Multi-UAV-Assisted MEC System: Joint Association and Resource Management Framework

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***Abstract*—In this paper, we study an energy-efficient multi-UAV-assisted multi-access edge computing (MEC) system in which unmanned aerial vehicles (UAVs) equipped with MEC servers offer computing services to the mobile devices. In particular, the mobile devices offload a portion of their computation-intensive and delay-sensitive tasks to the UAVs to minimize local computing energy consumption. However, the coupling constraints of limited energy budget at UAVs and task completion deadlines make it difficult to determine device association and the amount of task to be offloaded. Moreover, the amount of computing resources assigned to the mobile devices by each UAV might vary according to the number of associated users and the amount of task offloaded from them. Therefore, in this work, we formulate a joint device association, task assignment and computing resource allocation problem to minimize the energy consumption of mobile devices and UAVs by considering the energy budget and available computing resources at the UAVs and task completion deadline constraints. To that end, we show that the proposed optimization problem is a mixed-integer non-linear programming (MINLP) problem, which is generally a non-convex and NP-hard problem. To solve this, we first decompose the formulated problem into three subproblems which are then solved by applying an iterative block coordinate descent (BCD) algorithm. Through the extensive simulations, we verify that our proposed algorithm outperforms the other benchmark schemes, namely, random association and offloading all.**

***Index Terms*—Multi access edge computing, unmanned aerial vehicle, mixed integer non-linear programming, block coordinate descent.**

I. Introduction

With the evolution of IoT devices and the variety of resource-intensive and delay-sensitive applications such as augmented reality, virtual reality, video streaming, online gaming and so on, the significant increase in the requirements of data traffic and computing resources to meet the users' satisfaction is unavoidable. One of the promising solutions to cope with this issue is deploying MEC servers at the network edge such as the access points or base stations for bringing the computing resources closer to the devices so that the latency and energy consumption can be reduced. However, it is not always cost-effective to install terrestrial infrastructure such as access points or base stations, especially in the difficult-to-reach terrain or for the temporary event such as a football match or concert [1]. Due to the inherent abilities such as flexible deployment, mobility, provision of reliable wireless channel through the line of sight link and the network coverage enhancement [2] [3], UAVs attached with MEC servers can be deployed as the aerial computing platforms to assist the IoT devices which are normally unable to execute the computation-intensive and delay-critical tasks locally. By doing so, the battery life of the devices can be prolonged as well as the computing efficiency of the network is progressed.

There are many existing works in the literature that addressed the problem of computation offloading and resource allocation in an MEC system. For instance, the authors in [4] considered a partial offloading scheme in which users offload a portion of their tasks to either remote cloud or MEC servers so that the transmission and computing latency of the network is minimized. Recently, UAV-aided wireless communication has extensively been researched. The work in [5] proposed a conceptor-based echo state network to obtain the optimal user association, the locations of UAVs and content caching in order that the quality of experience of users is maximized while reducing the UAVs' transmit power. To cope with the issue of the UAV's energy limitation, we proposed a multiple UAVs-assisted network in which UAVs provide the wireless services to the ground users in the downlink [6]. We minimized the energy consumption of UAVs by determining the optimal cell association and the altitude of UAVs. However, these works did not consider UAV-assisted edge computing.

In the context of UAV-assisted MEC system, the authors in [7] considered a single UAV-assisted MEC system in which the users offload their computing tasks to UAV which acts as a computing platform to assist the execution of the offloaded tasks and as a relay to further offload users' tasks to the nearby base station that has rich computing resources. In [8], the authors jointly optimized the UAV trajectory, user's transmission power and computing resource allocation with the objective of maximizing the energy efficiency of UAV. Moreover, the authors in [9] addressed the problem of optimizing the task offloading, communication and computation resource allocation with the aim of minimizing the energy consumption of IoT devices and UAV by taking into account the delay and resource constraints. Similarly, in [10] and [11], the authors investigated the problem of optimizing the UAV trajectory, computation offloading and resource allocation for a single UAV-assisted MEC system. However, the above mentioned works are limited to a single UAV scenario.

