AoI-Optimal Cellular-Connected UAV Trajectory Planning for IoT Data Collection

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***Abstract*—Unmanned Aerial Vehicles (UAVs) can help data collection from ground sensors or Internet of Things (IoT) devices deployed even in hard to access areas and deliver them to their destinations as relays. However, the UAV trajectories should be planned carefully due to their limited battery lifetimes. Recently, Age of Information (AoI) has also been considered as a metric to quantify the freshness of the data collected during this process and the path of the UAVs are aimed to be optimized considering AoI. However, existing studies have defined the AoI of the collected data in the context of delivering the collected data to a specific destination only. Moreover, they assume the data is available at each IoT device before the UAV is dispatched. In this paper, we consider a set of base stations distributed in the area that a UAV travels through and define the AoI from the moment the data is generated till it is uploaded to any of the base stations by the cellular-connected UAV. We also consider data generation times at each IoT device requiring the UAV's arrival to an IoT device after this time. Our goal is to minimize the maximum AoI of any collected data while also minimizing the mission time and the path of the UAV for energy saving. We model and solve the problem using Integer Linear Programming (ILP) and with a heuristic based solution. The results obtained in different scenarios show that heuristic approach can provide close to optimal ILP based results while running much faster.**

***Index Terms*—Cellular-connected UAV, path planning, age of information, data collection.**

I. INTRODUCTION

The flexibility and maneuverability of Unmanned Aerial Vehicles (UAVs) have enabled the usage of them in many applications including but not limited to wireless communication, agriculture and search and rescue operations. In this study, we are interested in the application scenario where UAVs are employed to collect data from ground sensor nodes or Internet-of-Things (IoT) networks as a relay node and deliver the collected data to their destination. In order to receive the data from IoT devices, the UAV needs to get close to each of them following a path and finally should stop at its mission end point.

Since the UAVs run on limited battery supply and can only stay in air for a limited time, their path during this data collection period has to be planned carefully. Moreover, the data generation times at each IoT device should be considered in this planning process as the UAV should only visit the IoT device after the data is generated at the device. In most of the existing studies [1]–[3], however, the data is considered to be available before the UAV starts its mission, which may not be the case as always in practice. After the data is collected from IoT devices, the delivery of them to their target destinations should be performed by the relay UAV considering the application requirements.

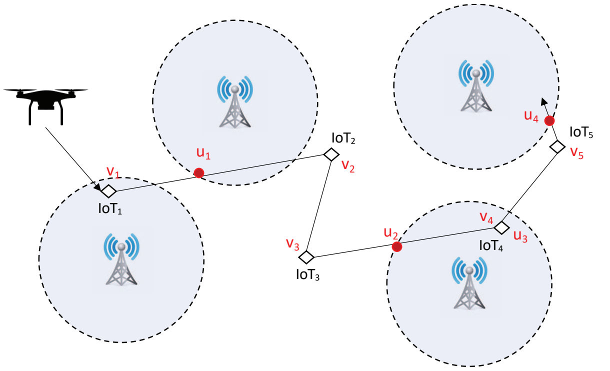

Fig. 1: An example scenario where a UAV collects data from five ground IoT devices considering their data generation times and uploads the collected data by visiting a base station. Age of Information is defined from the moment the data is generated at each IoT device until it is uploaded.

The path planning problem in UAV-assisted IoT networks has recently been studied considering different objectives. These objectives include minimizing total energy consumed by the UAVs [4], minimizing the connection outage time [5], and maximizing the throughput or the amount of data collected [6] from ground IoT devices. Since the timely delivery of information from the ground IoT devices is also important, the path planning of UAVs in such scenarios has also been made considering a new metric called age of information (AoI) [7]. Through this metric, the freshness of the information is aimed to be quantified once the data is delivered to the destination. While there are several studies [1]–[3], [7], [8] that consider AoI as the primary factor for determining the UAV paths, these studies typically assume that the data delivery occurs only when the UAV reaches a single destination. On the contrary, in this paper, we consider a more practical scenario where the cellular-connected UAV uploads the collected data to one of base stations in the area to deliver it to its destination (through Internet). Note that if the IoT device is already in range of a base station (BS), once the UAV downloads data from the IoT device, it can immediately upload to the BS. However, if there

