NOMA-Aided UAV Data Collection from Time-Constrained IoT Devices

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***Abstract*—Non-orthogonal multiple access (NOMA) is one of the promising access technologies to improve spectral efficiency and serve a higher number of users simultaneously. The latter proves important in time-sensitive services when data has to be collected before a set deadline, otherwise, the data is rendered useless. Therefore, in this paper, we utilize a NOMA-aided unmanned aerial vehicle (UAV) for data collection from time-constrained IoT devices. We optimize the trajectory of the UAV, IoT devices scheduling, and power allocation to maximize the number of served devices while considering the constraints of UAV energy and flight duration, and NOMA clustering. Given the complexity of the problem and the incomplete knowledge about the environment, it is divided into two subproblems. In the first subproblem, the UAV trajectory and the selection of the first device in the NOMA cluster at each time slot are modeled as a Markov Decision Process, and Proximal Policy Optimization is used to solve it. For the second device selection, a heuristic algorithm is used based on prioritizing devices with higher bit rate requirements and strict deadlines. The second subproblem considers power allocation inside the NOMA cluster, where it is formulated as an optimization problem for maximizing the sum rates of the two selected users. Finally, we demonstrate the performance gains of our solution in different scenarios while varying the system parameters as compared with alternative approaches. In particular, our proposed solution achieves a 10% to 30% performance gain compared to the traditional orthogonal multiple access scheme.**

***Index Terms*—Non-orthogonal multiple access (NOMA), Deep reinforcement learning (DRL), Internet of Things (IoT), Unmanned Aerial Vehicle (UAV).**

I. Introduction

With the current deployment of the fifth generation (5G) network, the focus of the research is shifting toward the six generation (6G) network that is expected to enable different use cases and applications that support a massive number of internet of things (IoT) devices. These devices are utilized for various applications in smart cities, remote areas, agriculture, and infrastructure. However, in practice, IoT devices are constrained by the data deadline, data reliability and their maximum transmit power. Therefore, energy- and time-efficient data collection is required to guarantee the different constraints of the IoT devices; otherwise, the data collected may lose its value. To this end, UAVs are being employed in the literature, for timely data collection from IoT devices, due to their flexibility, low cost, ease of deployment, and high mobility [1]. UAVs are also utilized as an energy-efficient data collection mechanism in wireless sensor networks. In [2], Zhan *et al.* jointly optimized the wake-up schedule of the sensor nodes and the trajectory of the UAV to minimize energy consumption. Similarly, the authors in [3] aim to minimize the maximum energy consumption of a rotary-wing UAV collecting data from a set of IoT devices, given the energy budget of the UAV and the size of data to be collected. UAVs can also provide connectivity in areas with disrupted communications due to disastrous events or absence of infrastructure [4]. All these use-cases highlight the role of UAVs in the next-generation mobile communication network.

Despite the benefits of using UAVs in IoT systems, UAV communication is limited by the mobility, flight time, and available energy of the UAV. Therefore, improving the radio access technology in UAV-based future networks can help address these limitations. Recently, non-orthogonal multiple access (NOMA) emerged as a promising technology for wireless communication and IoTs applications with limited resources. With NOMA, a large number of users (or devices) can be supported using the same available resources. In Uplink NOMA superposition coding (SC) is performed at the transmitter side, where multiple IoT devices transmit using the same resources simultaneously. The transmit power of the devices and the channel gain difference are used to differentiate between the signals of these devices. Then, at the receiver side (UAV or base station), successive interference cancellation (SIC) is performed to detect and decode the signals from the different IoT devices. Therefore, the benefits of uplink NOMA combined with the benefits of UAVs can provide flexibility, efficiency, and support a large number of IoT devices while managing the challenges caused by the limited UAV resources and the IoT devices' constraints.

