Fair Data Allocation and Trajectory Optimization for UAV-Assisted Mobile Edge Computing

Xianbang Diao, Jianchao Zheng, Yueming Cai, Yuan Wu, and Alagan Anpalagan

***Abstract*— This letter investigates fairness-aware task data allocation and trajectory optimization in unmanned aerial vehicles (UAV)-assisted mobile edge computing (MEC) systems, where a fixed-wing UAV is used as a flying computing server to receive task data of mobile terminals (MTs). Under the fairness consideration, we aim to minimize the maximum energy consumption among all MTs. Despite the non-convexity of the original formulated joint optimization problem, we transform the problem into two convex sub-problems by introducing auxiliary variables, and solve them jointly by proposing an iterative algorithm. Simulation results show that the proposed algorithm can effectively reduce the maximum energy consumption among all MTs.**

***Index Terms*— Fairness, mobile edge computing, task data allocation, trajectory optimization.**

I. Introduction

MOBILE edge computing (MEC) has attracted an increasing attention recently because of the explosive computing-intensive application tasks and resource-poor mobile terminals (MTs) [1]–[3]. Conventional edge servers are typically installed in cellular base stations at fixed locations, which makes them difficult to provide flexible services to MTs at the edge of the cellular coverage area. Compared to the conventional architecture, unmanned aerial vehicles (UAVs) equipped with computing servers can bring potential performance gains to MEC systems because of the mobility capability of the UAVs [4], [5]. In particular, the joint optimization of computing offloading (e.g., the computing offloading strategy and the radio resource allocation) and the UAV's trajectory is indispensable for reaping the benefits of the UAV-assisted MEC systems.

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Recently, some studies have investigated the UAV-assisted MEC systems. In [6], Zhou *et al.* regarded the UAV as a mobile aerial platform which not only provides energy for MTs, but also computing offloading services. In [7], Hu *et al.* minimized the sum of the maximum delay among MTs in each time slot by jointly optimizing the UAV's trajectory, the ratio of offloading tasks, and the user scheduling. In addition, there are some studies investigating the energy consumption optimization for UAV-assisted MEC systems. In [8], Jeong *et al.* minimized the energy consumption by jointly optimizing trajectory, task data and power allocations. Nevertheless, most prior studies did not take into account the fairness issue about energy consumptions of different MTs, which may cause some MTs to consume larger energies for the computing offloading than those for the local computing. Moreover, the unbalanced energy consumptions among different MTs may shorten the lifetime of the whole networks (e.g., when the MTs are sensor nodes with very limited battery capacities). As a result, it is of practical importance for us to take into account the fairness issue about the energy consumption of different MTs, which thus differs our work from the existing studies.

Motivated by these concerns, in this letter, we take into account the fairness among MTs in an UAV-assisted MEC system, and aim to minimize the maximum energy consumption among all MTs by optimizing the task data allocation and trajectory. Despite the non-convexity of the formulated joint optimization problem, we transform the original problem into a new problem by adding auxiliary variables, and then decompose the new problem into two sub-problems by identifying its structural characteristics, and finally develop a joint task data allocation and trajectory optimization algorithm to jointly solve the two sub-problems. Simulation results validate that the proposed algorithm can effectively reduce the maximum energy consumption among all MTs.

II. System Model and Problem Formulation

As shown in Fig. 1, we consider an UAV-assisted MEC system which consists of a fixed-wing UAV equipped with a computing server and K MTs, denoted by $\mathcal{K} = \{1, 2, \ldots, K\}$. In a finite time horizon T, each MT k has a task that adopts partial computation offloading, where the task data are bit-wise independent and can be arbitrarily divided into different groups and executed by the computing server [1]. Similar to [3], [4], we assume that all MTs' locations remain unchanged within the considered time horizon T of interest. To make the flight more trackable, T is divided into N equal time slots Δ, i.e., $T = N\Delta$, and denote $\mathcal{N} = \{1, 2, \ldots, N\}$. We assume that Δ is sufficiently small, and the position of the UAV during

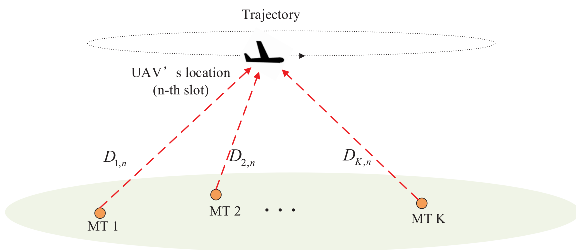

Fig. 1. Scenario illustration of UAV-assisted computing offloading for MTs.

