Energy-effective offloading scheme in UAV-assisted C-RAN system

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***Abstract*—In this paper, we aim to minimize the total power of all the Internet of Things devices (IoTDs) by jointly optimizing user association, computation capacity, transmit power, and the location of unmanned aerial vehicles (UAVs) in an UAV-assisted cloud radio access network (C-RAN). In order to solve this non-convex problem, we propose an effective algorithm by solving four subproblems iteratively. For the user association and the computation capacity subproblems, the non-convex constraints are relaxed and the optimal solutions are obtained. For the transmit power control and the location planning subproblems, successive convex approximation (SCA) technique is used to transform the non-convex constraints into convex ones. Moreover, to obtain the suboptimal solutions, slack variables are also introduced to deal with the feasibility-check problems. The simulation results demonstrate that the proposed algorithm can greatly reduce the total power consumption of IoTDs.**

***Index Terms*—UAV-assisted communication, resource allocation, user association, power control, location planning, C-RAN**

I. Introduction

NOwadays, the explosive growth of data services has posed an increasingly high burden on the existing communication systems. The connection of mobile devices is estimated up to 29.3 billion by the year of 2023 [1]. It is urgent to introduce new techniques to couple the technical challenge by such boosting. Unmanned aerial vehicles (UAVs) assisted communications is one of the promising candidates that have attracted extensive research attention [2]. Compared to the traditional ground wireless communication systems, UAV-assisted networks can provide higher mobility and probability of line-of-sight (LoS) networks links between the UAVs and the Internet of Things devices (IoTDs) [3]–[6]. Hence, UAVs can be utilized as flying base station (FBS) [7], [8], relaying [9], [10] and wireless power transfer station [11], [12], etc. Besides, thanks to the flexibility of UAV, it can handle special situations such as providing emergency communication in a disaster-stricken region [13] and enhancing communication safety [14].

Cloud radio access network (C-RAN) has been applied in the fifth generation (5G) communication [15], [16]. It divides the traditional base station (BS) into the baseband unit (BBU), remote radio heads (RRHs) and the high-speed, low-latency fronthaul links, which connect the RRHs to the BBU pool. This unique architecture can effectively reduce the capital expenditure (CAPEX) and operation expenditure (OPEX) [17]. Furthermore, C-RAN can significantly improve the spectral efficiency (SE) and energy efficiency (EE) by exploiting some measurements [18]–[21]. The authors in [22] proposed a service cloud logical architecture and parallel multi-cell cooperation processing scheme in the C-RAN to improve its performance, where the cloud service and a three-layer logical structure are used to improve the centralized processing. In [23], the impact of the constrained fronthaul on the SE, EE, and resource allocation was investigated in fronthaul-constrained C-RANs. However, there still exists many challenges in C-RAN such as the deployment of R-RHs in some complex geographical environments like malls and cities as well as high latency requirements for video conferences. Furthermore, ground RRHs may be destroyed by some emergencies such as fire and earthquake, which is very important to recover the communication service in incident area as soon as possible. UAV can be taken as FBS to provide service for the IoTDs when some ground RRHs are brokendown.

The cooperative data offloading technique is a promising solution to satisfy the boosting demands of the IoTDs [24], [25]. In order to meet the latency and power consumption requirements at IoTDs, we investigate the data offloading scheme in the UAV-assisted C-RAN architecture with multiple UAVs by satisfying the the latency, maximum transmit power, the self executing capacity of each IoTD and the fronthaul data rates constraints from each RRH to BBU. This problem is intractable because the coupled optimization variables. We obtain the optimal solution by transform it into solvable

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subproblems. The contributions of this work are concluded as follows:

1) We minimize the total power consumption of all IoTDs by jointly optimizing the user association, computation capacity allocation, transmit power control and the UAV location planning in UAV-assisted C-RAN system. Existing work [26] only taken UAV as a mobile data collector to gather a given amount of data from one ground IoTD. In this paper, UAVs are regarded as relays to offload tasks from the ground IoTDs to the baseband unit (BBU) pool, which is responsible for handling the task execution.
2) We exploit the block coordinate descent (BCD) method [27] to decoupled coupled variables in the transmit power minimization problem. Specifically, the coupled optimization variables are divided into four subproblems for user association, computation capacity allocation, transmit power control and UAVs' coordinates planning, respectively. Then, the variables in these four subproblems are alternately optimized in each iteration, in which one set of variables is optimized at each time by fixing the set of the other variables. However, even optimizing one set of the variables by fixing the other sets, the subproblems are still difficult to solve due to their non-convexity. For the user association problem, we relax the binary variables into continuous variables to transform this subproblem into a convex optimization problem. For the computation capacity optimization problem, we introduce the slack variables to deal with the feasibility subproblem when IoTDs decide to offload tasks to the BBU pool via UAVs or ground RRHs. For the transmit power control and UAVs' coordinates planning subproblems, we apply successive convex approximation (SCA) method and introduce slack variables to transform these two subproblems into their approximated convex optimization problems.
3) Simulation results demonstrate the effectiveness of our proposed iterative algorithm. Moreover, the results also show that the total transmit power consumption of IoTDs is significantly decreased by iteratively optimizing the user association, computation capacity allocation, transmit power control and the UAV location planning.

The rest of this paper is organized as follows. Section II introduces the system model and the transmit power minimization problem is formulated for an UAV-assisted C-RAN. In Section III, an efficient iterative algorithm is proposed by using BCD and SCA techniques. In Section VI, the total transmit power minimization problem is investigated. In Section V, simulation results are provided to demonstrate the effectiveness of the proposed algorithm. Finally, Section VI concludes the paper.

The main notations used in this paper are illustrated in Table I.

TABLE I
LIST OF MAIN NOTATIONS

Notation	Description
N	Number of the IoTDs
M	Number of ground RRHs
J	Number of UAVs (flying RRHs)
H	The flying height of RRHs
$a_i^L, a_{i,j}^U, a_{i,m}^U$	The offloading indicator of the ith IoTD to itself, the jth UAV and the mth RRH
U_i	The computational intensive task of the ith IoTD
F_i	The total number of the CPU cycles of U_i to be computed
D_i	The data size of task U_i of the ith IoTD
T	The latency requirement of IoTDs
f_i	The computation capacity of the ith IoTD
$f_{i,b}$	The computation capacity of the BBU providing to the ith IoTD
$r_{i,j}$	The offloading rate from the ith IoTD to the jth place
$p_{i,j}^T$	The transmit power from the ith IoTD to the jth place
p_i^E	The self execution power of the ith IoTD
$h_{i,j}^U$	The channel quality between the ith IoTD and the jth UAV
h_j^{RB}	The channel quality between the jth UAV and BBU
C_m^F	The maximum data rate between the mth RRH and BBU
r_j^{UB}	The data rate between the jth UAV and BBU

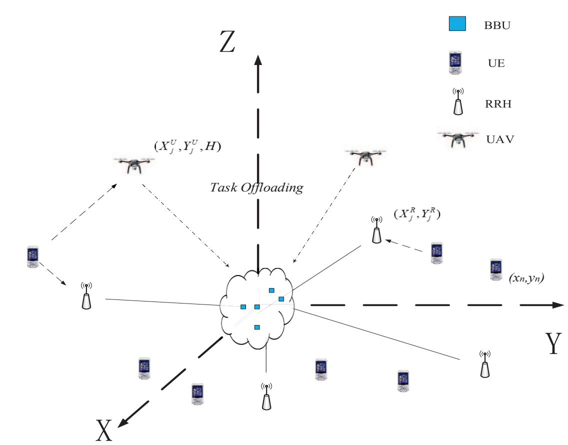

Fig. 1. UAV-assisted C-RAN system model.

II. System Model and problem formulation

A. System Model

As shown in Fig. 1, we consider an UAV-assisted C-RAN system with N IoTDs, M ground RRHs and J rotary-wing UAVs as flying RRHs. The sets of the IoTDs, UAVs and RRHs are denoted as $\mathcal{N} = \{1, 2, \cdots, N\}$, $\mathcal{J} = \{1, 2, \cdots, J\}$ and $\mathcal{M} = \{1, 2, \cdots, M\}$, respectively. The ground RRHs connect to BBU pool via high-speed fronthaul links. Each IoTD has a computation task to be executed, which can be offloaded to the BBU pool through UAVs or ground RRHs. The IoTD can choose a flying UAV or a ground RRH to offload its task. Assume that all the UAVs fly at a fixed attitude H.

