Energy-Efficient UAV-Mounted RIS Assisted Mobile Edge Computing

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Abstract—Unmanned aerial vehicle (UAV) and reconfigurable intelligent surface (RIS) have been recently applied in the field of mobile edge computing (MEC) to improve the data exchange environment by proactively changing the wireless channels through maneuverable location deployment and intelligent signals reflection, respectively. Nevertheless, they may suffer from inherent limitations, e.g., UAV’s low endurance and RIS’s finite coverage, which limit their wider applications. UAV-mounted RIS (U-RIS), as a promising integrated approach, can combine the advantages of UAV and RIS to break the limit. Inspired by this, we consider a novel U-RIS assisted MEC system, where a U-RIS is deployed to assist the communication between the ground users and an MEC server. The joint UAV trajectory, RIS passive beamforming and MEC resource allocation design is developed to maximize the energy efficiency (EE) of the system. To tackle the intractable non-convex problem, we divide it into two subproblems and solve them iteratively based on successive convex approximation (SCA) and the Dinkelbach method. Finally we obtain a high-performance suboptimal solution. Simulation results show that the proposed algorithm significantly improves the energy efficiency of the MEC system.

Index Terms—Energy efficiency, UAV-mounted RIS, mobile edge computing, trajectory design, passive beamforming.

I. INTRODUCTION

DRIVEN by the popularity of mobile users and unprecedented increase of network traffic in the Internet of Things (IoT), mobile edge computing (MEC) is regarded as an emerging paradigm that executes computation-intensive and latency-critical tasks at the network edges to meet the demands of the resource-constrained mobile devices [1]. However, imperfect offloading limits the exploitation of MEC. For example, since the direct offloading link may be blocked with a high probability, the poor channel condition forces the users to process their tasks locally to maintain strict latency requirements, which is unbearable for resource-limited mobile users. Hence, many works aim to improve the channel quality of MEC systems. Owing to the line-of-sight (LoS) transmission and flexible maneuverability, it is promising to enable unmanned aerial vehicles (UAVs) to carry an MEC server (UAV-carried server) for providing data exchange and computing services [2], [3]. Particularly, [2] proposed a joint resource allocation and UAV trajectory optimization scheme to maximize the energy efficiency (EE), and [3] deployed multiple ground servers and a UAV server in a cooperative manner to provide high-quality edge computing. As another way to improve the channel quality, reconfigurable intelligent surface (RIS) is a cost-effective and energy-efficient equipment that can be manipulated to alter the incident signal. It is considered as a win-win strategy to integrate RIS into MEC systems [4]. The work in [5] reported that up to 20% of the computing latency can be eliminated with the existence of RIS. Unfortunately, both UAV and RIS face their respective deficiencies, e.g., finite endurance and limited coverage. To overcome these issues, mounting RIS on UAV (named UAV-mounted RIS, U-RIS) to support terrestrial communication [6] is a promising approach. Compared with the UAV-carried server scheme, the U-RIS structure can be regarded as an effective upgrade to the traditional land server-based MEC system, without the need for routing change and system reconstruction. Furthermore, a RIS is usually much lighter than an MEC server [7], leading to a lower UAV’s on-board energy consumption. Besides, in the RIS-assisted MEC scheme, the RIS coated on the facade of buildings is only effective for the users in the front space. By contrast, on the aerial platform of UAV, RIS can enjoy a better full-angle panoramic beamforming capability towards users.

For the above reasons, we consider a U-RIS assisted MEC system. The main contributions are as follows: First, due to complex environments, e.g., an urban area for grand events or fire in a dense forest, the link between the ground users and the MEC server may be blocked. And a U-RIS is dispatched to assist the users in offloading their tasks where the signals of the users are reflected to the ground MEC server via the U-RIS. To balance the total processing bits and the energy consumption, our goal is to maximize the energy efficiency of the proposed system by jointly optimizing the UAV trajectory, passive beamforming, and resource allocation. Second, the formulated problem is a mixed-integer non-linear fractional programming problem. By leveraging the successive convex approximation (SCA) technique and the Dinkelbach method, we develop an efficient algorithm to obtain a suboptimal solution. Third, numerical results demonstrate that the proposed algorithm achieves a substantial EE improvement on the MEC system over other baseline schemes, and significant trade-off is made in the trajectory optimization.

