Power Efficient Temporal Routing and Trajectory Adjustment for Multi-UAV Networks

Ray-Hsiang Cheng*, Y.-W. Peter Hong†‡, and Jang-Ping Sheu*†

*Department of Computer Science, National Tsing Hua University, Taiwan
†Institute of Communications Engineering, National Tsing Hua University, Taiwan
‡MOST Joint Research Center for AI Technology and AII Vista Healthcare
Emails: qazwsx31243@gmail.com, ywhong@ee.nthu.edu.tw, sheujp@cs.nthu.edu.tw

***Abstract*—This work proposes power-efficient trajectory adjustment and temporal routing algorithms for a network of unmanned aerial vehicles (UAV) that are deployed to monitor or gather data from underlying sensors in the field. Here, we consider fixed-wing UAVs that are assumed to follow circular trajectories whose radius can be adjusted to reduce power consumption while maintaining coverage over its responsible service area. Given the multihop transmission paths from the UAVs to the data-gathering node, power-efficient flight-radius adjustment strategies are proposed based on the total power minimization and lifetime maximization criteria while maintaining the existence of the paths. Then, by establishing the relationship between routing in UAV networks and that in general temporal graphs, we propose a power-efficient (PE) temporal path algorithm based on the minimization of the accumulated square of the minimum achievable powers of all UAVs on the path. Computer simulations are provided to demonstrate the effectiveness of the radius adjustment strategies in terms of both total power minimization and lifetime maximization, and the power-savings provided by the PE temporal path algorithm.**

I. Introduction

The use of unmanned aerial vehicles (UAVs) in wireless communications [1], [2] has received much attention in recent years due to their ability to adapt rapidly to the environment and to extend coverage over hostile areas. Different from on-ground vehicles, UAVs need not be confined to the road and thus can move around with less obstacles. Hence, several works considered the use of UAVs in disaster recovery and management [3], [4] and also for serving as mobile wireless relays for highly dynamic users [5]. In sensor network applications, UAVs have also been used as mobile sink nodes to monitor certain areas or gather information from the sensors [6], [7]. In this case, it is important to maintain coverage over the entire sensor field as well as provide efficient communication paths between the UAVs and the data-gathering nodes.

Most works in the literature on the use of UAVs for sensor networks consider either the path planning problem [7], [8], where the goal is to determine the most efficient flight path for UAVs to traverse the entire sensor field, or the UAV placement and routing problems [9]–[11] for multi-UAV networks, where sensor information is to be relayed through multiple UAVs to reach the final data-gathering node without having them travel over long distances. Specifically, among the works on path planning, [7] proposed the joint optimization of sensors' wakeup schedules and UAVs trajectories to minimize the maximum energy consumption of all sensors; [8] uses bio-inspired algorithms to determine the optimal path between data acquisition points and selects one in accordance with sensing, energy, time, and risk utilities. Moreover, among the works on UAV placement and routing, [9] proposed a mobility and load aware mechanism on top of the well-known optimized link state routing (OLSR) to establish stable routes for UAV ad hoc networks; [10] proposed an improved B.A.T.M.A.N. protocol by leveraging a prediction of future trajectories of the UAVs in the routing protocol to avoid unexpected route breaks and packet loss; [11] proposed a reactive-greedy-reactive (RGR) routing protocol that combines the use of ad-hoc on-demand distance vector and greedy geographic forwarding protocols. Notice that the above works consider the use of rotary-wing UAVs that are capable of remaining afloat at fixed positions without constant movement. However, the lifetime of rotary-wing UAVs is typically short and cannot maintain usage over a long time period. Hence, we consider in this work the use of fixed-wing UAVs that typically can consume less power and carry larger batteries. However, for fixed-wing UAVs to hover over specific sensor areas, they must maintain constant movement, e.g., over a circular trajectory, causing the network topology to vary rapidly over time.

