Decentralized Data Offloading for Mobile Cloud Computing Based on Game Theory

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***Abstract*—In this paper, we propose two data offloading mechanisms among multiple mobile users based on game theory. We formulate the decentralized data offloading decision making problem as two decentralized data offloading game. We then design two decentralized data offloading mechanisms that can achieve Nash equilibriums of the game: multi-item auction (MIA) based data offloading and congestion game (COG) based data offloading. MIA can maximize the revenue of mobile operator (MO), while COG can minimize the payment of mobile subscribers (MSs). Moreover, both MIA and COG can improve cellular data offloading performance. Numerical results show that the proposed mechanisms can achieve efficient data offloading performance.**

I. Introduction

As mobile devices (e.g., smartphones and tablets) are gaining enormous popularity, more and more mobile services are emerging and consuming large amounts of cellular network resources. The growing speed of mobile traffic will push the current cellular network to the limit [1]. The Quality of Experience (QoE) of mobile services will not be guaranteed without the high speed and stable network connections. Due to the corresponding expensive investment in cellular network, it is impractical to keep extending the current cellular network infrastructure to improve QoE [2]. The tension between data-intensive services and resource-constrained cellular network poses a significant challenge for mobile operator (MO). Mobile data offloading is considered as a promising approach to address such a challenge, which can offload mobile data (originally targeted to cellular network) to alternative wireless networks such as WiFi and device-to-device (D2D) networks.

Furthermore, with more computational capability, mobile devices in proximity can interconnect with each other to form mobile cloudlet, where mobile devices work as either computational service providers or service subscribers [3]. In mobile cloud computing, computation task in mobile device is offloaded to local cloudlet node when D2D connection is available or remote cloud when cellular (or WiFi) connection is available. After finishing the computation task in local cloudlet node or remote cloud, the computation result will be sent back to mobile device. The computation offloading process includes there parts: computation related data transmission, computation task execution and computation result feedback. Compared with cellular data offloading, mobile services involving computation offloading data usually are more delay-sensitive. Therefore, the combination of cellular data offloading and mobile cloud computing can augment the network and computation capabilities of mobile devices.

Although mobile data offloading can improve the network data rates of mobile devices, it is still challenging to implement a stable mobile data offloading system [4]. A key challenge is how to deal with network resource competition among multiple mobile devices. Network resource competition affects the performance of mobile data offloading. For example, if multiple mobile devices in proximity offload data to the same WiFi access point (AP) simultaneously, they may cause serve network congestion problem, which can reduce cellular data offloading ratio and increase data transmission time. In this situation, it is not practical to offload mobile data to WiFi AP. Thus, how to design a cost-effective data offloading mechanisms while satisfying the QoE requirement becomes an important problem to be solved in this work.

In this paper, we propose two data offloading mechanisms based on game theory to address such a problem. From the perspective of MO, who aims to maximize the revenue, we propose a multi-item auction (MIA) based data offloading approach. From the perspective of mobile subscriber (MS), who aims to minimize the payment, we propose a congestion game (COG) based data offloading approach.

The remainder of the paper is organized as follows. Section 2 discusses the related work. Section 3 presents the system model. We then propose the MIA based offloading mechanism and COG based offloading mechanism in Sections 4 and 5. The numerical results are provided in Section 6 and conclusion is given in Section 7.

II. Related work

Some previous work has investigated the mobile data offloading techniques under the setting of integrated WiFi and cellular networks. Lee et al. in [5] demonstrated by experiments that significant cellular traffic can be reduced by WiFi offloading. Cheung et al. in [6] proposed an optimal WiFi offloading scheme based on Markov decision process for a single-user decision scenario. Siris et al. in [7] presented

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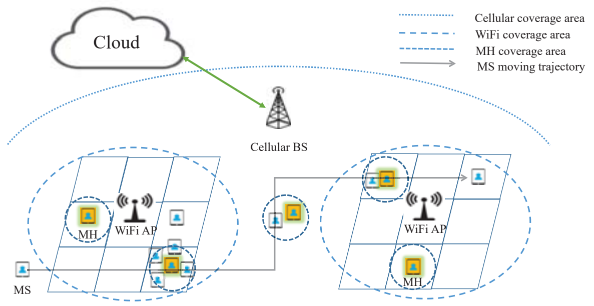

Fig. 1. An illustration of data offloading in Mobile Cloud Computing

procedures that exploit mobility prediction and prefetching to enhance offloading of traffic from mobile networks to WiFi APs. They proposed a prediction based decision making framework for determining when an offloaded data will outperform transferring by cellular network. Paris et al. in [8] formulated the cellular data offloading problem as a reverse auction by offloading partial traffic to third party access points and proposed greedy algorithms to solve the offloading problem.