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Different from the existing works, this paper introduce an energy-efficient multi-UAV-assisted MEC system in which we minimize the total energy consumption of devices and UAVs by jointly optimizing the device association, task assignment and computing resource allocation while meeting the latency requirement of devices, the energy budget and the available computing resources of UAVs. The main contributions of this work are summarized as follows:

- Firstly, we propose an energy-efficient multi-UAV-assisted MEC system where UAVs provide computing services to the mobile devices which in general have very limited power and CPU resources to completely perform the computing tasks locally. Our proposed system ensures to reduce the energy consumption of devices and UAVs by optimally associating the devices and managing the tasks to be offloaded to the UAVs and properly allocating UAVs' CPU resources to their associated devices.
- Secondly, with the objective of minimizing the energy consumption of mobile devices and UAVs, we formulate a joint device association, task assignment and computing resource allocation problem which is non-convex because of the association variable (0 or 1 binary integer variable), as well as the coupling among all three variables. Therefore, we divide our proposed problem into multiple subproblems that are iteratively solved by applying BCD algorithm.
- Finally, we conduct the simulation results to verify the superior performance of our proposed approach by comparing with the other baselines such as random association and offloading all.

The rest of this paper is arranged as follows. We present our proposed system model in Section II and the problem formulation is introduced in Section III. Section IV presents the proposed solution and the numerical results are illustrated in Section V. Finally, we conclude the paper in Section VI.

II. System Model

Fig. 1 depicts our proposed system model in which we consider an energy-efficient multi-UAV-assisted MEC system where there are a set of mobile devices denoted by $\mathcal{N} = \{1, 2, ..., N\}$, a set of edge server-equipped UAVs $\mathcal{M} = \{1, 2, ..., M\}$, which offer computing services to the mobile devices. We also assume that there is no terrestrial infrastructure available in the considered area of interest. Each device has a computing task characterized by three parameters, i.e., the total input data size B_n (in bits), the required CPU cycles to execute one bit of data c_n (in cycles/b), and the maximum tolerable time of the task T_n (in seconds). We assume that all devices and UAVs have the onboard computing capabilities. Moreover, the tasks of the devices are assumed to be in bit-wise-independence and can arbitrarily be separated into two portions, for local computing at the mobile device and for remote computing at the UAVs [7].

Each mobile device will offload some part of the tasks to its associated UAV in order that it can save the energy consumption not only for data transmission but also for the

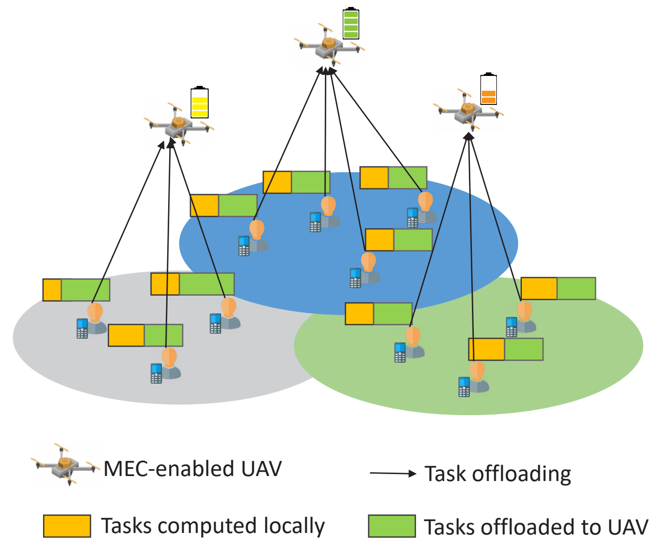

Fig. 1: Multi-UAV-Assisted MEC System.

execution of the task. This is because the mobile device can establish more reliable line of sight link as well as experience lower path loss by optimally associating to the UAV and this in turn enhances the performance of the system. It is noted that we will use the words device and mobile device interchangeably throughout this paper.

Regarding to the deployment of the UAVs over the area of interest, we apply K Means clustering algorithm [12]. It is noted that there is a central controller that has a full knowledge about the information of the mobile devices and the UAVs. After deciding the clusters of mobile devices by using K Means method, we set the centroid of the cluster as the position of UAV. Once the locations of UAVs are determined, they are assumed to hover at those locations with the minimum fixed altitude at which the mobile devices can have better channel gain. However, the optimal association of mobile devices to the UAVs are determined by using our proposed algorithm because applying K Means cannot guarantee to meet the constraints of UAV's energy budget and the available computing resources.