Define the a_i^L, $a_{i,j}^U$ and $a_{i,j}^R$ as the offloading indicator of the ith IoTD. Then we have

$$a_i^L = \{0, 1\}, \forall i \in \mathcal{N}, \tag{1}$$

$$a_{i,j}^U = \{0, 1\}, \forall i \in \mathcal{N}, \forall j \in \mathcal{J}, \tag{2}$$

$$a_{i,m}^R = \{0, 1\}, \forall i \in \mathcal{N}, \forall m \in \mathcal{M}, \tag{3}$$

where $a_i^L = 1$ denotes that the ith IoTD decides to execute the task itself, otherwise, $a_i^L = 0$. Similarly, $a_{i,j}^U = 1$ and $a_{i,m}^R = 1$ denote that the ith UE decides to offload the task via the jth UAV and the mth ground RRH, respectively. Since the ith IoTD only can choose one relaying i.e. UAV or RRH to offload tasks, we have

$$a_i^L + \sum_{j\in\mathcal{J}} a_{i,j}^U + \sum_{m\in\mathcal{M}} a_{i,m}^R = 1, i \in \mathcal{N}. \tag{4}$$

Similar to [28], we assume that the ith IoTD has the computational intensive task U_i to be executed as follows

$$U_i = (F_i, D_i, T), i \in \mathcal{N}, \tag{5}$$

where F_i denotes the total number of the central processing unit (CPU) cycles of U_i to be computed, D_i denotes the data size of the ith IoTD that will transmit to the BBU pool if offloading action is taken, T is the latency constraint or QoS requirement by this task. In this paper, we consider all the tasks have the same time requirement, without loss of generality. D_i and F_i can be obtained by using the approaches provided in [29].

Then, when the ith IoTD decides to offload tasks, the execution time of the task is give by

$$T_{i,j}^C = \frac{F_i}{f_{i,b}}, \tag{6}$$

where $f_{i,b}$ is the computation capacity of the BBU providing to the ith IoTD.

Furthermore, if the ith IoTD offloads tasks to the BBU pool through an UAV or a RRH, the time needed to offload the data is expressed as

$$T_{i,j}^{Tr} = \frac{D_i}{r_{i,j}}, \tag{7}$$

where $r_{i,j}$ is the offloading data rate from the ith IoTD to the jth place. Then, we have

$$\frac{D_i}{r_{i,j}} + \frac{F_i}{f_{i,b}} \leq T, \tag{8}$$

which means that each task must satisfy the latency requirement.

If this task is executed by the itself, we have

$$\frac{F_i}{f_i} \leq T, \tag{9}$$

where f_i is the local executing capacity of the ith IoTD. Then, we can have the latency constraint as follows

$$a_i^L \frac{F_i}{f_i} + \sum_{j\in\mathcal{J}} a_{i,j}^U \left(\frac{D_i}{r_{i,j}} + \frac{F_i}{f_{i,b}}\right) + \sum_{m\in\mathcal{M}} a_{i,m}^R \left(\frac{D_i}{r_{i,m}} + \frac{F_i}{f_{i,b}}\right) \leq T, i \in \mathcal{N}. \tag{10}$$

Also, we have the computing constraints for the IoTD and BBU, which are written as

$$a_i^L f_i \leq f_{i,max}^L, i \in \mathcal{N}, \tag{11}$$

$$\sum_{i\in\mathcal{O}} (\sum_{j\in\mathcal{J}} a_{i,j}^U f_{i,b} + \sum_{m\in\mathcal{M}} a_{i,m}^R f_{i,b}) \leq f_{max}^{BBU}, \tag{12}$$

where $\mathcal{O}$ is the offloading set.

The power consumption of the ith IoTD can be given by

$$p_i^{ue} = \begin{cases} \sum_{j\in\mathcal{J}} a_{i,j}^U p_{i,j}^T + \sum_{m\in\mathcal{M}} a_{i,m}^R p_{i,m}^T, \\ \qquad j \in \mathcal{J}, m \in \mathcal{M}, \quad \text{if} \quad \text{offloading}, \\ p_i^E, \quad \text{if} \quad \text{local execution}, \end{cases} \tag{13}$$

where $p_{i,j}^T$ is the transmitting power from the ith IoTD to the jth place and p_i^E is the execution power of the ith IoTD if it conducts the task itself. We have

$$p_i^E = \kappa_i (f_i)^{\nu_i}, i \in \mathcal{N}, \tag{14}$$

where $\kappa_i \geq 0$ is the effective switched capacitance and $\nu_i \geq 1$ is the positive constant. To match the realistic measurements, we set $\kappa_i = 10^{-15}$ and $\nu_i = 3$ for all IoTDs [30].

Then, the power constraint of IoTDs can be written as

$$a_i^L p_i^E + \sum_{j\in\mathcal{J}} a_{i,j}^U p_{i,j}^U + \sum_{m\in\mathcal{M}} a_{i,m}^R p_{i,m}^R \leq P_{i,max}^{ue}, i \in \mathcal{N}, \tag{15}$$

where $p_{i,j}^U$ and $p_{i,m}^R$ denote the transmit power of the ith IoTD offloading tasks to the jth UAV or the mth RRH, respectively, $P_{i,max}^{ue}$ is the maximum power for the ith IoTD.

Assume that the coordinate of the ith IoTD is denoted by $\mathbf{x}_i = (x_i, y_i)$, the horizontal coordinate of the jth UAV is denoted by $\mathbf{U}_j = (X_j^U, Y_j^U)$, and the coordinate of the mth RRH is denoted by $\mathbf{Q}_m = (X_m^R, Y_m^R)$. The distance between the ith IoTD and the jth UAV is formulated as

$$R_{i,j}^U = \sqrt{(X_j^U - x_i)^2 + (Y_j^U - y_i)^2 + H^2}, \forall i \in \mathcal{N}, \forall j \in \mathcal{J}. \tag{16}$$

We assume all IoTDs are located outdoors, then the channels between IoTDs and UAVs are mainly line-of-sight (LoS) path. If the ith IoTD decides to offload tasks to the BBU pool via UAV, the channel quality between them is expressed as

$$h_{i,j}^U = \beta^U (R_{i,j}^U)^{-2} = \frac{\beta^U}{\|\mathbf{U}_j - \mathbf{x}_i\|^2 + H^2}, \tag{17}$$

where β^U is the channel power gain between the ith IoTD and the jth UAV. Then, the data rate between them can be given by

$$r_{i,j}^U = B\log_2\left(1 + \frac{p_{i,j}^U h_{i,j}^U}{\sum_{k\in\mathcal{N},k\neq i} p_{k,j}^U h_{k,j}^U + \sigma^2}\right), i \in \mathcal{N}, j \in \mathcal{J}. \tag{18}$$

Due to the fact that IoTDs and ground RRHs are located on the ground, there are rich scattering during the communication process. Denote $h_{i,m}^R = \frac{\beta^R g_{i,m}}{\|\mathbf{Q}_m - \mathbf{x}_i\|^2}$ as the channel between the ith IoTD and the mth ground RRH, which includes the large-scale fading and small fading. $g_{i,m}$ denotes the small-scale fading of a wireless channel and is an independent and identically distributed complex Gaussian random variables with zero mean and unit variance. Then, the data rate between the ith IoTD and the mth ground RRH can be given by

$$r_{i,m}^R = B\log_2\left(1 + \frac{p_{i,m}^R h_{i,m}^R}{\sum_{k\in\mathcal{N},k\neq i} p_{k,m}^T h_{k,m}^R + \sigma^2}\right). \tag{19}$$

The distance between the jth UAV and the BBU pool is

$$R_j^{RB} = \sqrt{(X_j^U)^2 + (Y_j^U)^2 + H^2}, j \in \mathcal{J}. \tag{20}$$

The channel quality between them is expressed as

$$h_j^{RB} = \beta^R (R_j^R)^{-2} = \frac{\beta^R}{\|\mathbf{U}_j\|^2 + H^2}, j \in \mathcal{J}. \tag{21}$$

The data rate of the jth UAV sending information from the IoTD to the BBU pool can be modeled as

$$r_j^{UB} = B\log_2\left(1 + \alpha p_j^{UAV} h_j^{RB}\right), j \in \mathcal{J}, \tag{22}$$

where we do not consider the interference among UAVs, p_j^{UAV} is the transmit power of the jth UAV and α is the antenna gain.

For the fronthaul data rate between the UAV and BBU, the data rate constraint is expressed as

$$\sum_{i\in\mathcal{O}} a_{i,j}^U r_{i,j}^U \leq r_j^{UB}, j \in \mathcal{J}. \tag{23}$$

The total data rate of all IoTDs that offloading tasks to the BBU pool via ground RRH needs to small than the maximum fronhaul data rate, which is written as

$$\sum_{i\in\mathcal{O}} a_{i,m}^R r_{i,m}^R \leq C_m^F, m \in \mathcal{M}, \tag{24}$$

where C_m^F is the maximum data rate between the mth ground RRH and the BBU pool.