Other previous work has addressed the data offloading problem among multiple mobile devices based on opportunistic D2D networks. The authors in [9] studied the scenario that multiple users can connect to the cellular and WiFi networks, and designed an iterative double auction mechanism that ensures the efficient operation of the market by maximizing the differences between the mobile network operators offloading benefits and WiFi offloading costs. The authors in [10] considered user mobility information and proposed a centralized offloading decision scheme to solve the data offloading problem with multiple mobile users. The authors in [11] proposed a centralized scheduling algorithm to jointly optimize the communication and computation resource allocations among multiple users with the latency requirements. The authors in [12] developed an adaptive offloading algorithm based on opportunistic communication among mobile devices, without requiring any data on the mobility patterns or the mobile nodes contact rates. In our work, we consider data offloading problems in integrated cellular, WiFi and D2D networks and propose decentralized offloading mechanisms to implement a cost-effective data offloading scheme while satisfying the QoE requirement of MS.

III. System Model

We consider the data transmission problem (i.e., cloud data delivery or computation data feedback) in mobile cloud computing, in which MO sends data from cloud side to mobile devices. Every mobile device can access multiple wireless networks, as shown in Fig. 1. Therefore, mobile device can receive partial data from complementary networks (i.e., WiFi and D2D networks) instead of cellular network, which can reduce the data transmission cost and cellular network congestion. We assume that MO can provide seamless cellular network to mobile devices, while WiFi and D2D networks provide fixed and portable coverage area, respectively. Thus, opportunistic WiFi or D2D network is available when mobile devices enter the corresponding coverage area, i.e., MS can access WiFi network in locations covered by WiFi APs; MS can access D2D network when MS and mobile helpers (MH) are in proximity. MH is considered as a cloudlet node who carry the data that MS needs. As illustrated in Fig. 1, MS can opportunistically receive the data from WiFi APs or MHs. If MS cannot receive all the data via opportunistic access before the delay tolerance, it will require the remaining data by cellular network. When multiple MSs assemble in same location, only part of MSs can use WiFi or D2D networks. The rest of MSs can choose delay or use the always-on cellular network.

The data rate for cellular network is $\nu_c = \theta W$, where θ is the expected channel spectral efficiency and W is the cellular bandwidth for each MS. Moreover, the price per unit size of data by cellular transmission is χ_c.

We divide WiFi coverage area into grids; the size of each grid can be equal to a MH coverage area, as shown in Fig. 1. The data rate for each grid depends on its distance to central WiFi AP. Thus, the grids within the coverage area of an WiFi AP have distinct WiFi transmission rates $\mu_i, i = 1, 2, ...L$; L denotes the number of grids for each WiFi AP. MSs in the same gird share the WiFi channel resource in a contention-based manner. Thus, the WiFi data rate of MS j in gird i is defined in Eq. (1).

$$\mu_i^j = \frac{\mu_i \rho \xi_i(n)}{n} \tag{1}$$

where ρ, n and $\xi_i(n)$ are WiFi network efficiency factor, the number of MSs in gird i that access WiFi AP simultaneously, and the WiFi network utilization function, respectively [13]. ρ denotes the protocol overhead for data transmission. $\xi_i(n)$ is a decreasing function with n, which denotes the impact of WiFi network contention on available data rates in terms of n. Additionally, the price per unit time for WiFi transmission is χ_w.

In D2D mobility model, we assume that all MSs are mobile and behaving in the same way. Furthermore, all mobile devices are reliable and functioning over time. Denote χ_d the price per unit time in D2D network. Denote the minimum connection time between two MSs is τ_{min}. It represents the average time for establishing a D2D connection.

We use a satisfaction function $J(t)$ to model different types of MS. $J(t)$ is a non-increasing function of time t. It represents the maximum price that MS is willing to pay for offloading data at time t. Each MS has his own satisfaction function. We assume that MS has an upper bound of delay tolerance, denoted as $\mathcal{D}$. If $t > \mathcal{D}$, then $J(t) = 0$. It represents that MS will not use data offloading service when current time exceeds the upper bound of delay tolerance. $J(t)$ is defined in Section VI.

Inspired by [13], we assume that base stations are in charge of the functions of MS discovery and D2D establishment. Moreover, we can install an intelligent offloading decision component in base stations. This component can exchange offloading information with MSs and assist MSs in making offloading decisions.

