Green Mobile Edge Computing Resource Allocation

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Abstract: Mobile edge computing has emerged as a promising technology for the next network architecture. By bring the computing and storage closer to the user devices, more functions and services become possible. However, the energy-saving problem has been considered as a significant challenge in the era of big data. In this paper, we investigate the resource allocation problem in the green mobile edge computing network. The formulated problem is a mixed integer problem, considering transmit power constraint and total delay constraint. To solve this problem, we propose an iteration algorithm. First, the integer variables are handled by our proposed heuristic algorithm in each iteration. After handling the integer variables, the continuous problem has the form of sum-of-ratio. We solve the fractional programming by transforming the problem into an equivalent formulation. The simulation results show that our proposed algorithm is energysaving with good performances.

1. Introduction

Currently, the computing demand is increasing rapidly. With the explosive data throughout the network, the difficulty to manage the network is not comparable to the previous ones. How to execute computing efficiently and desirably becomes the primary challenge. Thus, mobile edge computing (MEC) is proposed to enhance the computing performance for the upcoming network. The principle of MEC is moving the computing and storage unit closer to the user equipment. Comparing to the traditional cloud computing, MEC has many advantages. First, MEC has a lower delay for the computing and transmission. The cloud center is always far away from end users, and a large number of devices are linked, which lead to a high delay and cost for cloud computing. MEC is better for the management of the local devices. Also, the transmission cost for MEC is negligible, since the transmission power is low and little management among devices should be done. Moreover, user privacy is protected by MEC, because there is no interaction with the cloud center. Also, if the computing task is heavy, MEC can reduce the burden for cloud center.

Green communication is essential for 5G communication. With a much larger scale of the network infrastructure, the limited resources should be utilized efficiently. In the next-generation networks, the

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energy cost is as significant as data rate maximization. For the network operators, the energy cost at the base station occupies the 70 percent of the network[1]. For the mobile end users, energy cost is the foremost challenge to the limited battery capacity. Green communication is not only for saving energy but also for reducing pollution to protect our environment. It is reported that the estimated carbon footprint for the cellular network is 0.5% to 1% of world emission[2]. The electromagnetic pollution caused by the usage of different frequency bands should be taken into consideration as well.

In this paper, we study the green MEC resource allocation problem. The tasks should be executed at the users' devices or the edge node. Both edge computing user and local user are constrained by the power and delay requirements. The formulated problem is a nonconvex mixed integer nonlinear programming (MINLP) problem. The proposed algorithm is an iteration algorithm, which solves the discrete and continuous problem sequentially. Our main contributions are summarized as follows:

- We formulate the resource allocation problem in a MEC network as a nonconvex MINLP problem, which aims to minimize the energy consumption. Both decision making problem and power control problem is considered.
- We propose an iteration algorithm based on a joint heuristic algorithm and sum-of-ratio fractional programming. The heuristic strategy decision algorithm is designed to find the current optimal solution of the decision variable. The sum-of-ratio fractional programming algorithm is adopted to reformulate the fractional programming into an equivalent form. The optimal solution is obtained after the iteration procedure is converged.
- We evaluate the performance of our proposed algorithm in the simulation section. The results show that our proposed algorithm is energy efficient.

The rest of the paper is organized as follows. In Section II, the related work is surveyed. The MEC system model and the resource allocation problem are described in the Section III. Then, the algorithm based on joint strategy decision heuristic algorithm and sum-of-ratio fractional programming algorithm is proposed in Section IV. The simulation results are shown in Section V, and conclusions are stated in Section VI.

2. Related Work

MEC provides end users with many advantages, including short delay, high quality of computing service, distributed application, etc. In[3], the authors survey the relevant research and technological developments in the area of MEC, including the challenges and possible solutions. In[4], the authors give a novel MEC architecture for mobile crowdsensing. The proposed architecture decreases the privacy threats and beneficial for data analytics. In[5], the authors discuss the MEC in the Internet of Things (IoT) applications compared to the cloud computing services, which is indispensable to the IoT consumers. In[6], the authors provide a comprehensive survey of the state-of-the-art MEC research, which focuses on the joint radio-and-computational resource management. Different kinds of MEC applications and recent standardization efforts are introduced as well. In[7], the authors point out the impact of the MEC and fog computing to the existing communication system as an extension to the cloud computing. In[8], the authors survey the MEC as a distributed technology to the new network, and the relations between the network virtualization and MEC are investigated. In[9], the authors present the architectural description of the MEC platform as well as the key functionalities, and the challenges towards 5G are discussed. In[10], the authors design an online reinforcement learning algorithm for incorporating renewables into the MEC system, which decomposes the offline iteration value to achieve a better performance online. In[11], the authors propose a graph-based algorithm to partition the MEC clusters, and the limited MEC server capacity is concerned.

