Energy Optimization for Cellular-Connected Multi-UAV Mobile Edge Computing Systems with Multi-Access Schemes

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Abstract—In this paper, a cellular-connected unmanned aerial vehicles (UAV) mobile edge computing system is studied in which the multiple UAVs are served by terrestrial base station (TBS) for computation task offloading. Our goal is to minimize the total UAVs energy consumption, including propulsion energy, computation energy and communication energy, while ensuring that the total number of bits of UAVs are completely computed. For tackling the large amount of bits for computation, we propose a resource partitioning strategy where one portion of tasks is migrated to TBS for computation and the other portion of tasks is locally computed at UAV. For deeply comprehending the impacts of access manners on the system performance, we consider four access schemes in the uplink transmission, i.e., time division multiple access (TDMA), orthogonal frequency division multiple access (OFDMA), One-by-One access and non-orthogonal multiple access (NOMA). The problem of jointly optimizing bit allocation, power allocation, resource partitioning as well as UAV trajectory under TBS’s energy budget is formulated and tackled by means of successive convex approximation (SCA) technique. The numerical results show that the proposed schemes save much energy compared with benchmark schemes.

Index Terms—Mobile edge computing, UAV trajectory, bit allocation, power allocation, resource partitioning, energy minimization.

I. INTRODUCTION

Recently, the use of unmanned aerial aircraft (UAV) as mobile vehicle is emerging as an effective complementary technique for future fifth generation due to the UAV’s flexible mobility [1]–[6]. In particular, the UAV can play a key role in enabling wireless connectivity in various scenarios, e.g., UAV-aided ubiquitous coverage, UAV-aided relaying and UAV-aided information dissemination, etc [7]–[15]. In some hot spots or in some harsh areas where the base stations are difficult to be deployed, by means of using multi-UAV deployed as aerial base stations (ABSs) has become an promising solution to provide seamless wireless coverage within the serving area [7]–[9]. The UAV used as mobile relaying provides new opportunities for system enhancement compared with conventional static relaying, since it can successively adjust its location for experiencing good channel condition [10], [11]. In addition, the UAV can be used for dispatching to disseminate data to the sensor nodes in internet of thing (IoT) scenario [12]–[15].

As briefly reviewed above, the prior works about UAV assume that they use UAV as either mobile relaying or ABS. However, the UAV used as flying cloudlet in which the small cloudlet has an abundance of computation resource as well as communication resource is obtaining great attention [16]–[20]. In the traditional cellular network, the processor unit always resides in the cloud and the distance between mobile user and cloud is always long, which may cause long latency and power consumption for transmission in the uplink when the mobile user located in cellular edge. In order to reduce the latency and power consumption, some researchers have been paying attention to dealing with it. However, by far, only a few works have studied the UAV-enabled mobile edge computing system. The authors in [16] proposed a UAV-mounted cloudlet scenario where the UAV provided offloading opportunities to a single mobile user. The goal of [16] was to minimize the mobile energy consumption by optimizing bit allocation with a pre-determined UAV trajectory. The same authors extended their work [16] into a more general case where the UAV was employed as cloudlet to offer computation offloading opportunities to multiple mobile users [17]. The [17] aimed at minimizing the total of mobile users energy consumption by jointly optimizing bit allocation and UAV trajectory. For maintaining the sustainable offloading task, a UAV-enabled wireless powered mobile edge computing system was studied in [19]. Specifically, [19] considered a scenario where the energy transmitter and cloudlet are mounted on UAV, the UAV firstly transmitted energy to multiple mobile users and then mobile users exploited the harvested energy for computation tasks offloading. In order to extend the coverage in the cellular networks, a cellular-connected UAV communication has being proposed as a promising solution where the UAV is integrated into cellular networks as a new mobile user [2], [18], [21], [22]. In addition, the emerging diverse mobile applications such as virtual reality (VR), high definition videos, mobile online gaming, etc., which require low latency and high computation capability. To tackle this issue, the work in [18] established a cellular-connected UAV networks, the goal of this work was to minimize the UAV’s mission completion time by jointly optimizing UAV trajectory and time allocation.

However, all the above mentioned works have not addressed the energy consumption problem of UAVs for computation tasks offloading. On the one hand, due to the on-board battery capacity is constrained by the limited size of UAVs, the energy consumption of UAVs becomes a huge challenging in a cellular-connected UAV system. Therefore, how to prolong the UAV flying time become an open problem. It should be pointed out that we should carefully consider three parts of energy consumption of UAV, including communication-
related energy consumption, computation energy consumption and propulsion-related energy consumption [13], [23]–[28]. On the other hand, for deeply comprehending the impacts of access manners on the system performance, the multi-access schemes should be carefully designed. Based on this fact, in this paper, we study a cellular-connected UAV system where multi-UAV simultaneously communicate with one TBS for computation task offloading under different access schemes. Different from previous works [16]–[19] where the authors assume that the computation tasks can be completely migrated from mobile users to TBS for computing, whereas it will not work as the number of bits for computing is very large. Indeed, the number of bits used for offloading for computing is constrained by many factors, such as the TBS energy budget, UAV transmit power, UAV-TBS channel condition, etc. For this, we propose a resource partitioning strategy where one portion of tasks is migrated to TBS for computation in the uplink transmission and the other portion of tasks is locally computed at UAV. Based on these, our goal is to minimize the total UAVs energy consumption while ensuring that the total number of bits of UAVs are completely computed in a given horizon time. Since the formulated problem is in a non-convex form, which cannot be efficiently solved by the standard optimization technique. To tackle this non-convex problem, we obtain a sub-optimal solution by leveraging successive convex approximation (SCA) technique. To the best of our knowledge, it is the first work to investigate the optimization of offloading process from multi-UAV to TBS by jointly considering the communication-related energy consumption, local computation energy consumption and propulsion-related energy consumption. The main contributions of this paper can be summarized as follows:

- We study a model for multi-UAV mobile edge computing system, where the tasks at UAVs are migrated to TBS for computation. For deeply comprehending the impacts of access manners on the system performance, we present four access schemes in the uplink transmission in our model, i.e., time division multiple access (TDMA), orthogonal frequency division multiple access (OFDMA), One-by-One access and non-orthogonal multiple access (NOMA). An energy minimization of UAVs is then formulated to jointly optimize bit allocation, UAV trajectory, UAV power allocation and resource partitioning with a given horizon time, subject to practical UAV mobility, transmit power and bit-casuality constraints.