B. Problem Formulation

In this paper, we aim to minimize the total transmit power of IoTDs by jointly optimizing the user association, computation capacity, transmit power control of IoTDs and the coordinates of UAVs. According to the above illustration, the optimization problem can be formulated as

$$\mathcal{P}: \min_{\mathbf{A},\mathbf{F},\mathbf{P},\mathbf{U}} \quad f(\mathbf{A},\mathbf{F},\mathbf{P},\mathbf{U}) \tag{25a}$$

$$\text{s.t.} \quad (1)-(4),(10)-(12),(15),(23),(24), \tag{25b}$$

where $\mathbf{A} = \{a_i^L, a_{i,j}^U, a_{i,m}^R\}_{i\in\mathcal{N},j\in\mathcal{J},m\in\mathcal{M}}$, $\mathbf{F} = \{f_i, f_{i,b}\}_{i\in\mathcal{N}}$, $\mathbf{P} = \{p_i^E, p_{i,j}^U, p_{i,m}^R\}_{i\in\mathcal{N},j\in\mathcal{J},m\in\mathcal{M}}$ and $\mathbf{U} = \{\mathbf{U}_j\}_{j\in\mathcal{J}}$, $f(\mathbf{A},\mathbf{F},\mathbf{P},\mathbf{U}) = \sum_{i\in\mathcal{N}} a_i^L p_i^E + \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{J}} a_{i,j}^U p_{i,j}^U + \sum_{i\in\mathcal{N}}\sum_{m\in\mathcal{M}} a_{i,m}^R p_{i,m}^R$.

This problem is very challenging to solve because of the coupled variables and the non-convexity of constraints (1)-(4), (10), (12), (23) and (24). In the following, we first adopt the BCD technique to decouple this non-convex problem into four tractable subproblems. Then, these subproblems are reformulated into convex problems and an effective iteration algorithm is proposed to solve Problem $\mathcal{P}$.

III. Proposed Algorithm for Total Power Minimization Problem

In this section, BCD method is used to devide the original problem $\mathcal{P}$ into four tractable subproblems to decouple the optimization variables. Then, Problem $\mathcal{P}$ can be solved by iteratively solving each subproblem.

A. Optimize IoTD association variables

When IoTDs offload tasks to the BBU pool with the help of UAV, the offloading data rate dependents on the minimum data rate of IoTD to UAV and UAV to BBU links, i.e. $r_{i,j} = r_{i,j}^U$. Similarly, the data rate is $r_{i,m}^R$ when the ith IoTD offloads tasks through RRH. With fixed $\mathbf{F}$, $\mathbf{P}$ and $\mathbf{U}$, original problem $\mathcal{P}$ can be simplified as IoTD user association problem, which can be formulated as

$$\mathcal{P}_1: \min_{\mathbf{A}} \quad f(\mathbf{A},\mathbf{F},\mathbf{P},\mathbf{U}) \tag{26a}$$

$$\text{s.t.} \quad a_i^L \frac{F_i}{f_i} + \sum_{j\in\mathcal{J}} a_{i,j}^U \left(\frac{D_i}{r_{i,j}^U} + \frac{F_i}{f_{i,b}}\right) + \sum_{m\in\mathcal{M}} a_{i,m}^R \left(\frac{D_i}{r_{i,m}^R} + \frac{F_i}{f_{i,b}}\right) \leq T, i \in \mathcal{N}, \tag{26b}$$

$$\sum_{i\in\mathcal{O}} a_{i,j}^U r_{i,j}^U \leq r_j^{UB}, j \in \mathcal{J}, \tag{26c}$$

$$\sum_{i\in\mathcal{O}} a_{i,m}^R r_{i,m}^R \leq C_m^F, m \in \mathcal{M}, \tag{26d}$$

$$(1)-(4),(11),(12),(15). \tag{26e}$$

Problem $\mathcal{P}_1$ is non-convex due to the binary constraints of (1)-(3). We can relax them into a convex set, which can be expressed as

$$0 \leq a_i^L \leq 1, 0 \leq a_{i,j}^U \leq 1, 0 \leq a_{i,m}^R \leq 1, i \in \mathcal{N}, j \in \mathcal{J}, m \in \mathcal{M}. \tag{27}$$

Then, Problem $\mathcal{P}_1$ can be transformed as

$$\mathcal{P}_{1-E1}: \min_{\mathbf{A}} \quad f(\mathbf{A},\mathbf{F},\mathbf{P},\mathbf{U}) \tag{28a}$$

$$\text{s.t.} \quad (4),(11),(12),(15),(26b)-(26d),(27). \tag{28b}$$

It's readily to know that Problem $\mathcal{P}_{1-E1}$ is a convex optimization problem, which can be solved by interior point method. Because the optimal solutions of Problem $\mathcal{P}_{1-E1}$ may not be integer, we use the rounding method in [31] to further obtain the suboptimal integer solution.

B. Optimize computation capacity variables

In this subsection, we fix IoTD association variable $\mathbf{A}$, power allocation variable $\mathbf{P}$ and the location of UAV $\mathbf{U}$ to optimize the computation capacity variables. We define $\mathcal{I}_L = \{i \in \mathcal{N} | a_i^L = 1\}$ as the set of IoTDs that conduct the tasks itself, $\mathcal{I}_U = \{i \in \mathcal{N}, j \in \mathcal{J} | a_{i,j}^U = 1\}$ and $\mathcal{I}_R = \{i \in \mathcal{N}, m \in \mathcal{M} | a_{i,m}^R = 1\}$ as the set of IoTDs offloading the tasks through UAV and RRH, respectively. Then, constraint (10) can be reformulated as

$$\frac{F_i}{f_i} \leq T, i \in \mathcal{I}_L, \tag{29}$$

$$\frac{D_i}{r_{i,j}^U} + \frac{F_i}{f_{i,b}} \leq T, i, j \in \mathcal{I}_U, \tag{30}$$

$$\frac{D_m}{r_{l,m}^R} + \frac{F_m}{f_{m,b}} \leq T, l, m \in \mathcal{I}_R. \tag{31}$$

Similarly, constraints (11) and (12) can also be transformed as

$$f_i \leq f^L_{i,max}, i \in \mathcal{I}_L, \tag{32}$$

$$\sum_{i \in \mathcal{I}_U} f_{i,b} + \sum_{l \in \mathcal{I}_R} f_{l,b} \leq f^{BBU}_{max}. \tag{33}$$

Power constraint in (15) can be rewritten as

$$\kappa_i (f_i)^{\nu_i} \leqslant P^{ue}_{i,\max}, i \in \mathcal{I}_L, \tag{34}$$

$$p^U_{i,j} \leq p^{ue}_{i,max}, i,j \in \mathcal{I}_U, \tag{35}$$

$$p^R_{l,m} \leq p^{ue}_{l,max}, l,m \in \mathcal{I}_R. \tag{36}$$

According to Problem $\mathcal{P}$, the computation capacity optimization problem can be decoupled into two subproblems, i.e. self and offloading computation capacity optimization problems. After ignoring the constant parts, the self computation capacity optimization problem can be formulated as

$$\begin{aligned} \mathcal{P}_{2-E1}: \quad \min_{\mathbf{f}_l} \quad & \sum_{i \in \mathcal{I}_L} \kappa_i (f_i)^{\nu_i} \\ \text{s.t.} \quad & (29), (32), (34), \end{aligned} \tag{37}$$

where $\mathbf{f}_l = \{f_i, i \in \mathcal{I}_L\}$. We can find that Problem $\mathcal{P}_{2-E1}$ is convex, which can be solved by convex optimization techniques.

Furthermore, the other IoTDs offload tasks to BBU via UAVs or ground RRHs. The original problem $\mathcal{P}$ is simplified as offloading optimization subproblem, which is a feasibility-check problem. In order to deal with it, we introduce the slack variables $\mathbf{s} = [s_1, \cdots, s_N]$ and $\mathbf{t} = [t_1, \cdots, t_N]$. Define $\widehat{\mathbf{F}} = \{f_{i,b}, f_{l,b}\}_{i \in \mathcal{I}_U, l \in \mathcal{I}_R}$, this subproblem is reformulated as

$$\mathcal{P}_{2-E2}: \quad \max_{\widehat{\mathbf{F}}, \mathbf{s}, \mathbf{t}} \quad \|\mathbf{s}\|_1 + \|\mathbf{t}\|_1 \tag{38a}$$

$$\text{s.t.} \quad \frac{F_i}{T - \frac{D_i}{r^U_{i,j}}} \leq f_{i,b} - s_i, i,j \in \mathcal{I}_U, \tag{38b}$$

$$\frac{F_l}{T - \frac{D_l}{r^R_{l,m}}} \leq f_{l,b} - t_l, l,m \in \mathcal{I}_R, \tag{38c}$$

$$\sum_{i \in \mathcal{I}_U} f_{i,b} + \sum_{l \in \mathcal{I}_R} f_{l,b} \leq f^{BBU}_{max}, \tag{38d}$$

$$\mathbf{s} \geq 0, \mathbf{t} \geq 0. \tag{38e}$$

Since Problem $\mathcal{P}_{2-E2}$ is a convex problem, which also can be solved by interior point method.

