Optimizing TDMA Schedule and SIC-Capable UAV Position via Gibbs Sampling

Saadullah Kalwar, Kwan-Wu Chin, and Zhenhui Yuan

***Abstract*—This letter considers a novel problem that aims to derive the shortest possible Time Division Multiple Access (TDMA) schedule for use by ground nodes to upload their data to an Unmanned Aerial Vehicle (UAV) over random channel gains. Its key novelties include equipping the UAV with a Successive Interference Cancellation (SIC) radio and applying a Gibbs sampling based approach to optimize the UAV's position. Our results show that the UAV is able to learn the optimal location whereby the average schedule length at the optimal position is up to 17% shorter as compared to other locations.**

***Index Terms*—Node placement, link scheduling, Markov chain Monte Carlo, TDMA.**

I. Introduction

UNMANNED Aerial Vehicles (UAVs) can be used as a mobile base station or a sink in a wireless sensor network to collect data from ground or sensor nodes [1]. In this respect, a channel access protocol plays a critical role in ensuring ground nodes have a high transmission rate to a UAV. To this end, we consider deriving a *short* Time Division Multiple Access (TDMA) schedule, whereby each ground node has a dedicated transmission slot. A short TDMA schedule means ground nodes are able to transmit frequently to the UAV in a collision-free manner. Moreover, they can be in low power state whenever they are not transmitting to a UAV.

An approach to reduce TDMA schedule length is to equip a UAV/receiver with a Successive Interference Cancellation (SIC) radio [2], which allows multiple nodes to transmit in the same time slot. Successful SIC decoding, however, is predicated on there being sufficient difference in received power at a receiver. This can be achieved by optimizing the UAV's location. As an example, in Figure 1, when the UAV is placed in cell '5', ground nodes A and B have to be scheduled to transmit a different time because their received power is the same. Otherwise, SIC decoding is likely to fail. However, when the UAV is placed at position '1', there is a significant difference in received power, which allows us to schedule both ground node A and B in the same slot, leading to a shorter TDMA schedule length. The main challenge when selecting a position is that the channel gain is random at each location.

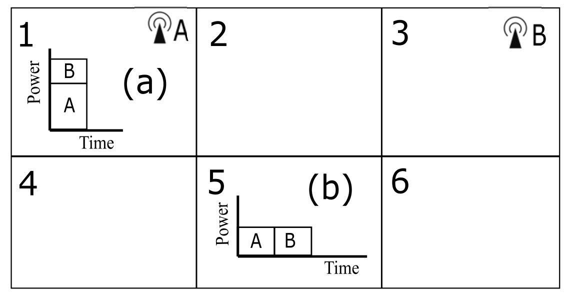

Fig. 1. An example with two possible locations (a) and (b), and their schedule.

Henceforth, in this letter, we outline a Gibbs sampling approach to optimize the UAV's location in order to construct a short TDMA schedule. The main advantage of our approach is that it allows the UAV to learn its position iteratively over random channel gains. We also outline a link scheduler that greedily includes ground nodes into a slot. Our simulation results show that the average TDMA schedule length is up to 17% shorter when the UAV is placed at the optimal location as compared to other locations.

To date, no past works have considered our problem. Specifically, they *do not* consider a UAV with a SIC radio, and their aim is not to derive a TDMA scheme. Example works include [3], [4], [5], [6], [7], which only aim to find the minimum number of UAVs required to cover a geographical area. Only a few works have considered SIC. In [8], the aim is to improve a UAV's energy efficiency. Shi *et al.* in [9] aim to optimize a UAV's trajectory as opposed to deriving a link schedule. We remark that trajectory planning is beyond the scope of this letter. The authors of [10] consider a UAV with Non-Orthogonal Multiple Access (NOMA). However, their problem is concerned with optimizing the altitude, antenna beam width and power allocation of an UAV. They do not consider optimizing a UAV's location nor transmission schedule. Lastly, the authors of [11], [12], [13] and [14] also consider TDMA channel access and a SIC capable receiver. However, these works do not optimize the position of a UAV.

