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Time Allocation Optimization and Trajectory Design in UAV-Assisted Energy and Spectrum Harvesting Network

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ABSTRACT The scarcity of energy resources and spectrum resources has become an urgent problem with the exponential increase of communication devices. Meanwhile, unmanned aerial vehicle (UAV) is widely used to help communication network recently due to its maneuverability and flexibility. In this paper, we consider a UAV-assisted energy and spectrum harvesting (ESH) network to better solve the spectrum and energy scarcity problem, where nearby secondary users (SUs) harvest energy from the base station (BS) and perform data transmission to the BS, while remote SUs harvest energy from both BS and UAV but only transmit data to UAV to reduce the influence of near-far problem. We propose an unaligned time allocation scheme (UTAS) in which the uplink phase and downlink phase of nearby SUs and remote SUs are unaligned to achieve more flexible time schedule, including schemes (a) and (b) in remote SUs due to the half-duplex of energy harvesting circuit. In addition, maximum throughput optimization problems are formulated for nearby SUs and remote SUs respectively to find the optimal time allocation. The optimization problem can be divided into three cases according to the relationship between practical data volume and theoretical throughput to avoid the waste of time resource. The expressions of optimal energy harvesting time and data transmission time of each node are derived. Lastly, a successive convex approximation based iterative algorithm (SCAIA) is designed to get the optimal UAV trajectory in broadcast mode. Simulation results show that the proposed UTAS can achieve better performance than traditional time allocation schemes.

INDEX TERMS Energy and spectrum harvesting network, UAV, resource allocation, trajectory design.

I. INTRODUCTION

With the rapid development of wireless communication network, the number of devices is growing at an exponential speed [1]–[5]. It is estimated that billions of devices will be connected with each other in the future, which brings much convenience to everyone daily life. However at the same time, energy consumption [6], [7] and spectrum scarcity [8] become two huge challenges as communication among large quantity pieces of equipment. First of all, battery replacement will bring huge economic cost and cause environmental pollution. Moreover, some devices may be placed in a special geographical location which is inaccessible to human beings. Thus battery power supply can not solve the problem of huge energy [9]. In addition, most intelligent devices work on unlicensed spectrum, which is vulnerable to signal collision due to spectrum congestion [10]. Therefore, how to provide energy and spectrum resource for a large number of devices becomes a hot research issue.

Energy and spectrum harvesting (ESH) technologies come up as an effective solution to the aforementioned problems. In ESH, energy harvesting mainly refers to radio-frequency (RF) energy harvesting, because RF energy is more stable and controllable compared with natural energy [11]. Spectrum harvesting depends on spectrum sensing in cognitive radio network which means secondary users (SUs) can use the

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licensed spectrum when a spectrum hole is sensed. By combining the energy harvesting and spectrum sensing, energy is self-sufficient, and the spectrum utilization is improved. Thus the problem of energy consumption and spectrum scarcity can be alleviated. ESH is widely used in sensor networks [12], IoT networks [13], D2D networks [14],etc.

Recently, the communication network assisted by unmanned aerial vehicle (UAV) has attracted extensive attention from academia and industry. In some situations where the communication links are in poor condition or obstacles exist between transmitter and receiver, UAV can play a role of relay to enhance data transmission [15]. In some areas without ground base stations (BSs), UAV can act as a mobile BS to communicate with ground nodes [16]. Due to it's maneuverability and flexibility UAV can avoid the influence of fading and shadowing to obtain line-of-sight (LoS) channels and improve the signal to noise ratio (SNR) [17]. UAV also can overcome the near-far problem caused by the fixed position of conventional BS. However, due to the fact that the UAV is battery-powered, we should attach importance to its energy consumption problem. For example, regarded as an air BS, the UAV consumes power to fly, hover and transmit signal. In addition, UAV also works in unlicensed spectrum and UAV needs to compete with other devices to obtain frequency band which exacerbates spectrum scarcity. Therefore, the trajectory and communication strategy of UAV should be well designed in order to extend the lifetime of UAV and better assist the communication system.

This paper studies the time resource allocation problem in a UAV-assisted ESH network to alleviate the near-far problem and achieve maximum throughput. In our system model, SUs is divided into the nearby SUs and the remote SUs. Compared with nearby SUs, remote SUs will harvest less energy from the BS due to the influence of path loss and fading. They will cost more power to send signals to BS, which is called the near-far problem. BS transmits energy to all SUs in the region but only nearby SUs send data back to BS. Remote SUs can receive additional energy from UAV as a supplement to reduce the influence of near-far problem [16], [18]. Moreover, in order to ensure that each SU has the opportunity to upload data, here we assume that all SUs use the idle spectrum in TDMA mode. Due to the different uplink communication objects and long distance between remote SUs and the nearby SUs, the idle spectrum can be reused. Then in order to achieve the best system performance with limited time duration, the trade off between energy harvesting time and data transmission time can be allocated reasonably [18]–[20]. The maximum throughput problem is formulated to find the optimal time allocation. Here we only study the scenario of downlink energy harvesting and spectrum sensing [21], because the BS has larger transmission power, that is more beneficial for energy harvesting and spectrum sensing.

The main contributions of this work are summarized as follows:

- We consider three cases in the UAV-assisted network according to the relationship between practical data volume and theoretical throughput. It avoids that some SUs obtain too much time resource which causes their throughput larger than actual data volume. We will part time resource from these SUs to other SUs in short supply to balance the time resource.
- We propose an unaligned time allocation scheme (UTAS) which makes the downlink and uplink time duration of nearby SUs and remote SUs different. Therefore, two different kinds of SUs can get more flexible time allocation in the UAV-assisted network according to their situation. Due to the half-duplex of energy harvesting devices, we consider schemes (a) and (b) for remote SUs and put forward scheme selection method in order to determine the communication mode of remote SUs.
- We formulate a UAV trajectory design problem after changing to the broadcast mode and solved it through a successive convex approximation based iterative algorithm (SCAIA). The optimal trajectory of the UAV-assisted network not only considers the energy harvested by all the remote SUs is optimal, but also ensures that the energy harvested by each remote SU is not insufficient. By this way, the energy harvested by SUs is relatively even and each SU has energy to transmit data.

The remaining parts of the paper are organized as follows. A summary of related works is provided in section II. Section III introduces the system model and UTAS. The time resource optimization problem of nearby SUs under three cases is formulated in Section IV. Section V studies the time scheme selection and optimization of remote SUs. UAV trajectory planning in broadcast mode and SCAIA is also proposed in this section. Section VI presents simulation results. Finally, Section VII concludes this paper. For the explanation of the parameters in this paper, please refer to TABLE 1.

