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Secure efficiency maximization for UAV-assisted mobile edge computing networks

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ABSTRACT

This paper considers an unmanned aerial vehicle (UAV)-assisted mobile edge computing (MEC) system, in which the intelligent reflecting surface (IRS) is applied to enhance the performance of the wireless transmission. The role of the UAV is twofold: (1) It is equipped with a MEC server and receives computing tasks from ground users and IRS at the same time; (2) It sends interference signals to counter the potential eavesdropper. Here, the UAV is working as a full duplex equipment, i.e., sending and receiving meanwhile. We comprehensively considered the flight speed constraint of the UAV, the total mission data constraint and the minimum security rate constraint of multiple users on the ground. The phase matrix constraints of IRS are also considered. Our system is dedicated to maximizing the efficiency of secure computing. The formulated problem is highly non-convex, we consider to propose an alternative optimization algorithm. The simulation results show that the proposed scheme not only achieves higher safe computing efficiency, but also has better performance in terms of energy consumption and security rate.

1. Introduction

Unmanned aerial vehicle is an emerging technology, which has a wide range of applications in military, transportation, communications, and civilian use [1,2]. In recent years, with the increase in communication demand, traditional communication bandwidth has been unable to meet the increasing communication demands of people [3,4]. As a device with both flexibility and maneuverability, UAV can not only realize flexible deployment in peripheral areas, but also increase communication efficiency, and therefore has attracted widespread attention.

Mobile edge computing is an important technology used to reduce latency [5]. Its main principle is to upload data to the MEC server for calculation, and then return the calculation result. Normally, the data size of the calculation result is much smaller than the size of the task data. And the time to transmit data is far less than the time required for the computing task [6]. Therefore, MEC technology can greatly reduce time delay. According to the ratio of transmitted data to total computing tasks, MEC is mainly divided into two modes: partial unloading and full unloading. In partial uninstallation, the user transfers all computing tasks to the MEC server [7]; in full uninstallation, the user transfers some tasks to the MEC server, and the remaining tasks are calculated locally [8]. Obviously, partial offloading is a more flexible mode, because many users have certain computing capabilities and can share part of the computing tasks. So in this article, we consider using partial uninstall [9].

There has been considerable research on mobile edge computing. In [10], the author considered the application of MEC in MISO scenarios, and through joint design of transmitting beamforming vector and reflection phase matrix, the transmission efficiency of the system was improved. In [11], the author considers the application of MEC in cognitive radio scenarios, and improves the communication rate of secondary users on the premise of ensuring the QOS of the primary user. In [12], the application of MEC in MIMO scenarios was further studied, and multiple MEC application scenarios were designed in [13]. The results show that multiple MECs have greater improvement and higher flexibility than a single MEC [14].

However, there is an important problem with mobile edge computing, that is, the deployment of MEC servers is limited, which is determined by factors such as server deployment costs and deployment sites [15]. The consequence of this situation is that users who are far away from the MEC server cannot make good use of the MEC server [16]. At this time, introducing drones as a transmission medium is a solution to the shortage of MEC servers. [17] has considered the scenario in which drones carry MEC to provide services to ground users, and the author of [18] has considered the scenario in which MEC assists drones to communicate with ground users.

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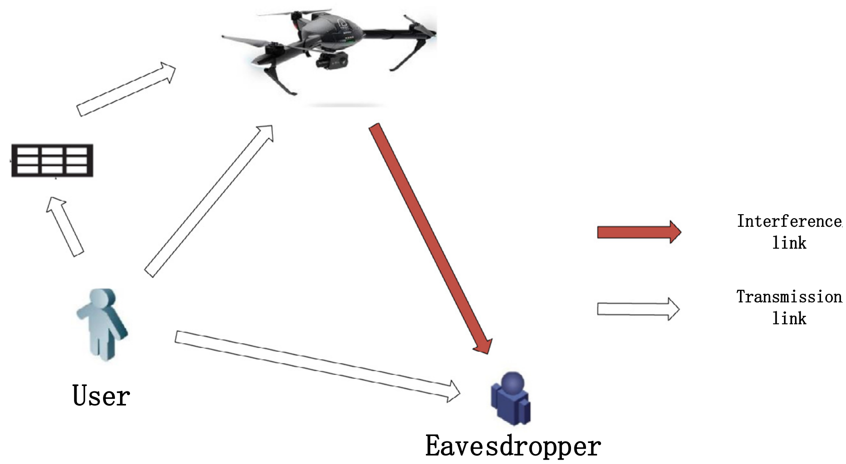

Fig. 1. System model.