IV. Multi-Item Auction Based Offloading Decision Making

In this section, we propose a Multi-Item Auction (MIA) based data offloading mechanism, where MO auctions WiFi and D2D access opportunities to MSs in same gird. MIA mechanism is considered as an iterated ascending price auction which uses a monotonic price adjustment procedure that takes bids from bidders in each iteration [14]. The main idea of MIA mechanism is that MO can sell multiple wireless access opportunities (i.e., WiFi and D2D) to MSs periodically. It assumes that each MS can only use one wireless access opportunity at a time. New auction is performed every time slot T, called offloading interval. At the begin of each offloading interval, called decision epoch, MIA auction procedure is performed. MS first calculates the maximum WiFi and D2D prices that it can afford, called bidder's private value. Then MIA auction iteration is performed and MO will allocate wireless access opportunities to MSs who win the bid.

During each offloading interval T, MO will maximize the revenue from selling WiFi or D2D access opportunities in the auction, which can be expressed by the following auctioneer's winner determination problem,

$$\max \sum_{b\in\mathcal{B}} \chi_b T \alpha_b \tag{2}$$

s.t.

$$\sum_{b\in\mathcal{B}_i} \alpha_b \le \mathcal{R}_i,\ \alpha_b \in \{0,1\},\ i \in \{1,2\} \tag{3}$$

where $\mathcal{B}$ denotes MSs who can participate in the auction, called potential bidders. $\mathcal{B}_i$ is the set of MSs who bid specified wireless network (i.e., $\mathcal{B}_1$ is for WiFi network and $\mathcal{B}_2$ is for D2D network). $\mathcal{R}_i$ is the set of wireless resource items (i.e., $\mathcal{R}_1$ and $\mathcal{R}_2$ are the total items of WiFi and D2D resources, respectively). χ_b is the price offered by potential bidder b. α_b is a label for auction (i.e. $\alpha_b = 1$ means winning a bid while $\alpha_b = 0$ means losing a bid).

During T, the expected utility for MS i is defined as

$$U_i(g) = \mathcal{O}_T^g \chi_c - T\chi_g - J(t) \tag{4}$$

where $g \in \{w, d\}$ is the kind of wireless networks MS i bids for, i.e., $g = w$ denotes WiFi network and $g = d$ denotes D2D networks. $\mathcal{O}_T^g$ is the expected offloading data size during T by using network g.

Given χ_g, MS i bids to use WiFi or D2D if its utility is positive. From (4), we can calculate the bidder's private value by

$$\chi_{i,g}^{max} = \frac{\mathcal{O}_T^g \chi_c - T_d \chi_d - J(t)}{T} \tag{5}$$

Algorithm 1 Multi-item auction based offloading mechanism

1: **Initialization**: MO initializes the WiFi price clock $m = 0$ and the D2D price clock $n = 0$. Set WiFi initial price $\chi_w^m = 0$ and D2D initial price $\chi_d^n = 0$. Set WiFi and D2D price increasing step as $\rho_w > 0$ and $\rho_d > 0$, respectively.
2: **repeat**
3: MO announces χ_w^m and χ_d^n to MS $\in \mathcal{B}$.
4: Each MS compares auctioneer's value (χ_w^m and χ_d^n) with his own private value ($\chi_{i,w}^{max}$ and $\chi_{i,d}^{max}$). If and only if $\chi_{i,w}^{max} \ge \chi_w^m$, add MS into $\mathcal{B}_1$. If and only if $\chi_{i,d}^{max} \ge \chi_d^n$, add MS into $\mathcal{B}_2$. If both of the above conditions satisfy, compare $\chi_{i,w}^{max} - \chi_w^m$ with $\chi_{i,d}^{max} - \chi_d^n$, add MS to the set with higher difference value. Otherwise, remove MS from $\mathcal{B}$, $\mathcal{B}_1$ and $\mathcal{B}_2$.
5: Set $\chi_w^{m+1} = \chi_w^m + \rho_w$ and $m = m + 1$ if $|\mathcal{B}_1| > |\mathcal{R}_1|$.
6: Set $\chi_d^{n+1} = \chi_d^n + \rho_d$ and $n = n + 1$ if $|\mathcal{B}_2| > |\mathcal{R}_2|$.
7: **until** $|\mathcal{B}_1| == |\mathcal{R}_1|$ and $|\mathcal{B}_2| == |\mathcal{R}_2|$, auction ends.
8: MSs in $\mathcal{B}_1$ wins the bid for WiFi network and MSs in $\mathcal{B}_2$ wins the bid for D2D communication.
9: **return**

Algorithm 1 illustrates the ascending auction based MIA mechanism. WiFi and D2D resources are sold to MSs who pay the highest price. Step 4 guarantees that MS can only bid for one kind of networks each time; this is known as truthful bidding. It can maximize the total revenue in (2).

