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IoT for Effective bandwidth allocation in Unmanned Aerial Vehicles (UAVs)

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Abstract-
Unmanned aerial vehicle (UAV) relaying is one of the main technologies for UAV communications. It uses UAVs as relays in the sky to provide reliable wireless connection between remote users. In fact, UAVs can easily fly and reach inspection points, record surveillance data, and send this information to a wireless base station (BS). Nonetheless, in many cases, such as operations at remote areas, the UAVs cannot be guided directly by the BS in real-time to find their path. Moreover, another key challenge of inspection by UAVs is the limited battery capacity. This paper aims to investigate relay-assisted Internet of Things (IoT) communication networks in which a UAV has been used as an aerial base station (BS) to collect time-constrained information from IoT gadgets and transmit it to a ground gateway (GW). In this context, we optimize the allocated bandwidth, transmission strength, and UAV trajectory at the same time to maximize overall device throughput while satisfying the user's latency requirement and the UAV's limited garage capability. Because the problem is highly non-convex, it may be difficult to solve optimally. To arrive at an appealing answer, we first add new variables to the equation. Numerical results are given to show significant performance improvement over benchmark schemes.

Keywords- *Internet of Things, unmanned aerial vehicle (UAV), bandwidth allocation*

I. Introduction

Unmanned aerial vehicle (UAV) communication has emerged as a prominent technology for emergency communications (e.g., natural disaster) in the Internet of Things (IoT) networks to enhance the ability of disaster prediction, damage assessment, and rescue operations promptly. A UAV can be deployed as a flying base station (BS) to collect data from time- constrained IoT devices and then transfer it to a ground gateway (GW). In general, the latency constraint at IoT devices and UAV's limited storage capacity highly hinder practical applications of UAV-assisted IoT networks.
Nowadays, IoT has won widespread penetration in lots of regions such as e-health, clever city, agriculture, and clever grid [1], [2]. The quantity of IoT devices is expected up to one hundred billions via 2025 [3]. Nevertheless, as the restriction of available resources for wi-fi communiqué systems, the layout of green IoT communications is becoming a daunting mission. More mainly, considering base stations (BSs) are typically set up in everlasting locations with fixed antenna top as nicely as their sparse distribution which

leads to a degraded overall performance in the case of excessive fading or overloaded scenarios. It is infeasible to resolve those issues through actually increasing the wide variety of BSs due to high set up and preservation expenses [4]. Therefore, conventional structures rarely fulfill the necessities of IoT networks. Moreover, in emergency instances such that BSs are destroyed/isolated after a catastrophe, they may be not able to function usually. Fortunately, UAV communications should turn out to be a promising generation to conquer the above drawbacks thanks to their mobility, agility, and bendy deployment [5]. More in particular, the UAV can fly toward the IoT gadgets which notably complements the network overall performance and decreases the overall electricity intake of IoT customers. The well timed data collection or facts freshness in UAV- assisted IoT verbal exchange networks has attracted recall- able interest recently [6]–[9]. In emergency eventualities, out- dated information may also reason untrustworthy controllable decisions, which may be catastrophic [9]. For instance, in latency-important IoT applications such as factory automation, clever grids, and clever delivery structures [10]. Since the IoT gadgets commonly have limited cache size, their records needs to be collected in time before it turns into obsolete or is overwritten by the new records. The authors in [6] proposed UAV trajectory design algorithms, namely, the Max-AoI-choicest and Ave-AoI- optimal for effective data collection while thinking about the age. The transfer of information and energy using UAVs can be illustrated in fig. 1