Another hidden danger of MEC is safety. When the user chooses to perform local calculations on all tasks, there will be no security issues [19]. However, when the user chooses to transmit the data to the MEC server, the data may be obtained by a potential eavesdropper, resulting in a loss of security [20]. The common strategy to deal with this situation is to add redundant information to the transmission signal to counter potential eavesdroppers [21]. However, this will also increase the communication load and reduce the communication efficiency. At this time, the introduction of drones can also improve the safety of the system. UAVs can act as facilitators, sending jamming signals to counter potential eavesdroppers [22].

Based on the above discussion, we considered the UAV-assisted MEC system, in which the UAV can receive mission data from ground-based downlink users while sending jamming signals to counter potential eavesdroppers. The contributions of this article are summarized as follows:

1. We have added a full-duplex UAV to the MEC system, so that it can assist MEC communication while enhancing the security of the system.

2. According to the proposed system, we established the original optimization problem, taking the safety and efficiency of the system as the goal, taking into account the flight speed constraints of the UAV, the user's total task load, and the UAV's energy consumption constraints.

3. By introducing multiple auxiliary variables, we decompose the highly non-convex original problem into equivalent problems that can be solved by a two-stage optimization algorithm.

4. The simulation results show that the performance of our proposed optimization algorithm is better than other existing algorithms in terms of safety and efficiency, and it also has good performance in terms of energy consumption and transmission rate.

We proposed the system model in Section 2 and established the original optimization problem based on the proposed model. In Section 3, we put forward the process of solving the problem, which specifically includes the optimization of the user's transmit power and the optimization of the UAV's trajectory; In Section 4, we simulated the proposed scheme and discussed the results, and Section 5 concludes this paper.

2. System model and problem formulation

2.1. System model

As shown in Fig. 1, we consider using single UAV to assist ground users to complete MEC tasks. Specifically, the proposed system includes multiple ground users, a single drone and a potential eavesdropper. The ground user sends the computing task to the drone, and the drone will also send jamming signals to counter potential eavesdroppers while receiving mission data from the ground user. The multiple antennas configured by the ground user and the drone are used for transmission; the receiving antenna of the drone is set to a single one to simplify the design of the transmitting beam.

We use a three-dimensional coordinate system to model the communication nodes in the system. We consider using a hang gliding UAV, which keeps flying during the entire communication process and is approximately static in the same time slot. Specifically, we take the corner of the communication area as the origin of the coordinates as $[0, 0, 0]$, and we define the initial and final positions of the UAV as $[x_i, y_i, H]$ and $[x_f, y_f, H]$. The flight time of the UAV is divided into N time slots. In each time slot, the UAV is assumed to be in quasi-static state. At this time, the coordinates of the UAV in each time slot are defined as $[x_n, y_n, H]$. It is worth noting that the UAV flies at a fixed height H, where H is a safe height to ensure that the UAV does not collide with the building. In addition, the coordinates of ground users and potential eavesdroppers are $[x_k, y_k, 0]$ and $[x_e, y_e, H]$, respectively.

Regarding the channel model of UAVs and ground users, there are different assumptions in the existing literature. In this paper, we consider that the MEC server is usually set in an open scene, that is, there are fewer airborne obstructions. As a result, the air-to-ground channel should be based on the line-of-sight link. Therefore, when we establish the nth time slot, the distance between the drone and the ground user is computed as

$$d_{UD}[n] = \|\mathbf{x}(n) - \mathbf{x}_i\|^2 + H^2, \tag{1}$$

Correspondingly, in the nth time slot, the channel gain of the space-to-ground channel is:

$$h_{UD}[n] = \frac{\rho_0}{d_{UD}[n]^2}, \tag{2}$$

where ρ_0 is the LoS channel gain corresponding to unit distance $d = 1$ m.