A. Communication Model

In this section, we present the communication link between devices and UAVs. Let us assume the coordinates of device n and UAV m be (x_n, y_n, h_n) and (x_m, y_m, h_m), respectively, in which $h_n = 0$ m and $h_m = 150$ m. Considering that the devices can establish line-of-sight links to the UAVs, the channel gain between device n and UAV m is denoted as [13]:

$$g_{n,m} = \frac{g_0}{||d_{n,m}||_2^2}, \tag{1}$$

where $d_{n,m} = (x_m - x_n)^2 + (y_m - y_n)^2 + h_m^2$, is the distance between device n and UAV m, and g_0 is the channel gain at reference distance of 1 m. Then, we define the binary variable

$\alpha_{n,m}$, which denotes whether mobile device n is associated with UAV m or not, as follows:

$$\alpha_{n,m} = \begin{cases} 1, & \text{if device } n \text{ is associated to UAV } m, \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

For simplicity, we consider that all UAVs adopt the frequency division multiple access (FDMA) technique while serving their associated mobile devices [14]. However, there are still inter-cell inferences from the mobile devices of other UAVs. Then, the data rate of device n associated with UAV m is described as

$$R_{n,m} = \frac{W_m}{\sum_{n=1}^{N} \alpha_{n,m}} \log_2 \left(1 + \frac{P_{n,m} g_{n,m}}{I_{n,m} + \sigma^2}\right), \quad (3)$$

where $I_{n,m} = \sum_{n'=1,n'\neq n}^{N} \sum_{m'=1,m'\neq m}^{M} \alpha_{n',m'} P_{n',m'} g_{n',m'}$ is the interference stemming from the mobiles devices associated with other UAVs and $\sum_{n=1}^{N} \alpha_{n,m}$ is the number of mobile devices associated with UAV m. $P_{n,m}$ is the transmit power of device n, W_m is the total available bandwidth of UAV m and σ^2 is the noise power spectral.

B. Computation Model

We assume that device n partially offloads $o_{n,m}$ amount of tasks to its associated UAV m for the remote computing and executes $(B_n - o_{n,m})$ tasks locally. Hence, the time taken for device n associated with UAV m to compute some of its tasks locally is given as

$$t_{n,m}^{l} = \frac{c_n (B_n - o_{n,m})}{f_n}, \quad (4)$$

where f_n is the computing capacity (cycles per second) of device n.

Under the association with UAV m, the energy consumption of device n for the local computing is calculated as

$$E_{n,m}^{l} = k t_{n,m}^{l} f_n^3 = k c_n (B_n - o_{n,m}) f_n^2, \quad (5)$$

where k is the constant that depends on the CPU chip architecture.

The delay for offloading part of device u's task to its associated UAV m for the remote computing is given as

$$t_{n,m}^{\text{off}} = \frac{o_{n,m}}{R_{n,m}}. \quad (6)$$

Therefore, the energy consumption of device u associated to UAV m for the task offloading is described as

$$E_{n,m}^{\text{off}} = P_{n,m} t_{n,m}^{\text{off}} = \frac{o_{n,m} P_{n,m}}{R_{n,m}}. \quad (7)$$

Then, the time taken for UAV m to compute the offloading tasks of its associated device n is given as follows:

$$t_{n,m}^{r} = \frac{c_n o_{n,m}}{\omega_{n,m}}, \quad (8)$$

where $\omega_{n,m}$ is the frequency allocated to device n by UAV m. The energy consumption of UAV m to execute tasks of its associated device n can be calculated as

$$E_{n,m}^{r} = k' t_{n,m}^{r} \omega_{n,m}^3 = k' c_n o_{n,m} \omega_{n,m}^2, \quad (9)$$

where k' is the constant which depends on the CPU chip architecture.