each Δ can be regarded as stationary. Moreover, each MT k offloads the task data $A_{k,n} \triangleq (D_{k,n}, X_{k,n})$ to the UAV in the orthogonal frequency division multiple access (OFDMA) protocol where equal bandwidth B is allocated to each MT, and $D_{k,n}$ is the input-data size of the MT k in the n-th time slot (in bits) and the required amount of task data of MT k is D_k^{req}. $X_{k,n}$ represents the computing intensity which is assigned to the MT k in the n-th time slot (in the unit of CPU cycles per bit). We construct a 3-Dimensional Cartesian coordinate system model, where the coordinate of MT k is $\mathbf{w}_k = [x_k, y_k, 0]^T, \forall k \in \mathcal{K}$ and the coordinate of UAV in the n-th time slot is $\mathbf{q}_{[n]} = [x_{[n]}, y_{[n]}, H]^T, \forall n \in \mathcal{N}$, where H is a constant. We denote the transmit power of MT k in the n-th time slot as $p_{k,n}$. The velocity of the UAV in the n-th time slot is $\mathbf{v}_{[n]}$. Due to the limited mobility capacity of the UAV, there are mobility constraints as follows:

$$C1: \begin{cases} \mathbf{q}_{[1]} = \mathbf{q}_I, \\ \mathbf{q}_{[N+1]} = \mathbf{q}_F, \\ \mathbf{v}_{[n]} = \dfrac{\mathbf{q}_{[n+1]} - \mathbf{q}_{[n]}}{\Delta}, \quad \forall n \in \mathcal{N}, \end{cases} \tag{1}$$

where $\mathbf{q}_I$ and $\mathbf{q}_F$ are the initial and final locations of UAV, respectively.

Suppose that the UAV-to-ground channel is dominated by line-of-sight link. Therefore, similar to [9], the channel gain between the UAV and the MT k in the n-th slot is given by:

$$g_{k,n} = \alpha_0 \left\| \mathbf{q}_{[n]} - \mathbf{w}_k \right\|_2^{-2}, \tag{2}$$

where parameter α_0 represents the channel power gain at the reference distance $d_0 = 1$ m, and the $\|\cdot\|_2$ represents the norm operator. Moreover, the transmission rate of the MT k in the n-th slot is given by:

$$R_{k,n} = B \log_2 \left(1 + \frac{p_{k,n} g_{k,n}}{\sigma^2} \right), \tag{3}$$

where parameter σ^2 is the noise power. Similar to [3], [6]–[8], the energy consumption and task delay of MT k in the n-th slot are respectively given by:

$$E_{k,n} = p_{k,n} \frac{D_{k,n}}{R_{k,n}}, \tag{4a}$$

$$T_{k,n} = \frac{D_{k,n}}{R_{k,n}} + \frac{X_{k,n} D_{k,n}}{f_{k,n}}, \tag{4b}$$

where $f_{k,n}$ is the computing rate assigned to MT k in the n-th slot (in the unit of CPU cycles per sencond). Moreover, similar to [3], we do not consider the delay for the computing server to send back the computing results.

To ensure min-max fairness among MTs [10], we aim to minimize the maximum energy consumption among all MTs by jointly optimizing the task data allocation and the UAV's trajectory. The optimization problem can be formulated as follows:

$$\mathbf{P1}: \min_{D_{k,n}, \mathbf{q}_{[n]}} \max_k \left\{ \sum_{n=1}^{N} E_{k,n} \right\}, \tag{5a}$$

$$\text{s.t. } C1, \tag{5b}$$

$$T_{k,n} \leq \Delta, \quad \forall k \in \mathcal{K}, \ \forall n \in \mathcal{N}, \tag{5c}$$

$$\left\| \mathbf{v}_{[n]} \right\|_2 \leq V_{max}, \quad \forall n \in \mathcal{N}, \tag{5d}$$

$$\left\| \mathbf{v}_{[n]} \right\|_2 \geq V_{\min}, \quad \forall n \in \mathcal{N}, \tag{5e}$$

$$\sum_{n=1}^{N} D_{k,n} = D_k^{\text{req}}, \quad \forall k \in \mathcal{K}, \tag{5f}$$

where V_{max} and V_{min} are the maximum and minimum flight rates of the UAV, respectively. Here, constraint (5b) represents the UAV's mobile capacity constraints given in (1), constraint (5c) represents that all MTs' task delays in each time slot cannot exceed the length Δ, constraint (5d) represents that the UAV's flight rate cannot exceed the maximum flight rate, constraint (5e) ensures the UAV can remain aloft, and constraint (5f) represents the constraint of task data. Since the objective function and the constraints (5c) and (5e) are non-convex, the problem is a non-convex optimization problem and cannot be directly solved by the convex optimization techniques.