- For tackling the large number of bits for computation, we propose a resource partitioning strategy where one portion of tasks is migrated to TBS for computation in the uplink transmission and the other portion of tasks is locally computed at UAV, which has been verified the effectiveness of this strategy in Section VII.

- Since the formulated problems are in different forms under different access schemes, we solve these formulated problems separately for different access schemes. For TDMA and OFDMA schemes, we obtain a sub-optimal solution by leveraging SCA technique. For One-by-One and NOMA schemes, we decompose the original problem into two subproblems, and develop an efficient iterative algorithm by optimizing the two subproblems alternately. The numerical results show that our proposed four schemes save a large amount of energy compared with propulsion minimization scheme. What’s more, while the NOMA scheme saves more energy consumption of UAVs compared with TDMA, OFDMA and One-by-One scheme, the successive interference cancellation (SIC) technique used for NOMA, which may bring an additional interference and implementation complexity of NOMA.

The rest of this paper is organized as follows. Section II describes the system model and introduces the energy consumption of UAV in mathematical expression. In Section III, we formulate the UAV energy consumption minimization problem based on TDMA scheme, and obtain a sub-optimal solution by applying SCA technique. In Section IV, we formulate the UAV energy consumption minimization problem based on OFDMA scheme, and obtain a sub-optimal solution by applying SCA technique. In Section V, we formulate the UAV energy consumption minimization problem based on NOMA scheme, and obtain a sub-optimal solution by applying SCA technique. In Section VI, we formulate the UAV energy consumption minimization problem based on One-by-One scheme, we decompose the original problem into two subproblems, and develop an efficient iterative algorithm by optimizing the UAV trajectory and UAV-TBS scheduling alternately. In Section VII, we formulate the UAV energy consumption minimization problem based on NOMA scheme, we decompose the original problem into two subproblems, and develop an efficient iterative algorithm by optimizing the UAV trajectory and UAV transmission power alternately. In Section VII, the simulation results are given to validate the performance of our proposed schemes. Finally, we conclude the paper in Section VIII.
II. SYSTEM MODEL

As shown in Fig. 1, we consider an uplink transmission scenario where a set $K$ of $K$ single-antenna UAVs are serviced by one single-antenna TBS for tasks offloading. We study the optimization of offloading process from the UAVs to TBS with the goal of minimizing the total energy consumption of all UAVs for a finite time horizon $H$. In Fig. 1, we can see that one portion of total bits of UAV $k$, $p_k$, is computed locally at UAV $k$, and the other portion of bits, $1 - p_k$, is migrated to TBS for computation. In particular, $p_k = 0$ means that all the number of bits at UAV $k$ are completely migrated to TBS for computation, and $p_k = 1$ indicates that all the number of bits at UAV $k$ are used for locally computing.

For the sake of mathematical description simplicity, we consider a three-dimensional Cartesian coordinate system, with all dimensions being measured in meters, where the horizontal coordinate of UAV $k$ at time instant $t$ is denoted by $q_k(t) = (x_k(t), y_k(t))^T \in \mathbb{R}^{2 \times 1}$. Without loss of generality, the TBS is located at origin of the horizontal coordinate, denoted as $w$. We assume that the UAVs move at a fixed altitude $H$ under the initial/final location, maximization UAV speed and acceleration constraints. For tackling the problem more tractable, the continuous horizontal time $T$ is equally divided into $N + 1$ time slots with each slot duration $\delta$. As such, the UAV trajectory $q_k(t)$, UAV speed $v_k(t)$, UAV acceleration $a_k(t)$ over time $T$ can be approximately denoted by $N + 2$-length sequences as $\{q_k[n]\}_{N+1}^{N+1}$, $\{v_k[n]\}_{N+1}^{N+1}$, $\{a_k[n]\}_{N+1}^{N+1}$, where $q_k[n] = q_k(n\delta)$, $v_k[n] = v(n\delta)$, $a_k[n] = a_k(n\delta)$, $k \in K$.

It can be assumed that the channels between the UAVs and TBS are dominated by line-of-sight (LoS) without small-scale fading, which have been verified by taking measurements in [29] and [30]. Thus, the channel power gain from UAV $k$ to TBS in the uplink at time slot $n$ can be modeled as [10], [14], [24],

\[ h_k[n] = \frac{\beta_0}{d_k[n]} = \frac{\beta_0}{\|q_k[n] - w\|^2 + H^2}, \]

where $d_k[n]$ denotes the distance between UAV $k$ and TBS at time slot $n$, $\beta_0$ represents the reference channel gain at $d = 1m$.

Next, we discuss the energy consumption models of UAV. As it is mentioned before, the total energy consumption of UAV consists of three parts, i.e., UAV's computation energy, UAV’s communication energy and UAV's propulsion energy, which are described in below.

1) Execution Energy Consumption Model: The energy consumption of local computation is directly determined by the CPU workload $W$, which is related to the data size and the complexity of application algorithm [31], [32], and is defined as

\[ W = LC, \]

where $L$ denotes the input data size, and $C$ represents the complexity of the application, which has been shown that follows Gamma distribution [32], [33]. Three factors can be contributed to the CPU power consumption including dynamic power, short circuit power and leakage power. As stated in [34], the energy consumption of CPU is dominated by dynamic power and other two factors can be neglected. In order to minimize the energy consumption of CPU power (dynamic power), the optimal clock-frequency scheduling in each CPU cycle is achieved in [32], [35]. Let denote the number of bits of UAV $k$ as $L_k$, $k \in K$. Based on [32], [35], the energy computation consumption model with data size $\rho_k L_k$ and completion execution time $T$ can be expressed as

\[ E_{comp}^k = G(\rho_k L_k)^3, \]

where the coefficient $G$ is a constant that accounts for the effective switched capacity and application execution completion probability. As we can see from formula (3), the increased number of bits or the reduced time $T$ will drastically increase the computation energy consumption.

