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Energy Efficiency Maximization in Mobile Edge Computing Networks via IRS assisted UAV Communications

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ABSTRACT

In this paper, we investigate the energy efficiency maximization for mobile edge computing (MEC) in intelligent reflecting surface (IRS) assisted unmanned aerial vehicle (UAV) communications. In particular, UAV can collect the computing tasks of the terrestrial users and transmit the results back to them after computing. We jointly optimize the users' transmitted beamforming and uploading ratios, the phase shift matrix of IRS, and the UAV trajectory to improve the energy efficiency. The formulated optimization problem is highly non-convex and difficult to be solved directly. Therefore, we decompose the original problem into three sub-problems. We first propose the successive convex approximation (SCA) based method to design the beamforming of the users and the phase shift matrix of IRS, and apply the Lagrange dual method to obtain a closed-form expression of the uploading ratios. For the trajectory optimization, we propose a block coordinate descent (BCD) based method to obtain a local optimal solution. Finally, we propose the alternating optimization (AO) based overall algorithm and analyzed its complexity to be equivalent or lower than existing algorithms. Simulation results show the superiority of the proposed method compared with existing schemes in energy efficiency.

KEYWORDS

Mobile edge computing (MEC); unmanned aerial vehicle (UAV); intelligent reflecting surface (IRS); energy efficiency

1 Introduction

Recently, unmanned aerial vehicle (UAV) technology has aroused widespread concern in industry and academia [1–3]. The unique advantages of the UAV are its flexibility and mobility [4,5]. The glider UAV can move to different positions at different time slots, while the rotor UAV can hover at the same position, which could significantly improve channel gain and thus improve the transmission rate [6–8].

In [9], the authors have done some basic research on the flexibility of UAVs, which can effectively improve the communication rate when a UAV is used as a base station. The author focuses on the flexible deployment of UAVs, and can adjust the position of UAVs under different channel conditions to improve channel gain; In [10], the author considered the mobility of UAVs. When the UAV hovers,



its energy consumption is a huge expense, and the glider UAV cannot hover. The author designs the trajectory of the UAV, making full use of the mobility of the UAV.

Intelligent reflector technology is also an emerging technology, which is used to improve the channel environment and is applied to scenes with poor channel conditions [11,12]. In [13], the authors combined the IRS technology with the UAV technology and uses the UAV to carry the IRS to further improve the flexibility of the IRS, thus further improving the communication rate.

With the continuous development of communication technology, the demand for communication rate is increasing [14,15]. Due to the limitation of Shannon's information theory, the upper limit of the communication rate is closely related to the communication bandwidth and the background noise in the communication [16,7]. Under the existing technical framework, the use of mobile edge computing technology is undoubtedly an important means to improve the communication user experience in a new way [17,18].

Mobile edge computing technology transmits the user's computing tasks to the ECS for computing [19,20], and then transmits the computing results back. Although the transmission of computing tasks will increase the communication frequency, the advantage of this is that the computing efficiency of cloud servers is usually higher than that of local computing [21–23]. The data volume of the calculation result is much smaller than that of the local calculation. The research on mobile edge computing has made some progress [24–26]. For example, in [26], two modes of partial unloading and full unloading were considered, and it is proposed that the total delay of computing can be greatly reduced under the partial unloading mode.

The research on the combination of mobile edge computing and IRS technology has also made great progress [27,28]. As a means of channel reconstruction, IRS can effectively reduce the transmission delay of data, thus reducing the overall delay of mobile edge computing.

In this paper, we consider using UAVs to carry IRS to assist mobile edge computing tasks. The main contributions of this paper are summarized as follows:

(1) We consider a new paradigm that uses IRS to assist users in mobile edge computing tasks. Meanwhile, the UAV is applied as a cloud server to improve the efficiency of computing and transmission.

(2) We propose an original optimization problem. We jointly design the unloading ratio, the phase shift matrix of the IRS, the flight path of the UAV, and the user's unloading strategy to minimize the computing delay.

(3) After relaxing the original optimization problem, we put forward three subproblems, put forward the results of closed expressions for two subproblems, and transform the other subproblem into a convex problem to solve.

(4) The simulation results show that the proposed scheme is better than the existing scheme in terms of energy efficiency.

The rest of the paper is organized as follows: In [Section 2](#), we introduce the system model and formulate the original problem; In [Section 3](#), we propose the solution to the original problem, which could be divided into several sub-problem solutions and the AO based algorithm is proposed; In [Section 4](#), we take a discussion of this paper; In [Section 5](#), we take the simulation results and [Section 6](#) concludes this paper.

2 System Model and Problem Formulation

As shown in Fig. 1, the system consists of a UAV, and IRS and several users. All transmission nodes are equipped with multi-antennas.

