UAV-Assisted Multi-Access Edge Computing System: An Energy-Efficient Resource Management Framework

Madyan Alsenwi, Yan Kyaw Tun, Shashi Raj Pandey, Nway Nway Ei, and Choong Seon Hong
Department of Computer Science and Engineering, Kyung Hee University, 17104, Republic of Korea
Email: {malsenwi, ykyawtun7, shashiraj, nwayei, cshong}@khu.ac.kr

***Abstract*—Unmanned Aerial Vehicles (UAVs) have been deployed to enhance the network capacity and provide services to mobile users with and without infrastructure coverage. At the same time, due to the exponential growth of the internet of things devices (IoTDs), more and more data-oriented applications are coming up. However, as IoTDs have limited computation capacity and power, it is challenging to process collected data locally at the IoTDs. Motivated by the aforementioned facts, we propose, in this work, a UAV-assisted mobile edge computing system. Specifically, the objective of this work is to minimize the energy consumption of IoTDs, including local computation energy and uplink transmission energy, and UAV energy consumption. To achieve that, we formulate an optimization problem that optimizes the task offloading, bandwidth resource allocation, local computation resource allocation, and UAV computation resource allocation subject to the latency constraint of all IoTDs and the limitation of communication and computation capacity resources. Although the formulated problem is a non-convex problem, it is composed of convex subproblems, i.e., the formulated optimization problem in the form of a multi-convex optimization problem. Therefore, we decompose the formulated problem into convex subproblems and then alternately solve them till converge to the desired solution by using the Block Coordinate Descent (BCD) algorithm. Simulation results show that the proposed approach significantly saves the system power consumption compared to other existing schemes.**

***Index Terms*—Unmanned aerial vehicles (UAVs), mobile edge computing (mec), tasks offloading, resource allocation, block coordinate descent (BCD).**

I. INTRODUCTION

Due to the exponential growth of the internet of things devices (IoTDs), such as metering devices and wearable devices, more computation oriented applications, such as smart farming, face recognition, virtual reality (VR), and augmented reality (AR) are coming up in our life. These IoTDs are low power devices and have limited computation capacity. Therefore, it is difficult for IoTDs to process their data locally. Fortunately, deploying the mobile edge computing (MEC) concept brings the computation resources nearer to the IoTDs and reduces the energy consumption of the IoTDs by offloading their data to the MEC server. However, in some areas, e.g., smart farming in rural areas, disaster rescue operations, and military operation, IoTDs will be far from the MEC services and out of the coverage of the mobile infrastructure. In the cases as mentioned above, it is difficult for the IoTDs to use the MEC services [1]–[4].

Unmanned aerial vehicles (UAVs) have been widely deployed due to its high flexibility, and low cost of deployment. By deploying the MEC-enabled UAV, we can save the deployment cost of the mobile infrastructures and provide the remote MEC services to the IoTDs on demand. Motivated by these facts, we propose an energy-efficient UAV-assisted edge computing system in this work. Recently, research works focusing on UAV are gaining attention in both academia and industry. For example, authors in [5] proposed a UAV-enabled MEC system, where a UAV can power the IoTDs by leveraging the wireless power transfer technology. They modeled the system as an optimization problem that optimizes the computing resource allocation, IoTDs association, wireless power duration, UAV hovering time, and the service sequence of the IoTDs while minimizing the energy consumption of the UAV. The work in [2] proposed a UAV-MEC system considering the physical layer security. A non-convex optimization problem for secure UAV-MEC system was formulated, with the objective is to minimize the system energy, and then transformed to convex problems. In [6], authors used a UAV as an MEC server to process offloaded tasks from users. They maximized the offloaded bits from users to the UAV by optimizing UAV trajectory, uploading power of users, and user association. In [7], authors studied the trajectory optimization in the cellular-enabled UAV communication systems, while authors in [8] maximized the throughput of mobile users in UAV-enabled OFDMA systems by optimizing UAV trajectory and resource allocation. The work in [9] has proposed an optimization problem that jointly optimizes the trajectory and offloading tasks from users to the UAV, where minimizing the delay experienced by the mobile devices. The study in [10] focused on minimizing the transmit power of UAVs by optimizing the altitudes of UAVs. The K Means clustering algorithm was leveraged to find the optimal altitude of each UAV.

In this work, we introduce an energy-efficient UAV-assisted

This work was partially supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (No.2015-0-00567, Development of Access Technology Agnostic Next-Generation Networking Technology for Wired-Wireless Converged Networks), and by Institute for Information & communications Technology Promotion(IITP) grant funded by the Korea government(MSIT) (No.2015-0-00557, Resilient/Fault-Tolerant Autonomic Networking Based on Physicality, Relationship and Service Semantic of IoT Devices). *Dr. CS Hong is the corresponding author.