The main objective of this work is to propose power-efficient trajectory adjustment and temporal routing algorithms for a network of fixed-wing UAVs following circular flight patterns above the sensor field. The constant movement of UAVs results in a so-called temporal graph [12] where the connectivity among UAVs exist only at certain time instants. A transmission path over the temporal graph can be represented by a causal sequence of temporal edges (i.e., edges that exist only at particular time instants) from the source to the destination. Given predetermined transmission paths between the UAVs and the data-gathering node, we first propose two flight-radius adjustment schemes based on the total power minimization and lifetime maximization criteria, respectively, subject to constraints on the existence of the predetermined paths. The total power minimization problem is solved using sequential quadratic programming (SQP) [13], which poten-

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tially can be converted into a distributed network protocol that requires only simple data exchanges among neighbors, whereas the lifetime maximization problem is solved using a successive convex approximation (SCA) approach [14] where the radius is constantly adjusted over time. Then, by treating the square of the minimum achievable power (i.e., the smallest power achievable through flight-radius adjustment) as the cost of each edge, we propose a power-efficient (PE) temporal path algorithm that finds the path with the minimum accumulated cost to further improve the power efficiency. Numerical simulations are provided to demonstrate the effectiveness of our proposed trajectory adjustment strategies in terms of total power consumption and network lifetime, respectively. The results show that the PE temporal path algorithm indeed achieves lower power consumption than the existing earliest arrival time algorithm [12] since the former determines routes that are more robust and easier to maintain even with adjustment in the radii of the flight trajectories along the path.

The remainder of this article is organized as follows. In Section II, we describe the system model and establish its relation with temporal graphs. Then, in Section III, two flight-radius adjustment algorithms are proposed, namely, the total power minimization and the lifetime maximization algorithms. In Section IV, the PE temporal path algorithm is proposed. Finally, we demonstrate the effectiveness of the proposed schemes in Section V, and conclude in Section VI.

II. System Model

Let us consider a multi-UAV network consisting of N UAVs, each responsible for monitoring a certain region within the sensor field, as illustrated in Fig. 1. Each UAV follows a circular trajectory whose speed and radius are constrained by the data-gathering frequency and sensing area, respectively. In particular, for UAV u, the radius r_u of the trajectory is confined to interval $[R_{u,\min}, R_{u,\max}]$, and the center of the circular trajectory has coordinates (x_u, y_u). The time required for each UAV to complete one circular trajectory (i.e., to gather one round of sensor data) is T. The data gathered by the UAVs are then forwarded periodically to the data-gathering node through multihop paths. By assuming that the initial angular offset of UAV u at time $t = 0$ is $\theta_{u,0}$, the location of UAV u at time t can be represented by

$$(x_u + r_u \cos\theta_u(t), y_u + r_u \sin\theta_u(t)) \tag{1}$$

where $(r_u, \theta_u(t))$ is the polar coordinate of UAV u's position relative to the center of its circular trajectory, and $\theta_u(t) = \theta_{u,0} + 2\pi t/T$. A connection from UAV u to UAV v exists at time t if UAV v is within the transmission radius δ_u of UAV u at this time, that is, if

$$D_{(u,v,t)}(r_u, r_v) \le \delta_u, \tag{2}$$

where

$$D_{(u,v,t)}(r_u, r_v) \triangleq \big\| (x_u + r_u \cos\theta_u(t), y_u + r_u \sin\theta_u(t)) - (x_v + r_v \cos\theta_v(t), y_v + r_v \sin\theta_v(t)) \big\| \tag{3}$$

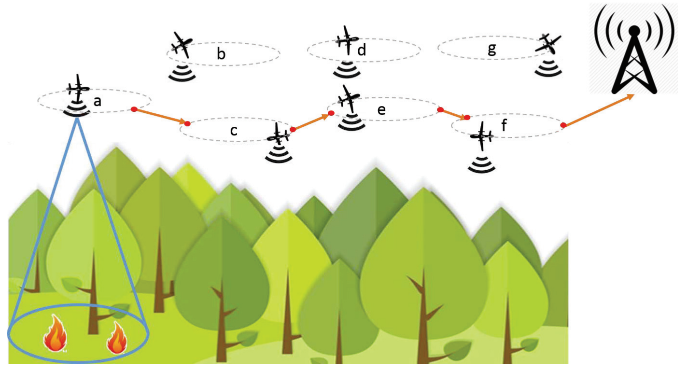

Fig. 1. Illustration of a multihop UAV network for monitoring and data-gathering.

is the distance between UAVs u and v at time t. This connection may not be bidirectional since the transmission radius may vary for different UAVs. Moreover, due to UAVs' mobility, this connection may also exist only intermittently within each cycle, resulting in a so-called temporal graph [12].

