System Revenue Maximization for Offloading Decisions in Mobile Edge Computing

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***Abstract*—Offloading decisions in mobile edge computing have been extended with multiple objectives, such as revenue maximization, energy conservation and latency reduction. Revenues of network/service operators, as the realistic and ultimate goal at intensive competitive markets, have not been thoroughly studied under a pricing scheme in combination with offloading decisions, especially with the aims of reducing and restricting energy consumption and latency. To bridge this important gap, this paper studies the revenue maximization of network operators through a pricing scheme in mobile edge computing, by explicitly formulating energy consumption and latency into the offloading strategy. A two-stage game-theory framework based on the Stackelberg game is established, through which the optimal price for both the network operator and the customer can be reached. The offloading data size can be dynamically adjusted according to the agreed price. The existence of equilibrium in the Stackelberg game is proved, and experiments are conducted to verify the effectiveness of our proposed model.**

***Index Terms*—Revenue maximization, offloading, mobile edge computing, energy consumption, game theory**

I. Introduction

Mobile edge computing (MEC) carries out computing tasks at the network edge in a broad range of industries under the support of 5G [1]. This computing paradigm is a good candidate to satisfy the expectations of ultra-reliable and latency-sensitive applications such as unmanned vehicles [2]. European Telecommunications Standards Institute (ETSI) issued the first edition white paper "Mobile Edge Computing-A key technology towards 5G" to elaborate the business value, the market drivers and the service scenarios of MEC [3]. Offloading in MEC brings new sophisticated applications by reducing energy consumption. Problems including proper selection of programming models, accurate estimation of energy consumption, virtual machine migration, have been raised and studied under specific scenarios. However, there is limited research in exploring the offloading decisions in MEC from the perspective of economics, such as revenues of network/service operators.

A. Motivations

Network economics is a result of the collaboration among communication, energy and finance, to tackle the real-world issues surrounding the decision-making in network strategies [4]. For example, profits of Edge Infrastructure Providers (EIP) were optimized in resource management of edge computing, where Cosimo et al. [5] presented an Online Profit Maximization (OPM) algorithm aiming to increasing the profit of EIPs without any priori knowledge.

However, most studies focusing on the optimization of energy consumption and time latency of offloading decisions in MEC ignore the important practical issues of cost and revenue. For instance, in fog computing, intelligent approaches were proposed for energy and latency reduction by detecting user behaviours and analyzing offloading decisions [6]. The speed perception, instantaneous response time and performance in massive data communications drive the effective decisions-making strategies in MEC.

There is no proper scheme of maximizing the revenue of service operators considering pricing schemes into offloading strategies that are formulated with energy consumption and time latency. The less cost in the computation and the offloading system, the more profits of the operator will gain. Therefore, even the energy consumption and the latency in MEC have been well studied, the research of offloading in MEC should still move forward with the purpose of revenue maximization of service operators.

B. Contributions

The main contributions of this paper are summarized as follows: 1) The offloading problem in MEC is formulated by a two-stage game model with the purpose of the tradeoff between network operators and mobile users in the price competition game. 2) The subgame perfect equilibria in the above formulated model are achieved for the instantaneous strategies, by which the best response of offloaded data size and the agreed price between network operators and mobile users are reached. The latency and energy consumption of the system can thus reach to the ideal equilibrium states.

The rest of this paper is organized as follows. In Section II, the related work is presented. Section III introduces the system model. Section IV describes the details of our game mechanism, followed by the equilibrium analysis in Section V. The experimental results and analysis are presented in Section VI. Finally, Section VII concludes this paper.

II. Related Work

Offloading in MEC has been widely researched in the literature. Energy consumption of an offloading system in both task computing and file transmission was investigated in [7]. Radio resource allocation and offloading for the energy conservation under the constraint of latency were jointly optimized by the

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energy-efficient computation offloading (EECO) scheme [8]. An interactive search algorithm was proposed for the energy-latency tradeoff by combining an interior penalty function with the difference of two convex functions programming to find the optimal solution [9]. Huang et al. [10] proposed a bilevel optimization approach for the joint offloading decision and resource allocation with the purpose of profitability improvement of operators. It is noticed that most of existing offloading algorithms aim at minimizing the energy consumption of mobile users, while meeting the latency constraints.