The next section discusses our system model. Section III presents our problem mathematically. Section IV presents our Gibbs sampling approach. We discuss our results in Section V and lastly, our conclusions are presented in Section VI.

II. System Model

We divide time into discrete slots, denoted as t_j, where j is the slot index. Let F_m be the m-th frame, and contains $|F_m|$ slots. We divide a geographical area into Z grid positions

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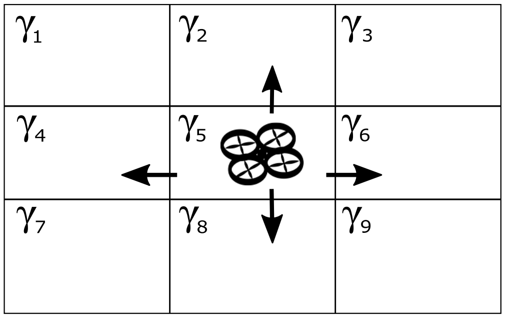


Fig. 2. An example cell with nine grid positions.

or cells that are recorded in the set $\Gamma = \{\gamma_1, \gamma_2, \ldots, \gamma_Z\}$. Figure 2 depicts an example cell with $Z = 9$. Note that our solution also works in 3D space, where the set Γ contains voxels of a 3D area. Let S denote the set of ground nodes. The UAV is denoted as u. We assume each ground node is equipped with a half-duplex radio. The coordinate or location of ground node s_i is denoted as (x_i, y_i), where $i = 1, 2, \ldots, |S|$. We assume ground nodes are saturated, meaning they always have data to transfer. The UAV can select any grid position in Γ. The altitude of the UAV is fixed at h meters. Note that the UAV's location is *fixed* after the conclusion of our algorithm. The transmit power from ground node $s_i \in S$ to the UAV is given as p_t^i. Let g_i^k denote the channel gain from ground node s_i to the UAV when the UAV is placed at the k-th position. The UAV can collect the channel gain to each ground node at the start of each frame via pilot symbols. Ground nodes are then assigned a distinct time slot where they send their responses to the UAV. Let $p_r^i = g_i^k p_t^i$ denote the received power at the UAV for ground node s_i at position k.

The UAV is equipped with a SIC capable radio [2], and thereby allowing multiple ground nodes to transmit simultaneously in a single time slot. To explain SIC decoding, suppose we have a set $L = \{a, b, \ldots, l\}$ of transmitters in time slot t_j. Assume the UAV is placed at the k-th grid position and the received power at the UAV for these $|L|$ ground nodes is ordered as follows: $p_r^a \geq p_r^b \geq \ldots \geq p_r^l$. Then, the UAV will start the decoding process from the ground node with the highest received power, namely ground node a. If the SINR of ground node a is greater than a fixed threshold, denoted as β, then it is successful. Formally,

$$\frac{p_t^a g_a^k}{\sigma^2 + \sum_{q \in L \setminus a} p_t^q g_q^k} \geq \beta. \tag{1}$$

If the decoding of ground node a's transmission is successful, the UAV proceeds to decode the transmission from the ground node b. That is, it first subtracts the signal of ground node a from the composite signal. Then, the transmission of ground node b is successful if,

$$\frac{p_t^b g_b^k}{\sigma^2 + \sum_{q \in L \setminus \{a,b\}} p_t^q g_q^k} \geq \beta. \tag{2}$$

The above process then continues to ground node c and so forth until the UAV decodes all $| L |$ transmissions. If a transmission fails to meet the SINR threshold β then all subsequent transmissions fail.