Hence, the total energy consumption of device n associated with UAV m can be described as

$$E_{n,m}^{\text{total}} = E_{n,m}^{l} + E_{n,m}^{\text{off}}. \quad (10)$$

III. Problem Formulation

Considering the constraints of the energy budget and available computing resources of UAV and task completion deadline, we formulate the problem of minimizing the energy consumption of both mobile devices and UAVs by controlling the device association, task assignment, and computation resource allocation variables. Then, the mathematical expression of the formulated problem can be written as follows:

$$\min_{\boldsymbol{A},\boldsymbol{o},\boldsymbol{\omega}} \sum_{n=1}^{N} \sum_{m=1}^{M} \alpha_{n,m} \left(E_{n,m}^{\text{total}} + E_{n,m}^{r}\right), \quad (11)$$

s.t.

$$t_{n,m}^{l} \leq T_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \quad (11a)$$

$$t_{n,m}^{\text{off}} + t_{n,m}^{r} \leq T_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \quad (11b)$$

$$\sum_{n=1}^{N} \alpha_{n,m} E_{n,m}^{r} \leq E_{\mathsf{max}}^{m}, \forall m \in \mathcal{M}, \quad (11c)$$

$$\sum_{m=1}^{M} \alpha_{n,m} \leq 1, \forall n \in \mathcal{N}, \quad (11d)$$

$$\sum_{n=1}^{N} \alpha_{n,m} \leq J_{\mathsf{max}}^{m}, \forall m \in \mathcal{M}, \quad (11e)$$

$$\sum_{n=1}^{N} \alpha_{n,m} w_{n,m} \leq w_{\mathsf{max}}^{m}, \forall m \in \mathcal{M}, \quad (11f)$$

$$w_{n,m} \geq 0, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \quad (11g)$$

$$0 < o_{n,m} \leq B_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \quad (11h)$$

$$\alpha_{n,m} \in \{0, 1\}, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}. \quad (11i)$$

Considering that the tasks are processed in parallel at the devices and edge server, constraint (11a) and (11b) guarantee the task completion deadline. Constraint (11c) means that the energy consumption of each UAV for remote computing does not exceed its maximum energy budget. In constraint (11d), it ensures that each device can only be associated with at most one UAV. However, each UAV can serve more than one device which is stated in constraint (11e). It is given in constraints (11f) and (11g) that the total CPU resources of each UAV assigned to its associated devices must be upper bounded by its maximum CPU capacity. Constraint (11h) ensures that each device offloads portion of the tasks less than its total input data size. Finally, constraint (11i) represents the decision variable for the association between device and UAV. Since the proposed problem is an MINLP problem which is difficult to solve in the polynomial time and the complexity is too high, we apply an alternative minimization method, namely BCD algorithm to get the optimal solutions.

IV. Proposed Solution

In this section, we present the solution of our proposed joint device association, task assignment and computing resource allocation problem which is non-convex due to the association variable and the existence of the coupling among the variables. To obtain the optimal solutions, we decompose our proposed problem into multiple convex subproblems and apply BCD method, an alternating minimization method that can solve the multiconvex problem which in general is composed of non-convex objective function and feasible sets, however, they are convex in each block of variable [15]. Hence, the original problem is partitioned into multiple subproblems (multiple blocks of variables) and each block is iteratively solved by fixing the other blocks until the convergence has reached. In this regard, we decompose our proposed problem in (11) into three sub-problems, (a) device association problem, (b) task assignment problem, and (c) computing resource allocation problem.

In specifically, first, we solve the device association problem with the given task assignment and computing resource allocation. Secondly, the task assignment problem is solved by using the previously obtained device association and the given computing resource allocation. Finally, we solve the computing resource allocation problem with the previously obtained device association and task assignment values. The three subproblems are iteratively solved until the convergence condition is satisfied.