MEC system. Unlike the above-mentioned works, we minimize the power consumption of both IoTDs and UAV. Specifically, we optimize the task offloading to the UAV, bandwidth allocation to IoTDs, and local computation resource allocation in order to minimize the computation and uplink transmission power of IoTDs. Furthermore, we minimize the consumption power of the UAV by optimizing the UAV computation resource allocation. In summary, the main contributions of this work are as follows:

1) We consider a UAV-assisted edge computing system that allows the UAV to process the offloaded tasks form the limited computation IoTDs.
2) We formulate a multi-convex optimization problem that minimizes the system power consumption. In our formulated problem, we consider the following:
   - We formulate the objective function as a weighted summation function of IoTDs energy consumption, including local computation energy and uplink transmission energy, and the energy consumption of the UAV.
   - We optimize the task offloading from IoTDs to the UAV, bandwidth allocation to IoTDs, local computation resource allocation, and UAV computation resource allocation to the offloaded task in order to minimize the formulated objective function.
3) We decompose the formulated optimization problem into four convex subproblems by optimizing one variable and fixing the others in each subproblem.
4) We leverage the Block Coordinate Descent (BCD) algorithm to solve the subproblems alternately.
5) We evaluate the performance of the proposed model by comparing it to the equal resources sharing approach of which the UAV allocates resources equally to IoTDs and the all local computing approach where all IoTDs process their tasks locally. Numerical results demonstrate that the proposed approach outperforms the other approaches.

The remaining parts of this paper are organized as follows: Section II presents the system model and problem formulation. In section III, we discuss the proposed solution approach. The performance evaluation of the proposed algorithm is introduced in section IV. Finally, section V concludes the paper and presents some directions for future work.

II. System Model and Problem Formulation

We consider a UAV-assisted MEC system, as shown in Fig. 1, which includes a single UAV working as an aerial base station attached with an edge server and a set of IoT mobile devices $\mathcal{S} = \{1, 2, \ldots, S\}$. The UAV is hovering above the ground mobile devices and provides computation services. At the UAV hovering period, the UAV can communicate and provide computation services to the ground devices. We divide the UAV's hovering period into equally-length time slots $\mathcal{N} = \{1, 2, \ldots, N\}$. The horizontal coordinate of each ground device is assumed to be fixed $c_s = [x_s, y_s]^T$, $\forall s \in \mathcal{S}$

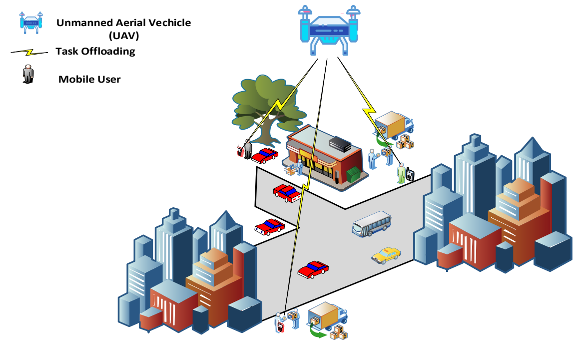

Figure 1: Illustration of the proposed system model.

while the UAV is hovering at a fixed altitude H with horizontal coordinates $u(n) = [x(n), y(n), H]^T$, $\forall n \in \mathcal{N}$. Therefore, we can calculate the distance between the UAV and a device s at time slot n as follows

$$d_s(n) = \sqrt{H^2 + ||\boldsymbol{u}(n) - \boldsymbol{c}_s||^2}, \quad \forall s \in \mathcal{S}, \forall n \in \mathcal{N}. \quad (1)$$

In [11], authors have shown that the communication channel (air-to-ground) can be modeled by the Line-of-Sight (LoS) link even if the UAV is at a moderate altitude. Moreover, the Doppler effect, which comes from the UAV mobility, is considered to be calculated at the receiver. Therefore, the LoS channel gain is given by

$$g_s(n) = g_0 d_s^{-2}(n) = \frac{g_0}{H^2 + ||u(n) - c_s||^2}, \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \quad (2)$$

where g_0 is the channel gain at the reference distance d_0.