III. The Problem

Our objective is to minimize $|F_m|$, in terms of slots, while ensuring each ground node is assigned a time slot. Let the random variable $\Phi(\gamma_k)$ represents the schedule length for location γ_k. We seek to identify the optimal UAV location γ^* that yields the minimum expected schedule length. Formally,

$$\gamma^* = \min_{\gamma \in \Gamma} \mathbb{E}[\Phi(\gamma)]. \tag{3}$$

The expectation is taken with respect to the joint probability distribution $\{g_i^k\}$ for all $k \in \Gamma$ and $i \in S$. In words, the problem at hand is to determine a location in Γ that allows the UAV to construct the shortest TDMA schedule *on average* to serve all ground nodes. Observe that each of the Z cells yields a different received power for each ground node, which may improve SIC decoding success. Hence, the basic idea is to search across these Z cells. However, a challenging issue is that the channel gain to ground nodes is time-varying, which is caused by environmental factors or node mobility.

IV. A Gibbs Sampling Solution

To address problem (3), we employ Gibbs sampling [15]. Gibbs sampling is a Markov Chain Monte Carlo (MCMC) method that can be used to obtain a sequence of observations from a probability distribution. Consider a probability distribution with K possible states. Let $\bar{\sigma}$ represent the probability distribution of these states, and the states at the n-th iteration are $\{b_1^n, b_2^n, \ldots, b_K^n\}$. The main idea is to sample from the said probability distribution to determine the most likely state in each iteration. Gibbs sampling then evaluates the reward of the sampled state and proceeds to update the probability distribution using the obtained reward.

Algorithm 1 operates as follows. Line 1 initializes the probability distribution $\bar{\sigma}$. The function *Sample()* selects a state from the probability distribution, and *Calc()* is used to update the probability distribution after each sample. In line 4, the Gibbs sampler samples b_1^n based on the current value of all other states $b_2^{n-1}, b_3^{n-1}, \ldots, b_K^{n-1}$. It then samples b_2^n based on $b_1^n, b_3^{n-1}, b_4^{n-1}, \ldots, b_K^{n-1}$, and so forth. After sampling each state, the Gibbs sampler updates the probability distribution $\bar{\sigma}$ based on the reward $\mathcal{U}(b_k^n)$. Its goal is to find state(s) that maximize the reward function. To find such state(s), each state is weighted or is assigned a high probability if it has a high reward. The probability of selecting state b_k^n in the n-th iteration, denoted as $\bar{\sigma}(b_k^n)$ is,

$$\bar{\sigma}(b_k^n) = \frac{e^{\mathcal{U}(b_k^n)/\tau}}{\sum_{b \in B} e^{\mathcal{U}(b)/\tau}}, \tag{4}$$

where $\tau > 0$ is the temperature parameter. A high τ value means the Gibbs sampler will more likely test or explore all other states, whereas a low τ value means it will quickly converge onto a possibly sub-optimal probability distribution. In our experiments, setting τ to 20 results in 55% faster convergence as compared to $\tau = 40$. Readers interested in the convergence and optimality properties of a Gibbs sampler are referred to [15].

We are now ready to present our solution. The aforementioned probability distribution corresponds to all locations

Algorithm 1 A Generic Gibbs Sampler

Input: J (Total number of iterations)

Initialize probability vector $\bar{\sigma}$
n = 1
while $n < J$ **do**
  Sample $(b_1^n \mid b_2^{n-1}, b_3^{n-1}, \ldots, b_K^{n-1})$, $Calc(\bar{\sigma}, b_1^n)$
  Sample $(b_2^n \mid b_1^n, b_3^{n-1}, \ldots, b_K^{n-1})$, $Calc(\bar{\sigma}, b_2^n)$
  $\vdots$
  Sample $(b_K^n \mid b_1^n, b_2^n, \ldots, b_{K-1}^n)$, $Calc(\bar{\sigma}, b_K^n)$
  n = n + 1
end while

in Γ; each state corresponds to a location in Γ. The probability of selecting a location γ_k is given as $\bar{\sigma}(\gamma_k)$. The reward function $\mathcal{U}(\gamma_k)$ of the *k*-th location is defined as,

$$\mathcal{U}(\gamma_k) = 1/\Phi(\gamma_k). \tag{5}$$

In words, the reward is inversely proportional to the schedule length, meaning a location that has a long schedule length will have a lower reward as compared to another location with a short schedule length.