III. Joint Data Allocation and Trajectory Optimization

In this section, we introduce auxiliary variables to transform the problem **P1** into two convex sub-problems. Firstly, we introduce the auxiliary variable $e \geq \max_k \left\{ \sum_{n=1}^{N} E_{k,n} \right\}$ to simplify the objective function. Thus, the problem **P1** can be equivalently reformulated as follows:

$$\mathbf{P2}: \min_{D_{k,n}, \mathbf{q}_{[n]}, e} e, \tag{6a}$$

$$\text{s.t. } e \geq \sum_{n=1}^{N} p_{k,n} \frac{D_{k,n}}{R_{k,n}}, \quad \forall k \in \mathcal{K}, \tag{6b}$$

$$C1, \tag{6c}$$

$$\frac{D_{k,n}}{R_{k,n}} + \frac{X_{k,n} D_{k,n}}{f_{k,n}} \leq \Delta, \quad \forall k \in \mathcal{K}, \ \forall n \in \mathcal{N}, \tag{6d}$$

$$\left\| \mathbf{v}_{[n]} \right\|_2 \leq V_{max}, \quad \forall n \in \mathcal{N}, \tag{6e}$$

$$\left\| \mathbf{v}_{[n]} \right\|_2 \geq V_{\min}, \quad \forall n \in \mathcal{N}, \tag{6f}$$

$$\sum_{n=1}^{N} D_{k,n} = D_k^{\text{req}}, \quad \forall k \in \mathcal{K}, \tag{6g}$$

where the constraint (6d) comes from constraint (5c). Moreover, since the constraints (6b) and (6d) have the product terms of different variables, and the constraint (6f) is non-convex with respect to $\mathbf{v}_{[n]}$, the problem **P2** is still intractable. To solve it, we introduce the auxiliary variables

$t_{k,n} \geq \frac{1}{R_{k,n}}$. Therefore, constraints (6b) and (6d) can be equivalently rewritten as:

$$e \geq \sum_{n=1}^{N} p_{k,n} D_{k,n} t_{k,n}, \quad \forall k \in \mathcal{K}, \tag{7a}$$

$$D_{k,n} t_{k,n} + \frac{X_{k,n} D_{k,n}}{f_{k,n}} \leq \Delta, \qquad \forall k \in \mathcal{K}, \quad \forall n \in \mathcal{N}, \tag{7b}$$

$$R_{k,n} \geq \frac{1}{t_{k,n}}, \qquad \forall k \in \mathcal{K},\ \forall n \in \mathcal{N}, \tag{7c}$$

$$t_{k,n} > 0, \qquad \forall k \in \mathcal{K}, \quad \forall n \in \mathcal{N}. \tag{7d}$$

Since $R_{k,n}$ is non-concave with respect to $\mathbf{q}_{[n]}$, the constraint (7c) is non-convex. There is already a transformation method in [9] that can handle this type of constraint. However, we utilize a new lower bound method to deal with the constraint (7c). First, we equivalently transform the constraint (7c) to the following inequality:

$$\frac{\gamma_0}{2^{(t_{k,n}B)^{-1}}-1} \geq \left\|\mathbf{q}_{[n]}-\mathbf{w}_k\right\|_2^2 + H^2, \quad \forall k \in \mathcal{K},\ \forall n \in \mathcal{N}, \tag{8}$$

where $\gamma_0 = \frac{p_{k,n}\alpha_0}{\sigma^2}$. To tackle (8), a local convex approximation is applied. Specifically, for any given local point $t_{k,n}^{\text{local}}$ in the feasible domain, we define the following function:

$$D_{\text{lb}}(t_{k,n}) = \gamma_0 \left(\frac{1}{2^{(t_{k,n}^{\text{local}}B)^{-1}}-1} - \frac{2^{(t_{k,n}B)^{-1}} - 2^{(t_{k,n}^{\text{local}}B)^{-1}}}{\left(2^{(t_{k,n}^{\text{local}}B)^{-1}}-1\right)^2} \right). \tag{9}$$

Theorem 1: For any $t_{k,n}$ in the feasible domain, we have $\frac{\gamma_0}{\left(2^{(t_{k,n}B)^{-1}}-1\right)} \geq D_{\text{lb}}(t_{k,n})$.

