Revenue-Maximized Offloading Decision and Fine-Grained Resource Allocation in Edge Network

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***Abstract*—For providing highly demanding services with powerful computational ability and ultra low-latency communication, mobile edge computing (MEC) has been recognized as a bright rising star among key technologies for the next-generation networking. Generally, jointly optimizing offloading decision and resource allocation in one multi-variable problem is complicated. To decrease computational scale and develop practicable strategy by splitting problems, we divide the workflow of MEC-enabled base station into two stages. First, through formulating a task offloading problem, we propose a low-complexity improved simulated annealing-based heuristic offloading decision (SAHOD) algorithm to maximize network revenue from the perspective of mobile network operator. Then, the optimal fine-grained resource allocation solution is obtained in closed forms via Lagrange duality decomposition method. Furthermore, an effective real-time sub-gradient-based resource allocation (SGRA) algorithm is presented to converge to a specific optimal allocation strategy within the adjustable accuracy. For given users, simulation results show that our SAHOD algorithm can earn about 20.5% more revenue than value-based greedy algorithm. Besides, our SGRA algorithm can converge within 4 iterations and obtain approximately 19.3% more sum rates than static scheduling method.**

***Index Terms*—mobile edge computing, offloading decision, communication resource allocation, improved simulated annealing, Lagrange duality decomposition**

I. Introduction

Mobile edge computing (MEC) as an extremely promising technology can be characterized by many advantages, such as vicinity access, low latency and energy consumption, high bandwidth, network context awareness and so on [1]. Therefore, the state-of-the-art MEC deployment is quite qualified for variety of innovative applications and services under the background of the explosive computation demands and the increasing high data rate requirements [2].

By pushing computation and storage capability to the edge network, the MEC-enabled *radio access network* (RAN) is a new revenue growth point for the *mobile network operator* (MNO). However, the network resources are limited in the edge network and not all tasks can be offloaded in the same offloading period. Hence, it is of great importance to make offloading decision and allocate communication resource for the selected users to obtain satisfying revenue and improve resource utilization.

Recently, offloading decision and resource allocation for MEC has been fully investigated [3]–[7]. The work [3] adopted Stackelberg game to model the trade between users and the edge cloud for maximizing the revenue of MNO. However, when users make offloading decisions based on the prices set by the edge cloud, the communication overhead was ignored in [3]. The work [4] proposed reinforcement learning-based solutions to minimize the sum cost of delay and energy in a multi-user MEC system. Whereas, if [4] had added communication resource allocation into the action set, the results might have been more convincing. The work [5] derived a distributed algorithm to reduce computation complexity. Nevertheless, each user still needs to exchange many informations with base station and the performance is degraded in [5] compared to the centralized algorithm. To minimize the total energy consumption, the work [6] took both offloading selection and resource allocation into consideration. However, [6] assumes that the sub-channel number is a continuous variable, which does not accurately characterize the mathematical characteristics of discrete sub-channel. The work [7] proposed a heuristic offloading decision algorithm to maximize a quality of experience (QoE)-based utility via convex optimization. But each user was allocated a fixed bandwidth in [7], which is detrimental to improve resource utilization. Therefore, if we expect to further improve resource utilization, we had better investigate a more fine-grained resource allocation strategy (e.g., jointly optimize energy and time-frequency resource during offloading period).

It is well known that the divide and conquer paradigm is a powerful tool for solving complex problems. In this paper, we divide the workflow of MEC-enabled edge network into two stages for readily analyzing problems and making valuable contributions. From the perspective of MNO, the MEC server need to make offloading decision in the first stage, and our objective is to obtain the maximum offloading revenue. To this end, we propose a low-complexity *simulated annealing-based heuristic offloading decision* (SAHOD) algorithm to cope with the NP-hard knapsack problem. In the second stage, the eNodeB need to allocate communication resource for the selected users. We aim to maximize the sum rates by jointly optimizing the *resource blocks* (RBs) allocation and transmission power for offloading tasks to the MEC server as soon as possible. We propose an effective *sub-gradient-based resource allocation* (SGRA) algorithm to find an approximate optimal solution within the adjustable convergence accuracy.