Our Gibbs-based placement process is shown in Figure 3. Initially, the UAV selects a location randomly and a schedule is constructed using Algorithm 2. The basic idea of Algorithm 2 is to greedily add a ground node into a slot t_m. At line 4, it sorts all ground nodes in non-decreasing order of their received power level. At line 6, it calls *GetGroundNode()* to retrieve the *k*-th ground node from the set *S*. It then calls *CheckCompatible()* to check whether the UAV is able to decode a transmission from ground nodes scheduled into slot t_m; see explanation of (1) and (2). If so, ground node s_k is included into slot t_m. After checking all ground nodes, those that have been scheduled are removed from the set *S*. The constructed time slot t_m is then added into the set *F*. Once the schedule is constructed for a given location, the UAV calculates (5), which is then used to update the probability mass function (Eq. 4) and the UAV moves to a new location as per Algorithm 1. Note, if there are multiple optimal locations, our solution converges to one of these locations. Lastly, Algorithms 1 and 2 can be shown to have a run-time complexity of $\mathcal{O}(|\Gamma|J)$ and $\mathcal{O}(|S|^3 log(|S|))$, respectively.

V. Evaluation

We conduct our experiments in MATLAB. The UAV is placed at a height of 200 meters from the ground. The UAV and ground nodes are equipped with a 2.4 GHz radio and transmit at a fixed power of 1 Watt [16]. For simplicity, we assume a square area with size 1 km^2, unless specified.

We note that our problem is new, see Section I. Consequently, there are no other solutions we can compare against fairly. As a benchmark, we only compare against the case whereby the UAV is placed at the center of an area, which provides the optimal coverage in terms of signal strength to all ground nodes. This location, however, is not ideal for a

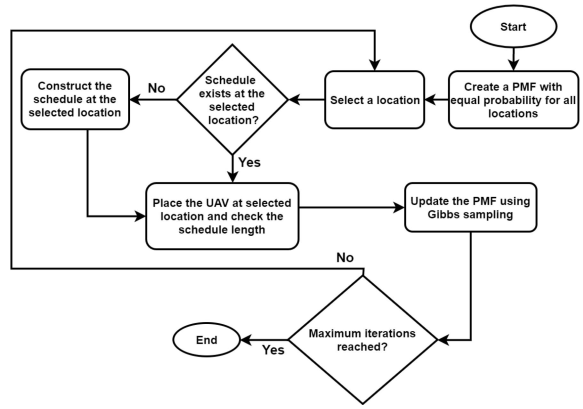


Fig. 3. The UAV's learning process.