The tradeoff between energy consumption and latency has been extended to full offloading and partial offloading studies. In MEC, increasing attention has been paid in optimization of services provision performance and cost efficiency of network operators, which are manifested in the study of core networks, radio access networks and mobile users distributions. The conflicts between mobile users and operators in terms of size in data offloading and profit maximization should be further explored for economic effectiveness [11]. Xiong et al. [12] proposed an MEC enabled blockchain game system, and modeled a hierarchical stackelberg game to solve the resource management in fog computing networks by pricing strategies.

Social welfare maximization was achieved by avoiding the strategic problems of analytical models [13]. An auction mechanism was demonstrated to ensure the truthfulness, individual rationality and computational efficiency in [14], where edge resource allocation was formulated into the blockchain network as an optimization constraint of social welfare maximization.

III. The System Model

A. System Architecture

We consider the sets $\mathbb{I} = \{1, ..i.., I\}$ and $\mathbb{J} = \{1, ..j.., J\}$ denoting mobile users (MUs) and network operators (OPs), respectively, where i stands for the ith MU and j is the jth OP. The details of the system architecture are shown in Fig. 1. Once an MU requires MEC services, an offloading request will be sent from the MU to an OP to negotiate an offloading strategy. Latency and energy consumption of the uploading through uplink, computation at MEC deployed in a base station (BS) and downloading through downlink for tasks will be formulated as the hard constraints in the model for the irreversibility of offloading [15]. In contrast, the latency and energy consumption of tasks processed locally are the variable constraints. An agreed price and size of data for offloading will be confirmed as the offloading strategy with the purpose of revenue maximization for OP. The local CPU frequencies of MUs can be denoted as $\psi_i \in \{\psi_1, ..., \psi_I\}$. It is assumed that MU i can process the data in bits in $[0, \bar{x}]$, where $\bar{x}_i$ is the total bits of data that MU i can execute or the upper bound of offloading data size to MEC. x_i is the data size that will be offloaded to MEC. Thus, $(\bar{x}_i - x_i)$ represents the bits of data that are executed locally by MU i.

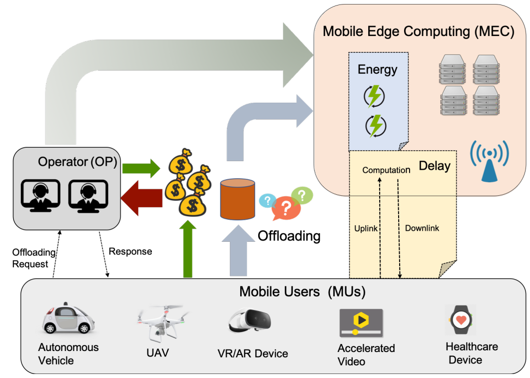

Fig. 1: The System Architecture.

B. Local Computing at MUs

Latency of local computing can be represented as

$$t_i^{MU} = (\bar{x}_i - x_i)\,\frac{a_i}{\psi_i^{MU}} \tag{1}$$

where a_i is the required number of CPU cycles to process a bit of data at an MU, and ψ_i^{MU} is the computational power (frequency) of the MU. The energy consumption of local computing can be represented by

$$E_i^{MU} = \sigma_i^{MU} \times t_i^{MU} \tag{2}$$

where σ_i^{MU} denotes the consumed energy per CPU cycle.

C. Mobile Edge Computing

Consider the physical layer characteristics of a network, the latency of MEC can be expressed with

$$t_{i,j}^{EC} = \left(\frac{b_i}{\gamma_{i,j}^{up}} + x_i\frac{a_j}{\xi_j} + \frac{c_i}{\gamma_{j,i}^{dn}}\right) \tag{3}$$

where x_i is the data size offloaded to and computed in MEC. a_j is the service rate required by x_i in the MEC server j, which is the number of CPU cycles for one bit of data computation. ξ_j is the assigned computational speed of server j to user i, where $\xi_i = \bar{\xi}_j / I$, $\bar{\xi}_j$ is the total computational resource, and I is the number of MUs. b_i and c_i are the input and output data size to and from the MEC server, respectively. $\gamma_{i,j}^{up}$ and $\gamma_{j,i}^{dn}$ are the data rates when uploading and downloading the data during the communication. The uplink data rate of uploading to an MEC server can be formulated as [16]

$$\gamma_{i,j} = \frac{W}{I} log_2(1 + \frac{p_i^{up} H_{ij}}{\frac{W}{I}\omega}), \forall i \in \{0, I\}, j \in \{0, J\} \tag{4}$$