We then obtain the channel between the UAV and the eavesdropper, which can be expressed as

$$h_{UE}[n] = \frac{\rho_0}{d_{UE}[n]^2}, \tag{3}$$

where $d_{UE}[n]$ is the distance between the UAV and the eavesdropper in nth time slot.

Due to the limitation of air resistance and UAV energy, the distance between UAVs in adjacent time slots should be less than a certain threshold. Specifically, it corresponds to unmanned speed constraints, which can be expressed as:

$$0 \leq v[n] = \frac{\|\mathbf{q}(n+1) - \mathbf{q}(n)\|}{\delta_t} \leq V_{\max}, n \in \{1, 2, \ldots, N\} \tag{4}$$

where $V_{\max}$ represents the maximum UAV speed, and $v[n]$ refers to the instantaneous speed in nth time slot.

Due to the large number of ground buildings, LoS channel modeling cannot be used, so we consider that all ground channels are Rayleigh channels and are fully known. The channel model is:

$$g[n] = \frac{\rho_0 \zeta}{\left(\sqrt{\|\mathbf{q_E}\|^2}\right)^{\phi}}, \tag{5}$$

where ζ is an exponentially random variable with unit mean and independently distributed, ϕ is the pathloss index corresponding to the specific environment.

In nth time slot, we define $P_S[n]$ as the transmitting power from the ground user to UAV. The average and the sum power constraints are expressed as follows:

$$\begin{aligned} &\frac{1}{N-1}\sum_{n=1}^{N-1} P_S[n] \leq \overline{P_S}, \\ &\quad 0 \leq P_S[n] \leq P_S^{\max}, \end{aligned} \tag{6}$$

where $\overline{P_S}$ and $P_S^{\max}$ refer to the maximum average power and the maximum instantaneous power, respectively.

We assume that the channels between the UAV and ground users and eavesdroppers are fully known, and the achievable rates in time slot n are expressed as:

$$R_{SU}[n] = \log_2\left(1 + \frac{P_S[n] h_{SU}[n]}{P_U[n]{\sigma_{UU}}^2 + \sigma^2}\right) \tag{7}$$

$$R_{SE}[n] = \log_2\left(1 + \frac{P_S[n] g[n]}{P_U[n] h_{UE}[n] + \sigma^2}\right) \tag{8}$$

in which ${\sigma_{UU}}^2$ represents the noise power caused by self-interference, and σ^2 refers to the Gaussian noise generated in the transmission.

In nth time slot, the achievable secrecy rate can be obtained as:

$$R_{\sec}[n] = R_{SU}[n] - R_{SE}[n] \tag{9}$$

We consider transmitting all mission data to the drone equipment. At this time, the communication energy consumption can be expressed as:

$$E^{offload} = \sum_{n=1}^{N} P_S[n] t[n] \delta_t \tag{10}$$

It is always assumed that the user keeps working all over the time. However, we define the first time slot as the case when the user begin to offload the task data, its energy consumption is expressed as:

$$E^{comp} = \sum_{n=1}^{N} \gamma_C \delta_t {f_U}^3[n], \tag{11}$$

in which γ_c and $f_U[n]$ represent the effective switched capacitance of CPU the CPU frequency of the UAV at the nth slot.

2.2. Problem formulation

In this paper, we comprehensively consider the trajectory of the UAV, the amount of mission data and the transmission power of the ground user to maximize the safe calculation rate. The original problem was formulated as:

$$(\text{P1}): \max_{P_S, q, f_U, t} \frac{\sum_{n=1}^{N} R_{\sec}[n]}{E^{offload} + E^{comp}} \tag{12}$$

$$s.t. P_S[n] \geq 0, \forall n \in \{1, 2, \ldots, N\} \tag{12a}$$

$$f_U[n] \geq 0, \forall n \in \{1, 2, \ldots, N\} \tag{12b}$$

$$0 \leq t[n] \leq 1, \forall n \in \{1, 2, \ldots, N\} \tag{12c}$$

$$0 \leq v[n] = \frac{\|\mathbf{q}(n+1) - \mathbf{q}(n)\|}{\delta_t} \leq v_{\max}, \quad \forall n \in \{1, 2, \ldots, N-1\}, \tag{12d}$$