A. Related Literature

Recent literature addressed different scenarios where NOMA and UAVs are used for IoT applications. The authors in [5] consider UAV-assisted data collection with NOMA, where the location of the UAV, the grouping of the sensors, and the power control are jointly optimized to maximize the rate of a wireless sensor network. Similarly, in [6], the authors consider a UAV collecting messages transmitted by ground sensors. They aim to maximize the sum rate of the users by optimizing the UAV deployment position and the power control given the transmission power constraints and the quality of service constraints. In [7], the authors consider UAVs collecting data from IoT nodes while NOMA is invoked in uplink transmission. They aim at maximizing the system capacity by jointly optimizing the subchannel assignment, the uplink transmit power of the IoT nodes, and the height of the UAVs. Moreover, the authors in [8] consider integrating NOMA into UAV communication system

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to collect data from large scale IoT devices within the UAV flight time. They aim at minimizing the total energy consumption of the IoT devices by optimizing the trajectory of the UAV, the transmit power, and the scheduling of the IoT devices. The work in [9] maximized the minimum throughput from the ground nodes for both NOMA and OMA transmission, subject to the energy budget of the ground nodes and the UAV. Their simulations propose that NOMA have higher performance gain than OMA when the ground nodes have enough energy budget. Accordingly, in this paper, we consider a UAV dispatched to collect data, using Uplink NOMA, from IoT devices placed in a remote area. The IoT devices are constrained by their release time and deadline; hence, the data should be fully collected within this window; otherwise, the devices are not considered served. The UAV is also limited by the available energy and the flight duration. Therefore, we aim to maximize the number of served IoT devices by optimizing the UAV trajectory, the selection of IoT devices in the NOMA cluster and their transmit power.

B. Our Contributions

Existing work on UAV data collection with uplink NOMA transmissions considers different scenarios where a UAV (mobile or stationary) is used to collect data from IoT devices. However, using NOMA with energy constrained UAV and time constrained IoT devices remains uncovered in the literature. Thus, this paper aims at bridging this gap through the following contributions:

- We consider a new scenario where a UAV is deployed to collect data using uplink NOMA from time-constrained IoT devices in a remote area. We aim at maximizing the number of served devices by optimizing the UAV trajectory, the IoT devices selection as part of a NOMA cluster and their power allocation, given the available UAV energy, NOMA SIC constraint, IoT devices release time, deadline, target data required and maximum transmit power. In NOMA, having effective SIC is based on the channel gain difference between the IoT devices, however, the channel gain varies due to the UAV mobility which makes the problem more difficult to solve.
- We use deep reinforcement learning to determine the trajectory of the UAV and select the first IoT device in a NOMA cluster at each time slot. Then, we develop a heuristic algorithm to select the second device in the NOMA cluster based on prioritizing devices with higher bit rate requirements to upload their data before it expires. As for power allocation, we optimize the transmit power of the selected IoT devices to maximize their sum rate.
- We present different simulations of our solution while varying the system parameters and we compare with alternative baseline approaches.

II. System Model and Problem Formulation

As shown in Fig. 1, we consider a NOMA-assisted UAV data collection for time constrained IoT devices. A UAV is dispatched to collect data from $\mathcal{M} = \{1, ..., M\}$ IoT devices that are randomly distributed in a remote area, with $q_i = (x_i, y_i)$ representing the coordinates of IoT device i. Each IoT device i has a release time ρ_i and a deadline δ_i, with the randomness of the release time modeled using a uniform distribution. The UAV should collect the data before δ_i expires, otherwise the data loses its value [1]. We denote by P_i the transmit power of IoT device i. Moreover, we use the discrete state model where the time horizon T is divided into $\mathcal{N} = \{1, 2, ...N\}$ intervals of equal size δ_t. The UAV flies at a fixed altitude H above the ground; the position of the UAV is denoted by $q_u = (x_u, y_u)$ and $q_u[n]$ determines the UAV position in the n^{th} time slot. The distance between the UAV and IoT device i at time n is:

$$d_i^u[n] = \sqrt{(x_u[n]-x_i)^2 + (y_u[n]-y_i)^2 + H^2} \quad \forall n \in N \tag{1}$$

Moreover, the UAV has a maximum flight speed V_{max}, so the change in position of the UAV during one time slot is constrained by:

$$||q_u[n] - q_u[n-1]||^2 \leq (V_{max}\delta_t)^2 \tag{2}$$

The UAV flies at a height that allows a clear line of sight with the IoT devices [7]. Following the free space model, the channel gain at IoT device i at time slot n is:

$$h_i[n] = \frac{\beta_0}{d_i^u[n]^2} \tag{3}$$

where β_0 is the channel gain at reference distance $d_0 = 1$ m.

