Green Offloading and Trajectory Scheduling of Rechargeable UAVs in Aerial Edge Networks

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***Abstract*—Aerial edge networks that leverage Unmanned Aerial Vehicles (UAVs) to provide task processing and data caching in infrastructure-less areas have emerged as a prominent paradigm in the upcoming 6G era. However, the endurance of UAV flight generally suffers from constrained onboard battery capacity. Thus, energy efficiency turns out to be a key issue for implementing aerial edge networks. In this paper, we focus on green mobile edge computing of rechargeable UAVs, and propose an aerial edge network aided by distributed charging services. In this network, an energy minimization problem that jointly considers aerial edge resource allocation, UAV trajectory planning and battery charging scheduling as well as task delay constraint is formulated. Due to the non-convexity and the coupled optimization variables of the problem, we adopt a deep reinforcement learning approach to design an intelligent iterative algorithm to obtain energy efficient aerial edge strategies, and demonstrate its convergence. Numerical simulations are conducted to verify the effectiveness of our proposed scheme as compared to two benchmark schemes.**

***Index Terms*—Aerial edge network, rechargeable UAV, energy efficient**

I. Introduction

Benefiting from flexible deployment, maneuverable trajectory and Line-of-Sight (LoS) air-ground communications, UAVs are foreseen to be a major part of the upcoming 6G era for enabling ubiquitous connectivity and full-coverage networks [1]. Equipped with advanced communication, sensing and processing devices, the UAVs have been employed in various applications, such as extending wireless coverage of terrestrial access points and restoring cellular communications in disaster-stricken areas [2].

Aerial Edge Computing (AEC) is one of the most promising paradigms in the aforementioned UAV applications, leveraging the powerful processing power and wide access range of UAVs to provide task offloading and computing services for IoT devices with constrained computing capability [3]. However, the AEC services always suffer from limited endurance. Due to strict space and payload constraints, commercial UAVs, especially small rotary-wing ones, often have inherent battery limitations to support their long-term flight and service operations. Thus, energy efficiency has turned out to be a key research issue in AEC management.

Recently, a lot of work has been devoted to the investigation on energy efficient aerial edge networks. In [4], the authors presented a UAV-assisted vehicular edge network that assigned UAVs to the traffic jam areas for offloading computing tasks from congested vehicles. The flight trajectory of the UAV was optimized to minimize flying energy costs. In [5], the authors introduced a UAV empowered two stage edge computing system, in which task offloading as well as communication and computation resources were jointly scheduled to save energy consumption of UAVs and user devices. In [6], the authors utilized the UAV to power rechargeable sensor nodes in a wireless energy transfer mode, and designed flight trajectories to maximize the UAV's energy utilization efficiency.

In order to cope with UAVs' constrained onboard battery capacity and the resulting limited flight time, there have been some previous works focused on using rechargeable UAVs. In [7], the authors applied wireless power transfer technique in a UAV communication network, and proposed a two-phase wireless charging and data transmission scheme that maximizes sum secrecy rate over finite time horizon. In [8], the authors leveraged vehicles with wireless charging equipment as mobile chargers to provide on-demand energy supply to rechargeable UAVs. Among these existing works, only a few have explored AEC with rechargeable UAVs. For instance, in [9], the authors investigated UAVs powered by laser beam transmitted from a ground base station, and optimized both task offloading and energy allocation in an edge-cloud system. However, these works only consider the scenario of employing a single charging service facility, whose limited service range may not meet the energy replenishment needs of UAVs flying across large-scale areas. Moreover, existing AEC works usually ignore the sequential dependencies among the three steps of task data uploading, data processing and result feedback in edge services, and allocate unnecessary resources for some steps, resulting in serious resource waste.

To bridge the above technical gaps, in this paper, we present an AEC network with distributed multi-charging facilities that cooperatively power the UAV for large-area edge service and long-distance flight. In this network, we formulate an optimization problem for UAV energy cost minimization, which considers the sequential dependencies between task execution steps, while guaranteeing safe UAV flight from an energy perspective. To solve this problem, we resort to a Deep Deterministic Policy Gradient (DDPG) approach, and propose energy-efficient task offloading and flight trajectory scheduling schemes.

The remainder of this paper is organized as follows. The system model is described in Section II. We formulate the optimization problem of UAV energy efficiency in Section III. The learning-based edge resource and flight trajectory scheduling schemes are proposed in Section IV. Numerical results are given in Section V. Finally, we conclude this paper in Section VI.