$$\mathbf{q}(1) = \mathbf{q}_I \tag{12e}$$

$$\mathbf{q}(N) = \mathbf{q}_F \tag{12f}$$

$$\sum_{i=2}^{n} f_U[i]\delta_t \leq \sum_{i=1}^{N-1} B\delta_t \log_2\left(1 + \frac{P_S[i] h_{SU}[i]}{\sigma^2}\right), \quad \forall n \in \{2, \ldots, N\} \tag{12g}$$

$$\frac{1}{N-1}\sum_{n=1}^{N-1} P_S[n] \leq \overline{P_S}, 0 \leq P_S[n] \leq P_S^{\max} \tag{12h}$$

$$0 \leq E^{offload} + E^{comp} \leq E_{\max} \tag{12i}$$

(12)a and (12)b respectively represent the transmit power constraints of ground equipment and UAVs. (12)c represents the proportion of data sent by ground users in the total task volume. (12)d, (12)e and (12)f represent the speed and trajectory constraints of the drone. (12)g Indicates the maximum amount of calculation constraint for UAV calculation. (12)h means that the average transmit power and maximum transmit power of the terminal equipment should both be less than the given threshold. (12)i represents the total energy consumption constraint.

Since the problem (12) is a non-convex form, it is difficult to obtain the optimal solution directly through the convex optimization method. We propose an alternate optimization method to solve this problem. First, we put forward two sub-problems. For the first sub-problem, we optimize the transmission power under the premise of a fixed trajectory; for the second sub-problem, we optimize the trajectory under the premise of a fixed transmission power. We alternate the two sub-problems until the algorithm converges.

3. The alternative optimization algorithm for energy efficiency maximization

3.1. Transmission power optimization

In this section, we try to optimize the power allocation problem when the trajectory of UAV is fixed. The original problem is reformulated as:

$$(\text{P2}): \max_{P_S, f_U, t} \frac{\sum_{n=1}^{N} R_{\sec}[n]}{E^{offload} + E^{comp}} \tag{13}$$

$$s.t. P_S[n] \geq 0, \forall n \in \{1, 2, \ldots, N\} \tag{13a}$$

$$f_U[n] \geq 0, \forall n \in \{1, 2, \ldots, N\} \tag{13b}$$

$$0 \leq t[n] \leq 1, \forall n \in \{1, 2, \ldots, N\} \tag{13c}$$

$$\sum_{i=2}^{n} f_U[i]\delta_t \leq \sum_{i=1}^{n-1} B\delta_t \log_2\left(1 + \frac{P_S[i] h_{SU}[i]}{\sigma^2}\right), \quad \forall n \in \{2, 2, \ldots, N\} \tag{13d}$$

$$\frac{1}{N-1}\sum_{n=1}^{N-1} P_S[n] \le \overline{P_S},\, 0 \le P_S[n] \le P_S^{\max} \tag{13e}$$

$$0 \le E^{offload} + E^{comp} \le E_{\max} \tag{13f}$$

We first substitute (7), (8) and (9) into the objective of (13), the following expression is obtained.

$$(\text{P3}):\ \max_{Ps,f_U,t} \frac{\sum_{n=1}^{N}\left(\log_2\left(1+\frac{P_S[n]h_{SU}[n]}{\sigma^2}\right)-\log_2\left(1+\frac{P_S[n]g[n]}{\sigma^2}\right)\right)}{\delta_t \sum_{n=1}^{N}\left(Ps[n]t[n]+\gamma_C {f_U}^3[n]\right)} \tag{14}$$

(P3) is a fraction optimization problem, which can be solved by introducing a new variable η. Then we transform (P3) into the following problem:

$$\max_{Ps,f_U,t} \frac{\sum_{n=1}^{N}\left(\log_2\left(1+\frac{P_S[n]h_{SU}[n]}{\sigma^2}\right)-\log_2\left(1+\frac{P_S[n]g[n]}{\sigma^2}\right)\right)}{\delta_t \sum_{n=1}^{N}\left(Ps[n]t[n]+\gamma_C {f_U}^3[n]\right)} = \eta \tag{15}$$