Algorithm 2 Link Schedule Construction

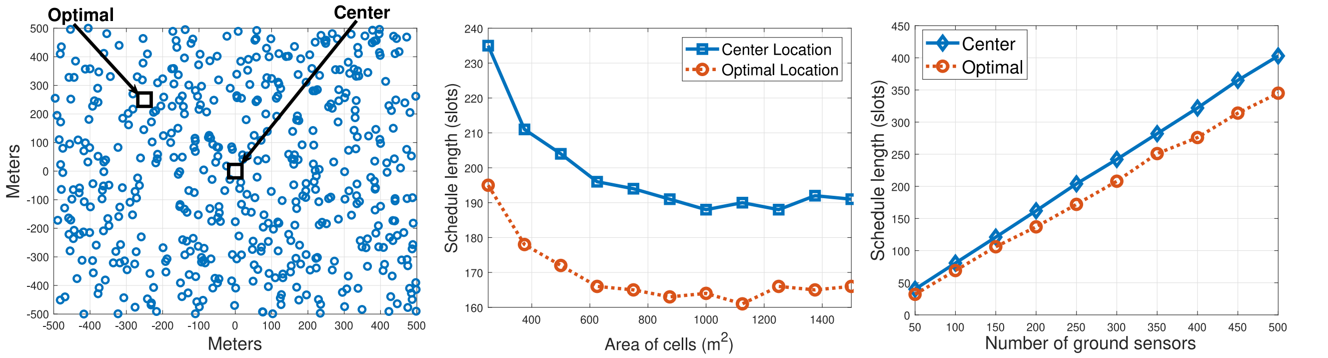
Input: ***S***

Output: ***F***

1: $m = 1, F = \emptyset$
2: **while** $|S| > 0$ **do**
3:   $k = 1, t_m = \emptyset$
4:   S = *Sort*(S)
5:   **while** $k \leq |S|$ **do**
6:     s_k = *GetGroundNode*(S, k)
7:     **if** *CheckCompatible*$(t_m,\, s_k)$ = true **then**
8:       $t_m = t_m \cup s_k$
9:     **end if**
10:     $k = k + 1$
11:   **end while**
12:   S = S $\setminus t_m$
13:   $F = F \cup t_m$
14:   $m = m + 1$
15: **end while**
16: return *F*

SIC-capable receiver. As an example, consider Figure 4(a) and the optimal location of the UAV computed by our approach. At the optimal location, a UAV is able to obtain the highest diversity in received power. On the other hand, at the center location, although the UAV has a high signal strength to all ground nodes, there is insufficient diversity in received power levels, meaning SIC is likely to fail. As we will show next, existing solutions such as [3] that aim to maximize coverage does not lead to good performance.

Figure 4(b) and 4(c) show the schedule length for both positions depicted in Figure 4(a). We can see in Figure 4(b) that the schedule length is significantly shorter when the UAV is placed at the optimal location as compared to the center location. Specifically, the TDMA schedule length is 195 slots for the optimal location when the area is 200 m^2. In comparison, the TDMA schedule length is 235 slots when the UAV is placed at the center. From Figure 4(b), we also observe that the schedule length decreases as we increase the area. The schedule length is longer for smaller areas such as 200 m^2 because the distance between the nearest and farthest nodes is very small. Consequently, SIC cannot perform well due



(a) (b) (c)

Fig. 4. (a) An example area with 250 ground nodes depicting the optimal UAV position. Results for (b) increasing area, and (c) number of ground nodes.

to a lower difference in received power levels. On the other hand, when we increase the size of the area, there is higher diversity in received power levels, leading to a decrease in average schedule length. For example, the TDMA schedule length for the optimal location is 195 time slots when the area is 200 m^2, which decreases to 167 time slots when the area is increased to 1500 m^2. This is due to the increase in distance between the ground nodes and the UAV, which results in a higher difference in received power levels. The schedule length for the center location also drops from 235 to 200 time slots. We also observe from Figure 4(b) that the schedule length decreases significantly when the area increases up to 800 m^2. However, it remains nearly the same when the area is increased further. This is because when the area is greater than 1000 m^2, the obtained SINR becomes very small. Consequently, transmissions are more likely to fail due to low SINR. As a result, the schedule length does not reduce further.

Figure 4(c) shows that the schedule length is longer when we increase the number of ground nodes. This is because having more ground nodes means we need more time slots to accommodate them. Therefore, the schedule length increases as we increase the number of ground nodes. In particular, the schedule length for the optimal UAV location increases from 32 to 345 time slots when the number of ground nodes increases from 50 to 500. The schedule length is approximately 15% higher when the UAV is placed at the center of an area. Lastly, we observe that the SIC decoding success is approximately 80% in all experiments.

VI. Conclusion

We have proposed a method to derive the TDMA schedule of a location over random channel gains. The proposed method employs Gibbs sampling to determine the best location to place a UAV in an area. Simulation results validate our method whereby at the optimal location, the UAV is able to construct a schedule length that is much shorter than other locations. Advantageously, our solution works in the presence of dynamic channel conditions. A possible future work is to consider multiple cells, each with a UAV and associated ground nodes, that interfere with one another.

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