In Fig. 1, two users are paired at each time slot and they utilize uplink NOMA to transmit, using the same channel, to the UAV. Moreover, due to the time varying position of the UAV, the channel gain of the users vary from one time slot to another. At the receiver side (i.e. UAV side), successive interference cancellation (SIC) is done according to the descending order of the channel gain at the receiver. Therefore, a binary variable $\alpha_{ij}[n]$ is used to determine the SIC decoding order. $\alpha_{ij}[n]$ is set to 1 if the channel gain of the i^{th} user at time slot n is greater than that of the j^{th} user and it can be expressed as:

$$\alpha_{ij}[n] = \begin{cases} 0, & \text{if } d_i^u \geq d_j^u. \\ 1, & \text{if } d_i^u[n] < d_j^u[n]. \quad \forall n \in N, \forall i,j \in \mathcal{M}, i \neq j \end{cases} \tag{4}$$

Equation (4) can be rewritten as:

$$\alpha_{ij}[n] \in \{0, 1\}, \tag{5}$$

$$\alpha_{ii}[n] = 0, \tag{6}$$

$$\alpha_{ij}[n] + \alpha_{ji}[n] = 1, \tag{7}$$

$$\alpha_{ij}[n](||q_u[n] - q_i||^2 + H^2) \leq (||q_u[n] - q_j||^2 + H^2), \tag{8}$$

where Constraint (5) sets $\alpha_{ij}[n]$ to binary. Constraint (6) ensures that the signal of device i is not considered interference when decoding the user message. (7) ensures that for any two users, one user only is considered a strong user at any time instant when its channel gain is higher than the second user.

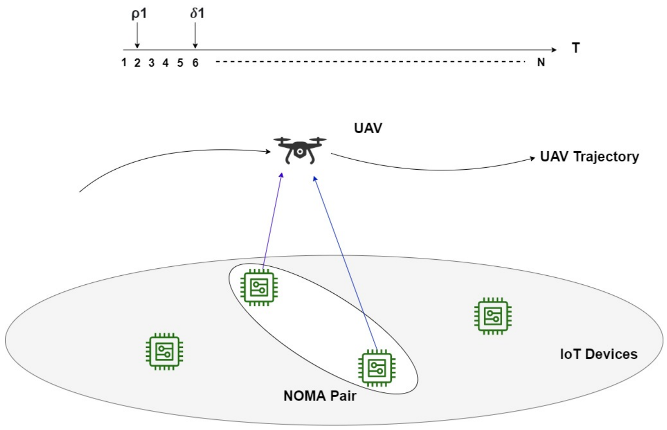

Fig. 1: A NOMA pair (2 IoT-devices) transmit to the UAV using the same resources at the same time slot.

(8) guarantees that $\alpha_{ij}[n]$ is set to 0 if $d_i^u[n] > d_j^u[n]$ and 1 otherwise. Moreover, a binary variable Γ_{ij}^n is introduced to determine if IoT devices i and j are scheduled at time slot n. At each time slot n, we pair one user with a high channel gain with another user with a weak channel gain, so Constraint (9) is added to ensure a maximum of two users scheduled at the same time slot as follows:

$$\sum_{i,j\in\mathcal{M},i\neq j} \Gamma_{ij}^n \leq 1 \quad \forall n \in N \tag{9}$$

Accordingly, the data rate of user i scheduled at time slot n in bps/Hz is given by

$$R_i[n] = log_2\left(1 + \frac{P_i[n]\lambda_i[n]}{\sum_{j=1}^{M}\alpha_{ij}[n]\Gamma_{ij}^n\lambda_j[n]P_j[n]+1}\right) \tag{10}$$

where $\lambda_i[n] = (h_i[n]/N_0)$ is the normalized channel gain, N_0 is the noise power and $\sum_{j=1}^{M}\alpha_{ij}[n]\Gamma_{ij}^n h_j[n]P_j[n]$ is the interference from the IoT device with a weaker channel gain that is scheduled at the same time slot n.