The objective of (P3) is difficult to solve, we thus rewrite its objective and formulate the following problem:

$$(\text{P4}):\ \max_{Ps,f_U,t} \times \left[\begin{array}{l}\sum_{n=1}^{N}\left(\log_2\left(1+\frac{P_S[n]h_{SU}[n]}{\sigma^2}\right)-\log_2\left(1+\frac{P_S[n]g[n]}{\sigma^2}\right)\right)\\ -\eta\delta_t\sum_{n=1}^{N}\left(Ps[n]t[n]+\gamma_C {f_U}^3[n]\right)\end{array}\right] \tag{16}$$

It is worth noting that (P4) is a non-convex problem, since the objective of (P3) is non-convex fir any given trajectory. To solve such a problem, we first obtain the optimal solution of the dual problem of (P3) as follows:

$$f_U^{opt}[n] = \sqrt{\frac{1}{3C\gamma_C(\eta+\mu)}}, \tag{17}$$

$$Ps^{opt}[n] = \begin{cases} 0,\ t[n]=0 \\ \left[\frac{B}{(\eta+\mu)v\ln 2} - \frac{\sigma_0^2}{h_{SU}[n]}\right],\ t[n]>0, \end{cases} \tag{18}$$

in which μ is a Lagrangian dual parameter for the constraint (16).

It is worth noting that (17) is a closed-form solution, then we would like to consider the condition about the duality gap is 0 [22].

We formulate the sub-gradient for μ as follows:

$$\mu(k+1) = [\mu(k) - \varpi(k)\Delta\mu(k)]^+, \tag{19}$$

$$\theta(k+1) = [\theta(k) - \lambda(k)\Delta\theta(k)]^+, \tag{20}$$

in which $\varpi(k)$ and $\lambda(k)$ refer to the Kth iteration step, $(a)^+ = \max(a, 0)$. We then define the gradient of μ and θ as

$$\Delta\mu(k) = E_{\max} - \delta_t \sum_{n=1}^{N}\left(Ps^{k,opt}[n]t[n] + \gamma_C\left({f_U}^{k,opt}[n]\right)^3\right) \tag{21}$$

$$\Delta\theta(k) = 1 - t^{k,opt}[n], \tag{22}$$

where $Ps^{k,opt}{f_U}^{k,opt}[n]$ and $t^{k,opt}[n]$ represent the optimal power allocation and the time slot at the kth iteration, respectively.

3.2. Trajectory optimization

When the allocated bits and transmission power of the data are fixed, both the calculation energy consumption and the communication energy consumption can be directly obtained. In this case, we design the flight trajectory of the UAV. In particular, we formulate the following problem:

$$(\text{P5}):\ \max_{\mathbf{q}(n)} \frac{\sum_{n=1}^{N} R_{\sec}[n]}{E^{offload}+E^{comp}}$$

$$\begin{aligned} s.t.\ & 0 \le v[n] = \frac{\|\mathbf{q}(n+1)-\mathbf{q}(n)\|}{\delta_t} \le v_{\max}, \\ & \forall n \in \{1,2,\ldots,N-1\} \\ & \mathbf{q}(1) = \mathbf{q_I} \\ & \mathbf{q}(N) = \mathbf{q_F} \\ & \sum_{i=2}^{n} f_U[i]\delta_t \le \sum_{i=1}^{n-1} B\delta_t \log_2\left(1+\frac{P_S[i]h_{SU}[i]}{\sigma^2}\right), \\ & \forall n \in \{2,3,\ldots,N\} \end{aligned} \tag{23}$$

We noticed that the problem (P5) is non-convex and difficult to solve directly. We consider using continuous convex approximation to obtain the lower bound of the target value of (P5). At this point we will rewrite (P5) as:

$$\begin{aligned} & \log_2\left(1+\frac{\rho_0 Ps[n]}{\sigma^2\left(H^2+\|\mathbf{q}[n]\|^2\right)}\right) \ge y_j \\ & = \log_2\left(1+\frac{\rho_0 Ps[n]}{\sigma^2\left(H^2+\left\|\mathbf{q}^j[n]\right\|^2\right)}\right) - Q_j[n]\frac{\|\mathbf{q}[n]\|^2-\left\|\mathbf{q}^j[n]\right\|^2}{H^2+\left\|\mathbf{q}^j[n]\right\|^2} \end{aligned} \tag{24}$$

$$Q_j[n] = \frac{\rho_0 Ps[n]\log_2 e}{\sigma^2\left(H^2+\left\|\mathbf{q}^j[\mathbf{n}]\right\|^2\right)+\rho_0 Ps[n]} \tag{25}$$

with equality is satisfied if and only if $\mathbf{q}[n] = \mathbf{q}^j[n]$.