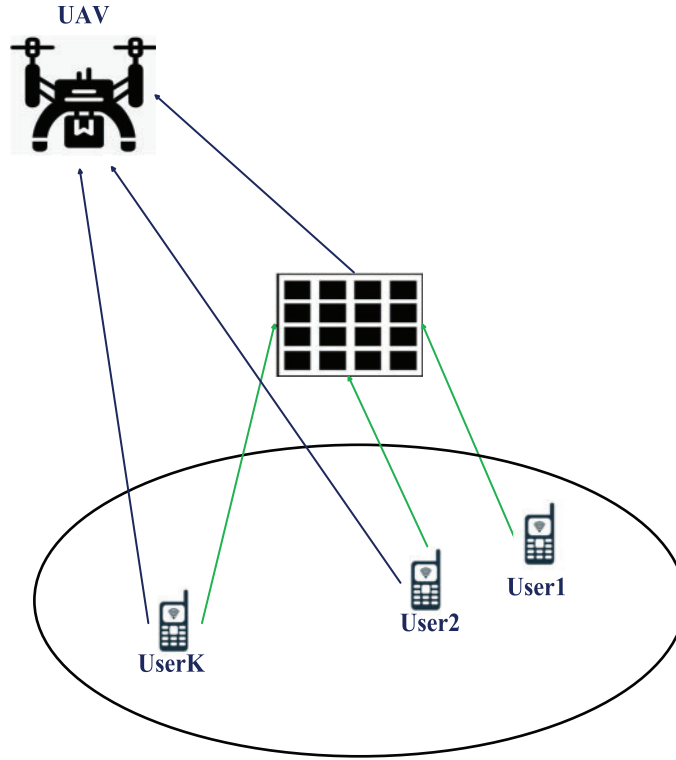


Figure 1: System model

If we consider a UAV as a mobile cloud server, its movement is limited by its hardware performance. We first obtain the flight speed of the UAV as

$$v[n] = \frac{Q[n] - Q[n - 1]}{\Delta T}, \quad (1)$$

Following the general assumption, we set the channel between the UAV and the ground user as the LOS link, that is, the channel gain is only related to the distance between the UAV and the ground user. Specifically, the air-ground channel is modeled as

$$h_k [n] = \frac{g_0}{\|Q[n] - q_k\|_2^2 + H^2}, \quad (2)$$

where g_0 represents the empirical gain of the line-of-sight link at the specified distance (set to 1 m for simplicity). Let q_k represent the physical position of user k , and H represents the fixed flight altitude of the UAV [29].

We consider that all users are transmitting in the same frequency band. At this time, the data between different users is not interconnected, and some interference will occur, which is expressed as

$$R_k [n] = B\Delta T \log \left(1 + \frac{p_k h_k [n]}{\sum_{j \neq k} p_j h_j [n] + \sigma^2} \right), \quad (3)$$

where p_j represents the transmission power of the user j , and j represents the background Gaussian white noise.

Consider the scenario of partial unloading. We define all tasks of the user k as D_k , and the local computing part is m , so the available offload part is $1 - m$. As in [30], the user's uninstall task constraint is

$$\sum_n R_k [n] \geq (1 - m_k) D_k. \quad (4)$$

In addition, considering the delay between the transmission task and the calculation task, we define the task amount to be calculated by each timeslot server as $W[n]$, and then we need to define the following constraints:

$$\sum_{n=1}^{n_0} R_k [n] \geq \sum_{n=1}^{n_0} W_k [n]. \quad (5)$$

When the UAV flight ends, all tasks are processed, namely

$$\sum_{n=1}^N R_k [n] = \sum_{n=1}^N W_k [n]. \quad (6)$$

Since all computing tasks are divided into two parts, the above constraints only restrict the transmission and computing tasks. For local computing tasks, the following constraints need to be met:

$$f_{\max} T \geq W_k. \quad (7)$$

In addition, both UAVs and users are subject to power limitations. The user's power consumption is divided into two parts. One part is the energy consumption generated in the communication process when the user sends a task. It can be expressed as

$$E_{k,1} [n] = P_{k,1} [n] T, \quad (8)$$

where $P_{k,1}$ is the communication energy consumption of the user k in unit time. It is worth noting that the communication energy consumption of users is mainly determined by channel gain. When the distance between the UAV and the user is longer, the user needs to consume more energy and vice versa. Therefore, air-ground channel gain can not only improve the communication rate but also reduce the energy consumption of users.

In addition, because some tasks are calculated locally by users, the calculation of tasks will consume additional energy at this time, expressed as

$$E_{k,2} = P_{k,2} m_k. \quad (9)$$

Unlike the communication energy consumption of users, the calculation energy consumption of users is independent of the channel state information but only depends on the local calculation task. In order to simplify the process, we assume that the energy consumption is linear with the local computing task share, which has been described in detail in [4].

Further, we consider the energy consumption of UAVs. Similar to the energy consumption of users, the energy consumption of UAVs consists of the following two parts: (1) the flight energy consumption

of UAVs; (2) the calculated energy consumption of UAVs. The flight energy consumption of UAV is expressed by the following formula:

$$E_{u,1}[n] = \alpha_1 \|v[n]\|^2 + \frac{\alpha_2}{\|v[n]\|^2} \left(1 + \frac{\|a[n]\|^2}{g^2}\right). \quad (10)$$