The rest of this paper is organized as follows. In Section II, we describe the system model of the MEC-enabled multi-user

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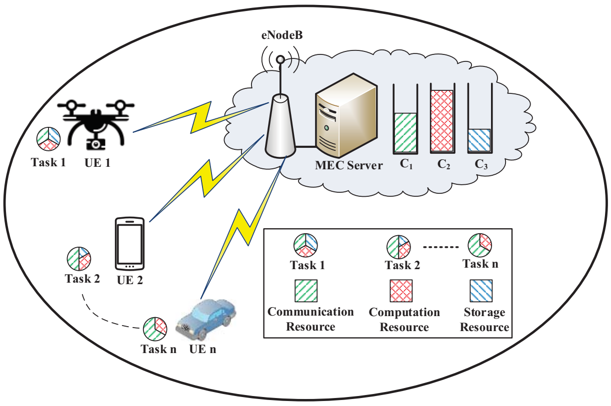

Fig. 1. MEC-enabled multi-user edge network model. The workflow of MEC-enabled eNodeB is divided into two stages. In the first stage, the MEC server need to make offloading decision of all users. In the second stage, the eNodeB need to allocate communication resource for the selected users.

edge network. Then, we investigate the offloading decision and communication resource allocation problems in Section III and IV, respectively. Next, we evaluate the performance of our proposed algorithms in Section V. Finally, the conclusion is drawn in Section VI.

II. System Model

A. Network Model

In this paper, we consider a MEC-enabled multi-user edge network with the centralized offloading architecture. The eNodeB is connected to one MEC server via a fiber link and it can be readily accessed by the *user equipment* (UE, e.g., unmanned aerial vehicle, smart phone and electric vehicle) through wireless channels within the effective coverage area. Therefore, the MEC server is generally regarded as a small data center with powerful computation resource to execute the energy-consumed and latency-intensive tasks (e.g., object recognition) for the resource-limited UEs [6], [7].

Fig. 1 illustrates the network model. Each UE can complete its task locally or offload it to the MEC server [4]–[7]. When offloading a task to the network edge, it will occupy network resources consisting of communication, computation and storage three parts. Upon the first transmission, we assume that each UE send its offloading request to the MEC server at the beginning of an offloading period. After receiving offloading request, the MEC server could choose whether to execute the task or not. The MNO possesses and operates the whole network, including the network resources and physical infrastructures, such as the eNodeB and MEC server. Stem from commercial consideration, the MNO will charge UE for providing communication, computation and storage service, which is collectively referred to as MEC service [5].

For convenience, we denote the index set of UEs as $\boldsymbol{N} = \{1, 2, \ldots, N\}$, and we use n to refer to the nth UE associating with task n. Besides, we denote the maximum available communication, computation and storage resource as C_1, C_2 and C_3, respectively.

B. Communication Model

The basic time-frequency resource is called RB in the OFDMA-based edge network. The set of RBs is denoted by $\boldsymbol{R} = \{1, 2, \ldots, R\}$, and we use r to refer to RB r at current time slot. Additionally, we regard transmission power as another part of communication resource. As a result, we take both RB allocation and transmission power control into consideration when we build the communication model.

In general, due to the different distance between UEs and eNodeB, the path loss varies from one UE to another. In a similar way, owing to the fact that there always exists different shadow fading and Rayleigh fading on different RB at the same time slot. Therefore, it is necessary to study a RB-level resource allocation and transmission power control scenario where RBs are quite distinct and users expect to allocate different transmission power on RBs rather than equal division.

We consider a quasi-static channel model, where wireless channels remain the same during each offloading period, but can be different between each other [3]. According to the Shannon theory, the bounded instantaneous data rate between UE n and eNodeB for uplink transmission over RB r can be formulated as

$$R_{n,r}(\alpha_{n,r}, P_{n,r}) = \alpha_{n,r}\omega \log_2(1 + \frac{P_{n,r}G_{n,r}}{N_0\omega}) \qquad (1)$$

where $\alpha_{n,r} \in \{0, 1\}, \forall n, r$ denotes the RB allocation index element of UE n and RB r. Specifically, we have $\alpha_{n,r} = 1$ if RB r is allocated to UE n, otherwise $\alpha_{n,r} = 0$. Hence, we have $\boldsymbol{\alpha} = \{\alpha_{n,r}\}_{n\in\boldsymbol{N}, r\in\boldsymbol{R}}$ as the RB allocation index matrix. Because a RB could only be allocated to at most one UE at a time slot, it is obvious that the constraint $\sum_{n=1}^{N} \alpha_{n,r} \leq 1, \forall r$ must be hold. We use $P_{n,r}$ to denote transmission power allocated to RB r by UE n. Hence, we have $\boldsymbol{P} = \{P_{n,r}\}_{n\in\boldsymbol{N}, r\in\boldsymbol{R}}$ as the transmission power allocation matrix. Moreover, the transmission power is non-negative, i.e., $P_{n,r} \geq 0$. For every UE n, the total transmission power cannot exceed the nth user's maximum transmission power P_n^{max}, thus $\sum_{r=1}^{R} P_{n,r} \leq P_n^{max}, \forall n$. We use $G_{n,r}$ to denote the channel gain of UE n over RB r. We use N_0 to refer to the power spectral density of additive white Gaussian noise, and ω denotes the RB bandwidth.