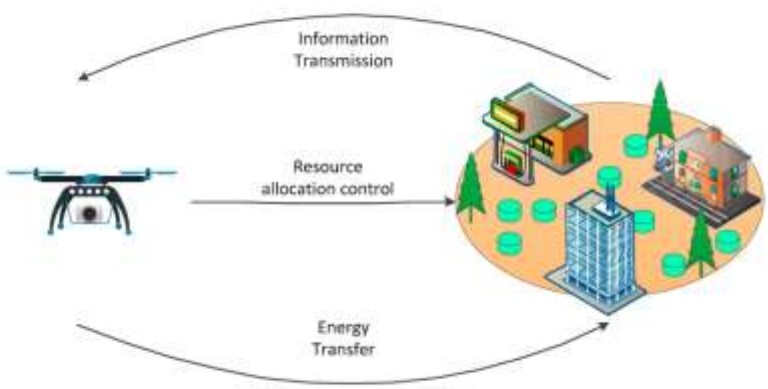

Fig. 1 Resource transfer in UAVs

In [7], the authors formulated an optimization hassle to collectively optimize the UAV's trajectory, electricity, and service time allocations to limit the common Peak Age-of-statistics (PAoI) for a source-destination link. In [9], both the UAV trajectory and the service bandwidth allocation are optimized to maximize the overall quantity of served ground IoT customers, whereas the UAV is needed to collect the gadgets' statistics inside their delay requirements.

Unlike the research [6]–[9], [11], [12], which focused solely on the UL or DL channel and did not use HD communication in their system? This is because the RT restriction should be viewed as the latency from edge users (or GW) to GW (or GW), with the GW connecting to the core network via stable connections, such as Ethernet cable. If the latency between the UAV and the GW is very minimal, it can be ignored.

II. An Empirical Design Survey

Ma et., al. (2021) resource allocation problem for a two-hop uplink UAV-LEO integrated data collection for the B5G IoRT networks, where numerous UAVs gather data from IoT devices and transmit the IoT data to LEO satellites. In order to maximize the data gathering efficiency in the IoT-UAV data gathering process, we study the bandwidth allocation of IoT devices and the 3-dimensional (3D) trajectory design of UAVs.relay role and the cache capacity limitations of UAVs, we merge the optimizations of IoT-UAV data gathering and UAV-LEO data transmission into an integrated optimization problem, which is solved with the aid of the successive convex approximation (SCA) and the block coordinate descent (BCD) techniques.

IoT-UAV data gathering process	Bandwidth allocation of iot devices and the 3-dimensional (3D) trajectory design of uavs.relay role and the cache capacity limitations of uavs,	Optimizations of iot-UAV data gathering and UAV-LEO data transmission into an integrated optimization problem	The successive convex approximation (SCA) and the block coordinate descent (BCD) techniques.

(Dinh-Hieu Tran et., al 2021) optimize the allocated bandwidth, transmission power, as well as the UAV trajectory to maximize the total system throughput while satisfying the user's latency requirement and the UAV's limited storage capacity for UAV Relay-Assisted IoT Communication Networks. auther adopted non-convex method to solve mentioned issues optimally, introduce new variables to convert the original problem into a computationally tractable form, and then develop an iterative algorithm for its solution by leveraging the inner approximation method.

UAV Relay-Assisted iot Communica tion Networks	Optimize the allocated bandwidth, transmission power, as well as the UAV trajectory to maximize the total system throughput while satisfying the user's latency requirement and the UAV's limited storage capacity	Non-convex method to solve mentioned issues optimally	Variables to convert the original problem into a computationally tractable form, and then develop an iterative algorithm for its solution by leveraging the inner approximation method.

(Tran et., al. 2020) half-duplex (HD) scheme for UAV-based relaying is also considered to provide a comparative study between two modes (viz., FD and HD). In this context, we aim to maximize the number of served IoT devices by jointly optimizing bandwidth, power allocation, and the UAV trajectory while satisfying each device's requirement and the UAV's limited storage capacity. By leveraging inner approximation framework, we derive newly approximated functions for non-convex parts and then develop a simple yet efficient iterative algorithm for its solutions. Next, we attempt to maximize the total throughput subject to the number of served IoT devices. Finally, numerical results show that the proposed algorithms significantly outperform benchmark approaches in terms of the number of served IoT devices and system throughput.