Symbol α_1, α_2, g are all fixed parameters, determined by the UAV structure, and represent the acceleration of the UAV, expressed by the following expression:

$$\frac{a[n] = v[n] - v[n-1]}{T}. \quad (11)$$

The calculated energy consumption of the UAV is as follows:

$$E_{u,1=2}[n] = P_{u,2} m_k. \quad (12)$$

Based on the above energy consumption expression, we can get the energy constraints for users and UAVs as follows:

$$\sum_n E_{k,1}[n] + E_{k,2} \leq E_{k,sum}, \quad (13)$$

$$\sum_n E_{u,1}[n] + E_{u,2} \leq E_{u,sum}. \quad (14)$$

In this paper, our goal is to maximize the system's computing power by assigning tasks to mobile edge computing, UAV flight path, and IRS dependency matrix. At this time, the problem is established as follows:

$$\begin{aligned} & \max_{m,Q,W,G} \sum_n \sum_k R_k[n] \\ & s.t. \quad 0 \leq m \leq 1, \\ & \quad \sum_n E_{k,1}[n] + E_{k,2} \leq E_{k,sum}, \\ & \quad \sum_n E_{u,1}[n] + E_{u,2} \leq E_{u,sum} \\ & \quad \sum_{n=1}^{n_0} R_k[n] \geq \sum_{n=1}^{n_0} W_k[n], \\ & \quad \sum_{n=1}^N R_k[n] = \sum_{n=1}^N W_k[n], \\ & \quad \sum_n R_k[n] \geq (1 - m_k) D_k, \\ & \quad v[n] \leq v_{\max}, \\ & \quad a[n] \leq a_{\max}, \end{aligned} \quad (15)$$

where v_{\max} and a_{\max} respectively represent the maximum instantaneous speed and maximum instantaneous acceleration allowed by UAVs. Since the variables of the problem are highly non-convex, we

use the method of iteratively finding the local optimal solution to solve the original problem in the subsequent solving process.

3 Proposed Solution

In this section, due to the highly non-convex nature of the original problem, we first introduce auxiliary variables according to the definition of R as follows:

$$R_k[n] \geq \frac{BT}{N} \log(1 + \kappa_{k,n}), \quad (16)$$

we convert rate maximization to rate lower bound maximization, and introduce the following equation:

$$\kappa_{k,n} = \frac{Ps_{k,n}}{q_{k,n}}, \quad (17)$$

$$q_{k,n} = \frac{1}{g_{k,n}}. \quad (18)$$

Note that non-convex variables in the target are converted into a linear format. Then, we deal with the non-convex form in the condition, mainly including the energy consumption form of UAV. We introduce new variables as follows [31]:

$$\alpha_1 \|v[n]\|^2 + \frac{\alpha_2}{\|v[n]\|^2} \left(1 + \frac{\|a[n]\|^2}{g^2}\right) \leq \alpha_1 \|v[n]\|^2 + \alpha_2 A[n]. \quad (19)$$

Further, we relax the upper bound of energy consumption into linear representation, and then the original problem is expressed as

$$\begin{aligned} & \max_{m, Q, W, G} \sum_n \sum_k \frac{BT}{N} \log(1 + \kappa_{k,n}) \\ & s.t. \quad 0 \leq m \leq 1, \\ & \quad \sum_n E_{k,1}[n] + E_{k,2} \leq E_{k,sum}, \\ & \quad \sum_n E_{u,1}[n] + E_{u,2} \leq E_{u,sum}, \\ & \quad A[n] \geq \left(1 + \frac{\|a[n]\|^2}{g^2}\right), \\ & \quad \sum_{n=1}^{n_0} R_k[n] \geq \sum_{n=1}^{n_0} W_k[n], \\ & \quad \sum_{n=1}^N R_k[n] = \sum_{n=1}^N W_k[n], \\ & \quad \sum_n R_k[n] \geq (1 - m_k) D_k, \\ & \quad v[n] \leq v_{\max}, \\ & \quad a[n] \leq a_{\max}. \end{aligned} \quad (20)$$

It is worth noting that the problem is still non-convex at this time. For this kind of problem, we use the first-order Taylor expansion method to solve it.

3.1 First-Order Taylor Based Method

In this subsection, we propose the local optimal solution for the beamforming vector and the phase shift matrix of IRS.

We first introduce the following variables:

$$f = - \sum_n \log \left(\sum_k \text{Tr} (g_k g_k^H W r) + \sigma_{n,k}^2 \right),$$

$$g = - \sum_n \log \left(\sum_{K \setminus k} \text{Tr} (g_k g_k^H W r) + \sigma_{n,k}^2 \right).$$
(21)

Further, we define the first order partial derivative as

$$R(W_k) \geq R(W_k^{(j)}) + \sum_k \text{Tr} \left(\frac{\partial R(W_k^{(j)})}{\partial W_k} \right)^H (W_k^{(j)} - W_k),$$
(22)

where

$$\text{Tr} \left(\frac{\partial R(W_k^{(j)})}{\partial W_k} \right) = - \frac{1}{\ln 2} \sum_{K \setminus k} \frac{g_k g_k^H}{\text{Tr} (g_k g_k^H W) + \sigma_{n,k}}.$$
(23)

The local optimal solution of the beamforming vector is thus obtained via CVX toolbox [32].