II. RELATED WORK

ESH has become a research hotspot in recent years as an effective method to solve energy and spectrum resource shortage. In [22], N. Jain *et al.* propose that SU's transmitter receives the signal from PU and uses part of the signal power to harvest energy. In [23], S. Yin *et al.* divide the timeslot into energy harvesting phase, spectrum sensing phase and data transmission phase. The optimal time allocation ratio, sample number and sensing threshold are solved to get the maximal throughput. Different time-division methods are adopted in [24] and each frame is divided into sensing time slot and data transmission time slot, and SUs harvest energy using the way of dividing sub-channels at the sensing time slot. In [12], D. Zhang *et al.* define that sensor nodes can supplement the energy of sensing and transmitting data through energy harvesting. And in their later paper [25], they further define two types of nodes as battery-powered data sensor and EH-enabled spectrum sensor. The abovementioned papers

TABLE 1. Parameters summary.

parameter	description
T	The available time duration
M	The number of nearby SUs
N	The number of remote SUs
t_{be}	Energy transmission time of BS
$t_{ue}[i]$	Energy transmission time of UAV for remote SU i
t_{ue}	$\sum_{i=1}^{M} t_{ue}[i]$
$t_{bi}[i]$	Data transmission time of nearby SU i to BS
$t_{ui}[i]$	Data transmission time of remote SU i to UAV
t_f	Fly time duration of UAV in uplink or downlink
$E_{bn}[i]$	The energy harvested by nearby SU i from BS
$E_{br}[i]$	The energy harvested by remote SU i from BS
$E_u[i]$	The energy harvested by remote SU from UAV
$e_b[i]$	$P_b h d_b[i]^{-2}$
$e_u[i]$	$P_u g d_u[i]^{-2}$
P_b	Transmitting power of BS
P_u	Transmitting power of UAV
h	The channel gains between BS and SU i
g	The channel gains between UAV and SU i
$d_b[i]$	The distance between BS and SU i
$d_u[i]$	The distance between UAV and remote SU i
$P_n[i]$	The transmitting power of nearby SU i
$P_r[i]$	The transmitting power of remote SU i
$R_n[i]$	The throughput of nearby SU i
$R_r[i]$	The throughput of remote SU i
K	Data volume of each SU
T^n_{max}	Maximum throughput of nearby SUs
T^r_{max}	Maximum throughput of remote SUs
t_{sum}	$\sum_{i=1}^{\hat{M}} t_{ue}[i] + \sum_{i=1}^{\hat{M}} t_{ui}[i]$.
$(x_n[i], y_n[i])$	The coordinates of nearby SU i
$(x[i], y[i])$	The coordinates of UAV's hover point i
H	Flight altitude of UAV
L	The maximum distance from original hover point

put forward different ESH system models. Most of them consider ESH as two phases which is also adopted in this paper.

The combination of UAV and spectrum sensing focuses on optimization and system performance analysis. In [26], X. Liu *et al.* use UAV to increase the detection probability due to better channel condition. UAV plays the role of SU in the CR network. Optimal sensing radian of the UAV is found to achieve the maximum throughput. In [27], F. Shen *et al.* propose a 3-D CR network by adding UAV to perform spectrum sensing. The spatial-temporal false alarm and detection probabilities of UAV is derived. An efficient energy management solution is proposed in [28] to improve the performance of UAV-Based cognitive radio system. Optimal sensing time and transmission power are got by particle swarm optimization algorithm. In [29], W.Xu *et al.* apply cognitive radio in the UAV communication network and propose a new compressive signal processing algorithm to improve the capacity of a UAV communication network. However, the trajectory design of UAV is not considered in these paper which is important to improve UAV's performance.

The combination of UAV and energy harvesting technology focuses on resource allocation and UAV trajectory optimization. [19] studies the throughput maximization of UAV assisted wireless energy harvesting network. The optimal power and time slot allocation of single UAV and multiple UAVs in linear model and nonlinear model is discussed, and the UAV trajectory is designed. J. Xu studies the scene of a single UAV charging multiple ground nodes [16]. The "near-far" problem and a successive hover-and- fly trajectory is proposed from the optimization results. In [30], L. Xie *et al.* study the optimization problem of maximizing the throughput of nodes on the basis of [16]. They carried out joint optimization of resource allocation and trajectory design. In [18], S. Cho *et al.* use UAV to assist the charging and data transmission of remote nodes. In order to maximize the throughput, the time slots of each node are allocated, and the UAV path planning is carried out. However, these papers fail to take practical data volume of each node into consideration and only theoretical throughput maximization problem is studied. It may waste resources when practical data volume is small.

At present, the combination of spectrum harvesting, energy harvesting and UAV technology is at a premature stage. In [31], UAV is responsible for sensing spectrum, charging and transmitting information to nodes. The optimal policy structure of UAV under the maximum throughput is obtained. In [32], B. Ji *et al.* use UAV as the relay between the transmitter and the receiver of SU, UAV and SU harvest energy from PU. However, the time allocation between energy harvesting and data transmission is not considered here. And also, they didn't take into account the UAV's trajectory planning. Time allocation is always a classical problem in ESH network. The difficulty lies in how to design the time allocation scheme. In [21], the time spent in energy harvesting and data transmission is divided and each point occupies the maximum available time duration alone. In [33], S. Park follows the synchronous slotted communication protocol and each slot is divided into a sensing phase and a transmission phase. Energy harvesting takes place according to energy arrival rate. On the other hand, since UAV is also an energy-limited device, it is necessary to plan its trajectory. The difficulty of trajectory optimization is that the optimization problem is not convex. Traditional, it can be solved by mathematical methods such as successive convex approximation (SCA) [34]. Recently, machine learning(ML) has been widely used in UAV trajectory optimization [35]. In addition, the above two articles only consider one SU. We study the UAV assisted ESH network when multiple SUs is taken into consideration, and the time allocation scheme and UAV trajectory are optimized.

III. SYSTEM MODEL

In this section, we consider an ESH network with a flying UAV acting as mobile BS to fix the near-far problem. As shown in Fig. 1, after sensing an idle spectrum, all $M + N$ SUs in the BS-based energy harvesting zone can obtain energy from the BS as a supplement. However, only M remote SUs which suffer from severe path loss can receive additional energy from UAV. After harvesting enough energy, these remote SUs transmit data to UAV instead of BS due to better channel state, and other SUs (nearby SUs) send data to

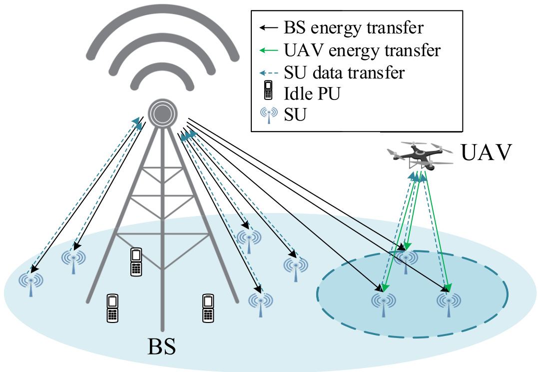

FIGURE 1. The system model of UAV-assisted ESH network with nearby SUs communicating with BS and remote SUs communicating with UAV.

BS at the same time. Even though UAV is an energy-limited equipment, its energy consumption mainly focuses on flight and hovering, and the energy consumption in communication is relatively small [36], [37]. Therefore, taking the UAV as the energy source will not have a great impact on its working time.