C. Offloading Model

Similar to many previous works in multi-user MEC system [6], [7], we consider a quasi-static offloading model where the set of UEs remains unchanged during an offloading period, while it may change a lot across different offloading period [7]. We denote $\beta_n \in \{0, 1\}, \forall n$ as the computation offloading decision index element of UE n. Specifically, we have $\beta_n = 1$ if the MEC server decides to offload the computation task requested by UE n and $\beta_n = 0$ otherwise [6]. Hence, we have $\boldsymbol{\beta} = [\beta_1, \beta_2, \ldots, \beta_N]$ as the computation offloading decision index vector.

Supposing that each UE n has a task and every task cannot be divided [7]. Upon the initial transmission, each UE will send an offloading request data packet which contains some information of the task to be offloaded, such as a tuple $(c_{n1}, c_{n2}, c_{n3}), n \in \boldsymbol{N}$. Here c_{n1}, c_{n2} and c_{n3} stand for the total amount of communication, computation and storage resource (e.g., RBs, CPU cycles and hard disk size) required by UE n, respectively. According to the information reported by all UEs, the MEC server can build a network resource requirements table via network context awareness.

D. Utility Function

The MNO will charge UEs for offloading tasks to MEC server [3], [5]. We assume that every task has an offloading revenue, which may directly impact on the offloading decision made by the MEC server. Here, we suppose the unit price for offloading tasks from UE n is v_n per task. Hence, we have $\boldsymbol{v} = [v_1, v_2, \ldots, v_N]$ as the offloading revenue vector. For sake of simplify, we consider the unit price is a constant, but it maybe vary among UEs. Motivated by the idea of divide and conquer, we consider a two-stage optimization problem in this paper. In the first stage, we study the optimal offloading decision to ensure the MEC server obtaining satisfying revenue under resource constraints. In the second stage, we jointly optimize RB allocation and transmission power control to improve the communication resource utilization during each offloading period. Therefore, from the MNO's perspective, each stage has a specific utility function as follows.

1) The first stage: In order to obtain the most satisfying revenue for the MNO, we set the maximization of the offloading revenue $\sum_{n=1}^{N} \beta_n v_n$ as our utility function in Section III.

2) The second stage: For purpose of maximizing the utilization of energy and time-frequency resource, we set the maximization of total data rate $\sum_{n=1}^{N} \sum_{r=1}^{R} R_{n,r}$ as our optimization goal in Section IV.

III. Offloading Decision

A. Offloading Decision Formulation

From the perspective of MNO, in order to maximize the network revenue by providing MEC services for users, the offloading decision problem can be formulated as

$$\begin{aligned} \mathcal{P}1: \quad & \max_{\boldsymbol{\beta}} \sum_{n=1}^{N} \beta_n v_n \\ s.t.\ C1: \quad & \sum_{n=1}^{N} \beta_n c_{ni} \leq C_i,\ i = 1, 2, 3 \\ C2: \quad & \beta_n \in \{0, 1\},\ \forall n \in \boldsymbol{N} \end{aligned} \tag{2}$$

where constraint (2) $C1$ is modeled to ensure that the communication, computation and storage resource used by the MEC server cannot exceed the all available resources belonging to the physical infrastructures. Constraint (2) $C2$ refers to the definition in Section II C.

Proposition 1: Problem $\mathcal{P}1$ is a *NP-hard* problem.

Proof: If we denote $\boldsymbol{C} = \{\boldsymbol{c_1}, \boldsymbol{c_2}, \boldsymbol{c_3}\}$ as the resource requirement matrix where $\boldsymbol{c_i} = [c_{1i}, c_{2i}, \ldots, c_{Ni}]^T, i = 1, 2, 3$ are the resource requirement vectors reported by users. Meanwhile, we denote $\boldsymbol{C_{max}} = [C_1, C_2, C_3]$ as the right-hand-side vector. Then $\mathcal{P}1$ can be vectorized as follows.

$$\begin{aligned} \mathcal{P}2: \quad & \max_{\boldsymbol{\beta}} \boldsymbol{\beta} \boldsymbol{v}^T \\ s.t. \quad & \boldsymbol{\beta} \boldsymbol{C} \preceq \boldsymbol{C_{max}} \ \text{ and } \ \beta_n \in \{0, 1\},\ \forall n \in \boldsymbol{N} \end{aligned} \tag{3}$$

