EPLA: Energy-balancing Packets Scheduling for Airborne Relaying Networks

Kai Li[1] Wei Ni[2] Xin Wang[3] Ren Ping Liu[2]
Salil S. Kanhere[1] Sanjay Jha[1]

[1] The University of New South Wales, Australia
{kail, salilk, sanjay}@cse.unsw.edu.au
[2] CSIRO, Australia
{wei.ni, ren.liu}@csiro.au
[3] Fudan University, China
{xwang11}@fudan.edu.cn

Technical Report
UNSW-CSE-TR-201419
August 2014

THE UNIVERSITY OF
NEW SOUTH WALES

School of Computer Science and Engineering
The University of New South Wales
Sydney 2052, Australia

Abstract

Airborne relaying has great potential to extend the coverage of wireless sensor network (WSN), relaying sensed data from remote, human-unfriendly terrains. However, the challenges of lossy airborne relaying channels and short lifetime arise, due to the high mobility and limited battery capacity of unmanned aerial vehicles (UAVs). We propose an energy-efficient relaying scheme which is able to overcome the lossy channels and extend the lifetime of cooperative UAVs substantially. The key idea is to employ a swarm of UAVs to listen to a remote sensor from distributed locations, thereby improving packet reception over lossy channels. UAVs report their reception qualities to the base station, which then schedules UAVs' forwarding with guaranteed success rates and balanced energy consumption. Such scheduling is a NP-hard binary integer programming problem and intractable in WSNs where there can be a large number of packets. We develop a practical suboptimal solution by decoupling the processes of energy balancing and modulation selection. The decoupled processes are carried out in an alternating manner, achieving fast convergence. Simulation results confirm that our method is indistinguishably close to the NP-hard optimal solution in terms of network yield (throughput). Meanwhile, the complexity of our method is significantly lower by orders of magnitude. Simulations also reveal that our scheme can save energy by 50%, increase network yield by 15%, and extend network lifetime by 33%, compared to existing greedy algorithms.

1 Introduction

Airborne relaying has great potential to extend the coverage of wireless sensor networks (WSN) to remote, human-unfriendly terrains, such as battlefields and bushfires [21]. It also has important applications to monitoring chemical clouds [27], precision agriculture [25], disaster management [20], as well as rescue operations [5]. The widespread availability of unmanned aerial vehicles (UAVs) such as Aerosonde, Quadrocopter, etc. has also contributed to their popularity as mobile relays and data sinks [15, 14].

Figure 1.1 illustrates a typical application scenario of airborne relaying, where a number of sensor nodes are deployed in remote areas to collect critical environmental data, for example, temperature changes for bushfire monitoring purpose. However, the radio path between the source node, i.e., the remote sensor, and the data processing center, i.e., the data collecting base station (BS), is obstructed; hence the radio signal is too weak to be detected at the data processing center. In this case, a swarm of UAVs can be employed to fly over the source and the destination, establishing a multi-hop wireless relaying transmission link.

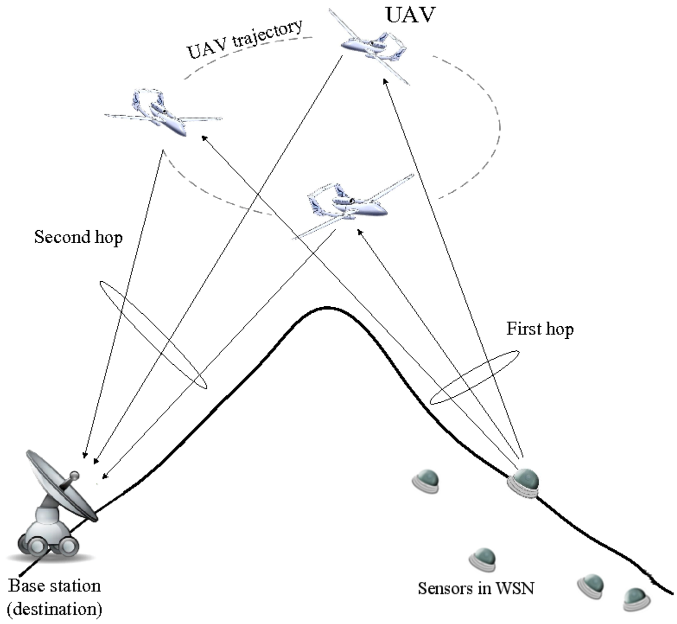

Figure 1.1: Airborne relaying networks using cooperative UAVs. The source node can be deployed to sense the environment as a sensor or collecting data from neighbor nodes as a cluster head in WSN.

Several critical challenges arise in such a UAV-assisted relaying network. First, the wireless channels between the ground nodes (i.e., sensors and BS) and the aerial relays are highly dynamic and prone to packet loss [4]. The impact of this is especially severe over the first hop from the sensor to the UAVs, as the sensor typically does not have capabilities of foreknowing the variation of channel conditions to adapt its transmissions. At one moment, a UAV may receive excellent signals from the sensor because they are close. At the next instance, the quality of this link may deteriorate significantly as the UAV flies away from the sensor. Another critical challenge arises from the fact that a UAV has limited battery capacity. Data collection would be frequently interrupted, because the UAV needs to be recharged. The use of multiple UAVs, each of which takes responsibility of forwarding part of the sensed data, can relieve this problem to some extent [22]. However, in this case, the problem of distributing the packet load amongst the relay nodes while ensuring a balanced energy drain amongst the UAVs is non-trivial, particularly, given the uncertain channel dynamics. To the best of our knowledge, no existing work has proposed a solution that addresses this critical issue.

In this paper, we propose an energy-efficient cooperative relaying scheme, which is able to overcome the lossy channels, and substantially extend the lifetime of cooperative UAVs. The key idea is to employ a swarm of UAVs to serve as relay network for collecting data from a remote sensor, thereby improving packet recovery over lossy channels. In our scheme, the UAVs report their reception qualities to the base station, which then schedules UAVs' forwarding with a high chance of success and balanced energy consumption among the UAVs. We note that calculating such an optimal schedule is a NP-hard binary integer programming problem, which makes it intractable in our context setting, since typically a large number of packets are transmitted by the sensor nodes over their lifetime [13, 18]. We develop a practical suboptimal solution by decoupling the processes of energy balancing and modulation selection. The decoupled processes are carried out in an alternating manner. Moreover, our proposed scheme achieves fast convergence.

Simulation results confirm that our suboptimal scheduling method is able to perform indistinguishably close to the NP-hard optimal solution in terms of network yield (throughput). Meanwhile, the complexity of our suboptimal method is dramatically lower, e.g., by three orders of magnitude in the case of five cooperative UAVs. Moreover, our suboptimal method is able to instantly schedule tens of cooperative UAVs. In contrast, the optimal solution can barely support five UAVs in real time. Simulations also reveal that the proposed cooperative UAV relaying scheme can save energy of the relaying nodes by 50% on average and extend network lifetime by 33%, compared to existing greedy algorithms. Our scheme is also 15% better in terms of network yield.

Extensive simulations have been carried out to investigate several practical issues that are relevant to the design of airborne relaying networks. They reveal that the cooperation of UAVs (to be specific, the number of cooperative UAVs) and the flight trajectory are important to the network lifetime. Specifically, the lifetime grows linearly with the number of UAVs but at a slower pace. This is because the improved network yield that stems from the increased number of UAVs incurs additional energy costs. The lifetime can also be extended by carefully designing the trajectory of UAVs. A flying range of $\frac{1}{3}$ between the sensor and the BS can leverage the packet loss over the first hop and the energy consumption over the second hop, achieving the longest network lifetime.