We then focus on the optimization of the phase shift matrix of IRS. We deal with the form of the sum of two non-convex terms in the target. It is worth noting that due to the high coupling of variables, direct derivation is very difficult. We therefore introduce the following inequality:

$$P \left(1 + \frac{\|w\|^2}{U_p^2} \right) + m_0 A \|w\|^3 + \alpha v^2 [n] \leq E_v [n],$$
(24)

which comes from the following triangular inequality:

$$(a^2 + b^2)^{\frac{1}{2}} \leq (a + b).$$
(25)

According to (24) and (25), we take the alternative definitions as

$$\frac{1}{L_k [n]} + (L_k [n] - L_k [n - 1]) \left(- \frac{1}{L_k^2 [n]} \right) \geq \frac{(f_k)^2}{U_k}.$$
(26)

Then we transform the numerator and denominator of the problem into convex form. Therefore, the problem can be transformed into a quasi-convex problem in general.

$$\begin{aligned}
& \max_{Q,y,P,f} \alpha \frac{\sum_k L_k}{\sum_n E[n] + \sum_k E_k + \chi_k}, \\
& s.t. \ y_k \geq \|q[n] - w_k\|^2 + H^2, \\
& \quad p_k \geq \|q[n]\|^2 + \|w_k\|^2, \\
& \quad \sum_{n=1}^{n_0} R_k[n] \geq \sum_{n=1}^{n_0} W_k[n], \\
& \quad \sum_{n=1}^N R_k[n] = \sum_{n=1}^N W_k[n], \\
& \quad \sum_n R_k[n] \geq (1 - m_k) D_k.
\end{aligned} \tag{27}$$

Here, the user beam transmission can be completed by solving multiple second-order convex cone constraints. However, due to the flexibility of UAV, with the passage of time, UAV needs to maintain communication with users to exchange information. Therefore, we consider using the distributed solution as follows.

We use the ADMM method in the following format to solve the above problems:

$$G = \begin{bmatrix} A_{1,1} & \cdots & A_{N,1} & B_{1,1} & \cdots & B_{N,1} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ A_{1,N} & \cdots & A_{N,N} & B_{1,N} & \cdots & B_{N,N} \end{bmatrix}^T, \tag{28}$$

where A represents the position of the UAV in each time slot, and B represents the beam vector of the user in different time slots. The user's beam will change according to the different position of the UAV. Then the UAV calculates the energy consumption required for its flight and whether it meets the constraints of speed and acceleration according to the information in A . If the above constraints are met, the user beam in B will be further updated. Finally, the updates of A and B will be stable and meet the constraints of the UAV's speed and computing ability.

The optimal G should meet the following conditions:

$$\begin{bmatrix} I_N & 0 \\ 0 & \Lambda \end{bmatrix} G = [I_N, V], \tag{29}$$

where I_N refers to a identity matrix with dimension N , and V is an orthogonal matrix.

However, we gradually optimize the composition of G by iteration, and the two sides of the equation are not fixed matrices, so we can not directly obtain the optimal solution by solving the inverse of the matrix. We try to reduce the interval of the equation as follows:

$$\begin{aligned}
\Delta = & - \sum_n \sum_k R_{n,k} + \alpha \left(\sum_n \sum_k E_k[n] + \sum_n E_{up}[n] \right) \\
& + Tr(U^T (P^T G - H)) + \frac{1}{2} \|P^T G - H\|^2 \\
& + \frac{\beta}{2} (e_{n,k} + \sigma_{n,k}^2)^2
\end{aligned} \tag{30}$$

By substituting the expression of Δ into (27), the problem (27) is then transformed as

$$\begin{aligned}
& \max_{Q,y,P,f} - \sum_n \sum_k R_{n,k} + \alpha \left(\sum_n \sum_k E_k[n] + \sum_n E_{up}[n] \right) \\
& + Tr(U^T(P^T G - H)) + \frac{1}{2} \|P^T G - H\|^2 \\
& + \frac{\beta}{2} (e_{n,k} + \sigma_{n,k}^2)^2, \\
& s.t. y_k \geq \|q[n] - w_k\|^2 + H^2, \\
& p_k \geq \|q[n]\|^2 + \|w_k\|^2, \\
& \sum_{n=1}^{n_0} R_k[n] \geq \sum_{n=1}^{n_0} W_k[n], \\
& \sum_{n=1}^N R_k[n] = \sum_{n=1}^N W_k[n], \\
& \sum_n R_k[n] \geq (1 - m_k) D_k.
\end{aligned} \tag{31}$$

According to the constraints in (31), we can obtain the local optimal solution of the $n+1$ th iteration according to the results of the n th iteration, so as to realize the distributed solution of the problem. Specifically,

$$\begin{aligned}
P_1^{(n)} &= P_1^{(n-1)} + \alpha_1 (P^T G - H)^{(n)} \\
P_2^{(n)} &= P_2^{(n-1)} + \alpha_2 \theta,
\end{aligned} \tag{32}$$

where θ is the difference between the preset variable and the actual variable used in the calculation process, which is calculated by the following:

$$\theta = \phi^{(n)} - \bar{\phi}^{(n)}. \tag{33}$$

According to the iterative solution process, we propose an iterative algorithm. By confirming the maximum iteration number and the minimum iteration interval, the algorithm can achieve the balance of time complexity and algorithm performance.

Algorithm 3.1: Beamforming design algorithm

Input: Maximum Iterations M_1 and M_2 .

Input: Number of time slot N , Channel state information \mathbf{G} , \mathbf{H}_{k_1} and \mathbf{H}_{k_2} and Maximum power P_{max} .