V. Congestion Game Based Offloading Decision Making

MIA mechanism can maximize the cellular data offloading performance and increase the utility of MO. However, from the perspective of MSs, the average utility for MS may be low since they pay very high WiFi or D2D access price due to the auction-based mechanism. In this section, based on a congestion game, we propose COG mechanism that can increase MSs utility.

Suppose MSs in $\mathcal{B}$ compete the WiFi and D2D resources in $\mathcal{R}$ and μ_b denote the data rate from $\mathcal{R}$ allocated to MS b. We assume that MS b receives a utility equal to $U_b(\mu_b)$ if the allocated data rate is μ_b. COG aims to maximize the total utility of all MSs instead of MO.

$$max \sum_{b\in\mathcal{B}} U_b(\mu_b) \tag{6}$$

s.t.

$$\sum_{b\in\mathcal{B}} \mu_b \le C \tag{7}$$

$$\mu_b \ge 0, \quad b \in \mathcal{B} \tag{8}$$

Given a price μ, MS b aims to maximize the following payoff function,

$$P_b(w_b;\mu) = U_b\left(\frac{w_b}{\mu}\right) - w_b \tag{9}$$

Algorithm 2 Congestion game based offloading mechanism

Initialization: MO initializes χ_c, χ_w and χ_d, and announces to all MSs.
If the number of MSs (or bidders) in a WiFi AP changes, MO inform all MSs that in the coverage area of WiFi AP and recalculate the data rate μ_i by Eq. (1). Then each MS calculates U_i by Eq. (12). If $U_i > 0$, MS i can use ω_w or ω_d network. Otherwise, MS makes a decision of using mode ω_c and ω_n.
if MS accesses WiFi AP **then**
  MO updates the number of MSs under the coverage are of WiFi AP. If the the number changes, MO announces the new number to all MSs within the coverage area.
  Each MS calculates its utility function using Eq. (12). If the utility function becomes positive, MS announces to MO to start using WiFi or D2D network. Otherwise, MS announces to MO to stop using WiFi or D2D network.
end if
return

where, w_b denotes the offloading decision, i.e., using WiFi network (ω_w), using D2D network (ω_d), using cellular network (ω_c) or delaying data transmission (ω_n).

$$\mu = \frac{\sum_b w_b}{C} \tag{10}$$

According to [15], if the utility function U_b is concave, strictly increasing, and continuously differentiable for $\forall b \in \mathcal{B}$. Then there exits a vector $\boldsymbol{w} = (w_1, ..., w_R) \geq 0$ and a scalar $\mu > 0$, such that:

$$P_r(w_r; \mu) = \max_{\overline{w}_b \geq 0} P_r(\overline{w}_b; \mu), \quad b \in \mathcal{B} \tag{11}$$

Thus, μ is unique, and the vector $\boldsymbol{d} = \boldsymbol{w}/\mu$ is the solution.

$$U_i^g(t) = \max\left[0, \mu^i(t)\chi_c - \chi_g - J_i(t)/T\right] \tag{12}$$

The procedure of COG Mechanism is described in Algorithm 2. If the utility function is positive, MS i uses mode ω_d or ω_w to transmit data through WiFi or D2D network, respectively; otherwise, MS i uses delaying mode ω_c or cellular mode ω_n to transmit data. Each time the number of bidders changes, MO will inform MSs to recalculate $U_i(t)$ using Eq. (12), and then makes offloading decision.

VI. Numerical Results

In this section, we evaluate the proposed decentralized data offloading mechanisms through numerical studies. We consider MSs are moving around in an geographical area which is divided into 100 (10×10) grids. MS can stay at the same gird or move to nearby girds (up, down, left, and right) at each decision epoch and the probabilities for choosing the next girds are the same (i.e., 0.2). The time interval that MS stays at each gird is $T = 10$ seconds. WiFi APs are randomly distributed in the discussed area with the coverage ratio 0.4. Each gird has an average WiFi data rate μ_i within the range of 10 Mbps and 40 Mbps [13]. The average D2D data rate ν_d is drawn from the range of 4 Mbps and 16 Mbps and the minimum connection time for D2D network is $\tau_{min} = 1$ seconds. For cellular network, the expected channel spectral efficiency θ is generated within the range of $[0, 8]$ and the cellular bandwidth is $W = 2$ MHz. Moreover, the price per unit size of data by cellular transmission is set to χ_c = \$1/Mb. The data size S is randomly chosen from 100 Mb to 400 Mb.