II. SYSTEM MODEL AND PROBLEM FORMULATION

The U-RIS assisted MEC network is shown in Fig. 1, consisting of $K$ users, an MEC server and a RIS that is mounted on a UAV. The U-RIS is deployed to assist the MEC server in providing edge computing service to the ground users. Denote by $\mathbb{K} \triangleq \{1, 2, \ldots, K\}$ the set of users. Without loss of generality, the time span $T$ is divided into $N$ time slots with size of $\delta_t$, which is indexed by $\mathcal{N} \triangleq \{1, 2, \ldots, N\}$.

It is assumed that all the nodes in the MEC system are located in the three-dimensional (3D) Cartesian coordinate
system, and the horizontal coordinates of the MEC server as well as user \( k \) can be denoted by \( w_k = [x_k, y_k] \) and \( w_k = [x_k, y_k] \), respectively. We assume that the U-RIS flies at a fixed altitude \( H \) and its position remains unchanged within each time slot.\(^1\) Thus, the horizontal trajectory of the U-RIS during the time span \( T \) can be denoted by the sequence \( q[n] = [x[n], y[n]], n \in N \), satisfying the following mechanical and flight constraints

\[
\begin{align}
\mathbf{v}[n] &= \frac{\mathbf{q}[n+1] - \mathbf{q}[n]}{\delta_t}, ||\mathbf{v}[n]|| \leq v_{\text{max}}, \forall n, \\
\mathbf{a}[n] &= \frac{\mathbf{v}[n+1] - \mathbf{v}[n]}{\delta_t}, ||\mathbf{a}[n]|| \leq a_{\text{max}}, \forall n, \\
\mathbf{q}[1] &= \mathbf{q}_0, \mathbf{q}[N+1] = \mathbf{q}_F, ||\mathbf{q}[n]|| \leq r_d, \forall n,
\end{align}
\]

where \( v_{\text{max}} \) and \( a_{\text{max}} \) are the UAV’s maximum speed and acceleration, \( \mathbf{q}_0 \) and \( \mathbf{q}_F \) denote the initial and final horizontal positions of the U-RIS, and \( r_d \) is the horizontal flight range of the U-RIS. The last part of (1c) is owing to that the U-RIS should be practically tethered to a fixed ground station for dependable power supply and stable control [6].

A. Communication Model

We assume that the MEC server and the ground users are equipped with a single omni-directional antenna for each. The U-RIS is equipped with \( M = M_x \times M_y \) reflective elements, forming an \( M_x \times M_y \) uniform rectangular array (URA). Let \( \theta_i[n] \in [0, 2\pi], i \in M \equiv \{1, \ldots, M\} \) denote the phase of the \( i \)th reflecting element in time slot \( n \), and \( \mathbf{\Theta}[n] = \text{diag}\{e^{j\theta_1[n]}, e^{j\theta_2[n]}, \ldots, e^{j\theta_M[n]}\} \) be the diagonal phase array for the RIS in the \( n \)th time slot.

We assume the links from the ground users to the U-RIS (G-U link) and from the U-RIS to the MEC server (U-S link) follow a quasi-static block fading LoS model [9]. The link between user \( k \) and the U-RIS in the \( n \)th time slot, denoted by \( h_k[n] \in \mathbb{C}^{M_x \times 1} \), can be expressed as [10]

\[
h_k[n] = \tau[n] \mathbf{a}^x_k[n] \otimes \mathbf{a}^y_k[n],
\]

where

\[
\begin{align}
\mathbf{a}^x_k[n] &= [1, e^{-j \frac{2\pi}{N} d \cos \phi_k[n] \sin \varphi_k[n]}, \ldots, e^{-j \frac{2\pi}{N} (M_x - 1) d \cos \phi_k[n] \sin \varphi_k[n]} T, \\
\mathbf{a}^y_k[n] &= [1, e^{-j \frac{2\pi}{N} d \sin \phi_k[n] \sin \varphi_k[n]}, \ldots, e^{-j \frac{2\pi}{N} (M_y - 1) d \sin \phi_k[n] \sin \varphi_k[n]} T, \\
\sin \phi_k[n] \sin \varphi_k[n] &= \frac{y[n] - y_k}{d_k[n]}, \\
\cos \phi_k[n] \sin \varphi_k[n] &= \frac{x[n] - x_k}{d_k[n]},
\end{align}
\]