Green communication has been a hot topic in decades. The consideration of energy consumption in communications is not only for protecting the environment but also for the economy for the operators. In[2], the authors survey different techniques for the power optimization in 5G, which mainly discuss the relay and small cell. In[12], the authors survey the directions and developments of the green communication. In[13], the authors use a stochastic inventory theory to determine the optimal energy storage levels of the nodes, and a Nash bargaining game is introduced to solve the benefit allocation problem for energy trading. In[14], the authors give a comprehensive survey for the cellular networks, which including device-to-device communication, spectrum sharing, ultra-dense networks, massive MIMO, and the IoT. In[15], the authors research the joint optimization of uplink subcarrier assignment (SA) and power allocation (PA) in D2D underlying cellular networks. The proposed mixed-integer nonlinear programming problem is solved by the heuristic algorithm and the difference between the concave function (D.C.) algorithm. In[16], the authors give the mathematical analysis of the optimal placement of the relay nodes and the number of relays required for energy-efficient communication.

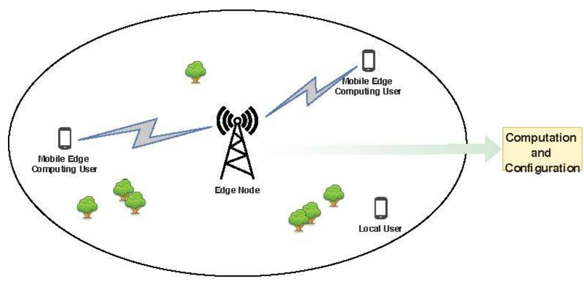

Figure 1: System model.

3. System Model and Problem Formulation

3.1. System Model

In this paper, we consider a mobile computing network with N computing users. The edge node performs as a controller with computation capability. For each user, a specific task should be executed. The task for the n^{th} user is modeled as $T_n = (f_n, L_n)$, where f_n is the CPU cycles needed to compute the task and L_n is the data size of the task. In this paper, the users can compute the tasks locally or offload the tasks to the edge node. For each task, the users can only choose one strategy to execute.

The channel gain between the n^{th} user and the edge node is h_n. In general, we assume that the channel states are unchanged with static users during the edge computing and the channel information is perfectly known at the edge node. Thus, the data rate of the n^{th} edge computing user is

$$r_n = B\log_2(1 + \frac{p_n h_n}{\sigma^2}), \quad (1)$$

where B is the channel bandwidth, p_n is the transmit power, and σ^2 is the noise power. We assume the edge computing users transmit using different orthogonal channels. Thus, there is no interference involved during the communication.

1) Local Computing: For the local computing users, we define ω_n as the computing capability for the n^{th} user. The time duration for the local task execution is computed as

$$t_n^l = \frac{f_n}{\omega_n}. \tag{2}$$

The energy consumption for the local computing is modeled as

$$E_n^l = \psi_n(\omega_n)^2 f_n, \tag{3}$$

where ψ_n is the parameter according to the different chip architecture.

2) Mobile Edge Computing: For the mobile edge computing, the two-step procedure should be considered. First, the users should offload the tasks to the edge node, and then the tasks are computed at the edge node. We assume that the sending computing results procedure is ignored in this paper. This is because the computing results are much smaller compared to the original data size. Furthermore, the downlink transmit data rate from the edge node to users is much higher than the uplink. Thus, the task duration is expressed as

$$t_n^e = \frac{L_n}{r_n} + \frac{f_n}{\Omega_n}, \tag{4}$$

where Ω_n is the computing resources from the edge node allocated to the n^{th} task as a constant. The energy consumption for mobile edge computing is expressed as

$$E_n^e = \frac{p_n L_n}{r_n} + \phi_n(\Omega_n)^2 f_n, \tag{5}$$

where ϕ is the parameter of the chip architecture from the edge node.