C. Optimize transmit power of IoTDs

With fixed IoTDs association variable $\mathbf{A}$, computation capacity distribution $\mathbf{F}$ and horizontal coordinates of UAVs $\mathbf{U}$, Problem $\mathcal{P}$ can be transformed as the following subproblem as

$$\mathcal{P}_3: \quad \min_{\widehat{\mathbf{P}}} \quad \sum_{i,j \in \mathcal{I}_U} p^U_{i,j} + \sum_{l,m \in \mathcal{I}_R} p^R_{l,m} \tag{39a}$$

$$\text{s.t.} \quad \sum_{i,j \in \mathcal{I}_U} r^U_{i,j} \leq r^{UB}_j, \tag{39b}$$

$$\sum_{l,m \in \mathcal{I}_R} r^R_{l,m} \leq C^F_m, \tag{39c}$$

$$(30), (31), (35), (36), \tag{39d}$$

where $\widehat{\mathbf{P}} = \{p^U_{i,j}, p^R_{l,m}\}_{i,j \in \mathcal{I}_U, l,m \in \mathcal{I}_R}$.

Problem $\mathcal{P}_3$ is a non-convex optimization problem since the non-convex constraints set. For the constraint (30), we can transform it as

$$r^U_{i,j} \geq \frac{D_i}{T - \frac{F_i}{f_{i,b}}}. \tag{40}$$

This constraint is still non-convex due to the non-convexity of its left hand side. But it can be decoupled as a difference of two concave functions with respect to the transmit power variables, which can be written as

$$\frac{r^U_{i,j}}{B} = \log_2(\sum_{i=1}^{I_U} p^U_{i,j} h^U_{i,j} + \sigma^2) - \log_2(\sum_{k=1, k \neq i}^{I_U} p^U_{k,j} h^U_{k,j} + \sigma^2). \tag{41}$$

It is still non-convex due to the fact that the second part is a concave function. In order to handle this non-convex constraint, SCA method is applied to approximate the second part. It is well known that any concave function is globally upper bounded by its first-order Taylor expansion at any point. Define $(\mathbf{P}^U)^r = [(p^U_{i,j})^r, i,j \in \mathcal{I}_U]$ as the transmit power of IoTDs that offload tasks to the BBU pool through UAV in the rth iteration. Hence, the second part of (41) is upper bounded by

$$\begin{aligned} &\log_2(\sum_{k=1, k \neq i}^{I_U} p^U_{k,j} h^U_{k,j} + \sigma^2) \\ &\leq \frac{\sum\limits_{k=1, k \neq i}^{I_U} h^U_{k,j} \log_2(e) \left[p^U_{k,j} - (p^U_{k,j})^r\right]}{\sum\limits_{k=1, k \neq i}^{I_U} (p^U_{k,j})^r h^U_{k,j} + \sigma^2} \\ &+ \log_2\left[\sum_{k=1, k \neq i}^{I_U} (p^U_{k,j})^r h^U_{k,j} + \sigma^2\right] = (A^U_{i,j})^{ub}. \end{aligned} \tag{42}$$

Similarly, the constraint (39b) can be approximated by

$$\sum_{i,j \in \mathcal{I}_U} \left[(B^U_j)^{ub} - \log_2(\sum_{k=1, k \neq i}^{I_U} p^U_{k,j} h^U_{k,j} + \sigma^2)\right] \leq \frac{r^{UB}_j}{B}, \tag{43}$$

where $(B^U_j)^{ub} = \frac{\sum_{i=1}^{I_U} h^U_{i,j} \log_2(e) \left[p^U_{i,j} - (p^U_{i,j})^r\right]}{\sum_{i=1}^{I_U} (p^U_{i,j})^r h^U_{i,j} + \sigma^2} + \log_2\left[\sum_{i=1}^{I_U} (p^U_{i,j})^r h^U_{i,j} + \sigma^2\right]$.

Constraint (31) can be reformulated as the following convex constraint

$$\log_2(\sum_{l=1}^{I_U} p^R_{l,m} h^R_{l,m} + \sigma^2) - (C^R_{l,m})^{ub} \geq \frac{D_l}{B(T - \frac{F_l}{f_{l,b}})}, l,m \in \mathcal{I}_R, \tag{44}$$

where $(C^R_{l,m})^{ub} = \frac{\sum_{k=1, k \neq l}^{I_R} h^R_{k,m} \log_2(e) \left[p^R_{k,m} - (p^R_{k,m})^r\right]}{\sum_{k=1, k \neq l}^{I_R} (p^R_{k,m})^r h^R_{k,m} + \sigma^2} + \log_2\left[\sum_{k=1, k \neq l}^{I_R} (p^R_{k,m})^r h^R_{k,m} + \sigma^2\right]$.

Constraint (39c) also can be transformed as

$$\sum_{l,m\in\mathcal{I}_R}\left[(D_m^R)^{ub}-\log_2(\sum_{k=1,k\neq l}^{I_R}p_{k,m}^R h_{k,m}^R+\sigma^2)\right]\leq\frac{C_m^F}{B},\tag{45}$$

where $(D_m^R)^{ub} = \frac{\sum\limits_{l=1}^{I_R}h_{l,m}^R\log_2(e)\left[p_{l,m}^R-(p_{l,m}^R)^r\right]}{\sum\limits_{l=1}^{I_R}(p_{l,m}^R)^r h_{l,m}^R+\sigma^2} + \log_2\left[\sum\limits_{l=1}^{I_R}(p_{l,m}^R)^r h_{l,m}^R+\sigma^2\right]$.

Then, Problem $\mathcal{P}_3$ can be transformed as

$$\mathcal{P}_{3-E1}:\ \min_{\widehat{\mathbf{P}}}\ \sum_{i\in\mathcal{I}_U}p_{i,j}^U+\sum_{l\in\mathcal{I}_R}p_{l,j}^R\tag{46a}$$

$$\text{s.t.}\quad (a),(b),(c),(d),(35),(36).\tag{46b}$$

where (a) is $\log_2\left(\sum\limits_{i=1}^{I_U}p_{i,j}^U h_{ij}^U+o^2\right)-(A_{i,j}^U)^{ub}\geq\frac{D_i}{B(T-\frac{F_i}{f_{i,b}})}, i,j\in\mathcal{I}_U$, (b) denotes $\log_2\left(\sum\limits_{l=1}^{I_R}p_{l,m}^R h_{l,m}^R+o^2\right)-(C_{l,m}^R)^{ub}\geq\frac{D_l}{B(T-\frac{F_l}{f_{l,b}})}, l,m\in\mathcal{I}_R$, (c) is $\sum_{i,j\in\mathcal{I}_U}\left[(B_j^U)^{ub}-\log_2(\sum\limits_{k=1,k\neq i}^{I_U}p_{k,j}^U h_{k,j}^U+\sigma^2)\right]\leq\frac{r_j^{UB}}{B}$ and (d) is $\sum_{l,m\in\mathcal{I}_R}\left[(D_m^R)^{ub}-\log_2(\sum\limits_{k=1,k\neq l}^{I_R}p_{k,m}^R h_{k,m}^R+\sigma^2)\right]\leq\frac{C_m^F}{B}$.

It is readily to know that Problem $\mathcal{P}_{3-E1}$ is a convex optimization problem, which can be solved by convex optimization methods such as interior point method.

D. Optimize the location of UAVs

When we fix IoTD association variable $\mathbf{A}$, computation capacity distribution $\mathbf{F}$ and transmit power allocation variables of UEs $\mathbf{P}$, the original problem is equivalent to a feasibility-check problem for the location of UAVs. Note that the coordinates of UAVs related constraints (30) and (39b) are non-convex. Hence, we first exploit the SCA technique to transform these two constraints into convex set. By introducing slack variables $\mathbf{S}=\{S_{i,j}=\|\mathbf{U}_j-\mathbf{x}_i\|^2, i\in\mathcal{N}, j\in\mathcal{J}\}$, constraint (30) can be written as

$$\begin{aligned}r_{i,j}^U&=\log_2\left(1+\frac{\frac{p_{i,j}^U\beta^U}{S_{i,j}+H^2}}{\sum\limits_{k=1,k\neq i}^{I_U}\frac{p_{k,j}^U\beta^U}{S_{k,j}+H^2}+\sigma^2}\right)\\&=\log_2\left(\sum_{i=1}^{I_U}\frac{p_{i,j}^U\beta^U}{S_{i,j}+H^2}+\sigma^2\right)-E_{i,j}\\&\geq\frac{D_i}{B(T-\frac{F_i}{f_{i,b}})}, i,j\in\mathcal{I}_U,\end{aligned}\tag{47}$$

where $E_{i,j}=\log_2\left(\sum\limits_{k=1,k\neq i}^{I_U}\frac{p_{k,j}^U\beta^U}{S_{k,j}+H^2}+\sigma^2\right)$.