By substituting (24) into (P5), we obtain the following problem:

$$(\text{P6}):\ \max_{\mathbf{q(n)}} \frac{\sum_{n=1}^{N}\left(y_j - \log_2\left(1+\frac{P_S[n]g[n]}{\sigma^2}\right)\right)}{\delta_t\sum_{n=1}^{N}\left(Ps[n]t[n]+\gamma_C {f_U}^3[n]\right)} \tag{26}$$

Note that (P6) is a convex problem, which can be solved efficiently by the existing toolbox, such as CVX solver, and so on. We then summary the solution to the original problem in Algorithm 1.

Algorithm 1 Alternative optimization algorithm for efficiency maximization

Output: $E^{\max}$, T, N, $V_{\max}$, q_F, q_0, and the tolerance errors ε_1, ε_2;
Input: $P_S^{\max}$, $V_{\max}$.
Initial:
$\eta_E^k = \eta_0$ the iterative index $k = 0$ and $q_u^k[n]$;
While 1:
Calculate $Ps^{k,opt}[n], f_U^{k,opt}[n]$ for given $q_u^k[n]$;
Obtain $t^{k,opt}[n]$ using the bisection method.
Update μ and θ using the subgradient method;
Initialize the iterative m=1;
  While 2:
  Solve P6 by using CVX for given $Ps^{k,opt}[n], f_U^{k,opt}[n], t^{k,opt}[n]$;
  Update $m = m+1$,and $q_u^k[n]$;
  If $\sum_{n=1}^{N}\left\|q_u^m[n]-q_u^{m-1}[n]\right\| \le \varepsilon_1$;

Table 1
Simulation parameters.

Parameter	Symbol	Value
Required CPU cycles per bit	C_k	1000 cycles/bit
The total system bandwidth	B	30 MHz
The fixed altitude of the UAV	H	10 m
The total task completion time	T	10 s
Number of time slots	N	50
The channel power gain at a reference distance of $d_0 = 1$ m	ρ_0	-30 dB
The noise power	N_0	-60 dB
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 position of the eavesdropper	$\mathbf{q_E}$	(0,10)
The effective switched capacitance of the UAV	κ	10^{-28}
Task input data size	$I_m in$	200 Kbits

$q_u^k[n] = q_u^m[n]$;
break;
end
End While 2
Update the iterative number $k = k + 1$;
If $\left|\max R^{opt} - \eta E^{opt}\right| \leq \varepsilon_2$
The maximum computation efficiency $\eta_E^{k,opt}$ is obtained;
break;
end
End While 1

4. Numerical results

In this section, we simulate and verify the proposed scheme and other comparison schemes. Specifically, we considered the following schemes: (1) the proposed scheme; (2) the ground relay scheme; (3) the scheme without eavesdroppers; (4) the maximum user ratio transmission scheme. The system settings of each scheme are the same, and the specific parameters are shown in Table 1.

We first show the approximate flight trajectory of the UAV in Fig. 2. For different total mission bits, the flight trajectory will also change. Specifically, when the total number of mission bits is low, the UAV tends to be close to the MEC server and far away from the ground users. This is better than when the number of task bits is low, the drone can still quickly collect task information under the condition of low signal-to-noise ratio, so as to send it to the MEC server as soon as possible, thereby reducing the overall delay. When the total number of mission bits is high, the drone is closer to the ground user to improve transmission efficiency.

In Fig. 3, we considered four kinds of schemes, including (1) the scheme proposed in this paper and (2) the fixed ground relay scheme. (3) No eavesdroppers solution (4) Half-duplex drone solution. In the fixed terrestrial relay scheme, the position of the relay is set to (5, 0, 0), and it is assumed that the terrestrial channel obeys the Rayleigh distribution and is fully known. In the half-duplex UAV solution, the UAV only receives signals from ground users and no longer sends interference signals. Compared with the fixed ground relay solution, the solution proposed in this paper has a significant advantage from the flexibility of the UAV. At the same time, compared with the half-duplex UAV solution, the design of the interference signal will also improve the system performance.

