An Optimal Pricing Scheme for the Energy-Efficient Mobile Edge Computation Offloading With OFDMA

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***Abstract*— The mobile edge computation offloading (MECO) system has emerged as a promising technology to address several problematic issues in cloud computing such as data throughput, capacity, and security. In this letter, we consider a single-cloud-multi-user MECO system with orthogonal frequency-division multiple access and propose an optimal pricing scheme to consider each mobile user's (MU) need for resources. The proposed model was formulated as a single-leader-multi-user Stackelberg game model, and the Stackelberg equilibrium was provided to optimize the utility of the MUs and the edge cloud. Here, the utility of the MU implies the energy efficiency and payment for using the computation capacity of the edge cloud, and the utility of the edge cloud implies the revenue for serving computation offloading. The optimal strategies of the MUs are uniquely given by closed-form expressions, and that of the edge cloud is given by gradient descent methods. Some numerical examples are provided to verify our approach.**

***Index Terms*— Cloud computing, mobile edge computing, computation offloading, Stackelberg game, pricing scheme.**

I. Introduction

MOBILE edge computing (MEC) [1] has emerged as a promising technology to address the problems in cloud computing, including data throughput, capacity, and security. MEC allows much of the work to be handled at the edge, physically located closer to the terminal than to the cloud data center. It can also provide appropriate solutions to several challenging problems in IoT, such as the finite lives of battery and limited computation capacities. In particular, the mobile edge computation offloading (MECO) system has been introduced to reduce the energy consumption of mobile devices by sending intensive computational workloads to neighboring MEC servers. In this regard, there have been several studies on how to design an energy efficient multi-user MECO system, see e.g., [1]. In [2], the authors jointly optimize computation offloading and bandwidth allocation to minimize energy consumption considering 5G heterogeneous network environments. In [3], the authors jointly optimize the computational speed, transmit power, and offloading ratio with two system design objectives: to minimize energy consumption and latency. In [4], an optimal resource allocation mechanism was proposed to maximize energy efficiency with TDMA (Time Division Multiple Access) and OFDMA (Orthogonal Frequency-Division Multiple Access) scenarios. In [5], the authors proposed a jointly optimal solution of offloading selection, bandwidth allocation, and computational resource allocation in order to minimize the energy consumption of MUs in a centralized manner. In [6], an online joint radio and computational resource management algorithm for multi-user MECO systems was proposed, with the objective of minimizing the long-term average weighted sum power consumption of the mobile devices and the MEC server, subject to a task buffer stability constraint.

However, these existing studies minimized total energy consumption in a centralized manner, i.e., energy efficiency could not be considered from the perspective of each user. In other words, these centralized optimization schemes do not consider each user's requirements for limited resources. To solve this problem, the method of paying a price based on the amount of allocated resources should be adopted [6], [7]. With this perspective in mind, in this letter we propose a weight factor that reflects the needs for resources, while considering the price of computation capacity. In addition, we propose an optimal amount of resource to buy for a fixed price, and propose an optimal price for the edge cloud's computation capacity with Stackelberg game model.

II. System Model

In this section, a system model for the resource allocation mechanism of a MECO system with OFDMA is described in detail, as illustrated in Fig. 1

A. Resource Allocation Model for MECO

Assume that there are M MUs with single antenna with their index set $I_M = \{1, \cdots, M\}$, and a mobile edge cloud which borrows the channel from a single-antenna base station as a gateway. Let F be the computation capacity of the edge cloud measured by the number of CPU cycles per unit time. To transmit data through a wireless channel, B denotes the maximum bandwidth of the channel which the edge cloud can borrow from the base station, and allocates it to the MUs. Since this system takes OFDMA, the total bandwidth is divided into multiple orthogonal H subchannels with its index set $I_H = \{1, \cdots, H\}$, and each of them can be allocated to one MU. Note that the bandwidth of each subchannel is B/H, denoted by $\bar{B}$. Now, the edge cloud will borrow $N = \min\{M, H\}$ channels from the base station, and allocates them to selected MUs.

