Wireless Powered Communication Networks Aided by an Unmanned Aerial Vehicle

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***Abstract*—This paper investigates an unmanned aerial vehicle (UAV)-aided wireless powered communication network where a mobile hybrid access point serves multiple energy-constrained ground terminals (GTs) in terms of wireless energy transfer and data collection. Specifically, to support information transmission of the GTs, the mobile UAV first transfers wireless energy in the downlink. Then, by harvesting this wireless energy, the GTs transmit their uplink information signals to the UAV in a time division multiple access manner. In this system, we jointly optimize the trajectory of the UAV and the uplink power control policy in order to maximize the minimum throughput of the GTs. By applying the concave-convex procedure, we propose an iterative algorithm which efficiently identifies a locally optimal solution. Simulation results verify the efficiency of the proposed algorithm compared to conventional schemes.**

I. Introduction

As unmanned aerial vehicle (UAV) has been implemented in various applications such as weather monitoring and traffic control [1], the usage of the UAV in wireless communication systems has also drawn great attention [2]–[7]. Unlike conventional wireless communications in which service providing nodes are assumed to be fixed at given locations, UAV-enabled systems can be applicable to impermanent events owing to the cost-efficiency of deployment and the tolerance on network fluidity. Moreover, the mobility of UAV enables condition of communication channels better, which results in the higher system throughput.

In the meantime, energy harvesting (EH) techniques based on radio frequency (RF) signals have been considered as promising solutions for extending lifetime of battery-limited wireless devices. Due to the dual usage of the RF signals, namely wireless energy transfer (WET) and wireless information transmission (WIT), the RF-based EH methods have been jointly studied with wireless communications, and wireless powered communication networks (WPCN) protocols have been widely investigated in recent literature [8]–[14]. Particularly, in the WPCN, a hybrid access point (H-AP) transfers wireless energy to energy-constrained devices in the downlink WET phase, and in the subsequent uplink WIT phase, the devices transmit their information signals to the H-AP by using the harvested energy. Most of the existing works on the WPCN have been restricted to a static H-AP setup, and thus it would suffer from the 'doubly near-far problem' [8] induced by the doubly distance-dependent signal attenuation both in the downlink and the uplink.

To tackle this issue, there have been several works combining the mobile vehicle techniques and the WPCN in which a moving H-AP supports the WET and the WIT of the devices. By moving the H-AP towards the devices, we can efficiently mitigate the doubly near-far problem of the traditional WPCN [15]–[17]. In [15] and [16], magnetic resonant based WET was considered, and thus the H-AP can only charge nearby nodes when it stops at a fixed position. The authors in [17] introduced UAV techniques to the WPCN by utilizing the RF WET methods, but they only considered a single-user case under a fixed line trajectory setup.

In this paper, we investigate UAV-aided WPCN where multiple energy-constrained GTs are served by a UAV with non-fixed trajectories. In this system, the UAV behaves as an H-AP in conventional WPCN so that it broadcasts RF energy signal to the GTs and decodes the information sent by the GTs in a time division multiple access (TDMA) manner where the WET of the UAV and the WIT at the GTs are performed over orthogonal time resources. We aim to jointly optimize the trajectory of the UAV and the uplink power control at the GTs so that the minimum throughput among the GTs is maximized. In order to solve this non-convex problem, we propose an iterative algorithm based on the concave-convex procedure (CCCP) framework [18] [19].

The rest of this paper is organized as follows. Section II explains a system model for UAV WPCNs and formulates a minimum throughput maximization problem. In Sections III, we propose an efficient algorithm for the optimization problem. Section IV presents simulation results of the proposed algorithm and compares performance with conventional schemes. Finally, the paper is terminated in Section V with conclusions.

Throughout this paper, normal and boldface letters represent scalar quantities and column vectors, respectively. We denote real numbers and the Euclidean space of dimension n as $\mathbb{R}$ and $\mathbb{R}^n$, respectively, and $(\cdot)^T$ indicates the transpose operation. Also, $|\cdot|$ and $\|\cdot\|$ stand for the absolute value and the 2-norm, respectively.

