iCoMe: A Novel Incentivized Cooperative Mobile Resource Management Mechanism

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***Abstract*—In this paper, we present a novel cooperative resource management mechanism in mobile cloud computing environment. This mechanism is based on cooperation between mobile devices using their short range radio technology such as WiFi with the goal of maximizing the revenue of the cellular service provider. Users with poor cellular link quality connect with nearby devices through their WiFi interface. The service provider provides incentives to mobile devices to motivate them to contribute in such cooperative scheme. We first formulate the resource management problem as a mixed integer linear programming model. The optimal solution has an NP-hard complexity. To tackle the complexity of the problem, we then propose iCoMe, which is an Incentivized COoperative MobilE resource management mechanism. The resource management problem in iCoMe is solved distributively by the service provider and mobile devices. We prove that iCoMe has a polynomial time computational complexity. Simulation results confirm the close to optimal performance of iCoMe. Results also show that our proposed mechanism considerably increases the revenue of the service provider compared to non-cooperative schemes.**

I. INTRODUCTION

In recent years, as mobile data traffic is growing at an unprecedented rate, designing efficient data transmission mechanisms has received much attention. Today's mobile devices are equipped with multiple radio access technologies (RATs). It is forecasted that devices will use different RATs including WiFi, Long Term Evolution (LTE) Direct as well as cellular system technologies at the same time in the 5G era [1].

Mobile cloud computing techniques are developing to overcome the restriction in computing power of mobile devices which require ubiquitous and efficient access to the cloud servers [2], [3]. Resource management in mobile cloud computing in terms of both computing and communicating resources is essential to ensure the performance of mobile cloud computing environment.

There have been recent works which consider the efficiency of mobile cloud computing environment [4]–[7], among them [6] and [7] focus on resource management mechanisms. Kaewpuang *et al*. [6] present a cooperation framework between cloud service providers which creates a resource pool of computing servers to share their computing resources with each other. In addition, an energy efficient mechanism for transmission between mobile devices and cloud servers is presented in [7]. In this scheme, in order to minimize the energy required for downloading, each mobile device decides to connect to either cellular base station or WiFi access point of a third-party owner according to channel quality of its wireless interfaces.

It is shown that cooperative schemes in which the mobile devices connect with each other to transfer their traffic improve the performance of cellular systems and provide higher transmission rates for users [8]–[10]. The mobile devices cooperatively share their communication resources with devices in close proximity to form a shared pool of resources. The short range technologies are used for communication between nearby devices while they maintain connectivity to the cellular network. The benefits of creating such cooperative schemes have been presented in [8] in which the mobile devices connect with each other to share the digital media content. Fitzek *et al*. [9] propose a cooperative framework for broadcasting multimedia content from the cellular base station to mobile users. Mobile devices connect together using WiFi interface to exchange different pieces of digital content received from the base station.

Computing and communicating resource management plays an important role to ensure the performance of mobile cloud computing environment. Cooperative transmissions between mobile devices improve their access to the cloud computing servers and increase the revenue that service provider gains from transferring users' traffic. Nevertheless, most of the existing works in this area utilizing cooperation among mobile devices do not consider efficient resource management [8]–[10]. In this paper, we propose a novel Incentivized Cooperative MobilE resource management mechanism called iCoMe in which the mobile devices create a cooperative framework to transfer the traffic of their nearby devices. Some users may experience a poor cellular connection due to fading, shadowing, or obstacles. Such devices can download their data traffic through their WiFi interface by connecting with those nearby devices that contribute in the cooperative framework and share their resources. In this way, the cellular service provider can improve the network coverage and increase the service revenue without installing additional base stations or utilizing third party femtocell access points.