This paper makes the following contributions:

- For an airborne relaying network, we model a novel energy-balancing packet load allocation problem by using *Min-Max* optimization to prolong the network lifetime.

- A novel Energy-balancing Packet Load Allocation (EPLA) algorithm that we propose balances the energy consumption among the UAV swarm. It approximates the performance of the optimal packet load solution with a significantly reduced complexity.

- We conduct extensive simulations to analyze the performance of the EPLA. Furthermore, by utilizing different UAVs flight trajectory, we evaluate how the number of UAVs and the variance of flight path affect the performance of packet load schedules.

The rest of the paper is organized as follows. Section 2 covers related work on UAV-based relaying and the issue of energy efficient scheduling in particular. Section 3 introduces the system model that is used in the rest of the paper. In Section 4, we propose a communication protocol and formulate the energy balancing packet load scheduling optimization problem. Furthermore, the sub-optimal solution, EPLA algorithm is presented. The simulation and evaluation are shown in Section 5. Finally, we conclude the paper and present the future work in Section 6.

2 Related Work

In this section, existing cooperative relaying techniques are reviewed with a particular emphasis on energy saving.

Many existing works focus on a delay-tolerant scenario where mobile sinks patrol a number of static sensor nodes and collect data [23, 16]. Patrol paths of the sinks were designed to improve the energy efficiency and lifetime of the WSN. However, these works assume that the sinks have unlimited battery. These schemes can not be directly applied to many real-time applications, such as disaster management and rescue operations.

In [1], Abdulla *et al.* formulated a potential game between a number of on-ground sensor nodes and a single UAV to maximize the energy efficiency of the sensors' transmissions. Unfortunately, the uniqueness of Nash Equilibrium (NE) is not evaluated in the formulated potential game. The authors point out that the game may converge to and stay at a local optimum NE. As a result, the energy efficiency degrades.

In [26] and [6], the authors focus on placement of cooperative UAV relays for ensuring connectivity and high throughput in mobile ad hoc networks. However, the proposed algorithms assume that the UAVs have unlimited battery capacities, which is unrealistic.

In [11, 9], a *Hive-Drone* model was developed in airborne relaying networks, where a centralized charging station, hive, is placed in the sensing field to recharge the UAVs (i.e., drones). The UAVs collect and carry data from the sensing field to the hive. Flying paths of the UAVs were designed to reduce information gathering latency. Unfortunately, the *Hive-Drone* model is inapplicable to human-unfriendly environments, such as battlefield and bushfire, where the cables required to feed energy to the hive cannot be deployed. In addition, the latency resulting from the data gathering process may be intolerable in real-time applications.

In our previous work [18], we proposed a scheduling optimization to maximize data harvesting in a bats monitoring sensor network with energy and link quality constraints. However, the scenario under consideration is very different, since the mobile nodes are responsible for sensing and not relaying. Moreover, the transmit power of the mobile nodes is not adjustable due to the application limitations. In this work, the transmit power of the UAV relays can be adjusted according to variations in the channel conditions. Further, we maximize the energy-efficiency of the cooperative UAVs so as to extend the network lifetime.

3 System Model

In this paper, we consider a network which has one source node, N_R number of UAVs and one BS (see Figure 1.1). Without generality, we focus on a single sensor node. However, our model and proposed algorithm can be readily extended to general scenarios where multiple sensors are involved. The swarm of N_R UAVs serve as airborne relays for forwarding packets from the source to the BS. The UAVs fly along a pre-determined trajectory between the source node and the BS such that each UAV is always in the communication range of the source node and the BS. In our previous work [2], we characterized the link behavior of air-to-ground and ground-to-air links with UAVs hovering at a fixed location using empirical measurements. While these results are insightful they cannot be directly applied in this work as the UAVs are mobile which in turn significantly impacts the channel conditions.

Let M_R denote the total number of data packets transmitted by the source node. Let $\mathbb{S}_i$ denote the number of packets successfully received by UAV i. Note that $\mathbb{S}_i \leq M_R$ depending on the channel condition of the link between the source node and UAV i. The path loss of the source-UAV channel at time t can be approximated as free-space path loss [10] and is given by,

$$L(d_{src,i}(t)) = K_1 d_{src,i}^{K_2}(t), \tag{3.1}$$

where K_2 indicates the path loss component. $d_{src,i}(t)$ is the distance between the source node and UAV i at time t. K_1 is denoted by

$$K_1 = \frac{(4\pi)^2}{G_{tx} G_{rx} \lambda_0^2}, \tag{3.2}$$

where G_{tx} and G_{rx} are the antenna gains of the transmitter and receiver, respectively. $\lambda_0 = c/f_0$, which is a ratio of speed of light c and carrier frequency f_0. We define Signal-to-Noise ratio (SNR) between the source node and UAV i at time t as $\gamma_i'(t)$. Given an additive white Gaussian noise (AWGN) with power N_0,

$$\gamma_i'(t) = \frac{|\hbar|^2 P_{src}^{tx}}{N_0 L(d_{src,i}(t))}, \tag{3.3}$$

where P_{src}^{tx} denotes the transmit power of the source node. The small-scale fading is indicated by $\hbar$. Then, the average SNR for UAV i is calculated by

$$\overline{\gamma}_i'(t) = \frac{P_{src}^{tx}}{K_1 N_0 d_{src,i}^{K_2}(t)}. \tag{3.4}$$

In this paper, we derive the packet error probability of the first hop channel (i.e. the source node-UAV link) based on its outage probability, which provides the lower bound of the packet error probability under an assumption of ideal coding and modulation. For illustration purpose, Rayleigh Block fading is considered [24]. The channel coefficient remains constant within each block, and varies between blocks. At time t, the outage probability at UAV i is given by

$$\Pr(\gamma_i'(t) < \gamma_0) = \int_0^{\gamma_0} p(\gamma_i'(t)) d(\gamma_i'(t)) = 1 - \exp(\frac{\gamma_0}{\overline{\gamma}_i'(t)}), \tag{3.5}$$

where γ_0 is the SNR threshold required for successful reception at the UAV.

Substitute Equation 3.4 into Equation 3.5. The packet error probability at UAV i can be given by

$$\Pr_{src,i}(t) = 1 - \exp(-K_{src} \cdot d_{src,i}^{K_2}(t)), \tag{3.6}$$

$$K_{src} = \frac{K_1 N_0 \gamma_0}{P_{src}^{tx}}. \tag{3.7}$$

It is worth mentioning that other fading channels or specific modulation and coding methods can also be considered for the first hop. The cooperative relaying scheme that we propose in this paper is general, and it is applicable to any channels, or modulation and coding methods.

Note that the source node maintains its transmit power to be P_{src}^{tx} at the first hop so that the operations at the source is kept simple. At the second hop, UAVs are scheduled to offload their received data packets to the BS (will be presented in Section 4.1). The transmit power of UAVs is varied according the adaptive modulation and coding (AMC) rate [19]. This is because the BS is able to schedule UAVs in real-time based on their reception qualities on the first hop. AMC rates can be adaptively determined for each UAV to ensure timely delivery of data packets. Consider Rayleigh fading channels with path loss that is related to the distance between each UAV and the BS [29]. At time t, the channels $H_i(t)$ from UAV i to the BS is given by

$$H_i(t) = \frac{\lambda H_i(t-1) + \sqrt{1-\lambda^2} \cdot n_i}{(d_{i,bs}(t))^{\alpha_i}}, \tag{3.8}$$

where $d_{i,bs}(t)$ indicates the distance between UAV i and the BS at time t. n_i is a Gaussian random number generated by AWGN. α_i is the path-loss exponent. Due to the movement of UAVs, the channel presented here consists of two components, namely, an autocorrelated component which relies on the previous channel condition, and an independent component which is independent of previous channels. A coefficient λ is considered to adjust the weights of the two components. Moreover, λ decreases with the growth of the speed of UAVs.