where W is the total bandwidth of the channel, and $\frac{W}{I}$ is the allocated bandwidth for the uplink of MU i. H_{ij} is the channel gain of MU i to the MEC server j. ω is the background noise power. p_i^{up} is the transmission power of MU i, which can be obtained through the power control algorithm [17]. P_i and $\mathrm{SIR}_i(k)$ correspond to the power level and the *signal-to-interference ratio* for MU i offloading tasks to an OP at the kth iteration. Let $G_{ij} > 0$ be the power gain (also known as *propagation loss*) of the jth MEC to the ith MU. We define the interference power received at the base station j from the

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uplink of MU i as $G_{ij}P_j$. The power control can be expressed by the uplink transmission data rate with

$$P_i(k+1) = \frac{\gamma_i}{SIR_i} P_i(k) = \frac{\gamma_i \left(\sum_{j \neq i} G_{ij} P_i + \theta_i\right)}{G_{ij} P_i} P_i(k) \tag{5}$$

where θ_i is the thermal noise power at the ith MU, and γ_i is the desired SIR threshold, $i = 1, 2, \ldots, n$. The constraint $SIR_i \geq r_i$ is enforced for each MU. The optimal power p_i^* is either $\widehat{p_i}$ or 0, leading to the large utility. Because of the low latency and energy consumption of the result (normally a value) downloaded from MEC to an MU, the latency and energy cost for downlink process can be ignored. Therefore, the energy consumption of an MEC can be illustrated as

$$E_i^{EC} = p_i^{up} \frac{b_j}{\gamma_{i,j}^{up}} + p_j x_i \frac{a_j}{\xi_j} \tag{6}$$

where p_i^{up} denotes the transmission power of MU i for data uploading. p_j is the computation power of the MEC server. The problem of this paper is described and formulated in Section IV.

IV. Game Mechanism

In this section, the latency and energy consumption in local computing and through offloading are formulated to assess the offloading decision making in our proposed two-stage game model.

A. Cost of Offloading

Each mobile user determines whether to offload its data x to the MEC server, which can be expressed with binary offloading decision $f_i \in \{0, 1\}$. $f_i = 0$ means that MU i decides to execute the data x_i locally, and $f_i = 1$ denotes that the MU performs the data offloading to the MEC server.

$$f_i = \begin{cases} 1, & \pi \leq \frac{1}{\psi_i}, \\ 0, & \text{otherwise}. \end{cases} \tag{7}$$

where the offloading threshold $\frac{1}{\pi}$ is greater or equal to the local MU i's CPU frequency ψ_i. The optimization problem of the system cost $C(\mathbf{x}, \mathbf{f}, \mathbf{t}, \mathbf{E})$ can be formulated with weighted sum of energy consumption and latency as

$$\begin{aligned} \mathbf{C}(\mathbf{x}, \mathbf{f}, \mathbf{t}, \mathbf{E}) = \sum_{i=1}^{I} \Bigg(\sum_{x=1}^{X} \left(E_{ix}^{MU}(1 - f_{ix}) + E_{ix}^{EC} f_{ix} \right) \\ + \beta \max \left\{ t_i^{MU}, t_{i,j}^{EC} \right\} \Bigg) \end{aligned} \tag{8}$$

where $\mathbf{x} = \{x_i | i \in \mathbb{I}\}$, $\mathbf{f} = \{f_{ix} | i \in \mathbb{I}, x \in \mathbb{X}\}$, and β is the weight of latency for performing computation locally and in MEC servers. Based on Eq. (8), the cost for the task $\mathbf{x}$ can be seen as a *mixed-integer programming problem*, which jointly integrates MU i's offloading decision strategy into the minimization objectives of the energy consumption and latency. It is expressed as

$$\begin{aligned} \mathbf{C}^*(\mathbf{x}^*) = \min \quad & \mathbf{C}(\mathbf{x}, \mathbf{f}, \mathbf{t}, \mathbf{E}) \\ \text{s.t.} \quad & \sum_{i}^{I} x_i \leq \bar{X}, x_i \geq 0, \forall i \in \mathbb{I}, f_i \in \{0, 1\} \end{aligned} \tag{9}$$

where the constraints mean that the uplink power is 0, or positive but not exceeding the maximum energy capacity.