II. System Model

Fig. 1 shows the proposed aerial edge network. We consider a ground area divided into N square grids with identical side length L_0. The coordinates of grid n are given as (x_n, y_n), where $n \in \mathcal{N}$, and the values of x_n and y_n are integers. A large number of IoT devices are spread in these grids following a Poisson distribution, and the average number of the devices located in grid n is λ_n. These IoT devices gather environmental states and require complex data processing. Considering the differences in the environmental characteristics of different grids, we assume that the IoT devices in different grids may generate various types of processing requirements. Thus, there are N types of processing tasks presented as $(f_n, c_n, w_n, T_n^{\max})$, $n \in \mathcal{N}$. Here, f_n and w_n are the size of input data and output result of type-n task, respectively. c_n denotes the required amount of computing resources in CPU cycles, and $T_n^{\max}$ is the maximum latency tolerance of this task.

A rechargeable rotary-wing UAV empowered with edge computing capabilities flies over the area at a fixed altitude h_0, providing task offloading services to the IoT devices. The aerial edge service operates in a discrete time mode with fixed length time slots. Let time slot t denote time interval $(t\tau, (t+1)\tau)$, where $t = \{0, 1, 2, ...\}$ and τ is the length of a slot. We focus on the energy consumed by the UAV in its edge service process, which includes the energy costs of flight, computing and communications.

As the UAV flies from one grid to another, propulsion energy is expended to keep the UAV aloft and support its movement. For a UAV flying at speed v_t at time slot t, its propulsion power consumption can be given as

$$E_t^{\mathrm{f}} = \tau[\alpha_0(1+3{v_t}^2/\beta_0^2) + \alpha_1\beta_1/v_t + \gamma_0\rho_0\gamma_1\rho_1{v_t}^3/2], \quad (1)$$

where α_0 and α_1 are UAV hovering power consumption, β_0 and β_1 denote rotor blade speed and induced velocity, γ_0 and γ_1 represent fuselage drag ratio and rotor solidity, and ρ_0 and ρ_1 are air density and rotor disc area, respectively [10]. To recharge the UAV during its edge service, m charging stations are randomly arranged in M area grids at coordinates (x_m, y_m), where $m \in \mathcal{M}$ and $\mathcal{M}$ is a subset of $\mathcal{N}$. Charged in a unit time slot, the amount of electricity that can be replenished into the UAV is E^{r}.

Another part of the energy consumption of the UAV is caused by the operation of the onboard processor. When the UAV receives input data of a type-n task from an IoT device, it allocates $d_{n,t}$ CPU cycles for the task's processing in time slot t. Given the energy consumption E_0^{c} per unit CPU cycle, the energy cost to complete the task in slot t can be calculated as

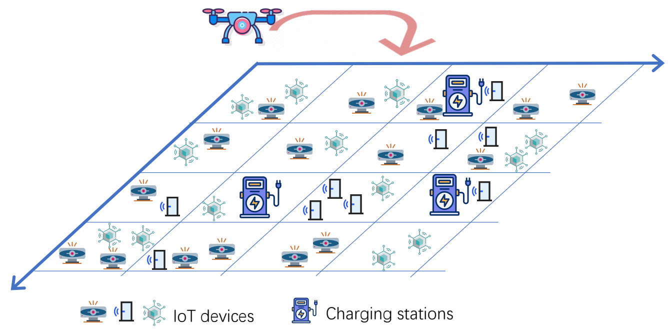

Fig. 1. Rechargeable UAVs in aerial edge computing networks.

$$E_{n,t}^{\mathrm{c}} = d_{n,t}E_0^{\mathrm{c}}. \quad (2)$$

In addition to flight and computational energy consumption, the UAV also takes some energy to send data processing results back to the IoT devices. We denote the transmit power of the UAV in grid n' taken for the result sending to the IoT devices located in grid n at time slot t as $P_{n',n,t}^{\mathrm{down}}$. Then, the communication energy consumption of the UAV in the slot is

