Journal of Computers Vol. 35 No. 5, October 2024, pp. 123-134
doi: 10.53106/199115992024103505009

Energy-Efficient Optimization of Multi-UAV Assisted Smart Grids Networks

Zhongyuan Nian[1], Jingxue Tian[2*], Xu Lu[3], Hua Wang[1], Heli Zhang[2], Chunfang Mu[1], and Yang Li[2]

[1] Information & Telecommunication branch company, State Grid Corporation of China,
010010, Hohhot, Inner Mongolia, China

{nianzhongyuan, luxu, wanghua, muchunfang}@md.sgcc.com.cn

[2] School of Information and Communication Engineering, Beijing University of Posts and Telecommunications
100876, Beijing, China

{tjx1023, zhangheli, li_yang}@bupt.edu.cn

[3] Power Dispatching & Control Center, State Grid Corporation of China,
010010, Hohhot, Inner Mongolia, China

luxu@md.sgcc.com.cn

Received 7 December 2023; Revised 30 April 2024; Accepted 25 June 2024

Abstract. Unmanned aerial vehicles (UAVs) are increasingly being deployed in wireless communication systems to assist with traffic offloading services because of their high flexibility and mobility. In traditional cellular networks, communication performance often degrades at the cell edges during high-demand periods when base stations are overloaded. So UAVs can serve as aerial base stations to enhance communication performance in such hotspots. However, there is a challenge of limited energy capacity and insufficient computing capabilities. This paper focuses on maximizing the energy efficiency of aerial base stations (ABS) by optimizing the number of UAVs, the division of users and the allocation of bandwidth. We explore two UAV deployment strategies: multi-UAV hovering and multi-UAV cruising. Our simulation results reveal that the cruise deployment strategy nearly doubles the energy efficiency compared to the hovering strategy, provided that the number and flight speed of the UAVs are appropriately managed. This result provides an effective solution for the energy efficiency optimization of multi-UAV in communications hotspots.

Keywords: unmanned aerial vehicle, cellular offloading, energy efficiency, multi-UAV deployment strategy, smart grid

1 Introduction

Unmanned aerial vehicles (UAVs), commonly known as drones, have rapidly gained popularity in recent years due to their highly controllable mobility and rapid deployment characteristics [1]. Due to the continuous reduction of manufacturing costs and the miniaturization of communication equipment, it has become more feasible to use UAVs as aerial base stations (ABS) to assist ground wireless communications [2]. UAV-based wireless communication systems offer new advantages compared to traditional wireless communication systems. For instance, UAVs typically have line-of-sight (LoS) links with ground terminals and exhibit high mobility and on-demand deployment flexibility, resulting in superior link quality for such systems [3]. These advantages make UAV-assisted communication capable of supporting the growing demand for highly dynamic wireless data traffic in future 5G and beyond cellular systems, especially in smart grid systems for cellular data offloading [4].

However, the energy efficiency of the UAV is a huge challenge due to its limited battery capacity. Therefore, how to reduce the power consumption of the UAV while guaranteeing the required Quality-of-Service (QoS) is of great significance [5]. In [6], an energy consumption model for rotary-wing UAVs, with closed-form expression as a function of the initial velocity, acceleration and time duration was derived. The propulsion power consumption of a rotary-wing UAV is convex concerning its speed. This paper jointly optimized the allocation of time and UAV trajectories to minimize the power consumption of the UAV. In [7], the authors proposed model-free deep reinforcement learning (DRL)-based collaborative computation offloading and resource allocation (CCORA-DRL) scheme in an aerial to ground (A2G) network in order to minimize task execution delay and

* Corresponding Author

energy consumption. The UAV-assisted Mobile Edge Computing (MEC) was studied in [8]. It aims to maximize the energy efficiency of a single UAV through the joint optimization of the UAV trajectory, user transmit power and computation load allocation. In [9], the authors studied the energy-efficient of the UAV based wireless sensor network. The power allocation and UAV scheduling schemes are jointly optimized to minimize energy consumption in this paper. In order to study the power consumption of UAVs, the authors first propose a heuristic energy model and provide experimental validation based on the measurement results for circular level flight in [10].

The above work primarily focused on the energy efficiency optimization of a single UAV wireless communication system. However, the continuous service capability of a single UAV is relatively limited due to constraints in energy and coverage. Therefore, multi-UAV communication solutions have been considered in some studies. A multi-UAV enabled Internet of Things (IoT) is studied in [11], where a UAV serves cell-edge users with a circular trajectory. By jointly considering the average data rate, the total energy consumption, and the fairness of coverage for the terminals, the trajectory design of UAV is optimized. In [12], the authors utilized Deep Reinforcement Learning (DRL) to address an energy efficiency optimization problem in multi-UAV communication, aiming to achieve a fair solution in terms of UAV energy consumption and coverage range. Meanwhile, in [13], the authors jointly optimized the trajectories of all UAVs considering the co-channel interference between different UAVs. To achieve maximum energy efficiency, an optimal trade-off between throughput and energy consumption needs to be found. To overcome the high complexity of centralized algorithms, [14] introduced a multi-agent distributed Q-learning approach to individually control the deployment and transmit power of multiple UAV-BSs, with the aim of maximizing energy efficiency while enhancing outage performance.