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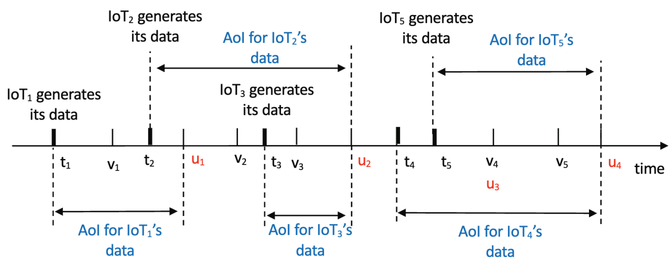


Fig. 2: AoI calculation for the data of each IoT device in Fig.1.

is no coverage at the IoT device location by a BS, UAV carries the data until it comes into the coverage range of a BS. AoI in this scenario is defined from the moment the data is generated till the data is delivered to a BS in the area by the UAV.

An example scenario is illustrated in Fig. 1, with a UAV collecting data from several ground IoT devices one by one and uploading the data collected to one of the ground base stations on the route. Fig. 2 shows the AoI calculation for each data on this example scenario. Note that each UAV visits (e.g., v_i) the IoT device's location to download its data after the data is generated (e.g., $v_i \geq t_i$) and the AoI is computed as the time passes from the data generation time till it is uploaded to a base station (e.g., $u_i - t_i$).

Our goal in this paper is to find the path of a UAV that will minimize the max AoI from any data collected from the field, given the data generation times and locations of IoT devices. To the best of our knowledge, there is only one recent work [9] that defines the AoI as it is considered in this study. However, that study aims only minimization of the worst case or maximum AoI without trying to optimize mission time and the path length for the UAV as well. The problem is modeled as a mixed integer convex optimization problem using graph theory and solved with CVX tools. Also, no heuristic-based, fast-running, practical solution is provided.

The rest of the paper is organized as follows. We discuss the related work in Section II. In Section III, we provide the system model together with the assumptions made, the problem statement, optimization model and our greedy heuristic based solution. In Section IV, we then provide our simulation results in various scenarios. Finally, we provide the concluding remarks and discuss the future work in Section V.

II. RELATED WORK

The path planning for UAVs have been studied extensively [10] considering the variety of ways they have been adopted in different applications with different objectives. In these studies, different parameters such as mission time [5], [11], throughput [12], connection outage [13], antenna patterns [14] and coverage [15] have been considered while designing the path of the UAV(s).

Recently, a new metric called Age of Information (AoI) has also been introduced [7] for UAV missions that aim to collect data from ground sensors or IoT devices and deliver them to their destinations. Since the timely delivery of the data as well as the freshness of the information obtained by the system can be vital for some applications, this problem has attracted a lot of attention by various researchers [1]–[3], [7], [8], [10], [16]. The problem is also considered together with other considerations such as wireless energy transfer [17], data acquisition mode selection, energy consumption [18], or power optimization [19] and solutions that are based on optimization techniques [7], [10], [20], dynamic programming [1] or learning models such as reinforcement learning [2], [16], [17] have been developed.

Despite this extensive number of studies that consider AoI in the path planning of UAVs, the delivery of the data is considered in terms of the data collection period by the UAVs only and the communication of the UAV with the core network (and Internet) is mostly not focused. However, if there are multiple base stations deployed in the area, a cellular-connected UAV can use any of them to upload the collected data and depending on which base station is used the AoI for the specific IoT device can be different. Moreover, in most of the studies, the data at each ground node is assumed to be generated before the UAV dispatch whereas in a more practical setting data could be generated even after the UAV dispatch. While a recent work [9] looks at these points similar to our work in this paper, it only considers AoI itself without considering the UAV mission time and path in the optimization design thus can result in longer paths for the UAV. Moreover, the proposed solution in that study is based on only a high complexity optimization based approach while in this paper, we also propose a heuristic based fast running solution.

III. SYSTEM MODEL

A. Assumptions

We assume a system model with a UAV, represented by u, a set $\mathcal{I}$ of ground IoT devices and a set $\mathcal{G}$ of ground base stations (GBS). Each IoT device is assumed to generate a data at some specific time defined by the application. The location of IoT device i is represented by l_i and its data generation time is denoted by t_i. Similarly, the location of GBS i is defined by z_i. The mission of the UAV is to begin its flight from a starting location, L_S and to arrive a final point L_F after collecting data from ground IoT devices within a given time constraint $T_{\max}$, which is defined as the maximum possible flight time for the UAV and can be computed based on its hardware specifications. The collection of data from an IoT device happens when UAV arrives in the vicinity of the IoT device. More specifically, we assume that when the distance between the UAV and an IoT device is less than R_I, the data can be transmitted. R_I can be determined by the transmission capabilities of the IoT device and can simply be considered as its range. The actual value of R_I can be computed by considering the signal level modeling (i.e., SNR) and the required transmission bandwidth for the specific application data [5], [14]. The upload of the data from the UAV is assumed to happen to a nearby GBS when the UAV arrives in the range of a GBS, which is assumed to be R_G. It is assumed that UAV can fly with a maximum speed of V at a fixed altitude of H. Note that this will allow the UAV to communicate with the