Moreover, to ensure effective SIC at the UAV the following power constraint should be satisfied:

$$\Gamma_{ij}^n\left(\frac{P_i[n]\lambda_i[n]}{\alpha_{ij}[n]P_j[n]\lambda_j[n]}\right) \geq \eta\Gamma_{ij}^n \quad \forall i,j\in\mathcal{M}, \forall n \in N \tag{11}$$

where η is the minimum power difference required to distinguish between the different users [5].

The service amount S_i in bits/Hz of an IoT device i over the flight trajectory of the UAV is expressed as

$$S_i = \delta_t \sum_{n=1}^{N} s_i^n \quad \forall i \in \mathcal{M} \tag{12}$$

where:

$$s_i^n = \begin{cases} R_i[n] & \text{if } \rho_i \leq n \leq \delta_i. \\ 0, & \text{otherwise.} \quad \forall n\in N, \forall s \in \mathcal{S} \end{cases} \tag{13}$$

We also introduce a binary variable κ_i that indicates if IoT device i was served during the flight time of the UAV. Therefore, the following constraints should be satisfied for κ_i:

$$\kappa_i > \frac{S_i - S_i^{min}}{S_g}, \forall i \in \mathcal{M} \tag{14}$$

$$\kappa_i \leq 1 + \frac{S_i - S_i^{min}}{S_g}, \forall i \in \mathcal{M} \tag{15}$$

where S_i^{min} is the minimum amount of data that needs to be uploaded by IoT device i (bits/Hz), and S_g is a large constant to ensure the validity of the equations.

Following [3], the power consumed by a rotary wing UAV at time slot n and speed $v_u[n]$ is expressed as:

$$P(v_u[n]) = c_1\left(1 + \frac{3||v_u[n]||^2}{W_{tip}^2}\right) + P_{hv}\left(\sqrt{1+\frac{||v[n]^4||}{4v_0^4}} - \frac{||v[n]^2||}{2v_0^2}\right)^{\frac{1}{2}} + \frac{1}{2}d_0 As\zeta||v[n]||^3, \tag{16}$$

where $v_u[n]$ is the speed of the UAV at time slot n. c_1 represents the blade profile power and P_{hv} is the induced power while UAV is hovering. W_{tip} is the rotator blade tip speed, d_0 is the fuselage drag ratio, v_0 is the mean rotor-induced velocity in hover, A is rotor disc area, ζ is the air density, and s is the rotor solidity. Therefore, the total energy consumed during the UAV flight can be estimated as follows:

$$E_{trj} = \sum_{n=1}^{N} \delta_t P(v_u[n]) \tag{17}$$

Accordingly, we formulate the problem as maximizing the number of served IoT devices by optimizing the trajectory of the UAV, the pairing of the IoT devices, scheduling of the IoT devices, and the power allocation. The NOMA-aided UAV data collection problem $\mathcal{P}$ can then be formulated as:

$$\mathcal{P}: \quad \max_{q_u[n],\Gamma_{ij}^n,P_i[n]} \quad \sum_{i\in\mathcal{M}} \kappa_i \tag{18a}$$

$$\text{subject to } E_{trj} \leq E_{max} \tag{18b}$$

$$\sum_{i,j\in\mathcal{M},i\neq j} \Gamma_{ij}^n \leq 1 \quad \forall n \in N \tag{18c}$$

$$(2),(5),(6),(7),(8),(11),(14),(15) \tag{18d}$$

$$\kappa_i, \Gamma_{ij}^n \in \{0,1\}, \forall i \ \forall n \tag{18e}$$

where (18a) is the objective function that aims at maximizing the number of served IoT-devices. Constraint (18b) guarantees that the energy consumed by the UAV is less than its available energy E_{max}. (18c) ensures that at each time slot there is a pairing of two different users. (18e) sets the variables to binary. Note that the formulated problem ($\mathcal{P}$) is a mixed integer non-convex problem due to the constraints (11), (14), (15), and (18b). Hence, it is hard to be solved optimally and we resort to DRL to determine the solution.