Specifically, let $\mathcal{G} = (\mathcal{V}, \mathcal{E}_{[t_0, t_0+\lambda]})$ be a directed temporal graph with $\mathcal{V}$ being the set of vertices (i.e., UAVs) and $\mathcal{E}_{[t_0, t_0+\lambda]}$ being the set of temporal edges that exist during time interval $[t_0, t_0 + \lambda]$. Here, we consider a time-slotted system and, thus, measure the time as an integer multiple of slot duration τ. An edge $e \in \mathcal{E}_{[t_0, t_0+\lambda]}$ is represented by a tuple (u, v, t), where $u, v \in V$ and $t \in [t_0, t_0 + \lambda]$ is the time instant at which UAV u can transmit to UAV v. In fact, an edge $e = (u, v, t)$ exists only if $D_{(u,v,t)}(r_u, r_v) \le \delta_u$. Here, t_0 can be viewed as the time for which the data is to be transmitted and λ can be viewed as the maximum tolerable delay. A temporal path $\mathrm{Path}_{v_1 \to v_{k+1}}$ from v_1 to v_{k+1} in graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}_{[t_0, t_0+\lambda]})$ is an ordered sequence of edges $\{(v_1, v_2, t_1), (v_2, v_3, t_2), \ldots, (v_k, v_{k+1}, t_k)\}$, where $(v_i, v_{i+1}, t_i) \in \mathcal{E}_{[t_0, t_0+\lambda]}$ and $t_i < t_{i+1}$ for $i = 1, \ldots, k-1$ ($t_{k+1} = \infty$). In the multi-UAV network under consideration, all UAVs need to forward their local information to the data-gathering node. Hence, a path from the source UAV s to the destination (i.e., the data-gathering node) d, denoted by $\mathrm{Path}_{s \to d}$, should exist for all $s \in \mathcal{V}$. An example of the temporal graph is illustrated in Fig. 2.

III. Power-Efficient Trajectory Adjustment

In this section, we determine the optimal radius adjustment for the circular trajectories of all UAVs with the goal of minimizing the total power consumption and of maximizing the network lifetime, respectively. Suppose that the paths from all UAVs to the destination have been established, e.g., by following the temporal path discovery methods proposed in [12]. The radius adjustment must be done while preserving the existence of all predetermined paths.

Specifically, let $\mathrm{Path}_{s \to d}$ be the path from the source UAV s to the destination (i.e., data-gathering node) d. To ensure the existence of the path, it must hold for all $(u, v, t) \in \mathrm{Path}_{s \to d}$ that

$$D_{(u,v,t)}(r_u, r_v)^2 \le \delta_u^2. \tag{4}$$

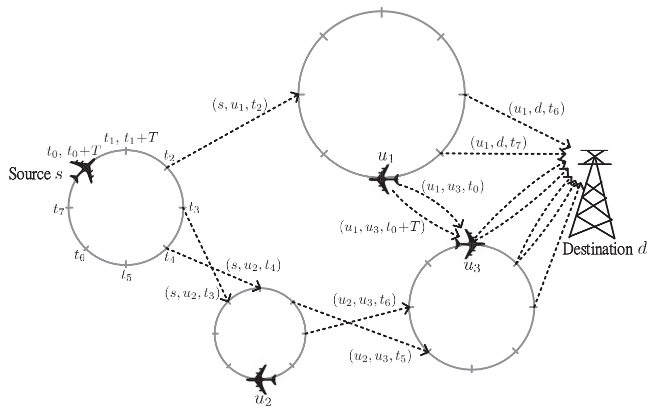

Fig. 2. Example of a temporal graph generated by the UAV network.

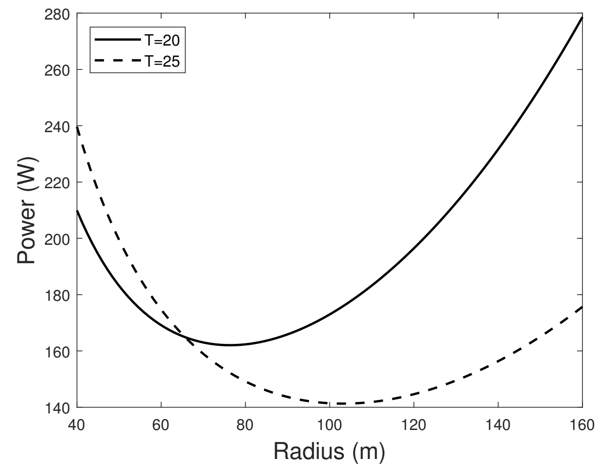

Fig. 3. Relation between the power consumption and the radius of the circular trajectory for $T = 20$ and 25.

