Distributed Real-Time Multimodal Data Forwarding in Unmanned Aerial Systems

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***Abstract*—UAVs can support different applications, such as forest fire surveillance and precise agriculture. UAVs' service-on-demand preference drives the need for multiple UAVs to enhance surveillance coverage and data stability. Due to the limited capacity of the UAV, UAVs desire network coordination based on the importances of collected data. For example, UAVs at different locations may have different priorities of data forwarding tasks while the required data sizes of different tasks are varying. In this paper, we propose a system framework for UAV array to structure and prioritize the data forwarding based on i) forward-looking channel quality; ii) priorities of tasks of multimodal data on demand. Our proposed distributed real-time framework aims to optimize effective data throughput given a channel quality and effective scheduling of the channel usage among multiple UAVs. We conducted extensive evaluations using multiple UAVs and results show that our modeling of forward-looking channel quality prediction achieves 90% accuracy. Moreover, our scheduling algorithms can effectively optimize the overall data quality of forwarding tasks between UAVs and the base station.**

I. Introduction

Unmanned Aerial Vehicle (UAV) has a lot of potential applications, such as forest fire surveillance and precise agriculture. To support different applications, UAV is normally equipped with multiple sensors (e.g., cameras, infrared cameras, temperature sensors, etc.) for collecting different types of data [6] [22] [23]. Due to the limited flying time of a single UAV, multiple UAVs are needed to cover the specific region and form unmanned aerial systems [11] [24]. During the flight, multiple UAVs need to forward the collected data to the base station. However, the wireless channel spectrum for the communications between UAVs and the base station is limited. In the meantime, different UAVs may fly in different regions for different tasks and the priorities and required data sizes of different tasks are varying, which introduces a challenge for the base station to coordinate the communications with UAVs in unmanned aerial systems.

To address this challenge, we utilize the unmanned aerial systems' important feature (i.e., channel quality correlation among different UAVs) to predict the future channel qualities between UAVs and the base station. Based on our experimental results, the channel quality between a UAV and the base station stays stable in a short time if the UAV stays in the same location. Therefore, if we know the future location of a UAV, we can estimate the prospective channel quality of the UAV based on its historical channel quality and channel quality of UAVs that have flown in the similar location in the past.

With the predicted channel quality, we schedule the forwarding tasks between UAVs and the base station. The design goal is to maximize the overall data quality of forwarding tasks with given channel qualities. In particular, we intend to optimize the system performance by considering two factors of forwarding tasks: (i) the priorities of different tasks are different. For example, the data from the thermal camera may have a higher priority than that from the regular camera in fire monitoring application; (ii) the required data sizes of different forwarding tasks are varying. For example, an object recognition task may only need the static image of the object while an object tracking task needs the video of moving object, thus the object tracking task needs higher quality of data compared to the object recognition task. To solve the problem, we propose a two-step scheduling approach: i) an optimal task scheduling algorithm (TSA) is proposed to schedule the tasks in a single UAV to maximize the data quality of forwarding tasks in the UAV; ii) an optimal channel allocation algorithm (CAA) is proposed to schedule the usage of the channel among multiple UAVs and the base station. We prove that these two algorithms can maximize the data quality of forwarded tasks.

However, the complexity of the optimal solution is so high that is not practical to apply it in real-time channel allocation between UAVs and the base station. Therefore, we adopt a heuristic algorithm to achieve similar performance with the optimal solution but with much lower complexity. To understand the performance of channel quality prediction, we provide a model for analyzing the expected prediction errors of our channel quality prediction algorithm. We discover that the prediction accuracy is highly related to prediction window size. The prediction accuracy decreases when the prediction window size increases. In the meantime, the flexibility of channel allocation increases when the prediction window size increases. Our main contributions are summarized as follows:

- We utilize the correlated channel qualities among different UAVs to predict future channel qualities between UAVs and the base station. Our evaluation results show that the accuracy of our prediction algorithm is more than 90% even when UAVs are moving rapidly and the channel qualities between UAVs and the base station change dynamically.
- We consider a forwarding tasks scheduling problem for tasks with different priorities and multimodal data. To solve the problem, we propose an optimal scheduling approach that maximizes the data quality of forwarding tasks with accurate channel quality prediction. Furthermore, we present a heuristic algorithm with lower com-

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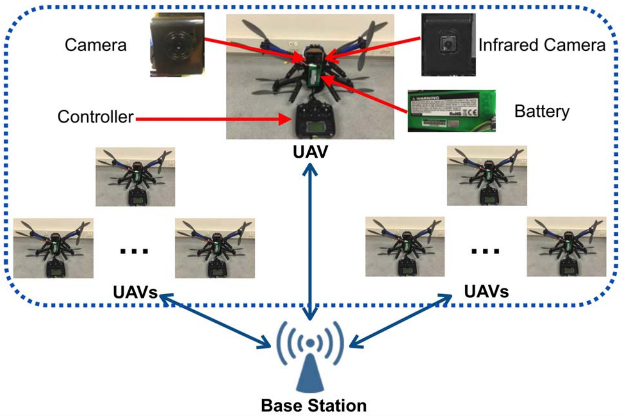


Fig. 1. A UAV network structure. Each UAV has one regular camera and one infrared camera.

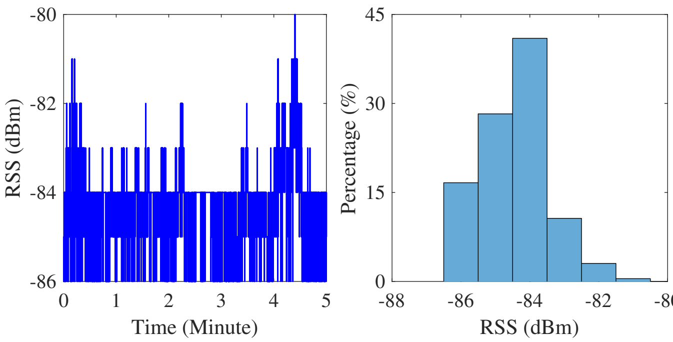


Fig. 2. RSS value of a UAV at a fixed location

plexity to improve the performance when the prediction is not perfect.

- We conduct extensive evaluations with empirical trace data of channel quality during the flights of UAVs. The evaluation results show that our proposed scheduling algorithms can effectively optimize the overall data quality of forwarding tasks between UAVs and the base station.