In Fig. 4, we show the relationship between energy efficiency and maximum energy. It is worth noting that there is a linear relationship between energy efficiency and maximum energy, which comes from the definition of energy efficiency. The proposed scheme can not only make full use of the maneuverability of the UAV to adjust the channel state information, but also the designed full-duplex scheme can reduce the communication rate of eavesdroppers, thereby increasing the security rate of the system. Fig. 4 shows that our proposed scheme can achieve an ideal situation that does not contain eavesdroppers when the energy is high.

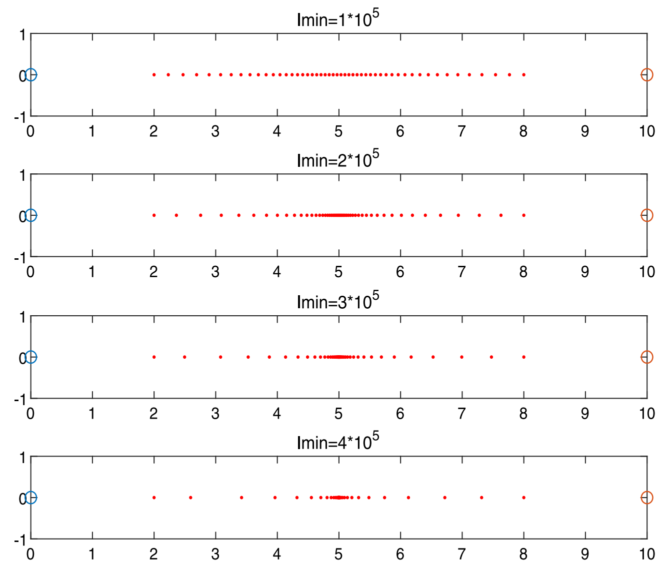

Fig. 2. Wireless legitimate surveillance via jamming in a MISO cognitive radio networks.

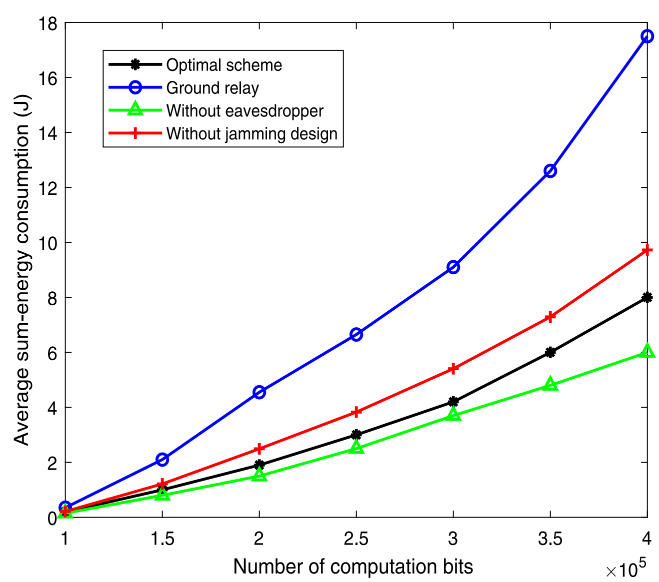

Fig. 3. Average sum-energy consumption versus the number of bits.

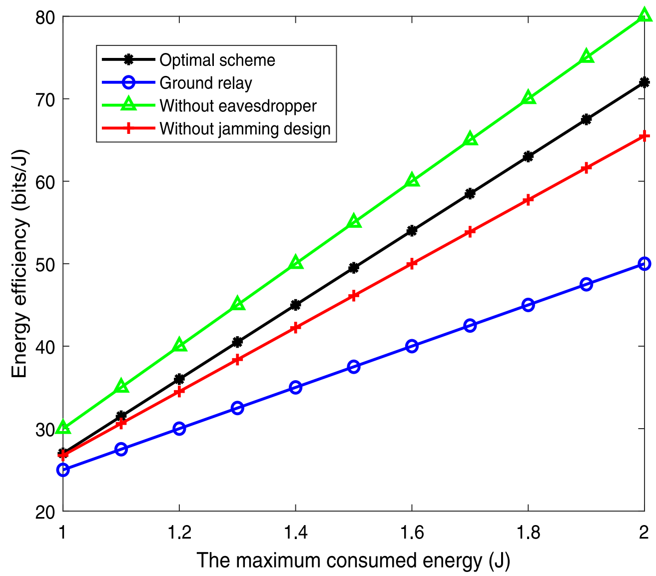

Fig. 4. Energy efficiency versus the maximum consumed energy.