In order to encourage mobile devices to share their resources to improve the overall service quality or reduce the network cost, we design an incentive reward mechanism. The service provider pays mobile devices with certain monetary compensation for transferring traffic of other devices. The key contributions of our work are as follows:

- We formulate the resource management problem as a mixed integer linear programming (MILP) model to maximize the revenue of the service provider assuming that both cellular and WiFi interfaces of each device can be used at the same time. Different mobile applications of each user are efficiently distributed between its cellular and WiFi interfaces while each application can transfer its data through only one interface. The MILP problem has an NP-hard complexity.
- To reduce the computational complexity of the MILP problem, we propose iCoMe, which is a resource management mechanism. In this mechanism, the optimization problem is decomposed and solved distributively by the service provider and mobile devices. We further prove the polynomial time computational complexity of iCoMe.
- Simulation results confirm the performance of iCoMe in comparison with the results of the MILP problem and non-cooperative schemes.

The rest of this paper is organized as follows: In Section II, the system model is introduced. We also present the resource management scheme and formulate the optimization problem as an MILP problem. In Section III, we introduce iCoMe that considerably reduces the complexity of the MILP problem. A discussion on the complexity of iCoMe is also provided. Section IV validates the performance of our proposed mechanism by evaluating the revenue of the service provider. Conclusions and directions for future work are provided in Section V.

II. System Model and Problem Formulation

We consider a wireless system that includes a set $\mathcal{M} = \{1, \dots, M\}$ of mobile devices associated with a base station of the service provider. Each mobile device downloads data associated with its applications using its cellular interface or through its WiFi interface by connecting to other nearby users. The total number of mobile applications in each device which are communicating with the cloud server is at most P. Each application in mobile device $m \in \mathcal{M}$ requires d_p^m amount of bandwidth to download its data from the servers, where $p \in \mathcal{P} = \{1, \dots, P\}$. The total required bandwidth at device m is $d^m = \sum_{p \in \mathcal{P}} d_p^m$ and the set $\mathcal{D} = \{d^1, \dots, d^M\}$ denotes the traffic demand of the users. A basic assumption is that the data of each application will be communicated over a specific interface while different applications can be distributed over cellular and WiFi interfaces.

We define the set of maximum transmission rate between the base station and mobile devices in downlink direction as the number of data bits that can be supported in unit of time, denoted by $\{w^1, \dots, w^M\}$. This is the available bandwidth of cellular links between the base station and mobile devices which is measured by running the probe-based tests [11]–[13] and is known for the service provider at each time. The same assumption is used in [7], [14].

We first introduce the cooperative framework in this section. Then, we formulate the resource management mechanism as an MILP problem which aims to maximize the revenue of the service provider.

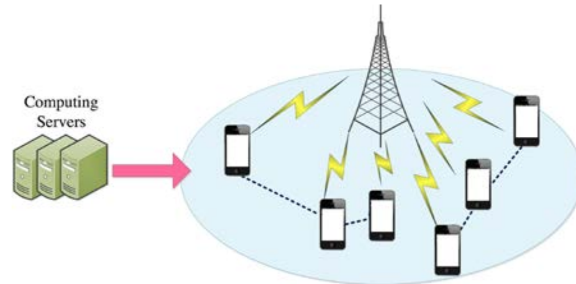

Fig. 1. The mobile devices cooperatively improve the service quality and the coverage of service provider. Different users experience different cellular link bandwidths. The dashed lines show the cooperation between mobile devices using their WiFi interface.

A. Cooperative Framework

Each mobile device can contribute in providing services for other devices. In other words, each mobile device can share its cellular link with those devices which experience poor channel quality in their cellular links. As illustrated in Fig. 1, mobile devices, which are distributed in the coverage area of the base station, may experience different channel qualities. They also form a cooperative framework in which the mobile devices locally connect with each other using their WiFi interface. We assume that the decision for sharing the resources in the cooperative framework is made locally in each device according to its internal resources such as battery power or CPU usage, while the cooperation framework and resource allocation mechanism are controlled by the service provider[1].