The paper is organized as follows: the motivation and problem formulation are introduced in §II and §III, then the detailed design and evaluation results are described in §IV and §V respectively; related work is discussed in §VI; finally, we conclude our paper in §VII.

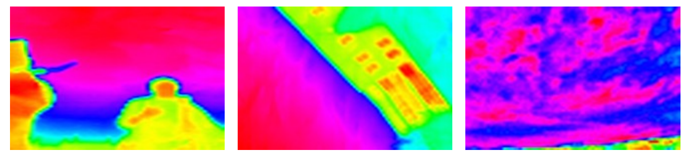
II. Motivation

Due to the limited flying time of a single UAV, multiple UAVs are needed to cover the specific region and form unmanned aerial systems. To beter understand the challenges for coordinations among multiple UAVs, in this section, we provide some experimental results to motivate this project.

1) ***Properties of Channel Quality****:* In this paper, we specifically focus on the channel usage scheduling and task scheduling in a typical scenario (shown in Figure 1). The UAVs are sent out to collect the data and transmit the collected data back to the base station via wireless communication [1] [25]. Because the channel spectrum of wireless communication between UAVs and the base station is limited, it is vitally

(a) Take off (b) Low altitude (c) High altitude

Fig. 3. Images from the camera at different positions during one flight



(a) Take off (b) Low altitude (c) High altitude

Fig. 4. Images from the infrared camera at different positions during a flight

important to design an algorithm for scheduling the usage of the channel between the UAVs and the base station. To investigate the properties of channel quality between the UAV and the base station, we conduct a series of experiments to collect the channel quality from the UAV over time. The UAVs we use in our experiment are X8+ and Iris+ from 3D Robotics. The XBee nodes are equipped in all the UAVs to communicate with the base station on the ground during the experiments. We find an ***observation*** during the experiments:

Observation: *RSS of wireless communication between the UAV and base station stays stable over time if the location is fixed.* In our experiments, we control the UAV in the hover mode, which lets the UAV to stays in the same location based on GPS. The results are shown in Figure 2. Thus, we can utilize the RSS correlation among different UAVs in the similar position for channel quality prediction.

2) ***Dynamic Priorities of Forwarding Tasks****:* Besides the uncertainty of UAV's channel quality, the priorities of data forwarding tasks in different UAVs are also dynamically changing. We conduct a series of experiments to illustrate how the priorities of data forwarding tasks will change. In these experiments, we attach both regular camera and infrared camera in UAV to collect real-time videos. The regular camera takes at most 720P videos and the infrared camera takes the video with the resolution of 80×60. During the flight, we fly the UAV both at a low altitude and high altitude and collect the data from both two cameras.

- The snapshots of videos from the regular camera are shown in Figure 3. In the experiment, we deployed the regular camera in the bottom of the UAV. Based on the snapshots of the videos from the regular camera, when the UAV takes off, the value of these data from the regular camera is not so useful because it only captures the grass. When UAV flies in the low and high altitude, the data from the regular camera can help us identify the people and structure of the buildings in this area.
- The infrared camera is deployed in the side of the UAV and the snapshots of videos from the infrared camera are also shown in Figure 4. Based on the snapshots, we can find that while UAV takes off and fly in the low

altitude, the infrared image can help us to identify the people on the ground and the buildings around the UAV. While the infrared image is not useful when UAV flies in high altitude capturing the sky and cloud.

Therefore, the priority of the forwarding task at different locations varies. For example, for a people tracking application, the tasks of forwarding the regular camera video for the UAVs in the low altitude and infrared camera video for the UAVs in the very low altitude should have higher priority. While for a building monitoring application, the tasks of forwarding regular camera video for the UAVs in the high altitude and infrared camera video for the UAVs in the low altitude should have higher priority.

With the properties of channel quality and dynamic priorities of forwarding tasks, it is critical to design an algorithm to schedule the channel between UAVs and the base station based on the dynamic priorities of data forwarding tasks to maximize the overall data quality of forwarding tasks.

III. Problem Formulation

In this paper, we investigate how to utilize the predicted channel qualities to improve the overall data quality of data forwarding from the UAVs to the base station. The parameters we use in our paper are listed in Table I. For UAV i, the ground truth of bandwidth at time t is $q_i(t)$ and the prediction is $q_i'(t)$. And at t, the task set that the UAV needs to execute is $\Gamma_i(t)$. For the tasks in task set, we use $\tau_{ij}(t)$ to define the task that needs to be executed in UAV i at time t. The priority of task $\tau_{ij}(t)$ is denoted as $p_{ij}(t)$. m_i is the number of tasks that need to be executed in UAV i. Note that the priority of each task at different time may vary. Based on different priorities, each task of the UAV may have multimodal data that needs to be sent. For example, if the priority of a task is the highest, then the UAV should send the raw data with all the information to the base station. Meanwhile, if the priority of a task is low, then the UAV can send partial of data with smaller size to the base station. Based on priority, the minimum data size required for task $\tau_{ij}(t)$ is defined as $r_{ij}(t)$. For each task, we define the size of transmitted data for tasks $\tau_{ij}(t)$ as $s_{ij}(t)$. To simplify the notation, we define $f_{ij}(t) = s_{ij}(t)/r_{ij}(t)$ as the data quality of task $\tau_{ij}(t)$. We formulate our problem as:

$$\begin{aligned} \max \quad & \sum_{t}\sum_{i=1}^{n}\sum_{j=1}^{m_i} f_{ij}(t) \\ \textit{s.t.} \quad & \sum_{j=1}^{m_i} s_{ij}(t) < q_i(t) \;\; \forall i && (a) \\ & s_{ij}(t) \geq r_{ij}(t) \;\; \forall i, j && (b) \\ & f_{ij}(t) \geq f_{ik}(t) \;\; \forall j, k, p_{ij}(t) > p_{ik}(t) && (c) \end{aligned}$$

The goal of our design is to maximize the overall data quality of all the tasks in n UAVs over time. Constraint (a) ensures that the total amount of data forwarded by UAV i can not be higher than the future available bandwidth between UAV i and the base station. Constraint (b) ensures that the size of forwarded data for each task should be higher than the minimum required data size of the task. Constraint (c) ensures that when task $\tau_{ij}(t)$ has higher priority than task $\tau_{ik}(t)$, the data quality $f_{ij}(t)$ of task $\tau_{ij}(t)$ should be also higher than $f_{ik}(t)$ of task $\tau_{ik}(t)$. In this optimization problem, the future channel quality $q_i(t)$ is not known at the beginning. In § IV-B, we present a method for accurate channel quality prediction and provide analysis of prediction error $q_i^e(t)$ over time. Because the prediction can not be perfectly accurate, we introduce task scheduling in a single UAV in § IV-C and channel allocation between multiple UAVs and the base station in § IV-D to maximize the expected overall data quality of all the tasks in UAVs.