II. System Model

As shown in Fig. 1, we consider a UAV-aided WPCN where K single antenna GTs are supported by a single antenna UAV which has the ability to transmit and receive the RF signals. It is assumed that the GTs do not have any embedded power

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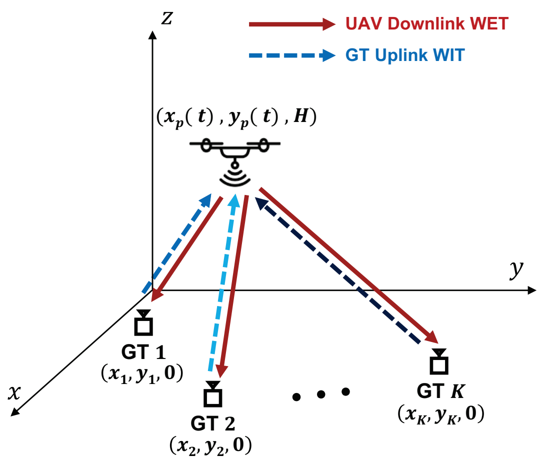

Fig. 1. Schematic diagram of UAV-aided WPCN.

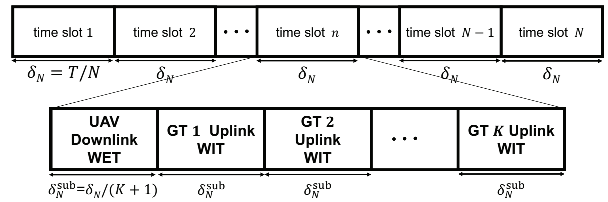

Fig. 2. Proposed protocol for UAV-aided WPCN.

supplies while the UAV is equipped with stable and constant source. Thus, to communicate with the GTs, the UAV flies through the area of interest and transfers energy to the GTs in the downlink. Then, by harvesting the wireless energy, the GTs send their information to the UAV in the uplink. In other words, the UAV acts as an H-AP as in the conventional WPCN. Also, it is assumed that the UAV flies at a constant altitude of H with the maximum speed v_{max} for a given time period T and all the GTs are located on the ground. Let us denote $\mathbf{p}(t) = [x_p(t), y_p(t)]^T$ as the position of the UAV at time instant $t \in [0, T]$ and $\mathbf{u}_k = [x_k, y_k]^T$ as the location of GT k $(k = 1, ..., K)$ which is assumed to be fixed for the time period T. We assume that the locations of all GTs are perfectly known to the UAV in advance. For ease of analysis, the time period T is equally divided into N time slots as in [5], where the number of time slots N is chosen as a sufficiently large number such that the distance between the UAV and the GTs within each time slot can be considered approximately static.

Therefore, the trajectory of the UAV can be represented by a sequence of locations $\{\mathbf{p}[n]\}$ at each time slot n $(n = 0, ..., N)$ as $\mathbf{p}[n] \triangleq \mathbf{p}(n \cdot \delta_N)$, where $\delta_N \triangleq T/N$ indicates the length of each time slot. Since we consider the discretized trajectory $\mathbf{p}[n]$ for $n = 1, ..., N$, the maximum speed constraint can be expressed as

$$\|\mathbf{p}[n] - \mathbf{p}[n-1]\| \leq \delta_N \cdot v_{max}, \quad \text{for} \quad n = 1, ..., N. \tag{1}$$

For the air-to-ground channel between the UAV and the GTs, as in [4] and [7], the deterministic propagation model is adopted in this paper which assumes the line-of-sight links without the Doppler effect. Then, the average channel power gain $\gamma_k[n]$ between the UAV and GT k at time slot n is expressed as

$$\gamma_k[n] = \frac{g_0}{\|\mathbf{p}[n] - \mathbf{u}_k\|^2 + H^2}, \tag{2}$$

where g_0 denotes the reference channel gain at distance of 1 meter.