The left hand side of (47) is still non-concave with respect to $S_{i,j}$. Specifically, the SCA technique is used to deal with the non-concave part, which is given as

$$\begin{aligned}\log_2\left(\sum_{i=1}^{I_U}\frac{p_{i,j}^U\beta^U}{S_{i,j}+H^2}+\sigma^2\right)&\geq\log_2\left(\sum_{i=1}^{I_U}\frac{p_{i,j}^U\beta^U}{S_{i,j}^r+H^2}+\sigma^2\right)\\&-\sum_{i=1}^{I_U}\frac{\frac{p_{i,j}^U\beta^U}{(S_{i,j}^r+H^2)^2}\log_2 e}{\sum\limits_{l=1}^{I_U}\frac{p_{l,j}^U\beta^U}{S_{l,j}^r+H^2}+\sigma^2}\left(S_{i,j}-S_{i,j}^r\right)=G_j,\end{aligned}\tag{48}$$

where $S_{i,j}^r=\left\|\mathbf{U}_j^r-\mathbf{x}_i\right\|^2$, and $\mathbf{U}_j^r$ is the given location of the jth UAV at the rth iteration.

The constraint (39b) can be reformulated as

$$\begin{aligned}\sum_{i\in\mathcal{I}_U}r_{i,j}^U-r_j^{UB}=\sum_{i=1}^{I_U}\log_2\left(\sum_{i=1}^{I_U}\frac{p_{i,j}^U\beta^U}{S_{i,j}+H^2}+\sigma^2\right)\\-\sum_{i=1}^{I_U}E_{i,j}^{lb}-W_j^{lb}\leq 0,\end{aligned}\tag{49}$$

where

$$\begin{aligned}E_{i,j}&\geq\log_2\left(\sum_{k=1,k\neq i}^{I_U}\frac{p_{k,j}^U\beta^U}{S_{k,j}^r+H^2}+\sigma^2\right)\\&-\sum_{k=1,k\neq i}^{I_U}\frac{\frac{p_{k,j}^U\beta^U}{(S_{k,j}^r+H^2)^2}\log_2 e}{\sum\limits_{l=1,l\neq i}^{I_U}\frac{p_{l,j}^U\beta^U}{S_{l,j}^r+H^2}+\sigma^2}\left(S_{k,j}-S_{k,j}^r\right)=E_{i,j}^{lb},\end{aligned}\tag{50}$$

and

$$\begin{aligned}W_j&=\log_2\left(\frac{\alpha p_j^{UAV}\beta^R}{\|\mathbf{U}_j\|^2+H^2}+1\right)\\&\geq\log_2\left(\frac{\alpha p_j^{UAV}\beta^R}{\left\|\mathbf{U}_j^r\right\|^2+H^2}+1\right)\\&-\frac{\alpha p_j^{UAV}\beta^R(\|\mathbf{U}_j\|^2-\left\|\mathbf{U}_j^r\right\|^2)}{(\left\|\mathbf{U}_j^r\right\|^2+H^2)(\alpha p_j^{UAV}\beta^R+\left\|\mathbf{U}_j^r\right\|^2+H^2)}=W_j^{lb}.\end{aligned}\tag{51}$$

To deal with this feasibility-check problem, we introduce the slack variables $\mathbf{b}=[b_{i,j}, i\in\mathcal{I}_U, j\in\mathcal{J}]$ and $\mathbf{c}=[c_1,\cdots,c_J]$. Then, the coordinates of UAV subproblem can be formulated as

$$\mathcal{P}_4 \quad \max_{\mathbf{S},\mathbf{U},\mathbf{b},\mathbf{c}} \quad \|\mathbf{b}\|_1 - \kappa^{(t)}\|\mathbf{c}\|_1 \tag{52a}$$

$$\text{s.t.} \quad G_j - E_{i,j} \geq \frac{D_i}{B(T-\frac{F_i}{f_{i,b}})} + b_{i,j}, i \in \mathcal{I}_U, j \in \mathcal{J}, \tag{52b}$$

$$\sum_{i=1}^{I_U} \log_2\left(\sum_{i=1}^{I_U} \frac{p_{i,j}^U \beta^U}{S_{i,j}+H^2} + \sigma^2\right) - \sum_{i=1}^{I_U} E_{i,j}^{lb} - W_j^{lb} \leq c_j, j \in \mathcal{J}, \tag{52c}$$

$$S_{i,j} \leq \left\|\mathbf{U}_j^r - \mathbf{x}_i\right\|^2 + 2(\mathbf{U}_j^r - \mathbf{x}_i)^T(\mathbf{U}_j - \mathbf{U}_j^r), \quad i \in \mathcal{I}_U, j \in \mathcal{J}, \tag{52d}$$

$$\mathbf{b} \geq 0, \mathbf{c} \geq 0, \tag{52e}$$

where $\kappa^{(t)}$ is the regularization factor to control the feasibility of the constraints in the tth iteration. It is readily to find that Problem $\mathcal{P}_4$ is convex for the coordinates of UAVs, which can be solved by the interior point method.

The overall algorithm of optimizing UAV coordinates $\mathbf{U}$ is summarized in Algorithm 1. By updating κ, ϵ must keep sufficiently low to ensure $\|\mathbf{c}\|_1 \leq \epsilon$, which makes sure constraint (52c) is guaranteed.

Algorithm 1 Optimizing UAV Coordinates $\mathbf{U}$

1: initialize feasible $\mathbf{U}^{(0)}$, $\gamma > 1$, $\kappa^{(0)}$, κ_{max}, ϵ, the iteration number $t = 0$, and the tolerance parameter ξ.
2: repeat
  Update $\mathbf{U}^{(t+1)}$ according to Problem $\mathcal{P}_4$;
  $\kappa^{(t+1)} = \max\{\gamma\kappa^{(t)}, \kappa_{max}\}$;
  $t = t + 1$;
3: until $\|\mathbf{c}\|_1 \leq \epsilon$ and $\|\mathbf{U}^{(t)} - \mathbf{U}^{(t-1)}\|_1 < \xi$.

E. Overall algorithm and convergence

According to the above discussions, we propose an iterative algorithm to solve Problem $\mathcal{P}$, which is shown in Algorithm 2. We prove the convergence of it as follows

$$\begin{aligned} V_{obj}^{(t-1)} &= O(\mathbf{A}^{t-1}, \mathbf{F}^{t-1}, \mathbf{P}^{t-1}, \mathbf{U}^{t-1}) \\ &\overset{(a)}{\geq} O(\mathbf{A}^{t}, \mathbf{F}^{t-1}, \mathbf{P}^{t-1}, \mathbf{U}^{t-1}) \\ &\overset{(b)}{=} O(\mathbf{A}^{t}, \mathbf{F}^{t}, \mathbf{P}^{t-1}, \mathbf{U}^{t-1}) \\ &\overset{(c)}{\geq} O(\mathbf{A}^{t}, \mathbf{F}^{t}, \mathbf{P}^{t}, \mathbf{U}^{t-1}) \\ &\overset{(d)}{\geq} O(\mathbf{A}^{t}, \mathbf{F}^{t}, \mathbf{P}^{t}, \mathbf{U}^{t}) \\ &\geq O(\mathbf{A}^{t}, \mathbf{P}^{t}, \mathbf{U}^{t}) = V_{obj}^{(t)}, \end{aligned} \tag{53}$$

where (a) holds due to the fact that $\mathbf{A}^t$ is one of the suboptimal user association solutions of Problem $\mathcal{P}_1$ with fixed $\mathbf{F}^{t-1}, \mathbf{P}^{t-1}, \mathbf{U}^{t-1}$. (b) holds due to the fact that $\mathbf{F}^t$ is the optimal computation capacity solutions of Problem $\mathcal{P}_{2-E1}$ and Problem $\mathcal{P}_{2-E2}$ with fixed $\mathbf{A}^t, \mathbf{P}^{t-1}, \mathbf{U}^{t-1}$. (c) follows from that $\mathbf{P}^t$ is the suboptimal transmitting power solutions of Problem $\mathcal{P}_3$. Inequality (d) holds due to $\mathbf{U}^t$ is the suboptimal UAV coordinates of Problem $\mathcal{P}_4$. Therefore, Algorithm 2 is non-increasing by iteratively updating UE association, computation capacity, transmit power and the location of UAVs.