III. Proposed Solution

Given the complexity of $\mathcal{P}$, we divide it into two subproblems: 1) UAV trajectory and IoT devices scheduling subproblem, and 2) power allocation subproblem.

A. UAV Trajectory and IoT Devices Scheduling Subproblem

We formulate the first subproblem as a Markov Decision Process (MDP) denoted by a tuple $\langle \mathcal{S}, \mathcal{A}, \gamma, \mathcal{R}, \mathcal{T} \rangle$ where :

- $\mathcal{S}$ is the state space where s_n is the state of the agent at time slot n. The state is a vector that includes the current position of the UAV q_u, the position of the IoT devices q_i, the deadline γ_i of the IoT devices, the amount of consumed energy, the total available energy of the UAV E_{max}, and the percentage of service for each IoT device $(\frac{S_i}{S_i^{min}} * 100)$.
- $\mathcal{A}$ is the action space, and $a_n \in \mathcal{A}$ is the action taken by the agent at time slot n. In our problem, the action is the trajectory of the UAV where the UAV can move forward, backward, to the left, to the right, or hover in its current position. The agent also selects the first IoT device in the pair to be served at each time slot, and the speed of the UAV where we discretize the speed into different values.
- γ is the discount factor $(0 \leq \gamma \leq 1)$.
- $\mathcal{R}$ is the discounted reward function where the agent receives a step reward of 1 whenever a device is served. $\mathcal{R}$ is defined as $\mathcal{R} = \sum_{n=1}^{N} \gamma^{n-1} r^n$, where r^n is the step reward at time slot n.
- $\mathcal{T}$ is the state transition probabilities. It denotes the probability of the agent taking an action a in a state s and moving to a state s', $Pr(s_{n+1} = s' \mid s_n = s, a_n = a)$.

For DRL, we use proximal policy optimization (PPO) to develop our agent and learn the UAV trajectory and the scheduling of the first IoT device. In PPO, the agent first initializes random sampling policy π and value function. Then for each iteration, the agent observes the state at each time slot n and selects an action a_n. Next, we move the UAV if there is enough available energy and if it stays inside the area of interest. Based on the agent action, a list of devices with low channel gain is formed and the one with the most urgent data is selected. The latter criterion is based on the remaining data required by the device $(S^i_{min} - S_i)$ divided by the remaining time in which the device is active $(\delta_i - \text{current time step } t)$. After the selection of the two devices, power allocation is performed as presented in the second subproblem. The reward is calculated at the end of each time slot. If the service amount of a selected device exceeds the minimum amount of data, a positive reward of 1 is given. Finally, PPO computes the estimated advantage function and optimizes the surrogate loss function (via Adam optimizer).

B. Power Allocation Subproblem

Let R_s and R_w be the data rates of the strong/near user and the week/far user, respectively. Given the current position of the UAV and the two selected IoT devices at each time slot (from the previous subproblem), this subproblem determines the channel gain at the current time slot and performs power allocation to maximize the sum rates of the two users and achieve the most gain, given the maximum transmit power constraints for the IoT devices and the effective SIC constraint. Therefore, we formulate the problem as follows:

$$\begin{aligned} \max_{P_s, P_w} \quad & R_s + R_w \\ \text{subject to} \quad & P_s\lambda_s/(P_w\lambda_w) \geq \eta \\ & P_s \leq P_{max} \\ & P_w \leq P_{max} \end{aligned} \tag{19}$$

Equation (19) can be rewritten as:

$$\begin{aligned} R_s + R_w &= log_2\left(1 + \frac{P_s\lambda_s}{P_w\lambda_w + 1}\right) + log_2(1 + P_w\lambda_w) \\ &= log_2(P_w\lambda_w + 1 + P_s\lambda_s) - log_2(P_w\lambda_w + 1) \\ &\quad + log_2(1 + P_w\lambda_w) \\ &= log_2(P_w\lambda_w + P_s\lambda_s + 1) \end{aligned} \tag{20}$$