Similar to the first hop, we define the SNR of the second hop as $\gamma_i(t)$,

$$\gamma_i(t) = H_i(t) \frac{\Gamma_i(t)}{N_0}, \tag{3.9}$$

where $\Gamma_i(t)$ indicates minimum transmit power of UAV i at time t.

4 Packet Load Scheduling for UAVs

In this section, we first propose a cooperative relaying protocol which is able to improve the end-to-end delivery of the sensing data. We then formulate the optimal scheduling problem, which extends the network lifetime by balancing the energy consumption of UAVs. Noting the problem is a NP-hard integer programming and intractable in real-time applications, we develop a low-complexity algorithm which can very closely match the optimal strategy in terms of network throughput. Our algorithm can be operated in real-time, where a large number of packets need to be scheduled and forwarded in a timely manner.

4.1 Relaying Protocol of Cooperative UAVs

In this paper, we propose a cooperative relaying protocol in which multiple UAVs relay the sensing data to the remote BS. The number of UAVs involved is critical to the packet loss and lifetime of the UAVs, as will be shown in Section 5. Figure 4.1 illustrates the protocol that we propose to enable multiple UAVs to collaboratively forward packets from the source to the BS. In the protocol, the source node broadcasts its sensing data to the cooperative UAVs. The number of packets received by UAV i is denoted by $|\mathbb{S}_i|$ ($i \in [1, N_R]$). Then, UAVs use their pilot channels to notify BS their reception qualities of the packets. To be specific, each UAV reports the indices to its successfully decoded packets which are used for packet load scheduling algorithm (as will be discussed in Section 4.3). Moreover, the BS is able to measure $\gamma_i(t)$ for every UAV. Based on the UAVs' report and the measurement results, the BS schedules packet load for every UAV, and also determine the associated AMC rates. After the execution of packet load scheduling algorithm, the BS sends the scheduling results to the UAVs. For each UAV, $|s_i|$ ($0 \leq |s_i| \leq |\mathbb{S}_i|$) packets are transmitted to the BS according to the schedules where s_i denotes the set of data packets that UAV i is scheduled to transmit. Since the transmissions of UAVs to the BS are scheduled, repeated transmission of the same packet from multiple UAVs is avoided. Namely, $s_i \cap s_{i-1} = \emptyset$ with $s_0 = \emptyset$. This ensures the limited energy of UAVs to be effectively utilized to forward packets.

A small amount of overhead is required in this protocol. For the reception quality report shown in Figure 4.1, each UAV can use one bit to indicate its reception quality of a packet, "1" for successful reception and "0" for unsuccessful reception. Consider a case where the source node sends 128 data packets. Each UAV needs to transmit a report of 16 bytes. For the packet of scheduling results that the BS broadcasts to the UAVs, shown in Figure 4.1, one selected UAV's ID is attached to every data packet. For example, given 8 relaying UAVs and 128 data packets from the source node, the packet of scheduling results has 48 bytes in total.

4.2 Problem Formulation

Based on Equation 3.9, the instantaneous bit error rate (BER) ϵ_i for UAV i is approximated by [8]

$$\epsilon_i \approx \kappa_1 \exp\left[\frac{-\kappa_2 \gamma_i(t)\Gamma_i(t)}{2^{\rho_i} - \kappa_3}\right], \tag{4.1}$$

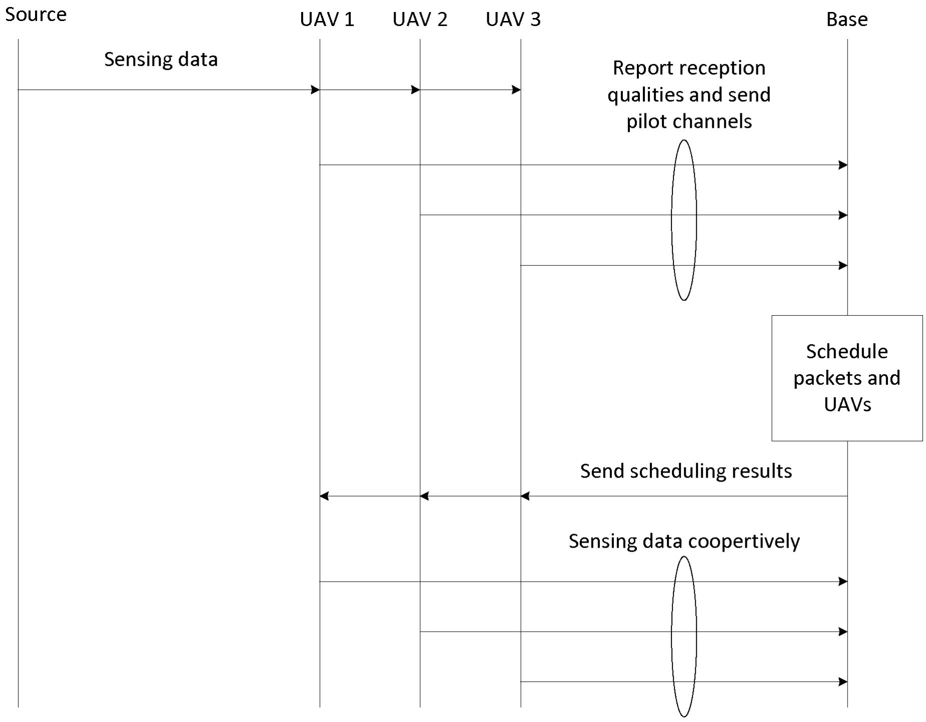

Figure 4.1: The communication protocol.

where κ_1 and κ_2 are two constants relating to the channel, and κ_3 is a real constant. ρ_i denotes a finite set of AMC modes for UAV i and the highest mode is denoted by ρ_M. Furthermore, ϵ_i is limited by the system requirement ϵ, namely, $\epsilon_i \leq \epsilon, i \in [1, N_R]$. According to [12], to fulfill the BER requirement, we have

$$\Gamma_i(t) = \frac{\kappa_2^{-1} \ln(\frac{\kappa_1}{\epsilon}) \cdot (2^{\rho_i} - 1)}{\gamma_i(t)}. \tag{4.2}$$

The only variable in Equation 4.2 is ρ_i since different AMC modes require different transmit power. So it can be written as

$$\Gamma_i(t) = \delta_i(t) \cdot (2^{\rho_i} - 1), \tag{4.3}$$

where $\delta_i(t) = \frac{\kappa_2^{-1} \ln(\frac{\kappa_1}{\epsilon})}{\gamma_i(t)}$.

Given the modulation level ρ_i and the packet size $\mathfrak{L}_p^{s_i}$, the energy that UAV i is consumed to forward packets s_i is given by

$$\pi(s_i, \rho_i, t) = \mathfrak{L}_p^{s_i} \cdot \delta_i(t) \cdot \frac{(2^{\rho_i} - 1)}{\rho_i}. \tag{4.4}$$

We consider that all the packets that the source node sends are of the same size in length. Therefore, we can suppress the superscript of $\mathfrak{L}_p^{s_i}$ in the rest of the paper.