Next, we explain a transmission protocol for the UAV-aided WPCN. As illustrated in Fig. 2, Each time slot n is equally divided into $K+1$ subslots. Here, the 0-th subslot of duration $\delta_N^{\text{sub}} \triangleq \frac{\delta_N}{K+1}$ is allocated to the dedicated downlink WET and the remaining K subslots are respectively assigned to uplink WIT of each GT $k = 1, ..., K$.

Now, we describe the WET and the WIT procedures of the UAV WPCN systems. At the 0-th subslot of each time slot n, the UAV broadcasts the wireless energy signals with transmit power P^{DL}. Then, the harvested energy $E_k[n]$ of GT k at time slot n can be written as

$$E_k[n] \triangleq \delta_N^{\text{sub}} \cdot \zeta_k \gamma_k[n] P^{\text{DL}}, \quad \text{for} \quad n = 1, ..., N \text{ and } k = 1, ..., K, \tag{3}$$

where $\zeta_k \in (0, 1]$ denotes the energy harvesting efficiency of GT k. For simplicity, we assume all the GTs have the same energy harvesting efficiency, i.e., $\zeta_k = \zeta$ for $k = 1, ..., K$.

Due to the processing delay of EH circuits at the GTs, harvested energy $E_k[n]$ may not be available at time slot n. Hence, GT k can utilize $E_k[n]$ at the future time slots $n+1, n+2, ..., N$. Defining $P_k^{\text{UL}}[n]$ as the uplink power of GT k in time slot n, the available energy at time slot n of GT k can be expressed as

$$\sum_{i=1}^{n-1} E_k[i] - \sum_{i=1}^{n-1} \delta_N^{\text{sub}} \cdot P_k^{\text{UL}}[i], \tag{4}$$

where the first term and the second term respectively represent the cumulative harvested energy and the consumed energy of GT k during time slots $2, 3, ..., n-1$. As a result, the uplink power constraint for GT k at time slot n is given as

$$\delta_N^{\text{sub}} \cdot P_k^{\text{UL}}[n] \leq \sum_{i=1}^{n-1} E_k[i] - \sum_{i=1}^{n-1} \delta_N^{\text{sub}} \cdot P_k^{\text{UL}}[i], \quad \text{for} \quad n = 2, ..., N \text{ and } k = 1, ..., K, \tag{5}$$

where we have $P_k^{\text{UL}}[1] = 0$ for $k = 1, ..., K$ due to the EH circuit delay.

Also, the instantaneous throughput $R_k[n]$ of GT k at time slot n can be obtained as

$$R_k[n] \triangleq \log_2\left(1 + \frac{\eta_k \gamma_k[n] P_k^{\text{UL}}[n]}{\sigma^2}\right), \quad \text{for} \quad n = 1, ..., N \text{ and } k = 1, ..., K, \tag{6}$$

where η_k is a fixed portion of stored energy used for the uplink information transmission at GT k, $\eta_k \in (0, 1]$. For simplicity, we assume $\eta_k = \eta$ for $k = 1, ..., K$. Thus, the average throughput of GT k for one time period T can be written by

$$R_k \triangleq \frac{1}{T} \sum_{n=1}^{N} \delta_N^{\text{sub}} R_k[n], \quad \text{for} \quad k = 1, ..., K. \tag{7}$$

In this paper, we maximize the minimum average throughput of among the GTs by jointly optimizing the UAV trajectory $\{\mathbf{p}[n]\}$ and the uplink power control $\{P_k^{\text{UL}}[n]\}$ at the GTs, which can be formulated as