$$E_{n',n,t}^{\mathrm{s}} = \tau P_{n',n,t}^{\mathrm{down}}. \quad (3)$$

III. Problem Formulation

At time slot 0, the UAV with initial energy E^{full} starts flying from the grid with coordinates (0, 0) and performs edge computing services. The flight action of the UAV at slot t can be described in three terms as $\{v_t, \Delta x_t, \Delta y_t\}$, where v_t is the flight speed, and Δx_t and Δy_t denote the flight directions. The values of Δx_t and Δy_t are chosen from set $\{-1, 0, 1\}$, respectively. Here Δx_t equal to 1 means the flight direction is parallel to the x-axis, while it equals -1 indicates that the UAV moves in the opposite direction of the x-axis, and 0 means no movement in the x-axis direction. The value of Δy_t has a similar meaning with y-axis. According to the above flight action description, the grid coordinates of the UAV at slot t can be expressed as

$$(x_t, y_t) = \left(\left\lceil \tau\sum_{t'=0}^{t} v_{t'}\Delta x_{t'}/L_0 \right\rceil, \left\lceil \tau\sum_{t'=0}^{t} v_{t'}\Delta y_{t'}/L_0 \right\rceil\right). \quad (4)$$

In order to facilitate the description of the grid where the UAV is located in a given time slot, we define the following two functions. One is used to determine whether the UAV is located in grid n' at time slot t, and can be presented as $\mathbf{1}(t,n') = \mathbf{1}\left((x_t, y_t) == (x_{n'}, y_{n'})\right)$. Here $\mathbf{1}(\hat{x})$ is an indicator function which equals 1, if $\hat{x}$ is true and 0 otherwise. The other function is used to determine whether the UAV can be recharged in time slot t, which is given as $\mathbf{1}(t,m) = \mathbf{1}\left((x_t, y_t) == (x_m, y_m), \forall m \in \mathcal{M}\right)$.

As this work focuses on the UAV's energy cost, next we discuss onboard energy changes during UAV flight and edge service. Recall that the energy consumption of the UAV includes three parts: flight, computing and communication, and the UAV can be supplemented by electrical energy through the grids equipped with charging facilities. Moreover, at no time slot can the UAV's charge exceed the total capacity of its battery, which is denoted as E^{full}. Thus, the remaining onboard energy of the UAV at slot t can be calculated as

$$E_t = \min\{E^{\mathrm{full}} - \sum_{t'=0}^{t}[\mathbf{1}\left(|\Delta x_t|, |\Delta y_t|\right)E^{\mathrm{f}}_{t'} + \sum_{n=1}^{N}(E^{\mathrm{c}}_{n,t'} + \sum_{n'=1}^{N}\mathbf{1}(t',n')E^{\mathrm{s}}_{n',n,t'}) - \mathbf{1}(t',m)E^{\mathrm{r}}], \quad E^{\mathrm{full}}\} \tag{5}$$

Both the task offloading from the IoT devices to the UAV and computing results sent from the UAV to the devices use the orthogonal frequency division multiple access (OFDMA) technique. The uplink rate of the IoT devices located in grid n communicate to the UAV in grid n' at slot t is

$$r^{\mathrm{up}}_{n',n,t} = \frac{B^{\mathrm{up}}_n}{\lambda_n}\log_2(1 + \frac{P^{\mathrm{up}}_n \bar{G}^{\mathrm{up}}_{n',n,t}}{\sigma^2}), \tag{6}$$

where B^{up}_n is the total uplink bandwidth allocated for the devices in grid n, P^{up}_n is the uplink transmit power of each IoT device located in this grid, σ^2 is the white noise power, and $\bar{G}^{\mathrm{up}}_{n',n,t}$ denotes the path loss between the devices in grid n and the UAV stays in grid n' at slot t [11]. Similar to the calculation of the uplink rate, the downlink rate of the UAV in grid n' at slot t sending results to the IoT devices located in grid n can be shown as

$$r^{\mathrm{down}}_{n',n,t} = \frac{B^{\mathrm{down}}_n}{\lambda_n}\log_2(1 + \frac{P^{\mathrm{down}}_{n',n,t} \bar{G}^{\mathrm{down}}_{n',n,t}}{\sigma^2}). \tag{7}$$

Considering the delay constraint of each task of the IoT devices, here we calculate the total number of time slots consumed for leveraging the UAV edge service to complete a type-n task, which can be divided into three parts, namely the task data upload time, the task processing time and the result download time. It is noteworthy that unlike most previous works, which mix these three parts of time together, we take into account the sequential dependencies among them. That is to say, the edge processing occurs after the task data is uploaded, and the download takes place after the processing result is obtained. Let T^{up}_n, T^{proc}_n and T^{down}_n denote the index of the time slot when task type-n is uploaded, processed and downloaded, respectively.