To maximize the number of served iot devices by jointly optimizing bandwidth, power allocation, and the UAV trajectory while satisfying each device's requirement and the UAV's limited storage capacity	On-convexity and combinatorial nature	Non-convex parts and then develop a simple yet efficient iterative algorithm	Maximize the total throughput subject to the number of served IoT devices

chen et., al. (2021)strict requirements of latency and reliability for URLLC with a fixed infrastructure is challenging, and unmanned aerial vehicles (UAVs) have been deemed as promising enablers to handle this issue due to its salient attributes, such as high maneuverability, flexible deployment, and high probability of line-of-sight links. a novel UAV-assisted URLLC service system, where the blocklength of channel codes is finite in Internet-of-Things (IoT) networks. Considering the limited energy of IoT devices, the average uplink transmit power of the IoT devices are minimized by jointly optimizing the device scheduling and association, power control and resource allocation, as well as UAV deployment. mixed-integer nonconvex optimization problem because of the finite blocklength regime. To tackle the problem, we derive the approximation of the achievable rate and propose an effective iteration algorithm by applying the block coordinate descent (BCD) and Lagrange dual decomposition techniques. The average bandwidth allocation scheme, our proposed algorithm can get a stable minimum as the total bandwidth increases.

UAV-assisted URLLC service system, where the blocklength of channel codes is finite in Internet-of-Things (IoT) networks	Limited energy of IoT devices, the average uplink transmit power of the IoT devices are minimized by jointly optimizing the device scheduling and association, power control and resource allocation, as well as UAV deployment.	mixed-integer no convex optimization problem because of the finite blocklength regime	Approximation of the achievable rate and propose an effective iteration algorithm by applying the block coordinate descent (BCD) and Lagrange dual decomposition techniques. average bandwidth allocation scheme

III. System Modeling for Identification of Problem

We consider a wireless communication system where a UAV acts as a relay to receive data from a set K , {1, . . . , K} of K IoT devices and then forward to a ground gateway (GW). Each IoT device is equipped with a single antenna and operates in the HD mode. The UAV is capable of adopting either FD or HD mode.

The total flying time of UAV is limited by T. Each device is active at different time instances t, where $0 \le t \le T$. The device k's location are represented by $r_k \in R^{2\times1}$, $k \in K$. We assume that the IoT locations, data sizes, the starting data transmission time (i.e., $n_{start,k}$), and deadline time (i.e., $n_{end,k}$) are known to the UAV through the control center.

It is assumed that the UAV must collect device k's data during period $n_{start,k} \le t \le n_{end,k}$. For simplicity, the UAV flies at fixed altitude H (meters), which is the minimum altitude to avoid obstacles [5].

Denote by $q(t) \in R^{2\times1}$ with $0 \le t \le T$ the UAV trajectory projected onto the horizontal plane. For tractability, T is divided into N equally slots, i.e., $T = N\delta t$ with δt denotes the duration of each time slot. Thus, q(t) can be represented as $(q[n])_{n=1}^{N}$, where q[n] is the UAV's horizontal location at n-th time slot.

Let V_{max} denote the maximum flying speed of the UAV. We then have the UAV's speed constraint $\|q[n] - q[n-1]\| \le \delta d = V_{max}\delta t$, n = 2, ..., N. Moreover, N = {1, . . . , N} denotes the set of all time slots.

Let k and U represent for the k-th IoT device and the UAV, respectively. Henceforth, 1k and 2k denote the channel k → U and U → GW to convey the data of user k, respectively. Then, the distance from q k → U or U → GW is $d_{ik}[n] = \sqrt{H^2 + \|q[n] - r\|^2}$, ∀n, k, where $i \in \{1, 2\}$, $r \in \{r_k, q_0\}$, with q_0 denotes the GW's location.

This work considers a practical channel model including both large-scale and small-scale fading [14].