We can formulate the optimization problem of scheduling packets to balance energy consumption between UAVs. Specifically, the goal of the optimization is to minimize the largest energy consumption of all the UAVs, given that the UAVs may have received different subsets of the packets the source node sent. The formulation is provided as follows.

$$\min_{x_{i,s,\rho_i}} \left\{ \max_{i\in[1,N_R]} \sum_{s\in\mathbb{S}_i} \sum_{\rho_i=1}^{\rho_{\mathbb{M}}} x_{i,s,\rho_i} \cdot \delta_i(t) \cdot \frac{2^{\rho_i}-1}{\rho_i} \right\} \tag{4.5}$$

$$subject\ to: \sum_{\rho_i=1}^{\rho_M} \Big[x_{i,s,\rho_i}\Gamma_i(t) \Big] \leq P_{max},\ \forall s\in\mathbb{S}_i \tag{4.6}$$

$$\sum_{\rho_i=1}^{\rho_M} x_{i,s,\rho_i} \leq 1,\ \forall s\in\mathbb{S}_i \tag{4.7}$$

$$\sum_{i\in\{j:s\in\mathbb{S}_j\}} \sum_{\rho_i=1}^{\rho_M} x_{i,s,\rho_i} = 1,\ \forall s\in\bigcup_{i=1}^{N_R}\mathbb{S}_i \tag{4.8}$$

$$\sum_{i\in\{j:s\in\mathbb{S}_j\}} \sum_{s\in\mathbb{S}_i} \sum_{\rho_i=1}^{\rho_M} \frac{x_{i,s,\rho_i}}{\rho_i} \leq \frac{T}{\mathfrak{L}_p} \tag{4.9}$$

where the binary variables x_{i,s,ρ_i} that are to be optimized are the indicator that UAV i is allocated to forward packet $s \in \mathbb{S}_i$ using $\rho_i \in [1, \rho_M]$, P_{max} is the maximum transmit power of a UAV, and T is the duration of a timeslot for all the UAVs to forward packets.

Constraint (4.7) states that any data packet can only be forwarded by one AMC mode of a UAV. Constraint (4.8) guarantees that each of the packets that have been correctly received by the UAVs is forwarded by one of the UAVs that have correctly received the packet. Any two UAVs can not transmit the same packet. Constraint (4.9) ensures all the UAVs complete forwarding packets in the scheduled timeslot of T, where $\sum_{i\in\{j:s\in\mathbb{S}_j\}} \sum_{s\in\mathbb{S}_i} \sum_{\rho_i=1}^{\rho_M} \frac{x_{i,s,\rho_i}}{\rho_i}$ is the time required for the UAVs to forward their correctly received packets.

To solve this *Min-Max* optimization problem, we can further reformulate it to a set of minimization problems. Specifically, for UAV i, we minimize

$$\min_{x_{i,s,\rho_i}} \left\{ \sum_{s\in\mathbb{S}_i} \sum_{\rho_i=1}^{\rho_{\mathbb{M}}} x_{i,s,\rho_i} \cdot \delta_i(t) \cdot \frac{2^{\rho_i}-1}{\rho_i} \right\} \tag{4.10}$$

$$\begin{aligned}
s.t.: \; & \sum_{\rho_i=1}^{\rho_M} \left[x_{i,s,\rho_i} \Gamma_i(t) \right] \leq P_{max}, \; \forall s \in \mathbb{S}_i \\
& \sum_{\rho_i=1}^{\rho_M} x_{i,s,\rho_i} \leq 1, \; \forall s \in \mathbb{S}_i \\
& \sum_{i\in\{j:s\in\mathbb{S}_j\}} \sum_{\rho_i=1}^{\rho_M} x_{i,s,\rho_i} = 1, \; \forall s \in \bigcup_{i=1}^{N_R} \mathbb{S}_i \\
& \sum_{i\in\{j:s\in\mathbb{S}_j\}} \sum_{s\in\mathbb{S}_i} \sum_{\rho_i=1}^{\rho_M} \frac{x_{i,s,\rho_i}}{\rho_i} \leq \frac{T}{\mathfrak{L}_p} \\
& \sum_{s\in\mathbb{S}_i} \sum_{\rho_i=1}^{\rho_{\mathbb{M}}} \left(x_{i,s,\rho_i} \cdot \delta_i(t) \cdot \frac{2^{\rho_i}-1}{\rho_i} \right) \geq \sum_{s\in\mathbb{S}_j} \\
& \qquad \sum_{\rho_j=1}^{\rho_{\mathbb{M}}} \left(x_{j,s,\rho_j} \cdot \delta_j(t) \cdot \frac{2^{\rho_j}-1}{\rho_j} \right), \; \forall j \neq i
\end{aligned} \tag{4.11}$$

where the maximization of the original *Min-Max* problem is avoided by including $(N_R - 1)$ new auxiliary constraints, as given by (4.11). The new minimization problem now becomes solvable, using standard optimization tools, e.g., the MATLAB bintprog function.

Note that the minimization problem needs to be solved with respect to each of the N_R UAVs. Their results are compared, and the one associated with the least energy consumption is taken. Unfortunately, the problem is a NP-hard integer programming. Solving N_R such problems require prohibitively high computational complexity. On the other hand, it is typical that a large number of packets are generated in WSNs. This would lead to an exponentially increased complexity for solving the NP-hard integer programming. For these reasons, optimal solutions to balancing energy consumption are intractable in practice, and cannot meet the real-time requirement of the system.

4.3 Proposed EPLA Heuristic

We proceed to propose a practical, sub-optimal solution to the energy balancing packet scheduling problem, since the optimal solutions are intractable and have limited value in practice, as discussed earlier. Details are provided in Algorithm 1.

In the proposed EPLA algorithm, we sort the UAVs by their energy consumptions in a descending order. The ith UAV in the ordered sequence is indexed by $\ell(i)$ (see Step 12). Next, we reduce the biggest difference of energy consumption between the UAVs by reassigning some packets from the UAV that would consume the most energy to the one that would consume the least, given that these packets have been correctly received by both of the UAVs (as described in Steps 13 and 14). We repeatedly do this, until the difference of

Algorithm 1 EPLA Algorithm

1: Initialize $\rho_i = 1$.
2: Sort all UAVs by $\frac{\kappa_2^{-1}\ln(\frac{\kappa_1}{\epsilon})}{\gamma_i}$ in ascending order.
3: **while** EPLA is not completed **do**
4: **for** $i = [1, N_R]$ **do**
5:   **if** $\frac{\kappa_2^{-1}\ln(\frac{\kappa_1}{\epsilon})\cdot(2^{\rho_{\ell(i)}}-1)}{\gamma_{\ell(i)}(t)} \leq P_{max}$ **then**
6:    Schedule UAV $\ell(i)$ to transmit the data packets which have not been allocated.
7:   **else**
8:    The $\gamma_{\ell(i)}(t)$ is too small, UAV $\ell(i)$ is not scheduled to transmit.
9:   **end if**
10: **end for**
11: **while** $|\pi(s_{\ell'(i)}, \rho_{\ell'(i)}, t) - \pi(s_{\ell'(j)}, \rho_{\ell'(j)}, t)|$ is minimized **do**
12:   Sort UAVs by $\left[|s_{\ell'(i)}| \cdot \delta_{\ell'(i)}(t) \cdot \frac{(2^{\rho_{\ell'(i)}}-1)}{\rho_{\ell'(i)}}\right]$ in descending order.
13:   UAV i has largest $\pi(s_{\ell'(i)}, \rho_{\ell'(i)}, t)$ and UAV j has smallest one.
14:   Allocate packet load from $s_{\ell'(i)}$ to $s_{\ell'(j)}$.
15: **end while**
16: **if** $\sum_{i=1}^{N_R} \frac{|s_{\ell'(i)}|}{\rho_{\ell'(i)}} \leq \frac{T}{\mathfrak{L}_p}$ **then**
17:   EPLA is completed.
18:   **break**
19: **else**
20:   Sort UAVs by $\frac{|s_{\ell'(i)}|(2^{\rho_{\ell'(i)}}-1)}{\rho_{\ell'(i)}}$ in descending order, $\ell'(i)$ has the largest value.
21:   $\rho_{\ell'(i)} \leftarrow \rho_{\ell'(i)} + 1$.
22: **end if**
23: **end while**

energy consumption stops decreasing; see Step 11. We then assess the time required for all the UAVs to complete forwarding, i.e., Constraint (4.9); see Step 16. If the time constraint cannot be met, we increase the AMC rate of one of the UAVs that requires the least energy of all the UAVs, as shown in Steps 20 and 21; and then repeat reducing the difference of energy consumption, as described above. If the time constraint is satisfied, the algorithm terminates.