Output: Beamforming matrix \mathbf{W}_k , covariance matrix \mathbf{G} , and shift matrix \mathbf{G} ,

- 1: **function** Beamforming Design
 - 2: Initial $\mathbf{W}_k = P_{max} \mathbf{I}$ and the shift matrix $\mathbf{G} = \mathbf{I}$, the index $n = 0$
 - 3: **for** $n \leq N$ **do**
 - 4: Compute the next state according to the current $p_k[n]$
 - 5: Calculate $\mathbf{W}_k^{(n+1)}$ and P_k for given $\mathbf{G}^{(n)}$
-

(Continued)

Algorithm 3.1 (continued)

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6:      $n = n + 1$ 
7:   end for
8: end function

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3.2 Offloading Allocation

For the fixed UAV flight path and user-sending strategy, we optimize the resource unloading scheme. At this time, the problem is simplified as follows:

$$\begin{aligned}
& \max_{m, Q, W, G} \sum_n \sum_k R_k [n] \\
& s.t. \ 0 \leq m \leq 1, \\
& \sum_n E_{k,1} [n] + E_{k,2} \leq E_{k,sum}, \\
& \sum_n E_{u,1} [n] + E_{u,2} \leq E_{u,sum}.
\end{aligned} \tag{34}$$

For the resource allocation problem, we first determine it as a convex problem according to its second derivative. Specifically, the first derivative of the target is

$$\frac{\partial R_k [n]}{\partial m_k} = -\frac{m_k^{-2}}{B \log \left(1 + \frac{PG}{\sigma^2} \right)}. \tag{35}$$

Further, its second partial derivative is

$$\frac{\partial^2 R_k [n]}{\partial^2 m_k} = -\frac{2m_k^{-3}}{B \log \left(1 + \frac{PG}{\sigma^2} \right)}. \tag{36}$$

The second order partial derivative of the objective is constantly positive, so the objective of the problem is convex. Further, the problem constraint is linear with respect to m , that is, the problem is convex.

In order to solve the problem, we simplified the energy constraint into a linear form as follows:

$$L(\beta_1, \beta_2, m_k) = \sum_n \sum_k \left(\frac{1}{B \log \left(1 + \frac{PG}{\sigma^2} \right)} \right) + \beta_1 \sum_k (E_{k,sum} - E_{u,sum}) + \beta_2 (1 - m), \tag{37}$$

At this time, (37) establishes a convex problem. According to Slater condition, we can obtain a unique optimal solution as follows.

We first calculate the partial derivative of (37) as follows:

$$\frac{\partial L(\beta_1, \beta_2, m_k)}{\partial m_k} = \sum_n \left(\frac{1}{B \log \left(1 + \frac{PG}{\sigma^2} \right)} \right) + \beta_1 \sum_k (E_{k,sum} - E_{u,sum}) - \beta_2. \tag{38}$$

Finally, the point where the partial derivative is 0 can be considered as the optimal solution of the KKT condition as follows:

$$m_k^* = \sqrt{\frac{1 + P}{B \log \left(1 + \frac{PG}{\sigma^2} \right)}}. \quad (39)$$

3.3 Trajectory Optimization

In this subsection, we focus on the trajectory optimization for the fixed beamforming vector in UEs, the phase shift matrix of IRS and the offloading allocation. The original problem is simplified as follows:

$$\begin{aligned} & \max_{m, Q, W, G} \sum_n \sum_k \frac{BT}{N} \log(1 + \kappa_{k,n}) \\ & s.t. \sum_n E_{k,1}[n] + E_{k,2} \leq E_{k,sum}, \\ & \sum_{n=1}^{n_0} R_k[n] \geq \sum_{n=1}^{n_0} W_k[n], \\ & \sum_{n=1}^N R_k[n] = \sum_{n=1}^N W_k[n], \\ & \sum_n R_k[n] \geq (1 - m_k) D_k, \\ & v[n] \leq v_{max}, \\ & a[n] \leq a_{max}. \end{aligned} \quad (40)$$

Note that (40) is non-convex due to the non-convex of the constraints. We introduce the following variables:

$$\begin{aligned} \mathbf{x} &= \{x_k[n], \forall k, n\}, \\ \mathbf{p} &= \{p[n], \forall n\}, \end{aligned} \quad (41)$$

where $x_k[n]$ and y_k could be obtained via the following consumption:

$$\begin{aligned} x_k[n] &\geq \|q[n] - w_k\|^2 + H^2, \\ y_k &= \frac{1}{N} \sum_{n=1}^N m_k B \tilde{R}_k[n], \forall k. \end{aligned} \quad (42)$$

We thus obtain the transmission rate as

$$\tilde{R}_k[n] = \log_2 \frac{1}{p[n] x_k[n] + \sigma_k}. \quad (43)$$

By introducing auxiliary variables, we transform the problem into a convex problem. Using SCA technology, we first established the following:

$$Q[n] = B \log \left(\sum_{j=1}^i p_j[n] \|h_j[n]\|^2 \right). \quad (44)$$

Further, we consider the reachability rate with noise and interference, expressed as

$$Q[n] = B \log \left(\sum_{j=1}^{i-1} p_j[n] \|h_j[n]\|^2 + \sigma^2 \right). \quad (45)$$

This means that in order to maximize the use efficiency of computing power at the achievable rate at the current time, it is necessary to transmit data not less than the sum of current computing power. This also indicates the physical distance required by the UAV at the current moment.

$$\begin{aligned} & \max_{m, Q, W, G} \sum_n \sum_k \frac{BT}{N} \log(1 + \kappa_{k,n}) \\ & s.t. \sum_n E_{k,1}[n] + E_{k,2} \leq E_{k,sum}, \\ & \sum_{n=1}^{n_0} R_k[n] \geq \sum_{n=1}^{n_0} W_k[n], \\ & \sum_{n=1}^N R_k[n] = \sum_{n=1}^N W_k[n], \\ & \sum_n R_k[n] \geq (1 - m_k) D_k, \\ & v[n] \leq v_{max}, \\ & a[n] \leq a_{max}. \end{aligned} \quad (46)$$

We can obtain the optimal solution of the problem (46) by means of first-order Taylor expansion.