Notations	Description
u	The UAV that travels over the field for data collection from a starting point to and end point.
$\mathcal{I}$	The set of ground sensors or IoT devices.
$\mathcal{G}$	The set of ground base stations (GBS).
V_i^D	The time UAV visits the IoT device i and downloads the generated data.
V_i^U	The time UAV uploads and delivers the data captured from IoT i to one of the GBSs.
L_{S}, L_{F}	Start and final location of UAV, respectively.
L, T	The ordered set of critical locations and times on the UAV path, respectively.
$L(t)$	Location of the UAV at time $t \in T$.
l_i	Location of ground IoT device i.
z_i	Location of GBS i.
$c_i(t)$	Connection status of the UAV to IoT device i at time $t \in T$. It is equal to 1 if the UAV can communicate to the IoT i and receive the data at time t; otherwise, it is 0.
t_i	The generation time of the data at IoT device i.
$d_i(t)$	Collection status of data from IoT device i at time $t \in T$. It is equal to 1 if the UAV collects IoT device i's data at time t; otherwise 0.
$u_i(t)$	Upload status of data that is downloaded from IoT i to a GBS at time $t \in T$. It is equal to 1 if the UAV uploads the data downloaded from IoT i to one of the GBSs at time t; otherwise 0.
$g_i(t)$	Connection status of the UAV to GBS i at time $t \in T$. It is equal to 1 if UAV can communicate to the GBS i and send the data at time t; otherwise, it is 0.
$G(t)$	If the UAV is in range of at least one GBS at time $t \in T$.
R_I	Max distance/range for a IoT-UAV link to maintain required SNR level.
R_G	Max distance/range for a UAV-GBS link to maintain required SNR level.
T_{max}	Maximum possible flight duration for the UAV to reach the destination.
T_F	The first time the UAV arrives to the final location (i.e., mission time).
V	Maximum speed of the UAV
A_{max}	Maximum AoI for the collected data.
D_{sum}	Total length of the path travelled by the UAV.

TABLE I: Notations and their descriptions.

ground IoT devices through Line-of-Sight (LoS) based signal without having interference. The location of the UAV at time t is denoted by $L(t) = (x(t),\ y(t),\ H)$ until its flight ends at time $T_{\max}$.

B. Problem Statement and ILP Formulation

In the proposed problem a UAV needs to travel from an initial point to collect data from all ground IoT devices and arrive to its final destination (which can be the same location as the initial starting point). Let $L = \{L_0, L_1, L_2, ..., L_{2|I|}, L_{2|I|+1}\}$ be the set of ordered locations that we are trying to identify on the route of the UAV. These locations correspond to the critical locations that define the path of the UAV which include the start (L_S) and end locations (L_F) as well as the download and upload locations for the data of each IoT device. Note that $L_0 = L_S$ and $L_{2|I|+1} = L_F$. We also define $T = \{T_0 = 0, T_1, T_2, ..., T_{2|I|}, T_{2|I|+1} = T_F\}$ as the set of times that the UAV is present at the corresponding locations in L, i.e., $L(T_i) = L_i$. Our main goal is to minimize the maximum AoI during this data collection process. In addition to this primary objective, we also consider minimizing the mission time data as secondary goal, and also aim to minimize the length of the total path travelled by the UAV as a third objective. Under these objectives and the notations given in Table I, we develop an Integer Linear Programming (ILP) based model as follows:

$$\min \quad (A_{max})\lambda + (u(T_F))\Theta + D_{sum} \tag{1}$$

$$\text{s.t.} \quad L(0) = L_S \tag{2}$$

$$L(T_F) = L_F \ \& \ T_F \leq T_{max} \tag{3}$$

$$\mathrm{dist}_{L_i}^{L_{i+1}} \leq V \times (T_{i+1} - T_i), \forall i \in [0, 2|I|] \tag{4}$$