The UAV follows the successive hover-and-fly trajectory design proposed in [16], and the hovering points are directly above each remote SU. By this way, the communication channel between UAV and the remote SUs can obtain the least path loss thus achieving the best channel link. UAV takes off from the first remote SU, and travels through all SUs in this region. UAV hovers over each point for a period of time to transfer wireless energy. Afterwards, UAV retraces its original route and receives data instead when hovering over each remote SUs. When SU is in the spectrum sensing stage, UAV can fly back to the BS for data unloading and power replenishment.

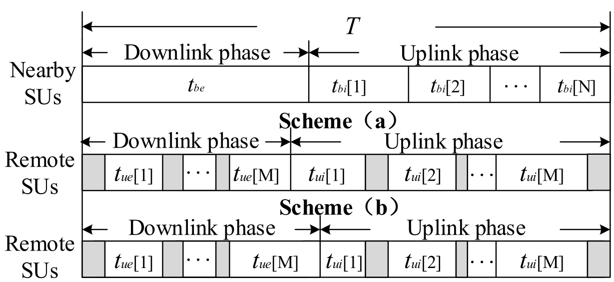

FIGURE 2. UTAS of nearby SUs and remote SUs with different uplink and downlink duration.

A. TIME ALLOCATION

Fig. 2 shows the UTAS of the UAV-assisted ESH network. When an idle spectrum is sensed, T is a constant value over a given channel [25]. The whole time period T is divided into two phases named the downlink phase and the uplink phase. Nearby SUs and remote SUs have different uplink and downlink time duration due to different communication objects and they can reuse the idle channel due to distance. In the downlink phase, BS performs energy signal broadcasting within transmitting time t_{be} to all SUs in the region. Meanwhile, UAV flies to each hover point and conducts energy transmission only for remote SUs and the energy harvesting time of each remote SU is $t_{ue}[i]$, $(i = 1, 2, \ldots, M)$.

In the uplink phase, N nearby SUs send data to BS following TDMA protocol and the information transmission time of each SU is $t_{bi}[i]$, $(i = 1, 2, \ldots, N)$. Remote SUs transfer uplink data each during $t_{ui}[i]$, $(i = 1, 2, \ldots, M)$, and the corresponding time constraints are

$$\sum_{i=1}^{N} t_{bi}[i] + t_{be} \leq T, \tag{1}$$

$$\sum_{i=1}^{M} t_{ui}[i] + t_{ue} + 2t_f \leq T, \tag{2}$$

where t_{ue} is $\sum_{i=1}^{M} t_{ue}[i]$. t_f is the grey part in Figure 2 and it is the same in both uplink and downlink phase due to UAV following the same path back and forth. The value of t_f is determined by the distance between remote SUs and flight speed of UAV, thus it will decrease with the decrease of M. In the case that the available time T is short, t_f decreases accordingly which means UAV will charge less remote SUs.

B. DOWNLINK ENERGY HARVESTING MODEL

In the downlink phase, BS charges all $M+N$ SUs in the area. And the energy harvested by each nearby SU i is given as

$$E_{bn}[i] = t_{be} P_b h d_b[i]^{-2}, \quad i = 1, 2, \ldots, N. \tag{3}$$

As shown in Fig.2, the actual charging time of remote SUs from BS is $min\{t_{be}, t_{ue} + t_f\}$ due to half-duplex property of most energy harvesting device [38]. In scheme (a) when remote SUs is ready to perform data transmission, BS carries on energy broadcasting but remote SUs can't harvest this part of energy. Thus the energy harvested by each remote SU from the BS in time allocation scheme (a) and (b) separately is

$$E_{br}[i] = \begin{cases} (t_{ue} + t_f) P_b h d_b[i]^{-2}, & t_{ue} + t_f \leq t_{be} \\ t_{be} P_b h d_b[i]^{-2}, & t_{be} \leq t_{ue} + t_f, \end{cases} \tag{4}$$

where P_b denotes the transmitting power of BS, h is the channel gains between BS and SU i including transmitting antenna gain of BS and receiving antenna gain of SUs, $d_b[i]$ is the distance between BS and SU i.

UAV only powers M remote SUs, And the energy harvested by each remote SU from the UAV is

$$E_u[i] = t_{ue}[i] P_u g d_u[i]^{-2}, \quad i = 1, 2, \ldots, M, \tag{5}$$

where P_u indicates transmitting power of UAV, g is the channel gains between UAV and SU i including transmitting antenna gain of UAV and receiving antenna gain of nodes, $d_u[i]$ is the distance between UAV and SU i. Because UAV hovers directly above each SU, so $d_u[i]$ equals to the flight height of UAV. We assume that the values of P_b and P_u here have already multiplied by the energy conversion efficiency factor. For the convenience of writing, we define $P_b h d_b[i]^{-2}$ as $e_b[i]$ and $P_u g d_u[i]^{-2}$ as $e_u[i]$.

C. UPLINK DATA TRANSMISSION MODEL

In the uplink phase, SUs use the harvested energy to transfer wireless information, and the transmitting power of nearby SUs and remotes SUs are given as

$$P_n[i] = \frac{E_{bn}[i]}{t_{bi}[i]}, \quad i = 1, 2, \ldots, N, \tag{6}$$

$$P_r[i] = \frac{E_{br}[i] + E_u[i]}{t_{ui}[i]}, \quad i = 1, 2, \ldots, M. \tag{7}$$

Thus the throughput of these two kinds of SUs are expressed as

$$R_n[i] = t_{bi}[i] ln(1 + \frac{P_n[i]}{\sigma^2}), \quad i = 1, 2, \ldots, N, \tag{8}$$

$$R_r[i] = t_{ui}[i] ln(1 + \frac{P_r[i]}{\sigma^2}), \quad i = 1, 2, \ldots, M. \tag{9}$$

The throughput mentioned above refers to the throughput of the SU's transmitter. And the throughput expression in our system model is not multiplied by bandwidth so it is the throughput per bandwidth. For the convenience of calculation, we take its unit as nats.

IV. TIME ALLOCATION OPTIMIZATION OF NEARBY SU

In this section, we obtain the maximum throughout of nearby SUs by optimizing energy transmission time t_{be} and information transmission time $t_{bi}[i]$. Due to different numerical relationship between the data volume K and throughput of each SU, optimization problem is divided into three cases.

A. CASE I: WHEN $K \geq T^n_{max}$

After harvesting enough energy from BS, $M - N$ nearby SUs perform uplink information transmission. Increasing charging time t_{be} will enhance energy level thus obtains higher transmission power and throughout. However, more harvesting time means less information transmission time due to fixed total duration T. Thus there exists a trade-off between t_{be}, and $t_{bi}[i]$. Besides, each transmission time $t_{bi}[i]$ for $i = 1, 2, \ldots, N$ also need reasonable planning, and the joint optimization problem is expressed as

$$\begin{aligned}
P1: \quad & \max_{t_{be}, t_{bi}[i]} \sum_{i=1}^{N} R_n[i] \\
& s.t.\ C1: \sum_{i=1}^{N} t_{bi}[i] + t_{be} \leq T \\
& \quad C2: R_n[i] \leq K, \quad i = 1, 2, \ldots, N \\
& \quad C3: t_{be} \geq 0 \\
& \quad C4: t_{bi}[i] \geq 0, \quad i = 1, 2, \ldots, N.
\end{aligned} \tag{10}$$

C1, C3 and C4 are time constraints which follow the time allocation scheme in section II. C2 means that the throughput of each SU has an upper limit. SUs are randomly distributed in the environment to collect data and the amount of data stored is almost the same in each SU, thus we assume each SU has K nats data to transmit which is also the upper limit of throughput. In the time allocation problem without considering the amount of data storage, the SUs with good channel conditions can often obtain more resources. Therefore, C2 avoids the waste of time resource caused by this kind of allocation strategy.