B. Price Anarchy

The pricing starts from the broadcast of the service price π_{OP} from an OP after an offloading request sent from an MU. As the feedback, the MU follows the step with offering its acceptable price π_{MU} accordingly. After receiving the response, the OP updates its quoted price in next round of price offer. A stable equilibrium price will be reached by enough rounds of iterations, otherwise the offloading service request will be rejected by the OP. Compared to the dynamic pricing evolutionary strategy, static pricing strategy may experience the loss of utility in reaching the equilibrium, especially when the evolution process is long [18].

C. Offloading Data Size Adjustment Model

The reached price of the dynamic process affects the size of the offloading data. In this paper, we study the best-response of the Nash equilibrium in price, and adjust the offloading data size to MEC servers according to the reached price. The game competition model of the pricing process is demonstrated in the Stage 1 in Fig. 2, which facilitates the update of the offloading data size in the offloading decision. The equilibrium price π^* can be achieved by the iterative competition through the offered price π_{OP} of OP and the π_{MU} of MU. Then, the size of data offloaded to the MEC server can be adjusted accordingly, which is described in the Stage 2 in Fig. 2. The Stage 1 and Stage 2 are defined as the **Leader** and the **Follower** in the game. This backward induction of the interactions in the Stackelberg game is introduced in two problems as follows.

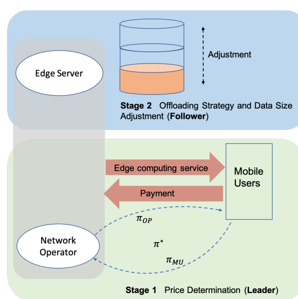

Fig. 2: Two Stage Price-Data Offloading Model.

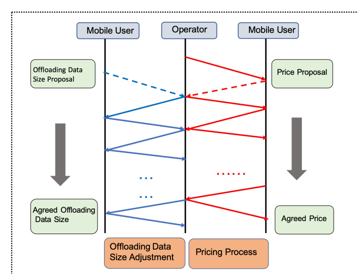

Fig. 3: Two Stage games Iteration Process.

1) Pricing Strategy in Stage 1: The profit of an OP is the difference of revenue obtained by charging from the customers and the cost spending on data offloading. The unit cost of the energy for the offloading service is denoted by η. Thus, the utility of an OP can be expressed as

$$\Phi(\pi_i, \hat{\boldsymbol{\pi}}_{-i}, \mathbf{x}) = \sum_{i \in \mathbb{I}} \sum_{x \in \mathbb{X}} \pi_i x_i a_i - \sum_{i \in \mathbb{I}} \sum_{x \in \mathbb{X}} \eta E_i^{EC} \tag{10}$$

The incentive mechanism of BSs for MUs offloading is introduced due to the market competition [19]. The random variable of the price follows the standard normal distribution $\boldsymbol{\pi} \sim N(0, 1)$. To avoid the confusion of the constant with

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price, the constant of the normal distribution is denoted by $\hat{\pi}$. Therefore, the utility performance is expressed as

$$\Phi(\pi_i, \hat{\boldsymbol{\pi}}_{-i}, \mathbf{x}) = \sum_{i \in \mathbb{I}} \sum_{x \in \mathbb{X}} \pi_i x_i a_i \left(\frac{1}{\sqrt{2\hat{\pi}}} e^{-\frac{\pi_i^2}{2}} \right) - \sum_{i \in \mathbb{I}} \sum_{x \in \mathbb{X}} \eta E_i^{EC} \tag{11}$$

where $\mathbf{x}_i = (\mathbf{x}_i^1, ..., \mathbf{x}_i^X)$ is the offloading data size, π_i is the price agreed by ith MU, $\hat{\boldsymbol{\pi}}_{-i}$ is the prices of MUs excluding the price of MU i. The pricing strategy of an OP follows Gaussian distribution for revenue maximization under constraints. $\pi \in [0, \bar{\pi}]$ is defined as the net payoff per time slot.

$$\Phi_\pi \triangleq \phi_\pi \left(\frac{1}{\rho\sqrt{2\pi}} e^{-\frac{(\pi-\mu)^2}{2\rho}} \right) \tag{12}$$

$$\Pi_x \triangleq \pi_x \left(\sum_{i \in \mathbb{I}} \sum_{x \in \mathbb{X}} log\,(1 + x_i) \right) - C_i \tag{13}$$

where the $\frac{1}{\sqrt{2\hat{\pi}}} e^{-\frac{\pi_i^2}{2}}$ term[1] represents the diminishing utility of all data flow from offloaded data size x_i. C_i represents the cost of the offloading of data size x_i. Function $\Phi_\pi(\mathbf{x}^*, f, \mathbf{t}^*, \mathbf{E}^*)$ represents the total utility of all offloaded data from all MEC. Suppose that the function ϕ_x is continuously differentiable, such as $\phi_x' > 0$, $\phi_x'' < 0$ and $\phi_x(0) = 0$.