The service provider encourages users to participate in the cooperative framework and pays mobile devices with certain monetary compensation according to their contribution. Each device will be rewarded by ry if it shares y amount of its cellular bandwidth with other devices, where r is a constant. Those devices interested in participating in the cooperative framework register at the service provider.

Each device can share its available cellular bandwidth with other nearby devices according to its demand and available resources. Therefore, a mobile device that has registered to participate in the cooperative framework shares its available bandwidth $(w^m - d^m)$ with other devices if $w^m > d^m$. The set of these contributing devices is denoted by $\mathcal{H} \subset \mathcal{M}$ whose WiFi interfaces operate in the access point mode. Let $\mathcal{C} = \{m \in \mathcal{M} \mid d^m > w^m\}$ denote the set of users which have a poor link quality due to fading, shadowing, or obstacles.

After collecting the required information, the service provider determines how each user $c \in \mathcal{C}$ downloads its traffic via its cellular or WiFi interface by connecting to a user $h \in \mathcal{H}$. Therefore, all possible links for mobile devices to download their data are their own cellular interface and the WiFi link of devices $h \in \mathcal{H}$. We define the set $\mathcal{I}^c = \mathcal{H} \cup \{c\}$ for each device $c \in \mathcal{C}$. Among this set, c can use the WiFi interface of device h only if $c \in \mathcal{N}_h$, where $\mathcal{N}_h$ denotes the set of neighbouring devices of h.

[1]Note that the decision in mobile devices for sharing their resources is beyond the scope of this paper. The focus of this work is on designing a mechanism for the service provider to manage the available resources of those devices which are interested in the cooperation framework.

B. Resource Management

The service provider allocates the resources with the goal of maximizing its revenue. The resource allocation mechanism is formulated as an MILP problem. Let $x_{i,p}^c$ denote the amount of bandwidth reserved in the cellular link of device $i \in \mathcal{I}^c$ for the application p of device $c \in \mathcal{C}$ to download its data. Note that $x_{i,p}^c$ is the bandwidth allocated to the application p of device c over its own cellular link when $i \in \{c\}$ while $x_{i,p}^c$ is the amount of bandwidth reserved over the cellular link of device i for the application p of device c when $i \in \mathcal{I}^c \setminus \{c\}$. In this case, device c connects with $i \in \mathcal{I}^c \setminus \{c\}$ using WiFi interface and downloads its data through the cellular link of device i. In addition, let $\alpha_{i,p}^c \in \{0,1\}$ indicate that if the device $i \in \mathcal{I}^c$ is used for the application p of device $c \in \mathcal{C}$. It should be mentioned that $x_{i,p}^c = 0$ when $\alpha_{i,p}^c = 0$. The service provider determines the pair $(x_{i,p}^c, \alpha_{i,p}^c)$ for the application $p \in \mathcal{P}$ of device c. The resource allocation hyper matrix can be written as $\mathbf{X} = (x_{i,p}^c)_{c\in\mathcal{C},\, i\in\mathcal{I}^c,\, p\in\mathcal{P}}$, and the hyper matrix $\mathbf{A} = (\alpha_{i,p}^c)_{c\in\mathcal{C},\, i\in\mathcal{I}^c,\, p\in\mathcal{P}}$ determines the allocation strategy.

The objective of the problem is to maximize the revenue of the service provider, which is proportional to the total bandwidth used by mobile devices.

$$\mathcal{V}(\mathbf{X},\mathbf{A}) = v \sum_{j\in\mathcal{M}\setminus\mathcal{C}} d^j + v \sum_{c\in\mathcal{C}} \sum_{i\in\mathcal{I}^c} \sum_{p\in\mathcal{P}} x_{i,p}^c \alpha_{i,p}^c - \sum_{h\in\mathcal{H}} r \sum_{j\in\mathcal{N}_h} \sum_{p\in\mathcal{P}} x_{h,p}^j \alpha_{h,p}^j, \tag{1}$$

where v is the cost of using a unit of bandwidth by a device in a unit of time. The first two terms in (1) represent the total cost that mobile devices pay the service provider for using the cellular bandwidth and the third term is the total reward that service provider pays the contributing devices. Note that the first term considers the total traffic of users $j \in \mathcal{M} \setminus \mathcal{C}$, which is downloaded through their cellular interface and has a constant value.