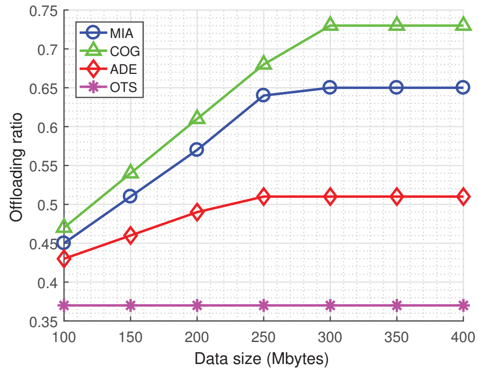

Fig. 2. Offloading ratio versus data size

The satisfaction function is defined as $J(t) = S\chi_c - \alpha t^\beta$, where α is the scale of $J(t)$ which determines the delay tolerance of mobile data. β denotes the shape of $J(t)$ which determines the delay sensitivity of MS, i.e., $\beta > 1$, $\beta = 1$ and $\beta < 1$ indicate that $J(t)$ is concave, linear and convex, respectively. α and β are drawn from the range of $[0.04, 0.08]$ and $[0.8, 1.2]$, respectively [16]. The satisfaction function can represent different types of MSs. The numerical results are averaged over 100 runs.

We compare the proposed offloading mechanisms with two existing offloading schemes, including always delayed offloading (ADE) scheme and on-the-spot offloading (OTS) scheme. In ADE, MS always delay data transmission in order to seek opportunities of using WiFi or D2D network; while in OTS, MS use cellular network whenever WiFi or D2D network is not available. In the evaluation, we use the following performance metrics:

- *Offloading ratio*. Percentage of mobile data that is offloaded to WiFi and D2D networks.
- *Completion time*. The average time that MS uses to receive the complete data from remote cloud.

The performance of proposed offloading mechanisms is shown in Figs. 2 and 3. Fig. 2 shows that for all of the offloading schemes (except for OTS), with the increase of data size, the mobile data offloading ratio increases accordingly, until reaching the data offloading bound. This is because when data size increases, more MSs use cellular network instead of WiFi network because of the possible WiFi network congestion. The number of MSs who use WiFi network will be stable. We observe that offloading ratio does not increase with data size in OTS. The reason behind this phenomenon is that OTS is a delay non-sensitive offloading scheme and

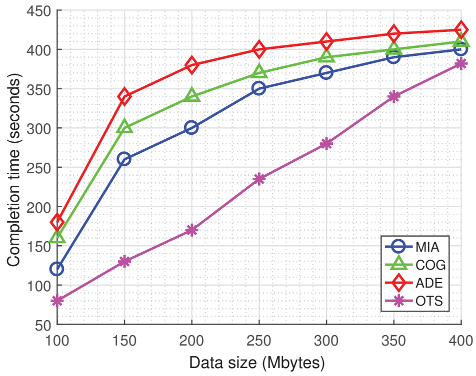

Fig. 3. Completion time versus data size

it cannot use delay tolerance to offload more data. Moreover, we observe that both MIA and COG mechanisms offload more cellular data to WiFi and D2D networks than ADE and OTS offloading schemes and COG outperforms other schemes. With the same size of data to be offloaded, MIA outperforms other schemes.

Fig. 3 shows that for all the offloading schemes, completion time increases with data size. We observe that OTS leads to the lowest completion time since it does not use delay tolerance, while ADE leads to the highest completion time since since it always delays mobile data until delay tolerance. Both MIA and COG mechanisms can achieve lower completion time than ADE. Furthermore, we observe that MIA uses less completion time than COG. This is because that only those MSs who win the auction can use WiFi and D2D networks, and the rest of MSs use cellular network.

VII. Conclusion

In this paper, we consider cellular data offloading problem among multiple mobile devices under the setting of mobile cloud computing and propose two cost-effective data offloading mechanisms based on game theory, namely multi-item auction based and congestion game based offloading mechanisms, for mobile users offload cellular traffic through WiFi and D2D networks while satisfying the QoE requirement. MIA can maximize the revenue of MO, while COG can minimize the payment of MSs. Numerical results shows that the proposed offloading mechanisms outperform existing offloading mechanisms in terms of data offloading ratio.

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