Resource Allocation and Offloading Decisions of D2D Collaborative UAV-assisted MEC Systems

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Abstract

In this paper, we consider the resource allocation and offloading decisions of device-to-device (D2D) cooperative UAV-assisted mobile edge computing (MEC) system, where the device with task request is served by unmanned aerial vehicle (UAV) equipped with MEC server and D2D device with idle resources. On the one hand, to ensure the fairness of time-delay sensitive devices, when UAV computing resources are relatively sufficient, an optimization model is established to minimize the maximum delay of device computing tasks. The original non-convex objective problem is decomposed into two subproblems, and the suboptimal solution of the optimization problem is obtained by alternate iteration of two subproblems. On the other hand, when the device only needs to complete the task within a tolerable delay, we consider the offloading priorities of task to minimize UAV computing resources. Then we build the model of joint offloading decision and power allocation optimization. Through theoretical analysis based on KKT conditions, we elicit the relationship between the amount of computing task data and the optimal resource allocation. The simulation results show that the D2D cooperation scheme proposed in this paper is effective in reducing the completion delay of computing tasks and saving UAV computing resources.

Keywords: Resource allocation, offloading decision, mobile edge computing, unmanned aerial vehicle, D2D.

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1. Introduction

With the rapid development and advancement of internet of things (IoT) technology, numerical wireless connected devices are emerging, and the deployment scale is also growing rapidly [1]. However, certain wireless devices face computing limitations due to cost or size constraints. Additionally, devices located far from external power sources, such as sensors deployed on smart farms, may have limited energy supply. Moreover, the increasing number of wireless devices has given rise to diverse IoT applications [2], including environmental monitoring [3], autonomous vehicles [4-5], consumer robotics [6]. These applications pose challenges to existing mobile communication networks, demanding high real-time performance, security, and other critical indicators.

Mobile edge computing (MEC) technology deploys computing resources at the network edge, offering advantages for delay-sensitive and computing-intensive services closer to devices, thereby reducing the communication overhead of the core network [7]. This approach presents an opportunity to address the aforementioned challenges. However, resource allocation becomes a crucial issue for MEC due to limited resources and the coupling relationship between communication and computing [8]. Existing research on MEC resource allocation focuses on the following optimization objectives: 1) task completion delay [9]; 2) system energy consumption and energy efficiency [10]; 3) weighted sum of delay and energy consumption [11]. Yet, certain scenarios like fire scenes or remote areas, may be beyond MEC service reach, preventing ground devices from utilizing computing services provided by the base station (BS). Moreover, the increasing mobile data traffic necessitates additional deployment of fixed BSs, resulting in long deployment time and high costs. In emergency communication scenarios, such as large-scale sports events, there is a higher demand for network computing capacity.

To address these issues, the unmanned aerial vehicle (UAV) can serve as a mobile communication platform due to its flexibility [12]. Equipped with MEC servers, UAVs can extend the MEC coverage area and provide on-demand services for time-sensitive and computing-intensive devices, surpassing the capabilities of ground-based BSs. In the UAV-assisted MEC systems, it is crucial to develop a resource allocation scheme that caters to the unique characteristics of UAVs, including their special communication channels. Existing literature primarily focuses on device time delay [13-16]. Notably, [13] employed UAVs and MEC for crowd monitoring, while [14] and [15] proposed multi-parameter optimization models using the successive convex approximation (SCA) technique and punishment duality decomposition (PDD) algorithm. Addressing energy consumption, [16] developed an optimization model for MEC mobility management, considering resource allocation, offload decisions, UAV flight scheduling constraints, and utilizing a joint optimization algorithm based on the Lyapunov Method.

While UAV-assisted Mobile Edge Computing (MEC) systems offer advantages for computing offloading, the exponential growth of IoT devices presents challenges like queuing delays and resource contention. Practical limitations in UAV computing resources hinder meeting massive data processing demands. To tackle this, direct device-to-device (D2D) communication is introduced, allowing devices to communicate directly and share task processing [17]. D2D communication enables devices to offload data to nearby devices with available resources, reducing resource consumption and improving processing efficiency. Combining MEC with D2D communication, researchers have studied resource allocation and offloading decisions. Notably, [18] proposed a MEC framework for multi-user collaborative partial offloading. [19] addressed delay and energy consumption minimization using the

Lagrange duality method. [20] adopted a combined MEC and D2D strategy to enhance computing capacity, while [21] introduced D2D-MEC technology to improve cellular network computing capacity. However, existing studies often focus on traditional MEC systems, emphasizing the need for research on integrating D2D collaboration into UAV-assisted MEC systems.

In this paper, we study the resource allocation and offload decisions in a D2D collaborative UAV-assisted MEC system, where UAV serves as the MEC platform. The main contributions are summarized as follows:

- A D2D collaborative UAV-assisted MEC system is designed, and a coexistence scheme of UAV offloading and D2D offloading based on partial offloading is proposed.
- We formulate a non-convex optimization problem for the goal of minimizing the maximum device delay. The problem involves optimizing device power allocation, UAV computing resource allocation, and offloading decisions. We obtain a suboptimal solution using an alternate iteration algorithm based on the Lagrange multiplier method.
- In order to solve the problem of minimizing the optimization of UAV computing resources, a joint optimization model for offloading decision and power allocation is established. The model considers the offloading priority of device tasks. Theoretical analysis based on KKT conditions reveals the relationship between computing task size and the optimal resource allocation scheme.
- The in-depth simulation and numerical results verify that the proposed D2D collaboration scheme is effective in reducing time delay and saving UAV computing resources.

2. System Model and Problem Formulation

A single UAV with an MEC server and computing capability serves multiple terminal devices. The UAV obtains channel state information and task data size to make offloading decisions. Terminal devices are classified into three categories: 1) cellular users cu capable of direct communication with the UAV; 2) requesting users $i \in M = \{1, 2, ..., M\}$ that lack communication and computing resources to complete tasks within time delay; and 3) idle users $k \in K = \{1, 2, ..., K\}$ who either have no computing tasks or can handle their computing tasks. We assume that idle users are devices without their own computing tasks, and requesting users can choose to offload tasks to either the UAV or nearby idle users for computing. This paper adopts a partial offloading model, allowing the division of computing tasks.

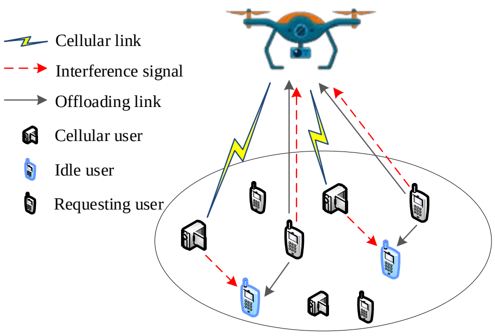

Fig. 1. The system model

As shown in **Fig. 1**, terminal devices are randomly distributed in the coverage area of the UAV, and each device can be connected to the UAV. It is assumed that each requesting user $i \in M$ has a computing task and the CPU instruction cycle required for computing 1 bit of data consistent for all terminal devices. For simplicity, the UAV is denoted as j. Since the cost of task offloading to the UAV is large and the computing resource of the UAV is limited, we assume a predefined group of requesting users offload tasks to the UAV. In this scenario, only idle users are considered to assist requesting users with computing. When the distance between device $i \in \mathcal{M}$ and $k \in \mathcal{K}$ is within R (the maximum communication distance between the devices), the two can establish a D2D communication link, and each requesting user can establish one D2D communication link. Since the data size of the task is typically small, the download delay can be neglected.

Orthogonal frequency division multiplexing (OFDM) is adopted for channel access with the bandwidth of B. Each device in set $\mathcal{M}$ allocates a subchannel for the UAV communication link, and independent subchannels for different D2D communication links. D2D pairs employ channel multiplexing, where uplink spectrum resources of cellular users are multiplexed. The transmit power for cellular users and requesting users in D2D offloading are P^{cu} and P^{d}, respectively. The channel gain between a user and the UAV is h_{cu}. The interference from cellular users to idle users in a D2D communication link is $I_{cu,k} = P^{cu} h_{cu,k}$, where $h_{cu,k}$ represents the channel gain from the cellular user to device k, and the interference to UAV reception is negligible.