Problem P1 is a convex problem because the Hessian matrix of each item in the summation is semidefinite cite4. Thus we can use convex optimization techniques to solve the problem, and the lagrangian of P1 is

$$\begin{aligned}
L(t_{be}, t_{bi}[i], \lambda, \boldsymbol{\mu}, \nu, \boldsymbol{\xi}) = & \sum_{i=1}^{N} R_n[i] + \lambda(\sum_{i=1}^{N} t_{bi}[i] + t_{be} - T) \\
& + \sum_{i=1}^{N} \mu[i](R_n[i] - K) \\
& - \nu t_{be} - \sum_{i=1}^{N} \xi[i] t_{bi}[i],
\end{aligned} \tag{11}$$

where λ, $\boldsymbol{\mu}$, ν, $\boldsymbol{\xi}$ are Lagrange multipliers. Bold letters represent vectors and lagrange dual function is defined as

$$g(\lambda, \boldsymbol{\mu}, \nu, \boldsymbol{\xi}) = \inf L(t_{be}, t_{bi}[i], \lambda, \boldsymbol{\mu}, \nu, \boldsymbol{\xi}). \tag{12}$$

The largest throughput of all nearby SUs is defined as T^n_{max}. In case I, we have $K \geq T^n_{max}$, which means under current time optimization scheme, C2 always holds and the throughput of all points is lower than the data volume, thus the corresponding Lagrange multipliers $\boldsymbol{\mu} = 0$. Besides,we have$\lambda \neq 0$, $\nu = 0$, $\boldsymbol{\xi} = 0$.

Proposition 1: The optimal t_{be} and $t_{bi}[i]$ of P1 in case I of nearby SUs are

$$t^*_{be} = \frac{xT\sigma^2}{\sum_{i=1}^{N} e_b[i] + x\sigma^2}, \tag{13}$$

$$t^*_{bi}[i] = \frac{t^*_{be} e_b[i]}{x\sigma^2}, \quad i = 1, 2, \ldots, N, \tag{14}$$

where x is the solution of $ln(1 + x) - \frac{x}{1+x} = \frac{\sum_{i=1}^{N} e_b[i]}{(1+x)\sigma^2}$.

Proof: please refer to Appendix A.

In case I, $R_n[i]$ is always less than K actually means C2 can be ignored, so the optimization result is consistent with previous researches which did n't take data volume into account. T^n_{max} and T^n_{min} is defined on this basis.

B. CASE II: WHEN $K \leq T^n_{min}$

The minimum throughput of all SUs is defined as T^n_{min}. In case II, we have $K \leq T^n_{min}$, which means the throughput of each SU under the existing optimization scheme can meet the needs of data capacity, so time resource is surplus and the actual throughput is fixed(NK) in this situation. Optimization problem changes from maximum throughput to minimum time:

$$\begin{aligned}
P2: \quad & \min_{t_{be}, t_{bi}[i]} t_{be} + \sum_{i=1}^{N} t_{bi}[i] \\
& s.t.\ C1: R_n[i] \geq K, \quad i = 1, 2, \ldots, N
\end{aligned}$$

$$C2: t_{be} \geq 0$$
$$C3: t_{bi}[i] \geq 0, \quad i = 1, 2, \ldots, N, \quad (15)$$

C1 ensures that all data transmission is completed, and then the minimum time resources is optimized. The lagrangian of P2 is

$$L(t_{be}, t_{bi}[i], \boldsymbol{\lambda}, \mu, \boldsymbol{\nu}) = t_{be} + \sum_{i=1}^{N} t_{bi}[i] - \sum_{i=1}^{N} \lambda[i](R_n[i] - K) - \mu t_{be} - \sum_{i=1}^{N} \nu[i] t_{bi}[i], \quad (16)$$

where $\boldsymbol{\lambda}$, μ, $\boldsymbol{\nu}$ are Lagrange multipliers and bold letters represent vectors.

To get the optimal scheme, we need to calculate the solution when the partial differential of L is equal to zero. And $2N + 1$ simultaneous equations are going to be solved which requires complex calculations and can't get analytical solution. To handle this problem, we carry out relaxation on the constraint. To ensure that all SUs' throughputs are greater than K, we only need to make the minimum throughput greater than K. Setting the serial number of the SU with minimum throughput as m (according to the analysis of Case I, the furthest SU N has the minimum throughput) the new optimization problem is

$$P3: \min_{t_{be}, t_{bi}[i]} t_{be} + \sum_{i=1}^{N} t_{bi}[i]$$
$$s.t.\ C1: R_n[m] \geq K$$
$$C2: t_{be} \geq 0$$
$$C3: t_{bi}[i] \geq 0, \quad i = 1, 2, \ldots, N. \quad (17)$$

And the lagrangian turns to

$$L(t_{be}, t_{bi}[i], \lambda, \mu, \boldsymbol{\nu}) = t_{be} + \sum_{i=1}^{N} t_{bi}[i] - \lambda(R_n[m] - K) - \mu t_{be} - \sum_{i=1}^{N} \nu[i] t_{bi}[i]. \quad (18)$$

Proposition 2: The optimal t_{be} and $t_{bi}[m]$ of P3 in case II of nearby SUs are

$$t_{be}^* = \frac{x t_{bi}^*[m]}{e_b[m]}, \quad (19)$$
$$t_{bi}^*[m] = \frac{K}{ln(1+x)}, \quad (20)$$

where x is the solution of $ln(1+x) - \frac{x}{1+x} = \frac{e_b[m]}{(1+x)\sigma^2}$. when t_{be} is fixed, the information transmission time for other nearby SUs is the solution of the equation:

$$t_{bi}[i] ln(1 + \frac{t_{be} P_b h d_b[i]^{-2}}{t_{bi}[i]\sigma^2}) = K. \quad (21)$$

Proof: please refer to Appendix B.