\(^1\)We assume that the U-RIS has a stable flight state [8], and has 2000 reconfigurable elements, which is reasonable in practice [7].

\[
\tau[n] = \sqrt{\beta_0 d_k^{-\alpha_L}[n]}, \quad \text{where} \quad \beta_0 \text{ is the channel gain with a distance of 1 meter, } d_k[n] = \sqrt{||q[n] - w_k||^2 + H^2} \text{ is the distance between user } k \text{ and the U-RIS in time slot } n, \alpha_L \text{ is the pass loss exponent due to the LoS transmission. Moreover, } \phi_k[n] \text{ and } \varphi_k[n] \text{ denote respectively the azimuth and elevation angles of user } k \text{ at time slot } n, \lambda \text{ is the wavelength of carrier and } d \text{ is the antenna separation. The U-S link in time slot } n, \text{ denoted as } h_k[n], \text{ can be modeled similarly.}
\]

We consider the TDMA scheme for the task offloading, which means that only one user communicates with the server in a time slot. Denote \( c_k[n] \) as the user scheduling variable. If user \( k \) is chosen to be served by the U-RIS in the \( n \)th time slot, we have \( c_k[n] = 1 \), yielding the following constraints

\[
\sum_{k=1}^{K} c_k[n] = 1, \quad c_k[n] \in \{0, 1\}, \forall k, n.
\]

Therefore, the achievable rate of user \( k \) in the \( n \)th time slot can be expressed as

\[
R_k[n] = c_k[n] B \log_2(1 + \frac{P_k \left\| (h_k[n])^{H} \mathbf{\Theta} n [h_k[n]] \right\|^2}{\sigma^2}),
\]

where the parameter \( B, P_k \) and \( \sigma^2 \) denote the channel bandwidth, fixed transmission power of users and the noise variance respectively. Thus, the average achievable rate of user \( k \) during the computing cycle \( T \) is given by \( R_k = \frac{1}{T} \sum_{n=1}^{N} R_k[n] \).

B. Computation Model

To exploit the full granularity in task partitioning and computing resources, we consider the way of partial offloading. Specifically, the computing tasks can be divided into arbitrary sizes, and part of the tasks can be offloaded to the server, while the remaining tasks are processed locally. Denote the total offloading and local computing tasks of user \( k \) over \( N \) time slots as \( r_k^o \) and \( l_k^o \) in bits, respectively. Let \( T_k \) be the maximum tolerable latency of user \( k \). Then we have [11]

\[
T_k \geq \max \left\{ \frac{r_k^o}{f_k^o} \chi_k, \frac{r_k^o}{f_k^o} + \frac{l_k^o}{R_k} \right\}, \forall k,
\]

where \( \chi_k \) denotes the number of CPU cycles required for processing one bit of user \( k \), \( f_k^o \) is user \( k \)’s fixed CPU frequency, and \( f_k^o \) is the allocated CPU frequency to compute the task of user \( k \) at the MEC server. This constraint is based on two assumptions: First, the edge computing for user \( k \) does not start until \( l_k^o \) bits are offloaded; second, using dynamic voltage and frequency scaling (DVFS) technique, the server can dynamically allocate its resources.

C. Energy Consumption Model

In the MEC system, the total energy consumption over \( N \) time slots is composed of three main parts: the energy consumed by the users for offloading and local computing, by the server for computing, and by the U-RIS flight. The energy consumption for user \( k \) can be formulated as\(^2\)

\[
E_k^{u} = T_k P_k + \varphi_u \chi_k h_k^4 (f_k^o)^2, \forall k,
\]

\(^2\)Actually, the offloading duration is \( l_k^o / R_k \), but \( T_k \) is mainly occupied by \( l_k^o / R_k \) and the energy used for transmission is relatively small [2]. So we can replace it with \( T_k \) to simplify the model without performance loss.
where $\varphi_k$ is the switched capacitance coefficient for the users. Denote $\varphi_k$ as the coefficient for the server, and the energy consumption of the server for computing user $k$’s tasks is

$$E_k^s = \varphi_k x_k t_k (f_k^u)^2, \forall k.$$  

(7)