Problem 1. (stage 1 sub-game, Leader): The utility of the leader is shown as

$$\begin{aligned} \pi^* = &\max_{\pi} \quad \Phi(\pi_i, \hat{\boldsymbol{\pi}}_{-i}, \mathbf{x}, C(t, E)) \\ \text{s.t.} \quad &\pi_j \in [0, \bar{\pi}], x_i \in [0, \bar{x}] \end{aligned} \tag{14}$$

where π is the price for MEC computing service. $\mathbf{x}$ stands for the data service vector, and x_j is the offloading data serviced by operator j.

2) Offloading Strategy in Stage 2: The cost utility of MU i can be formulated through the latency and the payment of energy consumption

$$C_i^{MU}(x_i, \pi_i) = \begin{cases} (\pi_i - \frac{1}{\psi_i}) x_i a_i + \frac{\bar{x}_i a_i}{\psi_i}, & 0 \le x_i \le r_i, \\ t_{i,j}^{EC} + \pi_i x_i a_i, & r_i < x_i \le \bar{x}_i. \end{cases} \tag{15}$$

where

$$r_i = \frac{\bar{x}_i a_i}{\left(\frac{1}{\gamma_{i,j}^{up}} + \frac{a_j}{\xi_j} + \frac{1}{\gamma_{i,j}^{dn}} \right) \psi_i + a_i} \tag{16}$$

is the threshold of data size offloaded to MEC.

Problem 2. (stage 2 sub-game, Follower): Suppose that there exists a Nash equilibrium point x_i^* satisfying

$$C^*(x_i^*) = \min_{x_i} \mathbf{C}_i^{MU} \left((x_i^1, f, t, E), ..., (x_i^X, f, t, E) \right) \tag{17}$$

$$\mathbf{C}^{MU}(x_i) = \min_{x_i} \sum_{i \in \mathbb{I}} \mathbf{C}_i^{MU} \tag{18}$$

where $\mathbf{x}$ is the data size of MUs for processing.

These two problems integrate the two parts of the Stackelberg game. The equilibrium utility under the best response of the data offloading can be described as follows.

[1]This term can be replaced by other types of utility functions.

Definition 1. *Suppose that $\hat{\boldsymbol{\pi}}^*$and $\boldsymbol{x}^*$ are the optimal price of service offered by the network operator, and the data size vector offloaded to MEC, respectively. The point $(\hat{\boldsymbol{\pi}}^*, \boldsymbol{x}^*)$ is the equilibrium point of this game if the condition holds*

$$\begin{aligned} &\Phi(\pi_i^*, \hat{\boldsymbol{\pi}}_{-i}^*, \mathbf{x}^*) \ge \Phi(\pi_i, \hat{\boldsymbol{\pi}}_{-i}^*, \mathbf{x}^*), \forall \pi_i \ge 0, i \in \mathbb{I} \quad and \\ &u_x(\mathbf{x}^*, \hat{\boldsymbol{\pi}}^*, C^*(\mathbf{t}, \mathbf{E})) \ge u_x(\mathbf{x}, \hat{\boldsymbol{\pi}}^*, C^*(\mathbf{t}, \mathbf{E})) \end{aligned} \tag{19}$$

where $\boldsymbol{x}^*$ is the best response of data vector offloaded to MEC. $\hat{\boldsymbol{\pi}} = \{\pi_i | i \in (I)\}$ and $\hat{\boldsymbol{\pi}}_{-i}$ is all prices excluding π_i.

The prices to different MEC services of BSs offered by the OP are supposed to be the same, which means there is no discriminatory pricing strategy in the game. Therefore, we focus on the utilities of local processing, MEC computation, and the revenue maximization of the OP. The iterative process of the data offloading and pricing is shown in Fig. 3.