Notice that $D_{(u,v,t)}(r_u, r_v)^2$ is a quadratic function of (r_u, r_v) and, thus, the above constraints are convex.

By [15], we know that the flight power consumption of a circulating UAV, say UAV u, depends nonlinearly on the speed v_u and radius r_u of the circular trajectory, and can be described by

$$P(\mathrm{v}_u, r_u) = \left(c_1 + \frac{c_2}{g^2 r_u^2}\right) \mathrm{v}_u^3 + \frac{c_2}{\mathrm{v}_u}. \tag{5}$$

Here, g is the gravitational acceleration with nominal value 9.8 m/s^2 whereas c_1 and c_2 are parameters related to the weight of the aircraft, wing area, and air density, etc. Typical values of c_1 and c_2 are given by $c_1 = 9.26 \cdot 10^{-4}$ and $c_2 = 2250$ [15]. In this work, we assume that the time required to complete one flight cycle is T and, thus, the speed of UAV u is given by $\mathrm{v}_u = 2\pi r_u / T$. By substituting this into (5), we have

$$\bar{P}(r_u) \triangleq P\left(\frac{2\pi r_u}{T}, r_u\right) \tag{6}$$

$$= \left(c_1 + \frac{c_2}{g^2 r_u^2}\right)\left(\frac{2\pi r_u}{T}\right)^3 + \frac{c_2 T}{2\pi r_u} \tag{7}$$

$$= \frac{c_1 8\pi^3}{T^3} r_u^3 + \frac{c_2 8\pi^3}{g^2 T^3} r_u + \frac{c_2 T}{2\pi}\frac{1}{r_u}. \tag{8}$$

Notice that the function $\bar{P}(r_u)$ is convex with respect to r_u, for $r_u > 0$. In fact, the first two terms in (8) increase monotonically with respect to r_u, for $r_u > 0$, whereas the last term decreases monotonically instead.

In Fig. 3, we plot the function with respect to r_u for different values of T. We can see that, when T is small, the last term has little impact on the power consumption and thus, the power consumption may increase monotonically with r_u. On the other hand, when T is large, the last term dominates and, thus, the power consumption may decrease for smaller values of r_u before it increases again. Hence, it is not always power-efficient to adopt the smallest radius possible.

A. Strategy I: Total Power Minimization

In the total power minimization strategy, we propose to find the optimal set of circular radii $\{r_s\}_{s\in\mathcal{V}}$ that minimizes the total power consumption subject to constraints given by the existence of paths from all nodes to the data-gathering node. The problem can be formulated as follows:

$$\min_{\{r_s\}_{s\in\mathcal{V}}} \sum_{s\in\mathcal{V}} \bar{P}(r_s) \tag{9a}$$

subject to

$$D_{(u,v,t)}(r_u, r_v)^2 \le \delta_u^2,\ \forall (u,v,t) \in \cup_{s\in\mathcal{V}} \mathrm{Path}_{s\to d} \tag{9b}$$

$$R_{s,\min} \le r_s \le R_{s,\max},\ \forall s \in \mathcal{V}. \tag{9c}$$

The optimization problem given above is convex and, thus, can be solved using off-the-shelf softwares. In our experiments, we adopt the sequential quadratic programming (SQP) algorithm [13] to solve the optimization problem. It is interesting to remark that, even though the optimization is performed in a centralized manner in this work, it is also possible to adopt a variant of the SQP algorithm where the optimization of each UAV's radius involves only the gradients associated with the radius of neihboring UAVs. This opens the possibility of developing distributed protocols for the implementation of such optimization procedure in our future work.

B. Strategy II: Lifetime Maximization

In the lifetime maximization strategy, we determine the optimal radius adjustment policy with the goal of maximizing the lifetime of the multi-UAV network. Here, lifetime is defined as the time for which all UAVs remain active (i.e., the time until one of the UAV's battery has been depleted).