We adopt the novel energy consumption model for rotary-wing UAVs proposed in [12], which takes the practical thrust-to-weight ratio into consideration, i.e.,

$$E_p[n] = P_0 \left( 1 + \frac{3||v[n]||^2}{U_f^2} \right) + \frac{1}{2} d_0 \rho s A ||v[n]||^3 + P_1 k[n] \left( ((k[n])^2 + \frac{||v[n]||^4}{4v_0^2})^2 - \frac{||v[n]||^2}{2v_0^2} \right), \forall n, \quad (8)$$

where $E_p[n]$ is a factor of the energy consumption for the U-RIS flight during the $n$th time slot, and $k[n] = (1 + \frac{4m}{\rho} ||v[n]||^2 + 4\rho P_f ||v[n]||^4 + 4m P_f ||F[n]||^2)^2$ with $F[n] = ||v[n]|| a[n] v[n]$. Here $m$ is the total weight of the UAV and the RIS; $P_0$, $U_f$, $d_0$, $\rho$, $A$, and $P_1$, $S_{FP}$ are all mechanical coefficients; see [12] for more details.

Generally speaking, the energy consumption of the U-RIS is much larger than that of the users and the server, but the latter two are crucial in real MEC networks. Hence, we introduce a weight factor $\alpha$ for the sum of $E_p[n]$, with the weighted total energy consumption formulated as

$$E_{\text{total}} = \alpha \sum_{n=1}^{N} E_p[n] + \sum_{k=1}^{K} (E_k^u + E_k^s). \quad (9)$$

D. Problem Formulation

In this letter, the definition of the energy efficiency (EE) is the ratio of total computed tasks in bits to the weighted total energy consumption of the system. Our main objective is to maximize the energy efficiency of the MEC system by jointly optimizing the user scheduling $\mathbf{C} \triangleq \{ c_k[n], k \in \mathcal{K}, n \in \mathcal{N} \}$, the phase-shift matrix of the U-RIS $\Phi \triangleq \{ \psi[n], n \in \mathcal{N} \}$, the U-RIS’s trajectory $\mathbf{Q} \triangleq \{ q[n], n \in \mathcal{N} \}$, the overall computed tasks in bits $I \triangleq \{ I_k, I_k^u, k \in \mathcal{K} \}$, and the CPU frequency allocation for different users of server $f \triangleq \{ f_k^u, f_k^i, k \in \mathcal{K} \}$. The problem can be formulated as

$$\begin{align*}
\max_{\mathbf{Q}, \mathbf{C}, \Phi, \mathbf{I}, \mathbf{f}} & \quad \alpha \sum_{n=1}^{N} E_p[n] + \sum_{k=1}^{K} (E_k^u + E_k^s) \\
\text{s.t.} & \quad 0 \leq |\theta_i| < 2\pi, \forall n, i, \\
& \quad I_k \leq I_k^u, \forall k, \\
& \quad \sum_{k=1}^{K} I_k \leq C_0, \\
& \quad (1a) - (1c), (4), (6),
\end{align*}$$

(10a)

where (10b) denotes the phase constraint of the U-RIS, (10c) indicates that there is a threshold $I_k$ for the minimum offloading tasks for user $k$, and (10d) means that the total server’s CPU frequency is limited by the maximum value $C_0$. Problem (10) is a challenging mixed-integer non-linear fractional programming problem where the objective function and the constraints (3) and (5) are not jointly convex w.r.t. the optimization variables. In the next section, we propose an iterative algorithm to efficiently obtain a suboptimal solution.

III. PROPOSED ALGORITHM

In this section, we propose an iterative algorithm based on the SCA to obtain a solution to problem (10). Specifically, we divide (9) into two subproblems, i.e., the joint optimization of $\mathbf{C}$ and $\Phi$ as well as that of $\mathbf{Q}, \mathbf{I}, \mathbf{f}$. We solve the two subproblems iteratively until convergence.