Algorithm 2 Iterative Algorithm for Total Power Minimization in UAV-assisted C-RAN

1: initialize feasible $\mathbf{A}^{(0)}$, $\mathbf{F}^{(0)}$, $\mathbf{P}^{(0)}$ and $\mathbf{U}^{(0)}$, the iteration number $t = 0$, maximum iteration number T_{max}, the tolerance parameter ξ.
2: Calculate objective function value $V_{obj}^{(0)} = O(\mathbf{A}^{(0)}, \mathbf{F}^{(0)}, \mathbf{P}^{(0)}, \mathbf{U}^{(0)})$, where $O(\mathbf{A}, \mathbf{F}, \mathbf{P}, \mathbf{U}) = \sum_{i\in\mathcal{N}} a_i^L p_i^E + \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{J}} a_{i,j}^U p_{i,j}^U + \sum_{l\in\mathcal{N}}\sum_{m\in\mathcal{M}} a_{l,m}^R p_{l,m}^R$.
3: repeat
  Set $t = t + 1$;
  With fixed $(\mathbf{F}^{(t-1)}, \mathbf{P}^{(t-1)}, \mathbf{U}^{(t-1)})$, obtain the optimal $\mathbf{A}^{(t)}$ by solving Problem $\mathcal{P}_{1-E1}$;
  With fixed $(\mathbf{A}^{(t)}, \mathbf{P}^{(t-1)}, \mathbf{U}^{(t-1)})$, obtain the optimal $\mathbf{F}^{(t)}$ by solving Problem $\mathcal{P}_{2-E1}$ and Problem $\mathcal{P}_{2-E2}$;
  With fixed $(\mathbf{A}^{(t)}, \mathbf{F}^{(t)}, \mathbf{U}^{(t-1)})$, obtain the optimal $\mathbf{P}^{(t)}$ by solving Problem $\mathcal{P}_{3-E1}$;
  With fixed $(\mathbf{A}^{(t)}, \mathbf{F}^{(t)}, \mathbf{P}^{(t)})$, obtain the optimal $\mathbf{U}^{(t)}$ by solving Problem $\mathcal{P}_4$;
  Calculate objective function value $V_{obj}^{(t)} = O(\mathbf{A}^{(t)}, \mathbf{F}^{(t)}, \mathbf{P}^{(t)}, \mathbf{U}^{(t)})$;
4: until $\frac{\left|V_{obj}^{(t)} - V_{obj}^{(t-1)}\right|}{V_{obj}^{(t-1)}} < \xi$ or $t > T_{max}$.

By using interior-point method, the complexity of solving Problem $\mathcal{P}_{1-E1}$ is $\mathcal{O}(t_1^{max}(NM)^{3.5})$ [28], [32], where t_1^{max} is the maximum iteration number of solving this problem. Similarly, when t_2^{max} and t_3^{max} are denoted the maximum iteration number of Problem $\mathcal{P}_{2-E1}$ and $\mathcal{P}_{2-E2}$, respectively. The complexity of them are expressed as $\mathcal{O}(t_2^{max}(N - I_U - I_R)^{3.5} + t_3^{max}(I_U J + I_R M)^{3.5})$, the complexity of solving Problem $\mathcal{P}_{3-E1}$ is $\mathcal{O}(t_3^{max}(I_U J + I_R M)^{3.5})$, and that of Problem $\mathcal{P}_4$ is $\mathcal{O}(\log(\frac{1}{\min\{\epsilon,\xi\}})\sqrt{2}(I_U + J + 1)^{0.5}[(I_U + 1)^4 + 2J^3])$. Hence, the total complexity of proposed Algorithm 1 is $\mathcal{O}(T_{max}t_1^{max}(NM)^{3.5} + t_2^{max}(N - I_U - I_R)^{3.5} + t_3^{max}(I_U J + I_R M)^{3.5} + t_3^{max}(I_U J + I_R M)^{3.5} + \log(\frac{1}{\min\{\epsilon,\xi\}})\sqrt{2}(I_U + J + 1)^{0.5}[(I_U + 1)^4 + 2J^3])$.

IV. Total transmit power minimization in C-RAN

According to the discussion in UAV-assisted C-RAN, the total transmit power of IoTDs in traditional C-RAN can be formulated as

$$\mathcal{P}^{'}: \min_{\mathbf{A}^{'},\mathbf{F}^{'},\mathbf{P}^{'},} \sum_{i\in\mathcal{N}} a_i^L p_i^E + \sum_{i\in\mathcal{N}}\sum_{m\in\mathcal{M}} a_{i,m}^R p_{i,m}^R \tag{54a}$$

$$\text{s.t.}\quad a_i^L \frac{F_i}{f_i} + \sum_{m\in\mathcal{M}} a_{i,m}^R \left(\frac{D_i}{r_{i,m}^R} + \frac{F_i}{f_{i,b}}\right) \le T, i\in\mathcal{N}, \tag{54b}$$

$$a_i^L + \sum_{m\in\mathcal{M}} a_{i,m}^R = 1, \tag{54c}$$

$$\sum_{i\in\mathcal{O}}\sum_{m\in\mathcal{M}} a_{i,m}^R f_{i,b} \le f_{max}^{BBU}, \tag{54d}$$

$$\sum_{i\in\mathcal{O}} a_{i,m}^R r_{i,m}^R \le C_m^F, m\in\mathcal{M}, \tag{54e}$$

$$a_i^L p_i^E + \sum_{m\in\mathcal{M}} a_{i,m}^R p_{i,m}^R \le P_{i,max}^{ue}, i\in\mathcal{N}, \tag{54f}$$

$$(1), (3), (11). \tag{54g}$$

where $\mathbf{A}^{'} = \{a_i^L, a_{i,m}^R\}_{i\in\mathcal{N},m\in\mathcal{M}}$, $\mathbf{F}^{'} = \{f_i, f_{i,b}\}_{i\in\mathcal{N}}$, $\mathbf{P}^{'} = \{p_i^E, p_{i,m}^R\}_{i\in\mathcal{N},m\in\mathcal{M}}$.

This problem is also non-convex due to the coupled optimization variables and the non-convex constraints set. We use BCD technique to decouple it into three subproblems and solve them iteratively in the following sections.

A. UE association optimization in C-RAN

With fixed computation variables $\mathbf{F}^{'}$ and transmit power $\mathbf{P}^{'}$, the IoTD association subproblem in C-RAN can be given by

$$\mathcal{P}_1^{'}: \min_{\mathbf{A}^{'}} \sum_{i\in\mathcal{N}} a_i^L p_i^E + \sum_{i\in\mathcal{N}}\sum_{m\in\mathcal{M}} a_{i,m}^R p_{i,m}^R \tag{55a}$$

$$\text{s.t.}\quad 0 \le a_i^L \le 1, 0 \le a_{i,m}^R \le 1, i\in\mathcal{N}, m\in\mathcal{M}, \tag{55b}$$

$$(11), (54\text{b}) - (54\text{f}). \tag{55c}$$

It is readily that Problem $\mathcal{P}_1^{'}$ is convex, which can be solved by using CVX.

B. Computation capacity optimization in C-RAN

By fixing UE association variables $\mathbf{A}^{'}$ and transmit power $\mathbf{P}^{'}$, the self computation capacity optimization subproblem is equal to Problem $\mathcal{P}_{2-E1}$ in Section III. According to Problem $\mathcal{P}^{'}$, the offloading computation capacity subproblem is simplified as a feasibility-check problem. After introducing slack variables $\mathbf{q} = [q_1, \cdots, q_N]$, it can be given by

$$\mathcal{P}_{2-E1}^{'}: \max_{\widehat{\mathbf{F}}^{'},\mathbf{q}} \|\mathbf{q}\|_1 \tag{56a}$$

$$\text{s.t.}\quad \frac{F_l}{T - \frac{D_l}{r_{l,m}^R}} \le f_{l,b} - q_l, l,m\in\mathcal{I}_R^{'}, \tag{56b}$$

$$\mathbf{q} \ge 0, (54\text{d}), \tag{56c}$$

where $\mathcal{I}_R^{'} = \{m\in\mathcal{M} | a_{i,m}^R = 1\}$, $\widehat{\mathbf{F}}^{'} = \{f_{l,b}\}_{l\in\mathcal{I}_R^{'}}$.

Then, this problem is convex and can be used to obtain the suboptimal solutions of offloading computation capacity.