2.1 Minimize the maximum delay of computing tasks

To ensure the fairness between devices with delay-sensitive computing tasks, we jointly optimize the offloading decision, power allocation and UAV computing resource allocation. Our goal is to minimize the maximum task delay for all terminal devices while considering limited computing and communication resources. The task of terminal device i is divided into three parts, i.e., local computing, D2D offloading and UAV offloading. The decision variable of task offloading $x_{i,j}$ is the offloading rate between the requesting user i and the UAV j, and $x_{i,k}$ is between the requesting user i and the idle user k when the computing task offloading to the UAV j and the idle user k, $0 \le x_{i,j} \le 1$, $0 \le x_{i,k} \le 1$.

2.1.1 Wireless channel model

The air-to-ground (A2G) transmission channel follows the LoS probabilistic model [22]. The LoS communication probability between device i and the UAV is determined by

$$p_i^{\text{LoS}} = \frac{1}{1 + \rho \exp\left[-\vartheta\left(\theta_i - \rho\right)\right]}, \tag{1}$$

so the non-line-of-sight (NLoS) communication probability is $p_i^{\text{NLoS}} = 1 - p_i^{\text{LoS}}$, where θ_i is the elevation angle from device i to UAV j, ϑ and ρ are the constants dependent on environment. The coordinate of device i and UAV j are (x_i, y_i) and (X, Y, H), respectively, resulting in a distance of $d_i = \sqrt{\left(x_i - X\right)^2 + \left(y_i - Y\right)^2 + H^2}$ between them. The pass loss of LoS and NLoS link are given by $L_i^{LoS} = \eta_{LoS}\left(4\pi f_c d_i / c\right)^{\alpha}$ and $L_i^{NLoS} = \eta_{NLOS}\left(4\pi f_c d_i / c\right)^{\alpha}$, where f_c is the communication frequency, α is the path loss index, c is the speed of light, and η_{LoS} and η_{NLoS} are the average additional path loss for LoS and NLoS link. The average path loss from device i to UAV j can be expressed as

$$L_{i,j} = \left[p_i^{LoS}\eta_{\mathrm{LoS}} + p_i^{NLOS}\eta_{NLOS} \right]\left(\frac{4\pi f_c d_i}{c}\right)^{\alpha}, \tag{2}$$

where the average channel gain between device i and UAV j is $h_{i,j} = 1/L_{i,j}$.

The requesting user can choose to offload the computing task to the UAV or a nearby idle device. This allows a device to establish both a UAV offloading link and D2D offloading link simultaneously. The achievable rate of UAV offloading link and D2D offloading link of device i are respectively expressed in (3), where σ_n^2 represents the noise power, P_i^u and P_i^d are the transmit power assigned by device i to the UAV offloading and D2D offloading, respectively.

$$R_{i,j} = B\log_2(1 + \frac{P_i^u h_{i,j}}{\sigma_n^2}), \forall i \in M \tag{3a}$$

$$R_{i,k} = B\log_2(1 + \frac{P_i^d h_{i,k}}{I_{cu,k} + \sigma_n^2}), \forall k \in K \tag{3b}$$

The total power of device i is P_i^{max}, and the sum of the power allocated to UAV offloading and D2D offloading cannot exceed the total power of the device,

$$P_i^u + P_i^d \le P_i^{\max}, \forall i \in \mathcal{M} \tag{4}$$

Cellular users are the primary users in the system, and D2D communication must satisfy the quality of service (QoS) requirement. The threshold of signal to interference plus noise ratio (SINR) of cellular users is denoted as ε, then the constraint that does not affect the QoS of cellular users is

$$\frac{P^{cu}h_{cu}}{I_{i,cu} + \sigma_n^2} \ge \varepsilon. \tag{5}$$

We set $S_{i,j} = h_{i,j} / \sigma_n^2$ and $S_{i,k} = h_{i,k} / \left(I_{cu,k} + \sigma_n^2\right)$, then the transmission time of offloading computing task from device i to UAV j and D2D device k are

$$t_{i,j}^{comm} = \frac{x_{i,j}I_i}{R_{i,j}} = \frac{x_{i,j}I_i}{B\log_2\left(1 + P_i^u S_{i,j}\right)} \tag{6a}$$

$$t_{i,k}^{comm} = \frac{x_{i,k}I_i}{R_{i,k}} = \frac{x_{i,k}I_i}{B\log_2\left(1 + P_i^d S_{i,k}\right)} \tag{6b}$$

2.1.2 Computing model

The number of CPU instruction cycles required by device i is $I_i C$, where I_i is the number of data bits and C is the task computing density. According to first dynamic voltage and frequency scaling (DVFS), the time of device i for local computing, offloading to UAV computing, and offloading to D2D-collaborative device computing are as follows

$$t_i^{\text{local}} = \frac{\left(1 - x_{i,j} - x_{i,k}\right) I_i C}{f_i} \tag{7a}$$

$$t_{i,j}^{\text{comp}} = \frac{x_{i,j} I_i C}{f_{i,j}} \tag{7b}$$

$$t_{i,k}^{comp} = \frac{x_{i,k} I_i C}{f_k} \tag{7c}$$

where f_i and f_k are the computing resources of device i and k, respectively, and $f_{i,j}$ is the computing resources allocated to device i from UAV j. Due to limited computing resources of UAV, the maximum computing resources that can be allocated are as $F_j^{\max}$

$$\sum_{i=1}^{M} f_{i,j} \le F_j^{\max} \tag{8}$$

The total delay of device i for offloading the task to UAV and the adjacent D2D device k includes the transmission time and calculation time, given by

$$t_{i,j}^{uav} = t_{i,j}^{comm} + t_{i,j}^{comp} \tag{9a}$$

$$t_{i,k}^{d2d} = t_{i,k}^{comm} + t_{i,k}^{comp} \tag{9b}$$

Considering that the communication and computing processes occur in parallel, each device can decompose the task into three parts and compute them simultaneously. The time of device i for computing task is $t_i = \max\left\{t_i^{\text{local}}, t_{i,j}^{uav}, t_{i,k}^{d2d}\right\}$. Assuming that the UAV provides computing services to multiple devices concurrently, the objective function to minimize the maximum delay of all terminal computing tasks can be expressed as

$$\min_{x_{i,j}, x_{i,k}, P_i^u, P_i^d, f_{i,j}} \max_{i \in M} t_i. \tag{10}$$

The above objective function is a maximum minimization problem, which is difficult to solve directly. By introducing auxiliary variables t to make $t = \max_{i \in M} t_i$, the optimization problem can be expressed in (11). (11a)-(11e) are constraints formed after the introduction of auxiliary variable, (11h) represents the offloading rate constraint of device i. Moreover, (11j) indicates that the value of each variable must be greater than 0.

$$\mathbf{P1}: \quad \min_{t_i, x_{i,j}, x_{i,k}, P_i^u, P_i^d, f_{i,j}} \quad t \tag{11a}$$

$$\text{s.t.} \quad t_i \le t \tag{11b}$$

$$\frac{\left(1 - x_{i,j} - x_{i,k}\right) I_i C}{f_i} \le t_i \tag{11c}$$

$$x_{i,j} I_i \left(\frac{1}{B \log_2 \left(1 + P_i^u S_{i,j}\right)} + \frac{C}{f_{i,j}} \right) \le t_i \tag{11d}$$

$$x_{i,k} I_i \left(\frac{1}{B \log_2 \left(1 + P_i^d S_{i,k}\right)} + \frac{C}{f_k} \right) \le t_i \tag{11e}$$

$$P_i^u + P_i^d \le P_i^{\max} \tag{11f}$$

$$\sum_{i=1}^{M} f_{i,j} \le F_j^{\max} \tag{11g}$$

$$x_{i,j} + x_{i,k} \le 1, \forall i \in M \tag{11h}$$

$$\frac{P^{cu} h_{cu}}{\sigma_n^2} \ge \varepsilon \tag{11i}$$

$$x_{i,j}, x_{i,k}, P_i^u, P_i^d, f_{i,j}, t_i \ge 0 \tag{11j}$$

2.2 Minimize the computing resources of the UAV

Given the limited computing resources of UAVs, this section explores scenarios where the terminal devices prioritize offloading tasks to nearby idle D2D devices only when local computing cannot meet deadline requirements. To maximize computing efficiency, devices are assumed to assist others when they have no computing tasks of their own. The objective is to minimize the average computing resources allocated by the UAV to each device.