According to the definition of $x_{i,p}^c$ and $\alpha_{i,p}^c$ and considering the traffic demand of each application, we have:

$$0 \le x_{i,p}^c \le d_p^c \alpha_{i,p}^c, \quad \forall c \in \mathcal{C}, i \in \mathcal{I}^c, p \in \mathcal{P}. \tag{2}$$

Each application should use one interface at most to download its data while different applications can be distributed over WiFi or cellular interfaces. This requires that

$$\sum_{i\in\mathcal{I}^c} \alpha_{i,p}^c \le 1, \qquad \forall c \in \mathcal{C}, p \in \mathcal{P}. \tag{3}$$

In addition, each mobile device $c \in \mathcal{C}$ can connect with only one device $h \in \mathcal{H}$ using WiFi interface. Constraint (3) along with the following constraint satisfies such condition.

$$\alpha_{i,p}^c = \alpha_{i,q}^c, \quad \forall c \in \mathcal{C}, i \in \mathcal{H}, p, q \in \mathcal{P}. \tag{4}$$

The total link rate of each device $h \in \mathcal{H}$ that can be shared with other devices in its neighbouring region ($\mathcal{N}_h$) should be less than its available cellular bandwidth while the total traffic carried over the cellular link of each device $c \in \mathcal{C}$ should be less than its cellular bandwidth. These constraints require that,

$$\sum_{j\in\mathcal{N}_h} \sum_{p\in\mathcal{P}} x_{h,p}^j \le w^h - d^h, \quad \forall h \in \mathcal{H}, \tag{5}$$

$$\sum_{p\in\mathcal{P}} x_{c,p}^c \le w^c, \qquad \forall c \in \mathcal{C}. \tag{6}$$

In (5) and (6), we use the constraint $x_{i,p}^c \le d_p^c \alpha_{i,p}^c$ implicitly. Note that for a device $h \in \mathcal{H}$, it is assumed that its data traffic will be downloaded through its own cellular link. Due to the uncertainty of communication channels, w^m changes randomly over time. We consider a quasi-static network scenario, where w^m remains unchanged within every resource allocation period. The total WiFi link capacity of device h is shared between mobile devices $j \in \mathcal{N}_h$ based on a random access method. Therefore,

$$\sum_{j\in\mathcal{N}_h} \sum_{p\in\mathcal{P}} x_{h,p}^j \le C^{\mathrm{W}}, \quad \forall h \in \mathcal{H}, \tag{7}$$

where C^{W} is the maximum link rate of WiFi interfaces. Since its variation is less than the cellular link rate, we assume a constant value for C^{W}. The optimization problem is presented as follows in which the objective function is obtained from (1) by considering the constraint (2) and eliminating the constant term:

$$\begin{aligned} \underset{\mathbf{X},\mathbf{A}}{\text{maximize}} \;& v \sum_{c\in\mathcal{C}} \sum_{i\in\mathcal{I}^c} \sum_{p\in\mathcal{P}} x_{i,p}^c - \sum_{h\in\mathcal{H}} r \sum_{j\in\mathcal{N}_h} \sum_{p\in\mathcal{P}} x_{h,p}^j \\ \text{subject to } \;& \alpha_{i,p}^c \in \{0,1\}, \quad \forall c \in \mathcal{C}, i \in \mathcal{I}^c, p \in \mathcal{P}, \\ & \text{constraints } (2)-(7). \end{aligned} \tag{8}$$