A. Optimizing $\mathbf{C}$ and $\Phi$ for Given $\mathbf{Q}, \mathbf{I}$ and $\mathbf{f}$

Note that the EE is not directly related to the optimization variable $\mathbf{C}$ and $\mathbf{I}$. To maximize the EE, we can equivalently minimize the sum rate according to constraint (4). To handle the coupled variables, we first consider the design of the phase shift $\Phi$. If the U-RIS chooses to serve user $k$ in time slot $n$, i.e., $c_k[n] = 1$, the achievable rate is denoted as

$$R_k[n] = B \log_2 \left( 1 + \frac{P_k(\tau[n])^2}{P \tau[n] \sum_{l=1}^{M} \psi[l][\theta[n] + \theta[l]]} \right),$$

(11)

where $\psi[l] = 2(m_x - 1) \pi d / (\cos \phi[k] - \sin \phi[k] - \cos \phi[k] - \sin \phi[k])$, $\phi[k] = \sin \phi[k] - \sin \phi[k]$ is related to the array response. Clearly, if the multipath signals superimpose coherently, the rate can reach the maximum. This means that the U-RIS can play an phase alignment role by setting $\theta_i[n] = -\psi_i[n] + \omega, \omega \in [0, 2\pi], i \in \mathcal{M}, n \in \mathcal{N}$, where $\omega$ is a pre-set fixed value, yielding the following maximum achievable rate

$$R_k[n] = c_k[n] B \log_2 \left( 1 + \frac{\tilde{\xi}_k}{\frac{d_k^u + \tau[n]}{d_k^u + \tau[n]}} \right),$$

(12)

where $\tilde{\xi}_k = \frac{P_k d_k^u M^2}{\sigma^2}$. After determining the value of $\Phi$, we relax the integer constraint (3) into a linear form, and obtain the following standard LP problem for the optimization of $\mathbf{C}$:

$$\begin{align*}
\max_{\mathbf{C}} & \quad \sum_{n=1}^{N} \sum_{k=1}^{K} c_k[n] R_k[n] \\
\text{s.t.} & \quad \sum_{n=1}^{N} c_k[n] R_k[n] \geq \frac{N \sum_{k=1}^{K} f_k^u}{f_k^u T_k - f_k^u T_k}, \forall k, \\
& \quad \sum_{n=1}^{N} c_k[n] = 1, 0 \leq c_k[n] \leq 1, \forall k, n,
\end{align*}$$

(13a)

$$\begin{align*}
\tilde{R}_k[n] &= B \log_2 \left( 1 + \frac{\tilde{\xi}_k}{\frac{d_k^u + \tau[n]}{d_k^u + \tau[n]}} \right).
\end{align*}$$

This problem can be solved by the CVX solver. Finally, $c_k[n], \forall k, n$, can be reconstructed as binary variables via the method in [13].

B. Optimizing $\mathbf{Q}$, $\mathbf{I}$ and $\mathbf{f}$ for Given $\mathbf{C}$ and $\Phi$

For any given $\mathbf{C}$ and $\mathbf{I}$, problem (10) can be recast as

$$\begin{align*}
\max_{\mathbf{Q}, \mathbf{I}, \mathbf{f}} & \quad \alpha \sum_{n=1}^{N} E_p[n] + \sum_{k=1}^{K} (E_k^u + E_k^s) \\
\text{s.t.} & \quad (1a) - (1c), (6), (11c), (11d)
\end{align*}$$

(14a)

Note that problem (14) is difficult to solve due to the non-convex objective function and constraint (5). We first consider convexifying the constraint. By introducing the slack variables $y = \{ y_k[n], \forall k, n \}, p = \{ p[n], \forall n \}$, where $y_k[n] \geq \| q[n] - w_k[n] \|_2^2 + H_k^2, p[n] \geq \| q[n] - w_k[n] \|_2^2 + H_k^2$, and the auxiliary variable $D = \{ d_k[n], \forall k \}$, constraint (5) can be transformed into