The maximum tolerable delay of the device is denoted as T. When the requesting user $i \in \mathcal{M}$ can complete the task within T, which satisfies $I_i C / f_i < T$, there is no need for offloading and the task can be compute locally. The computing tasks of device i are divided into three parts, local computing with data rate $x_{i,L}$, D2D offloading to adjacent device k with data rate $x_{i,k}$, and UAV offloading with data rate of $1 - x_{i,L} - x_{i,k}$. The device's computing capability is fixed, so the amount of data that can be processed is determined by the maximum tolerable delay and data size. When offloading is required, i.e, $I_i C / f_i \ge T$, the data rate for local computing can be expressed as

$$x_{i,L} = \min \left\{ 1, \frac{f_i T}{I_i C} \right\}. \tag{12}$$

Then, the transmission and computing time for offloading data from device i to UAV j and D2D device k are respectively expressed as

$$t_{i,j}^{comm} = \frac{\left(1 - x_{i,L} - x_{i,k}\right) I_i}{R_{i,j}} = \frac{\left(1 - x_{i,L} - x_{i,k}\right) I_i}{B \log_2 \left(1 + P_i^u S_{i,j}\right)} \tag{13a}$$

$$t_{i,k}^{comm} = \frac{x_{i,k} I_i}{R_{i,k}} = \frac{x_{i,k} I_i}{B \log_2 \left(1 + P_i^d S_{i,k}\right)} \tag{13b}$$

$$t_{i,j}^{comp} = \frac{\left(1 - x_{i,L} - x_{i,k}\right) I_i C}{f_{i,j}} \tag{14a}$$

$$t_{i,k}^{comp} = \frac{x_{i,k} I_i C}{f_k} \tag{14b}$$

where $f_{i,j}$ is the computing resources allocated from UAV j to device i. When $f_{i,j} > 0$, the task is offloaded from device i to the UAV, and vice versa. Furthermore, since devices in set K can only assist other devices after completing their own tasks, the assumption that idle users of assisting devices have non-computing tasks is reasonable. Based on (13) and (14), the total delay for UAV offloading and D2D offloading are respectively

$$t_{i,j}^{uav} = t_{i,j}^{comm} + t_{i,j}^{comp}, \tag{15a}$$

$$t_{i,k}^{d2d} = t_{i,k}^{comm} + t_{i,k}^{comp}. \tag{15b}$$

Parallel execution of UAV offloading and D2D offloading allows for timely task completion within the maximum tolerable delay. Hence, the following constraint applies:

$$\max\left\{t_{i,j}^{uav}, t_{i,k}^{d2d}\right\}. \le T \tag{16}$$

The task can be divided into three parts, thus the objective function of minimizing the UAV computing resources can be expressed as $\sum_{i=1}^{M} f_{i,j} / M$. Due to the independence of computing processes between devices, the optimization problem is formulated as follows:

$$\mathbf{P2}: \quad \min_{x_{i,k}, P_i^u, P_i^d, f_{i,j}} f_{i,j} \tag{17a}$$

$$\text{s.t.} \quad (1 - x_{i,L} - x_{i,k})\left(\frac{I_i}{B\log_2(1 + P_i^u S_{i,j})} + \frac{I_i C}{f_{i,j}}\right) \le T \tag{17b}$$

$$x_{i,k}\left(\frac{I_i}{B\log_2(1 + P_i^d S_{i,k})} + \frac{I_i C}{f}\right) \le T \tag{17c}$$

$$P_i^u + P_i^d \le P_i^{\max} \tag{17d}$$

$$1 - x_{i,L} - x_{i,k} \ge 0, \forall i \in M \tag{17e}$$

$$x_{i,k}, P_i^u, P_i^d, f_{i,j} \ge 0 \tag{17f}$$

3. Problem Solving and Analysis

3.1 Solving the problem of minimizing the maximum delay of the task

Due to the mutual coupling between the variables, P1 is a non-convex optimization problem that cannot be solved directly. For this reason, P1 is decomposed into two subproblems: subproblem 1 assumes that all devices have the same offloading decision, and jointly optimizes the device transmit power allocation and UAV computational resource allocation; subproblem 2 assumes that the power allocation and computational resource allocation schemes are known, and optimizes the device offloading decision. The suboptimal solution of the original problem P1 is obtained by alternately iterating subproblem 1 and subproblem 2 until the objective function converges.

3.1.1 Subproblem 1

Given the initial UAV offloading rate $x_{i,j}$ and D2D offloading rate $x_{i,k}$ as known conditions, the objective function and its corresponding transmit power allocation and UAV computing resource allocation scheme are to be solved. However, the optimization problem remains non-convex. To address this, we deform the non-convex constraints by setting $S_\varepsilon = \max\left\{\left(P^{cu}h_{cu} - \varepsilon\sigma_n^2\right)/\varepsilon h_{i,k}, P_i^{\max}\right\}$, transforming the problem into

$$\mathbf{P1.1}: \quad \min_{t,t_i,f_{i,j},P_i^u,P_i^d} \ t \tag{18a}$$

$$\text{s.t.} \quad t_i \le t \tag{18b}$$

$$\frac{\left(1 - x_{i,j} - x_{i,k}\right) I_i C}{f_i} \le t_i \tag{18c}$$

$$\frac{x_{i,j}}{t_i} - \left(\frac{I_i}{B\log_2\left(1 + P_i^u S_{i,j}\right)} + \frac{I_i C}{f_{i,j}}\right)^{-1} \le 0 \tag{18d}$$

$$\frac{x_{i,k}}{t_i} - \left(\frac{I_i}{B\log_2\left(1 + P_i^d S_{i,k}\right)} + \frac{I_i C}{f_k}\right)^{-1} \le 0 \tag{18e}$$

$$(11f)\text{-}(11j)$$

where (18d) and (18e) are convex constraints, which can be proved in Appendix A. Therefore, P1.1 becomes a convex optimization problem, which can be solved by KKT conditions [23]. The Lagrange function is expressed in (19) and the KKT conditions corresponding to Lagrange function are in (20). By solving (20b) and (20f), $f_{i,j} > 0$ and $P_i^u > 0$ are obtained. Then using (20d) and (20e), we find $\xi_i > 0$, $\lambda_i > 0$. Additionally, (20g) provides $\varphi_i > 0$ and $\mu_i > 0$ as a result. Finally, combining (20a)-(20c), we can get (21).