A. Device Association Problem

In this subsection, we solve the device association problem by fixing the task assignment and computing resource allocation values. The subproblem can then be rewritten as follows:

$$\min_{\boldsymbol{A}} \sum_{n=1}^{N}\sum_{m=1}^{M} \alpha_{n,m}\left(E^{l}_{n,m}+E^{\text{off}}_{n,m}+E^{r}_{n,m}\right), \tag{13}$$

s.t.

$$t^{l}_{n,m} \le T_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \tag{13a}$$

$$t^{\text{off}}_{n,m} + t^{r}_{n,m} \le T_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \tag{13b}$$

$$\sum_{n=1}^{N} \alpha_{n,m} E^{r}_{n,m} \le E^{m}_{\mathsf{max}}, \forall m \in \mathcal{M}, \tag{13c}$$

$$\sum_{m=1}^{M} \alpha_{n,m} \le 1, \forall n \in \mathcal{N}, \tag{13d}$$

$$\sum_{n=1}^{N} \alpha_{n,m} \le J^{m}_{\mathsf{max}}, \forall m \in \mathcal{M}, \tag{13e}$$

$$\alpha_{n,m} \in \{0,1\}, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}. \tag{13f}$$

Since this subproblem is an mixed-integer programming (MIP) problem, it can easily be solved by using GUROBI optimizer [16] to get the optimal device association matrix.

B. Task Assignment Problem

With the obtained device association and the given computing resource allocation, the optimal task assignment values, i.e., how much amount of tasks (in bits) each device must offload to its associated UAV, are determined by solving the following subproblem,

$$\min_{\boldsymbol{o}} \sum_{n=1}^{N}\sum_{m=1}^{M} \alpha_{n,m}\left(E^{l}_{n,m}+E^{\text{off}}_{n,m}+E^{r}_{n,m}\right), \tag{14}$$

s.t.

$$t^{l}_{n,m} \le T_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \tag{14a}$$

$$t^{\text{off}}_{n,m} + t^{r}_{n,m} \le T_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \tag{14b}$$

$$\sum_{n=1}^{N} \alpha_{n,m} E^{r}_{n,m} \le E^{m}_{\mathsf{max}}, \forall m \in \mathcal{M}, \tag{14c}$$

$$0 < o_{n,m} \le B_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \tag{14d}$$

where the task assignment problem is convex with respect to the task assignment variable, $o_{n,m}$. Then, using the CVXPY [17], the optimal task assignment values can be obtained while taking into account the energy budget of UAVs and the task completion deadline.

C. Computing Resource Allocation Problem

Similarly, with the optimal device association and task assignment values resulting from the two above subproblems, the computing resource allocation problem can be rewritten as follows:

$$\min_{\boldsymbol{\omega}} \sum_{m=1}^{M}\sum_{n=1}^{N} \alpha_{n,m} E^{r}_{n,m}, \tag{15}$$

s.t.

$$t^{l}_{n,m} \le T_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \tag{15a}$$

$$t^{\text{off}}_{n,m} + t^{r}_{n,m} \le T_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \tag{15b}$$

$$\sum_{n=1}^{N} \alpha_{n,m} E^{r}_{n,m} \le E^{m}_{\mathsf{max}}, \forall m \in \mathcal{M}, \tag{15c}$$

$$\sum_{n=1}^{N} \alpha_{n,m} w_{n,m} \le w^{m}_{\mathsf{max}}, \forall m \in \mathcal{M}, \tag{15d}$$

$$w_{n,m} \ge 0, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}. \tag{15e}$$

This subproblem is also convex with respect to the computing resource allocation variable, $\omega_{n,m}$ and the optimal solutions can easily be obtained by using CVXPY solver [17]. Since, all the subproblems are convex and the optimal solutions can be achieved by iteratively solving during the polynomial time as given in Algorithm 1.

V. Numerical Results

The evaluation results are demonstrated in this section to verify how our proposed approach is effective in terms of total energy consumption. The area of interest is assumed to be 300 m $\times$ 300 m where 30 mobile devices are randomly distributed and 5 MEC-enabled UAVs are deployed as the aerial computing platforms. For the ground to air communication link, the values of g_0 and σ^2 are set to -50 dB and -170 dBm, respectively. The available bandwidth of each UAV is