In the UAV-assisted smart grids scenario, the authors in [15] have modeled the UAV's resource allocation as a Markov process, based on the UAV flight and hovering communication protocol. [16] introduced an optimization scheme that integrates multi-UAV trajectories, transmit power, and user scheduling for UAVs. Additionally, a one-to-one communication scheduling protocol was designed for UAVs and cell-edge users to minimize co-channel interference. In the literature reviewed, most studies focus solely on the hovering strategy for UAVs and overlook the potential impact of the cruising strategy on optimizing energy consumption. This oversight is significant because a UAV moving at a moderate speed consumes less energy than one hovering at a constant altitude.

Building on the motivations outlined above, this paper addresses the optimization of energy efficiency for multiple UAVs operating at the edge of a single cell. Therefore, we established energy consumption optimization models for these two UAV deployment strategies to explore the impact of different strategies on UAV energy consumption optimization. We consider the following scenario: a ground base station (GBS) is located in the center of the smart grids cell, and multiple UAVs are deployed at the edge of the cell to offload the edge user traffic. Overall, the main contributions of this paper can be summarized as follows.

1) We proposed two deployment strategies to optimize energy efficiency, the multi-UAV hovering deployment strategy and the multi-UAV cruise deployment strategy. In the hovering deployment strategy, multiple UAVs are deployed in the edge area, and GBS serve users outside the UAV coverage area. In the cruise deployment strategy, the edge area outside the GBS's coverage radius is divided into multiple areas of the same size. The UAV coverage area is designed to avoid the unbalanced user service time under the circular area.

2) We establish models under two strategies and maximize energy efficiency by optimizing the number of UAVs, bandwidth allocation, and user division.

3) Moreover, through bisection search and block gradient descent, these two problem's optimal solutions are obtained, respectively.

4) The simulation results show that the highest energy efficiency can be obtained by deploying the appropriate number of UAVs under the cruise deployment strategy.

The remainder of this paper is organized as follows. The system model is given in Section 2. The multi-UAV hovering deployment strategy and multi-UAV cruise deployment strategy are investigated in Section 3 and Section 4. Numerical results are presented in Section 5 and Section 6 concludes the paper.

2 System Model

As shown in Fig. 1 and Fig. 2, multiple UAVs are deployed to offload traffic for cell-edge users. The downlink communication link between the GBS/UAV and the users is considered. The users within the cell are randomly and uniformly distributed with density λ.

In the hovering deployment strategy, depicted in Fig. 1, m homogeneous hovering UAVs are deployed at the cell's edge with a coverage radius of $r_{ABS} = r_{hov}$ and height $H_{ABS} = H_{hov}$. A ground base station (GBS) is located in the circular cell's center with the coverage radius r_{cell} and fixed altitude H_{GBS}. The UAV coverage area inscribes the edge of the cell, serving users within the coverage radius of r_{hov}. The remaining users are served by the GBS. The coverage areas of GBS and the UAVs do not overlap. Thus the area covered by a UAV is $S_{hov} = \pi r_{hov}^2$, and the area covered by the GBS is $\pi r_{cell}^2 - mS_{hov}$.

As shown in Fig. 2, in the cruise deployment strategy, users within the area with radius r_{GBS} are served by the GBS, while the edge area is divided into m segments at equal intervals. A cruise flight UAV with speed V is deployed in each segment, following a circular trajectory with a radius of $r_{mov} = (r_{cell} + r_{GBS})/2$ and a flight period of T. To balance the duration of UAV service for different users, a sector with a central angle of ϕ is selected as the coverage area of the UAV, instead of the circular coverage area. The horizontal distance between any user and the UAV in the sector is less than $d_{max} = \sqrt{r_{mov}^2 + r_{cell}^2 - 2r_{mov}r_{cell}\cos(\phi/2)}$. This paper investigates energy efficiency under two strategies: multi-hover UAV and multi-cruise UAV deployment. The symbols in our model are shown in Table 1.