$$\begin{aligned}
&L\left(t, t_i, P_i^u, P_i^d, f_{i,j}, \lambda_i, \mu_i, \omega_i, \eta_i, \varphi_i, \xi_i\right) \\
&= t + \lambda_i\left(\frac{x_{i,j}}{t_i} - \left(\frac{I_i}{B\log_2\left(1 + P_i^u S_{i,j}\right)} + \frac{I_i C}{f_{i,j}}\right)^{-1}\right) + \mu_i\left(\frac{x_{i,k}}{t_i} - \left(\frac{I_i}{B\log_2\left(1 + P_i^d S_{i,k}\right)} + \frac{I_i C}{f_k}\right)^{-1}\right) \\
&+\omega_i\left(\frac{\left(1 - x_{i,j} - x_{i,k}\right) I_i C}{f_i} - t_i\right) + \eta_i\left(t_i - t\right) + \varphi_i\left(P_i^u + P_i^d - P_i^{max}\right) \\
&+\xi_i\left(\sum_{i=1}^{M} f_{i,j} - F_j^{max}\right) + \delta_i\left(P_i^d - S_\varepsilon\right)
\end{aligned} \tag{19}$$

$$\varphi_i\left(P_i^u + P_i^d - P_i^{max}\right) = 0 \tag{20a}$$

$$\xi_i\left(\sum_{i=1}^{M} f_{i,j} - F_j^{max}\right) = 0 \tag{20b}$$

$$\eta_i\left(t_i - t\right) = 0 \tag{20c}$$

$$\frac{\partial L}{\partial P_i^u} = \varphi_i - \frac{\lambda_i f_{i,j}^2}{I_i\left(f_{i,j} + CB\log_2\left(1 + P_i^u S_{i,j}\right)\right)^2} \frac{BS_{i,j}}{\ln 2\left(1 + P_i^u S_{i,j}\right)} = \begin{cases} = 0 & P_i^u > 0 \\ > 0 & P_i^u = 0 \end{cases} \tag{20d}$$

$$\frac{\partial L}{\partial P_i^d}=\varphi_i-\frac{\mu_i f_k^2}{I_i\left(f_k+CB\log_2\left(1+P_i^d S_{i,k}\right)\right)^2}\frac{BS_{i,k}}{\ln 2\left(1+P_i^d S_{i,k}\right)}=\begin{cases}=0 & P_i^d>0\\ >0 & P_i^d=0\end{cases} \tag{20e}$$

$$\frac{\partial L}{\partial f_{i,j}}=\xi_i-\frac{\lambda_i CB^2\log_2^2\left(1+P_i^u S_{i,j}\right)}{I_i\left(f_{i,j}+CB\log_2\left(1+P_i^u S_{i,j}\right)\right)^2}=\begin{cases}=0 & f_{i,j}>0\\ >0 & f_{i,j}=0\end{cases} \tag{20f}$$

$$\frac{\partial L}{\partial t_i}=\eta_i-\frac{\lambda_i x_{i,j}}{t_i^2}-\frac{\mu_i x_{i,k}}{t_i^2}-\omega_i=0 \tag{20g}$$

$$\begin{aligned}&P_i^u+P_i^d=P_i^{\max},\forall i\in M\\ &\sum_{i=1}^{M} f_{i,j}=F_j^{\max}\\ &t=t_i,\forall i\in M\end{aligned} \tag{21}$$

In the final resource allocation scheme, the transmit power of the requesting user's device is fully allocated for UAV and D2D offloading. The available computing resources of the UAV are assigned to devices with computing task requirements, ensuring equal computation time for each device. We define $\psi\left(P_i^d\right)$ in (22), and ψ' is the inverse function of $\psi\left(P_i^d\right)$.

$$\psi\left(P_i^d\right)=\varphi_i-\frac{\mu_i f_k^2}{I_i\left(f_k+CB\log_2\left(1+P_i^d S_{i,k}\right)\right)^2}\frac{BS_{i,k}}{\ln 2\left(1+P_i^d S_{i,k}\right)} \tag{22}$$

Therefore, the Lagrange dual function and Lagrange dual problem of P1.1 are presented by

$$g\left(\lambda_i,\mu_i,\omega_i,\eta_i,\varphi_i,\xi_i\right)=\min_{t,t_i,P_i^u,P_i^d,f_{i,j}} L\left(t,t_i,P_i^u,P_i^d,f_{i,j},\lambda_i,\mu_i,\omega_i,\eta_i,\varphi_i,\xi_i\right) \tag{23}$$

$$\max_{\lambda_i,\mu_i,\omega_i,\eta_i,\varphi_i,\xi_i} g\left(\lambda_i,\mu_i,\omega_i,\eta_i,\varphi_i,\xi_i\right) \tag{24}$$

For a given set of Lagrangian multipliers, the expression of optimization variables t_i^*, $P_i^{d^*}$, $P_i^{u^*}$ and $f_{i,j}^*$ are denoted as follows, respectively.

$$t_i^*=\sqrt{\frac{\left(\lambda_i x_{i,j}+\mu_i x_{i,k}\right)I_i}{\eta_i-\omega_i}} \tag{25a}$$

$$P_i^{d^*}=\psi'(0) \tag{25b}$$

$$P_i^{u^*}=P_i^{\max}-P_i^{d^*} \tag{25c}$$

$$f_{i,j}^*=B\log_2\left(1+P_i^u S_{i,j}\right)\left(\sqrt{C/\xi_i}-C\right) \tag{25d}$$

Since Lagrange dual function (23) is not differentiable, the subgradient algorithm is utilized to update Lagrange multipliers η_i, ω_i, λ_i, μ_i, φ_i, ξ_i and δ_i, and the updating formulas are

$$\eta_i^{l+1}=\left[\eta_i^l-\pi_1^l\left(t_i-t\right)\right]^+ \tag{26a}$$

$$\omega_i^{l+1}=\left[\omega_i^l-\pi_2^l\left(\frac{\left(1-x_{i,j}-x_{i,k}\right)I_i C}{f_i}-t_i\right)\right]^+ \tag{26b}$$

$$\lambda_i^{l+1} = \left[\lambda_i^l - \pi_3^l \left(\frac{x_{i,j}}{t_i} - \left(\frac{I_i}{B \log_2 \left(1 + P_i^u S_{i,j}\right)} + \frac{I_i C}{f_{i,j}} \right)^{-1} \right) \right]^+ \tag{26c}$$

$$\mu_i^{l+1} = \left[\mu_i^l - \pi_4^l \left(\frac{x_{i,k}}{t_i} - \left(\frac{I_i}{B \log_2 (1 + P_i^d S_{i,k})} + \frac{I_i C}{f_k} \right)^{-1} \right) \right]^+ \tag{26d}$$

$$\varphi_i^{l+1} = \left[\varphi_i^l - \pi_5^l (P_i^u + P_i^d - P_i^{max}) \right]^+ \tag{26e}$$

$$\xi_i^{l+1} = \left[\xi_i^l - \pi_6^l \left(\sum_{i=1}^{M} f_{i,j} - F_j^{max} \right) \right]^+ \tag{26f}$$

$$\delta_i^{l+1} = \left[\delta_i^l - \pi_7^l (P_i^d - S_\varepsilon) \right]^+ \tag{26g}$$

where $x^+ = \max\{x, 0\}$, l is the number of iterations, $\pi_q^l = 1/l (1 \le q \le 7)$ is the step size. To ensure the convergence of the subgradient algorithm, the step size must satisfy that

$$\sum_{l=1}^{\infty} \pi_q^l = \infty, \quad \lim_{i \to \infty} \pi_q^l = 0, \quad 1 \le q \le 7 \tag{27}$$

We can solve the Lagrange dual problem based on equations (25) and (26). By iteratively updating the Lagrange multipliers until convergence, we obtain the final transmit power allocation scheme for the device and UAV computing resource allocation scheme. The convergence condition is expressed as

$$\sum_{i \in M} \left|\eta_i^{l+1} - \eta_i^l\right| + \left|\omega_i^{l+1} - \omega_i^l\right| + \left|\lambda_i^{l+1} - \lambda_i^l\right| + \left|\mu_i^{l+1} - \mu_i^l\right| + \left|\varphi_i^{l+1} - \varphi_i^l\right| + \left|\xi_i^{l+1} - \xi_i^l\right| + \left|\delta_i^{l+1} - \delta_i^l\right| \le \text{Eplison}_1 \tag{28}$$

where Eplison_1 represents the maximum difference value between two iterations.