Algorithm 1: Block Coordinate Descent Algorithm

1) Initialization: Set $\epsilon > 0$, $r = 0$ and find the initial feasible solutions, $\boldsymbol{A}^{(0)}$, $\boldsymbol{o}^{(0)}$ and $\boldsymbol{\omega}^{(0)}$;
2) **repeat**
3) Evaluate Problem (13) for given $\boldsymbol{o}^{(r)}$ and $\boldsymbol{\omega}^{(r)}$ to obtain $\boldsymbol{A}^{(r+1)}$;
4) Evaluate Problem (14) for given $\boldsymbol{A}^{(r+1)}$ and $\boldsymbol{\omega}^{(r)}$ to obtain $\boldsymbol{o}^{(r+1)}$;
5) Evaluate Problem (15) for given $\boldsymbol{A}^{(r+1)}$ and $\boldsymbol{o}^{(r+1)}$ to obtain $\boldsymbol{\omega}^{(r+1)}$;
6) Update $r = r + 1$;
7) **until** $|E^{\text{total}^{(r+1)}} - E^{\text{total}^{(r)}}| \le \epsilon$;
8) Finally, $\boldsymbol{A}^{(r+1)}$, $\boldsymbol{o}^{(r+1)}$ and $\boldsymbol{\omega}^{(r+1)}$ are set as the optimal solutions.

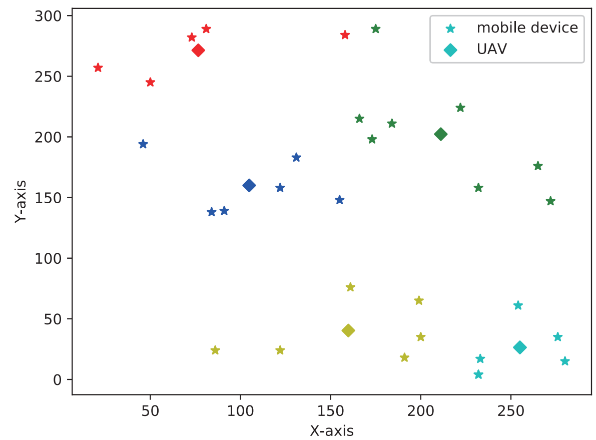

Fig. 2: Mobile device association with UAVs.

considered to be 10 MHz. We assume that each mobile device has the total task input data size between $[100, 400]$ Mb and the required CPU frequency to execute one bit of data is 1000 cycles. The available CPU capacity of the UAVs are randomly generated between $[5, 10]$ GHz and the transmit power of the mobile devices is 1 mW. The values of k and k' are set as 10^{-28}.

With the proposed approach, the number of mobile devices associated with UAVs is depicted in Fig. 2. It is observed that the number of mobile devices associated to UAV 1, UAV 2, UAV 3, UAV 4 and UAV 5 are respectively, 8, 6, 5, 6, and 5. UAV 1 has the highest number of associated devices because it has more energy budget and available computing resources than other UAVs. However, we can generally say that the mobile devices are fairly associated with the UAVs.

Fig. 3 shows the impact of task completion deadline on the total offloaded data size and the local computing energy of the mobile devices. According to Fig. 3, we can observe that the amount of data size offloaded by the mobile devices to the UAVs increases when the task completion deadline is longer. On the other hand, the local computing energy consumption of the devices becomes lower. This is because when the task completion deadline is more tolerable, the mobile devices prefer to offload most of their tasks to the UAVs so that they consume less energy on the local execution.

In Fig. 4, within the boundary of task completion deadline, we depict how the local computing energy and offloading energy of the mobile devices vary with the different number of UAVs. As we can see from Fig. 4 that when there are more number of available UAVs, the local computing energy of the mobile devices will significantly decreases while their offloading energy increases. The reason is that the mobile devices will offload their tasks to the UAVs in order that they can save their local computing energy. Nevertheless, the offloading energy is still lower than the local computing energy of the mobile devices.

In Fig. 5, we illustrate the normalized values of the total energy consumption with a different number of mobile devices by comparing with other two baselines such as random association and offloading all. It is obvious that the total energy consumption increases when there are more mobile devices. From Fig. 5, the proposed approach outperforms the random association scheme in which the mobile devices are randomly associated with the UAVs without taking into account the task completion deadline of the devices, the energy budget and the computing resources of the UAVs. The reason is that more energy might be consumed by the mobile devices to offload the tasks over a long distance or by the UAVs to serve its overloaded associated mobile devices. Moreover, the proposed approach has superior performance than offloading all because offloading all of the tasks incurs higher energy consumption of the mobile devices for data offloading and that of the UAVs for the remote computing. Hence, we can conclude that our proposed approach has the best performance in terms of the total energy consumption of the mobile devices and UAVs.