$$V_i^D \geq t_i, \forall i \in \mathcal{I} \tag{5}$$

$$V_i^U \geq V_i^D, \forall i \in \mathcal{I} \tag{6}$$

$$c_i(t) \ = \ \begin{cases} 1, & \text{if } \mathrm{dist}_{l_i}^{L(t)} \leq R_I \\ 0, & \text{otherwise.} \end{cases} , \forall t \in T, \forall i \in \mathcal{I} \tag{7}$$

$$d_i(t) \leq c_i(t), \forall t \in T, \forall i \in \mathcal{I}, \tag{8}$$

$$\sum_{\forall t \in T} d_i(t) = 1, \forall i \in \mathcal{I} \tag{9}$$

$$V_i^D = \sum_{\forall t \in T} (d_i(t) \times t)), \forall i \in \mathcal{I} \tag{10}$$

$$g_i(t) \ = \ \begin{cases} 1, & \text{if } \mathrm{dist}_{z_i}^{L(t)} \leq R_G \\ 0, & \text{otherwise.} \end{cases} , \quad \forall t \in T, \forall i \in \mathcal{G} \tag{11}$$

$$G(t) = min(1, \sum_{\forall i \in \mathcal{G}} g_i(t)), \forall t \in T \tag{12}$$

$$u_i(t) \leq G(t), \forall i \in \mathcal{I}, \forall t \in T \tag{13}$$

$$\sum_{\forall t \in T} u_i(t) = 1, \forall i \in \mathcal{I} \tag{14}$$

$$V_i^U = \sum_{\forall t \in T} (u_i(t) \times t), \forall i \in \mathcal{I} \tag{15}$$

$$A_{max} = \max \left\{ (V_i^U - t_i) \right\}, \forall i \in \mathcal{I} \tag{16}$$

$$D_{sum} = \sum_{i=0}^{2|I|} \mathrm{dist}_{L_i}^{L_{i+1}} \tag{17}$$

where, dist_u^v represents the distance between two coordinates u and v.

Here, in (1), we use the scalarization method (by multiplying the first goal with a large constant, λ, and multiplying the second goal with another large constant, Θ, which is smaller than the first one) and aim to first minimize the maximum or worst-case AoI, then minimize the mission completion time (i.e., when the UAV arrives the final location) and finally minimize the total travel path length of the UAV. In (2) and (3), we make sure the UAV is at the start location at the beginning and at the final point at the end of its mission, respectively. In (4), the UAV is constrained to move not more than what its maximum speed allows between consecutive critical points on the UAV path. Constraint (5) makes sure that UAV downloads the data after its generation at the IoT device. In addition,

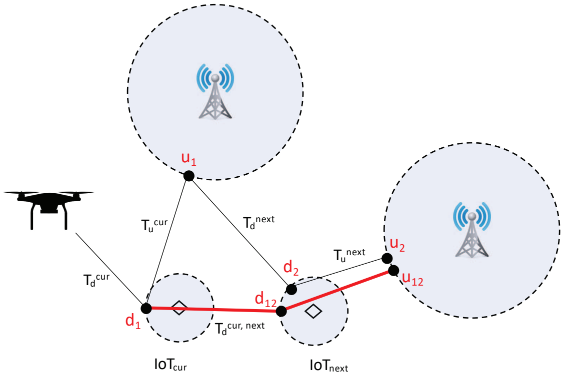


Fig. 3: Current and next IoT to be visited in greedy heuristic approach and the comparison of two possible paths.

since the collected data can be uploaded to a GBS after it is collected from the IoT device, constraint (6) is added.

In (7), the connectivity between the UAV and each IoT device is set based on the distance between the position of the IoT device and the UAV at that time. We then allow the collection of data by the UAV in range of IoT device in (8) and only one time as defined in (9). In (10), we assign the UAV's IoT visit time to its pre-defined variable V_i^D, and to do this we multiply the value of $d_i(t)$ by t and then compute the sum. Since $d_i(t)$ is equal to 1 in only one of the ts, the value of V_i^D becomes equal to the IoT visit time. In (12), we check the location of the UAV to see if it is in the range of at least one GBS at time t or not. The variable $G(t)$ equals to 1 if the UAV is in the range of at least one GBS and in order to calculate it, we sum the $g_i(t)$ (defined in (11)) for all the GBSs at time t. If the UAV is in the range of at least one GBS, it has the ability to upload data on that GBS (13). In (14), we force the UAV to upload all the data in order to finish its mission. In (15), we assign the UAV's GBS visit time for uploading data to its pre-defined variable V_i^U, and to do this we multiply the value of $u_i(t)$ by t and then compute the sum for all the ts. In (16), we then compute max AoI for any data collected from all IoT devices. AoI here is defined as the time elapsed from data generation time t_i to its delivery time at V_i^U. Finally, in (17), we calculate the total path length which is considered as the third priority in the objective function.