Figure 4.2 illustrates the proposed scheduling algorithm, where the two processes of energy balancing and modulation adjusting interact with each other. The convergence of the algorithm is demonstrated. Specifically, in the energy balancing process, the algorithm recursively reduces the energy consumption difference between any pair of UAVs, given the modulation of every UAV. As indicated by the red dash arrows, the largest difference of energy consumption is reduced by rescheduling some of the packets from the most energy-consuming UAV to the least energy-consuming UAV. The requirement of transmit time may increase. This is due to the fact that the energy efficiency is higher under better channel conditions. Our algorithm is designed to maximize energy efficiency, and therefore the UAVs with better channels are assigned with more packets whenever possible. The UAVs that consume more energy have better channels than the other UAVs. UAVs with worse channels utilize lower modulation orders. As a result, the required transmit time grows, and the constraint

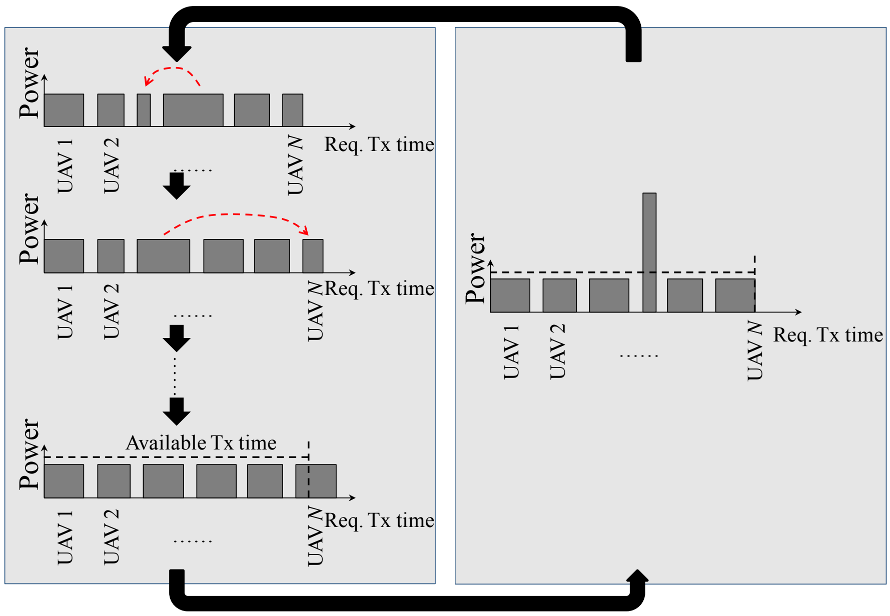

Figure 4.2: Pictorial illustration of the proposed algorithm, where the left box describes the energy balancing process given the modulation of every UAV; the right box shows increasing the modulation to fit into the available transmit time. The area of each grey block indicates the energy consumption of a UAV.

of the totally available transmit time may be violated.

The modulation adjusting process is carried out to address the violation of the transmit time constraint. As shown in the right-hand side of the figure, we pick up one of the UAVs and increase its modulation order. The UAV is chosen to require the least extra energy.

Clearly, the modulation adjustment results in a growth of the overall energy consumption, since the transmit power of the selected UAV increases exponentially while its required transmit time decreases just linearly. In other words, the overall energy budget is increased. A new round of energy balancing is then carried out to balance the energy consumption, given the increased energy budget.

The convergence of the proposed algorithm is obvious, because it gradually increases the energy budget until the constraint of the transmit time is met and the difference of energy consumption between any pair of UAVs is minimized.

5 Simulation Evaluation

In this section, we evaluate the performance of the EPLA. We also investigate the impact of cooperative UAVs setup (i.e., number, flying pattern, trajectory) on the proposed algorithm. Interesting findings will be discussed.

Table 5.1: Configuration of Simulations

Parameters	**Values**
Number of source node	1
Number of BS	1
h_{UAV}	50m
λ_0	0.125m
$\mathfrak{L}_p$	32 bytes
M_R	100 packets
P_{max}	5W
N_0	3.98 x 10^{-12}W
N_R	[1,20]
ϵ	0.5%
κ_1	0.2
κ_2	3
K_2	2.5
γ_0	3dB
G_{tx}	1dB
G_{rx}	1dB

5.1 Simulation Model and Parameters

We first study the performance of EPLA for different network sizes. The maximum number of UAVs is 20. The detailed system-level simulation parameters are shown in Table 5.1. Considering a cooperative fire surveillance scenario [3, 7], the flight path of UAVs is modeled as a circle between the source node and BS. The path length of each UAV is $2\pi r$. The UAVs are uniformly distributed on the circular trajectory between the source and BS. While we use the fire surveillance application as a case study of UAVs flight, the EPLA optimization and algorithm are application-agnostic and hence applicable to a wide variety of large-scale UAV relay networks. The distance between the source node and BS is 2km and all the UAVs fly at the same speed which is $10m/s$. The wireless links between the source node and UAVs, UAVs and the BS are modeled by block fading channels. Hence, the channel gain γ_i and γ_i' are not stable during the period of packet load scheduling.

Denote the initial energy of any UAV i as $E_i(0)$. There are two key performance metrics analyzed, i.e., network yield, and network energy consumption (NEC). The simulation duration is indicated by T and $E_i(T)$ is the remaining energy of UAV i at the end of simulation. Therefore, NEC is measured by $\sum_{i=1}^{N_R}(E_i(0) - E_i(T))$, which is the energy consumption of all relay UAVs. According to [28], network yield is calculated by

$$\text{Network Yield} = \frac{\text{the number of pkts received by BS}}{M_R} \tag{5.1}$$

Moreover, to see how much EPLA affects network lifetime, we also perform additional simulations where the source node keeps transmitting data to the BS. Specifically, since the data transmission will stop only when all relay UAVs die, the network lifetime is defined as a time span until all the relay nodes run out of their energy $E_i(0)$.

We also perform EPLA with different UAV's trajectories to evaluate the impact of our proposed scheduling algorithm on the network lifetime. In the trajectory test, the trajectories of UAVs that we consider are a set of concentric circles. The center of circular trajectories is fixed at the middle point between the source and the BS. The radius of the circular trajectory r changes from $200m$ to $1000m$ as shown in Figure 5.1.