C. CASE III: WHEN $T_{min}^n \leq K \leq T_{max}^n$

In case III we have $T_{min}^n \leq K \leq T_{max}^n$, which means some SUs have obtained surplus time resources while some other SUs have not allocated enough time, thus time resource needs to be reallocated. Case III is a combination of case I and case II, by defining $\hat{N}$ as the number of SUs whose throughput is greater than K, the optimization problem is

$$P4: \max_{t_{be}, t_{bi}[i]} \sum_{i=\hat{N}+1}^{N} R_n[i]$$
$$s.t.\ C1: \sum_{i=\hat{N}+1}^{N} t_{bi}[i] + t_{be} \leq T - \sum_{i=1}^{\hat{N}} t_{bi}[i]$$
$$C2: R_n[i] \leq K, \quad i = \hat{N}+1, \ldots, N$$
$$C3: R_n[i] = K, \quad i = 1, 2, \ldots, \hat{N}$$
$$C4: t_{be} \geq 0$$
$$C5: t_{bi}[i] \geq 0, \quad i = 1, 2, \ldots, N. \quad (22)$$

The maximum throughput of $\hat{N}$ SUs is fixed at $\hat{N}K$, thus we only need to maximize the throughput of the remaining SUs. C1 is new time constraints which emphasizes time resources available to the remaining SUs. C3 refers to that the time resource allocated to $\hat{N}$ SUs is exactly enough to meet K nats data transmission requirements, so as to spare as many resources as possible to the remaining SUs. C3 only constrains t_{be} and $t_{bi}[i], i = 1, 2, \ldots, \hat{N}$. The lagrangian of P4 is

$$L(t_{be}, t_{bi}[i], \lambda, \boldsymbol{\mu}, \boldsymbol{\nu}, \xi, \boldsymbol{\rho}) = \sum_{i=\hat{N}+1}^{N} R_n[i] + \lambda(\sum_{i=\hat{N}+1}^{N} t_{bi}[i] + t_{be} - T + \sum_{i=1}^{\hat{N}} t_{bi}[i]) + \sum_{i=\hat{N}+1}^{N} \mu[i](R_n[i] - K) + \sum_{i=1}^{\hat{N}} \nu[i](R_n[i] - K) - \xi t_{be} - \sum_{i=1}^{N} \rho[i] t_{bi}[i], \quad (23)$$

where λ, $\boldsymbol{\mu}$, $\boldsymbol{\nu}$, ξ, $\boldsymbol{\rho}$ are lagrange multipliers and bold letters represent vectors.

Proposition 3: t_{be}^* is the solution of following equations

$$ln(1+x) - \frac{x}{1+x} = \frac{\sum_{i=\hat{N}+1}^{N} e_b[i]}{(1+x)\sigma^2}, \quad (24)$$
$$\frac{t_{be} \sum_{i=\hat{N}+1}^{N} e_b[i]}{T - t_{be} - \sum_{i=1}^{\hat{N}} t_{bi}[i]} = x, \quad (25)$$
$$t_{bi}[i] ln(1 + \frac{t_{be} e_b[i]}{t_{bi}[i]\sigma^2}) = K, \quad i = 1, 2, \ldots, \hat{N}. \quad (26)$$

The optimal information transmission time for $i = \hat{N} + 1, \ldots, N$ SUs is

$$t_{bi}^*[i] = \frac{t_{be}^* e_b[i]}{x\sigma^2}, \quad i = \hat{N} + 1, \ldots, N. \quad (27)$$

And the information transmission time for other SUs$(i = 1, 2, \ldots, \hat{N})$ *is the solution of the equation* $t_{bi}[i]ln(1 + \frac{t_{be}e_b[i]}{t_{bi}[i]\sigma^2}) = K$.
The proof process is similar to proposition1 and 2 and will not be repeated afterwards.

V. TIME ALLOCATION OPTIMIZATION OF REMOTE SU AND UAV TRAJECTORY DESIGN

In this section, the maximum throughput of remote SUs is found by optimizing $t_{ue}[i]$ and $t_{ui}[i]$. Due to the received energy from the BS takes different time duration, the optimization problem is discussed separately. Each time allocation scheme also have three cases as shown in Section IV.

A. OPTIMIZATION OF TIME ALLOCATION SCHEME (A) AND (B)

In order to further optimize the throughput, we adopt a more flexible time allocation scheme compared with [18], which means the uplink and downlink time blocks of nearby SUs and remote SUs are not strictly aligned. For nearby SUs, the energy source is unique, and the uplink and downlink phase arrangements are independent. While for remote SUs, they not only receive energy from the BS, but also from the UAV. Therefore, the uplink time duration of nearby nodes t_{be} affects the actual throughput model and optimization results of remote SUs and in case I when $K \geq T^r_{max}$, the optimization problem is

$$
\begin{aligned}
P5: \quad & \max_{t_{ue}[i], t_{ui}[i]} \sum_{i=1}^{M} R_r[i] \\
& s.t.\ C1: \sum_{i=1}^{M} t_{ui}[i] + \sum_{i=1}^{M} t_{ue}[i] \leq T - 2tf \\
& \quad C2: R_{r1}[i] \leq K, \quad i = 1, 2, \ldots, M \\
& \quad C3: t_{ue}[i] \geq 0, \quad i = 1, 2, \ldots, M \\
& \quad C4: t_{ui}[i] \geq 0, \quad i = 1, 2, \ldots, M. \qquad (28)
\end{aligned}
$$

Under the situation that $t_{ue} + t_f \leq t_{be}$, remote SUs turn from energy harvesting mode to data transmission mode after the UAV completes the energy transmission. However, the BS still broadcasts energy signal at the same time, thus remote SUs can't get all energy from BS. In this instance, expressions of objective function and constraints do not contain t_{be} and the model becomes independent. The optimization problem is solved following the same convex optimization method in section IV and the calculation process is omitted in this section.

Proposition 4: The optimal t_{ue} *and* $t_{ui}[i]$ *in case I of remote SUs when* $t_{ue} + t_f \leq t_{be}$ *are*

$$
t^*_{ue} = \frac{\sum_{i=1}^{M} x[i](T - 2t_f)\sigma^2 - t_f \sum_{i=1}^{M} e_b[i]}{\sum_{i=1}^{M} e_b[i] + e_u[i] + \sum_{i=1}^{M} x[i]\sigma^2}, \qquad (29)
$$

$$
t^*_{ui}[i] = \frac{E_{br}[i] + E_u[i]}{x[i]\sigma^2}, \qquad (30)
$$

where $x[i]$ *comes from the equation*

$$
ln(1 + x[i]) - \frac{x[i]}{1 + x[i]} = \frac{e_u[i] + e_b[i]}{(1 + x[i])\sigma^2}, \quad i = 1, 2, \ldots, M. \qquad (31)
$$

In the process of solving the optimization problem, we find that optimal throughput is related to the sum of $t_{ue}[i]$. Therefore, when t^*_{ue} is found, no matter how time is allocated to each SU, the result is optimal anyway. The results here can be used as a basis to judge the relationship between $t_{ue} + t_f$ and t_{be}.