C. Greedy Heuristic Approach

While the ILP solution with a fine grained grid will help obtain the optimal solution, its run time complexity will be high, thus in this part, we develop a greedy heuristic based solution that runs much faster. To this end, from the initial start location (or UAV's current location T_{cur}), we first find the IoT device whose data could be uploaded the earliest if the UAV would go to that IoT device's location directly and after getting its data goes to the closest GBS to upload. Note that if the UAV arrives earlier than the data generation time, it needs to wait until the data is generated. Thus, we calculate the following to find this IoT device:

$$i_{min} = \arg\min\{\max(T_d^i + T_{cur}, g_i) + T_u^i\},$$

Scenario	**Mission time**	**Max AoI**	**Average AoI**	**Path length**
(a) Initial scenario (C)	29.63	4.48	1.12	59.24
(a) Initial scenario (H)	32	12.51	4.69	51.61
(b) Speed = 3 (C)	23.40	0.80	0.20	60.28
(b) Speed = 3 (H)	24	1.01	0.57	61.78
(c) Additional GBS/IoT (C)	33.78	6.80	1.70	66.54
(c) Additional GBS/IoT (H)	37	12.91	5.61	60.53
(d) Different data generation times (C)	27.78	3.60	0.72	50.15
(d) Different data generation times (H)	29	4.00	1.65	49.44
(e) IoT range = 0 (C)	33.24	8.19	2.04	66.65
(e) IoT range = 0 (H)	33	13.04	4.35	57.15

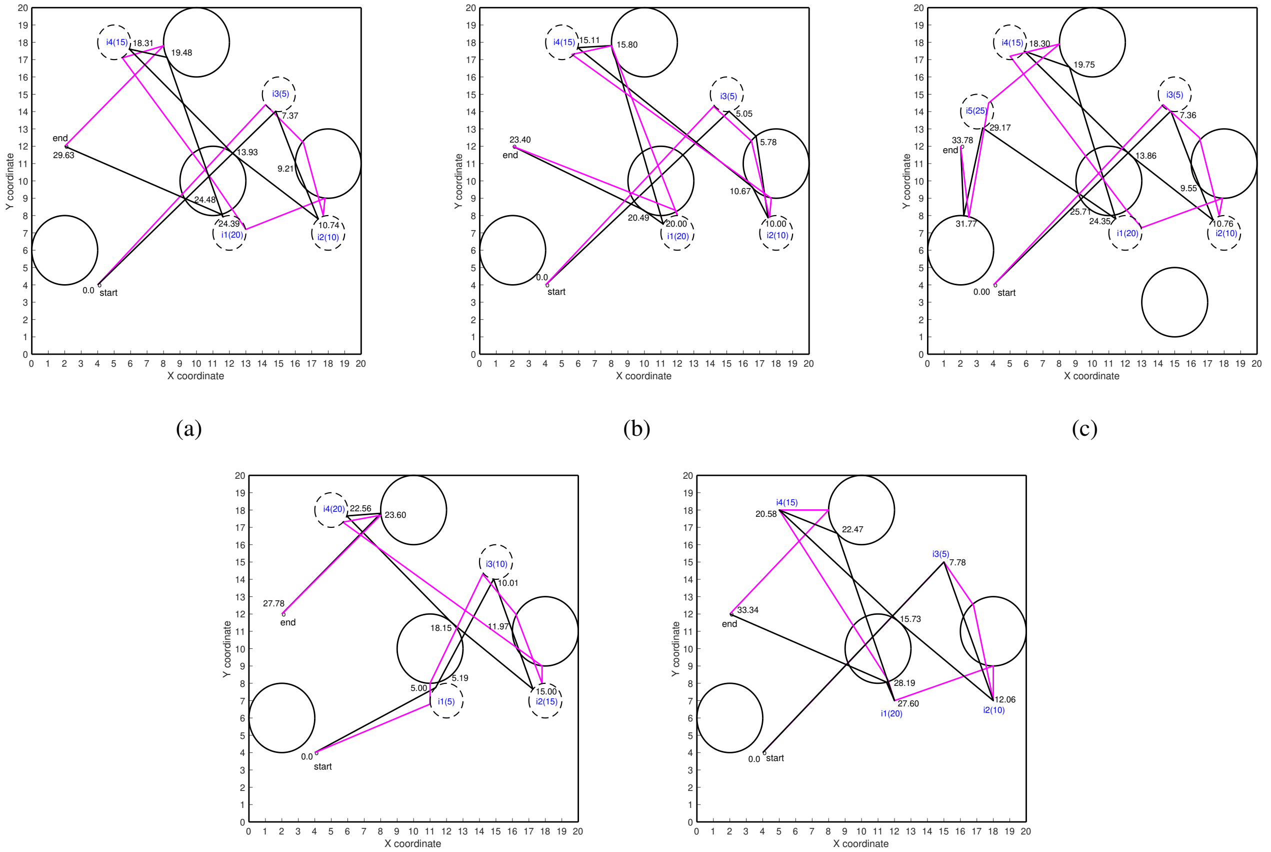
TABLE II: Simulation results for both ILP based model obtained by CPLEX (C) and heuristic based solution (H) for the scenarios in Fig. 4.