A. Local Computing Model

At each time slot n, each mobile device has a computation task, and it can be expressed as a tuple $\{\mu_s, I_s(n), T_s(n)\}$ where μ_s is the required computation capacity to execute one bit of input data, $I_s(n)$ and $T_s(n)$ are the total input data size and the computation deadline of the task. The mobile device offloads a portion of the computation task to the UAV because the edge server at the UAV has more powerful computation capability and executes the rest locally. Let us denote the portion of the task offloaded to the UAV as $l_s(n)$. Therefore, the fraction of the task executed locally on the mobile device is $(I_s(n) - l_s(n))$. Then, the local computation execution latency/delay of the device s at time slot n is as follows

$$t_s^l(n) = \frac{\mu_s(I_s(n) - l_s(n))}{\nu_s(n)}, \quad \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \quad (3)$$

where $\nu_s(n)$ is the local computation resources of the user s required to execute $(I_s - l_s)$ within t_s^l. Therefore, the local computation time t_s^l data depends mainly on the variables l_s and ν_s. Furthermore, the local energy consumption of the device s at time slot n is given by

$$E_s^l(n) = k^l \nu_s^2(n) \mu_s(I_s(n) - l_s(n)), \quad \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \quad (4)$$

where k^l is a constant which depends on the chip architecture of the IoTD.

Table I: Summary of Notations

Notation	Definition
S	Total number of IoTDs
N	Number of time slots
c_s	Horizontal coordinate of the device s
g_0	Channel gain at referenced distance d_0
h	Altitude of the UAV
μ_s	Required computation resources to execute one bit of data
$u(n)$	Horizontal coordinate of the UAV at time slot n
$d_s(n)$	Distance between the UAV and the device s at time slot n
$g_s(n)$	LoS channel gain of the device s at time slot n
$I_s(n)$	Total input data size of the user s at time slot n
$T_s(n)$	Computation deadline of the task offloaded from device s
$l_s(n)$	Portion of task offloaded to the UAV from device s
$\alpha_s(n)$	Fraction of the bandwidth allocated to device s
$\nu_s(n)$	Local computation resource of the device s used for local execution
$\gamma_s(n)$	Computation capacity of the UAV-mounted server allocated to the device s
$t_s^l(n)$	Local computation time of the device s
$t_s^{up}(n)$	Uplink transmission time
$t_s^{comp}(n)$	Computation time at the UAV experienced by the device s
$E_s^l(n)$	Energy consumption of the device s due to the local task execution
$E_s^{up}(n)$	Uplink transmission energy consumption
$E_s^{uav}(n)$	UAV energy consumption when executing the data l_s
$R_s(n)$	Data rate of user s at time slot n
$p_s(n)$	Transmission power of the user s
k^l	A constant depends on the chip architecture of the IoTD
k^u	A constant depending on the chip architecture of the UAV
B	Total system bandwidth
N_0	Noise power
F_s^l	Maximum computation capacity of device s
$F_{\max}^u$	Maximum computation capacity of the UAV
β	Weigh of the UAV energy consumption
λ, δ, θ	Lagrangian multipliers of the P1 Lagrangian function
ρ, η	Lagrangian multipliers of the P2 Lagrangian function
ϕ, ζ	Lagrangian multipliers of the P3 Lagrangian function
υ, ι	Lagrangian multipliers of the P4 Lagrangian function

B. UAV-Assisted Edge Computing Model

When a ground device $s \in \mathcal{S}$ offloads the portion of the task to the edge server, the UAV allocates a fraction of the system bandwidth to offload the input data to the edge server. Let B and $\alpha_s(n)$ be the total system bandwidth and the fraction of the system bandwidth allocated to the device s at the time slot n, respectively. Thus, the achievable data rate of the user s at the time slot n can be given based on Shannon's capacity model as follows [12], [13]

$$R_s(n) = \alpha_s(n) B \log_2\left(1 + \frac{p_s(n) g_s(n)}{N_0}\right), \forall s \in \mathcal{S}, \forall n \in \mathcal{N}. \tag{5}$$

Then we can express the uplink transmission time of the device s when assigning the portion of the task $l_s(n)$ to the UAV at time slot n as follows

$$t_s^{up}(n) = \frac{l_s(n)}{R_s(n)}, \quad \forall s \in \mathcal{S}, \forall n \in \mathcal{N}. \tag{6}$$

Therefore, the energy consumption for uplink transmission (from the device to the UAV) when offloading the portion of the task $l_s(n)$ to the UAV at time slot n is defined as

$$E_s^{up}(n) = \frac{p_s(n) l_s(n)}{R_s(n)}, \forall s \in \mathcal{S}, \forall n \in \mathcal{N}. \tag{7}$$

Moreover, the computation latency/delay experienced by the device s at the UAV at time slot n to execute the fraction of task offloaded to the UAV is given as follows

$$t_s^{comp} = \frac{\mu_s l_s(n)}{\gamma_s(n)}, \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{8}$$

where the variable $\gamma_s(n)$ is the computation resources (i.e., cycles/s) of the UAV-mounted server that is allocated to the device s at time slot n. Therefore, the energy consumption at UAV when executing the offloaded data l_s form an IoTD s at tim slot n is given as

$$E_s^{uav}(n) = k^u \gamma_s^2(n) \mu_s l_s(n), \quad \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{9}$$

where k^u is a constant depending on the chip architecture of the UAV. The summary of mathematical symbols used in this work is given in Table 1.