3.4 Alternate Optimization Algorithm Design

According to the local optimal solution, closed expression and iterative solution obtained in the above section, we can carry out the local optimal design for the user's transmitted beam, the user's unloading ratio and the flight path of the UAV. We finally get the overall algorithm summarized as Algorithm 1. The convergence and superiority of the algorithm are verified in the simulation experiment.

Due to the high coupling between variables, the convergence of the algorithm is given by simulation experiments.

4 Complexity Analysis

We focus on the complexity of proposed schemes and two traditional schemes: MRT scheme and OA algorithm. The specific expression is shown in Table 1.

Note that MRT scheme gets the minimum complexity since it has a closed-form solution. The proposed sub-optimal get less complexity than the optimal scheme.

Table 1: Complexity analysis

Parameter	Complexity in each iteration	Overall complexity
Algorithm 3.1	$\mathcal{O}(M(P_1 + P_2))$	$\mathcal{O}(M(P_1 + P_2)P_1)$
Algorithm 4.1	$\mathcal{O}(M(P_1 + 1))$	$\mathcal{O}(M(P_1 + 1)P_2)$
MRT scheme	$\mathcal{O}(M)$	$\mathcal{O}(M)$
OA scheme	$\mathcal{O}(MP^2)$	$\mathcal{O}(MP^3)$

5 Numerical Results

In this section, we first list the parameters required for the simulation environment, then simulate the results under different settings, and analyze the advantages of the proposed algorithm.

5.1 Simulation Results

In this section, we conducted simulation experiments on the proposed scheme, mainly including (1) the proposed scheme; (2) the full offloading scheme; (3) the maximum rate scheme; (4) the scheme against potential eavesdroppers; (5) no IRS scheme; (6) fixed IRS scheme. The setting of transmission is shown in Table 2 and the specific results are as follows.

Table 2: Simulation parameters

Parameter	Symbol	Value
Bandwidth of MEC system	B	20 MHz
Total completion time	T	10 s
Number of time slots	N	50
Unit gain for reference distance	ρ_0	-30 dB
The power of noise	N_0	-60 dB
Altitude of the UAV	H	10 m
The maximum available speed of the UAV	V_{max}	10 m/s
The initial and final position of the UAV	$\mathbf{q}_I, \mathbf{q}_F$	(0, 0), (0, 10)
The position of the BS	\mathbf{q}_T	(0, 0)
The effective switched capacitance of the UAV	κ	10^{-28}
CPU cycles	C_k	1000 cycles/bit

Algorithm 3.2: Alternative optimization based algorithm

Input: Maximum Iterations M_1 and M_2

Input: Number of time slot N , Channel state information \mathbf{G} , \mathbf{H}_{k_1} and \mathbf{H}_{k_2} and Maximum power P_{max}

Output: Beamforming matrix \mathbf{W}_k , covariance matrix \mathbf{G} , and shift matrix \mathbf{G}

1: **function** Beamforming Design

(Continued)

Algorithm 3.2 (continued)

```

2:   Initial  $\mathbf{W}_k = P_{max}\mathbf{I}$  and the shift matrix  $\mathbf{G} = \mathbf{I}$ , the index  $n = 0$ 
3:   for  $n \leq N$  do
4:     Compute the next state according to the current  $p_k[n]$ 
5:     Calculate  $\mathbf{W}_k^{(n+1)}$  and  $P_k$  for given  $\mathbf{G}^{(n)}$ 
6:      $n = n + 1$ 
7:   end for
8: end function
9: function PROPOSED ALGORITHM
10:  Substituting the initial point the the constraints
11:  repeat
12:    if  $m > M$  then
13:      break;
14:    else
15:      Obtain  $\mathbf{G}^{(H)}$  using the bisection method;
16:      for  $k \leq K$  do
17:        if  $|f(\mathbf{w}_k^{(n+1)}, \mathbf{G}^{(n+1)}) - f(\mathbf{w}_k^{(n)}, \mathbf{G}^{(n)})| \leq \varepsilon$  then
18:          continue;
19:        end if
20:      end for
21:      Update the trajectory
22:    end if
23:    The maximum energy efficient  $\eta_E^{n,opt}$  is obtained
24:    if  $m \leq M$  then
25:       $m = m + 1$ 
26:    end if
27:  until  $\|R_m - R_{m-1}\| \leq e$ 
28: end function

```

We first focus on the convergence of the algorithm. We have drawn three curves in Fig. 2, two of which represent the convergence curves of iteration from different initial points. In the two initial points, we assume that all the IRS phase-shift matrices are unit matrices, the flight path of the UAV is a straight flight from the initial point to the endpoint, and the unloading mode is full unloading. The difference is that the user-transmitted beam at the initial point 1 is the MRT scheme, and the user-transmitted beam at the initial point 2 is the unit vector. It can be seen that the MRT scheme will obtain higher initial energy efficiency than the unit vector, but with the increase in the number of iterations, both of them converge around 10 iterations. In addition, we also simulate the individual iteration scheme, and the results show that our proposed scheme has higher performance.