$$d_k \leq \frac{1}{N} \sum_{n=1}^{N} c_k[n] B \gamma_0[n], \forall k,$$

(15a)
where $\gamma_0[n] = \log_2(1 + \frac{p[n]}{(p[n])^{\alpha L/2}(y_k[n])^{\alpha L/2}})$. Since $y_k[n]$ and $p[n]$ can be increased to reduce the objective value, the constraints of $y_k[n]$ and $p[n]$ must hold with equality at the optimal solution to problem (14); hence, constraint (4) can be equivalently relaxed into (14) without loss of optimality. Note that $\gamma_0[n]$ is convex with respect to $y_k[n]$ and $p[n]$, so we apply the first-order Taylor expansion of $\gamma_0[n]$ at the given point $(p(t)[n], y_k(t)[n])$ in the $r$th iteration to convert the non-convex constraint (15a) to a convex form as follows

$$d_k \leq \frac{1}{N} \sum_{n=1}^{N} c_k[n] B\hat{R}_k[n], \forall k,$$

(16)

where

$$\hat{R}_k[n] = C_k(t)[n] + A_k(t)[n](p[n] - p(t)[n]) + B_k(t)[n] Y_k(t)[n]$$

$$A_k(t)[n] = -\log_2 e \frac{p(t)[n]\alpha L/2 y_k[n]\alpha L/2 + \xi_k}{\alpha L/2 \xi_k + \xi_k p(t)[n]}$$

$$B_k(t)[n] = -\log_2 e \frac{p(t)[n]\alpha L/2 y_k[n]\alpha L/2 + \xi_k}{\alpha L/2 \xi_k + \xi_k y_k[n]}$$

$$C_k(t)[n] = \log_2(1 + \frac{\xi_k}{p(t)[n]\alpha L/2 y_k[n]\alpha L/2 + \xi_k y_k[n]})$$

and $Y_k(t)[n] = (y_k[n] - y_k[t])[n]$. We next deal with the non-convex objective function. Note that $E_p[n]$ and $E_k$ are the two non-convex terms in the denominator of the objective function. To tackle the non-convexity of $E_p[n]$, we successively apply the inequalities $a \cdot b \leq \|a\|\|b\|$, $a, b \in \mathbb{R}^2$ and $(a^2 + b^2)\frac{1}{2} \leq |a + b|$, $a, b \in \mathbb{R}$ for the non-convex term $F[n]$ and \( (\|v[n]\|/\sqrt{\|v[n]\|^2 - \frac{1}{2}2^{\epsilon}}) \) in $E_p[n]$, respectively. Finally, we get a convex upper bound $E_{up}[n]$ of $E_p[n]$, expressed as

$$E_{up}[n] = P_0 \left( \frac{3\|v[n]\|^2}{B_{tip}} + \frac{1}{2} \frac{4\pi\nu\sigma\|A[v[n]]^3 + P_i \hat{n}[i]}{1} \right),$$

(17)

where $\hat{n}[n] = 1 + \frac{(2m\|a[n]\| + pSFP\|v[n]\|^2)}{4\pi^2\nu^2} \alpha \rho \frac{\sum_{k=1}^{K} E_k[n]}{\sum_{k=1}^{K} E_k[n]}$, and $\hat{n}[n] \geq 1$. To handle the non-convexity of $E_k$, similarly we introduce the slack variable $u_k \{u_k[n], \forall k\}$ satisfying $u_k \geq \frac{p_k(t)}{f_0^2}$. By inequality transformation and applying first-order Taylor expansion at given point $p_k(t)$ in the $r$th iteration, we have

$$\frac{1}{p_k(t)} + (p_k^0 - p_k(t)) \frac{1 - p_k(t)^2}{(p_k(t))^2} \geq \frac{p_k^0}{u_k}, \forall k.$$  

(18)

Therefore, problem (14) can be approximated as

$$\max_{Q, y, p, u, l, f} \alpha \sum_{n=1}^{N} E_{up}[n] + \sum_{k=1}^{K} (E_k[n] + \varphi_k \chi_k[u_k]),$$

(19a)

s.t. $y_k[n] \geq \|q[n] - w_k[n]\|^2 + H^2, \forall k, n,$

(19b)

$p[n] \geq \|q[n] - w_k[n]\|^2 + H^2, \forall n,$

(19c)

$E_k[n] \geq \|q[n] - w_k[n]\|^2 + H^2, \forall n,$

(19d)

This problem is quasi-convex [14] because the objective function consists of a linear numerator as well as a convex denominator and all constraints are convex. Therefore, it can be efficiently solved by existing fractional programming methods, such as the Dinkelbach algorithm.