3.1.2 Subproblem2: Offloading decision

Given the known transmit power allocation and UAV computing allocation, the original optimization problem P1 is transformed into the subproblem 2, which is expressed as

$$\mathbf{P1.2}: \quad \min_{t_i, x_{i,j}, x_{i,k}} t \tag{29a}$$

$$\text{s.t.} \quad t_i \le t \tag{29b}$$

$$\frac{\left(1 - x_{i,j} - x_{i,k}\right) I_i C}{f_i} \le t_i \tag{29c}$$

$$x_{i,j} I_i \left(\frac{1}{B \log_2 \left(1 + P_i^u S_{i,j}\right)} + \frac{C}{f_{i,j}} \right) \le t_i \tag{29d}$$

$$x_{i,k} I_i \left(\frac{1}{B \log_2 \left(1 + P_i^d S_{i,k}\right)} + \frac{C}{f_k} \right) \le t_i \tag{29e}$$

$$x_{i,j} + x_{i,k} \le 1, \forall i \in M \tag{29f}$$

$$x_{i,j}, x_{i,k}, t_i \ge 0 \tag{29g}$$

P1.2 is a linear programming (LP) problem about UAV offloading ratio $x_{i,j}$ and D2D offloading ratio $x_{i,k}$. The closed solution t_i^*, $x_{i,j}^*$ and $x_{i,k}^*$ can be obtained based on KKT conditions and the solution process is shown in Appendix B. The expression of P1.2 is

$$t_i^* = \frac{I_i C T_1 T_2}{f_i T_1 T_2 + I_i C\left(T_1 + T_2\right)} \tag{30a}$$

$$x_{i,j}^* = \frac{I_i C T_2}{f_i T_1 T_2 + I_i C\left(T_1 + T_2\right)} \tag{30b}$$

$$x_{i,k}^* = \frac{I_i C T_1}{f_i T_1 T_2 + I_i C\left(T_1 + T_2\right)} \tag{30c}$$

where $T_1 = I_i\left(\frac{1}{B\log_2\left(1+P_i^u S_{i,j}\right)} + \frac{C}{f_{i,j}}\right)$ and $T_2 = I_i\left(\frac{1}{B\log_2\left(1+P_i^d S_{i,k}\right)} + \frac{C}{f_k}\right)$.

By iteratively alternating between subproblem 1 and subproblem 2, the original optimization problem can be solved. Algorithm 1 outlines the implementation process for minimizing the maximum delay of all terminal device computing tasks.

Algorithm 1: Resource allocation algorithm by alternate iterative based on Lagrange multiplier

1： Set the maximum outer layer iterations $m^{\max}$ and maximum difference of objective function $\mathrm{Eplison}_2$;
2：Initialize the UAV offload rate and D2D offload rate within the given feasible region;
3： Set the number of outer iterations $m = 0$ ；
4： Outer layer loop
5： Set maximum iteration number for the inner layer $l^{\max}$ and maximum difference of multipliers $\mathrm{Eplison}_1$
6： Inner layer iteration
7： Initialization: Initializes the Lagrange multiplier λ_i , μ_i , ω_i , η_i , φ_i and ξ_i ;
8： Set the number of inner iterations $l = 0$ ；
9： Calculate P_i^{d*} , P_i^{u*} , $f_{i,j}^*$ according to equation (4.33);
10： Update the multiplier λ_i , μ_i , ω_i , η_i , φ_i and ξ_i according to equation (4.34);
11： If the convergence condition (28) is satisfied and the convergence of sub-gradient algorithm is satisfied, and P_i^{d*} , P_i^{u*} , $f_{i,j}^*$ are the optimal solution;
12： Otherwise, $l = l + 1$, continue;
13： Until convergence is satisfied or the set maximum number of iterations is reached;
14： end
15： Taking the power allocation scheme and UAV computing resource allocation scheme obtained by the inner Lagrange multiplier method as known conditions, the optimal objective function value is t_i^{l*}
16： The offloading decision $x_{i,j}^*$ and $x_{i,k}^*$ can be obtained, the optimal objective function value is t_i^{m*}
17： If condition $|t_i^{m*} - t_i^{l*}| \le \mathrm{Eplison}_2$ is satisfied, then exit the outer loop, and the optimal solution of the original problem is t^* ；
18： Otherwise $m = m + 1$, continue into the inner iteration
19：Reach the maximum number of iterations m , exit the outer loop *m*, break
20：The suboptimal solution of the original problem is obtained

3.2 Solving the problem of minimizing UAV computing resources

Since P2 is a non-convex optimization problem, (17b) and (17c) can be converted to convex constraints according to Appendix A, which is expressed in (31).

$$1 - x_{i,L} - x_{i,k} - T\left(\frac{I_i}{B\log_2\left(1+P_i^u S_{i,j}\right)} + \frac{I_i C}{f_{i,j}}\right)^{-1} \le 0 \tag{31a}$$

$$x_{i,k} - T\left(\frac{I_i}{B\log_2\left(1+P_i^d S_{i,k}\right)} + \frac{I_i C}{f}\right)^{-1} \le 0 \tag{31b}$$

Therefore, P2 is transformed into a convex optimization problem, and can be solved based on the KKT conditions. The analysis is presented in Appendix C in detail.

(a) KKT conditions determine the relationship between D2D offloading rate $x_{i,k}$ and the transmit power P_i^d for D2D offloading link

$$x_{i,k} = T\left(\frac{I_i}{B\log_2\left(1+P_i^d S_{i,k}\right)} + \frac{I_i C}{f_k}\right)^{-1} \tag{32}$$

(b) $\gamma\left(P_i^u, P_i^d\right)$ is defined as the power allocation function, representing the trade-off difference of power gain brought by power allocation to UAV offloading and D2D offloading.

$$\gamma\left(P_i^u, P_i^d\right) = \left(\frac{\left(1-x_{i,L}-x_{i,k}\right)I_i}{R_{i,j}\left(P_i^u\right)}\right)^2 \frac{dR_{i,j}\left(P_i^u\right)}{dP_i^u} - \left(\frac{x_{i,k}I_i}{R_{i,k}\left(P_i^d\right)}\right)^2 \frac{dR_{i,i}\left(P_i^d\right)}{dP_i^d} \tag{33}$$

Due to the fact that $P_i^u = P_i^{max} - P_i^d$, $\gamma\left(P_i^u, P_i^d\right)$ is a unary function of P_i^d, thus $\gamma\left(P_i^u, P_i^d\right)$ can be rewritten as $\gamma\left(P_i^d\right)$. Then according to (C.13), it can be obtained

$$\frac{\lambda_i}{T}\left(\frac{(1-x_{i,L}\text{-}x_{i,k})I_i}{R_{i,j}(P_i^{u*})}\right)^2 \frac{dR_{i,j}(P_i^{u*})}{dP_i^u} = \frac{\mu_i}{T}\left(\frac{x_{i,k}I_i}{R_{i,k}(P_i^{d*})}\right)^2 \frac{dR_{i,k}(P_i^{d*})}{dP_i^d} \tag{34}$$

when $\lambda_i^* = \mu_i^*$, $\gamma(P_i^{d*}) = 0$ and $P_i^{d*} = \gamma'(0)$; when $\lambda_i^* > \mu_i^*$ or $\lambda_i^* < \mu_i^*$, $P_i^{d*} < \gamma'(0)$, so we can get $P_i^{d*} = \min(\gamma'(0)\,|_{(P_i^u = P_i^{max} - P_i^d)}\ P_i^{max})$, where $\gamma(\cdot)'$ is the inverse function of $\gamma(\cdot)$.

(c) To determine the upper bound of the system's data processing capacity, we assume infinite computing resources for the UAV, ignoring the computing time, and only consider data transmission time. Then the upper bound of the data size that the system can process is

$$I_{i,k,j}^{\max} = T\left(\frac{1}{B\log_2(1+P_i^{d*}S_{i,k})} + \frac{C}{f_k}\right)^{-1} + \frac{f_iT}{C} + TB\log_2(1+P_i^{u*}S_{i,j}). \tag{35}$$

(d) To assess the advantages of D2D collaborative UAV-assisted MEC system, we consider a scenario where a device can only perform local computing or offload to the UAV. Assuming infinite UAV computing resources, we determine the maximum data size of the system as

$$I_{i,j}^{\max} = \frac{f_iT}{C} + TB\log_2(1+P_i^{max}S_{i,j}). \tag{36}$$

Due to the fact that $\phi(P_i^d) \ge \phi(P_i^d)\,|_{P_i^d=0} = TB\log_2(1+P_i^{max}S_{i,j})$, we can obtain $I_{i,k,j}^{\max} \ge I_{i,j}^{\max}$.