Notations	Definitions
$q_i(t)$	Bandwidth of UAV i at t
$q_i'(t)$	Predicted bandwidth of UAV i at t
$q_i^e(t)$	Prediction error of bandwidth
$\Gamma_i(t)$	Task set in UAV i at t
$\tau_{ij}(t)$	Task j in UAV i at t
$p_{ij}(t)$	Task priority of task j in UAV i at t
$r_{ij}(t)$	Minimum requirement of task j in UAV i at t
$s_{ij}(t)$	Size of transmitted data for task j in UAV i at t
$f_{ij}(t)$	Data quality of task j in UAV i at t
$w_{ij}(t_1, t_2)$	Distance between channel quality of UAV i and j
m_i	Number of tasks in UAV i
d_i	Data size of level i
K	Number of time slots in prediction window

TABLE I
DEFINITIONS OF NOTATIONS

IV. Design

To maximize the overall data quality of all the tasks in UAVs, we encounter three major challenges: i) how to predict dynamically changing future channel quality of UAVs; ii) how to balance the priorities and data qualities of tasks in a UAV; and iii) how to allocate channel between UAVs and the base station to maximize the overall data quality. In this section, we first provide an overview of system design and then describe the detailed design to address these three challenges.

A. System Overview

To address above three challenges, we propose three components to maximize the overall data quality in UAVs, which includes: i) channel quality predictor; ii) task scheduler in a single UAV; and iii) channel allocation between multiple UAVs and the base station. The overview of our design is shown in Figure 5. The channel quality predictor utilizes historical channel quality information $q_i(t)$ to predict future channel quality $q_i'(t+1), \cdots, q_i'(t+K)$ for prediction window size K. Task scheduler for a single UAV takes the task priority and data requirement information to maximize the data quality with the given channel quality. Finally, the predicted channel qualities and task scheduling results of different UAVs are used for channel allocation between multiple UAVs and the base station to maximize the overall data quality received by the base station.

- Channel quality predictor. The key idea of channel quality prediction is to utilize the correlation between channel

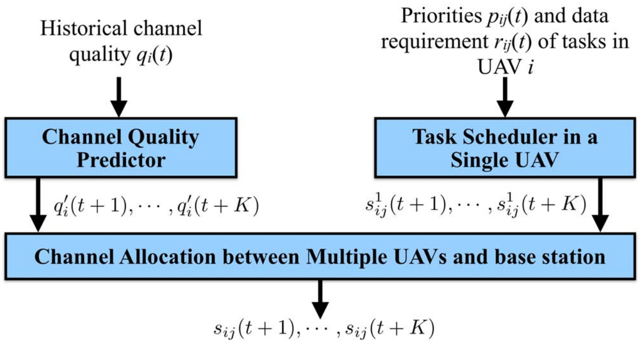


Fig. 5. Overview of our design

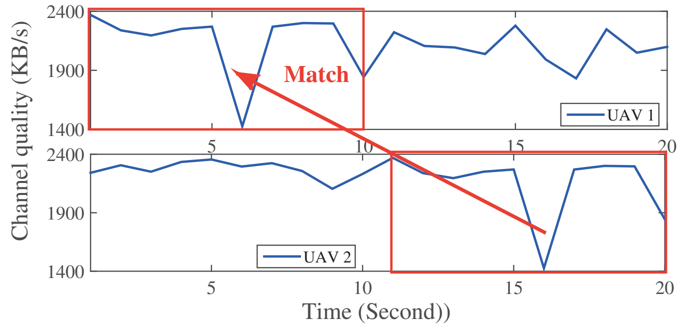


Fig. 6. An example of channel quality mapping

qualities of different UAVs. We consider a set of UAVs that fly in the similar areas to execute their assigned tasks. Then based on the channel correlations among UAVs, we can predict the future channel quality of a UAV based on its historical channel quality and the channel quality of UAVs that have flown in the similar location in the past. In our paper, we use Derivative Dynamic Time Warping (DDTW) to map the historical channel characteristics from trajectories of different UAVs and predict the future channel quality based on UAVs with similar trajectories.

- Task scheduler in a single UAV. Since channel quality between a UAV and the base station is dynamically changing, the UAV needs to decide which data sizes to send for different tasks based on predicted future channel quality. Thus, we propose an algorithm to produce the optimal solution with available channel quality to maximize data quality based on the given priorities and data requirements of tasks in the UAV.
- Channel allocation between multiple UAVs and the base station. Since UAVs typically use XBee or RC radio, they use the same channel to communicate with the base station. Thus, the channel needs to be allocated for different UAVs. Based on predicted channel qualities of different UAVs, we propose an optimal algorithm to allocate a channel to multiple UAVs in order to maximize the overall data quality. Because the optimal algorithm of channel allocation problem has high time complexity, we provide a heuristic algorithm to reduce the time complexity.

B. Channel Quality Prediction

In this section, we introduce how to predict the channel qualities of UAVs. We assume that these UAVs use the same channel to communicate with the base station. The design can be extended to multiple clusters of aircrafts that use multiple channels. Because the Signal-to-Noise measurements remain relatively constant over short periods of time, UAVs traveling in the same corridor experience similar channel quality as they pass through the same area. An example is shown in Figure 6. Two UAVs 1 and 2 are sharing the communication channel with base station and UAVs periodically sense the channel quality to base station. Because UAVs 1 and 2 are passing through the same area and UAV 2 follows the trajectory of UAV 1, the channel quality of UAV 2 also lags behind the channel quality of UAV 1. To utilize the channel quality of UAV 1 for channel quality prediction of UAV 2, we first map the channel quality sequences between UAVs 1 and 2.

