Energy-Efficient User Association and Resource Allocation in MEC-Enabled UAV-Assisted Network

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Abstract

In this paper, we investigate a mobile edge computing-enabled UAV-assisted network in which UAVs equipped with edge server provide computing services to the ground devices. We formulate the user association and resource allocation problem to minimize the energy consumption of devices and UAVs by taking into account the energy budget and the available computing resources of UAVs. Since the formulated optimization problem is non-convex and difficult to solve in a polynomial time, it is separated into two sub-problems which are solved iteratively to obtain the optimal solution. The simulation results verify that the minimum energy consumption can be achieved by using the proposed iterative approach.

I. Introduction

With unprecedented growth in the popularity of smart devices such as smartphones and various IoT devices, the applications running on them become more complex and require more computing resources. Mobile edge computing can be a promising solution to fulfill the computing resource requirements of such kinds of energy-limited devices for executing computation-intensive tasks. Generally, edge servers are installed at the edge of the network such as access points or base stations. However, installing terrestrial infrastructures sometimes incurs high cost for temporary events or for difficult-to-reach regions [1]. To solve that issue, unmanned aerial vehicles (UAVs) installed with edge servers can be deployed in those areas to support communication and computing services to the ground devices.

Since UAVs can be deployed flexibly on-demand, they can provide anywhere-anytime wireless services to the ground devices. In this work, we consider that UAVs are hovering over the area of interest for providing computing services to the ground devices. Specifically, ground devices offload their computing tasks to UAVs in order to save their energy consumption. However, it is challenging to determine how to associate devices to UAVs and allocate CPU resources of UAVs to devices in an energy-efficient manner. Therefore, in this work, we propose a user association and resource allocation problem to minimize the energy consumption of devices and UAVs. It is noted that we will use the words devices and ground devices interchangeably throughout this paper.

The rest sections of this paper are as follows. We present the system model and problem formulation in Section II and Section III, respectively. Then, Section IV shows the simulation results and the paper conclusion is in Section V.

II. System Model

As illustrated in Fig. 1, we study an MEC-enabled UAV-assisted network in which there are a set of ground devices denoted by $\mathcal{J} = \{1, 2, ..., J\}$ and a set of MEC server-equipped UAVs, $\mathcal{M} = \{1, 2, ..., M\}$, that assist ground devices with the computing services. Each device has a computing task denoted by a tuple (B_j, O_j), where B_j is the total task input data size of device j, and O_j is the CPU cycles needed to compute one bit of data. Since the ground devices are constrained by their energy and computing resources, it is efficient for them to offload their tasks to the UAVs which have more computing resources. For simplicity, we assume that ground devices tend to offload all of the computing tasks to their associated UAVs in order to save the energy consumption.

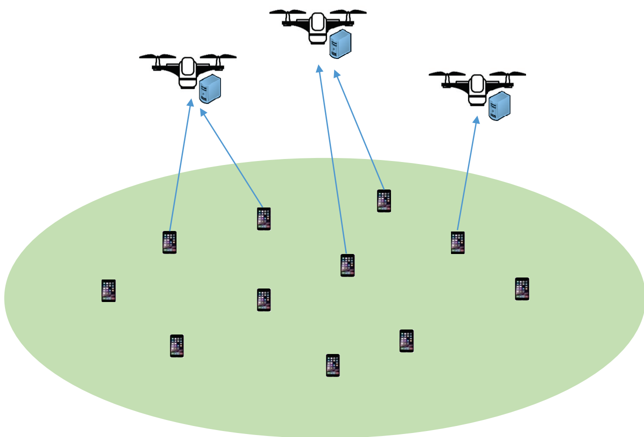

Fig. 1. System model.

A. Communication Model

Let (x_m, y_m, z_m) and (x_j, y_j, z_j) be the locations of UAV m and device j, respectively. It is noted that UAVs are assumed to be hovering at the fixed altitude. Considering that the ground devices can access to UAVs through line-of-sight links and the free-space path loss model is adopted, the channel gain between device j and UAV m is denoted as [2]:

$$h_{j,m} = \frac{h_0}{||d_{j,m}||_2^2}, \tag{1}$$

where $d_{j,m} = (x_m - x_j)^2 + (y_m - y_j)^2 + (z_m - z_j)^2$, is the distance between device j and UAV m and h_0 is the channel gain at reference distance of 1 m. Then, we define the device-UAV association variable as follow:

$$a_{j,m} = \begin{cases} 1, & \text{if device } j \text{ is associated with UAV } m, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Here, we assume that the OFDMA system is used for the communication between devices and UAVs so that there is no interference [3]. The achievable data rate when device j transmits task to its associated UAV m is described as

$$R_{j,m} = \gamma_{j,m} \log 2(1 + \frac{P_j h_{j,m}}{N_0}), \tag{3}$$

where $\gamma_{j,m}$ is the bandwidth allocated to each device, P_j is the transmit power of device j and N_0 is the noise power spectral. It is assumed that all devices have the same transmit power.