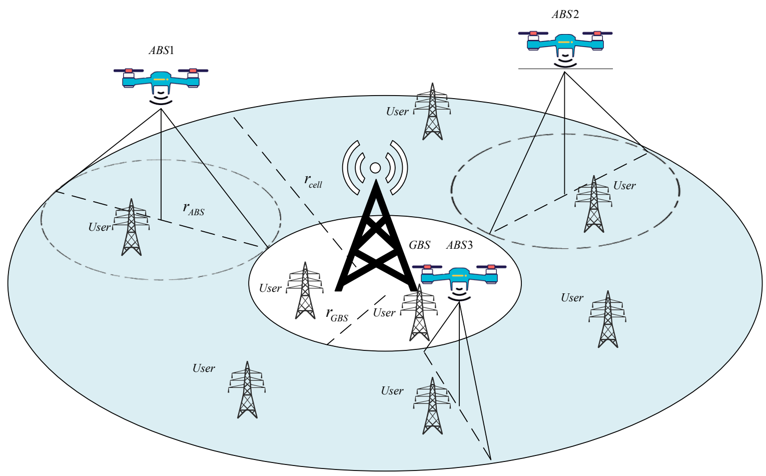

Fig. 1. Hovering deployment strategy

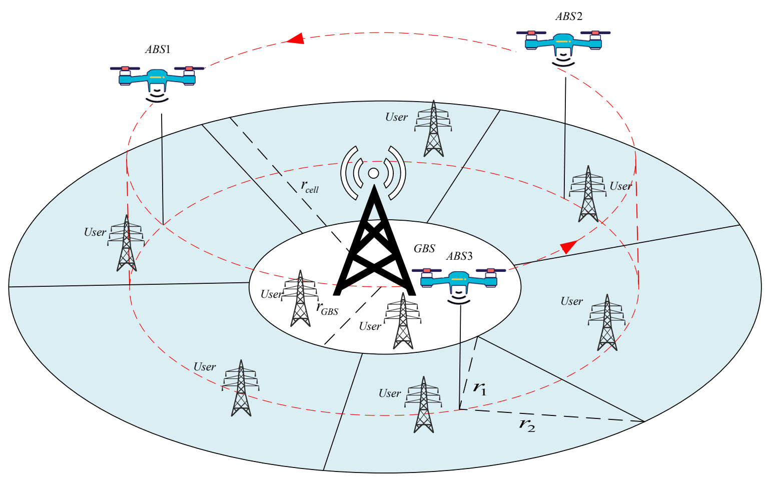

Fig. 2. Cruise deployment strategy

Table 1. List of main notations

Notations	Description
H_{GBS}	The height of the UAVs
d_{GBS}	Horizontal distance between the user and the GBS
r_{ABS}	UAV coverage radius
r_{cell}	Cell coverage radius
r_{GBS}	GBS service coverage radius
ρ	Bandwidth allocation factor
R_{th}	Instantaneous rate threshold

To avoid interference between UAVs and GBS, we divide the bandwidth into two parts. It is assumed that the total bandwidth available is B, which is divided into two portions, i.e., ρB, $0 \le \rho \le 1$ and $(1-\rho)B$, used for the UAV and GBS, respectively. The bandwidth allocated to the UAV is equally shared among the users associated with the UAV. Similarly, the GBS also adopts the equal bandwidth allocation scheme.

For GBS-user communication, the channel between the GBS and the user is a traditional fading channel model, including large-scale fading and small-scale path loss. Thus, the channel power gain from the GBS to the users is modeled as

$$g = \frac{\beta\xi}{(H_{GBS}^2 + d_{GBS}^2)^{\alpha/2}}, \tag{1}$$

where $\beta = (4\pi f_c/c)^{-2}$ denotes the channel power gain at the reference distance 1 m, ξ denotes the independent and identically distributed small-scale Rayleigh fading with unit mean $\xi \sim Exp(1)$, and d_{GBS} represents the horizontal distance between the user and the GBS, and α denotes the path loss exponent.

According to the analysis in [14], we define the user's average signal noise ratio (SNR) as γ and the signal transmission power of the GBS as P_{GBS} . The signal transmission power of the GBS is equally allocated to the users, so the average SNR of the user can be obtained as

$$\gamma = \frac{P_{GBS} G_{GBS} \beta}{\sigma^2 (1-\rho) B (H_{GBS}^2 + d_{GBS}^2)^{\alpha/2}}, \tag{2}$$

where the receiver noise is assumed to be additive white Gaussian noise with power spectrum density σ^2 and G_{GBS} is the fixed antenna gain with an omnidirectional antenna.

For UAV-user communication, it is assumed that each UAV is equipped with a directional antenna, and the angle of half of the antenna beam is θ, where $\theta = \arctan(r_{ABS}/H_{ABS})$. Therefore, the antenna gain of UAV can be approximately G_0/θ^2. The channel between UAV and ground users consists of two parts, the LoS link factor, and non-line-of-sight (NLoS) link factor. The probability of the LoS link between UAV and users depends on the maximum coverage distance r_{ABS}, $r_{ABS} = r_{hov}$ in hovering deployment strategy, and $r_{ABS} = r_{mov}$ in cruise deployment strategy. As the coverage radius of UAV is r_{ABS}, the probability of LoS link between UAV and users is

$$P_{LoS} = \frac{1}{1 + a\exp(-b\arctan(H_{ABS}/r_{ABS}) - a)}, \tag{3}$$

where a and b are constant and only related to the environment and frequency, $\arctan(H_{ABS}/r_{ABS})$ denotes the UAV service user's elevation angle, and H_{ABS} denotes UAV height. Thus, with horizontal distance r_{ABS} between the users and its serving UAV, the path loss expression is

$$L(r_{ABS}) = (\eta LoS - \eta NLoS) P_{LoS} + 20log(\frac{4\pi d f_c}{c}), \tag{4}$$

where $d = \sqrt{r_{ABS}^2 + H_{ABS}^2}$ denotes the distance between the UAVs and the users, c denotes the speed of light, ηLoS

and $\eta NLoS$ are the excessive pathloss corresponding to the LoS and NLoS links depending on the environment and frequency.

In the next section, we will present the problem formulation and solutions to maximize the energy efficiency for the hover deployment strategy and cruise deployment strategy, respectively.

3 Hovering Deployment Strategy

3.1 Problem Formulation

The minimum instantaneous rate of the GBS-user links is

$$R_{GBS} = B_{GBS,k} log_2(1+\gamma') \, , \tag{5}$$

where $\gamma' = \gamma\xi$ and $B_{GBS,k} = (1-\rho)B / \lambda(\pi r_{cell}^2 - mS_{hov})$.