Here, problem $\mathcal{P}2$ is equivalent to $\mathcal{P}1$. What calls for special attention is that $\mathcal{P}2$ is so called the knapsack problem of packing the most valuable or useful items without overloading the luggage. From [8], we can know that the knapsack problem is NP-hard and hence, so is $\mathcal{P}1$. ■

According to the *Proposition* 1, it can be known that we cannot directly get a closed-form solution of $\mathcal{P}1$ via common optimization methods. Therein, an alternative heuristic algorithm is proposed to solve $\mathcal{P}1$ in the following subsection.

B. Simulated Annealing-based Heuristic Offloading Decision

While the problem scale is small (e.g., no more than 20 users), we can use the classical *exhausted search algorithm* (ESA) to get the optimal offloading decision. Nevertheless, it incurs extremely huge time consumption when the dimension of $\boldsymbol{\beta}$ is large. Alternatively, we may as well apply a *value-based greedy algorithm* (VGA) to choose the UE with the maximum revenue to implement offloading firstly, and then repeat as needed. Although the VGA could finish this work quickly, yet it is a pity that the result is without quality assurance.

To solve problem $\mathcal{P}1$ in an efficient way, we propose a SAHOD algorithm where the acceptance criterion is the Metropolis criterion [9]. In this way, SAHOD is a probabilistic algorithm for approximating global optimization in a large search space, especially when the search space is discrete (e.g., the zero-one knapsack problem). The proposed SAHOD algorithm for solving $\mathcal{P}1$ is summarized in Algorithm 1, where T_0 is the start temperature, δ is the annealing rate, T_c is the stop temperature and K is the number of iterations at each temperature during the annealing process.

Algorithm 1 SAHOD Algorithm for Solving Problem $\mathcal{P}1$

Input: the initial values of $\boldsymbol{\beta}$, $\boldsymbol{C}$, $\boldsymbol{v}$, $\boldsymbol{C_{max}}$, T_0, δ, T_c, K.
Output: the optimal offloading decision $\boldsymbol{\beta}^*$.

```
repeat
    k = 1;    ▷ Initial state
    repeat
        Randomly generate a new solution β^(k) on the basis
        of β^(k−1);    ▷ Moving to a neighboring solution
        Calculate the change of resource occupied ΔC and
        the increased revenue Δv;
        According to the Metropolis criterion, determine to
        accept or reject the new solution β^(k);
        k := k + 1;    ▷ Update state
    until k > K;    ▷ Internal stopping criterion
    T := δT_0;    ▷ Annealing schedule
until T < T_c;    ▷ External stopping criterion
return the optimal offloading decision β*;
```

IV. Communication Resource Allocation

A. Resource Allocation Formulation

After obtaining the optimal offloading decision $\boldsymbol{\beta}^*$ from Algorithm 1, we only need to consider those selected users when the eNodeB allocates communication resource in the second stage. That is to say, if UE n executes its task locally, the eNodeB will not allocate any RB to UE n. Correspondingly, UE n also don't have to allocate any transmission power on RB. Hence, in order to avoid confusion, we reindex the set of selected users as $\boldsymbol{M} = \{1, 2, \ldots, M\}$ ($\boldsymbol{M} \subseteq \boldsymbol{N}$), and use m to refer to the mth selected user in the second stage.

From the perspective of MNO, in order to maximize the total data rate of multi-user edge network, the communication resource allocation problem can be formulated as

$$
\begin{aligned}
\mathcal{P}3: \quad & \max_{\alpha_{m,r}, P_{m,r}} \quad \sum_{m=1}^{M} \sum_{r=1}^{R} R_{m,r} \\
s.t.\ C1: \quad & \sum_{r=1}^{R} R_{m,r} \geq R_m^{min},\ \forall m \in \boldsymbol{M} \\
C2: \quad & \sum_{r=1}^{R} \alpha_{m,r} P_{m,r} \leq P_m^{max},\ \forall m \in \boldsymbol{M} \\
C3: \quad & P_{m,r} \geq 0,\ \forall m \in \boldsymbol{M}, \forall r \in \boldsymbol{R} \\
C4: \quad & \sum_{m=1}^{M} \alpha_{m,r} \leq 1,\ \forall r \in \boldsymbol{R} \\
C5: \quad & \alpha_{m,r} \in \{0, 1\},\ \forall n \in \boldsymbol{M}, \forall r \in \boldsymbol{R}
\end{aligned}
\tag{4}
$$