3.2. Problem Formulation

In this paper, we aim to minimize the energy consumption during the mobile edge computing. The strategy indicator is modeled as s_n for the n^{th} user. For the n^{th} edge computing user, $s_n = 1$; Otherwise, the n^{th} local computing user indicator is $s_n = 0$. Thus, the green mobile edge computing resource allocation problem is formulated as

$$\min_{s_n, p_n} \quad \sum_{n=1}^{N} s_n E_n^e + \sum_{n=1}^{N} (1 - s_n) E_n^l \tag{6}$$

$$\text{s.t.} \quad 0 \leq p_n \leq p^{max}, \forall n, \tag{7}$$

$$\sum_{n=1}^{N} (1 - s_n) t_n^l + \sum_{n=1}^{N} s_n t_n^e \leq t^{total}, \tag{8}$$

$$s_n \in \{0,1\}, \forall n, \tag{9}$$

where p^{max} is the maximum transmit power and t^{total} is the total delay requirement for the computing for all users. The first constraint constrains the maximum transmit power of users cannot exceed the threshold. The second constraint indicates that the total delay of the computing procedure should be time-sensitive. The last constraint shows that the strategy indicator is a binary variable.

4. Proposed Algorithm

The problem formulated is a nonconvex mixed integer programming problem. In order to solve it, we need to handle the mixed integer problem first. Moreover, the sum-of-ratio form should be tackled with proper transformation. The problem is solved iteratively and finally converge to the optimal solution.

The problem proposed can be considered as a problem including two subproblems in each iteration, which are strategy decision and power control. For the strategy decision, we design a heuristic algorithm to find the solution of the decision variables. We aim to minimize the energy cost in our objective function. For each user, the energy cost is generated from whether local computing or mobile edge computing. If the transmit power for users is fixed, we should compare the two kinds of energy cost to decide whether the n^{th} user is a local computing user or mobile edge computing user. Meanwhile, the delay constraint should be considered. Although the objective function should be minimized, we cannot violate the delay constraint. First of all, we calculate the ratio of edge computing energy cost to the computing delay and local computing energy cost to the computing delay of all users, separately. Then, we sort the users as two lists in a minimum to the maximum order according to the calculated ratios. The decision is made by comparison and update in each iteration. Thus, the heuristic strategy decision algorithm is designed as shown in Algorithm 1.

Algorithm 1 The heuristic strategy decision algorithm

1: In the kth iteration:

2: Calculate $E_n^e t_n^e$ and $E_n^l t_n^l$ for all the users

3: Sort the calculated results from the minimum to the maximum as two lists, **A** and **B**

4: i=1

5: while $i \le N$ do

6: Compare A(1) and B(1)

7: if A(1)≤B(1) then

8: The strategy decision variable of the corresponding n^{th} user of A(1) is 1. Delete the $E_n^e t_n^e$ and $E_n^l t_n^l$ from the two lists A and B

9: else

10: The strategy decision variable of the corresponding n^{th} user of A(1) is 0. Delete the $E_n^e t_n^e$ and $E_n^l t_n^l$ from the two lists A and B

11: end if

12: if The new strategy decision variable violates the delay constraint then

13: Change the current strategy decision variable

14: end if

15: i = i+1

16: end while

The continuous problem with the fixed decision variable is still a fractional programming problem. If the decision variable is given by $\tilde{s}_n$ as a constant, the original problem is transformed as

$$\max_{p_n} \sum_{n=1}^{N} \tilde{s}_n r_n \tag{10}$$

$$s.t. \quad (7),$$

$$\sum_{n=1}^{N} (1-\tilde{s}_n) t_n^l + \sum_{n=1}^{N} \tilde{s}_n t_n^e \le t^{total} \tag{11}$$

The reformulated problem is a sum-of-ratio problem. In[17], the authors propose a modified Dinkelbach algorithm in a general sum-of-ratio case. For our problem, the problem (10) is equivalently rewritten as

$$\max_{\theta_n, p_n} \sum_{n=1}^{N} 2\theta_n \sqrt{\tilde{s}_n r_n} - \sum_{n=1}^{N} \theta_n^2 p_n L_n \tag{12}$$

$$s.t. \quad (7),(11),$$

where θ_n is the introduced auxiliary variable. In each iteration, the convex optimization is solved with the fixed θ_n. After acquire the optimal solution, θ_n is updated by calculating $\frac{\sqrt{\tilde{s}_n r_n}}{p_n L_n}$. The sum-of-ratio fractional programming algorithm is described as Algorithm 2.