B. Computation Model

Generally, the communication energy is lower than the computation energy. Therefore, it is more energy-efficient for the energy-constrained devices to execute their computing tasks at UAV instead of locally computing at devices [4]. The time taken for device j to offload the task to its associated UAV m is given as

$$t^o_{j,m} = \frac{B_j}{R_{j,m}}. \tag{4}$$

Hence, the energy consumption of device j for the task offloading to its associated UAV m is calculated as

$$E^o_{j,m} = P_j t^o_{j,m} = \frac{P_j B_j}{R_{j,m}}. \tag{5}$$

Assuming that each UAV can handle executing tasks of more than one device, the time taken for UAV m to execute tasks of its associated device j is given as

$$t^e_{j,m} = \frac{O_j B_j}{f_{j,m}}, \tag{6}$$

where $f_{j,m}$ is the CPU frequency allocated to device j. Particularly, it depends on the number and total task input data size of the associated devices of each UAV.

The energy consumption of UAV m for computing the tasks from its associated device j is described as

$$E^e_{j,m} = k O_j B_j f^2_{j,m}, \tag{7}$$

where k is the constant that depends on the CPU chip architecture. Therefore, the total energy consumption of devices and UAVs in the network is expressed as

$$E^{\text{tot}} = \sum_{j=1}^{J} \sum_{m=1}^{M} a_{j,m} \left(E^o_{j,m} + E^e_{j,m} \right) \tag{8}$$

III. PROBLEM FORMULATION

The objective is to minimize the total energy consumption of the devices and UAVs in the network and the optimization problem is formulated as follow:

$$\min_{\boldsymbol{A},\boldsymbol{f}} \sum_{j=1}^{J} \sum_{m=1}^{M} a_{j,m} \left(E^o_{j,m} + E^e_{j,m} \right) \tag{8}$$

s.t.

$$\sum_{j=1}^{J} a_{j,m} E^e_{j,m} \leq E^{\mathsf{uav}}_{\mathsf{max}}, \forall m \in \mathcal{M}, \tag{9}$$

$$\sum_{m=1}^{M} a_{j,m} \leq 1, \forall j \in \mathcal{J}, \tag{10}$$

$$\sum_{j=1}^{J} a_{j,m} \leq N_{\mathsf{max}}, \forall m \in \mathcal{M}, \tag{11}$$

$$\sum_{j=1}^{J} a_{j,m} f_{j,m} \leq f_{\mathsf{max}}, \forall m \in \mathcal{M}, \tag{12}$$

$$f_{j,m} \geq 0, \forall j \in \mathcal{J}, \forall m \in \mathcal{M}, \tag{13}$$

$$a_{j,m} \in \{0, 1\}, \forall j \in \mathcal{J}, \forall m \in \mathcal{M}, \tag{14}$$

where $\boldsymbol{A}$ and $\boldsymbol{f}$ are the association matrix and CPU frequency resource allocation vector, respectively. Constraint (9) ensures that the total energy consumption of each UAV does not exceed its maximum energy capacity. In constraint (10), it is guaranteed that each device can only associate to at most one UAV. However, each UAV can serve N_{max} devices which is stated in constraint (11). Constraint (12) and (13) represent that each UAV allocates frequency resources not more than its capacity to its associated devices. Finally, constraint (14) defines the association of device to UAV.

The formulated optimization problem is non-convex because of the association variable and the dependence of the two variables. Moreover, the computing resource allocation variable $\boldsymbol{f}$ depends on the number of associated devices of each UAV. The formulated problem is NP-hard problem and it is difficult to solve in polynomial time. Therefore, the formulated optimization problem is divided into two sub-problems and apply the iterative algorithm to solve them. Particularly, given the CPU frequency allocation values, we find the optimal association matrix of devices to UAVs by using GUROBI optimizer [5]. Then, using CVXPY [6], the optimal CPU frequency resource allocation of UAVs to devices is obtained with the given association matrix. The two sub-problems are solved in an iterative manner until the convergence condition is satisfied. The detailed procedure is shown in Algorithm 1.