2) Communication Energy Consumption Model for Offloading: The required transmission power $p_k[n]$ of UAV $k$ for completely transmitting $L_k[n]$ bits in the uplink within time slot $n$ should satisfy Shannon theory, we thus have

\[ B\delta \log_2 \left(1 + \frac{p_k[n]h_k[n]}{\sigma^2}\right) = L_k[n], \]

where $B$ denotes the system bandwidth and $\sigma^2$ is the additive white Gaussian noise power. After some algebraic manipulations, the transmit power $p_k[n]$ can be expressed as

\[ p_k[n] = \left(2^{\frac{L_k[n]}{\delta B}} - 1\right) \frac{\sigma^2}{h_k[n]}. \]

As such, the required energy of UAV $k$ for completely transmitting $L_k[n]$ bits within time slot $n$ can be obtained as

\[ E_{com}^k[n] = p_k[n]\delta, \]

3) Propulsion-related Energy Consumption of UAV for Flying: Based on the model in [17], [24], the total UAV’s propulsion energy consumption of UAV over $T$ can be expressed as

\[ E_{fly}^k = \sum_{n=1}^{N} \left(c_1 \|v[n]\|^3 + c_2 \frac{|v[n]|}{\|v[n]\|} \left(1 + \frac{\|a[n]\|^2}{g^2}\right)\right) \delta + \Delta p, \]

where $\Delta p = \frac{m}{\delta \Delta t} \left(\|v(T)\|^2 - \|v(0)\|^2\right)$ represents the change of UAV’s kinetic energy, which is an invariant scalar with fixed final/initial location of UAV, and $c_1 > 0$ and $c_2 > 0$ are constants which are related to the UAV’s wing area, load factor and wing span efficiency etc. Without loss of generality, we assume that the UAV’s initial speed and final speed are same, thus, $\Delta p$ can be omitted in term (7). In addition, the formula (7) shows that the UAV’s propulsion energy is related to UAV velocity and acceleration. Especially, as UAV hovers over a fixed location, i.e., $\|v[n]\| = 0$, then $E_{fly}^k$ tends to be infinite.

In this paper, four access frame structures are discussed, namely TDMA, OFDMA, One-by-One access and NOMA. For the frame structure of TDMA scheme, each time slot duration $\delta$ is equally divided into $K$ sub-slot with duration $\delta_1$, i.e., $\delta_1 = \delta/K$. However, each UAV shares the same bandwidth $B$ with each sub-slot; For the frame structure of OFDMA scheme, each UAV occupies the same time slot...
duration, whereas shares the bandwidth $B/K$; For the frame structure of One-by-One scheme, we assume that at most one UAV can be scheduled within each time slot; For the frame structure of NOMA scheme, each UAV shares the same time and same bandwidth.

In addition, it should be mentioned that the bit-casuality in the processed phase at TBS must be carefully designed, i.e., the TBS can only process the bits that have already been received from UAVs [17], [19]. Without loss of generality, we assume that the processing delay at TBS is one slot. Furthermore, due to the fact that the size of computation outcome data in general is much smaller than that of the computation input data. Thus, the downlink transmission for bit allocation is ignored in this paper [18], [36], [37].

III. ENERGY MINIMIZATION FOR TDMA SCHEME

In this section, we tackle the problem of minimizing the total energy consumption of UAVs for offloading by assuming the system operated in TDMA scheme. Specifically, the joint bit allocation, resource partitioning, power allocation and UAV trajectory under the TBS’s budget energy and UAV mobility constraints are optimized for minimizing the total energy consumption of UAVs. As each time slot $\delta$ is equally split into $K$ sub-slot with duration $\delta_1 (\delta_1 = \delta / K)$, the communication-related energy consumption of UAV $k$ within time slot $n$, denoted as $E_{k,n}^{\text{com}}$, can be obtained by substituting the $\delta$ in (6) with $\delta_1$. For notation brevity, we define bit allocation as $A = \{L_k [n], L_{u,k} [n+1]\}_{n=1}^{N-1}$, UAV trajectory as $B = \{q_k [n], v_k [n], a_k [n]\}_{n=0}^{N+1}$, set $N$ $\in \{1, \cdots, N - 1\}$ and set $N_1$ $\in \{0, \cdots, N\}$. In this case, the energy minimization problem can be reformulated as

$$
(P0): \min_{\{A,B,\}} \sum_{k=1}^{K} E_{k}^{fly} + \sum_{k=1}^{K} E_{k}^{comp} + \sum_{k=1}^{K} \sum_{n=1}^{N-1} E_{k,n}^{\text{com}} \quad \text{(8a)}
$$

s.t.

$$
\sum_{n=1}^{N-1} G \left( \sum_{k=1}^{K} L_{u,k} [n + 1] \right) \delta_1^3 \leq E_{total} \quad \text{(8b)}
$$

$$
\log_2 \left( 1 + \frac{p_k[n] h_k[n]}{\sigma^2} \right) \geq \frac{L_k[n]}{\delta_1 B}, \forall k, n \in \mathcal{N}, \quad \text{(8c)}
$$

$$
\sum_{i=1}^{n} L_{u,k} [i + 1] \leq \sum_{i=1}^{n} L_k [i], n \in \mathcal{N}, \quad \text{(8d)}
$$

$$
\sum_{n=1}^{N-1} L_k [n] = (1 - \rho_k) L_k, \forall k, \quad \text{(8e)}
$$

$$
\sum_{n=1}^{N-1} L_{u,k} [n + 1] = (1 - \rho_k) L_k, \forall k, \quad \text{(8f)}
$$

$$
q_k [n + 1] = q_k [n] + v_k [n] \delta + \frac{1}{2} a_k [n] \delta^2, \forall k, n \in \mathcal{N}_1, \quad \text{(8g)}
$$

$$
v_k [n + 1] = v_k [n] + a_k [n] \delta, \forall n \in \mathcal{N}_1, \quad \text{(8h)}
$$

$$
q_k [0] = q_k, q_k [N + 1] = q_k, \forall k, \quad \text{(8i)}
$$

$$
||v_k[n]|| \leq V_{\max}, ||a_k[n]|| \leq a_{\max}, n \in \mathcal{N}_1, \quad \text{(8j)}
$$

$$
0 \leq \rho_k \leq 1, \forall k, \quad \text{(8k)}
$$

$$
0 \leq p_k[n] \leq P_{\max}, \forall k, n \in \mathcal{N}, \quad \text{(8l)}
$$

$$
L_k [n] \geq 0, \quad L_{u,k} [n + 1] \geq 0, \forall k, n \in \mathcal{N}. \quad \text{(8m)}
$$