V. Equilibrium Analysis

The backward induction is introduced in this section, by which we analyze the optimal price and offloading strategy to maximize the utility of an OP.

A. Leader's game: Pricing Game

Given the data size x in Stage 2, an OP plays with communicated MUs to maximize its utility, which forms the non-cooperative game. The strategic bargaining process is performed and described in Pricing Game (PG) with $\mathfrak{G}^u = \{K, \{x_k\}_{k \in K}, \{\Pi_k\}_{k \in K}\}$, where $k \in K = \{\mathbb{I} = \{1, ..., I\}, \mathbb{J} = \{1, ..., J\}\}$, and K is the set of players. $\{x_k\}_{k \in K}$ is the strategy set of offloading, and the $\{\Pi_k\}_{k \in K}$ represents the utility when the strategy is x_k. Therefore, the utility maximization can be rewritten as $\Pi(\pi_i, \bar{\pi}_{-i}, x)$. Once x is fixed, the latency and energy consumption are determined in Stage 2. Then the utility of Π in Stage 1 can be maximized and the uniqueness of Nash equilibrium of the PG can be proved.

Definition 2. *The price vector $\hat{\boldsymbol{\pi}}^* = (\pi_1^*, ..., \pi_I^*)$ is the Nash equilibrium of the PG $\mathfrak{G}^u = \{K = \{\mathbb{I}, \mathbb{J}\}, \{\pi_k\}_{k \in K}, \{\Pi_k\}_{k \in K}\}$, if each player meets $k \in K$, $\Phi_k(\pi^*, \boldsymbol{x}^*) \ge \Phi_k(\pi, \boldsymbol{x}^*)$, all $\pi_k \in [0, \bar{\pi}]$, where $\Phi_k(\pi, \boldsymbol{x}^*)$ is the utility under agreed prices.*

Theorem 1. *A Nash equilibrium exists in PG $\mathfrak{G}^u = \{K, \{\pi_k\}_{k \in K}, \{\Phi_k\}_{k \in K}\}$.*

Proof: The strategy space of PG is $\pi_k \in [0, \bar{\pi}]$, which is not empty and not concave. Due to the continuity of the Eq. (11), Eq. (10) can be expressed as

$$\Phi = \sum_{i \in \mathbb{I}} \sum_{x \in \mathbb{X}} \pi_i x_i a_i \left(\frac{1}{\sqrt{2\hat{\pi}}} e^{-\frac{\pi_i^2}{2}} \right) - \sum_{i \in \mathbb{I}} \sum_{x \in \mathbb{X}} \eta E_i^{EC} \tag{20}$$

$$\frac{\partial^2 \Phi}{\partial \pi_i^2} = \sum_{i \in \mathbb{I}} \sum_{x \in \mathbb{X}} \left[\left(\frac{1}{\sqrt{2\hat{\pi}}} e^{-\frac{\pi_i^2}{2}} \right) x_i a_i \pi_i \left(\pi_i^2 - 3 \right) \right] \tag{21}$$

Therefore, the concavity or convexity of Φ depends on $\left(\pi_i^2 - 3\right)$ with respecting to π_i.

$$\frac{\partial^2 \Phi}{\partial \pi_i^2} \begin{cases} < 0, & \pi_i \in \left(0, \sqrt{3}\right), \\ = 0, & \pi_i = \sqrt{3}, \\ > 0, & \pi \in \left(\sqrt{3}, +\infty\right). \end{cases} \tag{22}$$

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when $\pi_i \in \left(0, \sqrt{3}\right)$, the Φ is concave and the optimal price exists for the maximization of payoff. The existence of the Nash equilibrium is proved.

Theorem 2. *The uniqueness of the Nash equilibrium in the non-cooperative PG is reached.*

Let the first derivative of Eq. (20) be 0 for the response of PG. The price $\pi_i = \sqrt{3}, x_i \in [0, \bar{x}]$. Therefore, Theorem 2 is concluded and the proof process is provided.

B. Follower's game: Minimization of Utility in Energy Consumption and Latency

Given the price π of Stage 1, the offloading data size can be formulated as the cost minimization problem. Because $0 < r_i < \bar{x}$. The profit can be described and analyzed as follows.