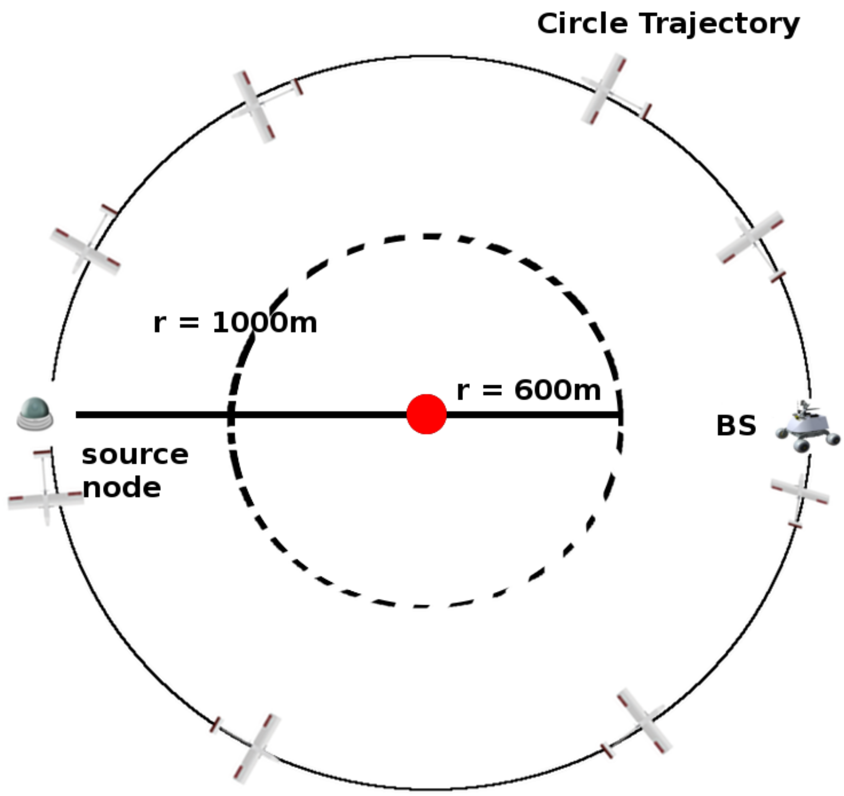

Figure 5.1: The top view of circular trajectory with different radius r. $N_R = 8$.

For comparison purpose, we also simulate three other generic packet load scheduling algorithms that are suitable in our context setting. The first one, referred to as "Low Transmission Power (Low TxPower)", is a greedy algorithm, where the packet load scheduling is based solely on the $\Gamma_i(t)$ [18]. Lower $\Gamma_i(t)$ implies that the UAV i has a higher γ_i. Hence, the UAV with higher $\Gamma_i(t)$ is assigned more packet load and the one with lower $\Gamma_i(t)$ transmits less packets. The second algorithm, referred to as "Average Allocation", is a non-adaptive strategy that schedules an equal number of packets to all UAV relays. Finally, the last benchmarking strategy is referred to as "Random Allocation" in which the packet load to each relay is randomly assigned.

Table 5.2: Comparison of runtime, where the variance is calculated based on 5 runs.

UAVs	Optimal Schedules		EPLA	
	mean	**variance**	**mean**	**variance**
1	0.56s	0.000022	0.039s	0.000015
2	19.06s	1.6291	0.0438s	0.000013
3	42.6540s	0.5993	0.0477s	0.000039
4	50.0191s	12.4113	0.0507s	0.000019
5	129.1360s	147.9916	0.0664s	0.00003

5.2 Comparison To Optimal Packet Schedules

Figure 5.2 compares our proposed EPLA algorithm, i.e., Algorithm 1, with the optimal strategy, the results for which are obtained by solving the optimization problem in Section 4 using MATLAB BINTPROG program. Two cases are considered. In the first case, the first hop reception quality is based on the distance and channel between the source and UAVs, as described in Section 5.1. Observe that, the network yield achieved by EPLA is fairly close to that of the optimal scheme. In particular, the performance of two schemes converge as the number of relays N_R increases. Note that, even in the worst case, the performance of EPLA is only 5% lower than that of the optimal scheme.

The second case we consider is that the first hop is ideal. In other words, no packet loss is experienced at this hop. We can see EPLA has very similar network yield to optimal scheme. Specifically, the difference is smaller than 3%.

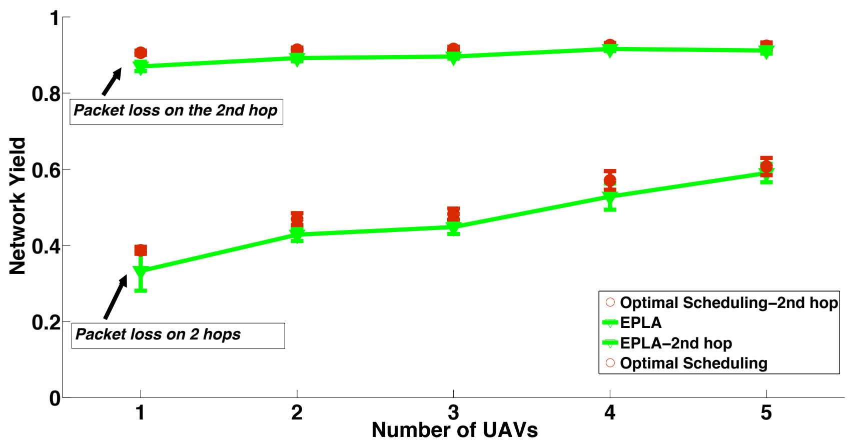

Figure 5.2: Comparison of network yield. The error bar shows the standard deviation over 5 runs.

Note that in Figures 5.2, the simulation results are based on 5 independent runs. Moreover, we only consider a network with up to 5 UAVs. The reason for the small-scale nature of these experiments is due to the prohibitive computational complexity that is required for solving the optimization problem in MATLAB BINTPROG program. Our MATLAB simulations are implemented using a 2.7 GHz Intel core processor with 8 GB of memory. Moreover, observed by Table 5.2, the runtime of the optimal scheme is increased significantly while increasing N_R. However, the variance of runtime of EPLA is less than 0.02 second. Specifically, when $N_R = 5$, EPLA is $2mins$ faster than the optimal scheme. Thus, our heuristic is much more efficient than the optimal scheme on runtime and can be directly applied to the real-time applications.

5.3 Network Yield and Energy Consumption

Figure 5.3 shows the network yield of the aforementioned four packet load scheduling algorithms. When the number of UAVs is small, they provide similar performance of network yield. As the number of relays N_R increases, so does the network yield since more UAVs cooperate with each other to forward data. However, observe that our proposed EPLA algorithm achieves significantly better performance, more so with higher N_R. Specifically, our algorithm achieves 15%, 30% and 38% higher network yield when $N_R = 20$. The network yield is improved by EPLA since the packets transmitted by the UAV with large δ_i has higher reception probability than the one with low δ_i.

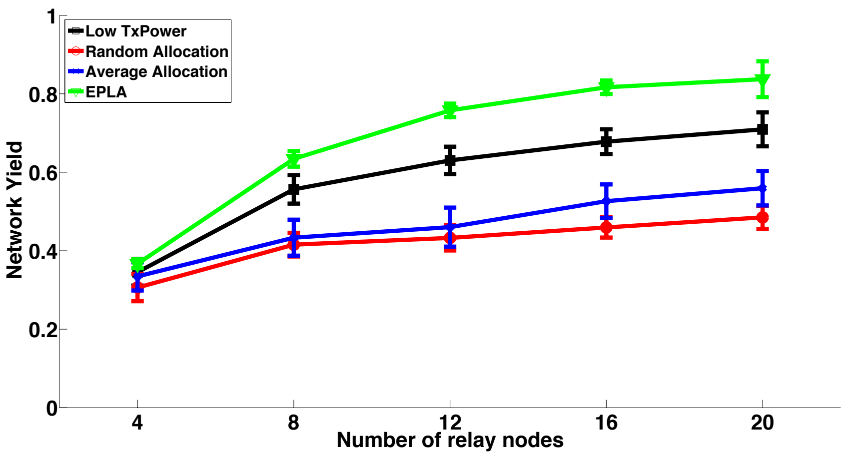

Figure 5.3: Comparison of network yield with different packet scheduling algorithms. The error bar shows the standard deviation over 100 runs.