C. Problem Formulation

In this work, we consider an energy-minimization problem in UAV-aided mobile edge computing system with the aim is to minimize the energy consumption of both IoTDs and the UAV by optimizing the task offloading ($\boldsymbol{l}$), bandwidth allocation to IoTDs ($\boldsymbol{\alpha}$), local computation resource allocation ($\boldsymbol{\nu}$), and the UAV computation resource allocation ($\boldsymbol{\gamma}$), where $\boldsymbol{l} = \{l_s(n), \forall n \in \mathcal{N}, \forall s \in \mathcal{S}\}$, $\boldsymbol{\alpha} = \{\alpha_s(n), \forall n \in \mathcal{N}, \forall s \in \mathcal{S}\}$, $\boldsymbol{\nu} = \{\nu_s(n), \forall n \in \mathcal{N}, \forall s \in \mathcal{S}\}$, and $\boldsymbol{\gamma} = \{\gamma_s(n), \forall n \in \mathcal{N}, \forall s \in \mathcal{S}\}$. Therefore, the objective function can be formulated as

$$\mathcal{Q} = \underbrace{\sum_{n=1}^{N}\sum_{s=1}^{S}\Big(E_s^l(n) + E_s^{up}(n)\Big)}_{\text{IoTDs Energy Consumption}} + \underbrace{\sum_{n=1}^{N}\sum_{s=1}^{S} E_s^{uav}(n)}_{\text{UAV Energy Consumption}}. \tag{10}$$

Therefore, we can formulate the optimization problem as follows

$$\min_{\boldsymbol{l},\boldsymbol{\alpha},\boldsymbol{\nu},\boldsymbol{\gamma}} \sum_{n=1}^{N}\sum_{s=1}^{S}\Big(E_s^l(n) + E_s^{up}(n)\Big) + \beta \sum_{n=1}^{N}\sum_{s=1}^{S} E_s^{uav}(n) \tag{11}$$

$$\text{s.t. } t_s^{up}(n) + t_s^{comp}(n) \le T_s(n), \quad \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{12}$$

$$t_s^l(n) \le T_s(n), \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{13}$$

$$l_s(n) \le I_s(n), \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{14}$$

$$\nu_s(n) \le F_s^l, \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{15}$$

$$\sum_{s \in \mathcal{S}} \gamma_s(n) \le F_{\max}^u, \forall n \in \mathcal{N}, \tag{16}$$

$$\sum_{s \in \mathcal{S}} \alpha_s(n) \le 1, \alpha_s(n) \ge 0, \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{17}$$

where β is a weight parameter that controls the preference of the UAV energy minimization, $F^u_{\max}$ is the total CPU capacity of the UAV, and F^l_s represents the maximum CPU capacity of the device s. The constraints (12) and (13) represent the latency constraint of the task of each IoTD at each time slot, (14) represents that the portion of the task of the device s offloaded to the UAV must be less than the total input data size of the task of the device. Finally, the constraints (15), (16), and (17) show the limitation constraints of the computation capacity of the UAV, the computation capacity of IoTDs, and the bandwidth allocation. The structure of the aforementioned problem is a non-convex because of the non-convexity nature of the energy function E^{up}_s in the objective function (11). Therefore, solving the problem mentioned above will take exponential time complexity.

III. Proposed Block Coordinate Descent (BCD) Based Approach

Even though the formulated optimization problem is a non-convex problem, the subproblems of optimizing one variable and fixing the others are convex problems. Therefore, the proposed problem is in the form of a multi-convex problem. To solve the proposed multi-convex problem, we decompose it into multiple subproblems such as 1) optimal task offloading problem, 2) bandwidth allocation problem, 3) local computation resource allocation problem and 4) UAV computation resource allocation problem. Thus, the BCD algorithm is adopted to solve the subproblems alternately.