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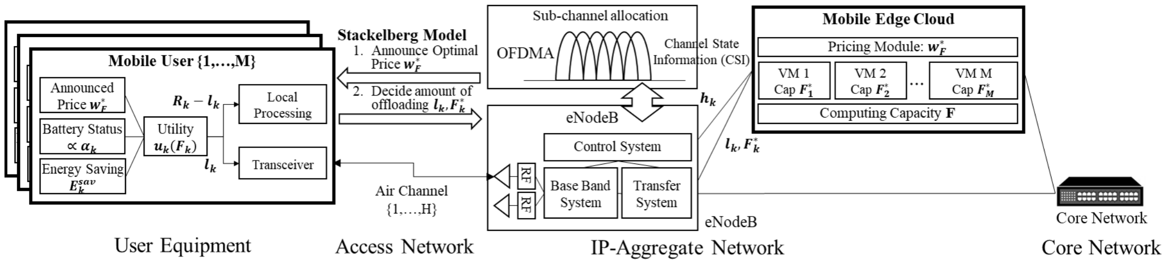

Fig. 1. Model configuration of mobile edge computation offloading with OFDMA.

B. Energy Consumption Model for MU

In this subsection, the energy consumption model for local computing in the kth MU in time T is considered; it basically follows the models in [4] and [8]. Since each MU uses a different application, the number of CPU cycles to compute is different for each mobile. In this regard, let C_k be the number of CPU cycles to compute 1-bit data depending on the application on the kth MU. Also, let P_k be the energy consumption per cycle for local computing at the kth MU, then the energy consumption for 1-bit data is C_kP_k at this mobile. Now, assume that there is R_k-bit data to be processed for the kth MU within this unit time interval; then this mobile can offload some of this data to edge cloud if it is selected to assign a subchannel. Also, let l_k denote the amoung of data offloaded to the edge cloud from this mobile in this unit time interval, then the total energy consumption to compute locally for this mobile is given by

$$E_k^{\text{loc}} = (R_k - l_k)C_kP_k. \tag{1}$$

For computation offloading, let p_k be the transmission power of the kth MU. Assume that the kth MU was selected to use the n_kth subchannel by the edge cloud if $n_k \neq 0$, and let h_k be the channel gain of this subchannel. Then, in the time interval T, the size of offloaded data l_k is given by

$$l_k = \begin{cases} \bar{B}T\log_2\left(1 + \dfrac{p_kh_k^2}{N_0}\right) & \text{if } n_k \neq 0; \\ 0 & \text{if } n_k = 0, \end{cases} \tag{2}$$

where N_0 is the variance of complex white Gaussian channel noise. Then from (2), the energy to transmit offloading data E_k^{off} can be obtained by

$$E_k^{\text{off}} = p_kT = \frac{N_0}{h_k^2}\left(2^{l_k/\bar{B}T} - 1\right)T. \tag{3}$$

Finally, we can obtain the total energy consumption E_k^{tot} of the kth MU as follows:

$$E_k^{\text{tot}} = E_k^{\text{loc}} + E_k^{\text{off}} = (R_k - l_k)C_kP_k + \frac{N_0}{h_k^2}\left(2^{l_k/\bar{B}T} - 1\right)T.$$

Here, if the kth MU doesn't offload any data in this time interval, then the energy consumption E_k^{no} is given by

$$E_k^{\text{no}} = R_kC_kP_k. \tag{4}$$

Thus, the energy saving from computation offloading E_k^{sav} is given by

$$E_k^{\text{sav}} = E_k^{\text{no}} - E_k^{\text{tot}} = l_kC_kP_k - \frac{N_0}{h_k^2}\left(2^{l_k/\bar{B}T} - 1\right)T. \tag{5}$$

C. Pricing Model for Computation Offloading

In this subsection, a pricing model for computation offloading is considered. Assume that the edge cloud allocates the computation capacity to the MUs who are allowed to use subchannels, and they have to pay w_F to borrow 1 computation capacity for time T. The important thing here is that the price w_F of the computation capacity is not given, but the edge cloud decides according to the current situation in which the MUs are competing. Also, note that we set the price of the resource equal to w_F for each MU to guarantee the fairness of each MU. Now, let F_k denote the computation capacity of the edge cloud allocated to the kth MU, then it is easily checked that $F_k = l_kC_k$. Now, let W_k be the required payment from the MU to the edge cloud, then it is given by

$$W_k = w_FF_k = w_Fl_kC_k. \tag{6}$$

MUs that have not been assigned sub-channels cannot obtain the computation capacity.

III. Stackelberg Game Analysis

In this section, the proposed model is formulated as a single-leader-multi-followers Stackelberg game model and the Stackelberg equilibrium (SE) is provided [9], [10].

A. Utility Function and Optimal Strategy of the MU

This subsection provides the utility of MU, which implies the MU's revenue from computation offloading, and the optimal strategy of each MU to maximize each utility. To this end, the strategy of the kth MU should be considered, F_k, the amount of the allocated computation capacity of the edge cloud to offload data. From the point of view of MU, the advantage of computation offloading is saving energy, and the disadvantage is the payment to the edge cloud.