Figure 5.4 compares the four algorithms based on NEC. Generally, greater the number of UAVs in the network, lower is the NEC, since the UAVs with smaller $\Gamma_i(t)$ relay more data. When $N_R = 1$, the NEC is the highest since there is only one relay node. The four algorithms have the same performance since the packet load scheduling is effective only when $N_R > 1$. Specifically, EPLA saves 50%, 75% and 78% more energy than TxPower, Average and Random allocations. The reason is, for EPLA, most of the packets are scheduled to the UAVs with small $\Gamma_i(t)$, which decreasing the energy consumption of the network.

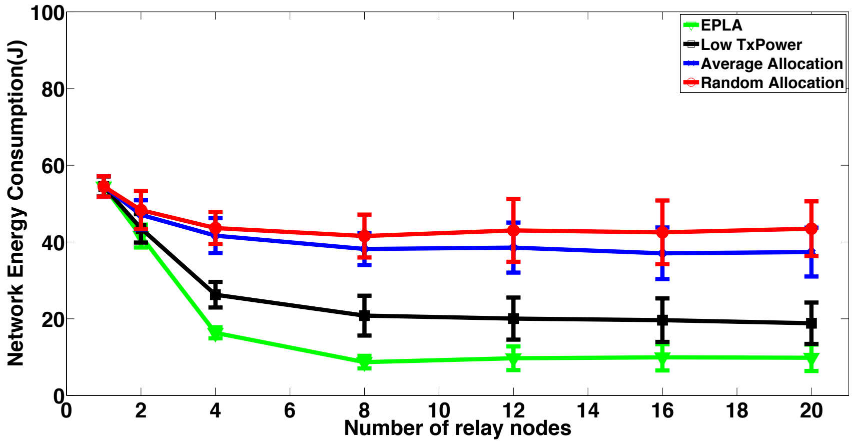

Figure 5.4: Comparison of NEC with different packet scheduling algorithms. The error bar shows the standard deviation over 100 runs.

5.4 Network Lifetime

Figure 5.5 illustrates the impact of the number of UAVs on the network lifetime given that the source node keeps transmitting data packets and the battery capacity of each UAV is around $80J$. We can see that the network lifetime is extended by increasing the N_R. The graph readily suggests that EPLA achieves significantly better performance than the other algorithms. Particularly, when $N_R = 20$, our proposed algorithm allows the cooperative UAVs to have a longer lifetime than the Low TxPower algorithm by 33%, the Average Allocation by 60% and 66.7% longer than the Random Allocation. The reason is that the energy consumptions of UAVs are balanced by adjusting the number of packets that each UAV is to forward and that the modulation the UAV is to use. Particularly, our algorithm requires the UAVs with better channels over the second hop to forward more packets, such that the energy can be most efficiently used. It also balances the energy consumption among UAVs by adjusting their modulations, such that the lifetime of the entire UAV swarm can be extended. In the figure, we also see that the network life of our proposed algorithm grows much faster with the increase of the number of cooperative UAVs, compared to the lifetime of the other three algorithms. Specifically, when N_R is smaller than 4, there is no much difference on the performances of four algorithms. When N_R = 20, the network lifetime with EPLA is $8mins$ longer than the Low TxPower scheduling.

5.5 Guideline for UAVs Trajectories Design

Figure 5.6 plots the network lifetime with respect to the radius of the circular trajectory of UAVs, where $N_R = 10$. The center of the circular trajectories is the halfway point between the source node and BS, as illustrated in Figure 5.1. We can see the network achieves the longest lifetime when r is around 600 meters. That is because this is the case where the packet error on the first hop and the channel gain on the second hop are leveraged, thereby achieving the best

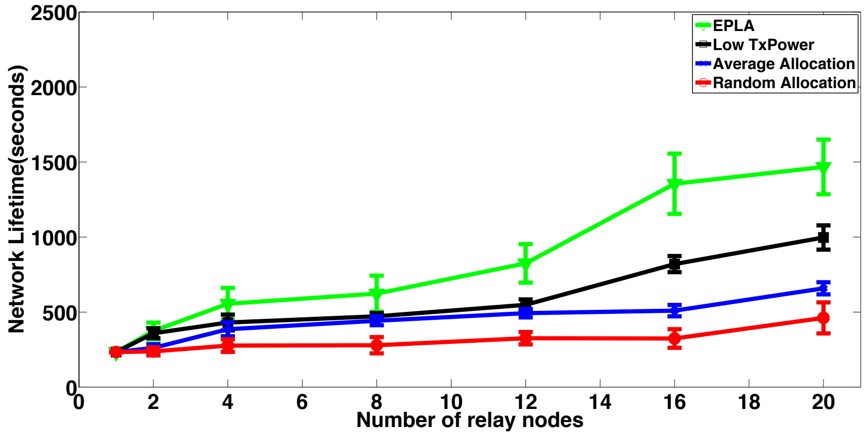

Figure 5.5: The performance of network lifetime with different packet scheduling algorithms. The error bar shows the standard deviation over 100 runs.

end-to-end performance on both two hops. For EPLA, it allocates the packet load from the UAVs with large $\Gamma_i(t)$ to the ones with small $\Gamma_i(t)$. When r is about $600m$, energy consumption of UAVs has minimum value which is higher than Low TxPower algorithm for 400 seconds. Whereas r is smaller or larger than $600m$, the lifetime goes down as most of UAVs has large $\Gamma_i(t)$ due to the fading on two hops.

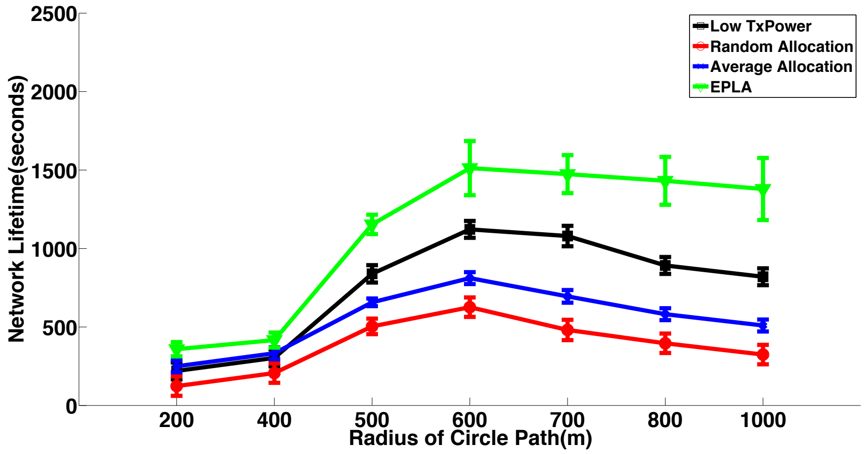

Figure 5.6: The performance of network lifetime with different packet scheduling algorithms. The error bar shows the standard deviation over 100 runs.