Concretely, the channel coefficient at n-th time slot, $h_{ik}[n]$, is decomposed as [9]

$h_{ik}[n] = \sqrt{\omega_{ik}[n]}\tilde{h}_{ik}[n]$, (1) where $\omega_{ik}[n] = \omega_0 d_{ik}^{-\alpha}[n]$

represents for the large-scale fading effects, with ω_0 is the average channel power gain at the reference distance d = 1 meter, and α is the path loss exponent. $\tilde{h}_{ik}[n]$ accounts for the Rician small-scale fading coefficient in the form of $\tilde{h}_{ik}[n] = \sqrt{\frac{G}{1+G}}\bar{h}_{ik}[n] + \sqrt{\frac{1}{1+G}}\hat{h}_{ik}[n]$.

Here, G is the Rician factor; $\bar{h}_{ik}[n]$ and $\hat{h}_{ik}[n] \sim CN(0, 1)$ denote the LoS and NLoS components, respectively.

$$r_{1k}[n] = \begin{cases} r_{1k}^{\mathrm{FD}}[n] = a_{1k}[n]B \\ \log_2\left(1 + \dfrac{\frac{p_{1k}[n]|\bar{h}_{1k}[n]|^2\omega_0}{\left(H^2+\|q[n]-r_k\|^2\right)^{\alpha/2}}}{\phi^{\mathrm{RSI}} \sum\limits_{k^*\in\mathcal{K}\setminus k}^{K} p_{2k^*}[n] + \sigma^2}\right), \\ r_{1k}^{\mathrm{HD}}[n] = a_{1k}[n]B \\ \log_2\left(1 + \dfrac{p_{1k}[n]|\bar{h}_{1k}[n]|^2\omega_0}{\left(H^2+\|q[n]-r_k\|^2\right)^{\alpha/2}\sigma^2}\right) \end{cases}$$

$$r_{2k}[n] = a_{2k}[n]B \log_2\left(1 + \frac{p_{2k}[n]|\bar{h}_{2k}[n]|^2\omega_0}{\left(H^2+\|q[n]-q_0\|^2\right)^{\alpha/2}\sigma^2}\right),$$

$$\begin{aligned} \mathcal{P} : \max_{\mathbf{q},\mathbf{a},\mathbf{p},\boldsymbol{\lambda}} \quad & \sum_{k\in\mathcal{K}} \delta_t \min(R_{1k}, R_{2k}) \\ \text{s.t.} \quad & (8), (9), (10), \\ & \lambda_k \in \{0,1\}, \forall k, n, \\ & \delta_t \min(R_{1k}, R_{2k}) \geq \lambda_k S_k, \forall k, \\ & \sum_{k=1}^{K} \delta_t R_{2k} \geq \sum_{k=1}^{K} \lambda_k S_k, \forall k, \\ & \sum_{k\in\mathcal{K}} \lambda_k \geq \lambda_{\mathrm{thresh}}, \forall k \\ & \sum_{k\in\mathcal{K}} a_{ik}[n] \leq 1, \forall n \\ & 0 \leq a_{ik}[n] \leq 1, \forall k, n. \\ & q[1] = q_I, q[N] = q_F, \\ & \|q[n] - q[n-1]\| \leq \delta_d, n = 2, \ldots, N, \\ & 0 \leq p_{1k}[n] \leq P_k^{\max}[n], \forall k, n, \\ & 0 \leq \sum_{k=1}^{K} p_{2k}[n] \leq P_{\mathrm{U}}^{\max}[n], \forall n, \end{aligned}$$

Fig. 2 Mathematical Equations used to solve P

Analytically, it is evident that problem P is a mixed-integer non-linear program (MINLP), which is generally NP-hard. There is no standard method for solving such a problem efficiently. Nevertheless, at least a locally optimal solution may be obtained by employing adequate relaxations to P. In the sequel, we introduce an approximation method for P, followed by its corresponding solution.

IV. Proposed Iterative Algorithm for Solving P

This section provides an iterative algorithm based on the IA method to solve the design problem.