Thus, from (5) and (6), the utility of the kth MU, denoted by $u_k(F_k)$, can be considered as

$$\begin{aligned} u_k(F_k) &= E_k^{\text{sav}} - \alpha_kW_k \\ &= F_k(P_k - w_F\alpha_k) - \frac{N_0}{h_k^2}\left(2^{\frac{F_k}{C_k\bar{B}T}} - 1\right)T \end{aligned} \tag{7}$$

where α_k is the weightfactor of the kth MU between two resources from computation offloading, the saved energy and the payment. This weightfactor is determined by how much this MU wants to conserve its battery in this time interval, for example, the current battery status of the mobile or the time before it can charge its battery. In the proposed utility, the smaller the alpha, the more likely the user wants to save more battery. One thing to note is that w_F is actually the edge cloud's strategy, however, the edge cloud is a leader and MUs are followers, so it can be treated as a constant. Here, if F_k is large, u_k may be lower than zero,then it is advantageous not to buy any computation power at that time.

Now, the optimal strategy of each MU is provided to maximize each utility in the following theorem. The proof is omitted because of page limitation.

Theorem 1: The optimal strategy of the kth MU, F_k^* to maximize its utility is given by

$$F_k^* = \begin{cases} 0, & \text{if } w_F \geq \frac{1}{\alpha_k}\left(P_k - \frac{N_0 \ln 2}{\bar{B}C_k h_k^2}\right); \\ R_k C_k, & \text{if } w_F < \frac{1}{\alpha_k}\left(P_k - \frac{N_0 \ln 2}{\bar{B}C_k h_k^2} e^{\frac{R_k \ln 2}{\bar{B}T}}\right); \\ \frac{\bar{B}TC_k}{\ln 2}\ln\left(\frac{\bar{B}C_k h_k^2 (P_k - w_F \alpha_k)}{N_0 \ln 2}\right), & \text{otherwise.} \end{cases}$$

B. Optimal Price for Edge Cloud

In this subsection, the optimal strategy of the edge cloud is proposed as a leader in the proposed Stackelberg game. Note that the edge cloud's strategy is w_F, the unit price of its computation capacity. It wants to find the price w_F^* that maximizes its revenue, which is the payment that all MUs will pay for using the computation capacity, by adjusting w_F. Here, w_F is the edge cloud's strategy, but from the perspective of the MU it is assumed to be a predetermined constant, and the MU responds with F_k^*, which maximizes its utility accordingly. Namely, F_k^* is the best response function of the kth MU as a follower according to w_F, edge cloud's strategy as a leader. Thus, in terms of the edge cloud, the optimal strategy of the kth MU can be expressed by the function of w_F, that is, $F_k^*(w_F)$ by Theorem 1.

Now, let $R(w_F)$ denote the revenue of it, then it is easily obtained by

$$R(w_F) = \sum_{k=1}^{N} w_F F_k^*(w_F). \tag{8}$$

w_F^* is the price that maximizes $R(w_F)$, however, if the price is too cheap so that every MU buys too much computation capacity, then the edge cloud will not be able to meet the purchase request. Thus, to find the optimal strategy of the edge cloud w_F^* which maximizes its revenue, we should solve the following optimization problem:

$$w_F^* = \underset{w_F}{\text{argmax}}\ R(w_F) \quad \text{s.t.} \sum_{k=1}^{N} F_k^*(w_F) \leq F. \tag{9}$$

It is checked that $R'(0) = \sum_{k=1}^{N} \frac{\bar{B}TC_k}{\ln 2}\ln\left(\frac{\bar{B}C_k h_k^2 P_k}{N_0 \ln 2}\right) > 0$ with $R(0) = 0$, thus it increases to positive at zero. To find out the optimal strategy of the edge cloud, define a set of discontinuous points D of $R(w_F)$ as follows:

$$D = \{d_k \mid d_k = 1/\alpha_k(P_k - N_0 \ln 2/\bar{B}C_k h_k^2), \forall k \in I_N\} \cup \{0\}$$
$$\cup \{\bar{d}_k \mid \bar{d} = 1/\alpha_k(P_k - N_0 \ln 2/\bar{B}C_k h_k^2) e^{\frac{R_k \ln 2}{\bar{B}T}}, \forall k \in I_N\}.$$

Now, rearrange D by descending order, and denote it by $\tilde{D} = \{\tilde{d}_k\}_{k \in I_{2N} \cup \{0\}}$ with ordered index where $I_{2N} = \{1, \cdots, 2N\}$. Clearly, $\tilde{d}_{2N} = 0$ and $\tilde{d}_k \geq \tilde{d}_{k+1}, \forall k \in I_{2N}$. Now, define a set $V(\tilde{D})$ be the set of intervals spanned by $\tilde{D}$, given by $V(\tilde{D}) = \{[\tilde{d}_k, \tilde{d}_{k-1}) \mid \forall k \in I_{2N}\}$. The first and the second derivative of $R(w_F)$ is not difficult, but not presented due to page limits. Now, from the first and the second derivative of $R(w_F)$, the revenue function R is concave and continuous on each interval $[\tilde{d}_j, \tilde{d}_{j-1}) \in V(\tilde{D})$, which gives the following lemma.