The optimal solution of problem (8) can be obtained by methods such as branch and bound algorithm [15]. The optimal solutions are denoted by $\mathbf{X}^*$ and $\mathbf{A}^*$, which result in $\mathcal{V}^* = \mathcal{V}(\mathbf{X}^*, \mathbf{A}^*)$ as the revenue of the service provider. Problem (8) is an MILP problem, which has an NP-complete complexity. Considering the size of the problem $(2P|\mathcal{C}|(|\mathcal{H}|+1))$, it is time consuming to obtain the optimal solution of (8). To tackle the complexity of this problem, we propose iCoMe, which is a resource management mechanism with polynomial computational complexity.

III. iCoMe: Incentivized Cooperative Mobile Resource Management Mechanism

In this section, we present iCoMe, which reduces the computational complexity of the MILP problem (8). In iCoMe, we first decompose problem (8) into $|\mathcal{C}|+1$ problems which are distributively solved by the service provider and mobile devices. We then propose a heuristic algorithm based on greedy algorithm. The proposed algorithm considerably reduces the complexity of the approach while we further show that it generates almost the same revenue for the service provider as what we expect from the resource management mechanism formulated in problem (8).

The service provider solves the resource management problem assuming that each user $m \in \mathcal{M}$ is running only one application requiring d^m amount of bandwidth whose data traffic can be distributed over cellular and WiFi interfaces. The management of different applications and distributing them between cellular and WiFi interfaces are assigned to users.

A. Service Provider Side

To formulate the resource management mechanism on the service provider side, let y_i^c denote the amount of cellular bandwidth of the link i which is allocated to the device c and $\mathbf{Y} = (y_i^c)_{c\in\mathcal{C},\, i\in\mathcal{I}^c}$. In addition, we define $\Gamma = (\gamma_i^c)_{c\in\mathcal{C},\, i\in\mathcal{I}^c}$ as resource allocation strategy where $y_i^c = 0$ when $\gamma_i^c = 0$. Thus,

$$0 \le y_i^c \le d^c \gamma_i^c, \quad \forall c \in \mathcal{C}, i \in \mathcal{I}^c. \tag{9}$$

In equivalent to (3)-(4), the following constraint ensures that each device connects to only one neighbour device.

$$\sum_{h\in\mathcal{H}} \gamma_h^c \le 1, \quad \forall c \in \mathcal{C}. \tag{10}$$

In addition, constraints (11)-(13) are required instead of (5)-(7) to restrict the total traffic carried over cellular interface of $h \in \mathcal{H}$, cellular interface of $c \in \mathcal{C}$, and WiFi interface of $h \in \mathcal{H}$, respectively.

$$\sum_{j\in\mathcal{N}_h} y_h^j \le w^h - d^h, \quad \forall h \in \mathcal{H}, \tag{11}$$

$$y_c^c \le w^c, \qquad \forall c \in \mathcal{C}, \tag{12}$$

$$\sum_{j\in\mathcal{N}_h} y_h^j \le C^W, \qquad \forall h \in \mathcal{H}. \tag{13}$$

Therefore, the optimization problem on the service provider side can be summarized as follows:

$$\begin{aligned} &\underset{\mathbf{Y},\Gamma}{\text{maximize}}\ v \sum_{c\in\mathcal{C}} \sum_{i\in\mathcal{I}^c} y_i^c - \sum_{h\in\mathcal{H}} r \sum_{j\in\mathcal{N}_h} y_h^j \\ &\text{subject to } \gamma_i^c \in \{0,1\}, \quad \forall c \in \mathcal{C}, i \in \mathcal{I}^c, \\ &\qquad\qquad \text{constraints } (9)-(13), \end{aligned} \tag{14}$$

in which only $d^c = \sum_{p\in\mathcal{P}} d_p^c$ appears. The optimal solution of problem (14) is denoted by resource allocation matrices $\mathbf{Y}^*$ and Γ^*. It should be mentioned that although the number of variables has been reduced P times, it is still an NP-hard problem. We further propose a sub-optimal algorithm which significantly reduces the complexity of problem (14). Our approach is illustrated in Algorithm 1.