The trajectory in a UAV simulation case is shown in Fig. 3. We randomly set 4 users. It can be found that the trajectory of the UAV will be as close as possible to each user. However, in order to maximize fairness and overall energy efficiency, no one has the opportunity to focus on different users in different time slots.

We also conducted simulation experiments on the impact of IRS elements. In Fig. 4, we mainly considered the change of IRS in the [10:10:40] range. When the number of IRS is small, that is, when the number of IRS is 10, our proposed scheme still has considerable advantages over other schemes. As the number of IRS elements increases, the proposed scheme will also increase. It is worth noting

that the role of the IRS is to reconstruct the channel. It cannot improve energy efficiency without limitation. When the number of IRS is large, the gain it can bring is limited. On the other hand, when IRS is not applicable in the scheme, the increase in the number of elements cannot bring benefits.

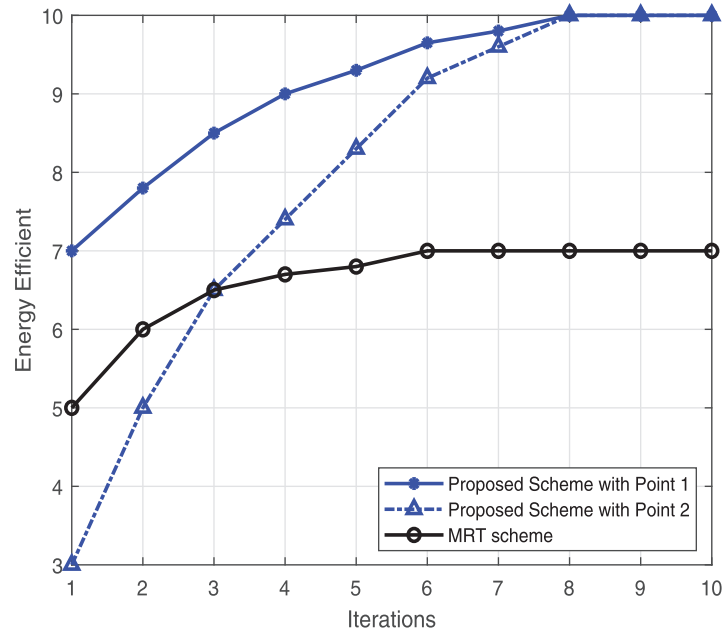


Figure 2: Convergence of the proposed algorithm

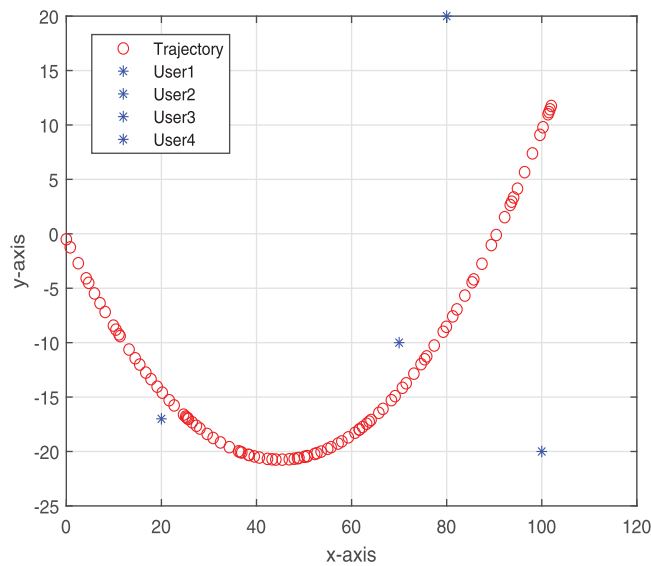


Figure 3: Trajectory of the UAV

In Fig. 5, we simulate the relationship between noise power and energy efficiency. The improvement of noise power will inevitably reduce energy efficiency. When the noise power increases, the

communication rate from the user to UAV decreases. This means that users need to consume more energy to achieve the set transmission target task.

In Fig. 6, we show the curve of energy efficiency changing with the maximum power of users. It is worth noting that with the increase in the maximum power of users, the growth rate of energy efficiency gradually slows down. Our proposed scheme is always superior to the existing scheme. In addition, when the maximum power of the user is increased, the energy efficiency of all unloading schemes will not be improved, because the extra energy cannot bring additional gain.