Due to the GBS-user link's small-scale fading, an outage event occurs when the instantaneous rate is smaller than a given throughput R_{th}. The outage probability of the worst GBS-user link is given by [17] as

$$\begin{aligned} P_{out,GBS} &= P_r\left(B_{GBS,k}\log_2(1+\gamma') < R_{th}\right) \\ &= P_r\left(\xi < \left(2^{R_{th}/B_{GBS,k}} - 1\right)/\gamma\right) \\ &= 1-\exp\left(-\left(2^{R_{th}/B_{GBS,k}} - 1\right)/\gamma\right) \end{aligned} \, . \tag{6}$$

It can be verified that $P_{out,GBS}$ is an increasing function of R_{th}, ρ, and r_{GBS}.

In order to avoid interference between multiple UAVs, the UAV coverage areas should not overlap. Therefore, the coverage radius of UAV satisfies $r_{hov} \le (r_{cell} - r_{hov})\sin(\pi/N)$. Ignoring the tangent effect,

$$r_{hov} \le \frac{r_{cell}\sin\left(\frac{\pi}{N}\right)}{1+\sin\left(\frac{\pi}{N}\right)} \overset{\Delta}{=} r_{hov}^{upper} \, . \tag{7}$$

Combined with the system model derivation in the previous chapter, the average rate of users served by the UAVs is given by

$$R_{hov} = \frac{\rho B}{\lambda S_{hov}} \log_2\left(1 + \frac{P_{hov}G_0}{\sigma^2 \rho B \theta^2 10^{0.1L(r_{ABS})}}\right) \tag{8}$$

The total power consumption of hovering UAVs consists of two parts, i.e., transmission power consumption and propulsion power consumption. The transmission power consumption is far less than propulsion power consumption and thus is neglected. The UAV propulsion power consumption is given by [18]

$$P_{hov} = \frac{c_1 + c_2}{\sqrt{mg^3}} \, , \tag{9}$$

where c_1 and c_2 are the inherent attributes of the UAV.

By optimizing the number of hovering UAVs, the coverage radius of UAVs, and the bandwidth allocation between UAVs and GBS, UAV's energy efficiency is maximized, and the outage of GBS is guaranteed to be less than the given threshold P_{th}. Therefore, the considered problem can be formulated as P1.

$$\begin{aligned}&P1:\max_{\{m,r_{hov},\rho\}}\frac{R_{th}}{P_{hov}}\\&C1:P_{out,GBS}\le P_{th}\\&C2:R_{th}\le R_{hov}\\&C3:0\le\rho\le 1\\&C4:0\le r_{hov}\le r_{hov}^{upper}\end{aligned}, \quad (10)$$

where C1 denotes the prescribed outage probability threshold, C2 indicates that the user's average rate cannot be smaller than the expected throughput, C3 are the feasible and boundary constraints of the involved variables.

3.2 Proposed Algorithm

The UAV's propulsion power consumption is only related to UAV attributes and does not correlate with the parameters in the objective function. Therefore, the simplified problem P1 can be obtained as P2

$$\begin{aligned}&P2:\max_{\{m,r_{hov},\rho\}} R_{th}\\&C1:P_{out,GBS}\le P_{th}\\&C2:R_{th}\le R_{hov}\\&C3:0\le\rho\le 1\\&C4:0\le r_{hov}\le r_{hov}^{upper}\end{aligned}. \quad (11)$$

Assume that R_{th} and m are given, it can be verified that R_{hov} and $P_{out,GBS}$ are increasing function of ρ and decreasing function of r_{hov}. Therefore, UAV's bandwidth allocation ρ and the coverage radius r_{hov} should be carefully designed to achieve the optimal trade-off between the GBS-user links and the UAV-user links. However, problem P2 is challenging to solve due to the non-convex constraints C1 and C2. By exploiting the inherent characteristics of $P_{out,GBS}$ and R_{hov}, problem P2 can be solved as follows.

Given the number of UAVs m, for each value of R_{th}, problem P2 can be transformed into P3. In order to verify whether the given R_{th} can be reached, we next solve problem P3

$$\begin{aligned}&P3:\min_{\{r_{hov},\rho\}} P_{out,GBS}\\&C1:P_{out,GBS}\le P_{th}\\&C2:R_{th}\le R_{hov}\\&C3:0\le\rho\le 1\\&C4:0\le r_{hov}\le r_{hov}^{upper}\end{aligned}. \quad (12)$$

If the optimal $P_{out,GBS}$ of problem P3 is no larger than $\overline{P}_{out,GBS}$, the corresponding R_{th} is a feasible solution to problem P2. Therefore, bisection search can be adopted to maximize the minimum throughput R_{th} iteratively. Problem P3 is still difficult to solved due to the non-convex objective function $P_{out,GBS}$, and the non-convex constraint C2. Therefore, the standard convex optimization techniques cannot be directly used to solve problem P3.

In order to minimize $P_{out,GBS}$, it is best to choose the minimum value of ρ that satisfies $R_{th}\le R_{hov}$. A bisection search for ρ ranging from 0 to 1 can be performed to check the feasibility of ρ. And then a one-dimensional search for r_{ABS} ranging from 0 to r_{ABS}^{upper} can be performed to get the feasible r_{ABS}. Furthermore, the values of ρ^{opt} and r_{GBS}^{opt} can be obtained iteratively. If the optimal $P_{out,GBS}$ of problem P3 is no larger than $\overline{P}_{out,GBS}$, the R_{th} is a feasible solution. Finally, the optimal UAVs number m^{opt} can be obtained via a one-dimensional search.