Maximizing (20) is equivalent to maximizing the sum of the powers of the strong user and the weak user. Therefore, we can rewrite (19) as follows:

$$\begin{aligned} \max_{P_s, P_w} \quad & P_s + P_w \\ \text{subject to} \quad & P_s\lambda_s \geq \eta P_w\lambda_w \\ & P_s \leq P_{total} \\ & P_w \leq P_{total} \end{aligned} \tag{21}$$

The obtained problem (21) is a linear problem, so we use Python *revised simplex* method to solve this problem.

IV. PERFORMANCE RESULTS AND ANALYSIS

In this section, we study the performance of our solution approach under various circumstances and compare it with 4 baseline methods. In our simulations, we consider 15 IoT devices that are randomly distributed. The total number of time slots is 90 with each time slot set to 1. For the UAV, it flies at a fixed altitude of 100 meters with a maximum speed of 50 m/s. Since the agent selects the speed of the UAV, the values are discretized to [0, 30, 50] m/s. Further, the parameters used for the energy consumption model of the UAV are similar to [9]. For the wireless channel, we set $\beta_0 = -50$ dB, $N_0 = -110$ dBm/hz, and $\eta = 5$ dB. For the DRL, we use 3 layers with the activation functions *Tanh* and *Softmax*. The number of variables in the hidden layer is 64 and *Adam* optimizer is used to minimize the loss function. The learning rate is set to 0.002, $\gamma = 0.99$, and the clip parameter is 0.2. The remaining parameters are presented in each subsection of the results. Moreover, all the simulation results are generated using Python and PyTorch and they are averaged over 100 data samples to ensure consistency.

For the training of the DRL agent, we consider a geographical area of size 1.5 × 1.5 km^2 where the IoT devices are randomly distributed. The available energy of the UAV is set to 20 Kilo-joules (kJ), and the minimum amount of data required by the IoT devices is 10 bits/Hz. The initial location of the UAV is set to the center of the considered area.

As shown in Fig. 2. the cumulative reward (number of served IoT devices) increases with the increase of the number of iterations and it starts to converge before reaching 1000

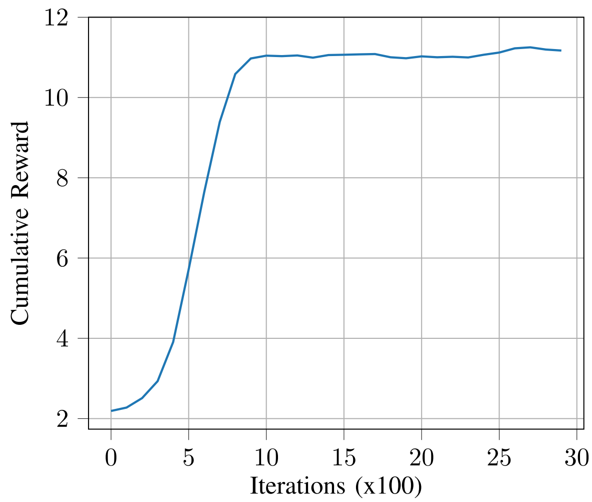

Fig. 2: DRL Convergence.

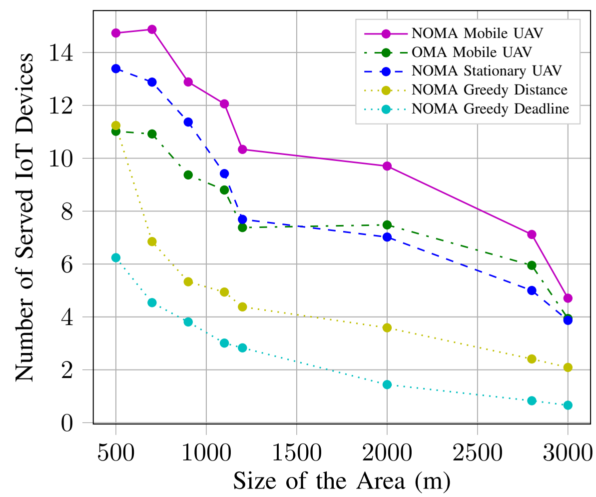

Fig. 3: Effect of the Area Size.