$$\begin{aligned}
&\text{(P1):} \\
&\max_{R_{lb},\{P_k^{\text{UL}}[n]\},\{\mathbf{p}[n]\}} R_{lb} \\
&s.t. \\
&\frac{\delta_N^{\text{sub}}}{T}\sum_{n=1}^{N}\log_2\left(1+\frac{g_0\eta}{\sigma^2}\frac{P_k^{\text{UL}}[n]}{\|\mathbf{p}[n]-\mathbf{u}_k\|^2+H^2}\right) \\
&\geq R_{lb}, \quad \text{for } k=1,...,K, && (8)\\
&\sum_{i=2}^{n} P_k^{UL}[i] \leq \sum_{i=1}^{n-1}\frac{g_0\zeta_k P^{\text{DL}}}{\|\mathbf{p}[i]-\mathbf{u}_k\|^2+H^2}, \\
&\text{for } \ n=2,...,N \text{ and } k=1,...,K, && (9)\\
&\|\mathbf{p}[n]-\mathbf{p}[n-1]\| \leq \delta_N\cdot v_{max}, \quad \forall n, && (10)\\
&\mathbf{p}[N]=\mathbf{p}[0], && (11)\\
&0\leq P_k^{\text{UL}}[n]\leq P_{max}^{UL}, \quad \forall n \text{ and for } k=1,...,K, && (12)
\end{aligned}$$

where the uplink energy constraint in (9) is derived from (5), (11) represents periodical constraint that the UAV needs to get back to the starting position after one time period T [5], and (12) is the peak uplink power constraint. One can check that (P1) is non-convex due to the constraints in (8) and (9), and therefore it is not easy to obtain the globally optimal solution for (P1).

III. Proposed Solution

In this section, we propose an iterative algorithm for the proposed system which yields at least a locally optimal solution for (P1). To this end, we employ the CCCP framework which finds the solution for the trajectory $\{\mathbf{p}[n]\}$ and the uplink power $\{P_k^{\text{UL}}[n]\}$. The details are given in the next subsections.

A. Joint Trajectory and Uplink Power Optimization

To tackle the non-convex problem (P1), let us first introduce auxiliary variables $\{z_k[n]\}$ such that $\|\mathbf{p}[n]-\mathbf{u}_k\|^2\leq z_k[n]$ for $k=1,...,K$ and $n=1,...,N$. Then, the left-hand-side (LHS) of (8) and the right-hand-side (RHS) of (9) are respectively lower-bounded by

$$\begin{aligned}
&\frac{\delta_N^{\text{sub}}}{T}\sum_{n=1}^{N}\log_2\left(1+\frac{g_0\eta}{\sigma^2}\frac{P_k^{\text{UL}}[n]}{\|\mathbf{p}[n]-\mathbf{u}_k\|^2+H^2}\right) \\
&\geq \frac{\delta_N^{\text{sub}}}{T}\sum_{n=1}^{N}\log_2\left(1+\frac{g_0\eta}{\sigma^2}\frac{P_k^{\text{UL}}[n]}{z_k[n]+H^2}\right), \\
&\text{for } \ k=1,...,K, && (13)
\end{aligned}$$

and

$$\begin{aligned}
&\sum_{i=1}^{n-1}\frac{g_0\zeta P^{\text{DL}}}{\|\mathbf{p}[i]-\mathbf{u}_k\|^2+H^2}\geq\sum_{i=1}^{n-1}\frac{g_0\zeta P^{\text{DL}}}{z_k[i]+H^2}, \\
&\text{for } \ n=2,...,N \text{ and } k=1,...,K. && (14)
\end{aligned}$$

Based on these bounds, we can construct an equivalent problem for (P1) as

$$\begin{aligned}
&\text{(P2):} \\
&\max_{R_{lb},\{P_k^{\text{UL}}[n]\},\{\mathbf{p}[n]\},\{z_k[n]\}} R_{lb} \\
&s.t. \\
&\frac{\delta_N^{\text{sub}}}{T}\sum_{n=1}^{N}\log_2\left(1+\frac{g_0\eta}{\sigma^2}\frac{P_k^{\text{UL}}[n]}{z_k[n]+H^2}\right) \\
&\geq R_{lb}, \ \text{for } \ k=1,...,K, && (15)\\
&\sum_{i=2}^{n} P_k^{\text{UL}}[i]\leq\sum_{i=1}^{n-1}\frac{g_0\zeta_k P^{\text{DL}}}{z_k[i]+H^2}, \\
&\text{for } \ n=2,...,N \text{ and } k=1,...,K, && (16)\\
&\|\mathbf{p}_n-\mathbf{u}_k\|^2\leq z_k[n], \ \forall n \text{ and for } k=1,...,K, && (17)\\
&(10) \text{ - } (12).
\end{aligned}$$