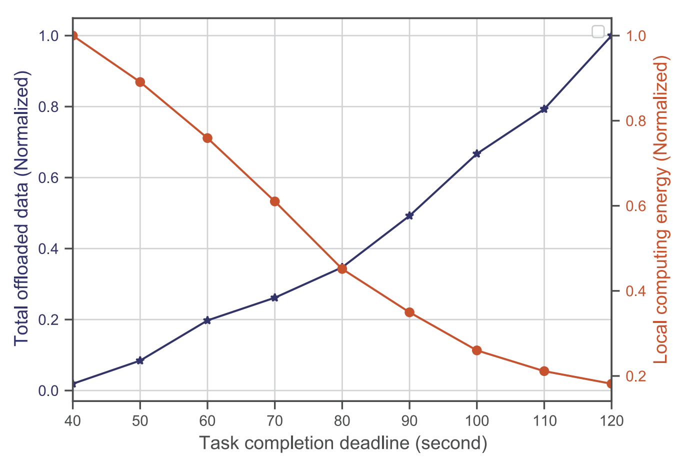

Fig. 3: The impact of task completion deadline on total offloaded data and local computing energy of mobile devices.

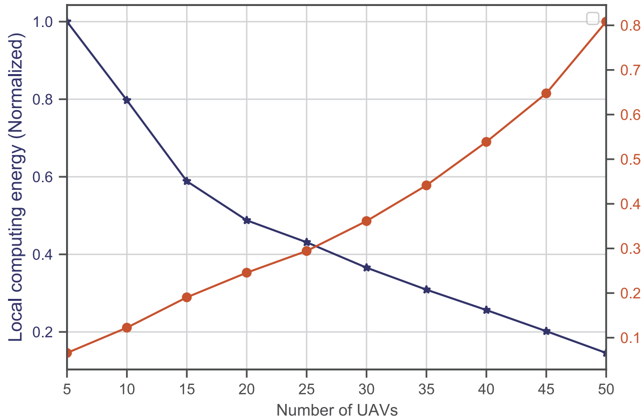

Fig. 4: The impact of number of UAVs on the mobile device's energy.

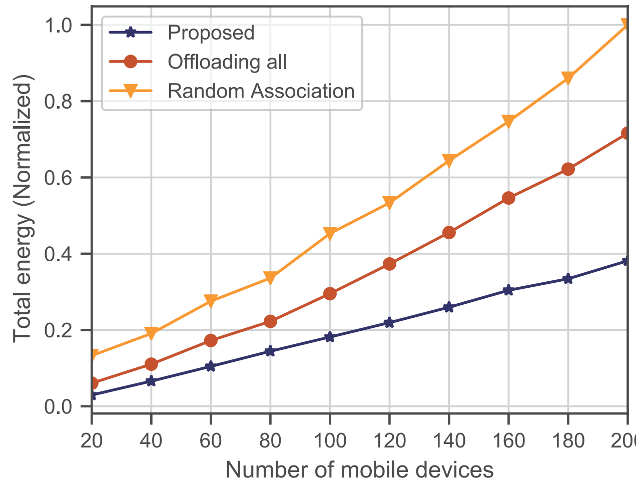

Fig. 5: Total energy consumption vs number of devices.

VI. Conclusion

In this paper, we studied a joint device association, task assignment and computing resource allocation problem in an energy-efficient multi-UAV-assisted MEC system where the mobile devices offload a portion of their tasks to the associated UAVs. Taking into account the task completion deadline of the mobile devices, the energy budget and available computing resources at the UAVs, we minimize the total energy consumption of the devices and UAVs by determining the optimal device association, task assignment and computing resource allocation. To solve the proposed non-convex problem, we decompose it into multiple convex subproblems and apply BCD method. Simulation results have shown that our proposed approach outperforms the other baselines, random association and offloading all. In the future, we will investigate the problem of optimizing UAV's trajectory and communication and computation resource allocation for multi-UAV-assisted MEC system by taking into account the UAV's mobility constraint such as collision, velocity and acceleration and the QoS requirements of the mobile devices.

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