4 Cruise Deployment Strategy

4.1 Problem Formulation

In this strategy, the service duration that all users covered by UAVs can obtain is approximately $T_k = \phi T/2\pi$. In order for the UAV to cover the users in d_{max}, it must be guaranteed $d_{max} \le H_{mov} \tan\theta$. Therefore, the maximum available antenna gain is $G_{mov,max} = G_0(\arctan(d_{max}/H_{mov}))^{-2}$.

Combined with the analysis in the system model derivation, the minimum instantaneous rate of the GBS-user links is

$$R_{GBS} = B_{GBS,k} \log_2(1+\gamma') , \tag{13}$$

where $\gamma' = \gamma\xi$, $B_{GBS,k} = (1-\rho)B / \lambda\pi r_{GBS}^2$.

Due to the small-scale fading of the GBS-user links, an outage event occurs when the instantaneous rate is smaller than a given throughput R_{th} . The outage probability of the worst GBS-user link is given as

$$\begin{aligned} P_{out,GBS} &= P_r\left(B_{GBS,k} \log_2(1+\gamma') < R_{th}\right) \\ &= P_r\left(\xi < \left(2^{R_{th}/B_{GBS,k}} - 1\right)/\gamma\right) \\ &= 1 - \exp\left(-\left(2^{R_{th}/B_{GBS,k}} - 1\right)/\gamma\right) \end{aligned} . \tag{14}$$

The average rate of all users served by

$$R_{mov} = \frac{\rho B}{\lambda\pi\left(r_{cell}^2 - r_{GBS}^2\right)} \log_2\left(1 + \frac{P_c G_{mov,\max}}{\sigma^2 \rho B \theta^2 10^{0.1L(d_{\max})}}\right). \tag{15}$$

In the same way as hovering deployment strategy, the transmission power consumption is much smaller than the propulsion power consumption of the UAV, so the transmission power consumption of is ignored. Different from the hovering deployment strategy, the propulsion power consumption of cruising UAVs is not only related to the fixed attributes of the UVA but also depends on the UAV's speed V. The UAV's propulsion power consumption is given by [5] as

$$P_{mov} = P_1\left(1 + \frac{3V^2}{U_{tip}^2}\right) + \frac{P_2 V_0}{V} + \frac{1}{2} f\eta s_1 s_2 V^3 , \tag{16}$$

where P_1 denotes the blade profile power, P_2 is the induced power, U_{tip} denotes the rotor blade's tip speed, V_0 denotes the mean rotor induced velocity, f is the fuselage drag ratio, s_1 is known as rotor solidity, η indicates the air density, and s_2 denotes the rotor disc area.

By optimizing the number of cruising UAVs, the coverage radius of GBS, and the bandwidth allocation between UAVs and GBS, UAV's energy efficiency is maximized, and the outage of GBS is guaranteed to be smaller than the given threshold. Therefore, the considered problem can be formulated as P4

$$\begin{aligned} & P4: \max_{\{m, r_{GBS}, \rho, V\}} \frac{R_{th}}{P_{mov}} \\ & C1: P_{out,GBS} \le P_{th} \\ & C2: R_{th} \le R_{mov} \\ & C3: 0 \le r_{GBS} \le r_{cell} \\ & C4: 0 \le \rho \le 1 \\ & C5: V \le V_{\max} \\ & C6: \pi\left(r_{cell} + r_{GBS}\right) \le mVT \end{aligned} , \tag{17}$$

where constraint C6 indicates that the UAVs must serve all cell-edge users within period T.

4.2 Proposed Algorithm

Due to the objective function and constraints C1 and C2, the problem P4 is a complex non-convex optimization problem. To solve this problem, we divide it into two subproblems and obtain the original problem's suboptimal solution by an iterative algorithm. Assuming that V is known, the propulsion power consumption of UAV can be directly calculated, and the objective function is simplified into P5

$$\begin{aligned} & P5:\max_{\{m,r_{GBS},\rho\}} R_{th} \\ & C1: P_{out,GBS} \le P_{th} \\ & C2: R_{th} \le R_{mov} \\ & C3: 0 \le r_{GBS} \le r_{cell} \\ & C4: 0 \le \rho \le 1 \\ & C5: \pi\left(r_{cell} + r_{GBS}\right) \le mVT \end{aligned} . \tag{18}$$

$P_{out,GBS}$ is an increasing function of ρ, r_{GBS} and R_{th} with a maximum P_{th}. It can be verified that R_{th} is also an increasing function of ρ, r_{GBS}. For a given V, to maximize the objective function, the values of r_{GBS} and ρ should be maximized under the constraint $P_{out,GBS} \le P_{th}$. Through bisection search, the maximum values of ρ and r_{GBS} satisfying the constraints are obtained in [0,1] and $[0, r_{cell}]$. Thus, m can be calculated directly. With the values of m, ρ and r_{GBS} obtained, the objective function can be expressed as follows, which is defined as problem P6

$$\begin{aligned} & P6:\min_{\{V\}} P_{mov} \\ & C1: V \le V_{\max} \\ & C2: \pi\left(r_{cell} + r_{GBS}\right) \le mVT \end{aligned} . \tag{19}$$

It can be verified that this is a linear constraint cubic programming problem so that it can be solved directly by the classical convex optimization method. In this paper, the CVX toolbox is adopted to solve it.