Algorithm 1 Energy Efficient Optimal Pricing Algorithm for MEC System with OFDMA

Input : System Parameters: $(M, H, L, C_k, P_k, F, \alpha_k)$
$\tilde{D} = \text{SortDesc}(D) \cup \{0\} = \{\tilde{d}_k \mid \tilde{d}_j < \tilde{d}_{j-1}, \forall j \in I_{2N}\}$
$V = \{v_k = [\tilde{d}_k, \tilde{d}_{k-1}) \mid \forall k \in I_{2N}\}$
For $v_i, \forall i \in I_{2N}$:
  If $\sum_{k=1}^{N} F_k^*(\tilde{d}_{i-1}) \geq F$:
    break
  ElseIf $\sum_{k=1}^{N} F_k^*(\tilde{d}_i) \geq F$ & $\sum_{k=1}^{N} F_k^*(\tilde{d}_{i-1}) < F$
    $\tilde{d}_i = w_F : \frac{\bar{B}TC_k}{\ln 2}\ln\left(\frac{\bar{B}C_k h_k^2 (P_k - \alpha_k w_F)}{N_0 \ln 2}\right) - F = 0$
  EndIf
  While
    $w_{F,prev} = w_{F,cur}$
    $dw_F = \sum_{k=1}^{N} A_k(w_{F,prev})$
    $w_{F,cur} = w_{F,prev} - \gamma dw_F$
  EndWhile
EndFor
$w_F^* = \text{argmax}_{w_F} \sum_{k=1}^{N} w_F F_k^*(w_F)$
Output : Optimal price of the edge cloud w_F^*, result of offload decision making for each MUs F_k^*

TABLE I
SIMULATION PARAMETERS AND VALUES [4]

Parameters	Values
N_0, B	10^{-9}W, 10MHz
Number of MU and Sub-channel (M, H)	$\{10, 11, \cdots, 40\}$
Time slot (T), Number of Channel Tab (L)	1 sec, 5
CPU computation capacity (F_k)	$\{0.1, 0.2, \cdots, 1.0\}$GHz
Required number of CPU cycles per bit (C_k)	$\{500, 1500\}$cycles/bit
Energy consumption of local computing per cycle (P_k)	$U(0, 20 \times 10^{-11})$J/cycle
Computing Capacity of MEC (F)	$U(0, 2 \times 10^{10})$cycle/time
Weightfactor between energy and price (α_k)	$\{1, \cdots, 5\}$

Lemma 1: There is a unique point to maximize the revenue in each interval $[\tilde{d}_j, \tilde{d}_{j-1}) \in V(\tilde{D})$; that is, for all $j \in I_N$, there exists a unique solution $w_{F,j}^* \in [\tilde{d}_j, \tilde{d}_{j-1})$ such that $R(w_{F,j}^*) \geq R([\tilde{d}_j, \tilde{d}_{j-1}))$.

The points in Lemma 1 imply the local maximum of the revenue function. The following theorem provides the global maximum constrained in (9) such that $\sum_{k=1}^{N} F_k^*(w_F) \leq F$, which is Stackelberg equilibrium of the proposed model.

Theorem 2: There are at least one optimal price to maximize the revenue function of the edge cloud.

Note that through the gradient-descent method, algorithm 1 finds optimal price provided in Theorem 2, considering constraint that has been found by Newton-Raphson method.

IV. NUMERICAL RESULTS

This section presents the numerical evaluation of the optimal pricing scheme for energy efficient MEC offloading in OFDMA environment, to analyze policies in terms of the MUs' behavior under the Stackelberg competition when the leasing cost of an edge cloud resource varies. We performed the simulation with extended system parameters in [4], [8]. We assumed that the Channel State Information (h_{k,n_k}) for OFDMA sub-channels is provided to the edge cloud as independent Rayleigh fading. In Table I, parameters for participating entities and resources are assigned [4].