Eq. (8b) represents the TBS energy budget allocated to UAVs for computation. Note that in (P0), the constraint (8c) is obtained from (4) by replacing the equality sign with inequality constraints. Indeed, this will not change the optimal solution to problem (P0). To see this, suppose that the optimal solution to problem (P0) is satisfied with the strict inequality, one can always decrease the power allocation $p_k[n]$ to obtain a strictly less objective value. As a result, at the optimal solution to (P0), the constraint (8c) must be satisfied with equality. (8d) denotes the bit-casuality constraint. (8e) represents that the total number of bits for transmission in the uplink, and (8f) denotes that the transmitted bits are completely processed by TBS. (8g) represents the UAV trajectory constraints. (8h)-(8j) are the feasible and boundary constraints of the optimization variables. We can see that the constraints set (8b) and (8d)-(8j) are all convex, however, the constraint set (8c) and objective function are not convex, which cannot be solved by standard convex technique. To proceed, we first introduce slack variable $\{\tau_n\}$ in term $E_{k,n}^{fly}$, then the UAV’s propulsion energy consumption, denoted as $E_{k,n}^{fly}$, can be reformulated as

$$
E_{k,n}^{fly} = \left( c_1 ||v[n]||^3 + c_2 \frac{||a[n]||^2}{\tau_n} + 1 + \frac{||a[n]||^2}{\tau_n^2} \right) \delta, \quad \text{(9)}
$$

with additional constraint

$$
||v[n]||^2 \geq \tau_n^2, n \in \{1, \cdots, N\}, \quad \text{(10)}
$$

$$
\tau_n \geq 0, n \in \{1, \cdots, N\}. \quad \text{(10)}
$$
However, the new first constraint of (10) is not convex. To tackle this non-convex constraint, we develop an SCA technique. Specifically, with a given local point \( \{ v_i[n] \} \) over \( l \)-th iteration, we have
\[
\|v[n]\|^2 \geq \|v_i[n]\|^2 + 2v_i^T[n](v[n] - v_i[n]) \overset{a}{=} f^{ib}(v[n]),
\]
where (11) follows from the fact that its first-order Taylor expansion of convex function is a global under-estimator [38]. It can be seen that \( f^{ib}(v[n]) \) is a linear function with respect to \( v[n] \), which is convex. As such, the constraint (10) can be rewritten as
\[
f^{ib}(v[n]) \geq \tau_n^2, n \in \{1, \cdots, N\},
\]
and
\[
\tau_n \geq 0, n \in \{1, \cdots, N\}.
\]
In the next, we tackle the non-convex constraint (8c). To this end, we first relax constraint (8c) by introducing slack variable \( \{ y_k[n] \} \), which can reformulate constraint (8c) as
\[
\log_2 \left( 1 + \frac{p_k[n]}{y_k[n] + H^2} \right) \geq \frac{L_k[n]}{\delta B}, \forall k, n \in \mathcal{N}
\]
and
\[
\|q_k[n] - w\|^2 \leq y_k[n], \forall k, n \in \mathcal{N},
\]
where \( \gamma_0 = \frac{\delta B}{\sigma^2} \) denotes the reference signal-to-noise (SNR). Similarly, by taking the first-order Taylor expansion of left hand side (LHS) in constraint (13) with given local point \( y_{l,k}[n] \) over \( l \)-th iteration, the following global lower bound can be obtained as
\[
\log_2 \left( 1 + \frac{p_k[n]}{y_k[n] + H^2} \right) \geq \frac{A_k[n] - r_k^{up}[n]}{b^{ib}[n]},
\]
where \( A_k[n] = \log_2 \left( y_k[n] + H^2 + p_k[n] \gamma_0 \right) \) and \( r_k^{up}[n] = \log_2 \left( y_{l,k}[n] + H^2 + \log_{10} \left( \frac{y_k[n]}{y_{l,k}[n]} \right) (y_k[n] - y_{l,k}[n]) \right) \).

By replacing the non-convex objective function and (8c) of (P0) with their corresponding lower bounds at given local point obtained above, we have the following optimization problem
\[
(P0.1) : \min_{\{A,B,y_k[n]\},\{p_k,p_k[n],\tau_n\}} \sum_{k=1}^{K} \hat{E}_k^{fly} + \sum_{k=1}^{K} E_k^{comp} + \sum_{k=1}^{K} \sum_{n=1}^{N-1} \hat{E}_k^{com}[n]
\]
s.t. \( (8b), (8d)-(8j), (12), (14), (15) \).

It can be verified that the problem (P0.1) is a convex optimization problem, which can be efficiently solved by standard convex technique. By successively updating the local point at each iteration via solving (P0.1), an efficient algorithm is obtained for the non-convex optimization problem (P0).

IV. ENERGY MINIMIZATION FOR OFDMA SCHEME

In this section, we study the design of bit allocation, power allocation, resource partitioning and UAV trajectory for OFDMA scheme. In OFDMA system, the total bandwidth \( B \) is equally divided into \( K \) sub-bandwidth, each with a bandwidth of \( B_0 = B/K \). The formulated problem, denoted as P1, can be obtained by substituting the new bandwidth allocation \( B = B_0 \) and time allocation \( \delta_1 = \delta \) in P0. We summarized the resulting problem as
\[
(P1) : \min_{\{A,B\}} \sum_{k=1}^{K} E_k^{fly} + \sum_{k=1}^{K} E_k^{comp} + \sum_{k=1}^{K} \sum_{n=1}^{N-1} \hat{E}_k^{com}[n]
\]
s.t. \( \log_2 \left( 1 + \frac{p_k[n]}{\sigma_k[n]} \right) \geq \frac{L_k[n]}{\delta B_0}, \forall k, n \in \mathcal{N}, \)
\[
\hat{E}_k^{com}[n] = \left( 2 L_k[n] - 1 \right) \frac{\sigma_k^2}{\Delta \delta_1}[n],
\]
where \( \hat{E}_k^{com}[n] = \frac{x_k[n]}{E_k^{com}[n]} \). Note that the term \( x_k[n] \) in the first constraint of problem (P2) makes sure that when UAV \( k \) is in a ‘mute’ condition, there have no bits transmitted in the uplink; The term \( x_k[n] \) in \( \hat{E}_k^{com}[n] \) ensures that as UAV is not scheduled by TBS, the power allocation must be zero.

One can find that problem (P2) is a non-convex and mixed-integer optimization problem due to the non-convex objective function and integer constraints (16b) and (16d). To tackle this non-convex and mixed-integer optimization problem, we decompose the original problem into two sub-problems, namely UAV trajectory optimization with fixed UAV-TBS scheduling and UAV-TBS scheduling optimization with fixed UAV trajectory.