$$T^{\mathrm{up}}_n = \arg\min_{T'}(f_n - \tau\sum_{t'=0}^{T'}\sum_{n'=1}^{N}\mathbf{1}(t',n')r^{\mathrm{up}}_{n',n,t'} \le 0). \tag{8}$$

$$T^{\mathrm{proc}}_n = \arg\min_{T'}(c_n - \sum_{t'=T^{\mathrm{up}}_n}^{T'} d_{n,t'} \le 0). \tag{9}$$

$$T^{\mathrm{down}}_n = \tau\arg\min_{T'}(w_n - \tau\sum_{t'=T^{\mathrm{proc}}_n}^{T'}\sum_{n'=1}^{N}\mathbf{1}(t',n')r^{\mathrm{down}}_{n',n,t'} \le 0). \tag{10}$$

The formulated optimization problem that minimizes the energy costs of the UAV during its edge service process is given as follows

$$\begin{aligned} &\min_{\{v_t,\Delta x_t,\Delta y_t,d_{n,t},P^{\mathrm{down}}_{n',n,t}\}} \sum_{t=0}^{T^{\max}}\left(\mathbf{1}\left(|\Delta x_t|,|\Delta y_t|\right)E^{\mathrm{f}}_t + \sum_{n=1}^{N}\left(E^{\mathrm{c}}_{n,t}+E^{\mathrm{s}}_{n',n,t}\right)\right)\\ &\mathrm{C1}: \ \sum_{n=1}^{N} d_{n,t} \le d^{\max}, \quad 0 \le t \le T^{\max}\\ &\mathrm{C2}: \ \sum_{n=1}^{N} P^{\mathrm{down}}_{n',n,t} \le P^{\max}, \quad 0 \le t \le T^{\max}\\ &\mathrm{C3}: \ T^{\mathrm{down}}_n \le T^{\max}_n, \quad \forall n \in \mathcal{N}\\ &\mathrm{C4}: \ E_t \ge E^{\min}, \quad 0 \le t \le T^{\max} \end{aligned} \tag{11}$$

where $T^{\max} = \max\{T^{\max}_n, n \in \mathcal{N}\}$, and function $\mathbf{1}\left(|\Delta x_t|, |\Delta y_t|\right)$ indicates whether the UAV has a valid moving direction. In (11), the first two constraints indicate that in a time slot, the computing resources and down link transmit power allocated to all N types of tasks shall not exceed the computing capability constraint and maximum wireless power limitation of the UAV, respectively. Constraint C3 shows the completion time that each task needs to meet its maximum delay tolerance. In C4, $E^{\min}$ is the minimum energy reserve threshold to ensure flight safety of the UAV during its edge service process.

IV. Optimal Offloading and Trajectory Scheduling Scheme in a Learning Approach

Due to the incorporation of the tasks' step sequential dependencies shown in (8), (9) and (10) into constraint C3, it is costly and impractical to solve optimization problem (11) directly. To address this issue, we leverage Lagrange multiplier and DDPG learning to design an iterative optimal task offloading and flight trajectory scheduling scheme, which minimizes UAV energy cost with low computational complexity. In the designed scheme, the optimization problem of (11) is further divided into two sub-problems, which are the UAV's trajectory planning and the edge resource scheduling in task offloading.

For time slot t, given allocated UAV computing resource $\{d_{n,t}, n \in \mathcal{N}\}$ and transmit power $\{P^{\mathrm{down}}_{n',n,t}, n, n' \in \mathcal{N}\}$, the trajectory planning sub-problem can be written as

$$\begin{aligned} &\min_{\{v_t,\Delta x_t,\Delta y_t\}} \mathbf{1}\left(|\Delta x_t|,|\Delta y_t|\right)E^{\mathrm{f}}_t + \sum_{n=1}^{N}\left(E^{\mathrm{c}}_{n,t}+E^{\mathrm{s}}_{n',n,t}\right)\\ &\mathrm{C1}: \ \sum_{n'=1}^{N}\mathbf{1}(t,n)\sum_{n=1}^{N}(\zeta_1\tau(r^{\mathrm{up}}_{n',n,t}+r^{\mathrm{down}}_{n',n,t})\\ &\quad +\zeta_2 d_{n',t}) \ge \sum_{n=1}^{N}\frac{\zeta_1(f'_{n,t}+w'_{n,t})+\zeta_2 c'_{n,t}}{T'^{\max}_n}\tau\\ &\mathrm{C2}: \ E_t \ge E^{\min} \end{aligned} \tag{12}$$

where $\{f'_{n,t}, c'_{n,t}, w'_{n,t}\}$ and $T'^{\max}_{n,t}$ are the amount of data and computation that are yet to be uploaded, downloaded and processed of task type n in slot t, respectively. ζ_1 and ζ_2 are coefficients. When the values of $|\Delta x_t|$ and $|\Delta y_t|$ are not 0, the function takes 1, and vice versa. At each slot, given $\{d_{n,t}\}$ and $\{P^{\mathrm{down}}_{n',n,t}\}$, the objective function of (12) drives the