C. Overall Algorithm

The overall algorithm is summarized in Algorithm 1. To be specific, the respective complexities are $O((KN)^{3.5} \log(1/\epsilon))$ for optimizing $C$ and $O((N + K + KN)^{3.5} \log(1/\epsilon))$ for optimizing $Q, L, f$. Considering the complexity of BCD iteration, the overall complexity is $O((N + K + KN)^{3.5} \log^2(1/\epsilon))$. In general, Algorithm 1 yields a lower bound of the original problem, and its performance is verified in Section IV.

IV. NUMERICAL RESULTS

In this section, we analyze the effectiveness of the proposed algorithm with numerical results. The objective of the proposed algorithm is to maximize the total energy efficiency of the whole MEC system (denoted as max total EE), at the expense of the quality of task processing for some individual users. When each user has urgent tasks and it is important to ensure high energy efficiency and fairness, we also propose an algorithm to maximize the minimum energy efficiency over all users (denoted as max min EE) by replacing the objective function in (10) with $\alpha \sum_{n=1}^{N} E_p[n] + \sum_{k=1}^{K} E_k[n]$ where $l_{min} \leq p_k^0 + n_k^0, \forall k$. This problem can be solved similarly, and the algorithm will not be described due to space limitations. Besides, we set two baseline algorithms aiming to maximize the system total energy efficiency for comparison: 1) Heuristic-traj means that the U-RIS traverses each user node along the pre-defined shortest route at a constant speed, with optimized $C, \Phi$ and $f$; 2) UAV-Server means that a UAV-carried server is used to provide edge computing [2, 3], with optimized $C, Q, L$ and $f$. This is the traditional practice of the UAV-assisted MEC system which will not lead to a cascade channel. However, we note that RIS passive elements are generally quite small and light [7], but the hardwares for providing edge computing in the MEC server are relatively complex, leading to a larger weight. Simulation parameters are set as $B = 1$ MHz, $\sigma^2 = -160$ dBm, $\beta_0 = -40$ dB, $H = 100$ m, $\nu = 50$ m/s, $\omega_{max} = 30$ m/s, $\delta = 1$ s, $N = 27$, $q_0 = [600, 50]^T$ m, $q_F = [600, 50]^T$ m, $w_s = [0, 800]^T$ m, $r_d = 700$ m, $\varphi_u = 10^{-5}$, $\varphi_r = 10^{-5}$, $C_0 = 3000$ MHz, $\alpha = 0.02$. $P_k = 0.1$ W, $\chi_k = 10^5$ cycles/bit, $f_0^2 = 100$ MHz, $T_k = 30$ s, $I_k = 1$ Mbits, for $\forall k$, the weight of UAV, RIS and MEC server are 2 kg, 2 kg and 6 kg, respectively.

Fig. 2 shows the U-RIS or UAV trajectories of the various algorithms when $T = 70$ s (each trajectory is sampled every 2 s), all of which are significantly different. We observe that in the proposed max total EE algorithm, the U-RIS first flies towards user 1, and then approaches the server along the
The trajectory gets close when $T$ is large enough due to the trade-off between high-quality channel and long flight span. As the period gets longer, the EE peaks at 70 s in the EE curve of the U-RIS only. Moreover, the U-RIS can achieve the trade-off mentioned above, which is the reason why the proposed max total EE algorithm has a considerable performance gain compared to the baseline algorithms. It is worth noting that the Heuristic-traj algorithm can be treated as a lower bound of the EE. Besides, the EE under UAV-Server shows a downward trend even in the early stage.

V. CONCLUSION

In this letter, the UAV-mounted RIS technique has been introduced to enhance the user offloading link, thereby further improving the performance of the MEC system. We proposed a joint RIS passive beamforming, UAV trajectory and MEC resource allocation optimization algorithm to maximize the EE and obtained a high-quality suboptimal solution. Numerical results gave evidence of the significant benefits that the U-RIS can provide in the MEC system.