A. Task Offloading Problem

For a given $\boldsymbol{\alpha}, \boldsymbol{\nu}$, and $\boldsymbol{\gamma}$, the task offloading problem can be expressed as follows

$$\text{(P1)} \quad \min_{\boldsymbol{l}} \sum_{n=1}^{N}\sum_{s=1}^{S} E^l_s(n) + E^{up}_s(n) \tag{18}$$

$$\text{s.t. } t^{up}_s(n) + t^{comp}_s(n) \le T_s(n), \quad \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{19}$$

$$t^l_s(n) \le T_s(n), \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{20}$$

$$l_s(n) \le I_s(n), \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{21}$$

Lemma 1. *The problem (P1) is a convex optimization problem.*

Proof. The Lagrangian function of P1 is given as

$$\begin{aligned}\mathcal{L}_1(\boldsymbol{l}, \boldsymbol{\lambda}, \boldsymbol{\delta}, \boldsymbol{\theta}) &= \sum_{n=1}^{N}\sum_{s=1}^{S} E^l_s(n) + E^{up}_s(n) \\ &+ \sum_{n=1}^{N}\sum_{s=1}^{S} \lambda_s(n)\Big(t^{up}_s(n) + t^{comp}_s(n) - T_s(n)\Big) \\ &+ \sum_{n=1}^{N}\sum_{s=1}^{S} \delta_s(n)\Big(t^l_s(n) - T_s(n)\Big) \\ &+ \sum_{n=1}^{N}\sum_{s=1}^{S} \theta_s(n)\Big(l_s(n) - I_s(n)\Big).\end{aligned} \tag{22}$$

We need to show that $\frac{\partial^2 \mathcal{L}_1}{\partial l^2} \ge 0$ in order to proof the convexity of P1. Thus, we calculate the second derivative of (22) as follows

$$\begin{aligned}\frac{\partial \mathcal{L}_1}{\partial l_s(n)} &= -k^l \nu^2_s(n)\mu_s(n) + \frac{p_s(n)}{R_s(n)} + \lambda_s(n)\Big(\frac{1}{R_s(n)} + \frac{\mu_s(n)}{\gamma_s(n)}\Big) \\ &- \frac{\mu_s(n)}{\nu_s(n)} + \theta_s(n) \Rightarrow \frac{\partial^2 \mathcal{L}_2}{\partial l^2_s(n)} = 0.\end{aligned} \tag{23}$$

Hence, the problem P1 is a convex optimization problem. ■

B. Bandwidth Allocation Problem

For any given $\boldsymbol{l}, \boldsymbol{\nu}$, and $\boldsymbol{\gamma}$, the optimal bandwidth allocation problem can be described as follows:

$$\text{(P2)} \quad \min_{\boldsymbol{\alpha}} \sum_{n=1}^{N}\sum_{s=1}^{S} E^l_s(n) + E^{up}_s(n) \tag{24}$$

$$\text{s.t. } t^{up}_s(n) + t^{comp}_s(n) \le T_s(n), \quad \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{25}$$

$$\sum_{s=1}^{S} \alpha_s(n) \le 1, \alpha_s(n) \ge 0, \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{26}$$

Lemma 2. *The problem (P1) is a convex optimization problem.*

Proof. The Lagrangian function of P2 is defined in (27). Thus, the second derivative of (27) is given as

$$\begin{aligned}\frac{\partial \mathcal{L}_2}{\partial \alpha_s(n)} &= \frac{-p_s(n)l_s(n) - l_s(n) - \rho_s(n)l_s(n)}{\alpha_s(n)R_s(n)} + \eta(n) \\ \frac{\partial^2 \mathcal{L}_2}{\partial \alpha^2_s(n)} &= \frac{p_s(n)l_s(n) + l_s(n) + \rho_s(n)l_s(n)}{\alpha^2_s(n)R_s(n)} \ge 0.\end{aligned} \tag{28}$$

It is clear from (28) that the $\frac{\partial^2 \mathcal{L}_2}{\partial \alpha^2_s(n)}$ is always positive and hence the problem P2 is a convex optimization problem. ■

C. Local Computation Resource Allocation Problem

For any given $\boldsymbol{l}, \boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$, the local computation resource allocation problem can be expressed as follows

$$\text{(P3)} \quad \min_{\boldsymbol{\nu}} \sum_{n=1}^{N}\sum_{s=1}^{S} E^l_s(n) \tag{29}$$

$$\text{s.t. } t^l_s(n) \le T_s(n), \forall s \in \mathcal{S}, \forall n \in \mathcal{N}, \tag{30}$$

$$\nu_s(n) \le F^l_s, \forall s \in \mathcal{S}, \forall n \in \mathcal{N}. \tag{31}$$