iterations. At the beginning of the learning, the agent wastes resources by moving the UAV randomly and depleting the available energy, while the IoT devices are not properly scheduled. With training, the number of served devices increases (reward increases), which indicates that the agent starts adapting to the randomness in the release time of the IoT devices and learns how to move the UAV given the deadline constraints of the IoT devices, the effective SIC constraints, and the UAV available energy.

To validate the performance of our proposed solution, we develop four methods to compare with:

- *Orthogonal Multiple Access (OMA)*: we use DRL with time division multiple access to determine the trajectory of the UAV and the selection of one IoT device only.
- *NOMA Stationary UAV*: The UAV is placed at the center of the area, and DRL is used to select the devices in the NOMA cluster at each time slot.
- *NOMA Greedy Distance*: The UAV moves to and selects the closest IoT device in each time slot.
- *NOMA Greedy Deadline*: The UAV moves to and selects the devices with the shortest deadline in each time slot.

A. *Effect of the Area Size*

In Fig. 3, the UAV available energy is 30 kJ, the maximum transmit power of the IoT devices is 1 mW, and the minimum amount of required data S_i^{min} = 10 bits/Hz for all the devices. We compare the number of served IoT devices using each approach while varying the size of the considered area. Accordingly, the increase in the size of the area leads to a decrease in the number of served devices for all the approaches. However, our proposed solution (NOMA with mobile UAV) provides better performance compared to the other approaches for all the considered test cases. Compared to NOMA with stationary UAV, our method yields an increase in performance by 1 to 2 served devices. The gain compared to OMA is clear, where an increase in 2 to 3 served devices is present. Moreover, the advantages of using DRL for UAV trajectory and selection of IoT devices are present compared to the greedy approaches, where our algorithm serves 6 to 7 more devices compared to the greedy distance and greedy deadline when the size of the area is between 500 $\times$ 500 m^2 and 2×2 km^2. This is mainly because greedy methods waste the UAV available energy and have a bad scheduling of the IoT devices. However, the greedy approach based on the distance performs better than the one based on the deadline, because the selection of the IoT devices that are closer to the UAV results in higher data rates. Further, with a small area size ($< 1.5 \times 1.5$ km^2), the performance of stationary UAV with NOMA is better than that of mobile UAV with OMA; however, with the increase in the size of the area, OMA becomes better due to the mobility of the UAV. For the very large areas the difference in performance becomes negligible for all the methods due to the lack of available resources (UAV energy) and the deadline constraints of the IoT devices.

B. *Effect of Available Energy of the UAV*

In Fig.4, the IoT devices are distributed in an area of size 1000 $\times$ 1000 m^2 with their maximum transmit power set to 1 mW and S_i^{min} set to 15 bits/Hz. We examine the effect of the UAV available energy on the performance (number of served devices) of each algorithm. In general, the increase in the UAV available energy yields better gain for all the approaches used, because the UAV has more resources to serve more devices. First, we notice that with low available energy, the performance of OMA is slightly better than NOMA, mainly because with OMA only 1 device is being served, so no interference is present and the data rate of the selected IoT device is high, thus less time is required to serve this device. However, with enough energy ($E_{max} \geq 8$ kJ) the performance of NOMA with stationary UAV or mobile UAV outperforms that of OMA, where mobile UAV with NOMA achieves a gain of 2 to 3 served devices compared to OMA. We also observe that our method achieves higher performance gain compared to the greedy methods (6 to 7 more devices are served using our proposed algorithm when $E_{max} = 25$ kJ) because the greedy approaches are somehow unaware of the objective of maximizing the total number