UAV to adjust its flight speed and direction targeting at the grid with lowest energy consumption. In (12), constraint C1 indicates that the amount of tasks performed by the UAV in one time slot should be greater than the average of the ratios of various remaining tasks to their left time, so that the UAV can complete each task under its delay constraint.

To obtain optimal UAV trajectory planning strategies, we transform (12) to a Lagrangian multiplier problem, and solve it in a sub-gradient approach. The Lagrangian relaxation function of (12) is expressed as

$$\begin{aligned} L\left(v_t,\Delta x_t,\Delta y_t,\eta\right) &= \mathbf{1}\left(\left|\Delta x_t\right|,\left|\Delta y_t\right|\right)E_t^{\mathrm{f}} + \sum_{n=1}^{N}(E_{n,t}^{\mathrm{c}} \\ &+E_{n',n,t}^{\mathrm{s}}) + \eta_1(\sum_{n'=1}^{N}\mathbf{1}(t,n)\sum_{n=1}^{N}\zeta_1\tau(r_{n',n,t}^{\mathrm{up}} + r_{n',n,t}^{\mathrm{down}}) \\ &+\zeta_2 d_{n',t}) - \sum_{n=1}^{N}\frac{\zeta_1(f'_{n,t}+w'_{n,t})+\zeta_2 c'_{n,t}}{T'^{\max}_n}\tau) + \eta_2(E_t - E^{\min}) \end{aligned} \quad (13)$$

Then, the dual problem of (12) takes the form

$$g\left(\eta\right) = \inf_{\{v_t,\Delta x_t,\Delta y_t\}} L\left(v_t,\Delta x_t,\Delta y_t,\eta\right) \quad (14)$$

The optimal trajectory planning strategies can be obtained by maximizing $g\left(\eta\right)$ function under domain constraints, which is shown as

$$\begin{aligned} &\max_{\eta} g\left(\eta\right) = \max_{\eta} \inf_{\{v_t,\Delta x_t,\Delta y_t\}} L\left(v_t,\Delta x_t,\Delta y_t,\eta\right) \\ &\mathrm{C1}: \quad \eta_1,\eta_2 \in \mathscr{R}^{+} \end{aligned} \quad (15)$$

To solve (15), we initialize the Lagrangian multiplier set $\eta = \{\eta_1,\eta_2\}$, and find a feasible solution of the internal minimization problem of (15) by calculating the following equations

$$\left\{\begin{array}{l} \frac{dL}{dv_t} = \frac{dL}{d\Delta x_t} = \frac{dL}{d\Delta y_t} = 0 \\ \Delta x_t = \{-1,0,1\} \\ \Delta y_t = \{-1,0,1\} \end{array}\right. , \quad (16)$$

where $\frac{dL}{dv_t}$, $\frac{dL}{d\Delta x_t}$ and $\frac{dL}{d\Delta y_t}$ are the partial derivatives of Lagrangian relaxation function $L\left(v_t,\Delta x_t,\Delta y_t,\eta\right)$ with respect to variables v_t, Δx_t and Δy_t, respectively. Based on the obtained UAV trajectory planning strategies, Lagrangian multiplier set η can be updated in a sub-gradient approach, until the value changes of η in two adjacent iterations are less than a preset threshold δ. In these iterations, the sub-gradient updates of $g(\eta)$ in terms of η are presented as

$$\begin{aligned} \eta_1\left(h+1\right) &= [\eta_1\left(h\right) - \kappa_1(\sum_{n'=1}^{N}\mathbf{1}(t,n)\sum_{n=1}^{N}\zeta_1\tau(r_{n',n,t}^{\mathrm{up}} \\ &+r_{n',n,t}^{\mathrm{down}}) + \zeta_2 d_{n',t}) - \sum_{n=1}^{N}\frac{\zeta_1(f'_{n,t}+w'_{n,t})+\zeta_2 c'_{n,t}}{T'^{\max}_n}\tau)]^{+} , \\ \eta_2\left(h+1\right) &= \left[\eta_2\left(h\right) - \kappa_2(E_t - E^{\min})\right]^{+} \end{aligned} \quad (17)$$