Proposition 5: The optimal t_{ue} *and* $t_{ui}[i]$ *in case I of remote SUs when* $t_{be} \leq t_{ue} + t_f$ *are*

$$
t^*_{ue} = \frac{x(T - 2t_f)\sigma^2 - \sum_{i=1}^{M} E_{br}[i]}{e_u[i] + x\sigma^2}, \qquad (32)
$$

$$
t^*_{ui}[i] = \frac{E_{br}[i] + t^*_{ue}[i]e_u[i]}{x\sigma^2}, \qquad (33)
$$

where x comes from the equation

$$
ln(1 + x) - \frac{x}{1 + x} = \frac{e_u[i]}{(1 + x)\sigma^2}, \quad i = 1, 2, \ldots, M. \qquad (34)
$$

In case II when $K \leq T^r_{min}$, all MK nats data can be transferred and the objective function turns from maximizing throughput to minimizing time resource. The new optimization problem is

$$
\begin{aligned}
P6: \quad & \min_{t_{ue}[i], t_{ui}[i]} \sum_{iN+1}^{M} t_{ue}[i] + \sum_{i=1}^{M} t_{ui}[i] \\
& s.t.\ C1: R_r[i] \geq K, \quad i = 1, 2, \ldots, M \\
& \quad C3: t_{ue}[i] \geq 0, \quad i = 1, 2, \ldots, M \\
& \quad C4: t_{ui}[i] \geq 0, \quad i = 1, 2 \ldots, M. \qquad (35)
\end{aligned}
$$

When $t_{ue} + t_f \leq t_{be}$, C1 is unrelated to BS and the result doesn't contain t_{be}.

Proposition 6: The optimal $t_{ue}[i]$ *and* $t_{ui}[i]$ *in case II of remote SUs when* $t_{ue} + t_f \leq t_{be}$ *are*

$$
t^*_{ui}[i] = \frac{K}{ln(1 + x[i])}, \qquad (36)
$$

$$
t^*_{ue} = \frac{\sum_{i=1}^{M} x[i] \sum_{i=1}^{M} t^*_{ui}[i] - t_f \sum_{i=1}^{M} e_b[i]}{e_u[i] + \sum_{i=1}^{M} e_b[i]}, \qquad (37)
$$

$$
t^*_{ue}[i] = \frac{x[i]t^*_{ui}[i] - (t^*_{ue} + t_f)e_b[i]}{e_u[i]}, \qquad (38)
$$

where $x[i]$ *is the same* $x[i]$ *from equation (31). Whether* $t_{ue}+t_f$ *is smaller than* t_{be} *or not is determined by solution(37).*

Proposition 7: The optimal $t_{ue}[i]$ *and* $t_{ui}[i]$ *in case II of remote SUs when* $t_{be} \leq t_{ue} + t_f$ *are*

$$
t^*_{ui}[i] = \frac{K}{ln(1 + x)}, \qquad (39)
$$

$$
t^*_{ue}[i] = \frac{xt_{ui}[i] - E_{br}[i]}{e_u[i]}, \qquad (40)
$$

where x is the same x in (34).

In case III when $T^r_{min} \leq K \leq T^r_{max}$, assuming that $\hat{M}$ remote SUs have throughput larger than their amount of date

K which lead to a waste of time. The new optimization problem P7 spares time from these $\hat{M}$ remote SUs to the remaining $M-\hat{M}$ SUs.

$$\begin{aligned} P7:\ &\max_{t_{ue}[i],t_{ui}[i]} \sum_{i=\hat{M}+1}^{M} R_r[i] \\ &s.t.\ C1: \sum_{i=\hat{M}+1}^{M} t_{ui}[i] + \sum_{i=\hat{M}+1}^{M} t_{ue}[i] \\ &\quad \le T-2tf-t_{sum} \\ &\quad C2: R_r[i] \le K, \quad i=\hat{M}+1,\ldots,M \\ &\quad C3: t_{ue}[i] \ge 0, \quad i=\hat{M}+1,\ldots,M \\ &\quad C4: t_{ui}[i] \ge 0, \quad i=\hat{M}+1,\ldots,M, \end{aligned} \tag{41}$$

t_{sum} here refers to $\sum_{i=1}^{\hat{M}} t_{ue}[i] + \sum_{i=1}^{\hat{M}} t_{ui}[i]$. Different from P4 of nearby SUs, only SUs with throughput less than K are optimized in P7 due to each SU has its own energy harvesting time $t_{ue}[i]$. And other $\hat{M}$ SUs follow the results (38) and (39) from P6 which aims to spare as much time as possible. Thus P7 is similar to P4, only the number of SUs and disposable time is reduced.

Proposition 8: The optimal $t_{ue}[i]$ and $t_{ui}[i]$ for $i=\hat{M}+1,\ldots,M$ in case III of remote SUs when $t_{ue}+t_f \le t_{be}$ are

$$\sum_{i=\hat{M}+1}^{M} t_{ue}^*[i] = \frac{\sum_{i=\hat{M}+1}^{M} x[i](T-2t_f-t_{sum})\sigma^2 - t_f\sum_{i=\hat{M}+1}^{M} e_b[i]}{\sum_{i=\hat{M}+1}^{M} e_b[i] + e_u[i] + \sum_{i=\hat{M}+1}^{M} x[i]\sigma^2}, \tag{42}$$

$$t_{ui}^*[i] = \frac{E_{br}[i]+E_u[i]}{x[i]\sigma^2}. \tag{43}$$

Proposition 9: The optimal $t_{ue}[i]$ and $t_{ui}[i]$ for $i=\hat{M}+1,\ldots,M$ in case III of remote SUs when $t_{be} \le t_{ue}+t_f$ are

$$\sum_{i=\hat{M}+1}^{M} t_{ue}^*[i] = \frac{x(T-2t_f-t_{sum})\sigma^2 - \sum_{i=\hat{M}+1}^{M} E_{br}[i]}{e_u[i]+x\sigma^2}, \tag{44}$$

$$t_{ui}^*[i] = \frac{E_{br}[i]+t_{ue}^*[i]e_u[i]}{x\sigma^2}. \tag{45}$$

B. UAV TRAJECTORY DESIGN

In previous section, we followed the charging method adopted in [18] and nodes harvest energy from UAV one-by-one in unicast mode, which is applicable to the scenarios where the transmission power of UAV is small and the coverage region is very limited. But in fact, many papers also study the model of UAV charge all nodes in broadcast mode [16], [19], [39]. Here, we aim to maximize the energy harvested by remote SUs and find the optimal trajectory when the coverage of UAV is sufficient.

Here, we still use the previously mentioned hover-and- fly trajectory. We assume that the number of hovering points remains the same that is equal to the number of remote SUs M. Furthermore, the distance between hovering points and each node cannot be too far, so as to ensure that each node can be charged by UAV at a relatively short distance. Supposed that the coordinate of hover point i is $(x[i], y[i])$, and the coordinate of remote SUs i is $(x_n[i], y_n[i])$. Combined with the energy harvesting time $t_{ue}[i]$ in section V, the optimal trajectory of UAV with the maximum harvested energy can be obtained as follows:

$$\begin{aligned} P8:\ &\max_{x[i],y[i]} E_u(x[i], y[i]) \\ &s.t.\ C1: (x[i]-x_n[i])^2 + (y[i]-y_n[i])^2 \le L, \\ &\qquad i=1,2,\ldots M, \end{aligned} \tag{46}$$

in which

$$E_u(x[i], y[i]) = \sum_{j=1}^{M} \frac{t_{ue}[i]P_u g}{(x[i]-x_n[j])^2 + (y[]-y_n[j])^2 + H^2}, \tag{47}$$