A. UAV Trajectory Optimization with Fixed UAV-TBS Scheduling

In this subsection, we consider the first sub-problem of (P2), denoted as (P2.1), for optimizing UAV trajectory, bit allocation, resource partitioning and power allocation by assuming
that UAV-TBS scheduling is fixed, which can be formulated as

$$(P2.1): \min_{\{A, B, \{\rho_k, p_k[n]\}\}} \sum_{k=1}^{K} E_{k}^{fly} + \sum_{k=1}^{K} E_{k}^{comp} + \sum_{k=1}^{K} \sum_{n=1}^{N-1} \tilde{E}_{k}^{comp}[n]$$

s.t. \ (8b), (8d)-(8j), (16b).

We can see that the problem (P2.1) have same structure as (P0). Therefore, it can be tackled with same way as (P0) and the detailed manipulations can refer to Section III.

B. UAV-TBS Scheduling Optimization with Fixed UAV Trajectory

In this subsection, we consider the second sub-problem of (P2), denoted as (P2.2), for jointly optimizing UAV-TBS scheduling, bit allocation, resource partitioning and power allocation by assuming that UAV trajectory is fixed, which can be formulated as

$$(P2.2): \min_{\{A, x_k[n]\}} \min_{\{\rho_k, p_k[n]\}} \sum_{k=1}^{K} E_{k}^{fly} + \sum_{k=1}^{K} E_{k}^{comp} + \sum_{k=1}^{K} \sum_{n=1}^{N-1} \tilde{E}_{k}^{comp}[n]$$

s.t. \ (8b), (8d)-(8j), (16b), (16c), (16d).

Though the problem (P2.2) is in a non-convex and mixed-integer form, we can obtain a sub-optimal solution by using relaxing method and SCA technique. Firstly, we relax the binary scheduling variable \(x_k[n]\) into continuous variable, as such, the constraint (16d) can be reformulated as

$$0 \leq x_k[n] \leq 1, \forall k, n \in \mathcal{N}. \quad (18)$$

Secondly, for non-convex term \(\tilde{E}_{k}^{com}[n]\) in objective function, we tackle with it by taking first-Taylor expansion of \(x_k[n]p_k[n]\) at given local points. Specifically, for any given local points \(x_{l,k}[n]\) and \(p_{l,k}[n]\) over \(l\)-th iteration, we have the following inequality

$$(x_k^2[n] + p_k^2[n]) \geq (x_{l,k}[n] + p_{l,k}[n])^2 + 2x_{l,k}[n] \left( x_k[n] - x_{l,k}[n] + 2p_{l,k}[n] \right) \leq \tilde{x}_{l,k}[n]. \quad (19)$$

As such, the term \(\tilde{E}_{k}^{com}[n]\) can be replaced by its upper bound result, which is given by

$$\tilde{E}_{k}^{com}[n] \leq \frac{(x_k[n] + p_k[n])^2 - z_k[n]}{2} = \tilde{E}_{k}^{com,up}[n]. \quad (20)$$

We can easily see that the expression \(\tilde{E}_{k}^{com,up}[n]\) is convex with respect to \(x_k[n]\) and \(p_k[n]\). For the non-convex expression \(E_{k}^{fly}\) with respect to \(v[n]\) and \(a[n]\), we first introduce a slack variable \(\tau[n]\), and then take the first-Taylor expansion of \(||v[n]\|^2\), the detailed procedures can refer to Section III. At last, for non-convex constraint (16b), we first introduce the slack variable \(s_k[n]\), as a consequence, the constraint (16b) can be reformulated as

$$s_k[n] \leq \log_2 \left( 1 + \frac{p_k[n]h_k[n]}{\sigma^2} \right), \forall k, n \in \mathcal{N}. \quad (21)$$

$$x_k[n] s_k[n] \geq \frac{L_k[n]}{\delta_B}, \forall k, n \in \mathcal{N}. \quad (22)$$

We can see that the reformulated constraints are still non-convex due to the coupled variables \(x_k[n]\) and \(s_k[n]\) in (22). However, this constraint can still approximately obtained by leveraging SCA technqiue, we thus have

$$\frac{g_{lb}[n] - (x_k^2[n] + s_k^2[n])^2}{2} \geq \frac{L_k[n]}{\delta_B}, \forall k, n \in \mathcal{N}, \quad (23)$$

where \(g_{lb}[n]\) is given in (24) (see the expression on top of the next page).

By replacing the new convex constraints (12), (18), (20), (21) and (23) of (P2.2) at the \(l\)-th iteration obtained above, we have the following optimization problem:

$$(P2.3): \min_{\{A, x_k[n]\}} \min_{\{\rho_k, p_k[n]\}, s_k[n]} \sum_{k=1}^{K} E_{k}^{fly} + \sum_{k=1}^{K} E_{k}^{comp}$$

$$+ \sum_{k=1}^{K} \sum_{n=1}^{N-1} \tilde{E}_{k}^{com,up}[n]$$

s.t. \ (8b), (8d)-(8j), (16c), (12), (18), (20), (21), (23).

It can be verified that problem (P2.3) is a convex optimization problem, which can be efficiently solved by standard convex technique. To reconstruct the binary variable, we have

$$x_k[n] = \begin{cases} 1 & \text{if } x_k[n] \geq 0, \\ 0 & \text{if } x_k[n] < 0. \end{cases} \quad (26)$$

It should be noted that the feasible region of (P2.2) is in general a subset of that (P2.3), as a result, and the optimal value of (P2.3) provides an upper bound solution to that of (P2.2). Based on the solutions to its two subproblems obtained by optimizing UAV trajectory and UAV-TBS scheduling via solving (P2.1) and (P2.3), we propose an iterative algorithm for problem (P2), which is summarized in Algorithm 1. Note that after each iteration in Algorithm 1, the objective value of (P2) is monotonically non-increasing. In addition, the objective value of (P2) is lower bounded by a finite value, Algorithm 1 is thus guaranteed to converge.

**Algorithm 1 Joint optimization of UAV-TBS scheduling and UAV trajectory**

1. **Initialize** the UAV-TBS scheduling \(x_k^m[n]\), iterative number \(m = 0\), and a maximum iterative number \(M_{\text{max}}\).

2. **Repeat**

3. Solve problem (P2.1) for given UAV-TBS scheduling \(x_k^m[n]\), and denote the optimal UAV trajectory as \(B^{m+1}\).

4. Solve problem (P2.3) for given UAV trajectory \(B^{m+1}\), and denote the optimal UAV-TBS scheduling as \(x_k^{m+1}[n]\).