IV. SIMULATION RESULTS

In this section, we present the simulation results of our proposed problem. We consider 300 m $\times$ 300 m area in which 5 UAVs are deployed and 30 devices are randomly generated. We set the values of h_0 and N_0 as -30 dB and -174 dBm,

Algorithm 1 Proposed Iterative Algorithm

1) Initialization: Set $\epsilon > 0$, $r = 0$ and find the initial feasible solutions, $\boldsymbol{A}^{(0)}$ and $\boldsymbol{f}^{(0)}$;
2) **repeat**
3) Evaluate $\boldsymbol{A}^{(r+1)}$ for given $\boldsymbol{f}^{(r)}$;
4) Evaluate $\boldsymbol{f}^{(r+1)}$ for given $\boldsymbol{A}^{(r+1)}$;
5) **until** $|E^{\text{tot}^{(r+1)}} - E^{\text{tot}^{(r)}}| \leq \epsilon$;
6) Finally, $\boldsymbol{A}^{(r+1)}$ and $\boldsymbol{f}^{(r+1)}$ are set as the optimal solutions.

respectively. The total task input data size of users and required CPU cycles per bit are randomly generated between $[0.1, 0.4]$ MB and $[10, 25]$ cycles, respectively. Fig. 2 illustrates the association of devices to the UAVs. There are 6, 8, 4, 7, and 5 devices associated to UAV 1, UAV 2, UAV 3, UAV 4 and UAV 5, respectively. We can observe from Fig. 2 that devices are almost fairly associated to UAVs while minimizing the total energy consumption.

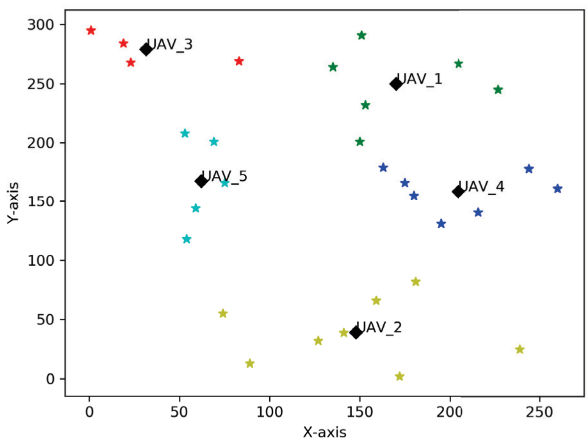

Fig. 2. Association of devices to UAVs.

In Fig. 3, we randomly choose one UAV and its associated devices to show the energy consumption of devices. As we can see from Fig. 3, the energy consumption of devices is higher when they compute their tasks locally. This is because the communication energy is generally lower than the computation energy. Moreover, the communication energy is minimized by optimally associating the devices to UAVs.

V. Conclusion

In this paper, we study the user association and resource allocation problem to minimize the energy consumption of devices and UAVs. We divide the proposed problem into two sub-problems and iteratively solve them to get the optimal solutions. For our future work, we will investigate the joint trajectory optimization and resource allocation of multiple UAVs-assisted network for the delay minimization.

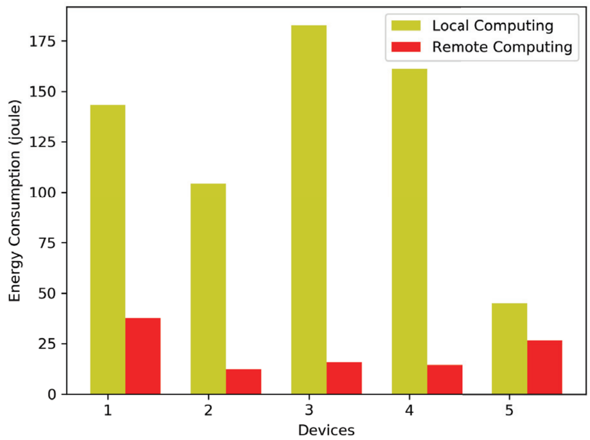

Fig. 3. Energy consumption of devices.

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