where R_m^{min} is the minimum data rate which is the QoS requirement of the mth selected user. The remaining constraints (4) $C2-C5$ have been explained in the system model, and so won't be repeated here. Due to the existing of binary variables $\{\alpha_{m,r}\}_{m \in \boldsymbol{M}, r \in \boldsymbol{R}}$, continuous variables $\{P_{m,r}\}_{m \in \boldsymbol{M}, r \in \boldsymbol{R}}$ and the product term $\alpha_{m,r} P_{m,r}$, the optimization problem $\mathcal{P}3$ is a *mixed integer non-linear programming* (MINLP) problem which is non-convex and NP-hard. Therefore, it is necessary to transform $\mathcal{P}3$ into a tractable convex optimization problem.

Proposition 2: If we use linear relaxation method to relax the binary variables $\alpha_{m,r} \in \{0, 1\}$ into real ones $\tilde{\alpha}_{m,r} \in [0, 1]$ and introduce auxiliary variables $\tilde{P}_{m,r}$ to substitute the product terms $\tilde{\alpha}_{m,r} P_{m,r}$. Meanwhile, we define $\tilde{R}_{m,r} = \tilde{\alpha}_{m,r} \omega \log_2[1 + (\tilde{P}_{n,r} G_{n,r})/(\tilde{\alpha}_{m,r} N_0 \omega)] = 0$, when $\tilde{\alpha}_{m,r} = 0$ [5], [10]. Then, problem $\mathcal{P}3$ can be transformed into a jointly convex optimization problem with respect to the optimization variables $\tilde{\alpha}_{m,r}$ and $\tilde{P}_{m,r}$.

Proof: Suppose $f(x, y) = x \log_2(1 + y/x), x \geq 0, y \geq 0$. The **dom** f is convex and the Hessian matrix of f is negative semidefinite for all $(x, y) \in$ **dom** f. Then f is concave via the second-order condition [11]. Next we prove the continuity of f on the point $x = 0$. Let $t = y/x$,

$$
f(0, y) = \lim_{x \to 0} x \log_2(1 + \frac{y}{x}) = y \lim_{t \to \infty} \frac{\log_2(1 + t)}{t} = 0 \tag{5}
$$

Hence, if we use binary variables relaxation $\alpha_{m,r} \in \{0, 1\} \to \tilde{\alpha}_{m,r} \in [0, 1]$ and product terms substitution $\tilde{P}_{m,r} = \tilde{\alpha}_{m,r} P_{m,r}$, all the constraints become linear. Furthermore, the data rate $\tilde{R}_{m,r}(\tilde{\alpha}_{m,r}, \tilde{P}_{n,r}) = \tilde{\alpha}_{m,r} \omega \log_2[1 + (\tilde{P}_{n,r} G_{n,r})/(\tilde{\alpha}_{m,r} N_0 \omega)]$ is a concave function like $f(x, y)$. So $\mathcal{P}3$ is transformed into a convex optimization problem. ■

According to *Proposition* 2, it can be known that the MINLP problem $\mathcal{P}3$ can be rewritten as a jointly convex optimization problem $\mathcal{P}4$ as follows.

$$
\begin{aligned}
\mathcal{P}4: \quad & \max_{\tilde{\alpha}_{m,r}, \tilde{P}_{m,r}} \quad \sum_{m=1}^{M} \sum_{r=1}^{R} \tilde{R}_{m,r} \\
s.t.\ C1: \quad & \sum_{r=1}^{R} \tilde{R}_{m,r} \geq R_m^{min},\ \forall m \in \boldsymbol{M} \\
C2: \quad & \sum_{r=1}^{R} \tilde{P}_{m,r} \leq P_m^{max},\ \forall m \in \boldsymbol{M} \\
C3: \quad & \tilde{P}_{m,r} \geq 0,\ \forall m \in \boldsymbol{M}, \forall r \in \boldsymbol{R} \\
C4: \quad & \sum_{m=1}^{M} \tilde{\alpha}_{m,r} \leq 1,\ \forall r \in \boldsymbol{R} \\
C5: \quad & \tilde{\alpha}_{m,r} \in [0, 1],\ \forall n \in \boldsymbol{M}, \forall r \in \boldsymbol{R}
\end{aligned}
\tag{6}
$$