5. **m=m+1.**

6. **Until** a maximum iterative number has been reached or convergence.
\((x_k[n] + s_k[n])^2 \geq (x_{l,k}[n] + s_{l,k}[n])^2 + 2 (x_{l,k}[n] + s_{l,k}[n]) (x_k[n] - x_{l,k}[n]) + 2 (x_{l,k}[n] + s_{l,k}[n]) (s_k[n] - s_{l,k}[n])\)
\(\leq g_k^{lb}[n]\)

VI. ENERGY MINIMIZATION FOR NOMA SCHEME

In this section, we tackle the problem of minimizing the total energy consumption of UAVs for offloading by assuming the system operated in NOMA scheme. For NOMA scheme [39][41], each UAV occupies the same bandwidth resource and time resource. Based on this access manner, the problem can be formulated as

\[
(P3): \min_{\{A, B, \rho_k[n]\}} \sum_{k=1}^{K} E_k^{fly} + \sum_{k=1}^{K} E_k^{comp} + \sum_{k=1}^{K} \sum_{n=1}^{N-1} E_n^{com} [n] \\
\text{s.t. } \log_2 \left( 1 + \frac{p_k[n] h_k[n]}{\sigma^2 + \sum_{k' \neq k} p_{k'}[n] h_{k'}[n]} \right) \geq \frac{L_k[n]}{\delta B}, \forall k, n \in \mathcal{N},
\]
\[(8b), (8d)-(8j), \]

The problem (P3) is different from previous problems due to the signal interference involved in (27), which is non-convex and hard to tackle. In general, there is no standard method for solving this non-convex problem efficiently. In the following, we develop a two-layer iterative algorithm and solve it using SCA technique. We first split problem (P3) into two subproblems, namely UAV trajectory optimization with fixed power allocation and transmission power optimization with fixed UAV trajectory. Based on the solutions obtained, an iterative algorithm is proposed for problem (P3) via alternately optimizing the above two subproblems.

A. UAV Trajectory Optimization with Fixed power Allocation

In this section, we consider the first subproblem of (P3) for optimizing UAV trajectory with fixed transmission power allocation. The problem can be written as

\[
(P3.1): \min_{\{A, B, \rho_k[n]\}} \sum_{k=1}^{K} E_k^{fly} + \sum_{k=1}^{K} E_k^{comp} \\
\text{s.t. } \log_2 \left( 1 + \frac{p_k[n] h_k[n]}{\sigma^2 + \sum_{k' \neq k} p_{k'}[n] h_{k'}[n]} \right) \geq \frac{L_k[n]}{\delta B}, \forall k, n \in \mathcal{N},
\]
\[(8b), (8d)-(8h), (8j), \]

Note that the problem (P3.1) is still a non-convex problem due to the non-convex term \(E_k^{fly}\) in objective function and non-convex constraint in (27). In the following, we adopt the SCA technique for solving the trajectory optimization problem. To this end, we define \(R_k[n] = \log_2 \left( 1 + \frac{p_k[n] h_k[n]}{\sigma^2 + \sum_{k' \neq k} p_{k'}[n] h_{k'}[n]} \right)\), and \(R_k[n]\) can be rewritten as

\[
R_k[n] = \tilde{R}_k[n] - \log_2 \left( \sigma^2 + \sum_{k' \neq k} p_{k'}[n] h_{k'}[n] \right), \quad (28)
\]

where \(\tilde{R}_k[n] = \log_2 \left( \sigma^2 + \sum_{k \in \mathcal{K}} p_k[n] h_k[n] \right)\). Define \(Q_k[n] = ||q_k[n] - w||^2, k \in \mathcal{K}\), then the constraint (27) can be rewritten as

\[
\tilde{R}_k[n] - \log_2 \left( \sigma^2 + \sum_{k' \notin \mathcal{K}} Q_{k'}[n] \right) \geq L_k[n] / \delta B, \quad (29)
\]

and

\[
Q_k[n] \leq ||q_k[n] - w||^2, \forall k, n \in \mathcal{N}. \quad (30)
\]

While the term \(\log_2 \left( \sigma^2 + \sum_{k' \notin \mathcal{K}} Q_{k'}[n] \right)\) in (29) is convex with respect to \(Q_k[n]\), the term \(\tilde{R}_k[n]\) is not convex with respect to \(q_k[n]\). In addition, it also introduces a non-convex set in (30). To tackle the non-convex constraints (29) and (30), we apply the SCA technique. For the term \(\tilde{R}_k[n]\), we take the first-order Taylor expansion of \(\tilde{R}_k[n]\) with respect to any given point \(||q_{l,k}[n] - w||^2\) over \(l\)-th iteration, we thus have the following inequality (31) (see the inequation on top of the next page), where \(U_{l,k}[n] = \frac{\sum_{k' \notin \mathcal{K}} p_{k'}[n] h_{k'}[n]}{\sigma^2 + \sum_{k' \notin \mathcal{K}} p_{k'}[n] h_{k'}[n]}\).

Then, (29) can be replaced by its lower bound approximation result as

\[
\tilde{R}_k^{lb}[n] - \log_2 \left( \sigma^2 + \sum_{k' \notin \mathcal{K}} \frac{Q_{k'}[n]}{Q_{k'}[n] + H^2} \right) \geq L_k[n] / \delta B, \quad \forall k, n \in \mathcal{N}. \quad (32)
\]

It is not difficult to verify that constraint (32) is now convex. To tackle the non-convex (30), a local convex approximation is still applied. Specifically, for given local point \(q_{l,k}[n]\) over \(l\)-th iteration, we have

\[
||q_k[n] - w||^2 \geq ||q_{l,k}[n] - w||^2 \geq (q_{l,k}[n] - w)^T (q_k[n] - w) \quad (33)
\]

Define the new constraint

\[
Q_k[n] \leq \varphi (q_k[n]), \forall k, n \in \mathcal{N}. \quad (34)
\]

For non-convex term \(E_k^{fly}\) in objective function of (P3.1), it can still be replaced by a convex form by introducing the slack variable \(\tau_n\), which can refer to Section III. As a result, for
\[
\hat{R}_k[n] \geq \log_2 \left( \sigma^2 + \sum_{k \in K} \frac{\beta_k[n]}{\|q_{l,k}[n] - \omega\|^2 + H^2} \right) - \sum_{k=1}^{K} U_{l,k}[n] \left( \|q_{l,k}[n] - \omega\|^2 - \|q_{l,k}[n] - \omega\|^2 \right) \equiv \hat{R}_k^{ub}[n] \tag{31}
\]

any given point \( \{q_{l,k}[n]\} \), define the following optimization problem

\[
(P3.2) : \min_{\{A,B,T,\tau_i\}} \sum_{k=1}^{K} E_k^{comp} + \sum_{k=1}^{K} \sum_{n=1}^{N-1} E_k^{comp}[n] \]

s.t. \((8b), (8d)-(8h), (8j), (12), (32), (34)\)

Problem \((P3.2)\) is now convex, which can be efficiently solved by standard convex optimization technique. Note that it can be readily verified that the objective value of \((P3.2)\) gives a upper bound result to that of problem \((P3.1)\).