Specifically, let $E_{\mathrm{res},u}$ be the residual battery energy at UAV u, in which case, $E_{\mathrm{res},u}/\bar{P}(r_u)$ will be the residual lifetime of UAV u. Therefore, the lifetime maximization problem can be formulated as

$$\max_{\{r_s\}_{s\in\mathcal{V}}} \min_{s\in\mathcal{V}} \frac{E_{\mathrm{res},s}}{\bar{P}(r_s)} \tag{10a}$$

$$\text{subject to } \ (9b),\ (9c). \tag{10b}$$

By introducing the auxiliary variable η, this problem can be formulated equivalently as

$$\max_{\{r_s\}_{s\in\mathcal{V}},\eta} \quad \eta \tag{11a}$$
$$\text{subject to} \quad \text{(9b), (9c)} \tag{11b}$$
$$\frac{E_{\mathrm{res},s}}{\bar{P}(r_s)} \geq \eta,\ \forall s \in \mathcal{V}. \tag{11c}$$

Here, η can be viewed as the lifetime of the UAV network (i.e., the shortest lifetime among all UAVs). Notice that the constraint in (11c) can be written equivalently as

$$\frac{1}{\eta} \geq \frac{\bar{P}(r_s)}{E_{\mathrm{res},s}}. \tag{12}$$

This constraint is non-convex, making the optimization problem difficult to solve in general. Hence, instead of solving the problem in one shot, we propose to solve the problem gradually over time through multiple iterations.

Specifically, let $\eta^{(\ell)}$ be the solution of η obtained in the ℓ-th iteration (i.e., the residual lifetime of the UAV network starting from the time of the ℓ-th iteration, assuming that the radii do not change from that point on). Suppose that time Δt elapses between iterations ℓ and $\ell+1$. Then, in iteration $\ell+1$, the value of η can be written as $\eta^{(\ell+1)} = \eta^{(\ell)} - \Delta\eta^{(\ell+1)}$, where $\Delta\eta^{(\ell+1)}$ is non-negative since the residual lifetime is non-increasing over time. Then, for $\Delta\eta^{(\ell+1)}/\eta^{(\ell)}$ sufficiently small, the left-hand-side of (12) can be approximated as

$$\frac{1}{\eta^{(\ell+1)}} = \frac{1}{\eta^{(\ell)} - \Delta\eta^{(\ell+1)}} \approx \frac{1}{\eta^{(\ell)}}\left(1 + \frac{\Delta\eta^{(\ell+1)}}{\eta^{(\ell)}}\right), \tag{13}$$

which is the first-order Taylor approximation of $\frac{1}{\eta^{(\ell)} - \Delta\eta^{(\ell+1)}}$ about the point $\Delta\eta^{(\ell+1)} = 0$. By replacing the constraints in (11c) with the approximation in (13), the optimization problem we solve at time t can be written as

$$\max_{\{r_s\}_{s\in\mathcal{V}},\Delta\eta} \quad \eta^{(\ell)} - \Delta\eta \tag{14a}$$
$$\text{subject to} \quad \text{(9b), (9c)},\ \Delta\eta \geq 0, \tag{14b}$$
$$\frac{1}{\eta^{(\ell)}}\left(1 + \frac{\Delta\eta}{\eta^{(\ell)}}\right) \geq \frac{\bar{P}(r_s)}{E_{\mathrm{res},s}^{(\ell+1)}},\ \forall s \in \mathcal{V}, \tag{14c}$$

where $E_{\mathrm{res},s}^{(\ell+1)} = E_{\mathrm{res},s}^{(\ell)} - \bar{P}(r_s^{(\ell)})\Delta t$ is the residual battery energy of UAV s at the time of iteration $\ell+1$. Notice that this problem is convex and can be solved using off-the-shelf solvers such as CVX [16].

IV. Power-Efficient Temporal Path Algorithm

In this section, we propose a power-efficient (PE) temporal path algorithm that determines the path from source s to destination d that has more flexibility in reducing power consumption through trajectory adjustment.

Suppose that the UAVs' radii are initially set as their maximum values $R_{u,\max}$, for all u. and that the edge (u,v,t) exists under this initial setting. Constrained on the existence of edge (u,v,t), the radius that achieves the minimum power for UAVs u and v is given by

$$\hat{r}_{(u,v,t)} \triangleq \min\{r : D_{(u,v,t)}(r,r) = \delta_u, r \geq \arg\min_{r'} \bar{P}(r')\}. \tag{15}$$

Here, we refer to $\hat{r}_{(u,v,t)}$ as the minimum-power radius of edge (u,v,t). The condition $D_{(u,v,t)}(r,r) = \delta_u$ implies that

$$\begin{aligned}&\big(x_u - x_v + r\cos\theta_u(t) - r\cos\theta_v(t)\big)^2 \\ &\quad + \big(y_u - y_v + r\sin\theta_u(t) - r\sin\theta_v(t)\big)^2 = \delta_u^2,\end{aligned} \tag{16}$$

which is a quadratic equation that can be solved analytically to obtain $\hat{r}_{(u,v,t)}$.