Mapping the channel quality sequences of UAV 1 to channel quality of UAV 2 based on the "distance" between them shows the time warp between the two series of data. The two series are combined to create a matrix which represents the distances between the two series using Derivative Dynamic Time Warping Algorithm (DDTW). Let the channel quality sequence of aircraft 1 be $q_1(1), q_1(2), \cdots, q_1(t_1)$ and channel quality of aircraft 2 be $q_2(1), q_2(2), \cdots, q_2(t_2)$. Then we calculate the distances between two sequences and the pair with minimum distance for each point and build the distance matrix as follow:

$$\zeta_{i,j} = (q_1[i] - q_2[j])^2 + min(\zeta_{i,j-1}, \zeta_{i-1,j}, \zeta_{i-1,j-1}) \quad (1)$$

$\zeta_{i,j}$ is the value in the matrix. $q_1[1 : t_1]$ and $q_2[1 : t_2]$ are two channel quality series. Then these two sequences are mapped. With the mapping results, we know which part of channel quality sequences can be used for prediction.

Then linear regression is applied to these two series to calculate α and β as:

$$q_2[1 : t_2] = q_1[f(1) : f(t_2)] \cdot \beta + \alpha. \quad (2)$$

Finally, we predict the future channel quality sequence of UAV 2 based on historical channel quality of UAV 1 with the results of α and β.

C. Task Scheduling in a Single UAV

Based on the predicted channel quality, we can design a distributed and dynamic task scheduling algorithm to maximize the data quality of all the tasks. In this section, to simplify the problem, we first investigate how to maximize the data quality forwarded by a single UAV. In a single UAV i, the optimization problem can be formulated as:

$$\begin{aligned} \max \quad & \sum_{j=1}^{m_i} E[s_{ij}(t)]/r_{ij}(t) & \\ \textit{s.t.} \quad & s_{ij}(t) \geq r_{ij}(t) & (a) \\ & f_{ij}(t) \geq f_{ik}(t) \;\; \forall j, k, p_{ij}(t) \geq p_{ik}(t) & (b) \end{aligned}$$

Algorithm 1: Task Scheduling Algorithm

Input: Channel quality $q_i(t)$ and properties of tasks $[\tau_{i1}(t), \cdots, \tau_{im_i}(t)]$ for UAV i at time t.
Output: Task scheduling results for UAV i $[s_{i1}(t), \cdots, s_{im_i}(t)]$ that maximizes $\sum_{j=1}^{m_i} f_{ij}(t)$.

1: **if** $m_i = 1$ **then**
2: $\quad s_{i1}(t) = q_i(t)$, return;
3: **end if**
4: **for** different data sizes $u_{i1k}(t)$ of task $\tau_{i1}(t)$ **do**
5: $\quad$ Calculate maximum $\sum_{j=2}^{m_i} f_{ij}(t)$ with channel quality $q_i(t) - u_{i1k}(t)$;
6: $\quad$ **if** $\tau_{ij}(t)$ and $\tau_{il}(t)$ fulfills constraint (b) **then**
7: $\quad\quad \eta_k = u_{i1k}/r_{i1}(t) + \sum_{j=2}^{m_i} f_{ij}(t)$;
8: $\quad$ **end if**
9: **end for**
10: $s_{i1} = u_{i1k}$ with maximum η_k;
11: return s_{i1} and $[s_{i2}(t), \cdots, s_{im_i}(t)]$

where

$$E[s_{ij}(t)] = \max\{0, s_{ij}(t) - q_i'(t) + q_i(t) + \sum_{k=m_i}^{k=j+1} s_{ik}(t)\} \quad (3)$$

Because $E[s_{ij}(t)]$ is determined by the channel quality prediction accuracy. If the actual channel quality is better than predicted value, then $E[s_{ij}(t)] = s_{ij}(t)$; otherwise, $E[s_{ij}(t)] < s_{ij}(t)$. The detailed optimal solution is described in Algorithm 1. The input of Algorithm 1 is the channel quality $q_i(t)$ and properties of tasks $[\tau_{i1}(t), \cdots, \tau_{im_i}(t)]$ for UAV i at time t and output is the task scheduling results for UAV i $[s_{i1}(t), \cdots, s_{im_i}(t)]$ that maximizes the overall data quality $\sum_{j=1}^{m_i} f_{ij}(t)$ in UAV i. The algorithm first checks if the number of tasks is 1, if yes, we assign $s_{i1}(t) = q_i(t)$ and return (Lines 1-3). Otherwise, for every possible data size u_{i1k} of task $\tau_{i1}(t)$, we recursively calculate the maximum $\sum_{j=2}^{m_i} f_{ij}(t)$ (Lines 4-5). Then we check if the solution fulfills the constraint (b) in the optimization problem (Line 6). If the solution fulfills the constraint, we calculate the maximum data quality $\sum_{j=1}^{m_i} f_{ij}(t)$ if task task $\tau_{i1}(t)$ is assigned with u_{i1k} (Lines 7-9). Finally, we have $s_{i1} = u_{i1k}$. s_{i1} and $[s_{i2}(t), \cdots, s_{im_i}(t)]$ from subproblem that maximizes $\sum_{j=2}^{m_i} f_{ij}(t)$ are returned (Lines 10-11). Due to the limited space, the proof of the optimal solution is not included. Since the number of the tasks in a UAV is limited, the complexity of optimal solution is not high. Therefore, it is possible for each UAV to apply optimal solution to schedule the task if the given bandwidth of each UAV is determined.

Algorithm 2: Optimal Solution for Channel Allocation

Input: Channel quality $q_i(t)$ and minimum data requirement of tasks $r_{ij}(t)$ in n UAVs for time slot t_1 to t_K
Output: Transmitted data size for each task $[s_{11}(t), \cdots, s_{1m_1}(t), \cdots, s_{n1}(t), \cdots, s_{nm_n}(t)]$.

1: **for** time slot t_k from t_K to t_1 **do**
2: $\quad$ **if** k=1 **then**
3: $\quad\quad$ Assign time slot t_1 to UAV i with highest $Q_1 = \sum_{j=1}^{m_i} f_{ij}(t_1)$
4: $\quad$ **else**
5: $\quad\quad$ Calculate the bandwidth $q_i(t_k)$ for all UAVs;
6: $\quad\quad$ Calculate the current overall quality Q_k^i if time slot t_k is assigned to UAV i;
7: $\quad\quad$ Assign time slot t_k to the UAV i with highest Q_k^i
8: $\quad$ **end if**
9: **end for**

D. Channel Allocation Between Multiple UAVs

With the task scheduling in a single UAV, we describe in details for how UAVs can coordinate with each other to maximize the overall data quality of all the UAVs. The main problem is that for every UAV, its channel quality at different time changes dynamically, thus we need to decide when each UAV would use the channel to transmit data back to the base station. The problem can be rewritten as:

$$\begin{aligned} \max \quad & \sum_t \sum_{i=1}^{n} \sum_{j=1}^{m_i} E[s_{ij}(t)]/r_{ij}(t) \\ \textit{s.t.} \quad & s_{ij}(t) \geq r_{ij}(t) \quad \forall i, j \qquad\qquad (a) \\ & f_{ij}(t) \geq f_{ik}(t) \quad \forall j, k, p_{ij}(t) > p_{ik}(t) \quad (b) \end{aligned}$$

For each prediction window size, we divide the window into K slots and define the K time slots as $t_1, \cdots, t_K$. We assume that in one single slot, the bandwidth of a UAV is constant. Then the problem becomes to assign slots to the UAVs. We can solve the problem with a dynamic approach, but with some additional constraints.