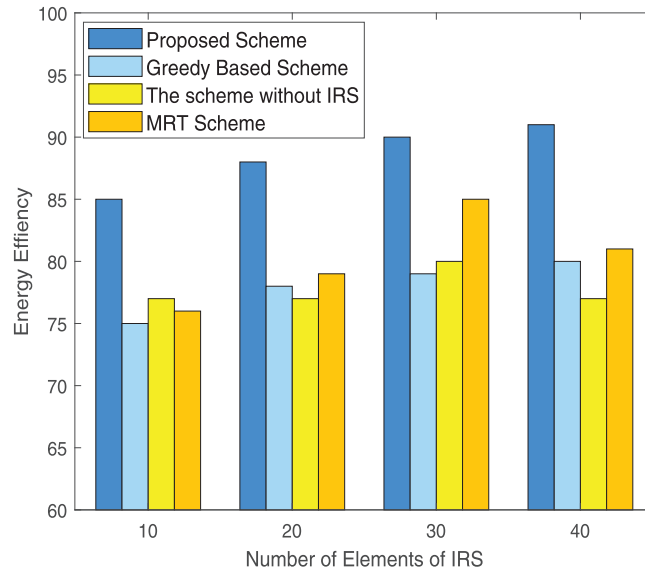


Figure 4: Energy efficiency vs. the number of IRS elements

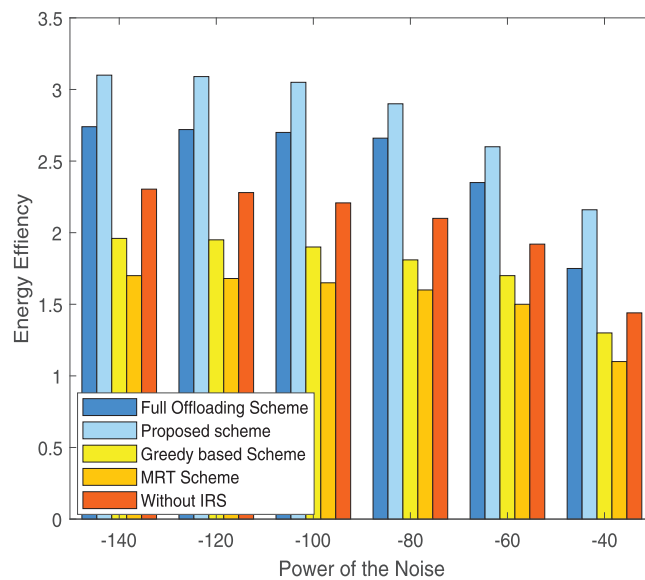


Figure 5: Energy efficiency vs. the maximum power of noise

In Fig. 7, we focus on the impact of total tasks on energy efficiency. It is worth noting that the scope of the total task is limited. When the total task is too large, the unloading and calculation of all tasks cannot be completed within the agreed time. When the total number of tasks is small, most of the energy consumed is used to support the UAV flight and the user’s transmission consumption. At this time, the energy efficiency is low. When the total number of tasks increases, the proportion of calculated energy consumption gradually increases, and the energy efficiency also increases. At this point, our proposed scheme can effectively allocate the energy required for calculation and flight transmission energy to improve energy efficiency.

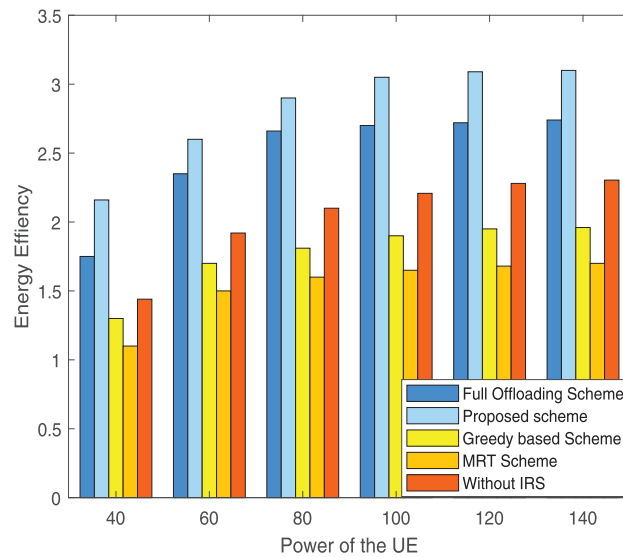


Figure 6: Energy efficiency vs. the maximum power of users

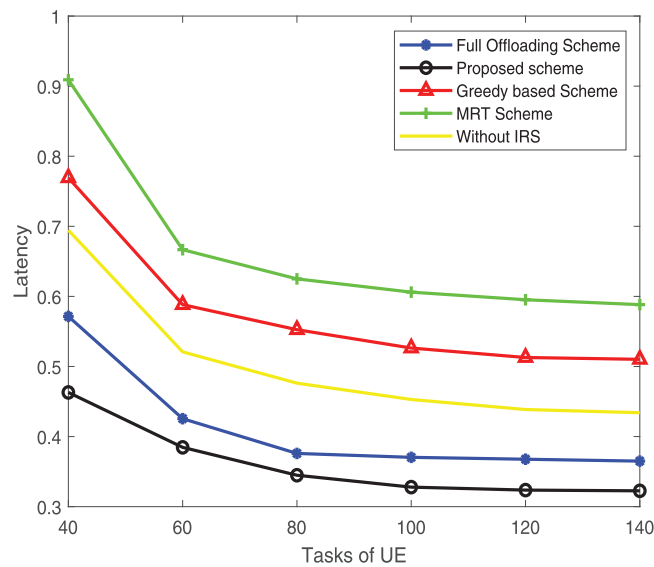


Figure 7: Energy efficiency vs. the tasks

6 Conclusion

In this paper, we design the transmitting beam of the user, the trajectory of the UAV, and the phase shift matrix of the IRS to maximize the user's secrecy rate. We analyze the two working modes of the eavesdropper and potentially control its transmitting beam. We add the influence factor of the eavesdropper as an optimization variable into the design scheme and propose a local optimization scheme based on the interior point method and alternative optimization. In addition, we designed a suboptimal scheme based on the zero forcing method to reduce the computational complexity. The simulation results show that the proposed iterative scheme is superior to the suboptimal scheme and has a higher secrecy rate than the existing schemes.

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Availability of Data and Materials: All data is synthesized using MATLAB and the generation method is described in detail in the simulation section.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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