A. Tractable Formulation for P To bypass the difficulty of binary nature of P, we relax binary variables to continues ones as 0 ≤ λk ≤ 1, ∀k. Then, we respectively introduce slack variables z1k[n], z2k[n], and t1k[n] such that H2 + kq[n] − rkk 2 ≤ (z1k[n])2/α, H2 + kq[n] − q0k 2 ≤ (z2k[n])2/α.

$$
\begin{aligned}
\mathcal{P}_{\text{relaxed}}: \max_{\mathbf{q},\mathbf{a},\mathbf{p},\boldsymbol{\lambda},\mathbf{z},\mathbf{t}} \quad & \sum_{k\in\mathcal{K}} \delta_t \min(R^{\text{lb}}_{1k}, R^{\text{lb}}_{2k}) \\
\text{s.t.} \quad & (12\text{f}), (12\text{g}), (12\text{h}), (12\text{i}), (12\text{j}), (12\text{k}), (12\text{l}), \\
& 0 \le \lambda_k \le 1, \forall k \\
& \left(H^2 + \|q[n] - r_k\|^2\right) \le (z_{1k}[n])^{2/\alpha}, \forall k, n, \\
& \left(H^2 + \|q[n] - q_0\|^2\right) \le (z_{2k}[n])^{2/\alpha}, \forall n, \\
& (\phi^{\text{RSI}} \sum_{k^*=1, k^* \neq k}^{K} p_{2k^*}[n] + \sigma^2) \le t_{1k}[n], \forall k, n, \\
& \lambda_k \frac{S_k}{R^{\text{lb}}_{1k}} \le (n_{\text{end},k} - n_{\text{start},k})\delta_t, \forall k, \\
& \lambda_k \frac{S_k}{R^{\text{lb}}_{2k}} \le (N - n_{\text{end},k})\delta_t, \forall k, \\
& \delta_t \min(R^{\text{lb}}_{1k}, R^{\text{lb}}_{2k}) \ge \lambda_k S_k, \forall k, \\
& \sum_{k=1}^{K} \delta_t R^{\text{lb}}_{2k} \ge \sum_{k=1}^{K} \lambda_k S_k, \forall k \in \mathcal{K} \\
& \sum_{k\in\mathcal{K}} \left(\lambda_k S_k - \sum_{l=n+1}^{N} \delta_t R^{\text{lb}}_{1k}[l] - \sum_{l=1}^{n-1} \delta_t R^{\text{lb}}_{2k}[l] \right) \\
& \forall k, n.
\end{aligned}
$$

Algorithm 1: Proposed IA Based Design to Solve (12)

Initialization: Set $j := 0$ and generate an initial feasible point $\Psi^{(0)}$ for all constraints in (30).

1: **repeat**

2: Solve (30) to obtain the optimal solution $\Psi^\star \triangleq (\mathbf{q}^\star, \mathbf{a}^\star, \mathbf{p}^\star, \boldsymbol{\lambda}^\star, z^\star, t^\star, \Phi^\star, r^\star)$.

3: Update $\mathbf{q}^{(j+1)} := \mathbf{q}^\star, \mathbf{a}^{(j+1)} := \mathbf{a}^\star, \mathbf{p}^{(j+1)} := \mathbf{p}^\star, \boldsymbol{\lambda}^{(j+1)} := \lambda^\star, z^{(j+1)} := z^\star, t^{(j+1)} := t^\star$.

4: Set $j := j + 1$.