1) Optimal Algorithm: To maximize the overall quality of all the tasks, we first provide an optimal algorithm. Then we provide a heuristic approach to solve the problem with lower complexity. The optimal algorithm is presented in Algorithm 2.The input of Algorithm 2 is the channel quality $q_i(t)$ and minimum data requirement of tasks $r_{ij}(t)$ for UAV i at time slot t_1 to t_K and output is the task scheduling results $[s_{11}(t), \cdots, s_{1m_1}(t), \cdots, s_{n1}(t), \cdots, s_{nm_n}(t)]$ for each task in each UAV that maximizes the overall data quality all the UAVs $\sum_t \sum_{i=1}^{n} \sum_{j=1}^{m_i} E[s_{ij}(t)]/r_{ij}(t)$. The algorithm calculates the optimal solution to maximize overall quality of tasks. First, if the number of time slot is 1, then we just allocate the UAV i that maximizes $\sum_{j=1}^{m_i} f_{ij}(t_K)$ (Lines 1-3). Otherwise, we go through every UAV to calculate the optimal overall quality

Algorithm 3: Heuristic Solution for Channel Allocation

Input: $q_i(t)$ and $r_{ij}(t)$ in n UAVs for time slot t_1 to t_K
Output: $[s_{11}(t), \cdots, s_{1m_1}(t), \cdots, s_{n1}(t), \cdots, s_{nm_n}(t)]$.

1: **for** time slot t_l **do**
2: Calculate the optimal overall quality $Q_{l+1,K}$ for time slot t_{l+1} to t_K;
3: **for** UAV i **do**
4: Calculate the bandwidth $q_i(t_K)$;
5: Assign time slot t_K to UAV i virtually;
6: Calculate the overall quality for time slot t_l;
7: **end for**
8: Assign the time slot t_l to the UAV i with highest $\sum_{j=1}^{m_i} s_{ij}(t_l)/r_{ij}(t_l) + Q_{l+1,K}$
9: **end for**

Q_k^i if we assign t_k to UAV i (Lines 4-8). The optimal overall quality if we assign t_k to UAV i can be calculated as:

$$Q_k^i = Q_{k-1} + \sum_{j=1}^{m_i} f_{ij}(t_k) \tag{4}$$

Finally, we assign time slot t_k to the UAV i that has the highest overall quality Q_k^i for time slot t_1 to t_k (Line 9). Due to the limited space, the proof of the optimal solution is not provided in this paper.

E. Advanced Design

Although Algorithm 2 can provide the optimal solution, the time complexity of Algorithm 2 is very high. Because Algorithm 2 works in a recursive way, the overall time complexity is $O(n^K)$. When the number of UAVs (n) or time slots (K) is high, the time complexity of Algorithm 2 would be very high. Because the UAV allocation needs to be decided in real-time, thus we can't apply the optimal solution among multiple UAVs and we introduce a heuristic algorithm.

1) Heuristic Algorithm: The key idea of the heuristic algorithm is to reduce the search space of the optimal algorithm. Thus, instead of searching every combinations of time slot allocation, we only search the combinations in a greedy way. An example of searching is shown in Figure 7. We first allocate $t+1$ to UAV 1 because it has highest data quality. For $t+2$, because data quality of UAV 1 already reaches data requirement $r_1 = 4$, we allocate $t+2$ to UAV 2 with second highest data quality. The process continues until the end of the prediction window. The detailed algorithm is shown in Algorithm 3. For every time slot t_l, we first calculate the optimal overall quality for time slot t_{l+1} to t_K. Then, for each UAV i, we calculate the maximum overall quality for time slot t_l if time slot t_l is assigned for UAV i. Finally, we assign the time slot t_l to the UAV i with the highest $\sum_{j=1}^{m_i} s_{ij}(t_l)/r_{ij}(t_l) + Q_{l+1,K}$.

The time complexity of heuristic algorithm is much lower than the optimal algorithm. Because it only has two loops in Algorithm 3, the overall time complexity is $O(n \cdot K)$. At the mean time, we will show that its performance is at least d_i/d_{i+1} compared to the optimal algorithm, where d_i is the data size of i level. Compared to the optimal algorithm, in every time slot, heuristic algorithm tries to assign the channel to the UAV that maximizes the current overall data quality. If the channel assignment for previous slots of heuristic algorithm is the same as optimal algorithm, then heuristic algorithm should have the same performance as optimal algorithm. If they are different, optimal algorithm assigns channel to another UAV to maximize the overall data quality. Because data quality increase can only obtained from current data quality to one step better data quality than heuristic algorithm. Therefore, in this case, the performance of heuristic algorithm is d_i/d_{i+1} compared to optimal algorithm.

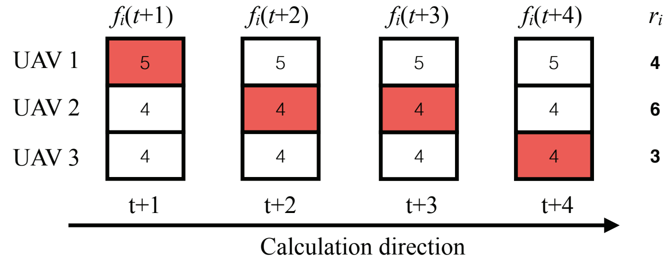


Fig. 7. An example of heuristic algorithm

2) Prediction Accuracy Analysis: The previous design assumes that the channel quality prediction is always accurate, which is not possible in reality. In this section, we analyze the prediction errors with our proposed prediction algorithm.