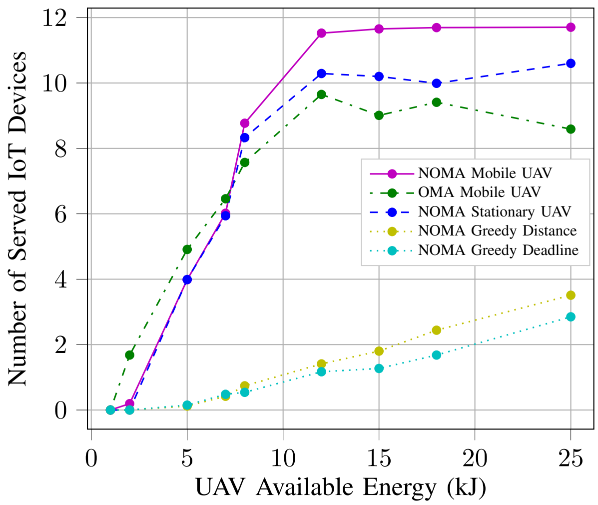

Fig. 4: Effect of UAV Available Energy.

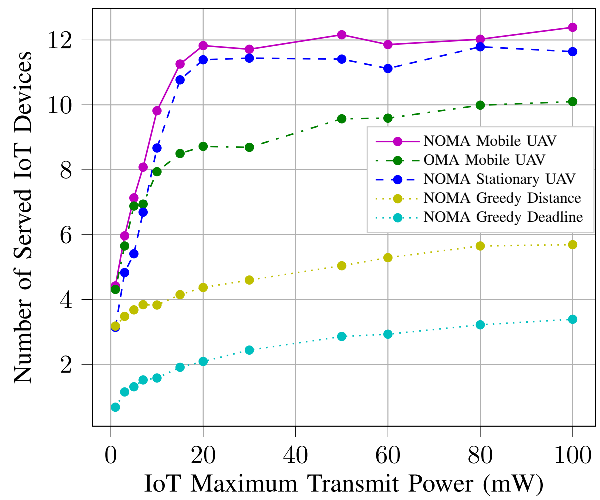

Fig. 5: Effect of IoT Devices Maximum Transmit Power.

of served devices. Further, Fig. 4 shows that the distance-based greedy method achieves better performance than the deadline-based greedy method because in the deadline-based method the UAV wastes more time and energy to fly to the IoT devices with strict deadlines.

C. Effect of the Maximum Transmit Power of the IoT Devices

In Fig. 5, we consider an $1.8 \times 1.8\ km^2$ area with UAV available energy set to 30 kJ and the minimum amount of required data for the IoT devices $S_i^{min} = 30$ bits/Hz. First, we observe that increasing the maximum transmit power of the IoT devices helps in improving the performance of all the approaches because more resources are available to the IoT devices. Moreover, we notice that the performance difference between NOMA stationary UAV and NOMA mobile UAV is similar; however, compared to time division multiple access, NOMA has a gain of 2 to 3 served devices with enough transmit power. Furthermore, using NOMA with DRL for UAV trajectory yields a $3\times$ performance gain compared to the trajectory based on distance (NOMA Greedy Distance) and a $6\times$ gain compared to the one based on the deadline of IoT devices (NOMA Greedy Deadline). Our proposed algorithm achieves 20% to 30% gain (with enough transmit power) compared to OMA. Moreover, using DRL to determine the UAV trajectory and selection of the first IoT device leads to a significant improvement compared to the greedy heuristics.

V. Conclusion

This paper studied uplink NOMA for UAV data collection from time-constrained IoT devices. The problem is formulated as an optimization problem for maximizing the number of served devices, but due to its complexity, we used DRL to determine the trajectory of the UAV and the selection of the first IoT devices in the NOMA cluster. The second IoT device is selected based on prioritizing devices with higher bit rate requirements to upload their data before it expires. Power allocation is then optimized to maximize the sum rate of the selected IoT devices. Simulation results show the advantages of our proposed method against four alternative methods. Mainly, NOMA achieves an improvement of $10\% - 30\%$ more served devices compared to OMA. Future works can investigate using multiple UAVs and planing their trajectories to avoid collisions and maximize the number of served IoT devices. Further, future work can also consider pairing more than 2 devices in one NOMA cluster.

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