5: **until** Convergence

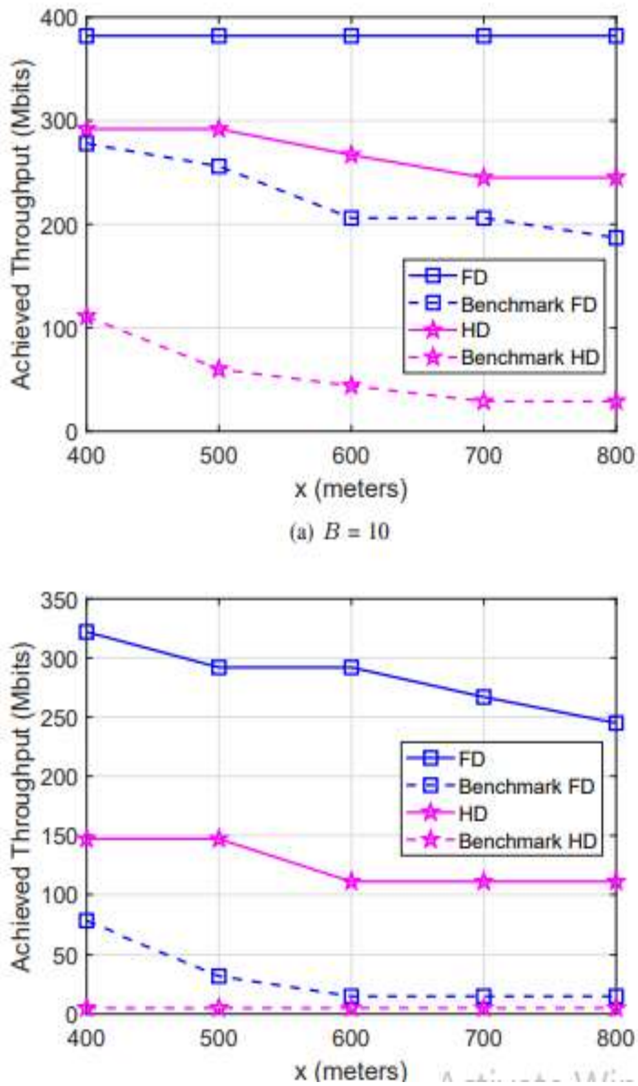

Fig. 3: Total achievable throughput vs. Different network

V. Discussion & Results

In this section, we perform the numerical evaluations to validate the proposed designs. Specifically, we consider K IoT devices randomly distributed within the considered area, i.e., 500 m x 500 m, and the ground gateway is located at (0, 500 m). The parameters are set as follows: K = 20, H = 100 meters, B = 10 MHz, path loss exponent α = 2.3, σ 2 = −110 dBm, ω0 = -40 dB, P max U = 20 dBm, P max k = 15 dBm, Sk = 30 Mbits, Rician factor G = 12 dB, the maximum collection time deadline for each device k nend,k is uniformly distributed between n min end,k and n max end,k. The UAV's initial and final locations are deployed at qI = [300 m, 200 m] and qF = [100 m, 0], respectively.

For comparison purpose, two benchmark schemes are considered. More specifically, the Benchmark FD and Benchmark HD are implemented similar to Algorithm 1 with the equal bandwidth allocated to each user, i.e., a1k[n] = a1k[n] = B K . In Fig. 2, we evaluate the total collected data (in Mbits) versus network sizes i.e., Area = x 2 . It is observed that the larger the network size, the lower the throughput can be achieved. This is because IoT devices are distributed a wider area. Thus, the UAV must fly at a higher speed to satisfy the time requirement of each device which is in contradiction with the Vmax constraint. Moreover, the FD and HD methods outperform the benchmark ones due to the benefits of optimizing bandwidth allocation.

VI. Conclusion and Future Research Directions

The trajectory design for FD/HD UAV aided IoT communication networks under latency limitations were examined in this study. The overall realized throughput was optimized by combining the UAV trajectory, allocated bandwidth, and transmission power for the devices/UAV while adhering to delay-sensitive data collecting and restricted storage capacity. We changed the original problem into a convex form, which was solved by an IA-based iterative technique, because it was a mixed-integer non-convex programme. Finally, our proposed solutions outperformed benchmark approaches, according to numerical data.

Future work is to consider communication technologies for ground and aerial connectivity, and data analytics. The dynamic interconnection and transmission optimization among satellites for massive LEO satellite networking to provide better data collection services in B5G IoRT networks. There are several open research areas in this area that need attention.

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