where $\{\mathbf{1}(t,n), r_{n',n,t}^{\mathrm{up}}, r_{n',n,t}^{\mathrm{down}}, E_t\}$ is the value of the feasible solution to the internal minimization problem, and $\kappa = \{\kappa_1,\kappa_2\}$ denotes the update step size for η in each iteration. For given $\hat{x}$, function $[\hat{x}]^{+} = \max(0,\hat{x})$.

The main steps of the proposed UAV trajectory planning scheme are shown in Algorithm 1.

Algorithm 1 UAV trajectory planning scheme

Initialization:

Initialize Lagrangian multiplier set $\eta(0)$ at time slot 0

For Index of iterations $h = 1,2,...,h^{\max}$ **Do**

  Based on the multiplier set $\eta(h-1)$, obtain UAV trajectory planning strategies $\{v_t,\Delta x_t,\Delta y_t\}$ according to (16);

  Calculate multiplier set $\eta(h)$ in current iteration according to (17);

  if $(\eta_1(h) - \eta_1(h-1)) \parallel (\eta_2(h) - \eta_2(h-1)) \geq \delta$; **then**

    Continue;

  else

    Return strategy set $\{v_t,\Delta x_t,\Delta y_t\}$;

    Break;

  end if

End For

After determining the flight speed and direction of time slot t in the UAV trajectory planning sub-problem, we move into the edge resource scheduling sub-problem to optimize the allocation of UAV computing capability and communication power, thereby minimizing UAV energy costs. The scheduling sub-problem can be shown as the following target function with the same constrains as in (11).

$$\min_{\{d_{n,t},P_{n',n,t}^{\mathrm{down}}\}} \mathbf{1}\left(\left|\Delta x_t\right|,\left|\Delta y_t\right|\right)E_t^{\mathrm{f}} + \sum_{n=1}^{N}\left(E_{n,t}^{\mathrm{c}} + E_{n',n,t}^{\mathrm{s}}\right) . \quad (18)$$

Since allocated computing resource $\{d_{n,t}\}$ and transmit power $\{P_{n',n,t}^{\mathrm{down}}\}$, which are two continuous variables, jointly affect UAV energy consumption and task completion delay, we take Deep Deterministic Policy Gradients (DDPG) to address (18). DDPG is an actor critic approach designed for strategy learning in environments with continuous action spaces, and thus it is suitable for optimizing resource scheduling of the UAV [12]. The state, action and reward of this DDPG learning are defined as the following three equations, respectively.

$$S_t = \{c'_n, f'_n, w'_n, T'^{\max}_n, v_{t-1}, \Delta x_{t-1}, \Delta y_{t-1}\} \quad (19)$$

$$A_t = \{d_{n,t}, P_{n',n,t}^{\mathrm{down}}\} \quad (20)$$

$$R_t = -\left(\mathbf{1}\left(\left|\Delta x_t\right|,\left|\Delta y_t\right|\right)E_t^{\mathrm{f}} + \sum\nolimits_{n=1}^{N}\left(E_{n,t}^{\mathrm{c}} + E_{n,t}^{\mathrm{s}}\right)\right) \quad (21)$$

The main process of the proposed DDPG-based UAV edge resource scheduling scheme is presented in Algorithm 2, which integrates Algorithm 1 as one of its steps. According to [13], given step size κ for sub-gradient updates shown in (17), the lower bound of iterative number of the Lagrange multiplier sub-gradient can be presented as

$$W_L > \frac{\left\|\eta_{1,g}(0) - \eta_{1,\mathrm{op}}\right\|^2/\xi^2}{\left(\kappa_1\right)^2} + \frac{\left\|\eta_2(0) - \eta_{2,\mathrm{op}}\right\|^2/\xi^2}{\left(\kappa_2\right)^2}, \quad (22)$$

where η_{op} is the optimal solutions of η in its feasible region, and ξ is a Lipschitz constant of $L\left(\eta\right)$. Further, given that the complexity of the DDPG learning process is $o(N_D)$, then the lower bound of the complexity of Algorithm 2 can be expressed as $o(W_L \cdot N_D)$.