6 Conclusion and Future Work

In this paper, we proposed an energy-efficient relaying scheme which can extend the lifetime of cooperative UAVs in human-unfriendly environments. An NP-hard optimization problem was formulated to guarantee packet success rates and balance energy consumption. A practical suboptimal solution was developed by decoupling energy balancing and modulation selection. Simulation results confirm that our suboptimal method can reduce the computational complexity by three orders of magnitude with negligible degradation of network yield and lifetime, compared to the NP-hard optimal solution. It is also revealed that our scheme can save energy by 50%, increase network yield by 15%, and extend network lifetime by 33%, compared to existing greedy algorithms. As a future direction of this study, we plan to build a testbed and start the UAVs flight test. More UAV trajectories will be investigated in our experiment. To increase communication range of the UAV, a hybrid antenna for the UAV as we proposed in previous work [17] will be combined with EPLA algorithm.

Acknowledgment

This work was supported by the Australian Research Council Discovery Grant DP110104344.

Bibliography

[1] Ahmed EAA Abdulla, Zubair Md Fadlullah, Hiroki Nishiyama, Nei Kato, Fumie Ono, and Ryu Miura. An optimal data collection technique for improved utility in UAS-aided networks. In *INFOCOM*, pages 736–744. IEEE, 2014.

[2] Nadeem Ahmed, Salil S Kanhere, and Sanjay Jha. Utilizing link characterization for improving the performance of aerial wireless sensor networks. *Journal on Selected Areas in Communications*, 31(8):1639–1649, 2013.

[3] Randal W Beard, Timothy W McLain, Derek B Nelson, Derek Kingston, and David Johanson. Decentralized cooperative aerial surveillance using fixed-wing miniature UAVs. *Proceedings of the IEEE*, 94(7):1306–1324, 2006.

[4] İlker Bekmezci, Ozgur Koray Sahingoz, and Şamil Temel. Flying ad-hoc networks (fanets): a survey. *Ad Hoc Networks*, 11(3):1254–1270, 2013.

[5] Markus Bernard, Konstantin Kondak, Ivan Maza, and Anibal Ollero. Autonomous transportation and deployment with aerial robots for search and rescue missions. *Journal of Field Robotics*, 28(6):914–931, 2011.

[6] Oleg Burdakov, Patrick Doherty, Kaj Holmberg, and Per-Magnus Olsson. Optimal placement of UV-based communications relay nodes. *Journal of Global Optimization*, 48(4):511–531, 2010.

[7] David W Casbeer, Derek B Kingston, Randal W Beard, and Timothy W McLain. Cooperative forest fire surveillance using a team of small unmanned air vehicles. *International Journal of Systems Science*, 37(6):351–360, 2006.

[8] Seong Taek Chung and Andrea J Goldsmith. Degrees of freedom in adaptive modulation: a unified view. *IEEE Transactions on Communications*, 49(9):1561–1571, 2001.

[9] Karthik Dantu, Bryan Kate, Jason Waterman, Peter Bailis, and Matt Welsh. Programming micro-aerial vehicle swarms with karma. In *SensSys*, pages 121–134. ACM, 2011.

[10] Andrea Goldsmith. *Wireless communications*. Cambridge university press, 2005.

[11] Zhaoquan Gu, Qiang-Sheng Hua, Yuexuan Wang, and Francis Lau. Reducing information gathering latency through mobile aerial sensor network. In *INFOCOM*, pages 656–664. IEEE, 2013.

[12] Tianzhou He, Xin Wang, and Wei Ni. Optimal chunk-based resource allocation for ofdma systems with multiple ber requirements. In *International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 4774–4778. IEEE, 2013.

[13] Frederik Hermans, Hjalmar Wennerström, Liam McNamara, Christian Rohner, and Per Gunningberg. All is not lost: Understanding and exploiting packet corruption in outdoor sensor networks. In *Wireless Sensor Networks*, pages 116–132. Springer, 2014.

[14] Dac-Tu Ho, EI Grotli, Shigeru Shimamoto, and Tor Arne Johansen. Optimal relay path selection and cooperative communication protocol for a swarm of UAVs. In *Globecom Workshops*, pages 1585–1590. IEEE, 2012.

[15] Imad Jawhar, Nader Mohamed, Jameela Al-Jaroodi, and Sheng Zhang. A framework for using unmanned aerial vehicles for data collection in linear wireless sensor networks. *Journal of Intelligent & Robotic Systems*, 74(1-2):437–453, 2014.

[16] Charalampos Konstantopoulos, Grammati Pantziou, Damianos Gavalas, Aristides Mpitziopoulos, and Basilis Mamalis. A rendezvous-based approach enabling energy-efficient sensory data collection with mobile sinks. *IEEE Transactions on Parallel and Distributed Systems*, 23(5):809–817, 2012.

[17] Kai Li, Nadeem Ahmed, Salil S Kanhere, and Sanjay Jha. Reliable communications in aerial sensor networks by using a hybrid antenna. In *Conference on Local Computer Networks (LCN)*, pages 156–159. IEEE, 2012.

[18] Kai Li, Branislav Kusy, Raja Jurdak, Aleksandar Ignjatovic, Salil S Kanhere, and Sanjay Jha. κ-fsom: Fair link scheduling optimization for energy-aware data collection in mobile sensor networks. In *Wireless Sensor Networks*, pages 17–33. Springer, 2014.

[19] Qingwen Liu, Shengli Zhou, and Georgios B Giannakis. Cross-layer combining of adaptive modulation and coding with truncated arq over wireless links. *IEEE Transactions on Wireless Communications*, 3(5):1746–1755, 2004.

[20] Iván Maza, Fernando Caballero, Jesús Capitán, JR Martínez-de Dios, and Aníbal Ollero. Experimental results in multi-UAV coordination for disaster management and civil security applications. *Journal of intelligent & robotic systems*, 61(1-4):563–585, 2011.

[21] Luis Merino, Fernando Caballero, J Ramiro Martínez-de Dios, Iván Maza, and Aníbal Ollero. An unmanned aircraft system for automatic forest fire monitoring and measurement. *Journal of Intelligent & Robotic Systems*, 65(1-4):533–548, 2012.

[22] Liqian Peng, Doug Lipinski, and Kamran Mohseni. Dynamic data driven application system for plume estimation using UAVs. *Journal of Intelligent & Robotic Systems*, 74(1-2):421–436, 2014.

[23] Aveek Purohit, Zheng Sun, and Pei Zhang. Sugarmap: location-less coverage for micro-aerial sensing swarms. In *IPSN*, pages 253–264. ACM, 2013.

[24] David Tse and Pramod Viswanath. *Fundamentals of wireless communication*. Cambridge university press, 2005.

[25] João Valente, David Sanz, Antonio Barrientos, Jaime del Cerro, Ángela Ribeiro, and Claudio Rossi. An air-ground wireless sensor network for crop monitoring. *Sensors*, 11(6):6088–6108, 2011.

[26] Haibo Wang, Da Huo, and Bahram Alidaee. Position unmanned aerial vehicles in the mobile ad hoc network. *Journal of Intelligent & Robotic Systems*, 74(1-2):455–464, 2014.

[27] Brian A White, Antonios Tsourdos, Immanuel Ashokaraj, S Subchan, and Rafał Zbikowski. Contaminant cloud boundary monitoring using network of UAV sensors. *Sensors Journal, IEEE*, 8(10):1681–1692, 2008.

[28] Shuguang Xiong, Jianzhong Li, Zhenjiang Li, Jiliang Wang, and Yunhao Liu. Multiple task scheduling for low-duty-cycled wireless sensor networks. In *INFOCOM*, pages 1323–1331. IEEE, 2011.

[29] Pengcheng Zhan, Kai Yu, and ALee Swindlehurst. Wireless relay communications with unmanned aerial vehicles: Performance and optimization. *IEEE Transactions on Aerospace and Electronic Systems*, 47(3):2068–2085, 2011.