Because our prediction is based on the assumption that the channel quality in a fixed position is stable. The prediction accuracy then can be modeled as the expected channel quality change in the fixed position. In this paper, if we have accurate information of channel quality $q_i(t)$, then the prediction error in the next time slot is

$$P(q_i^e(t+1) = x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}} \tag{5}$$

V. IMPLEMENTATION AND EVALUATION

In this section, we evaluate the performance of our design. We collect the empirical data of channel quality from 5 UAVs during a typical mission. Then we evaluate the channel quality prediction accuracy. Finally, we verify that our approach achieves good performance of overall data quality of tasks and provide stable performance for different UAVs.

A. Data Collection

To collect the RSS information between UAV and the base station, we conduct extensive experiments of UAV flights. The UAVs we use in our experiment are X8+ and Iris+ (shown in Figure 8(a) and 8(a)). The XBee nodes are equipped in all the UAVs to communicate with the base station on the ground during the experiments. The 3D flight trajectory in one experiment is shown in Figure 8(c). The RSS (Received Signal Strength) of wireless communication between the UAV and base station changes dynamically during one flight. The

(a) UAV X8+ (b) UAV Iris+ (c) 3D Trajectory

Fig. 8. Experiment setup and 3D trajectory during one flight

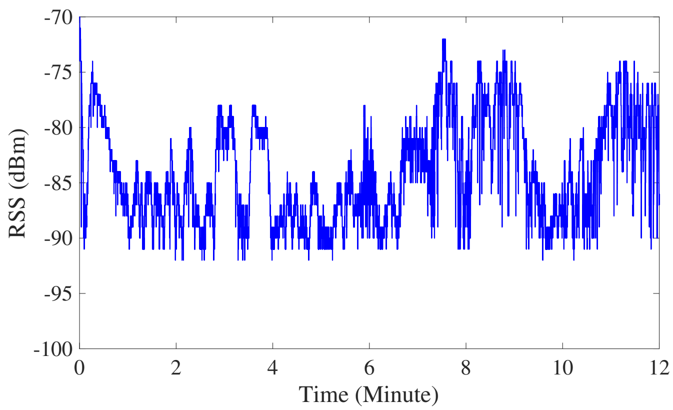


Fig. 9. RSS value of a UAV during one flight

Resolution	720P	480P	360P	240P	144P	60P
Data Rate (kbps)	200	100	40	20	10	5

TABLE II
DATA RATES FOR DIFFERENT RESOLUTIONS

detailed RSS is shown in Figure 9. This is because the speed of UAV is rather fast and the RSS varies at different locations. The speed and height of the flight shown in Figure 10 confirms that and the maximum speed we observe is around 96km/h.

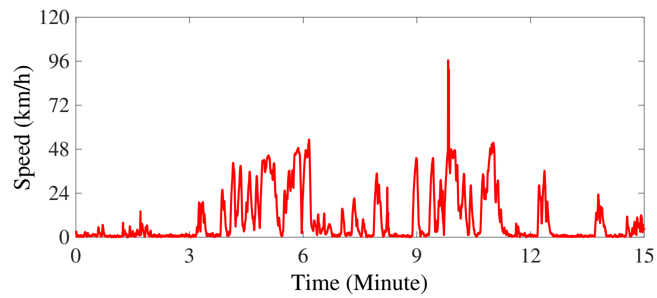
The UAVs communicate with the base station via XBee and the collected RSS is then used simulate the channel quality in the simulations. During the simulations, we define the task as sending back the pictures from the cameras to the base station and the six different data qualities of the pictures are: 60P, 144P, 240P, 360P, 480P and 720P. Note that the XBee devices only only support at most 200 $kbps$ data rate, we only take one picture per second for each UAV. The data rate required for different resolution is listed in Table II. The required data size and priority of the task are randomly generated with gaussian distribution for each UAV.

B. Metrics

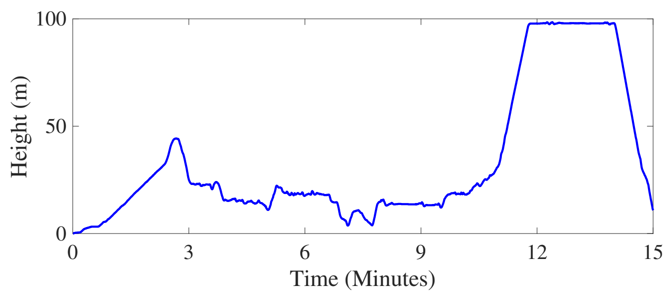
We evaluate the performance of data management for both optimal and heuristic solutions. And the metrics for the performance are:

i) average data quality of UAVs over time $\sum\limits_{t}\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m_i} f_{ij}(t)$;

ii) data quality distribution of different UAVs;



(a) Speed of a UAV



(b) Altitude of a UAV

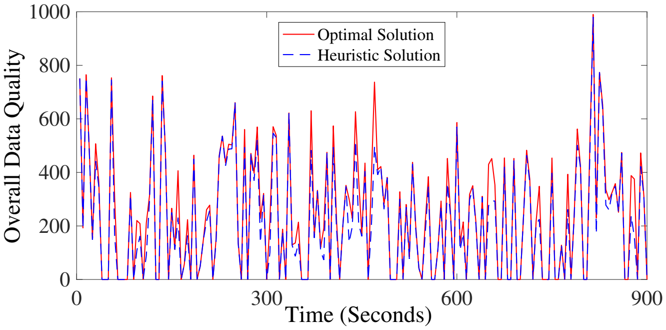
Fig. 10. Speed and altitude of a UAV during one flight

iii) data quality distribution of different priorities.

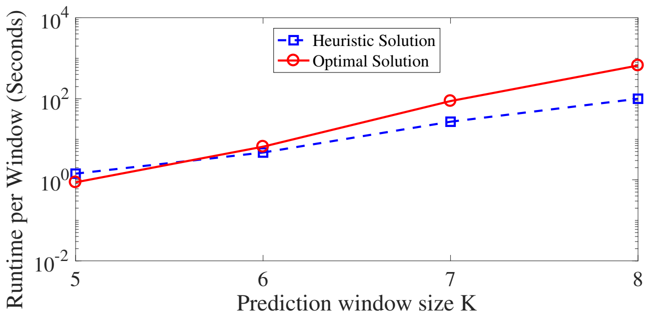
C. Optimal V.S. Heuristic Solution

In this section, we compare the performance of optimal and heuristic solutions. During the simulations, we set the prediction window size as 8 seconds for optimal and heuristic solutions. The overall data quality of all the UAVs over time is shown in Figure 11(a). The performance of optimal and heuristic solution is quite close.