Based on the above analysis, we propose an iterative algorithm, which uses the block gradient descent method to achieve the overall optimization of bandwidth allocation and UAV trajectory to achieve maximum energy efficiency. Specifically, in the l–th iteration, we first solved the problem P5 to optimize r_{GBS} and ρ then calculate m. Finally, the r_{GBS}^{opt}, ρ^{opt}, and m^{opt} obtained by the above calculation is used to solve the problem P6 to get the value of V^{opt}.

5 Results and Discussion

In this section, the numerical simulations are provided to evaluate the performance of our proposed UAV deployment strategies. We simulate the two deployment strategies proposed in this paper and compared them with the hybrid deployment strategy. In the hybrid deployment strategy, an equal number of hovering and cruise UAVs are deployed in the cell's edge, and a cruise UAV is deployed between the two hovering UAVs. Without loss of generality, the parameters are set as the following Table 2.

Table 2. System parameters

Parameters	Value	Parameters	Value
H_{mov} H_{hov}	100m	c_1 c_2 [18]	1.49
H_{GBS}	20m	b	0.28
r_{cell}	1000m	φ	$\pi/6$
B	10MHZ	T	60s
c	$3\times10^8 m/s$	P_c	2W
α	3	U_{tip}	120
P_{GBS}	15W	V_0	4.03
σ^2 [11]	$-174dBm$	f	0.6
G_{GBS} [17]	16dBi	s_1 [19]	0.05
G_0	2.2846	s_2 [19]	0.503
a	11.95	η [11]	1.225

As the Fig. 3 shows, MHS is defined as a multi-hover UAV deployment strategy, MMS indicates a multi-cruising UAV deployment strategy, and MDS denotes a multi-UAV hybrid deployment strategy. Based on the hovering deployment strategy, one cruise UAV is deployed between every two hovering UAVs, and the number of hovering UAVs and cruise UAVs is equal. It can be seen from the figure that the energy efficiency of MMS has been higher than the other two deployment strategies, and the energy efficiency of MDS is higher than that of MHS. In the MMS deployment mode, when the optimal number of cruise UAVs are deployed, cruise UAVs' power consumption is close to half of the power consumption of hovering UAVs.

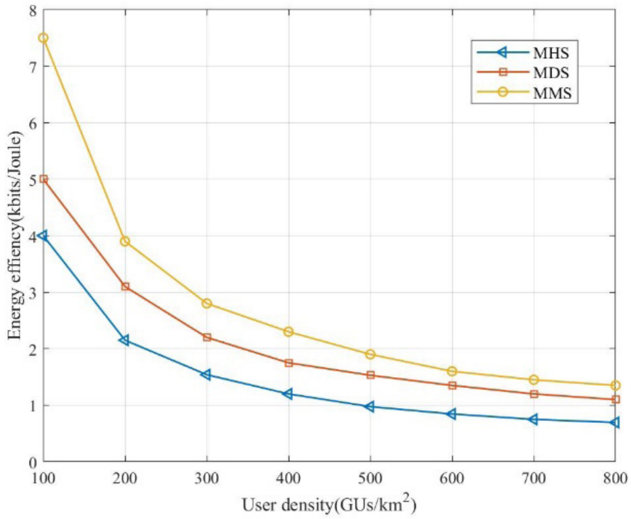

Fig. 3. Energy efficiency with different user density

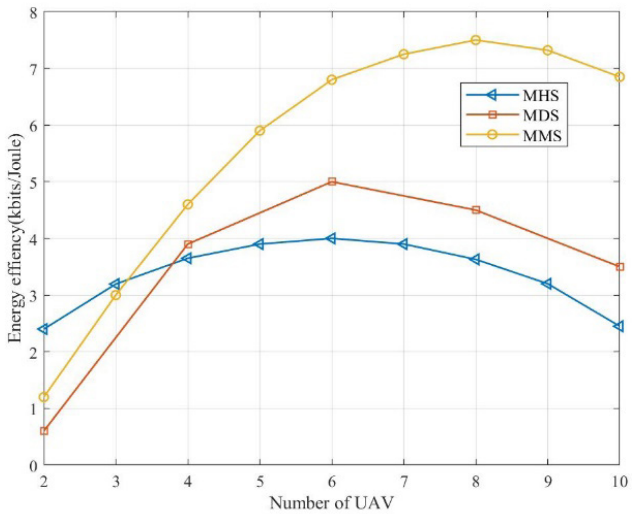

Fig. 4. Energy efficiency with different number of UAVs

Furthermore, in the cruise deployment mode, the GBS only needs to serve users in r_{GBS}, and the channel condition is better because the users are relatively close to the GBS. Besides, it can be seen from the results that when the user density is more significant than 500, the energy efficiency of the three strategies is lower than 2.

Therefore, the system has a capacity limitation on user density. In summary, adopting the MMS strategy and deploying an appropriate number of UAVs can achieve the best energy efficiency.

In the Fig. 4, the energy efficiency is mainly related to the transmission rate for MHS, since the hovering power of the UAV is fixed. It can be seen from the figure that when the number of UAVs is 6, MHS has the highest energy efficiency. As the number of UAVs goes from 2 to 6, the energy efficiency of the MHS strategy continues to increase. This is because as the number of UAVs increases, r_{ABS} is decreasing, and the distance between UAV service users and UAVs is closer, and the channel conditions are better.