where T_d^i is the time it takes to arrive into the range of IoT device i from its current location, T_u^i is the time it takes to go from the download location to the upload location (i.e., closest GBS range). These durations are also illustrated in Fig. 3 where IoT$_{cur}$ represents the current selected node, i_{min}.

Once this device is found, the UAV is then headed towards that IoT device's location and stops when it enters into its range for data collection. At this point (e.g., d_1 in Fig. 3), we, however, do not let the UAV go directly to the closest GBS. Instead, we first find the next IoT device (e.g., IoT$_{next}$ in Fig. 3) that would be visited with the same criteria after the first IoT's data is uploaded in the closest GBS range (e.g., at u_1 in Fig. 3). Then, we compare the time duration for two different cases. In the first case, we find the AoI if the UAV visits the next IoT device after it uploads the first one's data to the closest GBS and goes to the next IoT device to get and upload its data (e.g., path that follows d_1, u_1, d_2, u_2 in Fig. 3). In the second case, we find the max AoI if the UAV would visit the next IoT device directly from the download location of the current IoT device, then upload the data of both of them to the closest GBS from the next IoT's data download location (e.g., path that follows d_1, d_{12}, u_{12} in Fig. 3). If the latter provides smaller AoI, then the UAV goes to the next IoT's location (e.g., d_{12} from d_1); otherwise, the UAV first uploads the first one's data and goes to the next IoT device's download location (e.g., d_2). The procedure is then repeated similarly until all IoT devices are visited and their data are uploaded.

IV. SIMULATION RESULTS

In this section, we provide simulation results in a set of different scenarios. We consider a map of size 20 by 20 units and consider different number of GBSs and IoT devices with different data generation times (shown in parenthesis next to device). The range for IoT-UAV communication is set as $R_I = 1$ unit, while the range for UAV-GBS link is set as $R_G = 2$ units. Each IoT device is assumed to be not in the coverage area of any of the GBSs to make the scenarios more challenging.



(a) (b) (c)

(d) (e)

Fig. 4: The UAV path for the ILP based model (black) and heuristic approach (pink) for different scenarios. (a) Initial scenario with 4 GBS and 4 IoT devices with UAV speed of 2 units, (b) when the speed is set to 3 units, (c) with one additional GBS and one additional IoT device, (d) with different data generation times of IoT devices, (e) when IoT range (R_I) is set to almost zero i.e., UAV needs to be at the same coordinate with IoT to download its data.

Fig. 4 shows the UAV paths obtained via CPLEX from the described ILP model as well as by using the greedy heuristic approach in five different scenarios. The values of four metrics (i.e., mission time, max and average AoI, and path length) associated with these scenarios are also provided in Table II.

First of all, within each scenario, we observe that the order of UAV visits of IoT devices and GBSs, determined by ILP, exhibits a certain resemblance to the heuristic outcome (though not entirely identical). For instance, in cases (b) and (d), both the ILP and heuristic approaches share the same visit order, leading to a comparable maximum AoI for these particular scenarios. However, in other cases, we observe different visit orders, thus a substantial disparity arises in the maximum AoI.