The equivalence between problem (P1) and (P2) is shown as follows. First, let R_{lb}^* and $\tilde{R_{lb}}^*$ denote the optimal value of problem (P1) and (P2), respectively. Then, it can be easily checked that $R_{lb}^*\geq\tilde{R_{lb}}^*$, where the equality holds when $z_k[n]=\|\mathbf{p}[n]-\mathbf{u}_k\|^2$, $\forall n,k$. Next, by contradiction, we can show that the optimum of in (P2) is attained only when $z_k[n]=\|\mathbf{p}[n]-\mathbf{u}_k\|^2$, $\forall n,k$. Supposed that there exists at least one $z_k[n]$ satisfying $z_k[n]>\|\mathbf{p}[n]-\mathbf{u}_k\|^2$ at the optimum of (P2). Then, we can always increase the minimum throughput by decreasing $z_k[n]$ due to constraints (15) and (16). Since it contradicts the assumption, we can conclude that the optimal solution of (P2) should satisfy $z_k[n]=\|\mathbf{p}[n]-\mathbf{u}_k\|^2$, $\forall n,k$. As a result, the optimal solution of (P1) can be equivalently obtained by solving (P2).

Still, (P2) is non-convex in general. To this end, we provide the CCCP [18] approach to solve (P2) efficiently. First, we consider the throughput constraint in (15). By using the first-order Taylor approximation at $z_k[n]=\hat{z}_k[n]$, we can derive the concave lower bound for the LHS of (15) as

$$\begin{aligned}
&\log_2\left(1+\frac{g_0\eta}{\sigma^2}\frac{P_k^{\text{UL}}[n]}{z_k[n]+H^2}\right) \\
&\geq\log_2\left(\frac{z_k[n]+H^2+\frac{g_0\eta}{\sigma^2}P_k^{\text{UL}}[n]}{\hat{z}_k[n]+H^2}\right)-\frac{z_k[n]+H^2}{\hat{z}_k[n]+H^2}+1 \\
&\triangleq R_k^L[n](z_k[n],P_k^{\text{UL}}[n]\mid\hat{z}_k[n]). && (18)
\end{aligned}$$

Note that $R_k^L[n]$ is a jointly concave function with respect to $z_k[n]$ and $P_k^{\text{UL}}[n]$, and gives a tight lower bound in which equality holds at $\hat{z}_k[n]=z_k[n]$. In a similar way, the RHS of constraint (16), which is convex with respect to $z_k[n]$, can be lower-bounded by

$$\begin{aligned}
\frac{\zeta_k g_0 P^{\text{DL}}}{z_k[n]+H^2} \quad &\geq \quad \frac{\zeta g_0 P^{\text{DL}}}{\hat{z}_k[n]+H^2}\left(2-\frac{z_k[n]+H^2}{\hat{z}_k[n]+H^2}\right) \\
&\triangleq \quad E_k^L[n](z_k[n]\mid\hat{z}_k[n]). && (19)
\end{aligned}$$

With (18) and (19) at hand, the approximated convex problem for (P2) with given $\hat{z}_k[n]$ can be obtained as

$$\begin{aligned}
&\text{(P3):} \\
&\max_{R_{lb},\{P_k^{\text{UL}}[n]\},\{\mathbf{p}[n]\},\{z_k[n]\}} \quad R_{lb} \\
&s.t. \\
&\frac{\delta_N^{\text{sub}}}{T}\sum_{n=1}^{N} R_k^L[n](z_k[n], P_k^{\text{UL}}[n] \mid \hat{z}_k[n]) \\
&\geq R_{lb}, \ \text{for} \ \ k = 1, ..., K, \qquad (20) \\
&\sum_{i=2}^{n} P_k^{\text{UL}}[i] \leq \sum_{i=1}^{n-1} E_k^L[i](z_k[i] \mid \hat{z}_k[i]), \\
&\text{for} \ \ n = 2, ..., N \text{ and } k = 1, ..., K, \qquad (21) \\
&(10) \text{ - } (12), (17).
\end{aligned}$$

Now, (P3) can be solved by existing convex solvers such as the CVX [20]. Since the feasible region of (P3) is a subset of that of the non-convex original problem (P2), we can always obtain the lower bound solution for (P2) by solving (P3).