Let us define the cost of the edge (u,v,t) as

$$\rho_{(u,v,t)}(r_{u'}, r_{v'}) \triangleq \bar{P}(\hat{r}_{(u,v,t)})^2, \tag{17}$$

which is the square of the minimum achievable power. By the above definition, the smaller the cost, the more power efficient the UAVs associated with the edge can be. The cost of path $\mathrm{Path}_{s\to d} = \{(v_1 = s, v_2, t_1), (v_2, v_3, t_2), \ldots, (v_k, v_{k+1} =$

Algorithm 1 Power-Efficient (PE) Temporal Path Algorithm

Input: A temporal graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, source vertex s, time interval $[t_0, t_0 + \lambda]$.

Output: The minimum total cost from source vertex s to destination vertex d within $[t_0, t_0 + \lambda]$, and the corresponding path $\mathrm{Path}_{s\to d}$.

Initialize sorted lists $L_v = \emptyset$, for all $v \in \mathcal{V}$. (An element in L_v is $(\mathrm{Pre}[v], \mathrm{AccCost}[v], \mathrm{Time}[v])$, where $\mathrm{AccCost}[v]$ is the cost accumulated on the path from s to v, $\mathrm{Time}[v]$ is the time that the path arrives at v and $\mathrm{Pre}[v]$ is the node preceding v on the path.)
for each incoming edge $e = (u, v, t)$ in temporal order **do**
  if $u = s$ and $(0, t) \notin L_s$ **then**
    Insert $(0, t)$ into L_s;
  end if
  Let $(\mathrm{Pre}'[u], \mathrm{AccCost}'[u], \mathrm{Time}'[u])$ be an element in L_u where $\mathrm{Time}'[u] = \max\{\mathrm{Time}[u] : (\mathrm{Pre}[u],$ $\mathrm{AccCost}[u], \mathrm{Time}[u]) \in L_u, \mathrm{Time}[u] \leq t\}$;
  $\mathrm{AccCost}[v] \leftarrow \mathrm{AccCost}'[u] + \rho_{(u,v,t)}(r_u, r_v)$;
  $\mathrm{Time}[v] \leftarrow t$;
  Insert $(\mathrm{u}, \mathrm{AccCost}[v], \mathrm{Time}[v])$ into L_v;
  Remove dominated elements in L_v;
end for
$a \leftarrow d$;
$t \leftarrow t_0 + \lambda$;
while $a \neq s$ **do**
  Let $(\mathrm{Pre}'[a], \mathrm{AccCost}'[a], \mathrm{Time}'[a])$ be an element in L_a, where $\mathrm{Time}'[a] = \max\{\mathrm{Time}[a] : (\mathrm{Pre}[a],$ $\mathrm{AccCost}[a],\ \mathrm{Time}[a]) \in L_a, \mathrm{Time}[a] \leq t\}$;
  Prepend edge $(\mathrm{Pre}'[a], a, \mathrm{Time}'[a])$ to $\mathrm{Path}_{s\to d}$;
  $a \leftarrow \mathrm{Pre}'[a]$;
  $t \leftarrow \mathrm{Time}'[a]$;
end while
return $\mathrm{Path}_{s\to d}$;

$d, t_k)\}$ can thus be defined as the sum of the cost over all edges on the path, i.e., $\sum_{(u',v',t')\in \mathrm{Path}_{s\to d}} \rho_{(u',v',t')}(r_{u'}, r_{v'})$. Notice that, by taking $\bar{P}(\hat{r}_{(u,v,t)})^2$ instead of $\bar{P}(\hat{r}_{(u,v,t)})$ as the cost, the power-adjustment flexibility tends to be more balanced among the edges of the selected path.

The PE temporal path algorithm proposed in this work aims to minimize the accumulated cost over the selected path. In fact, by treating $\rho_{(u,v,t)}$ as a measure of distance between nodes u and v at time t, finding the PE temporal path is equivalent to finding the shortest distance path in a temporal graph. However, this problem is non-trivial since the prefix subpath to a "shortest" temporal path may not be a "shortest" temporal path to an earlier node [12]. Hence, commonly adopted greedy or Djikstra-type algorithms would not work in this case. In Algorithm 1, we modify the shortest path-distance algorithm proposed in [12] using the new distance measure mentioned above to solve the problem.