Algorithm 2 DDPG-based UAV edge service scheduling scheme

Initialization:

initial policy parameters θ, Q-function parameters ϕ, and empty replay buffer;

Initialize target network with parameters $\theta_{tar} \leftarrow \theta$ and $\phi_{tar} \leftarrow \phi$.

For time slot $t = \{1, 2, ..., T^{\max}\}$ **Do**

Repeat

Observe state S_t and select action A_t based on $\mu_\theta(S_t)$ with random disturbance ε;

Take action A_t, and execute **Algorithm 1** to obtain UAV's trajectory planning strategies $\{v_t, \Delta x_t, \Delta y_t\}$.

Derive next state $S_t{}'$ and reward R_t, and store $(S_t, A_t, S_t{}', R_t)$ into replay buffer.

Randomly get a batch of samples $R_B = \{(S_t, A_t, S_t{}', R_t)\}$ from replay buffer, and compute target

$$Y(R_t, S_t{}') = R_t + \gamma Q_{\phi_{tar}}(S_t{}', \mu_{\theta_{tar}}(S_t{}'))$$

Update Q-function in gradient descent

$$\nabla_\phi \frac{1}{|R_B|} \sum_{(S_t, A_t, R_t, S_t{}') \in R_B} (Q_\phi(S_t, A_t) - Y(R_t, S_t{}'))^2$$

Update policy in gradient ascent

$$\nabla_\theta \frac{1}{|R_B|} \sum_{S_t \in R_B} Q_\phi(S_t, \mu_\theta(S_t))$$

Update target network parameters with

$$\phi_{tar} \leftarrow \rho \phi_{tar} + (1-\rho)\phi$$
$$\theta_{tar} \leftarrow \rho \theta_{tar} + (1-\rho)\theta$$

Until Learning convergence

End For

V. Numerical Results

In this section, we evaluate the performance of the proposed UAV trajectory planning and resource scheduling schemes. The aerial edge service area is divided into 100 square grids with 100 meters side length. A UAV flies at a maximum speed of 1 m/s at an altitude of 100 meters. The input and output data size, required computing resources and delay tolerance of each type of tasks are randomly chosen from (1.5, 7.5) MB, (0.75, 3.75) MB, $(1.5, 7.5) \times 10^6$ CPU cycles and (40, 50) time slots, respectively [14]. There are 10 charging stations randomly distributed in these grids, and the charging rate E^{r} is 2000 joules per time slot. For the parameters of the UAV processing and transmission service, we set E_0^{c} to 0.0008 joules, $d^{\max}$ to 10^6 CPU cycles and $P^{\max}$ to 1 watt.

Fig. 2 shows the convergence of the proposed DDPG learning based UAV edge service scheduling scheme. When

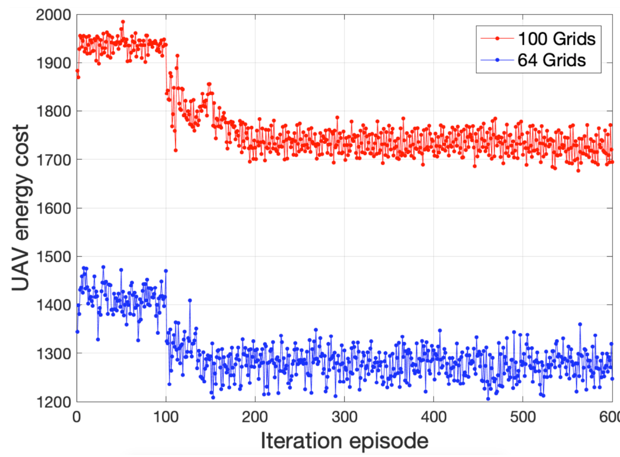

Fig. 2. Convergence of the DDPG-based UAV edge service scheduling scheme.

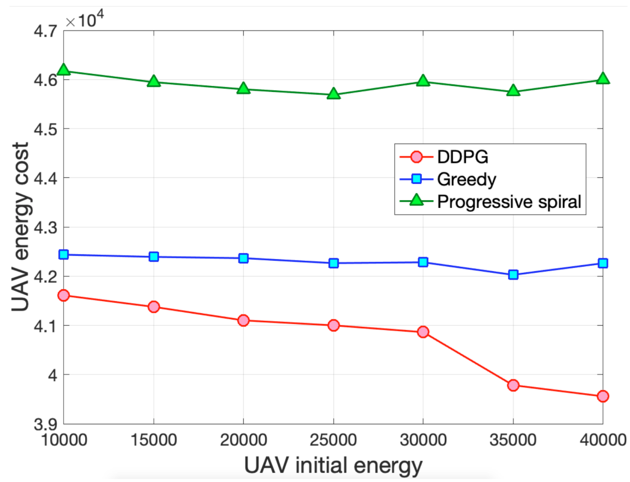

Fig. 3. Comparison of UAV energy costs with different schemes.