Though the performance of optimal solution is slightly better than heuristic solution, the computation complexity of optimal solution is way much higher than heuristic solution. The runtime of two solutions are provided in Figure 11(b). When prediction window size increases, the runtime of optimal solution increases very fast. When the prediction window size is 8 seconds, the runtime with optimal solution for each window is 7.1 seconds (the total runtime is around 800 seconds and the the flight duration of UAV is 900 seconds), which is almost the same as the prediction window size. Meanwhile,



(a) Overall data quality



(b) Runtime performance

Fig. 11. Heuristic V.S. Optimal Solution

	Optimal	Heuristic
Avg. Quality (kbps)	156.3	142.6
Runtime per window (Seconds)	7.1	0.9

TABLE III
COMPARISON BETWEEN OPTIMAL AND HEURISTIC SOLUTIONS

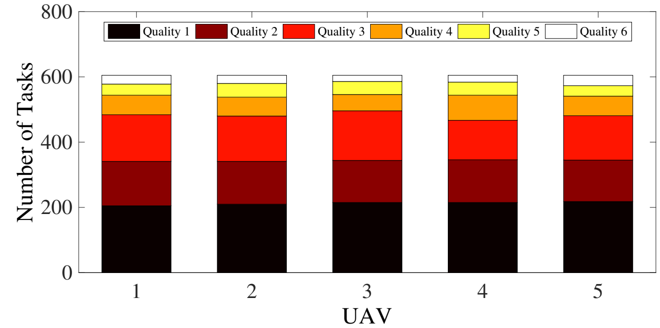
because heuristic solution reduces the search space, thus the runtime of heuristic solution increases much slower than optimal solution, which is around 100 seconds (0.9 second per each prediction window).

D. Detailed Results of Our Design

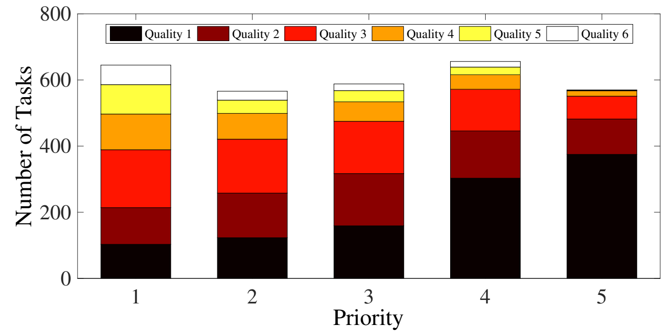
In this section, we provide the detailed results of our design with data quality prediction of different UAVs and tasks with different priorities. We also verify the performance of our design with different prediction window sizes.

The data quality of different UAVs are shown in Figure 12(a). The data quality of task is divided into 6 types. The dark blue in the bottom means the highest data quality of task and the red color in the top means the lowest data quality of task. For each UAV, most of the tasks are sent with highest quality and very few tasks are sent with lowest data quality. That means our design utilizes the channel quality among UAVs and base station very well. Among different UAVs, the distribution of data quality is almost the same, which means that our design can allocate channels for UAVs very fairly.

The data quality of different tasks with different priorities are shown in Figure 12(b). The data quality of tasks is also divided into 6 types. The dark blue in the bottom means the highest data quality of task and the red color in the top means the lowest data quality of task. For tasks with different



(a) Data quality of different UAVs



(b) Data quality of different priorities

Fig. 12. Data quality distribution

priorities, the data quality distribution is quite different. For tasks with higher priority 5 (the bar in the right), more than 50% of the tasks are sent with highest data quality while no tasks are sent with lowest data quality. For tasks with lower priority, the portion of the tasks sent with highest data quality decreases while the portion of the tasks sent with lowest data quality increases. The main reason for that is that when there are extra bandwidth for tasks, our design always select the tasks with higher priority to ensure the tasks with higher priority are sent with higher data quality. Therefore, our design can work well with the tasks with different priorities.

VI. RELATED WORK

This work aims to propose distributed multimodal data forwarding from multiple UAVs to the base station. The related work includes:

Channel Quality Prediction. Channel quality prediction in wireless network has been a research topic for a long time [3], [12], [14]. Some of the earlier works in this area include an adaptive signaling using the error correcting codes [18], while some of the prediction strategies combines artificial intelligence with domain knowledge. An approach employs Bayesian inference using Gibbs sampling [27] for quality prediction in Cognitive Radio Networks. Link correlation of wireless link has been investigated recently to improve the performance of wireless communication [7], [15]. For example, link correlation is utilized to speed up the flooding and minimize the number of transmissions [13], [31].

Different from existing prediction algorithm, for channel quality prediction of a UAV, our approach utilizes the historical channel quality of both the UAV and its nearest neighbor to improve the prediction accuracy.

Task Scheduling. Many investigations have studied efficient scheduling methods with delay constraints under unreliable communications [20], [26], [29]. Scheduling algorithms have been widely used by most modern systems to balance load [5], [30], improve throughput [8], share bandwidth between user flows [16], [21], reduce pipeline interlock [17], [28] and minimize the energy consumption [9], [19]. Furthermore, researchers have proposed specific scheduling methods to improve the performance of particular systems, such as storage systems [2], routers [4], and servers [10].

Different from previous scheduling algorithms, we consider different factors, including priorities, multimodal data management and the dynamically changing channel qualities of UAVs, for data forwarding scheduling to maximize the overall data quality of forwarding tasks.

VII. Conclusion

In this paper, we investigated the distributed real-time multimodal data forwarding between UAVs and the base station. Due to the limited channel spectrum between UAVs and the base station, it is important to assign the channel to different UAVs dynamically to achieve high overall data quality. Furthermore, the priorities and required data sizes of tasks are varying in different UAVs. To address these challenges, we propose a distributed framework for multimodal data forwarding in UAV system, which includes: 1) the channel quality prediction based on the correlation of the channel qualities among UAVs; 2) the data forwarding task scheduling algorithm in a single UAV; and 3) the channel allocation among multiple UAVs. We conducted extensive evaluations and results show that our proposed prediction algorithm can achieve more than 90% accuracy and scheduling algorithms can effectively optimize the overall data quality.

VIII. Acknowledgment

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References

[1] A. Agogino, C. HolmesParker, and K. Tumer. Evolving large scale UAV communication system. In *Annual Conference on Genetic and Evolutionary Computation*, 2012.

[2] E. Bachmat and J. Schindler. Analysis of methods for scheduling low priority disk drive tasks. In *SIGMETRICS*, 2002.