B. Lagrange Duality Decomposition

If we introduce non-negative Lagrange multipliers λ_m and μ_m associated with constraints (6) $C1 - C2$, the partial Lagrange function of problem $\mathcal{P}4$ can be given as

$$
\begin{aligned}
L(\tilde{\alpha}_{m,r}, \tilde{P}_{m,r}, \lambda_m, \mu_m) = & \sum_{m=1}^{M} \sum_{r=1}^{R} \tilde{R}_{m,r} \\
& + \sum_{m=1}^{M} \lambda_m (\sum_{r=1}^{R} \tilde{R}_{m,r} - R_m^{min}) \\
& + \sum_{m=1}^{M} \mu_m (P_m^{max} - \sum_{r=1}^{R} \tilde{P}_{m,r})
\end{aligned}
\tag{7}
$$

Then, the Lagrange dual problem can be expressed as

$$
\min_{\{\lambda_m, \mu_m\}} \max_{\{\tilde{\alpha}_{m,r}, \tilde{P}_{m,r}\}} L(\tilde{\alpha}_{m,r}, \tilde{P}_{m,r}, \lambda_m, \mu_m) \tag{8}
$$

where the optimal resource allocation strategy $\tilde{\alpha}_{m,r}^*$ and $\tilde{P}_{m,r}^*$ can be obtained by solving (8) with given λ_m, μ_m.

Next, for the specific λ_m and μ_m, the maximization part of dual problem (8) can be formulated as

$$
\max_{\tilde{\alpha}_{m,r}} \max_{\tilde{P}_{m,r}} L(\tilde{\alpha}_{m,r}, \tilde{P}_{m,r}, \lambda_m, \mu_m) \tag{9}
$$

where the optimal transmission power $\tilde{P}_{m,r}^*$ can be obtained by solving (9) with given $\tilde{\alpha}_{m,r}$.

Finally, according to *Karush-Kuhn-Tucker* (KKT) condition (i.e., $\partial L(\tilde{\alpha}_{m,r}, \tilde{P}_{m,r}^*, \lambda_m, \mu_m)/\partial \tilde{P}_{m,r}^* = 0$), we can derive the optimal transmission power $\tilde{P}_{m,r}^*$ as

$$
\tilde{P}_{m,r}^* = \tilde{\alpha}_{m,r} \omega [\frac{(1 + \lambda_m)}{\mu_m \ln 2} - \frac{N_0}{G_{m,r}}]^+ \tag{10}
$$

where $[x]^+ = max(0, x)$. This implies that (10) meets the non-negative power constraint (6) $C3$ which is not considered in the partial Lagrange function (7).

Due to the optimality $\tilde{P}^*_{m,r} = \tilde{\alpha}_{m,r} P^*_{m,r}$, the optimal transmission power $P^*_{m,r}$ for problem $\mathcal{P}3$ can be further given by

$$P^*_{m,r} = \omega \Big[\frac{(1+\lambda_m)}{\mu_m \ln 2} - \frac{N_0}{G_{m,r}}\Big]^+ \tag{11}$$

Since we have known the $\tilde{P}^*_{m,r}$, we can obtain the optimal RB allocation strategy $\tilde{\alpha}^*_{m,r}$ by substituting $\tilde{P}^*_{m,r}$ back into (9) and consider the remaining constraints (6) $C4-C5$. Then, the problem (9) can be reformulated as

$$\begin{aligned} \mathcal{P}5: \quad & \max_{\tilde{\alpha}_{m,r}} \; L(\tilde{\alpha}_{m,r}, \lambda_m, \mu_m) \\ s.t. \quad & (6) \; C4, \; C5 \end{aligned} \tag{12}$$

where

$$\begin{aligned} L(\tilde{\alpha}_{m,r}, \lambda_m, \mu_m) = & \sum_{m=1}^{M} \sum_{r=1}^{R} \big[(1+\lambda_m) R^*_{m,r} - \mu_m P^*_{m,r}\big] \tilde{\alpha}_{m,r} \\ & + \sum_{m=1}^{M} \mu_m P^{max}_m - \sum_{m=1}^{M} \lambda_m R^{min}_m \end{aligned} \tag{13}$$

and

$$R^*_{m,r} = \omega \log_2 [1 + (P^*_{m,r} G_{m,r})/(N_0 \omega)] \tag{14}$$

It is obvious that $\mathcal{P}5$ is a linear program problem with respect to $\tilde{\alpha}_{m,r}$, which can be solved by many approaches (e.g., simplex method). If we denote the weight coefficient of $\tilde{\alpha}_{m,r}$ as $H_{m,r} = (1+\lambda_m) R^*_{m,r} - \mu_m P^*_{m,r}$, the optimal RB allocation strategy $\tilde{\alpha}^*_{m,r}$ can be straightforwardly obtained by using the following column search method.