Proof: We first define the function $f(x) \triangleq \frac{\gamma_0}{x}$. Its second derivative is $\frac{2\gamma_0}{x^3}$. When $x > 0$, $f(x)$ is a convex function. Therefore, $\frac{\gamma_0}{x} \geq \frac{\gamma_0}{y} - \frac{\gamma_0}{y^2}(x-y)$, where $y > 0$. In addition, we define $x = \left(2^{(t_{k,n}B)^{-1}} - 1\right) > 0$ and $y = \left(2^{(t_{k,n}^{\text{local}}B)^{-1}} - 1\right) > 0$. Thus, we have $\frac{\gamma_0}{\left(2^{(t_{k,n}B)^{-1}}-1\right)} \geq D_{\text{lb}}(t_{k,n})$. ■

Therefore, constraint (7c) can be approximately transformed to the following inequality:

$$D_{\text{lb}}(t_{k,n}) \geq \left\|\mathbf{q}_{[n]} - \mathbf{w}_k\right\|_2^2 + H^2, \quad \forall k \in \mathcal{K},\ \forall n \in \mathcal{N}. \tag{10}$$

Theorem 2: The constraint (10) is convex with respect to $\mathbf{q}_{[n]}$ and $t_{k,n}$.

Proof: We first define the function $h(t_{k,n}) \triangleq 2^{(t_{k,n}B)^{-1}}$, where $B > 0$. Its second derivative is $\frac{\ln 2}{B}\left(\frac{\ln 2 \cdot 2^{(t_{k,n}B)^{-1}}}{Bt_{k,n}^4} + \frac{2^{\left((t_{k,n}B)^{-1}+1\right)}}{t_{k,n}^3}\right)$. Combined with (7d), we can know that $h(t_{k,n})$ is a convex function with respect to $t_{k,n}$. Thus, function $D_{\text{lb}}(t_{k,n})$ is a concave function with respect to $t_{k,n}$. Obviously, the constraint (10) is convex with respect to $\mathbf{q}_{[n]}$ and $t_{k,n}$. ■

For the constraint (6f), it can be rewritten as:

$$\left\|\mathbf{v}_{[n]}\right\|_2^2 \geq V_{\min}^2, \quad \forall n \in \mathcal{N}. \tag{11}$$

Since $\left\|\mathbf{v}_{[n]}\right\|_2^2$ is a convex and differentiable function with respect to $\mathbf{v}_{[n]}$, for any given local point $\mathbf{v}_{[n]}^{\text{local}}$ in the feasible domain, we utilize the first-order Taylor expansion to obtain the following inequality:

$$\left\|\mathbf{v}_{[n]}\right\|_2^2 \geq \left\|\mathbf{v}_{[n]}^{\text{local}}\right\|_2^2 + 2(\mathbf{v}_{[n]}^{\text{local}})^T(\mathbf{v}_{[n]} - \mathbf{v}_{[n]}^{\text{local}}), \quad \forall \mathbf{v}_{[n]}, \tag{12}$$

where the right term of (12) is affine with respect to $\mathbf{v}_{[n]}$. After the above operations, the problem **P2** can be reformulated as:

$$\mathbf{P3}: \quad \min_{D_{k,n},\mathbf{q}_{[n]},t_{k,n},e} e, \tag{13a}$$

$$\text{s.t.} \quad e \geq \sum_{n=1}^{N} p_{k,n} D_{k,n} t_{k,n}, \quad \forall k \in \mathcal{K}, \tag{13b}$$

$$D_{\text{lb}}(t_{k,n}) \geq \left\|\mathbf{q}_{[n]} - \mathbf{w}_k\right\|_2^2 + H^2, \quad \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \tag{13c}$$

$$t_{k,n} > 0, \quad \forall k \in \mathcal{K},\ \forall n \in \mathcal{N}, \tag{13d}$$

$$C1, \tag{13e}$$

$$D_{k,n} t_{k,n} + \frac{X_{k,n} D_{k,n}}{f_{k,n}} \leq \Delta, \quad \forall k \in \mathcal{K},\ \forall n \in \mathcal{N}, \tag{13f}$$

$$\left\|\mathbf{v}_{[n]}\right\|_2 \leq V_{max}, \quad \forall n \in \mathcal{N}, \tag{13g}$$

$$\left\|\mathbf{v}_{[n]}^{\text{local}}\right\|_2^2 + 2(\mathbf{v}_{[n]}^{\text{local}})^T(\mathbf{v}_{[n]} - \mathbf{v}_{[n]}^{\text{local}}) \geq V_{\min}^2, \quad \forall n \in \mathcal{N}, \tag{13h}$$

$$\sum_{n=1}^{N} D_{k,n} = D_k^{\text{req}}, \quad \forall k \in \mathcal{K}. \tag{13i}$$

Although problem **P3** is still non-convex, it can be transformed into different convex problems under different given variables. Specifically, we identify that the trajectory and task data are independent of each other, and utilize the characteristic to transform problem **P3** into the following two sub-problems and solve them.