[3] K. Balachandran, S. Kadaba, and S. Nanda. Channel quality estimation and rate adaptation for cellular mobile radio. *IEEE Journal on Selected Areas in Communications*, 17(7):1244–1256, 1999.

[4] E. W. Biersack, B. Schroeder, and G. Urvoy-Keller. Scheduling in practice. *SIGMETRICS*, 2007.

[5] T. Bonald, M. Jonckheere, and A. Proutière. Insensitive load balancing. In *SIGMETRICS*, 2004.

[6] N. Boroujeni, S. Etemad, and A. Whitehead. Robust horizon detection using segmentation for UAV applications. In *Conference on Computer and Robot Vision*, 2012.

[7] F. Chai, T. Zhu, and K.-D. Kang. A link-correlation-aware cross-layer protocol for iot devices. In *Communications (ICC), 2016 IEEE International Conference on*, pages 1–6. IEEE, 2016.

[8] P. Chaporkar, K. Kar, X. Luo, and S. Sarkar. Throughput and fairness guarantees through maximal scheduling in wireless networks. *IEEE Transactions on Information Theory*, 54(2):572–594, 2008.

[9] L. Cheng, J. Niu, Y. Gu, C. Luo, and T. He. Achieving efficient reliable flooding in low-duty-cycle wireless sensor networks. *IEEE/ACM Transactions on Networking*, 24(6):3676–3689, 2016.

[10] D. Eager, M. Vernon, and J. Zahorjan. Optimal and efficient merging schedules for video-on-demand servers. In *MULTIMEDIA*, 1999.

[11] P. Fahlstrom and T. Gleason. *Introduction to UAV systems*. John Wiley & Sons, 2012.

[12] K. Gulati, R. K. Ganti, J. G. Andrews, B. L. Evans, and S. Srikanteswara. Characterizing decentralized wireless networks with temporal correlation in the low outage regime. *Wireless Communications, IEEE Transactions on*, 11(9):3112–3125, 2012.

[13] S. Guo, S. M. Kim, T. Zhu, Y. Gu, and T. He. Correlated flooding in low-duty-cycle wireless sensor networks. In *Network Protocols (ICNP), 2011 19th IEEE International Conference on*, pages 383–392. IEEE, 2011.

[14] Z. Huang, D. Corrigan, S. Narayanan, T. Zhu, E. Bentley, and M. Medley. Distributed and dynamic spectrum management in airborne networks. In *Military Communications Conference, MILCOM 2015-2015 IEEE*, pages 786–791. IEEE, 2015.

[15] J. Jun, L. Cheng, L. He, Y. Gu, and T. Zhu. Exploiting sender-based link correlation in wireless sensor networks. In *Network Protocols (ICNP), 2014 IEEE 22nd International Conference on*, pages 445–455. IEEE, 2014.

[16] A. Kortebi, L. Muscariello, S. Oueslati, and J. Roberts. Evaluating the number of active flows in a scheduler realizing fair statistical bandwidth sharing. In *SIGMETRICS*, 2005.

[17] S. S. Muchnick and P. B. Gibbons. Efficient instruction scheduling for a pipelined architecture. *ACM SIGPLAN Notices*, 39(4):167–174, 2004.

[18] M. B. Pursley and J. M. Shea. Channel quality estimation with channel error counts for adaptive signaling in wireless communications. In *IEEE International Symposium on Information Theory*, 2000.

[19] S. Ren, P. Yi, D. Hong, Y. Wu, and T. Zhu. Distributed construction of connected dominating sets optimized by minimum-weight spanning tree in wireless ad-hoc sensor networks. In *Computational Science and Engineering (CSE), 2014 IEEE 17th International Conference on*, pages 901–908. IEEE, 2014.

[20] N. Salodkar, A. Bhorkar, A. Karandikar, and V. S. Borkar. An on-line learning algorithm for energy efficient delay constrained scheduling over a fading channel. *IEEE Journal on Selected Areas in Communications*, 26(4):732–742, 2008.

[21] J. Tadrous, A. Sultan, and M. Nafie. Admission and power control for spectrum sharing cognitive radio networks. *Wireless Communications, IEEE Transactions on*, 10(6):1945–1955, 2011.

[22] Y. Tang, H. Gao, J. Kurths, and J. an Fang. Evolutionary pinning control and its application in UAV coordination. *IEEE Transactions on Industrial Informatics*, 8(4):828–838, 2012.

[23] J. Torres-Sánchez, F. López-Granados, A. I. De Castro, and J. M. Peña-Barragán. Configuration and specifications of an unmanned aerial vehicle (UAV) for early site specific weed management. *PLoS One*, 8(3):e58210, 2013.

[24] D. Turner, A. Lucieer, and C. Watson. An automated technique for generating georectified mosaics from ultra-high resolution unmanned aerial vehicle (UAV) imagery, based on structure from motion (SfM) point clouds. *Remote Sensing*, 4(5):1392–1410, 2012.

[25] K. P. Valavanis and G. J. Vachtsevanos. UAV communication issues: Introduction. *Handbook of Unmanned Aerial Vehicles*, 2015.

[26] H. Wang and N. B. Mandayam. A simple packet-transmission scheme for wireless data over fading channels. *IEEE Transactions on Communications*, 52(7):1055–1059, 2004.

[27] X. Xing, T. Jing, Y. Huo, H. Li, and X. Cheng. Channel quality prediction based on bayesian inference in cognitive radio networks. In *INFOCOM*, 2013.

[28] S. Zhang, Q. Zhang, S. Xiao, T. Zhu, Y. Gu, and Y. Lin. Cooperative data reduction in wireless sensor network. *ACM Transactions on Embedded Computing Systems (TECS)*, 14(4):84, 2015.

[29] X. Zhong and C.-Z. Xu. Online energy efficient packet scheduling with delay constraints in wireless networks. In *INFOCOM*, 2008.

[30] T. Zhu, A. Mohaisen, Y. Ping, and D. Towsley. Deos: Dynamic energy-oriented scheduling for sustainable wireless sensor networks. In *INFOCOM, 2012 Proceedings IEEE*, pages 2363–2371. IEEE, 2012.

[31] T. Zhu, Z. Zhong, T. He, and Z.-L. Zhang. Achieving efficient flooding by utilizing link correlation in wireless sensor networks. *IEEE/ACM transactions on networking*, 21(1):121–134, 2013.