Lemma 3. *The problem (P3) is a convex optimization problem.*

Proof. We defined the Lagrangian function of P3 in (32). Therefore, the second derivative of the Lagrangian function is given as

$$\begin{aligned}\frac{\partial \mathcal{L}_3}{\partial \nu_s(n)} &= 2k^l \nu_s(n)\mu_s\Big(I_s(n) - l_s(n)\Big) + \zeta_s(n) \\ \frac{\partial^2 \mathcal{L}_3}{\partial \nu^2_s(n)} &= 2k^l \mu_s\Big(I_s(n) - l_s(n)\Big) \ge 0.\end{aligned} \tag{33}$$

Hence, the subproblem P3 is a convex optimization problem. ■

$$\mathcal{L}_2(\boldsymbol{\alpha},\boldsymbol{\rho},\eta)=\sum_{n=1}^{N}\sum_{s=1}^{S}E_s^l(n)+E_s^{up}(n)+\sum_{n=1}^{N}\sum_{s=1}^{S}\rho_s(n)\Big(t_s^{up}(n)+t_s^{comp}(n)-T_s(n)\Big)+\sum_{n=1}^{N}\eta(n)\left[\sum_{s=1}^{S}-1\right]. \quad (27)$$

$$\mathcal{L}_3(\boldsymbol{\nu},\boldsymbol{\phi},\boldsymbol{\zeta})=\sum_{n=1}^{N}\sum_{s=1}^{S}k^l\nu_s^2(n)\mu_s\Big(I_s(n)-l_s(n)\Big)+\sum_{n=1}^{N}\sum_{s=1}^{S}\phi_s(n)\Big(t_s^l(n)-T_s(n)\Big)+\sum_{n=1}^{N}\sum_{s=1}^{S}\zeta(n)\Big(\nu_s-F_{\max}^l\Big). \quad (32)$$

$$\mathcal{L}_4(\boldsymbol{\gamma},\boldsymbol{\upsilon},\iota)=\sum_{n=1}^{N}\sum_{s=1}^{S}k^u\gamma_s^2(n)\mu_s l_s(n)+\sum_{n=1}^{N}\sum_{s=1}^{S}\upsilon_s(n)\Big(t_s^{up}(n)+t_s^{comp}(n)-T_s(n)\Big)+\sum_{n=1}^{N}\iota(n)\left[\sum_{s=1}^{S}\gamma_s-F_{\max^u}\right]. \quad (37)$$

Algorithm 1 : Block Coordinate Descent (BCD) Algorithm

Initialization: Set $k=0$, $\epsilon_1,\epsilon_2,\epsilon_3,\epsilon_4>0$, and find initial feasible solutions $(\boldsymbol{l}^{(0)},\boldsymbol{\alpha}^{(0)},\boldsymbol{\nu}^{(0)},\boldsymbol{\gamma}^{(0)})$;
repeat
  Compute $\boldsymbol{l}^{(k+1)}$ from (P1) at given $\boldsymbol{\alpha}^k,\boldsymbol{\nu}^k$ and $\boldsymbol{\gamma}^k$;
  Compute $\boldsymbol{\alpha}^{(k+1)}$ from (P2) at given $\boldsymbol{l}^{(k+1)},\boldsymbol{\nu}^k$ and $\boldsymbol{\gamma}^k$;
  Compute $\boldsymbol{\nu}^{(k+1)}$ from (P3) at given $\boldsymbol{l}^{(k+1)},\boldsymbol{\alpha}^{(k+1)}$ and $\boldsymbol{\gamma}^k$;
  Compute $\boldsymbol{\gamma}^{(k+1)}$ from (P4) at given $\boldsymbol{l}^{(k+1)},\boldsymbol{\alpha}^{(k+1)}$ and $\boldsymbol{\nu}^{(k+1)}$;
  $k=k+1$;
until $\parallel \boldsymbol{l}^{(k+1)}-\boldsymbol{l}^k\parallel\le\epsilon_1$, and $\parallel\boldsymbol{\alpha}^{(k+1)}-\boldsymbol{\alpha}^k\parallel\le\epsilon_2$, and $\parallel\boldsymbol{\nu}^{(k+1)}-\boldsymbol{\nu}^k\parallel\le\epsilon_3$, and $\parallel\boldsymbol{\gamma}^{(k+1)}-\boldsymbol{\gamma}^k\parallel\le\epsilon_4$;
Then, set $\left(\boldsymbol{l}^{(k+1)},\boldsymbol{\alpha}^{(k+1)},\boldsymbol{\nu}^{(k+1)},\boldsymbol{\gamma}^{(k+1)}\right)$ as the desired solution.