For each column (e.g., the mth column) of matrix $\boldsymbol{H} = \{H_{m,r}\}_{\forall m \in \boldsymbol{M}, \forall r \in \boldsymbol{R}}$, if the r^*th weight coefficient H_{m,r^*} is the largest and $H_{m,r^*} > 0$, we set $\tilde{\alpha}_{m,r^*}$ to 1 and set the rest elements of this column to 0.

$$\forall m \in \boldsymbol{M}, \; \tilde{\alpha}^*_{m,r} = \begin{cases} 1, & r^* \leftarrow \underset{r \in \boldsymbol{R}}{\text{argmax}} \{H_{m,r} | H_{m,r} > 0\} \\ 0, & \forall r \in \boldsymbol{R} \backslash \{r^*\} \end{cases} \tag{15}$$

Repeat the above column search method (15) until all columns of $\tilde{\boldsymbol{\alpha}}$ have been searched. The final solution $\tilde{\alpha}^*_{m,r}$ is an exactly binary variable, so we don't have to recover continuous variable $\tilde{\alpha}_{m,r}$ back into binary variable $\alpha_{m,r}$ to satisfy constraint (4) $C5$. Eventually, the optimal RB allocation strategy to problem $\mathcal{P}3$ can be obtained as $\alpha^*_{m,r} = \tilde{\alpha}^*_{m,r}$.

C. Sub-Gradient-based Resource Allocation

According to the closed-form solutions obtained by the Lagrange duality decomposition method, we propose a SGRA algorithm to find the optimal resource allocation strategy within the adjustable convergence accuracy. The proposed SGRA algorithm for solving problem $\mathcal{P}3$ is summarized in Algorithm 2 where K_m is the maximum iteration number, η_1 and η_2 are adjustable convergence accuracies. During each iteration, the Lagrange multipliers are updated as follows [12].

$$\lambda^{(k)}_m = \big[\lambda^{(k-1)}_m - \epsilon_1 (\sum_{r=1}^{R} \tilde{R}^{(k-1)}_{m,r} - R^{min}_m)\big]^+ \tag{16}$$

$$\mu^{(k)}_m = \big[\mu^{(k-1)}_m - \epsilon_2 (P^{max}_m - \sum_{r=1}^{R} \tilde{P}^{(k-1)}_{m,r})\big]^+ \tag{17}$$

where k denotes the kth iteration, ϵ_1 and ϵ_2 are two constant step lengths.

Algorithm 2 SGRA Algorithm for Solving Problem $\mathcal{P}3$

Input: the initial values of $\tilde{\alpha}_{m,r}, \tilde{P}_{m,r}, \lambda_m, \mu_m, \eta_1, \eta_2, K_m$.
Output: the resource allocation strategy $\alpha^*_{m,r}$ and $P^*_{m,r}$.

```
Initialize α̃(0)_{m,r}, P̃(0)_{m,r}, λ(0)_m, μ(0)_m, η1, η2, K_m;
for k = 1 to K_m do
  if k ≤ K_m then
    According to (10) and (11), using λ(k-1)_m, μ(k-1)_m and
    α̃(k-1)_{m,r} to calculate P̃(k)_{m,r}, P(k)_{m,r};
    According to (15), solving P5 to obtain α̃(k)_{m,r} by
    substituting P̃(k)_{m,r}, P(k)_{m,r} back into problem (9);
    if |α̃(k)_{m,r} − α̃(k-1)_{m,r}| ≤ η1 && |P̃(k)_{m,r} − P̃(k-1)_{m,r}| ≤ η2
    then
      Loop end;
    else
      According to (16) and (17), using α̃(k-1)_{m,r} and
      P̃(k-1)_{m,r} to update the Lagrange multipliers λ(k)_m and
      μ(k)_m;
    end if
  end if
end for
α*_{m,r} = α̃(k)_{m,r};   P*_{m,r} = P(k)_{m,r};
return the resource allocation strategy α*_{m,r} and P*_{m,r};
```

V. Numerical Simulation

In this section, consider a scenario as shown in Fig. 1, we evaluate the performance of our proposed algorithms in comparison with several baseline methods. Specifically, in Algorithm 1, the start temperature T_0 is 100, the annealing rate σ is 0.9, the stop temperature T_c is 10, and the number of iterations at each temperature K is 1000. In Algorithm 2, the number of RBs is 100, and the bandwidth of each RB is 180 kHz, the maximum transmission power is 23 dBm, the addictive white Gaussian noise is -174 dBm/Hz, the distance between UEs and eNodeB is in the range of [80, 200] meters.