C. Transmit power optimization in C-RAN

Fixing IoTD association variables $\mathbf{A}^{'}$ and computation variables $\mathbf{F}^{'}$, Problem $\mathcal{P}^{'}$ can be simplified as transmit power subproblem, which is given by

$$\mathcal{P}_3^{'}: \min_{\widehat{\mathbf{P}}^{'}} \sum_{l,m\in\mathcal{I}_R^{'}} p_{l,m}^R \tag{57a}$$

$$\text{s.t.}\quad \sum_{l,m\in\mathcal{I}_R^{'}} r_{l,m}^R \le C_m^F, \tag{57b}$$

$$\frac{D_m}{r_{l,m}^R} + \frac{F_m}{f_{m,b}} \le T, l,m\in\mathcal{I}_R^{'}, \tag{57c}$$

$$p_{l,m}^R \le p_{l,max}^{ue}, l,m\in\mathcal{I}_R^{'}. \tag{57d}$$

Due to the non-convex constraints (57b) and (57c), it is very challenge to solve. Similarly, we transform it into a approximated convex problem, which is given by

$$\mathcal{P}_{3-E1}^{'}: \min_{\widehat{\mathbf{P}}^{'}} \sum_{l,m\in\mathcal{I}_R^{'}} p_{l,m}^R \tag{58a}$$

$$\text{s.t.}\quad \log_2\Big(\sum_{l=1}^{I_R^{'}} p_{l,m}^R h_{l,m}^R + o^2\Big) - (C_{l,m}^R)^{ub} \ge \frac{D_l}{B(T - \frac{F_l}{f_{l,b}})}, l,m\in\mathcal{I}_R^{'}, \tag{58b}$$

$$(e), (57\text{d}). \tag{58c}$$

where (e) denotes $\frac{C_m^F}{B} \ge \sum_{l,m\in\mathcal{I}_R^{'}} \left[(D_m^R)^{ub} - \log_2\Big(\sum_{k=1,k\ne l}^{I_R^{'}} p_{k,m}^R h_{k,m}^R + o^2\Big)\right]$.

This subproblem is convex, which can be solved by using CVX.

D. Overall algorithm and convergence

According to the above discussions, we propose an iterative algorithm to solve Problem $\mathcal{P}^{'}$, which is shown in Algorithm 3. Similar to Algorithm 2, Algorithm 3 is non-increasing by iteratively updating IoTD association, computation capacity and transmit power, which make sure it converges. The complexity of it mainly depends on solving three subproblems. The maximum iteration number of solving Problem $\mathcal{P}_1^{'}$, $\mathcal{P}_{2-E1}^{'}$ and $\mathcal{P}_{3-E1}^{'}$ are denoted by $t_1^{'max}$, $t_2^{'max}$ and $t_3^{'max}$, respectively. Then, the complexity of it is $\mathcal{O}(t_1^{'max}(NM)^{3.5})$. The complexity of Problem $\mathcal{P}_{2-E1}^{'}$ is $\mathcal{O}(t_2^{'max}(I_R^{'})^{3.5})$, and the complexity of Problem $\mathcal{P}_{3-E1}^{'}$ is $\mathcal{O}(t_3^{'max}(I_R^{'}M)^{3.5})$. Finally, the complexity of Algorithm 3 is $\mathcal{O}(t_1^{'max}(NM)^{3.5} + t_2^{'max}(I_R^{'})^{3.5} + t_3^{'max}(I_R^{'}M)^{3.5})$.

V. Simulation Results

In this section, simulation results are provided to demonstrate the effectiveness of the proposed algorithm. We consider an UAV-assisted C-RAN system with $J = 3$ UAVs and $M = 3$ ground RRHs. The bandwidth of the system is $B = 1$ MHz. We set the altitude as $H = 20$ m for all UAVs. Ground RRHs and IoTDs are uniformly and randomly distributed in a communication cell with radius $R = 1000$ m. The transmit power

Algorithm 3 Iterative Algorithm for Total Power Minimization in C-RAN

1: initialize feasible $\mathbf{A}^{'(0)}$, $\widehat{\mathbf{F}}^{'(0)}$, $\widehat{\mathbf{P}}^{'(0)}$, the iteration number $t=0$, maximum iteration number T_{max}, the tolerance parameter ξ.

2: Calculate objective function value
$V_{obj}^{'(0)} = O(\mathbf{A}^{'(0)}, \widehat{\mathbf{F}}^{'(0)}, \widehat{\mathbf{P}}^{'(0)})$, where $O(\mathbf{A}, \mathbf{F}, \mathbf{P}, \mathbf{U})$
$= \sum_{i\in\mathcal{N}} a_i^L p_i^E + \sum_{i\in\mathcal{N}} \sum_{m\in\mathcal{M}} a_{i,m}^R p_{i,m}^R$.

3: repeat

Set $t=t+1$;

With fixed $\widehat{\mathbf{F}}^{'(t-1)}$ and $\widehat{\mathbf{P}}^{'(t-1)}$, obtain the optimal $\mathbf{A}^{'(t)}$ by solving Problem $\mathcal{P}_1^{'}$;

With fixed $\mathbf{A}^{'(t)}$ and $\mathbf{P}^{'(t-1)}$, obtain the optimal $\mathbf{F}^{'(t)}$ by solving Problem $\mathcal{P}_{2-E1}$ and Problem $\mathcal{P}_{2-E1}^{'}$;

With fixed $\mathbf{A}^{'(t)}$ and $\mathbf{F}^{'(t)}$, obtain the optimal $\mathbf{P}^{'(t)}$ by solving Problem $\mathcal{P}_{3-E1}^{'}$;

Calculate objective function value
$V_{obj}^{'(t)} = O(\mathbf{A}^{'(t)}, \mathbf{F}^{'(t)}, \mathbf{P}^{'(t)})$;

4: until $\frac{\left|V_{obj}^{'(t)} - V_{obj}^{'(t-1)}\right|}{V_{obj}^{'(t-1)}} < \xi$ or $t > T_{max}$.

of UAV sets as $p^{UAV} = 100$ W, the maximum transmit power of IoTD is $p_{i,max}^{ue} = 30$ dBm, the channel power gain at the reference distance 1 m is set as $\beta^U = \beta^R = 10^{-5}$, the noise power $\sigma^2 = -114$ dBm. We assume equal offloading tasks for all IoTDs, i.e. $D_i = D = 10^{12}$ bit, $F_i = F = 10^5$ CPU cycles and the maximal latency $T = 1$ s. The computation capacity of BBU and IoTD are set as $f_{max}^{BBU} = 10^9$ cycles/s and $f_{i,max}^L = 10^5$ cycles/s [28], [33], respectively. For the channel between the lth IoTD and the mth ground RRH, the contained large-scale path loss in dB can be denoted by $\mathrm{PL} = \mathrm{PL}_0 - 10\mu\log_{10}(\frac{d_{l,m}}{d_0})$, where $\mathrm{PL}_0 = -30$ dB denotes the path loss at the reference distance of $d_0 = 1$ m, $\mu = 3.75$ is the path loss between IoTDs and the ground RRHs and $d_{l,m}$ denotes the distance between them.

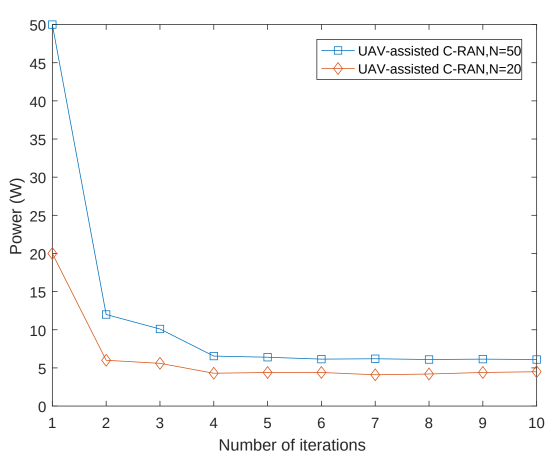

Fig. 2. Convergence behavior of the proposed algorithm

Fig. 2 presents the convergence performance for the proposed algorithm under different IoTD number. It is readily to know that the proposed algorithm converges very fast, which demonstrates the effectiveness of the proposed Algorithm 1. Specifically, the total power at the initial point are very high, which is equal to the sum of all IoTDs' maximum transmit power. After several iterations, the total power is greatly decreased, and even when the IoTD number is very large, the proposed algorithm still can converge in several iterations.

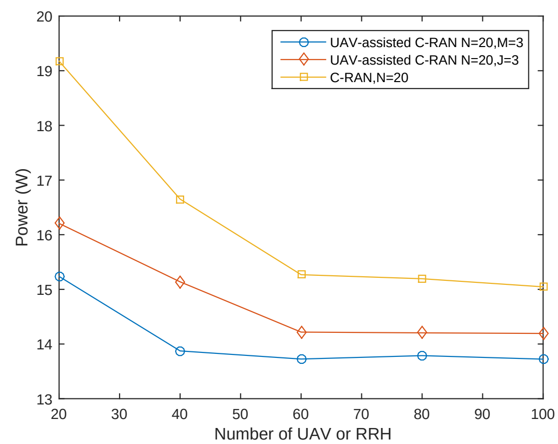

Fig. 3. Total power of the system versus the number of UAV or RRH.