- **Sub-problem to optimize the task data $D_{k,n}$ under given $\mathbf{q}_{[n]}$ and $t_{k,n}$.** The sub-problem can be formulated as:

$$\mathbf{P3.1}: \quad \min_{D_{k,n},e} e, \tag{14a}$$

$$\text{s.t. Constraints (13b),(13f),(13i).} \tag{14b}$$

- **Sub-problem to optimize the trajectory $\mathbf{q}_{[n]}$ and auxiliary variable $t_{k,n}$ under given $D_{k,n}$.** The sub-problem can be formulated as:

$$\mathbf{P3.2}: \quad \min_{\mathbf{q}_{[n]},t_{k,n},e} e, \tag{15a}$$

$$\text{s.t.} \quad \text{Constraints (13b)-(13h).} \tag{15b}$$

It can be verified that **P3.1** and **P3.2** are two convex optimization problems which can be solved via conventional optimization toolbox such as CVX [11]. Based on the above results, we propose an iterative joint task data allocation and trajectory optimization algorithm (i.e., JTDATO-Algorithm) to solve the problem **P3**. The $t_{k,n}^{\text{local}}$ and $\mathbf{v}_{[n]}^{\text{local}}$ do not change with the iteration, which is different from the common iterative algorithm [6] and the SCA [9]. Moreover, each iteration is optimized on the basis of the previous iteration. Thus, a series of non-increasing objective function values can be obtained. Meanwhile, the objective function of **P3** must be

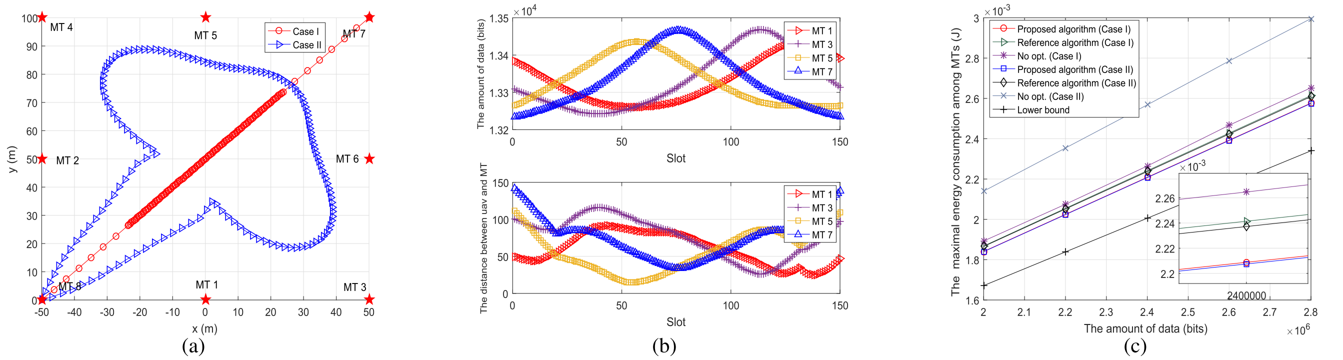

Fig. 2. (a) Trajectory optimization of the UAV in two cases, with $D_k^{\text{req}} = 2$Mbits, $\forall k \in \mathcal{K}$. (b) Data allocation and distance in Case II, with $D_k^{\text{req}} = 2$Mbits, $\forall k \in \mathcal{K}$. (c) The maximal energy consumption among MTs under the condition of MTs' random deployment.

Algorithm 1 JTDATO-Algorithm: to Jointly Optimize Task Data Allocation and Trajectory

1: Initialize $\{D_{k,n}, \mathbf{q}_{[n]}, t_{k,n}, e\}^0$ and set the iteration number $l = 0$, $t_{k,n}^{\text{local}} = t_{k,n}^0$, $\mathbf{v}_{[n]}^{\text{local}} = \mathbf{v}_{[n]}^0$ and the error tolerance $\varepsilon = 10^{-4}$

2: **Repeat**

3: Solve the problem **P3.1** with given $\{\mathbf{q}_{[n]}^l, t_{k,n}^l\}$ and obtain the optimal solutions $\{D_{k,n}^*\}$.