As a result, the solution for the original non-convex problem (P2), which is equivalent to that for (P1), can be calculated by iteratively solving its approximate convex problem (P3) based on the CCCP. Specifically, at the i-th iteration of the CCCP algorithm, we obtain the solution $z_k^{(i)}[n]$ and $P_k^{\text{UL}(i)}[n]$ of (P3) by setting $\hat{z}_k[n] = z_k^{(i-1)}[n]$, where $z_k^{(i)}[n]$ and $P_k^{\text{UL}(i)}[n]$ are the solution obtained at the i-th iteration. It has been proved that this CCCP method converges to at least a locally optimal point [18]. We summarize an overall optimization algorithm for solving (P1) in Algorithm 1.

Algorithm 1 : Proposed Algorithm for (P1)

1) **Initialize** $i \leftarrow 0$, $R_{lb}^{(0)} = 0$ and $z_k^{(0)}[n]$ $\forall n, k$.
2) **Repeat**
   1: Set $i \leftarrow i + 1$.
   2: Obtain $R_{lb}^{(i)}, \{P_k^{\text{UL}(i)}[n], \mathbf{p}^{(i)}[n], z_k^{(i)}[n]\}$ for given $\hat{z}_k[n] = z_k^{(i-1)}[n]$ by solving (P3).
3) **Until** $R_{lb}^{(i)}$ converges.

Note that for Algorithm 1, we need to initialize the UAV trajectory variable $\{\mathbf{p}[n]\}$. This will be explained in the following subsection.

B. Initial UAV Trajectory

To initialized UAV trajectory variables $\{\mathbf{p}[n]\}$ for Algorithm 1, we employ the circular path whose center $\mathbf{c} \in \mathbb{R}^2$ and radius r on xy-plane are respectively set to

$$\mathbf{c} \triangleq \frac{1}{K}\sum_{k=1}^{K} \mathbf{u}_k, \qquad (22)$$

$$r \triangleq \max(r^{md}, r^{mt}), \qquad (23)$$

where (22) represents the centroid of the GTs, $r^{md} \triangleq \frac{1}{K}\sum_{k=1}^{K} \|\mathbf{c} - \mathbf{u}_k\|$ and $r^{mt} \triangleq \frac{v_{max}T}{2\pi}$ indicates the mean distance between $\mathbf{c}$ and the GTs and the maximum allowable

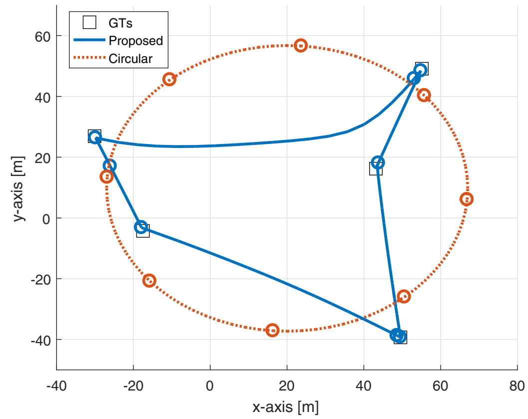

Fig. 3. Trajectories of UAV optimized by Algorithm 1.

radius with given speed constraint v_{max}, respectively. As a result, the trajectory of the initialization scheme becomes

$$\mathbf{p}[n] = [x_c + r\cos(2\pi n/N), y_c + r\sin(2\pi n/N)]^T, \qquad (24)$$

for $n = 0, ..., N$.