If the data size satisfies $I_i \le f_iT / C$, all tasks can be computed locally. If the data size meets $f_iT / c \le I_i \le I_{i,k}^{\max}$, the cooperation of adjacent D2D devices is required. In this case, devices in set offload tasks to D2D devices for computing and allocate all power for D2D offloading without requiring UAV computing resources. The optimal power allocation and D2D offloading rate are given by, respectively

$$P_i^{d^*} = P_i^{\max} \tag{37a}$$

$$x_{i,k}^* \le T\left(\frac{I_i}{B\log_2\left(1+P_i^{d^*}S_{i,k}\right)}+\frac{I_iC}{f_k}\right)^{-1} \tag{37b}$$

When the data size satisfies $I_{i,k}^{\max} \le I_i < I_{i,k,j}^{\max}$, only D2D collaborative computing is not sufficient, and offloading to UAV is also required for computing. In this case, the device needs to allocate resources for D2D and UAV offloading effectively, thus the optimal resource allocation scheme can be expressed as

$$P_i^{d^*} = \min\left(\gamma'(0)\Big|_{\left(P_i^u = P_i^{max} - P_i^d\right)}, P_i^{\max}\right) \tag{38a}$$

$$P_i^{u^*} = P_i^{\max} - P_i^{d^*} \tag{38b}$$

$$x_{i,k}^* = T\left(\frac{I_i}{B\log_2\left(1+P_i^{d^*}S_{i,k}\right)}+\frac{I_iC}{f_k}\right)^{-1} \tag{38c}$$

$$f_{i,j}^* = I_iC\left(\frac{T}{1-x_{i,L}-x_{i,k}^*}-\frac{I_i}{B\log_2\left(1+P_i^{u^*}S_{i,j}\right)}\right)^{-1}. \tag{38d}$$

When the data size is too large, i.e., $I_i \ge I_{i,k,j}^{\max}$, no feasible resource allocation scheme exists. Moreover, if a device has numerous requested tasks but no adjacent D2D collaboration, only the allocation of UAV computing resources is possible. The power distribution and UAV computing resources are presented as

$$P_i^{u^*} = P_i^{\max} \tag{39a}$$

$$f_{i,j}^* = I_iC\left(\frac{T}{1-x_{i,L}}-\frac{I_i}{B\log_2\left(1+P_i^{\max}S_{i,j}\right)}\right)^{-1}. \tag{39b}$$

4. Simulation Results and Discussion

Simulation results analyze the performance enhancement of UAV-assisted MEC systems through D2D collaboration. The scenario consists of a single UAV, multiple users, and a circular area with a radius of 100m. Two optimization problems are considered: minimizing maximum delay of computing tasks and minimizing average computing resources allocated by the UAV. Factors such as task data size, maximum tolerable delay, and device transmit power are analyzed. **Table 1** specifies the simulation parameters. "UAV-assisted" refers to only UAV-assisted MEC systems, while "UAV-D2D collaboration" denotes D2D collaborative UAV-assisted MEC systems.

Table 1. Simulation parameter setting

Parameters	Value
Subchannel bandwidth B	4MHz
Maximum computing resources of UAV F_j^{max}	10-70GHz
Terminal device computing resources f	1GHz

Parameters	Value
Noise power σ^2	-174dBm
Transmission power of device P	20 - 40dBm
Cellular communication path loss	$128.1+37.6\log_2 d(Km)$
D2D communication path loss	$148.1+40\log_2 d(Km)$
Instruction cycles per bit C	10^3 cycles/bit
D2D maximum communication distance R	30m
Task data size I_i	2-12Mbits

4.1 Maximum Delay of the Task Minimization

Fig. 2 shows the task computing rate as a function of task data size. As task data size increases, more tasks are offloaded to the UAV for computing due to its stronger computing power. The gain from UAV computing outweighs the transmission time for offloading large data. However, the amount of data offloaded to D2D devices is smaller than that computed locally. This is because offloading to adjacent devices adds extra transmission time compared to local computing, especially when the computing capabilities of the devices are similar.

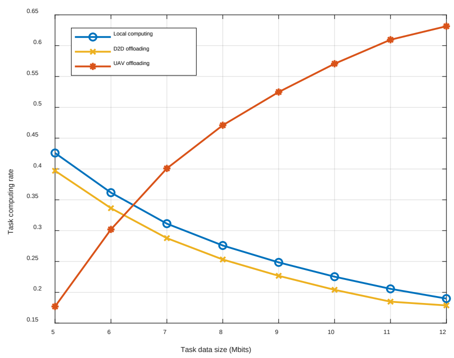

Fig. 2. Offloading decision

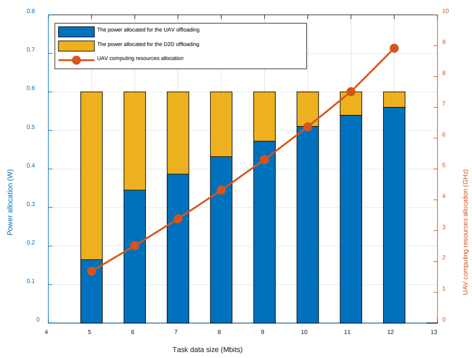

Fig. 3. Power allocation and UAV computing resource allocation

Fig. 3 illustrates the changes in transmit power allocation and UAV computing resource allocation with task data size under a total device power of 600mW. As the task data size increases, more power is allocated for UAV offloading, consistent with the trend observed in **Fig. 2**. Moreover, the device allocates all power for D2D and UAV offloading, while the UAV allocates all computing resources to the user, in line with the theoretical analysis.

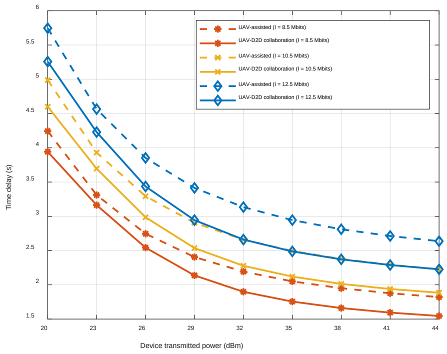

Fig. 4. Time delay versus transmitted power

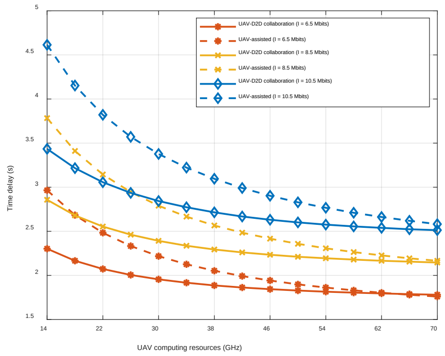

Fig. 5. Time delay versus UAV computing resource

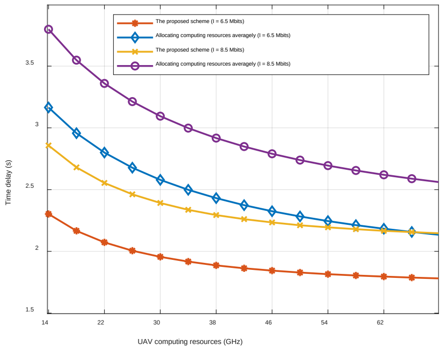

Fig. 6. The computing resources

In **Fig. 4**, device transmit power's impact on task completion time is shown. Increasing the total device power reduces the maximum task processing delay for both UAV-assisted and UAV-D2D collaborative systems. Higher transmit power decreases the transmission delay, leading to shorter overall delay. Additionally, smaller average task data size results in lower maximum completion delay. With the introduction of D2D collaboration, the task completion time is reduced due to an optimized power allocation scheme, resulting in greater gains from UAV-D2D collaboration compared to UAV-assisted alone.