At the same time, the distance between the user and the GBS is relatively short, and has not been significantly affected by the constraint threshold. With the number of UAVs ranging from 6 to 10, the energy efficiency of the MHS strategy is constantly decreasing. This is because with the decrease of r_{ABS}, the coverage of GBS continues to increase. In order to meet the threshold of GBS service users, more bandwidth is allocated to GBS, which results in a greatly reduced bandwidth for UAV service users. Similar to MHS, MDS and MMS strategies have similar trends. The optimal number of MDS is equal to MHS, and the optimal number of MMS is 8, which is greater than 6 of the former. When the number of UAVs under the MMS strategy is 8, their flying speed can approach the speed with the lowest power consumption. When the number is too small, each UAV needs to cover a larger range during the cycle, and its flying speed will be greater than the optimal speed.

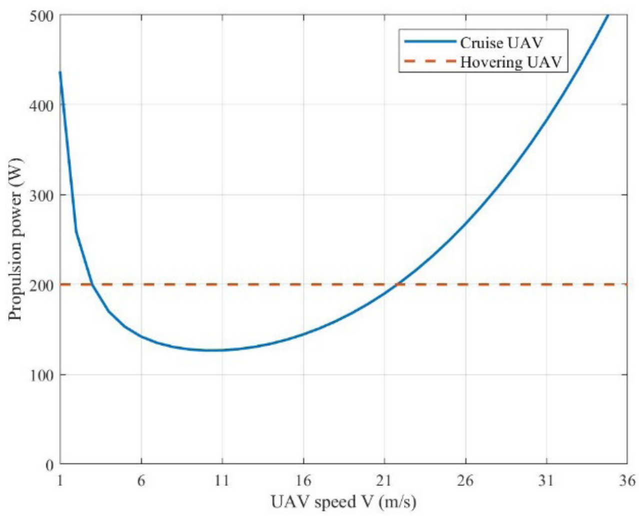

Fig. 5. Propulsion power with different speed

It can be seen from the Fig. 5 that when the number of UAVs is greater than or equal to 4, the energy efficiency of the MHS strategy is lower than the other two strategies, and when the number of UAVs is less than or equal to 3, the result is the opposite. This is because as the number of UAVs continues to increase, the coverage area of a single cruise UAV continues to decrease, and its flight speed is gradually approaching the optimal flight speed. When the cruise UAV speed is lower than 22m/s, its flight power consumption is lower than that of the hovering UAV.

As shown in the Fig. 5, the flight power consumption of a cruise UAV and a hovering UAV at different speeds are compared. Since the flying power consumption of hovering UAVs has nothing to do with speed, but only related to environmental factors such as air resistance and wind power, the flying power of hovering UAVs is constant. In the simulation, we set it to 200 as [18]. The flight power of cruise UAVs is a concave function with respect to speed. The flying power of the cruise flying UAV reaches its minimum value at a speed of 10. It can be obtained from the simulation results that when the speed of the UAV is between 2.5 and 22, the power consumption of the cruise UAV is less than the hovering UAV. In the rest of the range, the power consumption of the cruise UAV is larger than hovering UAV.

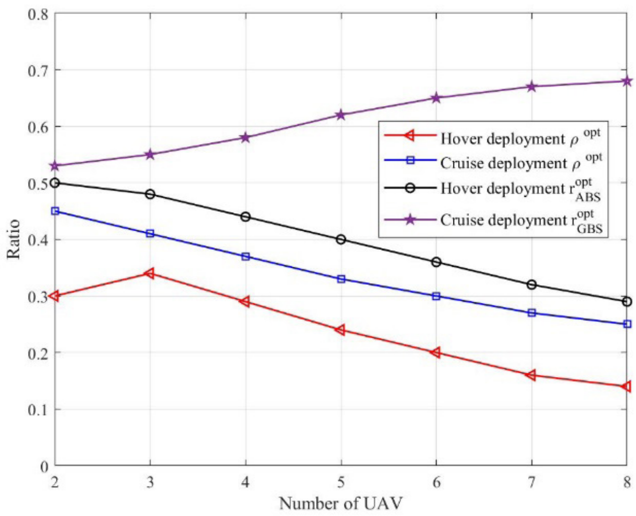

Fig. 6. Optimal ratios under different number of UAV

It can be seen from the Fig. 6 that under the hovering deployment strategy, the bandwidth allocation first increases and then decreases. Because as the number of UAVs increases, although the coverage area of a single hovering UAV continues to decrease, the proportion of the total area covered by all hovering UAVs in the entire area is increasing. The number of users served by GBS is reduced so that more bandwidth can be allocated to UAVs. As the number of UAVs increases, the proportion of the UAV coverage area decreases, and more bandwidth is allocated to GBS. Under the cruise deployment strategy, GBS's coverage continues to increase, and bandwidth allocation decreases. Because as the number of UAVs increases, the distance that they can cover at the optimal speed is longer, and the UAV's flight trajectory is closer to the edge of the cell, so the number of users covered by the GBS is more extensive, and more bandwidth is allocated to the GBS.

6 Conclusion

This paper proposed a heterogeneous cellular network, where a GBS locates in the center of the cell, and multiple UAVs are deployed at the edge to offload the cell-edge user traffic. We proposed two deployment strategies to optimize energy efficiency, the multi-UAV hovering deployment strategy, and the multi-UAV cruise deployment strategy. We established models under two strategies and maximized energy efficiency by optimizing the number of UAVs, bandwidth allocation, and user division. The simulation results show that the maximum energy efficiency can be achieved by adopting the cruise deployment strategy and deploying the optimal number of UAVs. However, this article solves the traditional single-objective optimization problem. In the future, artificial intelligence algorithms can be considered to effectively solve complex non-convex optimization problems through continuous interaction with the environment, and guide the agent to obtain the maximum reward.