IV. Simulation Results

In this section, we evaluate the performance of the proposed algorithm by numerical results. The maximum uplink power constraint at the GTs and downlink transmission power at the UAVs are set to $P_{max}^{\text{UL}}[n] = -10$ dBm and $P^{\text{DL}} = 30$ dBm, respectively, and the EH efficiency ζ and the portion of harvested energy used for the uplink transmission η are fixed as $\zeta = 0.6$ and $\eta = 0.9$, respectively. Also, we set the reference channel gain g_0 to $g_0 = -30$ dB, and the noise power is given by $\sigma^2 = -90$ dBm. The speed of the UAV is limited as $v_{max} = 10$ m/s and the altitude of the UAV is fixed to $H = 10$ m.

Fig. 3 illustrates the optimized trajectory of the UAV in the UAV WPCN systems for $T = 80$ s with $K = 5$ GT deployed at points marked by squares. The circular markers represent the positions of the UAV sampled every 10 s. From Fig. 3, we can see that the UAV following the optimized trajectory in the proposed system tries to cover all GTs by traveling a path which seems to be line segments connecting the locations of the GTs, while the UAV following circular trajectory cannot pass by all the GTs.

Fig. 4 illustrate the max-min throughput of the proposed algorithm with respect to the time interval T for the same GTs distribution as in Fig. 3. For comparison, we also plot the performance of the following baseline schemes.

- Static : The conventional WPCN with a static H-AP is adopted where the H-AP [9] is fixed at the centroid of GTs, i.e., $\mathbf{p}[n] = \frac{1}{K}\sum_{k=1}^{K} \mathbf{u}_k, \forall n$, with altitude of 10 m.
- Circular trajectory: The UAV follows the circular path described in Section III-B. The uplink power and the time resource allocation are optimized from Algorithm 1 with fixed $\{\mathbf{p}[n]\}$.

From the figure, we can check that with the aid of mobile UAV, although the trajectory is simply fixed to the circular path, the

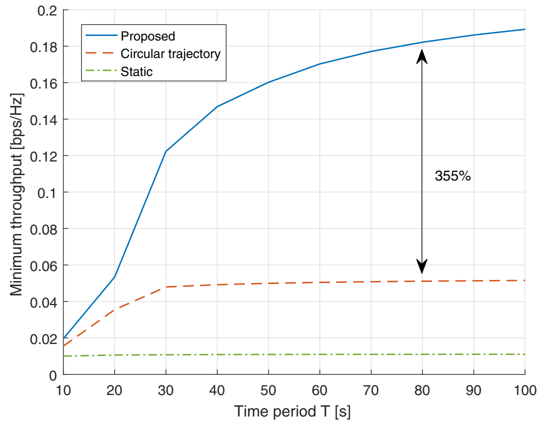

Fig. 4. Minimum throughput versus time interval T.

minimum throughput can be substantially improved compared to the conventional static WPCN. This infers that the proposed UAV WPCN well compensate the doubly near-far problem of the static WPCN. The minimum throughput performance of the proposed algorithm first increases as the time period T grows, and then get saturated for a large T, since the optimized trajectory converges to a certain path connecting all the GT locations as discussed in Fig. 3. The baseline circular trajectory scheme exhibits a similar tendency, but the proposed algorithm significantly outperforms the circular trajectory scheme for all simulated T. When $T = 80$ s, the proposed system offers about 355% gain over the circular trajectory. Therefore, we can conclude that optimizing trajectory of the UAV is crucial for the UAV WPCN.

V. Conclusion

This paper has investigated the UAV WPCN where a mobile UAV supports the WET and the WIT of the multiple GTs. For the proposed system, we have jointly optimized the trajectory of the UAV and the uplink power at the GTs in order to maximize the minimum throughput among the GTs. To solve this non-convex problem, we have adopted the CCCP optimization framework. As a result, a locally optimal solution of the original non-convex problem can be efficiently computed by the proposed iterative algorithm whose convergence has been proved. From the simulation results, we have demonstrated the efficiency of the proposed algorithm over the conventional schemes.

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