**B. Power Allocation Optimization with Fixed UAV Trajectory**

In this section, we consider the second subproblem of problem \((P3)\) in which the transmission power of UAV is optimized while the trajectory is fixed. The problem can be reformulated as

\[
(P3.3) : \min_{\{A,p[n,\tau]\}} \sum_{k=1}^{K} E_k^{comp} + \sum_{k=1}^{K} \sum_{n=1}^{N-1} E_k^{comp}[n] \]

s.t. \(\log_2 \left( 1 + \frac{\sigma^2}{\sigma^2 + \sum_{k' \neq k} \beta_k[n] h_k[n] h_{k'}[n]} \right) \geq \frac{L_k[n]}{\delta B}, \forall k, n \in \mathcal{N}, \tag{35}\)

\((8b), (8d)-(8f), (8h)-(8j)\).

Problem \((P3.3)\) is a non-convex optimization problem due to the non-convex constraint in \((35)\). Define \(\hat{R}_k[n] = \log_2 \left( \sigma^2 + \sum_{k' \neq k} \beta_k[n] h_k[n] h_{k'}[n] \right)\). To tackle the non-convex constraint of \((35)\), we apply the successive convex optimization technique to approximate \(\hat{R}_k[n] \) with a convex function in each iteration. Specifically, for any given local point \(p_{l,k}[n]\) over \(l\)-th iteration, we have the inequality given in \((36)\) (see the inequation on top of the next page). As a result, for any given point \(p_{l,k}[n]\), problem \((P3.3)\) is approximated as

\[
(P3.4) : \min_{\{A,p[n,\tau]\}} \sum_{k=1}^{K} E_k^{comp} + \sum_{k=1}^{K} \sum_{n=1}^{N-1} E_k^{comp}[n] \]

s.t. \(\hat{R}_k[n] - \hat{R}_k^{up}[n] \geq \frac{L_k[n]}{\delta B}, \forall k, n \in \mathcal{N}, \tag{37}\)

\((8b), (8d)-(8f), (8h)-(8j)\).

The problem \((P3.4)\) is a convex optimization problem, which can be efficiently solved by standard optimization technique. As a consequence, \((P3.3)\) can be approximated solved by successively updating the power allocation based on the optimal solution to \((P3.4)\). It should be pointed out that the obtained solution by solving problem \((P3.4)\) can be served as the upper bound of problem \((P3.3)\).

Based on the solutions to its two subproblems obtained by optimizing UAV trajectory and power allocation via solving \((P3.2)\) and \((P3.4)\), we propose an iterative algorithm for problem \((P3)\), which is summarized in Algorithm 2. The proof of convergence of Algorithm 2 can refer to Algorithm 1 provided in Section V.

**Algorithm 2 Joint optimization of UAV trajectory and power allocation**

1. **Initialize** the UAV-TBS scheduling \(p_k^{m}[n]\), iterative number \(m = 0\), and a maximum iterative number \(M_{max}\).

2. **Repeat**

3. Solve problem \((P3.2)\) for given power allocation \(p_k^{m}[n]\), and denote the optimal UAV trajectory as \(\beta_k^{m+1}\).

4. Solve problem \((P3.4)\) for given UAV trajectory \(\beta_k^{m+1}\) and denote the optimal UAV-TBS scheduling as \(p_k^{m+1}[n]\).

5. \(m = m+1\).

6. **Until** a maximum iterative number has been reached or convergence.

**VII. NUMERICAL RESULTS**

In this section, we present the numerical results to illustrate the effectiveness of our proposed four schemes. In the simulations, the altitude of UAV is fixed at \(H = 80m\) with the maximum transmission power \(P_{max} = 2W\). The communication bandwidth is \(B = 1MHz\) with the reference SNR \(\gamma_0 = 5 \times 10^3W\). We assume that the maximum energy budget of TBS allocated for computing is \(E_{total} = 4 \times 10^5J\) unless otherwise specified. The total number of bits for UAV 1 and UAV 2 are set to be 0.5Mbits and 1Mbits, respectively. We assume that there are two UAVs, i.e., \(K = 2\), which can move to any direction subject to the maximum UAV speed 50m/s and acceleration 5m/s². In addition, we assume that \(c_1 = 0.002\), \(c_2 = 70.698\) as in [25] and [42], and the computation coefficient is set to \(G = 10^{-11}\) as stated in [35]. In addition, the time slot is assumed to be \(\delta = 0.5s\). It is worth mentioning that we plot the curves of UAV trajectory, bit allocation and resource partitioning for TDMA scheme, and the curves of UAV trajectory, bit allocation and resource partitioning for other schemes are not plotted. This is because the similar results can be obtained compared with TDMA scheme.