where H is the flight altitude of UAV. It represents sum energy harvested form UAV by remote SUs. L is the maximum distance from original hover point which is also the location of remote SUs. C1 restricts the hover point from being too far away from the ground SU, so as to avoid the energy harvested by some SUs being particularly insufficient. In broadcast mode, if the hover point of UAV is very close to a certain SU and far away from other SUs, it will cause certain node to harvest too much energy, but the total energy harvested will not be optimal. So there is a trade-off between the distance of each hover point from one certain node and other nodes. The objective function of P8 is not a concave function, so P8 can not be solved by convex optimization tools. By using SCA, the first order Taylor expansion of the objective function can be obtained to approximate the objective function and the first-order Taylor expansion at $(\hat{x}[i], \hat{y}[i])$ is

$$\begin{aligned} E_u(x[i], y[i]) = &E_u(\hat{x}[i], \hat{y}[i]) \\ &+ (x[i]-\hat{x}[i])E_u'(\hat{x}[i], \hat{y}[i]) \\ &+ (y[i]-\hat{y}[i])E_u'(\hat{x}[i], \hat{y}[i]). \end{aligned} \tag{48}$$

Thus the objective function becomes an affine function, and we can solve it by CVX method. Based on this, SCA-based iterative algorithm (SCAIA) for trajectory design is designed in Algorithm 1 to find the optimal hover point.

The optimization result is shown in Figure 3. We can see that the hover point is closer after optimization. This is because the UAV wants to be as close to other remote SUs as possible when charging the closest remote SU.

VI. SIMULATION RESULTS

In this section, we simulate the optimal results of the nearby SUs and the remote SUs, and analyze the simulation results compared with the optimization results in the previous paper [18]. We set up $P_b = 40W$, $P_u = 5W$, $H = 3m$, $t_f = 20s$, $g = h = 30dBm$ and the simulation area is assumed to be a rectangle of $100 * 100$, in which 10 nearby SUs and 10 remote SUs are randomly distributed. The nearby

Algorithm 1 SCAIA for UAV Trajectory Optimization

Initialize $(\hat{x}[i], \hat{y}[i])$, the initial value can be set to the corresponding SU coordinates.
repeat
  Use CVX tool of MATLAB to solve P8 after transformation of objective function and the optimal coordinate is $(x^*[i], y^*[i])$.
  Updata $(\hat{x}[i], \hat{y}[i])$ according to the latest $(x^*[i], y^*[i])$
  Update coefficient in $E_u(\hat{x}[i], \hat{y}[i])$.
  Update $t_{ue}[i]$ according to the optimal solution in part A under the corresponding case and time allocation scheme.
until
The algorithm converges and the optimal $(\hat{x}[i], \hat{y}[i])$ is found with the maximum energy harvested.

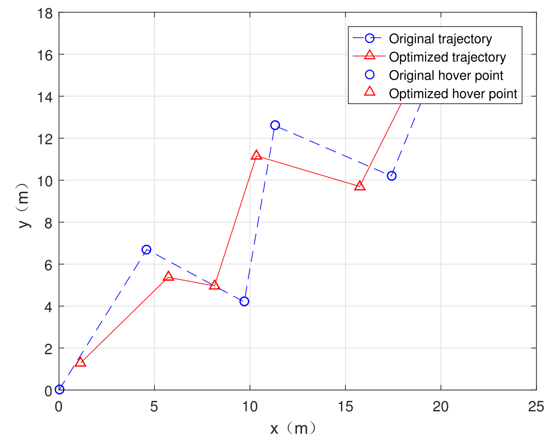

FIGURE 3. UAV trajectory design when energy harvested is maximum.

SUs and remote SUs is divided according to the distance from BS. In case III of this paper, K is set to make the theoretical throughput of the first two nearby or remote SUs exceed the actual data volume.

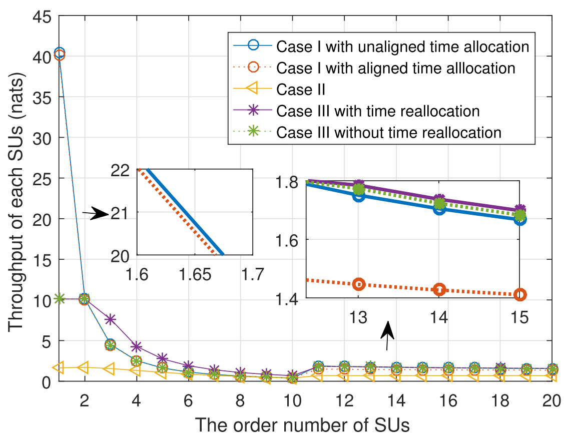

FIGURE 4. The throughput of each SU when $T = 100s$.

The throughput of each SU is shown in Figure 4 (per unit bandwidth) when $T = 100s$. We can see that the throughput decreases with the increase of SU's distance from BS. This is not only due to path loss, but also because more resources are allocated to the SU close to BS. The throughput increases after SU 10 which reflects the performance improvement of remote SU under the assistance of UAV. Different from nearby SUs, the throughput of each remote SU is relatively close, that is because they all receive little energy from BS, and the energy harvested from UAV is very average. In case I, the data volume in each SU is large enough, so time resources are allocated to the first node as much as possible to ensure system performance. Our UTAS is better than the aligned time allocation scheme. This is because nearby SUs and remote SUs can separately optimize their energy harvesting time and data transmission time and their time allocation results are not limited by each other's values. In case II, because the data volume is very small, the nodes can complete all data transmission without consuming 100 seconds. In case III we can see that by the time reallocation method which spares the surplus time from the former SUs to the later SUs, the throughput is improved.

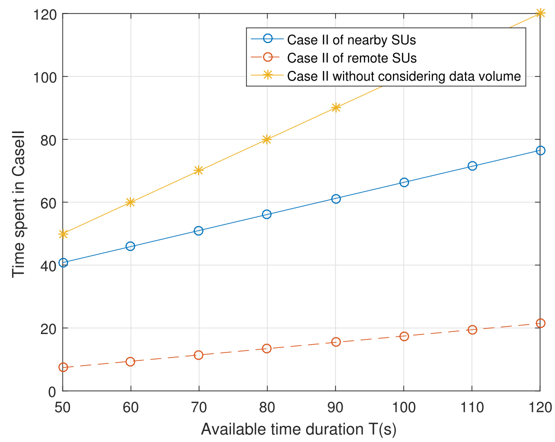

FIGURE 5. Time spent in case II of nearby SUs and remote SUs.

Figure 5 shows the time spent in case II when T ranges from 50s to 120s under the minimum time duration optimization problem. $K = 0.4nats$ in both nearby SUs and remote SUs. We can see that nearby SU consumes more time than remote SUs. That is because all nearby SUs share the same energy harvesting time t_{be}, but remote SUs have their own charging time. The charging time of nearby SUs is forced to extend because it is necessary to guarantee the SU with the worst performance (that is the farthest SU) to transmit K nats information.