D. UAV Computation Resource Allocation Problem

For any given $\boldsymbol{l},\boldsymbol{\alpha}$ and $\boldsymbol{\nu}$, the optimal UAV computation resource allocation problem can be written as follows

$$\text{(P4)}\quad \min_{\boldsymbol{\gamma}}\ \sum_{n=1}^{N}\sum_{s=1}^{S}E_s^{uav}(n) \quad (34)$$

$$\text{s.t. } t_s^{up}(n)+t_s^{comp}(n)\le T_s(n),\quad \forall s\in\mathcal{S},\forall n\in\mathcal{N}, \quad (35)$$

$$\sum_{s=1}^{S}\gamma_s(n)\le F_{\max}^u,\forall n\in\mathcal{N}. \quad (36)$$

Lemma 4. *The problem (P4) is a convex optimization problem.*

Proof. We define the Lagrangian function of P4 as in (37). Thus, we can calculate the second derivative of (37) as

$$\frac{\partial\mathcal{L}_4}{\partial\nu_s(n)}=2k^u\gamma_s(n)\mu_s l_s(n)+\iota(n)$$
$$\frac{\partial^2\mathcal{L}_4}{\partial\gamma_s^2(n)}=2k^u\mu_s l_s(n)\ge 0. \quad (38)$$

From (38), we can clearly see that the problem P4 is a convex problem. ∎

As the subproblems P1, P2, P3, and P4 are convex optimization problems, we can use ECOS solver in the CVXPY to solve each subproblem individually and then update it alternately based on the BCD algorithm until convergence as shown in Algorithm 1.

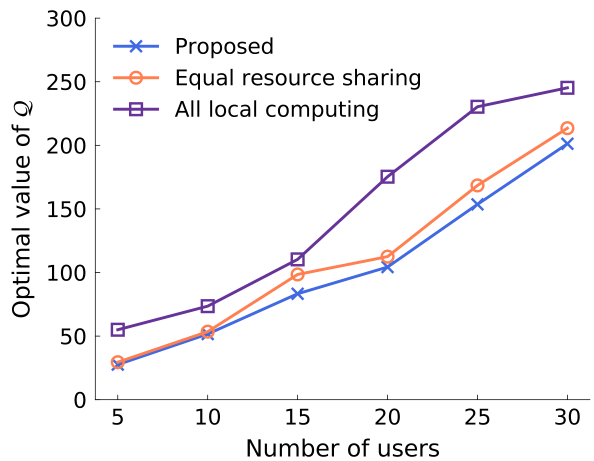

Figure 2: Energy Consumption under different number of users at $\beta=1$.

IV. Performance Evaluation

To evaluate the performance of the proposed algorithm, we consider a multiuser MEC system with a single UAV, where the MEC server having a maximum computation capacity of 1GHz is deployed at the UAV. The maximum system bandwidth is 10MHz. The users are randomly scattered within the UAV's coverage area and every user has computation tasks to be executed. The input data size of tasks and the required CPU cycles to execute one bit of input data are randomly generated between [0.1, 0.4]MB and [10, 25]cycles. The maximum tolerable latency to execute a computation task of each user is between [30, 100]s. We set the maximum computation capacity of users between [0.1, 0.72]MHz and the transmission power of each user as 1mW.

In Fig. 2, the optimal value of $\mathcal{Q}=\sum_{n=1}^{N}\sum_{s=1}^{S}\Big(E_s^l(n)+E_s^{up}(n)\Big)+\sum_{n=1}^{N}\sum_{s=1}^{S}E_s^{uav}(n)$ is calculated for different number of users. Moreover, we compare the performance of the proposed algorithm with other schemes such as equal resources sharing and all local computing. Under equal resources sharing scheme, the UAV allocates its physical resource to all users equally, and all users execute their computation

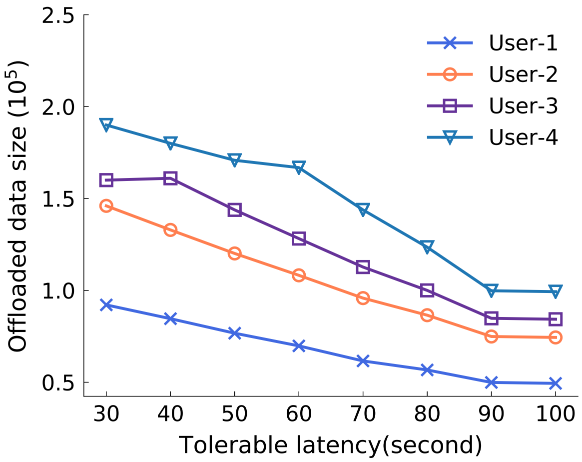

Figure 3: Offloaded data size for different tolerable latency.

tasks locally under the all local computing scheme. From Fig. 2, we observe that the proposed scheme outperforms the other two schemes. Furthermore, the performance gap between the proposed scheme and other schemes increases when the number of users increases. Therefore, the proposed scheme is more efficient when there are a large number of users in the system.