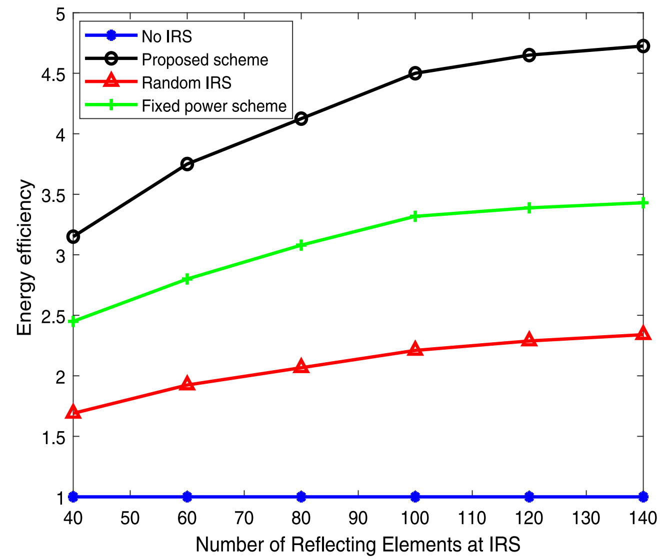

Fig. 6. Energy efficiency versus the number of IRS elements.

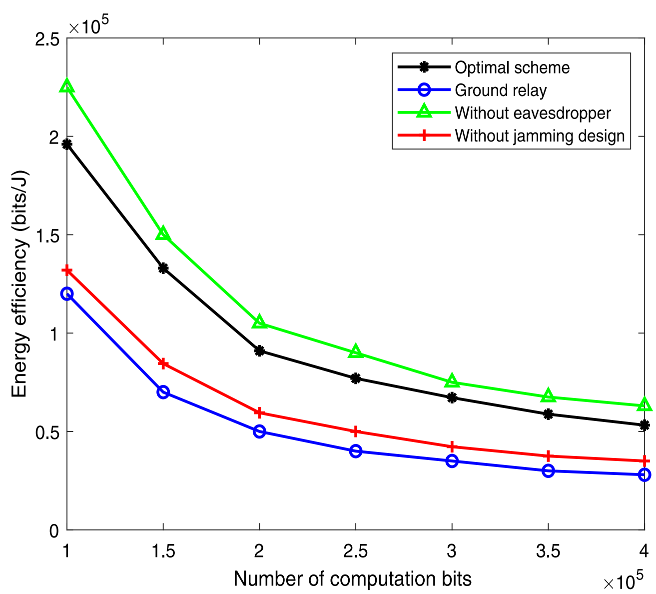

Fig. 5. Energy efficiency versus the number of bits.

Fig. 5 shows the relationship between energy efficiency and maximum bits. When the maximum number of bits is small, the UAV will allocate more energy to the interference signal transmission, thereby improving the safety of the system. When the maximum number of bits is large, the UAV will reduce the power of the interference signal, thereby improving the transmission efficiency of ground users.

Fig. 6 shows that as the number of IRS elements increases, energy efficiency also increases. When the number of IRS elements is small, the growth rate is faster. When the number of IRS elements is too large, the improvement speed of energy efficiency will slow down, which is better than IRS, which is a passive device, and the upper limit of energy efficiency is limited by the energy of the base station.

5. Conclusion

We considered a UAV-assisted mobile edge computing system, where the UAV undertakes the dual task of collecting user mission data and sending interference signals. We comprehensively consider the UAV's trajectory design and transmission power to maximize the safety rate. The problem proposed is highly non-convex and difficult to solve directly. By introducing auxiliary variables, we transform the original problem into an equivalent problem that is easy to solve. The simulation results prove the superiority of our proposed scheme.

CRediT authorship contribution statement

Leibing Yan: Conceptualization, Writing – original draft, Software. **Cuiqin Wang:** Software, Methodology, Writing – review & editing. **Wei Zheng:** Validation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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