In Fig. 2, we plot the optimized UAVs’ trajectories obtained by the TDMA scheme with horizon time \(T = 60s\). We let UAV 1’s initial location and final location respectively as \(q_{1,l} = [-500, -500]^T\) and \(q_{1,f} = [500, -500]^T\) with corresponding UAV 1’ initial velocity \(v_1[0] = [20, 20]^T\) (m/s) and final velocity \(v_1[N + 1] = [20, -20]^T\) (m/s), and UAV
\[ \hat{R}_k[n] \leq \log_2 \left( \sigma^2 + \sum_{k' \neq k} p_{k,k'}[n] h_{k'}[n] \right) + \sum_{k' \neq k} \frac{h_{k'}[n] \log_2 (e)}{\sigma^2 + \sum_{k' \neq k} p_{k,k'}[n] h_{k'}[n]} (p_k[n] - p_{l,k}[n]) \leq \hat{R}^up[n] \] (36)

2’s initial location and final location respectively as \( q_{2,1} = [-500, 500]^T \) and \( q_{2,2} = [500, 500]^T \) with corresponding UAV 2’s initial velocity \( v_2[0] = [20, -20]^T \) (m/s) and final velocity \( v_2[N+1] = [20, 20]^T \) (m/s). In addition, the horizon coordinate of TBS is located at \( w = (0, 0)^T \). Three prominent insights can be achieved in Fig. 2. Firstly, the curves of UAVs’ trajectories for minimizing the total UAVs energy consumption yield a straight flight mostly, which indicates that the energy-minimization strategy is simply a straight flight manner with constant UAV speed. Secondly, for offloading bits from UAVs to TBS as more as possible, the UAVs tend to adjust their location to shorten the distance between UAV and TBS. Thirdly, the propulsion-related energy consumption of UAVs is dominated compared with communication-related energy consumption, otherwise the UAVs prefer to move directly to TBS and hover above TBS for saving communication energy. For describing more detailed information about UAV’s mobility, the curves of UAV 1 speed and acceleration are plotted in Fig. 3. We can observe that UAV 1 firstly flies at a higher speed, and then flies at a constant lower speed. In addition, the UAV 1 acceleration almost equal to 0 from time slot \( n = 16 \) to \( n = 108 \), which results in a low energy consumption for flying. The results of speed and acceleration for UAV 2 have similar results as UAV 1, and is not discussed here for brevity.

Fig. 4 shows the achieved bit allocation of uplink transmission phase and TBS local computation phase for UAV 1 and UAV 2. From the first sub-figure of Fig. 4 for UAV 1, we can see that a large number of bits are allocated in
the uplink transmission for UAV 1 at begin, and then the number of bits are allocated in uplink transmission for UAV 1 decrease. This conclusion is contrary to the results stated in [17], which shows that as the UAV is closer to mobile user, a larger number of bits should be allocated. This is attributed to the fact that the work [17] focuses on minimizing the mobile users’ communication energy, however, our work pays attention to minimizing the total energy consumption of UAVs, including communication-related energy consumption, local computation energy consumption and propulsion-related energy consumption. While as the distance between UAV and TBS become shorter, the larger number of bits allocated for TBS will reduce the communication-related energy consumption of UAVs, the energy used for flying and computing will increase. For TBS local computation phase, the TBS prefers to process the equal number of bits in each time slot for saving TBS’ computation energy, which has same conclusion as in [17]. Moreover, we can see that the second sub-figure of Fig. 4 for UAV 2, the number of bits allocated for uplink transmission and computation is almost same as in the sub-figure of Fig. 4 for UAV 1. The reason can be explained as the energy budget for computation is limited, thus it only can process a limited number of bits received from UAVs.

Fig. 5 shows the impacts of TBS energy budget on UAV resource partitioning strategy. Two dash lines, i.e., blue dash line and red dash line, represent the maximum resource partitioning values for UAV 1 and UAV 2, respectively. The maximum resource partitioning values are derived from the special case for TDMA which discussed in Fig. 6. In Fig. 5, we can observe that the optimized resource partitioning, \(1 - \rho_k; \forall k\), is monotonically increasing with TBS energy budget, which means that the more number of bits of UAVs can be offloaded to TBS for computation as TBS energy budget increases. This can be explained as the more TBS energy budget, the more number of bits can be processed. Furthermore, it can be observed that the resource partitioning of UAV 1 is higher than UAV 2. This is because from Fig. 4, it shows that the number of bits of two UAVs allocated for TBS is almost same, and also the total number of bits of UAV 1 is smaller than the total number of bits of UAV 2, thus the results can be directly obtained.

At last, we compare our proposed four schemes with comparison benchmarks in terms of minimizing the total energy consumption of UAVs as shown in Fig. 6. For propulsion minimization scheme, the UAV’s trajectory is firstly optimized for minimizing the UAV’s propulsion-related energy, then with the obtained UAV trajectory, we optimize bit allocation and resource partitioning of UAV for jointly minimizing communication-related energy and local computation energy.

We also consider four special schemes as comparison benchmarks which the TBS allocated energy budget for computation is sufficient large and the bit-casuality constraint (namely we assume that the TBS can completely process the bits received from UAVs within one time slot) is ignored. Obviously, these four special benchmarks can be served as lower bound results for the proposed four schemes. In Fig. 6, it can be observed that the adopted propulsion minimization scheme consumes more energy than the other schemes. We can conclude that the propulsion-related UAV energy consumption is not the only prominent factor for the total UAV energy consumption, it also indicates that the bits used for computation consume a large amount of energy. It can also be see that the NOMA scheme has better performance than the orthogonal schemes (TDMA, OFDMA, One-by-One), the larger gain for NOMA scheme can be attributed to the property of sharing of entire time and bandwidth resource simultaneously among UAVs. However, the successive interference cancellation (SIC) technique used for NOMA may bring an additional interference and implementation complexity compared with orthogonal schemes [40], [41]. Furthermore, the gap among proposed four schemes is not large, thus, there exists a tradeoff between implementation complexity and performance gain. In addition, we can see that the four solid curves plotted in Fig. 6 firstly decrease with horizon time \(T\) from \(T = 25s\) to \(T = 75s\), and increase with horizon time \(T\) from \(T = 75s\) to \(T = 95s\). This can be explained since the horizon time \(T\) is small in the first phase, the energy consumption used for computation is larger than the UAV used for flying; In the second phase, as horizon time \(T\) becomes larger, the energy consumption used for flying is larger than the UAV used for computation; In other words, the energy of UAV used for flying increases with horizon time \(T\) and the energy of UAV used for computation decreases with time \(T\). Therefore, there exists a tradeoff between propulsion energy consumption of UAVs and local computation energy consumption of UAVs, and the optimal time \(T\) for minimizing the total energy consumption of UAVs is left in our future work.

**VIII. Conclusion**

In this paper, we propose four types of access schemes in the uplink transmission for mobile edge computing system. We formulate the problem as a energy minimization problem while ensuring the large number of bits of UAVs are completely computed in a given horizon time. For solving the non-convex optimization problem, a sub-optimal result is achieved by using successive convex approximation technique. The
numeral results show that there exists a tradeoff between propulsion energy consumption of UAVs and computation energy consumption of UAVs. In addition, it also shows that our proposed four schemes save a large amount of energy compared with the propulsion minimization scheme.

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