Figure 6 shows the total throughput of the nearby SUs when T ranges from 50s to 120s. Since the data volume K is unlimited, case I has the largest total throughput. In the same way, case II has the lowest K, so the total throughput is the smallest. However, case II does not use up all the time resources and causes no resource waste. It can be seen that, due to the redundant resource reallocation of the first two SUs, case III in this paper obtains better system performance than case III in the previous paper. However, due to the fact that the first two nodes are very close to the BS and the theoretical throughput is very large, the throughput of case III still does not exceed case I.

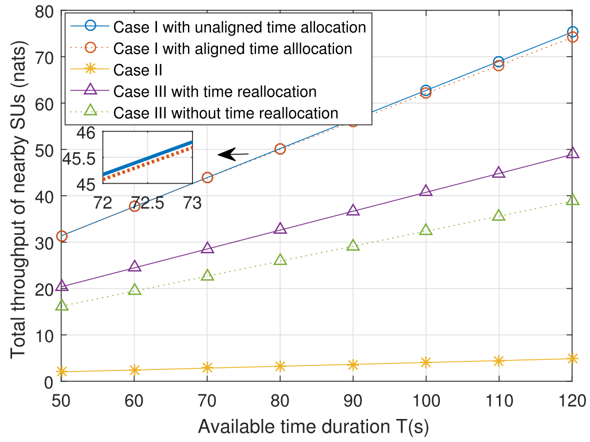

FIGURE 6. Total throughput of nearby SUs.

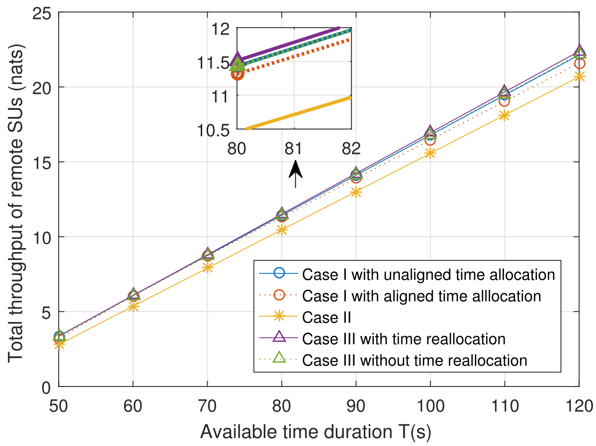

FIGURE 7. Total throughput of remote SUs.

The total throughput of the remote SUs is shown in Figure 7. The throughput of remote SUs and the gap between T^n_{min} and T^n_{max} is small, so the four lines in Figure 7 are close to each other. Because of this, in case III, after reallocation of redundant time resources, not only the performance is better than that of the previous paper, but also exceeds the throughput of case I. It can be seen that the time resource allocation scheme proposed in this paper achieves better system performance.

VII. CONCLUSION

In this paper, we study the time allocation and trajectory design in UAV-assisted ESH network. We consider the practical data volume as optimizing the throughput of the system, and divide the optimization problem into three cases to reduce the waste of time. Moreover, we propose an UTAS, where the uplink and downlink phases of nearby SUs and remote SUs are unaligned, to achieve a more flexible time schedule. In UTAS, we consider schemes (a) and (b) for remote SUs due to its half-duplex. Finally, we propose a SCAIA to design the trajectory of UAV with the objective of maximizing the energy harvested by all remote SUs. The simulation results show the superiority of our time allocation scheme compared to aligned time allocation and the situation without time reallocation. In the future, we will study the spectrum allocation problem in UAV-assisted ESH network where false alarm and detection probability is taken into consideration.

APPENDIX A

To obtain the optimal answer, the partial differential of (11) is calculated as

$$\begin{aligned}\frac{\partial L}{\partial t_{be}} &= \sum_{i=1}^{N} \frac{e_b[i]}{(1+\frac{E_{bn}[i]}{t_{bi}[i]\sigma^2})\sigma^2} + \lambda \\ &\quad + \sum_{i=1}^{N} \mu[i] \frac{e_b[i]}{(1+\frac{E_{bn}[i]}{t_{bi}[i]\sigma^2})\sigma^2} - \nu, \qquad (49)\\ \frac{\partial L}{\partial t_{bi}[i]} &= (1+\mu[i])(ln(1+\frac{E_{bn}[i]}{t_{bi}[i]\sigma^2}) \\ &\quad - \frac{1}{1+\frac{E_{bn}[i]}{t_{bi}[i]\sigma^2}} \cdot \frac{E_{bn}[i]}{t_{bi}[i]\sigma^2}) + \lambda - \xi[i]. \qquad (50)\end{aligned}$$

In case I, we have $\lambda \neq 0$, $\boldsymbol{\mu} = 0$, $\nu = 0$, $\boldsymbol{\xi} = 0$,and by replacing $\frac{E_{bn}[i]}{t_{bi}[i]\sigma^2}$ with x, we get

$$ln(1+x) - \frac{x}{1+x} - \frac{\sum_{i=1}^{N} e_b[i]}{(1+x)\sigma^2} = 0. \qquad (51)$$

The function on the left of the equal sign is a monotone function about x, thus we have

$$\begin{aligned}x &= \frac{E_{bn}[1]}{t_{bi}[1]\sigma^2} = \frac{E_{bn}[2]}{t_{bi}[2]\sigma^2} = \ldots = \frac{E_{bn}[i]}{t_{bi}[i]\sigma^2} \\ &= \frac{\sum_{i=1}^{N} E_{bn}[i]}{\sum_{i=1}^{N} t_{bi}[i]\sigma^2} = \frac{\sum_{i=1}^{N} E_{bn}[i]}{(T-t_{be})\sigma^2}. \qquad (52)\end{aligned}$$

Thus we get the optimal answer as (13) and (14).

APPENDIX B

The partial differential of (18) is calculated as

$$\begin{aligned}\frac{\partial L}{\partial t_{be}} &= 1 - \lambda(\frac{e_b[m]}{(1+\frac{E_{bn}[m]}{t_{bi}[m]\sigma^2})\sigma^2}), \qquad (53)\\ \frac{\partial L}{\partial t_{bi}[i]} &= 1 - \lambda(ln(1+\frac{E_{bn}[m]}{t_{bi}[m]\sigma^2}) \\ &\quad - \frac{1}{1+\frac{E_{bn}[m]}{t_{bi}[m]\sigma^2}} \cdot \frac{E_{bn}[m]}{t_{bi}[m]\sigma^2}). \qquad (54)\end{aligned}$$

By replacing $\frac{E_{bn}[m]}{t_{bi}[m]\sigma^2}$) with x, we get

$$\begin{aligned}ln(1+x) - \frac{x}{1+x} &= \frac{e_b[m]}{1+x}, \qquad (55)\\ ln(1+x) - \frac{x}{1+x} &= \frac{e_b[m]}{1+x}, \qquad (56)\\ t_{bi}[m]ln(1+x) &= K. \qquad (57)\end{aligned}$$

Thus we get the optimal answer as (19) and (20).

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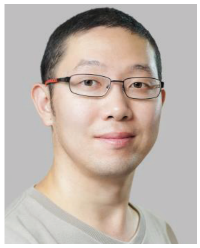

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