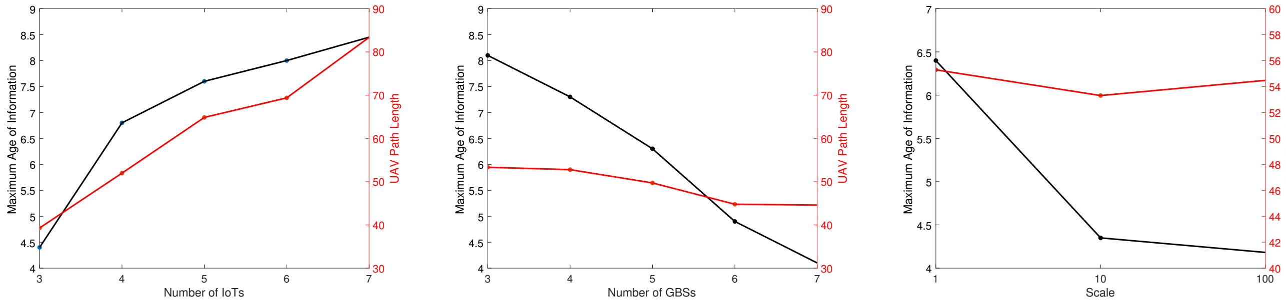
Concerning path length, as the primary objective of ILP based solution is to minimize the maximum AoI, it occasionally compromises path length to achieve a lower maximum AoI. Consequently, the path lengths obtained in ILP solution in cases (a), (c), (d), and (e) exceed the path lengths obtained in the heuristic approach.

In terms of mission time, both approaches yield similar and closely aligned results across all cases. This observation is reasonable as both algorithms strive to visit all GBSs and IoTs once, differing solely in the visit order.

Next, we look at the impact of some parameters on the ILP results in some random scenarios. We first look at the impact of number of IoTs on the maximum AoI when the other parameters are the same. To this end, we generate 100 different scenarios with a specific number of randomly placed IoT devices on the map, while the GBS count stays fixed as 4. We then calculate the average of the maximum AoI and UAV path length. The data generation time of IoT devices is set as the multiples of 5, i.e., $t_i = 5i$. As it is shown in Fig. 5 (a), both the maximum AoI and UAV path length increases as the number of IoT devices increases.

Next, we look at the impact of number of GBSs in the same way while keeping the number of IoT devices as 4. As shown in Fig. 5 (b), increasing the number of GBSs results in a reduction of the maximum AoI and UAV path length thanks to the more coverage provided with more GBSs.

Finally, we look at the impact of scale used in our ILP



(a)

(b)

(c)

Fig. 5: Impact of varying (a) number of IoTs, (b) number of GBSs and (c) scale on maximum AoI and UAV path length in ILP results.

model design, where the scale provides more finer movement opportunity to the UAV and thus more precise results (the results in Fig. 4 are with scale 100). We obtained results for 100 different scenarios with different scales while having 4 IoT devices and 4 GBSs. In Fig. 5 (c), we observe a significant reduction in the maximum AoI when we increase the scale from 1 to 10, while there is only a slight reduction when the scale change from 10 to 100. The UAV travel distance remains the same across all scales with slight variations.

V. CONCLUSION

In this paper, we have explored the path planning problem for a cellular-connected UAV considering minimization of the maximum AoI for any data collected as the main criteria. Different from previous works, AoI is defined as the time passes from the moment data is generated till it is uploaded to any of the nearby ground base stations by the UAV. We developed both an ILP based model and a greedy heuristic based algorithm to find the path for the UAV. Through simulations with different scenarios, we have compared the results obtained by both approaches and showed how their results differ in terms of several metrics.

In the future work, we will consider an online algorithm for the UAV where only limited information about the IoT devices and the field (e.g., GBS locations) is known. We will also consider multi-UAV scenarios and more realistic communication models.

REFERENCES

[1] J. Liu, X. Wang, B. Bai, and H. Dai, “Age-optimal trajectory planning for uav-assisted data collection,” in *IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, 2018, pp. 553–558.

[2] M. A. Abd-Elmagid, A. Ferdowsi, H. S. Dhillon, and W. Saad, “Deep reinforcement learning for minimizing age-of-information in uav-assisted networks,” in *IEEE Global Communications Conference (GLOBECOM)*, 2019, pp. 1–6.

[3] S. Zhang, H. Zhang, Z. Han, H. V. Poor, and L. Song, “Age of information in a cellular internet of uavs: Sensing and communication tradeoff design,” *IEEE Transactions on Wireless Communications*, vol. 19, no. 10, pp. 6578–6592, 2020.

