a deep queue learning problem and develop a framework to address those aforementioned challenges. The framework enables the agent (i.e., controller) to decides on UAVs next location, cell association, radio resource block allocation, and transmit power level. Simulation results have shown that DQN framework achieves better energy efficiency as well as spectral efficiency for UAVs, and less interference

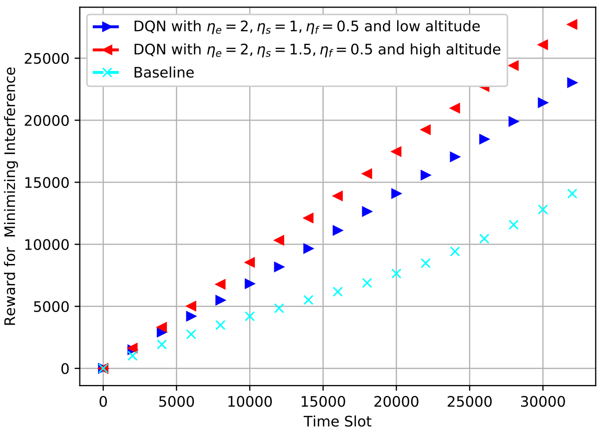

Fig. 4: Reward for minimizing interference to terrestrial users from aerial users. One further can observe the impact of changing the altitude of aerial user in the reward function.

to the terrestrial users that is comparable to the RSS as baseline scheme. The results have also shown that a UAV's altitude plays a vital role in maximizing the energy efficiency and spectral efficiency of the UAVs, and minimizing the interference level on the terrestrial users. In particular, we have shown that as the altitude of UAVs decreases the energy efficiency and spectral efficiency of aerial users increases while the interference incurred from the aerial to the terrestrial users increases.

Acknowledgement

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