In particular, in the PE temporal path algorithm described in Algorithm 1, we let each node record a list consisting of the incoming time of potential edges and its accumulated cost up to that point. It has been shown in [12, Lemma 13] that, given two temporal paths from s to v, denoted by $\mathrm{Path}_{s\to v}$ and $\mathrm{Path}'_{s\to v}$, if both the accumulated cost and the arrival time of path $\mathrm{Path}'_{s\to v}$ are greater than that of path $\mathrm{Path}_{s\to v}$, then it is possible to safely prune $\mathrm{Path}'_{s\to v}$ from the computation of the minimum cost path from s to d. In this case, we say that $\mathrm{Path}_{s\to v}$ is said to be dominated by $\mathrm{Path}'_{s\to v}$. The corresponding accumulated cost and arrival time of the edge is thus not recorded in the list associated with node v. Consequently, the search for the element in L_u that has the latest arrival time is equivalent to searching for the path with the largest accumulated robustness up to that point.

V. Numerical Results and Performance Comparisons

In this section, we demonstrate the effectiveness of the proposed temporal routing and trajectory adjustment strategies through computer simulations using Matlab. In these experiments, the UAVs are deployed randomly according to a uniform distribution within a 1000×1000 m^2 area. The minimum and maximum radii of the UAVs' circular trajectories (i.e., $R_{\min}$ and $R_{\max}$) are given by 40 and 160 meters, respectively. The UAVs' inital radii are set as $R_{\max}$ to ensure high connectivity. The time slot duration is $\tau = 0.5$ seconds. The battery capacity is 5300 mAh and operates at 18.5 V (i.e., 353 Joules). Here, we shall consider cases where $T = 20$, and shall set $N = 40$ and $\lambda = 150$ unless otherwise mentioned. The curves are averaged over 40 network realizations.

In Fig. 4, we show the average power consumption versus the number of UAVs for the proposed total power minimization strategy. The average power consumption is shown for both the proposed PE temporal path algorithm and the earliest arrival time (EAT) algorithm proposed in [12]. The case with no radius adjustment (i.e., the case where all UAVs fly at the maximum radius) is also shown for comparison. The EAT algorithm aims to minimize the arrival time of the information at the destination, but does not consider the efficiency of power consumption. Hence, we can see that the proposed PE temporal path algorithm significantly outperforms the EAT algorithm in terms of power savings. Moreover, we can see that the average power consumption per UAV slightly reduces as the number of UAVs increase under the PE temporal path algorithm. This is due to the fact that more path options are available when more UAVs are deployed within the area.

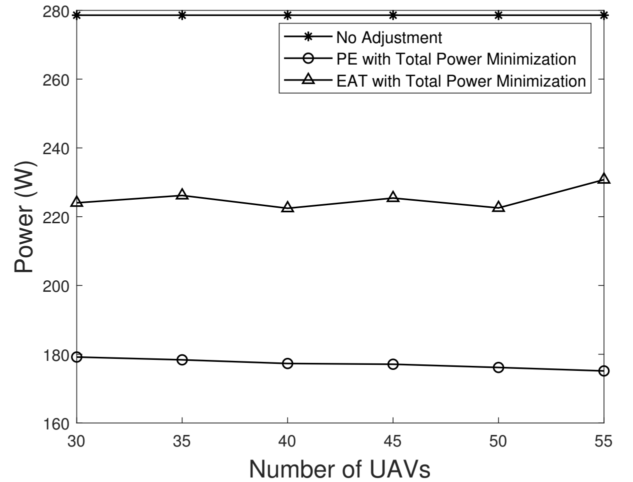

Fig. 4. Average per-UAV power consumption versus the number of UAVs.

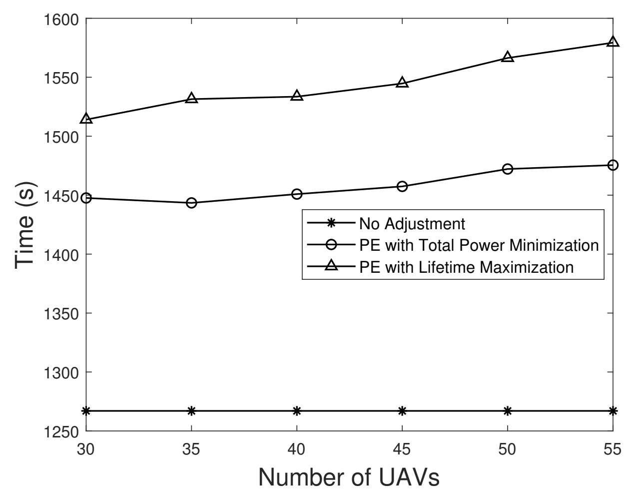

Fig. 5. Network lifetime versus the number of UAVs.