Fig. 5 demonstrates the impact of UAV computing resources on task completion time. Abundant UAV computing resources lead to increased offloading of computing tasks, resulting in shorter completion time for tasks of the same data size. D2D collaboration further enhances the overall computing capability of the system, utilizing idle computing resources from adjacent devices, and reducing task completion time compared to UAV-assisted alone.

Fig. 6 compares task completion time under the proposed joint resource allocation scheme and the average allocation scheme. The joint resource allocation scheme achieves shorter completion time, with the gap narrowing as UAV computing resources increase. Sufficient UAV computing resources reduce differences in task processing time among devices. These findings validate the effectiveness of the proposed resource allocation scheme.

4.2 UAV Computing Resource Minimization

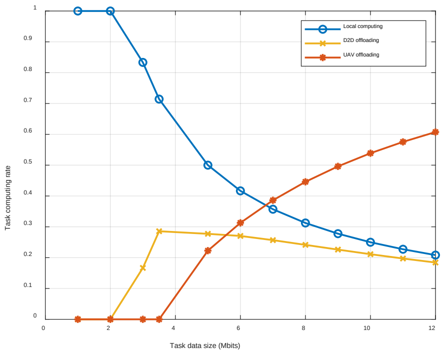

Fig. 7. Task data size on offloading decision

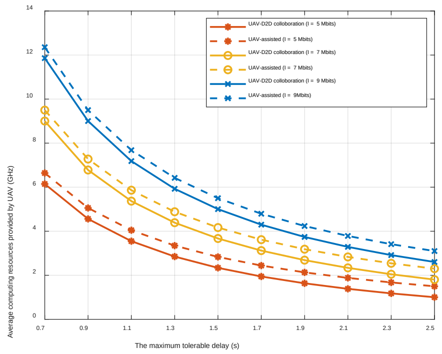

Fig. 8. UAV computing resource

In **Fig. 7**, task data size influences offloading decisions with a maximum tolerable delay of $T = 2s$. For small data sizes, local computing suffices. As data size increases, local computing fails to meet the delay requirement, prompting offloading to adjacent idle D2D devices. When D2D resources are insufficient, tasks are offloaded to both UAV and idle D2D devices to meet the delay requirement.

Fig. 8 shows the impact of the maximum tolerable delay of the device and the average computing resources provided by UAV. With the increase of the maximum tolerable delay, the UAV computing resources required by the device decrease and finally reach the plateau. This is because if the required delay is low, the computing resources needed for the requirement of delay is shorten. When the maximum task tolerable delay of the device is large enough, the delay requirement can be met without allocating more computing resources. As the task data size increases, the amount of data offloaded to the UAV for computing also increases, thus more computing resources of the UAV are required. D2D collaboration reduces the computing resource consumption of UAVs, since the device preferentially utilizes the resources of adjacent D2D devices.

5. Conclusion

This paper studies resource allocation and offloading decisions in D2D collaborative UAV-assisted MEC systems. Two scenarios are considered: delay-sensitive tasks and limited UAV computing resources. For the first scenario, an optimization model minimizes the maximum task delay using a two-subproblem approach. The second scenario prioritizes task offloading based on maximum tolerable delay. A joint optimization model and theoretical analysis provide optimal resource allocation schemes. Simulation and numerical results demonstrate the effectiveness of the proposed scheme in reducing task completion delay and saving UAV computing resources in D2D collaborative UAV-assisted MEC systems.

Appendix

A Proof of convexity

Proof. Let $A_1 = I_i \ln 2 / B$, $A_2 = I_i C$. The binary function of two variables P_i^u and $f_{i,j}$ is

$$f\left(P_i^u, f_{i,j}\right) = -\left(\frac{A_1}{\log_2\left(1+S_{i,j}P_i^u\right)} + \frac{A_2}{f_{i,j}}\right)^{-1} \tag{A.1}$$

The Hessian matrix of the binary function can be expressed as:

$$\mathbf{H} = \begin{bmatrix} \dfrac{\partial^2 f}{\partial (P_i^u)^2} & \dfrac{\partial^2 f}{\partial P_i^u \partial f_{i,j}} \\ \dfrac{\partial^2 f}{\partial f_{i,j} \partial P_i^u} & \dfrac{\partial^2 f}{\partial (f_{i,j})^2} \end{bmatrix} = \begin{bmatrix} A & B \\ B & C \end{bmatrix} \tag{A.2}$$

where $A = \dfrac{\partial^2 f}{\partial (P_i^u)^2} = \dfrac{A_1 S_{i,j}^2 f_{i,j}^2 (2A_2 + A_2 \ln(1+S_{i,j}P_i^u) + A_1 f_{i,j})}{(1+S_{i,j}P_i^u)^2 (A_2 \ln(1+S_{i,j}P_i^u) + A_1 f_{i,j})^3}$, $B = \dfrac{\partial f}{\partial P_i^u \partial f_{i,j}} = -\dfrac{2A_1 A_2 S_{i,j} \ln(1+S_{i,j}P_i^u)}{(1+S_{i,j}P_i^u)(A_2 \ln(1+S_{i,j}P_i^u) + A_1 f_{i,j})^3}$

and $C = \dfrac{\partial^2 f}{\partial (f_{i,j})^2} = \dfrac{2A_1 A_2 \ln^2(1+S_{i,j}P_i^u)}{(A_2 \ln(1+S_{i,j}P_i^u) + A_1 f_{i,j})^3}$. Since the discriminant $\Delta = AC - B^2 > 0$ is permanent established, the Hessian matrix of the binary function of two variables P_i^u and $f_{i,j}$ is positive definite, thus the binary function $f(P_i^u, f_{i,j})$ is a convex function.

Similarly, the unary function about P_i^d is a convex function

$$g(P_i^d) = -\left(C_1 / \ln(1+S_{i,k}P_i^d) - \ln(1+S_{i,k}P_i^d) + C_2\right)^{-1} \tag{A.4}$$

where $C_1 = I_i \ln 2 / B$ and $C_2 = I_i C / f$. Since $\partial^2 g / \partial (P_i^d)^2 > 0$ is permanent established, the constraint condition (18d) and (18e) are both convex constraints.

B Solving the subproblem P1.2

The Lagrange function of P1.2 is expressed as

$$\begin{aligned} L(t, t_i, x_{i,j}, x_{i,k}, \lambda_i, \mu_i, \omega_i, \eta_i, \varphi_i) &= t + \lambda_i (x_{i,j} I_i (\frac{1}{B\log_2(1+P_i^u S_{i,j})} + \frac{C}{f_{i,j}}) - t_i) + \omega_i (\frac{(1-x_{i,j}-x_{i,k}) I_i C}{f_i} - t_i) \\ &+ \mu_i (x_{i,k} I_i (\frac{1}{B\log_2(1+P_i^d S_{i,k})} + \frac{C}{f_k}) - t_i) + \eta_i (t_i - t) + \varphi_i (x_{i,j} + x_{i,k} - 1) \end{aligned} \tag{B.1}$$

the KKT conditions of which are

$$\frac{\partial L}{\partial t} = 1 - \eta_i = 0 \tag{B.2}$$

$$\frac{\partial L}{\partial t_i} = \eta_i - \lambda_i - \mu_i - \omega_i = 0 \tag{B.3}$$

$$\frac{\partial L}{\partial x_{i,j}} = \frac{\lambda_i I_i}{B\log_2\left(1+P_i^u S_{i,j}\right)} - \frac{\omega_i I_i C}{f_i} + \varphi_i = 0 \tag{B.4}$$

$$\frac{\partial L}{\partial x_{i,k}} = \frac{\mu_i I_i}{B\log_2\left(1+P_i^d S_{i,k}\right)} - \frac{\omega_i I_i C}{f_i} + \varphi_i = 0 \tag{B.5}$$

$$\lambda_i\left(x_{i,j}I_i\left(\frac{1}{B\log_2\left(1+P_i^uS_{i,j}\right)}+\frac{C}{f_{i,j}}\right)-t_i\right)=0 \tag{B.6}$$

$$\mu_i\left(x_{i,k}I_i\left(\frac{1}{B\log_2\left(1+P_i^dS_{i,k}\right)}+\frac{C}{f_k}\right)-t_i\right)=0 \tag{B.7}$$

$$\omega_i\left(\frac{\left(1-x_{i,j}-x_{i,k}\right)I_iC}{f_i}-t_i\right)=0 \tag{B.8}$$

$$\eta_i\left(t_i-t\right)=0 \tag{B.9}$$

$$\varphi_i\left(x_{i,j}+x_{i,k}-1\right)=0 \tag{B.10}$$

In the above KKT conditions, if (B.2) is to be satisfied, $\eta_i>0$ is required to be permanent established. According to (B.3), $\lambda_i+\mu_i+\omega_i>0$ is permanent established. We can obtain $t=t_i,\forall i\in M$ according to (B.9), and obtain $\lambda_i>0$, $\omega_i>0$, $\mu_i>0$, according to (B.4)-(B.8).