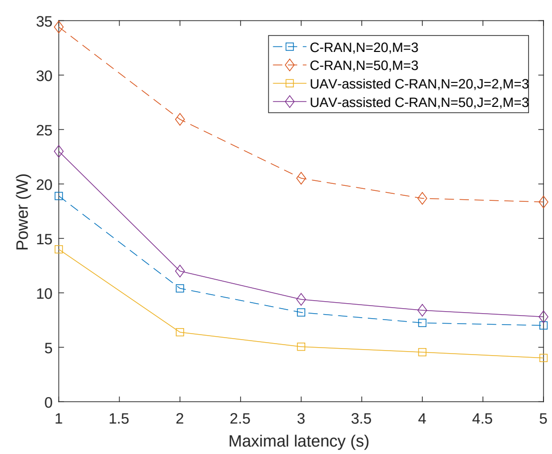

Fig. 4. Total power of the system versus the maximal latency T.

The total power of all IoTDs versus the maximal latency is illustrated in Fig. 4. It is easy to seen that the total power decreases with the maximal latency, which means IoTDs can transmit tasks by using low power under the requirement of large maximal latency. Moreover, this results become more obvious when the number of IoTD is large. In this figure, the minimum power of the UAV-assisted C-RAN by using proposed algorithm is much lower than traditional C-RAN, which is more obvious when the number of IoTD is large. For example, in C-RAN, the total power consumption is 18.35 W when the number of IoTD is 50 and $T=5$ s. After using the proposed Algorithm 1 in the UAV-assisted C-RAN system, the total power is decreased to 7.8W, but the total power only decreases 2.9 W when the number of IoTD is 20.

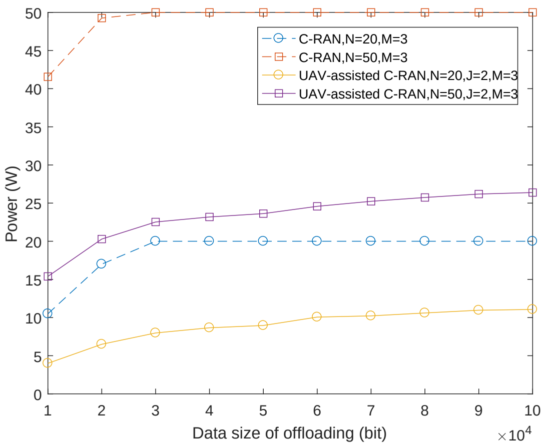

Fig. 5. Total power of the system versus the data size D.

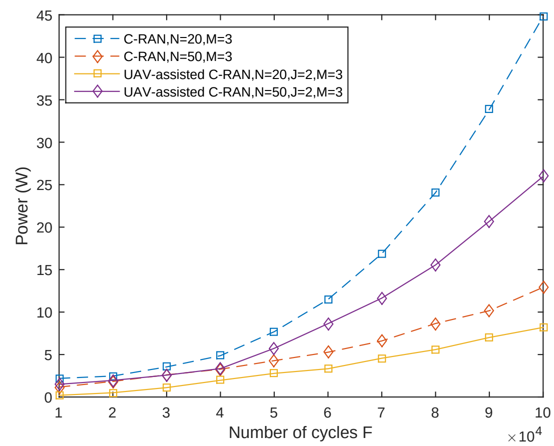

Fig. 6. Total power of the system versus the number of CPU cycles F.

Fig. 5 shows the total power versus the data size of IoTDs' tasks. It can be seen that the total power increases with the growth of data size because more data needs more transmit power and computation capacity to meet the latency requirements. Besides, with the increase of IoTDs' number and data size, they need much more power to satisfy the latency demands. Especially, when the data size becomes large, all IoTDs need to use full power to deal with their tasks in C-RAN system but the total power is decreased to 26.39 W when the number of IoTD is 50 in the UAV-assisted C-RAN system by using the proposed algorithm. Furthermore, the proposed algorithm in the UAV-assisted C-RAN still has good performance even when the number of IoTD is small.

Fig. 6 shows the total power of all IoTDs versus the CPU cycles for the tasks of IoTDs that need to be executed. From this figure, we can seen that the total power consumption increases with the total number of CPU cycles of tasks. This is mainly because IoTDs can not execute the large number of CPU cycles of tasks as well as satisfying the maximal latency and they need more power to offload the tasks to the BBU pool, which is more obvious when the number of IoTD is very large. Moreover, by using the proposed algorithm in the UAV-assisted C-RAN, the total power consumption can be effectively decreased.

Fig. 7 illustrates the running time of the proposed algorithm in UAV-assisted C-RAN system and proposed algorithm in traditional C-RAN versus different number of UAV or RRH. It can be seen that the running time of all the proposed algorithms in different systems increases with the number of UAV or RRH, especially when the number of UAV or RRH becomes larger. Furthermore, considering the proposed algorithm in UAV-assisted C-RAN system, the running time of increasing the number of UAV is larger than that of increasing the number of RRH. This is because the UAVs location optimization needs extra execution time.

Fig. 8 presents the convergence of the proposed algorithm in UAV-assisted C-RAN system under different benchmark schemes. It readily to know that the power consumption becomes larger when any of the subproblems is lacking than

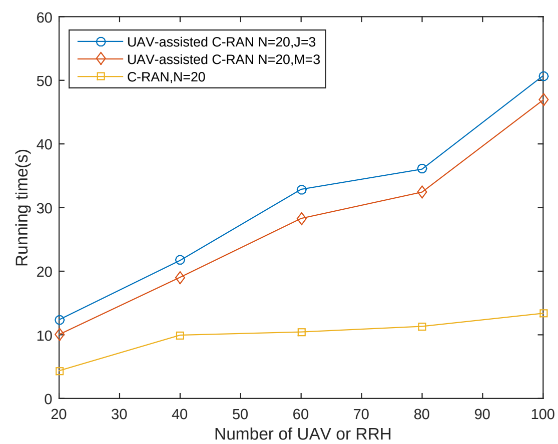

Fig. 7. Running time versus different number of UAV or RRH in different systems.

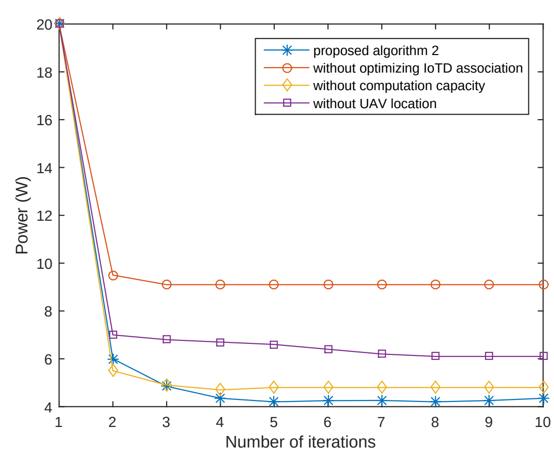

Fig. 8. Running time versus different number of UAV or RRH in different systems.

the proposed algorithm. Specifically, when considering the proposed algorithm without optimizing IoTD association, the power consumption is the largest of all the schemes. Therefore, the IoTD association is the most important measurement to decrease the power consumption of all IoTDs. After UAV location optimization, many IoTDs can choose the most appropriate UAV as relay to offload tasks, which can fully use the LoS channels of UAVs. Due the total transmit power of IoTDs depends on the IoTD association and computation capacity allocation, it is meaningless for the proposed algorithm to ignore the importance of the transmit power of IoTDs. We also obtain that the computation capacity optimization slightly reduces the power consumption.

VI. Conclusions

In this paper, we investigated the total power minimization problem in an UAV-assisted C-RAN system. In order to deal with this non-convex optimization problem, we proposed an effective iteration algorithm that was based on the BCD technique. we applied this technique to decouple the original problem into four subproblems. For the user association and computation capacity allocation subproblems, we transformed them into convex optimization problems by relaxing the non-convex constraints and introducing the slack variables. Moreover, after using SCA technique, the transmit power optimization of IoTD was approximated by a convex optimization problem. For the UAV location planning subproblems, we introduced slack variables to transform this feasibility-check subproblem into a convex optimization problem. Simulation results demonstrated that the proposed algorithm can greatly reduce the total consumption power of IoTDs, especially when the number of IoTD is very large.

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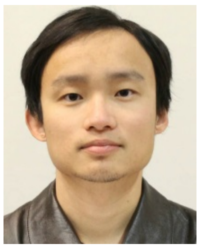

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