In Fig. 5, we show the network lifetime versus the number of UAVs for both the total power minimization and the lifetime maximization strategies for radius adjustment. The proposed PE temporal path algorithm is considered in both cases. In the lifetime maximization strategy, the radius is adjusted (i.e., the optimization problem in (14) is solved) every $\Delta t = \lambda/10 = 10$ seconds. As expected, we can see that the network lifetime is largest under the lifetime maximization strategy, and improves as the number of UAVs increases due to the increased number of path options in denser networks.

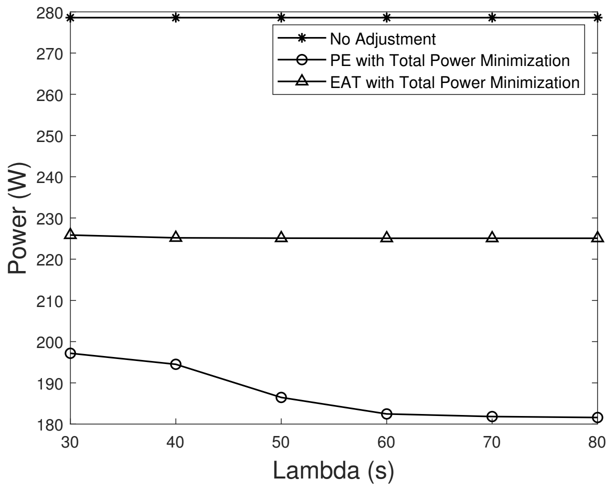

Fig. 6. Average per-UAV power consumption versus λ.

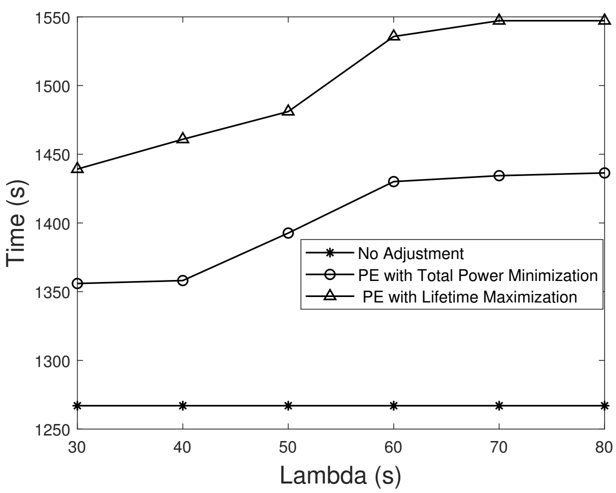

Fig. 7. Network lifetime versus λ.

In Fig. 6, we show the average power consumption per UAV versus the delay tolerance λ for both the PE temporal path and the existing EAT algorithms. Here, we adopt the total power minimization strategy for radius adjustment, and set $N = 40$. We can see that the average power consumption reduces as λ increases for the PE temporal path algorithm since increasing λ provides more opportunity to find a better route. In contrast, the path determined by the EAT algorithm does not change as λ increases and, thus, the average power consumption remains the static. Similarly, in Fig. 7, we show the network lifetime versus λ for both the total power minimization and the lifetime maximization strategies for radius adjustment. The proposed PE temporal path algorithm is considered in both cases. The lifetime maximization strategy is again implemented by solving (14) every $\Delta t = 10$ seconds. We can see that network lifetime increases with λ since the number of path options also increases in this case.

VI. Conclusion

In this work, we proposed two radius adjustment strategies, namely, the total power minimization and the lifetime maximization strategies for a network of fixed-wing UAVs that follow a circular trajectory to maintain coverage over its responsible sensing area. The lifetime maximization algorithm takes into consideration the residual battery at the UAVs when computing the UAVs's circulating radii. Then, by establishing the relationship between routing in this highly dynamic UAV network and that in temporal graphs, the PE temporal path algorithm was proposed to further improve upon the power efficiency by taking into account each UAV's flexibility in adjusting its flight-radius. Finally, numerical simulations were performed to demonstrate the effectiveness of the proposed schemes in terms of reducing the total power consumption and extending network lifetime.

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