Fig. 3 demonstrates the offloaded data size of the task from each user to the UAV. From Fig. 3, we observe that users offload more data to the server when the tolerable latency (i.e., computation deadline) of the task is low. This is due to that users have a limited computation capacity compared to the MEC server, and thus it is difficult for each user to complete their task execution within the deadline. However, each user will offload less data to the server and will do more local computing when the tolerable latency is high enough.

V. Conclusion

In this work, we have proposed a UAV-aided mobile edge computing system. Specifically, we have formulated an energy-efficient resource allocation problem that aims to minimize the energy consumption of IoTDs and UAV by optimizing task offloading, communication resource allocation,local computation resource allocation, and UAV computation resource allocation. After that, we have decomposed the formulated problem into four convex subproblems and solved them alternately until convergence. Simulation results have shown the efficiency of the proposed algorithm. In the future, we will consider multiple UAVs scenario and take into account the power control of IoTDs.

References

[1] P. Mach and Z. Becvar, "Mobile edge computing: A survey on architecture and computation offloading," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 3, pp. 1628–1656, 2017.

[2] T. Bai, J. Wang, Y. Ren, and L. Hanzo, "Energy-efficient computation offloading for secure UAV-edge-computing systems," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 6, pp. 6074–6087, jun 2019.

[3] M. Alsenwi, N. H. Tran, M. Bennis, A. K. Bairagi, and C. S. Hong, "eMBB-URLLC resource slicing: A risk-sensitive approach," *IEEE Communications Letters*, vol. 23, no. 4, pp. 740–743, apr 2019.

[4] M. Alsenwi, I. Yaqoob, S. R. Pandey, Y. K. Tun, A. K. Bairagi, L. won Kim, and C. S. Hong, "Towards coexistence of cellular and WiFi networks in unlicensed spectrum: A neural networks based approach," *IEEE Access*, vol. 7, pp. 110 023–110 034, 2019.

[5] Y. Du, K. Yang, K. Wang, G. Zhang, Y. Zhao, and D. Chen, "Joint resources and workflow scheduling in uav-enabled wirelessly-powered mec for iot systems," *IEEE Transactions on Vehicular Technology*, 2019.

[6] Y. Qian, F. Wang, J. Li, L. Shi, K. Cai, and F. Shu, "User association and path planning for UAV-aided mobile edge computing with energy restriction," *IEEE Wireless Communications Letters*, vol. 8, no. 5, pp. 1312–1315, oct 2019.

[7] S. Zhang, Y. Zeng, and R. Zhang, "Cellular-enabled uav communication: A connectivity-constrained trajectory optimization perspective," *IEEE Transactions on Communications*, vol. 67, no. 3, pp. 2580–2604, 2018.

[8] Q. Wu and R. Zhang, "Common throughput maximization in uav-enabled ofdma systems with delay consideration," *IEEE Transactions on Communications*, vol. 66, no. 12, pp. 6614–6627, 2018.

[9] Q. Hu, Y. Cai, G. Yu, Z. Qin, M. Zhao, and G. Y. Li, "Joint offloading and trajectory design for uav-enabled mobile edge computing systems," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1879–1892, 2018.

[10] N. N. Ei, C. W. Zaw, M. K. Lee, and C. S. Hong, "Cell association in energy-constrained unmanned aerial vehicle communications under altitude consideration," in *2019 International Conference on Information Networking (ICOIN)*. IEEE, 2019, pp. 93–97.

[11] X. Lin, V. Yajnanarayana, S. D. Muruganathan, S. Gao, H. Asplund, H.-L. Maattanen, M. Bergstrom, S. Euler, and Y.-P. E. Wang, "The sky is not the limit: Lte for unmanned aerial vehicles," *IEEE Communications Magazine*, vol. 56, no. 4, pp. 204–210, 2018.

[12] M. Alsenwi, S. R. Pandey, Y. K. Tun, K. T. Kim, and C. S. Hong, "A chance constrained based formulation for dynamic multiplexing of eMBB-URLLC traffics in 5g new radio," in *2019 International Conference on Information Networking (ICOIN)*. IEEE, jan 2019.

[13] M. Alsenwi, H. Elsayed, and M. Elghoneimy, "Optimization of channel selection in cognitive heterogeneous wireless networks," in *2015 11th International Computer Engineering Conference (ICENCO)*. IEEE, dec 2015.