Algorithm 2 The sum-of-ratio fractional programming algorithm
1: Initialize the auxiliary variable θ_n and a certain threshold ε
2: while $\sum_{n=1}^{N} 2\theta_n \sqrt{\tilde{s}_n r_n} - \sum_{n=1}^{N} \theta_n^2 p_n L_n \leq \varepsilon$ do
3: Solve problem (12)
4: Update $\theta_n = \frac{\sqrt{\tilde{s}_n r_n}}{p_n L_n}$
5: end while

5. Simulation Results

In this section, we present the simulation results of our proposed algorithm. The users are uniformly distributed in one cell with a radius of 100 m. In our scenario, the users are static while executing the tasks, which means that the locations information is certain to the edge node. We assume that the channel state information is perfectly known at the edge node, and the channel is modeled as the distance-based path loss and the Rayleigh multi-path fading channel. The bandwidth for the offloading transmission is set as 20 MHz, and the power of Gaussian noise is $2 * 10^{-13}$ W. The tasks parameters are randomly picked according to the probability distribution. All shown results are generated after over 100 times simulation.

In Figure 2, we present the convergence performance for our proposed algorithm. The maximum transmit power is set as 23 dBm. The inner loop is the Dinkelbach sum-of-ratio problem, and the outer loop is the proposed algorithm framework. With the number of users increasing, both the outer loop and inner loop iteration numbers increase. The outer loop iteration is harder to converge than the inner loop. This is because we introduced the heuristic algorithm for decision making, and the optimal solution is not guaranteed. However, the proposed algorithm framework can converge in most cases.

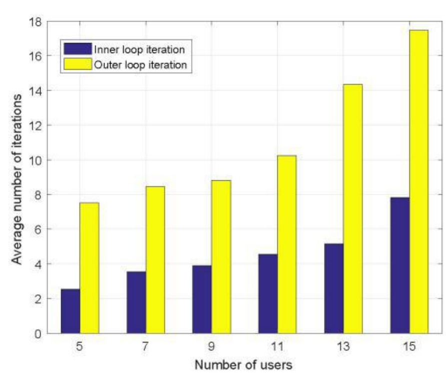

Figure 2: The average number of iterations versus the number of users.

As shown in Figure 3, the total energy cost for our MEC network increases with the increasing maximum transmit power, generally. Constrained by the execution time constraints, more transmit power will generate more energy cost. Moreover, the total energy cost tends to increase with more users. However, the increasing rate for the total energy cost decreases with increasing number of users.

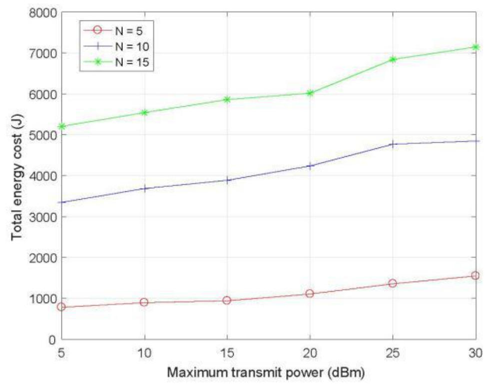

Figure 3: The energy cost versus the maximum transmit power with different number of users.

6. Conclusions

In this paper, we study the resource allocation problem in the MEC network. The formulated problem is a nonconvex MINLP problem. We propose a joint heuristic strategy decision-making and sum-of-ratio fractional programming algorithm, and obtain the optimal solution by iterations. The heuristic algorithm is designed to solve the discrete problem according to the energy cost and constraints. The sum-of-ratio fractional programming algorithm is proposed to handle the continuous sum-of-ratio problem after the integer variables are fixed. The simulation results show that our proposed algorithm is energy efficient with a good convergence performance.

Acknowledgments

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