Fig. 2 shows that our proposed SAHOD algorithm can earn approximately 20.5% more offloading revenue than VGA algorithm when there are 20 users. What's more, although the ESA algorithm always achieves the highest offloading revenue, it is worth noting that the gap between SAHOD and ESA keeps narrow, and sometimes SAHOD can obtain the global optimal solution as ESA do. That is because the Metropolis criterion can avoid local optimum and strike a good balance between exploration and exploitation.

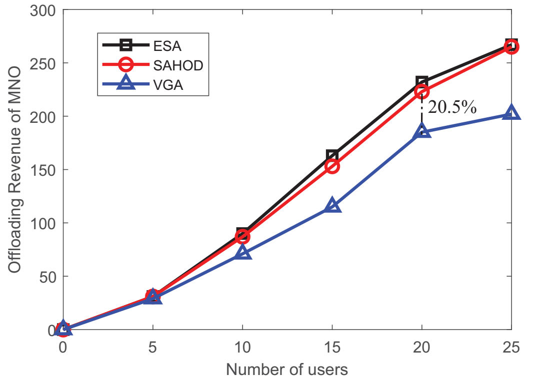

Fig. 2. MNO offloading revenue versus the number of users.

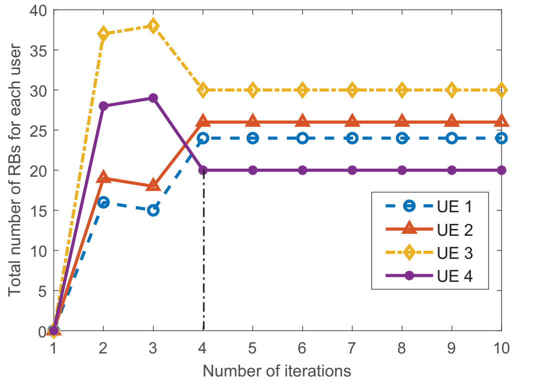

Fig. 3. Convergence of the SGRA algorithm.

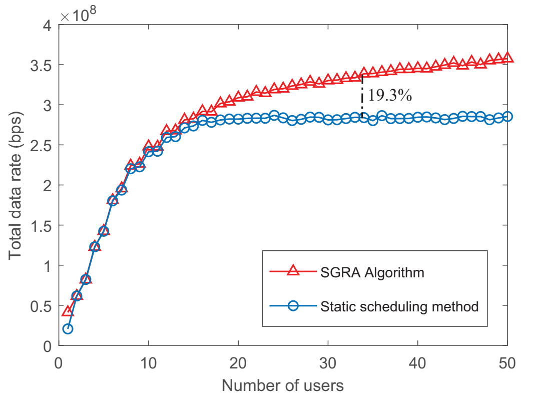

Fig. 4. Total data rate versus the number of users.

Fig. 3 shows the convergence of our SGRA algorithm for 4 users. It can be seen that the optimal RB allocation can be obtained within 4 iterations for given convergence accuracy. If the accuracy is more demanding or there are more users, the number of iterations will be absolutely non-decreasing. In addition, because transmission power $P_{m,r}$ simultaneously converges with RB allocation $\alpha_{m,r}$, its convergence curve is omitted here.

Fig. 4 shows that our SGRA algorithm can obtain approximately 19.3% more sum rates than static scheduling method when there are 34 users. Furthermore, while the number of users is greater than 15, the total data rate of SGRA algorithm is continuously increasing, yet the static scheduling has reached its saturation level. That is largely because our SGRA algorithm can provide more fine-grained RB allocation and transmission power control.

VI. Conclusion

In this paper, we investigated the offloading decision and communication resource allocation in the MEC-enabled multi-user edge network. At first, in order to maximize the revenue of MNO, we proposed a low-complexity SAHOD algorithm which was a probabilistic algorithm for avoiding local optimum and approximating global optimization. Next, we jointly optimized the RB allocation and transmission power for uplink. To solve the MINLP problem, we proposed a fine-grained SGRA algorithm to get a specific optimal resource allocation strategy within the adjustable convergence accuracy. Finally, the simulations are conducted to verify the effectiveness of proposed algorithms, which shows that our methodology could serve as a reference on the related field.

Acknowledgement

This paper is supported by the National Science and Technology Major Projects (Grant No. 2018ZX03001019-003), the National Natural Science Foundation of China (Grant No. 61801044), the BUPT Excellent Ph.D. Students Foundation (Grant No. XTCX201830), and the fundamental research funds for the central universities.

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