Definition 3. *The offloaded data size $\mathbf{x}^* = (x_1^*, x_2^*, ..., x_N^*)$ is optimal satisfying $C_i(\pi^*, \mathbf{x}_i^*, t_i, E_i) \leq C_i(\pi^*, \mathbf{x}_i, t_i, E_i)$,* where

$$x_i^*(\pi) = r_i f_i, i \in \mathbb{I} \tag{23}$$

Proof: According to the optimal π, the best solution of the Problem 2 is

$$x_i^*(\pi) = \begin{cases} r_i, & \pi < \frac{1}{\psi_i}, \\ (0, r_i), & \pi = \frac{1}{\psi_i}, \\ 0, & otherwise. \end{cases} \tag{24}$$

The probability for case $\pi = \frac{1}{\psi_i}$ is 0, therefore, let $x_i = r_i$, the cost minimization at the edge side can be concluded as

$$\max_{x \geq 0} u_i(x) = x \sum_{i=i}^{I} r_i f_i \psi_i \tag{25}$$

Theorem 3. *Through the optimal price of the stage 1, the OP can obtain the profit optimization.*

Definition 4. *The offloaded data size vector $\boldsymbol{x}^* = (x_1^*, x_2^*, ..., x_N^*)$ is the Nash equilibrium of the cooperative game, if the two players satisfy $u_k(\pi^*, \boldsymbol{x}_k^*, t_i, E_i) \geq u_k(\pi^*, \boldsymbol{x}_k, t_i, E_i)$.*

Theorem 4. *Consider a multistage game with T stages. If $\sigma^{1*}, \sigma^{2*}, ..., \sigma^{T*}$ is a sequence of Nash equilibria strategy profile for the independent stage games, there exists a subgame perfect equilibrium in a multistage game where the equilibrium path coincides with the path generated by $\sigma^{1*}, \sigma^{2*}, ..., \sigma^{T*}$.*

VI. Performance Experiments and Analysis

In this section, we conduct numerical experiments to verify the effectiveness of the proposed model. The power gain is set as 600W from base station to MU, which is consistent with base station systems [20]. Local CPU frequencies of MU ψ are selected from $\{0.1, 0.3, 0.5, 0.7, 0.9\}$GHz, which is equal to $\{1, 3, 5, 7, 9\} \times 10^8$Hz. Local CPU cycles a_i^{MU} is set in $[1000, 2000]$ cycles/bit. Service rate of edge server a_j^{EC}, known as CPU cycles per bit, is 15000 cycles/bit [9]. Energy consumption per CPU cycle of MU σ_i^{MU} is $\frac{1}{480 \times 10^6}$ J/cycle [21]. The CPU frequency of edge server ξ_j is assumed to be 6×10^9 cycle/s. The total CPU cycles of computing for the sum of offloaded data $\bar{Q}$ is 8×10^9 cycle/s, and the cost of unit energy of the edge service η is 0.3. The other settings of the experiments are shown in Table I, which are in line with the parameter settings in [9], [10], [22].

Algorithm 1 Optimal Pricing Strategy for Game (OPG)

Input: Initialize iteration times n of MU i, $i = N$ and $\pi_i = 1/\psi_i$. CPU frequency ψ_i^n, CPU cycle price for an MU, $x_i^n = 1/\psi_i^n$, local execution latency and energy t^{MU}, E^{MU}, MEC execution latency and energy t^{EC}, E^{EC}.

Output: $C_i^{MU}(x_i, \pi_i) = \begin{cases} (\pi_i - \frac{1}{\psi_i}) x_i a_i + \frac{\bar{x}_i a_i}{\psi_i}, & 0 \leq x_i \leq r_i, \\ t_i^{EC} + \pi_i x_i a_i, & r_i < x_i \leq \bar{x}_i. \end{cases}$

1: $x_i^* \leftarrow r_i f_i$
2: According to the optimal price, the payoff of the corresponding operator can be obtained from $\Phi(\pi_i, \hat{\boldsymbol{\pi}}_{-i}, \mathbf{x}) = \sum_{i \in \mathbb{I}} \sum_{x \in \mathbb{X}} \pi_i x_i a_i \left(\frac{1}{\sqrt{2\hat{\pi}}} e^{-\frac{\pi_i^2}{2}} \right) - \sum_{i \in \mathbb{I}} \sum_{x \in \mathbb{X}} \eta E_i^{EC}$
3: **if** $\sum_{i=1}^{I} x_i^*(\pi_i^n) \psi_i \leq \bar{\psi}$ **then**
4: $\quad n \leftarrow n - 1$,
5: $\quad$ update the price $\pi_i^{n-1} = 1/\psi_i^{n-1}$;
6: **else**
7: $\quad \Phi(\pi^n) = 0$;
8: **end if**