Proof. Since each device has certain computing capability, $x_{i,j}+x_{i,k}<1$ is established. To satisfy (B.10), $\varphi_i=0$ must be established. Based on (B.4) and (B.5), when $\lambda_i=0$, $\omega_i=0$ and $\mu_i=0$ coexist, which inconsistent with the condition $\lambda_i+\mu_i+\omega_i>0$. Thus $\lambda_i>0$, $\omega_i>0$ and $\mu_i>0$ must be established. Then according to the KKT conditions of (B.6) - (B.8)

$$x_{i,j}I_i\left(\frac{1}{B\log_2\left(1+P_i^uS_{i,j}\right)}+\frac{C}{f_{i,j}}\right)-t_i=0 \tag{B.11}$$

$$x_{i,k}I_i\left(\frac{1}{B\log_2\left(1+P_i^dS_{i,k}\right)}+\frac{C}{f_k}\right)-t_i=0 \tag{B.12}$$

$$\frac{\left(1-x_{i,j}-x_{i,k}\right)I_iC}{f_i}-t_i=0 \tag{B.13}$$

Therefore, the closed expression of t_i^*, $x_{i,j}^*$ and $x_{i,k}^*$ can be obtained by jointly solving (B.11)-(B.13).

C Analysis of minimizing the UAV computing resources

The Lagrange function of P2 is presented in (C.1),

$$\begin{aligned}L(f_{i,j},x_{i,k},P_i^u,P_i^d,\lambda_i,\mu_i,\omega_i) &= f_{i,j}+\lambda_i(1-x_{i,L}\text{-}x_{i,k}-T(\frac{I_i}{B\log_2(1+P_i^uS_{i,j})}+\frac{I_iC}{f_{i,j}})^{-1})+\omega_i(x_{i,L}+x_{i,k}-1)\\ &+\mu_i(x_{i,k}-T(\frac{I_i}{B\log_2(1+P_i^dS_{i,k})}+\frac{I_iC}{f_k})^{-1})+\varphi_i(P_i^u+P_i^d-P_i^{max})\end{aligned} \tag{C.1}$$

where λ_i, μ_i, φ_i and ω_i are the Lagrange multipliers associated with the constraints of P2, and $f_{i,j}^*$, $x_{i,k}^*$, P_i^{u*}, P_i^{d*} represent the optimal solution. There are part of the KKT conditions shown in (C.2) - (C.7). The closed expression of the optimal solution can be obtained based on KKT condition, and theoretical analysis is carried out below.

$$\frac{\partial L}{\partial f_{i,j}} = 1 - \frac{\lambda_i TCB^2 \log_2^2\left(1+P_i^u S_{i,j}\right)}{I_i\left(f_{i,j} + CB\log_2\left(1+P_i^u S_{i,j}\right)\right)^2} \begin{cases} = 0 & f_{i,j} > 0 \\ > 0 & f_{i,j} = 0 \end{cases} \tag{C.2}$$

$$\frac{\partial L}{\partial P_i^u} = \varphi_i - \frac{\lambda_i Tf_{i,j}^2}{I_i\left(f_{i,j} + CB\log_2\left(1+P_i^u S_{i,j}\right)\right)^2}\frac{BS_{i,j}}{\ln 2\left(1+P_i^u S_{i,j}\right)} = \begin{cases} = 0 & P_i^u > 0 \\ > 0 & P_i^u = 0 \end{cases} \tag{C.3}$$

$$\frac{\partial L}{\partial P_i^d} = \varphi_i - \frac{\mu_i Tf_k^2}{I_i\left(f_k + CB\log_2\left(1+P_i^d S_{i,k}\right)\right)^2}\frac{BS_{i,k}}{\ln 2\left(1+P_i^d S_{i,k}\right)} = \begin{cases} = 0 & P_i^d > 0 \\ > 0 & P_i^d = 0 \end{cases} \tag{C.4}$$

$$\lambda_i\left(1 - x_{i,L} - x_{i,k} - T\left(\frac{I_i}{B\log_2\left(1+P_i^u S_{i,j}\right)} + \frac{I_i C}{f_{i,j}}\right)^{-1}\right) = 0 \tag{C.5}$$

$$\mu_i\left(x_{i,k} - T\left(\frac{I_i}{B\log_2\left(1+P_i^d S_{i,k}\right)} + \frac{I_i C}{f_k}\right)^{-1}\right) = 0 \tag{C.6}$$

$$\varphi_i\left(P_i^u + P_i^d - P_i^{max}\right) = 0 \tag{C.7}$$

(a) When $f_{i,j}^* = 0$, the computing task of device i does not need to be offloaded to the UAV for computing, and the computing resource provided by the UAV is none. Thus, $P_i^u = 0$, $P_i^{d^*} = P_i^{max}$, $x_{i,k}^* \le 1 - x_{i,L}$, the amount of data that the system can process satisfies the following inequality.

$$I_i \le I_{i,k}^{\max} = T\left(\frac{1}{B\log_2(1+P_i^{d^*} S_{i,k})} + \frac{C}{f_k}\right)^{-1} + \frac{f_i T}{C} \tag{C.8}$$

(b) When $f_{i,j}^* > 0$, device i can offload some tasks respectively to the D2D collaborative device and the UAV for computing. We can obtain $\lambda_i > 0$, $\varphi_i > 0$ and $\mu_i > 0$ based on (C.3) and (C.4). In addition, according to (C.5)-(C.7), the constrains (17b)-(17d) are constraints of equality, i.e.

$$1 - x_{i,L} - x_{i,k} = T\left(\frac{I_i}{B\log_2\left(1+P_i^u S_{i,j}\right)} + \frac{I_i C}{f_{i,j}}\right)^{-1} \tag{C.9}$$

$$x_{i,k} = T\left(\frac{I_i}{B\log_2\left(1+P_i^d S_{i,k}\right)} + \frac{I_i C}{f_k}\right)^{-1} \tag{C.10}$$

$$P_i^u + P_i^d = P_i^{\max} \tag{C.11}$$

The above conclusions indicate that, in order to minimize the allocation of computing resources, as long as the UAV and D2D device can complete the task within the maximum tolerable delay, the device will allocate the maximum power to UAV offloading and D2D offloading. Due to the fact that $\varphi_i > 0$, combining (C.9) and (C.10), we can obtain

$$\frac{\lambda_i Tf_{i,j}^2 \cdot S_{i,j}(1+P_i^{u^*} S_{i,j})^{-1}}{(f_{i,j}^* + CB\log_2(1+P_i^{u^*} S_{i,j}))^2} = \frac{\mu_i Tf_k^2 \cdot S_{i,k}(1+P_i^{d^*} S_{i,k})^{-1}}{(f_k + CB\log_2(1+P_i^{d^*} S_{i,k}))^2} \tag{C.12}$$

The definition of $\phi(P_i^d)$ is

$$\phi(P_i^d) = T(1/(B\log_2(1+P_i^d S_{i,k})) + C/f_k)^{-1} + TB\log_2(1+(P_i^{max} - P_i^d)S_{i,j}) \qquad \text{(C.13)}$$

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