7 Acknowledgement

This work was funded by the State Grid Corporation of China Science and Technology Project (No. SGMDXTOOJSJS2100034).

References

[1] Z. Xiao, L. Zhu, Y. Liu, P. Yi, R. Zhang, X. Xia, A Survey on Millimeter-Wave Beamforming Enabled UAV Communications and Networking, IEEE Communications Surveys & Tutorials 24(1)(2022) 557–610.
[2] Y. Hu, C. Tian, F. Zhang, D. Ma, Z. Shi, A Dynamic Cellular Network Framework for Multi-UAV-BS Deployment, Wireless Personal Communications 131(2023) 2991–3007.
[3] C. Zhan and Y. Zeng, Energy-Efficient Data Uploading for Cellular-Connected UAV Systems, IEEE Transactions on Wireless Communications 19(11)(2020) 7279–7292.
[4] Z. Ullah, F. Al-Turjman, L. Mostarda, Cognition in UAV-Aided 5G and Beyond Communications: A Survey, IEEE Transactions on Cognitive Communications and Networking 6(3)(2020) 872–891.
[5] Q. Wu, J. Xu, Y. Zeng, D.W.K. Ng, N. Al-Dhahir, R. Schober, A Comprehensive Overview on 5G-and-Beyond Networks With UAVs: From Communications to Sensing and Intelligence, IEEE Journal on Selected Areas in Communications 39(10)(2021) 2912–2945.
[6] H. Yan, Y. Chen, S.-H. Yang, New Energy Consumption Model for Rotary-Wing UAV Propulsion, IEEE Wireless Communications Letters 10(9)(2021) 2009–2012.
[7] A.M. Seid, G.O. Boateng, S. Anokye, T. Kwantwi, G. Sun, G. Liu, Collaborative Computation Offloading and Resource Allocation in Multi-UAV-Assisted IoT Networks: A Deep Reinforcement Learning Approach, IEEE Internet of Things Journal 8(15)(2021) 12203–12218.
[8] M. Li, N. Cheng, J. Gao, Y. Wang, L. Zhao, X. Shen, Energy-Efficient UAV-Assisted Mobile Edge Computing: Resource Allocation and Trajectory Optimization, IEEE Transactions on Vehicular Technology 69(3)(2020) 3424–3438.
[9] F. Zeng, Z. Hu, Z. Xiao, H. Jiang, S. Zhou, W. Liu, D. Liu, Resource Allocation and Trajectory Optimization for QoE Provisioning in Energy-Efficient UAV-Enabled Wireless Networks, IEEE Transactions on Vehicular Technology 69(7)(2020) 7634–7647.
[10] X. Liu, Z. Liu, B. Lai, B. Peng, T.S. Durrani, Fair Energy-Efficient Resource Optimization for Multi-UAV Enabled Internet of Things, IEEE Transactions on Vehicular Technology 72(3)(2023) 3962–3972.
[11] L. Zhang, A. Celik, S. Dang, B. Shihada, Energy-Efficient Trajectory Optimization for UAV-Assisted IoT Networks, IEEE Transactions on Mobile Computing 21(12)(2022) 4323–4337.
[12] C.H. Liu, X. Ma, X. Gao, J. Tang, Distributed Energy-Efficient Multi-UAV Navigation for Long-Term Communication Coverage by Deep Reinforcement Learning, IEEE Transactions on Mobile Computing 19(6)(2020) 1274–1285.
[13] N. Lin, Y. Fan, L. Zhao, X. Li, M. Guizani, GREEN: A Global Energy Efficiency Maximization Strategy for Multi-UAV Enabled Communication Systems, IEEE Transactions on Mobile Computing 22(12)(2023) 7104–7120.
[14] S. Lee, H. Yu, H. Lee, Multiagent Q-Learning-Based Multi-UAV Wireless Networks for Maximizing Energy Efficiency: Deployment and Power Control Strategy Design, IEEE Internet of Things Journal 9(9)(2022) 6434–6442.
[15] T. Lyu, J. An, M. Li, F. Liu, H. Xu, UAV-assisted wireless charging and data processing of power IoT devices, Computing 106(2024) 789–819.
[16] Z. Feng, Z. Na, M. Xiong, C. Ji, Multi-UAV Collaborative Wireless Communication Networks for Single Cell Edge Users, Mobile Networks and Applications 27(2022) 1578–1592.
[17] J. Lyu, Y. Zeng, R. Zhang, UAV-Aided Offloading for Cellular Hotspot, IEEE Transactions on Wireless Communications 17(6)(2018) 3988–4001.
[18] X. Li, H. Yao, J. Wang, X. Xu, C. Jiang, L. Hanzo, A Near-Optimal UAV-Aided Radio Coverage Strategy for Dense Urban Areas, IEEE Transactions on Vehicular Technology 68(9)(2019) 9098–9109.
[19] Y. Zeng, J. Xu, R. Zhang, Energy Minimization for Wireless Communication With Rotary-Wing UAV, IEEE Transactions on Wireless Communications 18(4)(2019) 2329–2345.