According to Theorem 2, there is an optimum convergence price according to Stackelberg equality; it is shown in Fig. 2

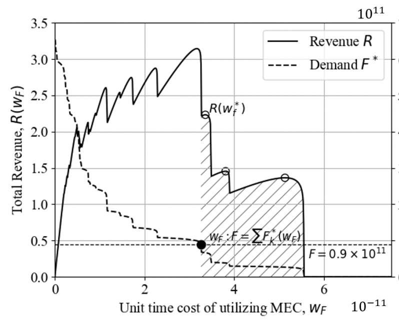

Fig. 2. The total revenue of MEC and the total demand of MU for varying w_F. ($M = 30, F = 0.9 \times 10^{11}$).

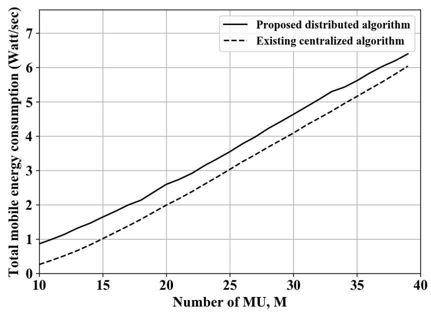

Fig. 3. Total energy consumption for the existing algorithm and the proposed algorithm.

when $M = 30, F = 0.9 \times 10^{11}$. Note that shaded interval indicates the resource constraint, and the optimal price w_F^* of energy efficient MECO can be found with $R(w_F^*)$. The total revenue of MEC $R(w_F)$ is discontinuous over the interval, due to the MU refusing to perform offloading where $w_F \geq \frac{1}{\alpha_k}\left(P_k - \frac{N_0(\ln 2)}{BC_k h_k^2}\right)$. Within the constraint $F = \sum F_k^*(w_F)$ so that the total demand of MUs does not exceed the capacity (shaded interval), we can find optimal points on given continuous intervals using algorithm 1 according to Lemma 1. In this example, we found the global optimum $R(w_F^*)$ of the Stackelberg game. As a result, the solution guarantees the maximum utility to the MUs and the maximum revenue to the edge cloud providers.

Fig. 3 and 4 show the simulation results of the proposed algorithm on the distributed system and the performance of the existing algorithm on the centralized system in [4]. For performance comparison, we used two system metrics: total energy consumption of MUs and social welfare; social welfare is the sum of all the users' utilities. For the performance comparison, we took the average of two performance metrics over 500 randomly generated MECO systems as we increased the number of MUs. Here, since the existing algorithm does not consider the price of computational resource at all, the unit price was set to be the same as the value determined in the proposed algorithm. As a result, shown in Fig. 3, the proposed algorithm consumed 30.3%, 13.3%, and 5.9% more energy than the existing algorithm where there are 20, 30, and 40 MUs, respectively. Although the proposed algorithm is less energy efficient than the existing algorithm, we can see that the difference in energy efficiency decreases as the number of MUs increases.

On the other hand, in Fig. 4, the social welfare of the proposed algorithm is remarkably superior to that of the existing algorithm; in existing algorithm, even users are dissatisfied

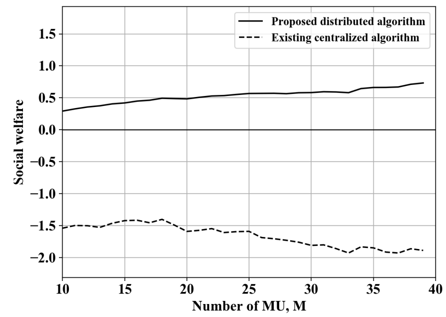

Fig. 4. Social welfare for the existing algorithm and the proposed algorithm.

with computational offloading because the social welfare does not exceed 0. This result is caused by the fact that the existing algorithm is a centralized system, thus the users have to forcibly purchase computational resources even though they do not want to buy too much at a given price. Also, in the existing algorithm, users with good channel gain should buy offloading resources to increase energy efficiency throughout the system, even though they do not need that much resources.

V. Conclusion

In this letter, we considered a single-cloud-multi-user MECO system with OFDMA and proposed an optimal pricing scheme to consider each MUs' needs for resources. The proposed model was formulated as a single-leader-multi-user Stackelberg game model, and Stackelberg equilibrium was provided to optimize the utility of the MUs and the edge cloud. Here, the utility of the MU implies energy efficiency and payment for using the computation capacity of the edge cloud, and the utility of the edge cloud implies the revenue for serving computation offloading. The optimal strategies of the MUs are uniquely given by closed-form expressions, and that of the edge cloud is given by gradient descent methods. Some numerical examples were provided to verify our approach.

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