[4] C. Zhan and Y. Zeng, “Aerial–ground cost tradeoff for multi-UAV-enabled data collection in wireless sensor networks,” *IEEE Transactions on Communications*, vol. 68, no. 3, pp. 1937–1950, 2019.

[5] A. Chapnevis, I. Güvenç, L. Njilla, and E. Bulut, “Collaborative trajectory optimization for outage-aware cellular-enabled uavs,” in *IEEE 93rd Vehicular Technology Conference (VTC2021-Spring)*, 2021, pp. 1–6.

[6] K. K. Nguyen, T. Q. Duong, T. Do-Duy, H. Claussen, and L. Hanzo, “3d uav trajectory and data collection optimisation via deep reinforcement learning,” *IEEE Transactions on Communications*, vol. 70, no. 4, pp. 2358–2371, 2022.

[7] M. A. Abd-Elmagid and H. S. Dhillon, “Average peak age-of-information minimization in UAV-assisted IoT networks,” *IEEE Transactions on Vehicular Technology*, vol. 68, no. 2, pp. 2003–2008, 2018.

[8] O. A. Amodu, U. A. Bukar, R. A. R. Mahmood, C. Jarray, and M. Othman, “Age of Information minimization in UAV-aided data collection for WSN and IoT applications: A systematic review,” *Journal of Network and Computer Applications*, p. 103652, 2023.

[9] G. Chen, C. Cheng, X. Xu, and Y. Zeng, “Minimizing the age of information for data collection by cellular-connected uav,” *IEEE Transactions on Vehicular Technology*, 2023.

[10] S. Aggarwal and N. Kumar, “Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges,” *Computer Communications*, vol. 149, pp. 270–299, 2020.

[11] H. Binol, E. Bulut, K. Akkaya, and I. Guvenc, “Time optimal multi-uav path planning for gathering its data from roadside units,” in *Proc. of 88th IEEE Vehicular Technology Conference (VTC-Fall)*, 2018, pp. 1–5.

[12] Q. Wu, Y. Zeng, and R. Zhang, “Joint trajectory and communication design for multi-uav enabled wireless networks,” *IEEE Transactions on Wireless Communications*, vol. 17, no. 3, pp. 2109–2121, 2018.

[13] E. Bulut and I. Guevenc, “Trajectory optimization for cellular-connected UAVs with disconnectivity constraint,” in *IEEE International Conference on Communications (ICC) Workshops*, 2018, pp. 1–6.

[14] M. M. U. Chowdhury, S. J. Maeng, E. Bulut, and I. Güvenç, “3-d trajectory optimization in uav-assisted cellular networks considering antenna radiation pattern and backhaul constraint,” *IEEE Trans. on Aerospace and Electronic Systems*, vol. 56, no. 5, pp. 3735–3750, 2020.

[15] J. Li, Y. Xiong, J. She, and M. Wu, “A path planning method for sweep coverage with multiple uavs,” *IEEE Internet of Things Journal*, vol. 7, no. 9, pp. 8967–8978, 2020.

[16] Z. Li, P. Tong, J. Liu, X. Wang, L. Xie, and H. Dai, “Learning-based data gathering for information freshness in uav-assisted iot networks,” *IEEE Internet of Things Journal*, 2022.

[17] O. S. Oubbati, M. Atiquzzaman, H. Lim, A. Rachedi, and A. Lakas, “Synchronizing uav teams for timely data collection and energy transfer by deep reinforcement learning,” *IEEE Transactions on Vehicular Technology*, vol. 71, no. 6, pp. 6682–6697, 2022.

[18] Z. Jia, X. Qin, Z. Wang, and B. Liu, “Age-based path planning and data acquisition in uav-assisted iot networks,” in *IEEE International Conference on Communications (ICC) Workshops*, 2019, pp. 1–6.

[19] E. Eldeeb, J. M. de Souza Sant’Ana, D. E. Pérez, M. Shehab, N. H. Mahmood, and H. Alves, “Multi-uav path learning for age and power optimization in iot with uav battery recharge,” *IEEE Transactions on Vehicular Technology*, 2022.

[20] Y. Liao and V. Friderikos, “Energy and age pareto optimal trajectories in uav-assisted wireless data collection,” *IEEE Transactions on Vehicular Technology*, vol. 71, no. 8, pp. 9101–9106, 2022.