TABLE I: Experimental settings

Parameters	Meaning	Values
$\bar{x}$	Total tasks	1Mbits=10^6 bits
H_{ij}	Channel gain of MU to edge server	-30 dBm
ω	Background of noise power	-180dBm/Hz
p^{up}	Uplink power	0.1W =20dBm
p^{dn}	Downlink power	1W=30dBm
p_j	The computation power of the MEC server	750W=58.75dBm
γ_{up}	Data rate of uploading	3Mbps=3×10^6 B/s
γ_{dn}	Data rate of downloading	1Mbps=10^6 B/s
W_{up}	The total channel bandwidth of uplink	10MHz
W_{dn}	The total channel bandwidth of downlink	10MHz
θ	Thermal noise power	-104dBm/HZ

The variations of offloading data size with different parameters in the continuous games are demonstrated in the results. Fig. 4 shows the latency comparisons of 5 MUs under different sizes of tasks $\left[5 \times 10^6, 3.5 \times 10^6, 2.5 \times 10^6, 1 \times 10^6, 0.7 \times 10^6\right]$ with different computing modes. Along with the decrease of tasks size, the latencies decline accordingly, and the proposed solution OPG spends the least time, which is caused by the energy restriction during the offloading. Fig. 5 displays the convergence time of 5 MUs with different task sizes under the proposed OPG. Experiments are executed five times for each task size, and the average convergence time reduce due to the decreases in task sizes.

Fig. 6 shows the revenues of OP corresponding to 5 MUs under different sizes of tasks. The MU 5 has the least data

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size in MUs, but it contributes the largest revenue share for OP in the MEC computation. MU 1 with the largest task size unexpectedly help the OP gain the second-last revenue in the rank. MU 3 contributes the least revenue to the OP with the third largest data size in the MUs. It is worth noting that the revenue trend shows the amount of earned revenue that is not just depending on the data size of MUs. The proposed OPG algorithm shows the merits in revenue maximization under the latency and energy conservation.

Fig. 7 compares the revenues produced by the JOOA algorithm [23], greedy algorithm, and the proposed OPG. The upward lines demonstrate that the earned revenues of OP rise along with the increase in task sizes. OPG gains the largest revenue for OP, showing its superiority than the other two existing algorithms. The revenue tending to smooth at the task size 2×10^6 is caused by the incentive mechanism of market and the cost (energy) restriction, which is benefit for OP to determine the services provision range in the competitive market.

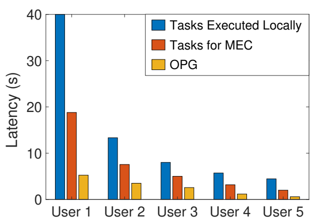

Fig. 4: Latency vs. MUs with different tasks.

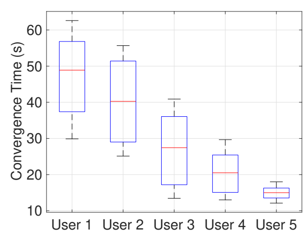

Fig. 5: Convergence time under OPG vs. MUs with different tasks.

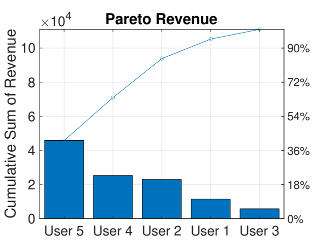

Fig. 6: Revenues of OP corresponding to MUs with different size of tasks.

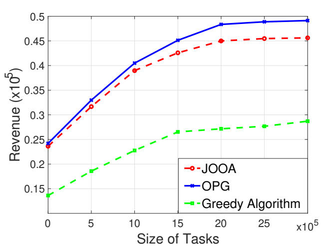

Fig. 7: Revenue performance under different algorithms.

VII. Conclusion

In this paper, we investigated revenue maximization for the offloading problem in MEC and proposed an OPG scheme which is based on the two-stage game model by integrating the pricing-offloading strategy. Latency reduction and energy conservation were formulated with the objective of revenue maximization for a network operator. The proposed model was proved, and the experiments were conducted to verify its correctness, effectiveness and superiority.

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