the scheme is applied to aerial edge networks with different sizes of serving areas that consist of 100 grids and 64 grids, the UAV energy consumption converges to 1730 and 1280 joules around 200 iterations, respectively. Furthermore, this figure demonstrates that the operational efficiency of our scheme is rarely affected by the scale of UAV coverage areas and the diversity of IoT task types. Thus, this scheme can obtain the optimal UAV service strategies with low time overhead in various service scenarios, and has good efficiency and applicability.

Fig. 3 compares the UAV energy costs during its edge service process scheduled by different schemes. For all the scenarios where the UAV has different initial onboard energies, our proposed DDPG-based scheme achieves the lowest energy consumption among the three schemes. In the progressive spiral approach, the UAV performs edge computing services following a circular trajectory with a gradually decreasing radius, and replenishes onboard energy at the nearest charging stations it is passing by. Although this approach saves energy costs of UAV flight, it spends too much power for down

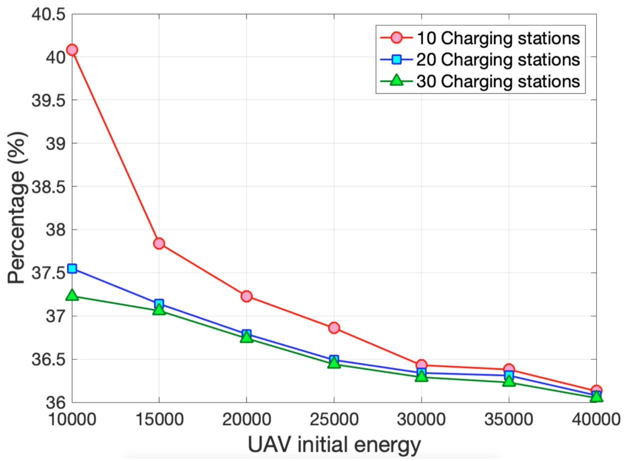

Fig. 4. Comparison of the proportion of flight energy consumption in UAV total energy cost with different number of charging stations.

link communication and task computing, thus resulting in an excessively high total energy consumption. The greedy scheme, which allocates edge resources to the UAV's current covering grids only according to the delay urgency of the tasks, lacks efficient UAV trajectory planning, and also produces high energy consumption. Unlike the previous two approaches, our proposed scheme not only jointly optimizes the resource scheduling and UAV flight planning under tasks' delay constraints, but also considers the timing correlation between task execution steps. Consequently, the scheme avoids inefficient service during the UAV charging process and reduces long-distance high-power communication overhead, thus significantly saving the UAV's total energy cost.

Fig. 4 presents the comparison of the proportion of flight energy consumption in the UAV's total energy cost under different UAV initial energy and different number of charging stations. With the increase of the initial energy, the UAV can have more sufficient battery to increase its transmission power, and only needs to move in a smaller range to provide edge services for IoT devices in a wider area. Therefore, the proportion of flight energy consumption in both three scenarios with different numbers of charging stations shows a downward trend. It is noteworthy that the fewer charging stations, the higher the proportion of flight energy consumption, and the difference in proportion is more significant as the UAV's initial energy decreases. When there are large numbers of charging stations, some stations' location may be coincident with or close to the UAV's optimal service coordinates, so the UAV does not need to fly back and forth between the service points and the charging stations to replenish the battery. Correspondingly, sparsely distributed charging stations may generate more flight energy consumption.

VI. Conclusion

In this paper, we investigated aerial edge networks with rechargeable UAVs, and focused on the energy consumption of the UAVs for flight, computing and communications in their edge services. We formulated an energy minimization problem, which jointly considered UAV trajectory planning, battery charging scheduling and edge resource allocation, while taking account the sequential dependencies between task execution steps. To address this problem and obtain the optimal UAV edge service strategies, we leveraged Lagrangian sub-gradient and DDPG learning approaches to propose an efficient iterative algorithm. Demonstrative numerical results proved that our schemes significantly reduced UAV energy costs compared to the benchmark approaches.

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