4: Solve the problem **P3.2** with given $\{D_{k,n}^*\}$ and obtain the optimal solutions $\{\mathbf{q}_{[n]}^*, t_{k,n}^*, e^*\}$.

5: Update $l \leftarrow l + 1$ and $\{D_{k,n}, \mathbf{q}_{[n]}, t_{k,n}, e\}^l \leftarrow \{D_{k,n}^*, \mathbf{q}_{[n]}^*, t_{k,n}^*, e^*\}$.

6: **Until** $\left|e^l - e^{l-1}\right| \leq \varepsilon$

lower bounded by the optimal solution to the **P1**. Therefore, the convergence is guaranteed. Since the **P3.1** and **P3.2** are solved in turn in an iteration, the complexity of an iteration depends on the **P3.2** which has a higher computational complexity. The **P3.2** contains KN second-order cone (SOC) constraints with dimension of 4 and $KN + 2N$ variables. As a result, similar to [7], we can calculate that the complexity of **P3.2** is $O(K^3N^3)$.

IV. Simulation Results

In this section, simulation results are presented to demonstrate the effectiveness of our JTDATO-Algorithm. There are $K = 8$ MTs. Moreover, based on the typical settings in [8] and [9], we set other related system parameters as follows: $N = 150$, $T = 10$ s, $B = 1$ MHz, $H = 50$ m, $V_{max} = 50$ m/s, $V_{min} = 3$ m/s, $\alpha_0 = -50$ dB, $f_{k,n} = 1.2$ Gcps and $p_{k,n} = 10$ dBm, $\forall k \in \mathcal{K}, \forall n \in \mathcal{N}$, and $\sigma^2 = -110$ dBm. To verify the effectiveness of our JTDATO-Algorithm, we use two different flight cases, i.e., Case I and Case II. Specifically, the initial position of Case I and Case II is $(-50, 0, 50)$, and the final positions of Case I and Case II are $(50, 100, 50)$ and $(-50, 0, 50)$, respectively. In addition, we compare JTDATO-Algorithm with the algorithm based on the transformation method in [9] (which is referred as a reference algorithm in Fig. 2(c)). Moreover, the "No opt." represents the performance average of sufficient and random solutions.

It can be observed from Fig. 2(a) that in Case I, the trajectory is symmetrical about all MTs, and the UAV slows down its moving speed in the middle of its trajectory, since in this area, the gaps of distances between the UAV and different MTs are minimal in the whole flight. As a result, the differences of different MTs' energy consumptions can be reduced. In addition, the trajectory in Case II is not only close to each MT, but also symmetrical. Therefore, despite the difference in the optimized trajectories in Case I and Case II, they both take into account the fairness among the MTs.

Due to symmetry of the trajectory, Fig. 2(b) only presents several representative MTs. It can be seen that the allocation of task data is not always inversely related to the distance. The reason is as follows. To ensure the fairness among MTs, in some time slots, as the distance becomes larger or smaller, the amount of data transmitted becomes larger or smaller correspondingly. To better reflect the performance of our proposed algorithm, we perform numerical simulation under the condition where MTs are randomly deployed, and the results are shown in Fig. 2(c). In both cases, the maximal energy consumption of the proposed algorithm is not only smaller than "No opt." but also smaller than the reference algorithm. In addition, we change the rate of each MT to its maximal reachable rate $B\log_2(1 + \frac{p_{k,n}\alpha_0}{H^2\sigma^2})$ in each time slot, and then optimize the task data allocation to obtain a loose lower bound. It can be seen from the Fig. 2(c) that the gap between our proposed algorithm and the lower bound is small, which validates the effectiveness of our algorithm.

V. Conclusion

We have investigated the fairness among different MTs' energy consumptions in the UAV-assisted MEC systems in this letter, and adopted an min-max approach that aims at minimizing the maximum energy consumption among all MTs. Despite the non-convexity of the formulated optimization problem, we have proposed an iterative yet efficient algorithm to obtain the optimal solution. The obtained results have revealed that compared with the reference algorithm and the "No opt.", our proposed algorithm can reduce the maximum energy consumption among all MTs and reflect the fairness among MTs. Regarding our future direction, we will further investigate the case when the MTs are mobile in the UAV-enabled MEC.

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