For the sake of notation tractability, we denote the output results of Algorithm 1 by $\tilde{\mathbf{Y}}^*$ and $\tilde{\Gamma}^*$ as resource allocation matrices. According to this algorithm, the available bandwidth of each user $c \in \mathcal{C}$ will be allocated to its own traffic and $\tilde{y}_c^{c*}$ will be initialized by $\min\{w^c, d^c\}$. The device with the maximum available bandwidth will be chosen to offload the traffic of its nearby devices at each iteration (Step 7). The set Λ denotes the available cellular bandwidth at each iteration of the algorithm. Among the nearby devices of the candidate device, its available bandwidth will be allocated to the device with maximum traffic demand in Step 9. This device will be removed from the devices' list $\mathcal{D}$ (Step 12) and the available cellular capacity of the candidate device will be updated in Step 13. At each iteration, the resource allocation algorithm

Algorithm 1 Resource allocation in the service provider side

1: input: *Available bandwidth*: $\Lambda := \{\lambda^h = w^h - d^h,\, h \in \mathcal{H}\}$
2: input: *Users' demand*: $\mathcal{D} := \{d^c,\, c \in \mathcal{C}\}$
3: initialize: $\tilde{y}_c^{c*} := \min\{d^c, w^c\}, \quad \forall c \in \mathcal{C}$
4: initialize: $\tilde{\gamma}_c^{c*} := 1$ if $\tilde{y}_c^{c*} > 0, \quad \forall c \in \mathcal{C}$
5: initialize: $d^c := d^c - \tilde{y}_c^{c*}, \quad \forall c \in \mathcal{C}$
6: **while** $\{(c,h) \in \mathcal{C}\times\mathcal{H} \mid c \in \mathcal{N}_h, d^c > 0, \lambda^h > 0\} \neq \emptyset$
7: $\quad j := \arg\max_{\mathcal{H}} \Lambda$
8: $\quad k := \arg\max_{\mathcal{N}_j \subset \mathcal{C}} \mathcal{D}$
9: $\quad \tilde{y}_j^{k*} := \min\{\lambda^j, d^k - w^k, C^W - \sum_{q\in\mathcal{N}_j} \tilde{y}_j^{q*} \tilde{\gamma}_j^{q*}\}$
10: $\quad$ **if** $\tilde{y}_j^{k*} > 0$
11: $\qquad \tilde{\gamma}_j^{k*} := 1$
12: $\qquad$ Update $\mathcal{D}$: $d^k := 0$
13: $\qquad$ Update Λ: $\lambda^j := \lambda^j - \tilde{y}_j^{k*}$
14: $\quad$ **end if**
15: **end while**
16: output: *Resource allocation matrices*: $\tilde{\mathbf{Y}}^*, \tilde{\Gamma}^*$

should satisfy the WiFi links capacity constraint (Step 9). The algorithm will be terminated when there is no available resources in the nearby devices of $c \in \mathcal{C}$ to download its applications through them. The outputs of this algorithm are the resource allocation and strategy matrices.

B. Users Side

On the users side, we use the results of Algorithm 1 to formulate another optimization problem. The goal of this problem is to maximize the traffic downloaded for different mobile applications via its cellular and WiFi interfaces assuming that each application can only use one interface for data downloading. Each application can download its data from either cellular or WiFi according to the results of Algorithm 1. Each user aims to maximize the total data traffic downloaded by its application which is equal to $\sum_{p\in\mathcal{P}} \sum_{i\in\mathcal{I}^c} x_{i,p}^c$. In addition to (2), the following constraint is required.

$$0 \le x_{i,p}^c \le \tilde{y}_i^{c*} \quad \forall p \in \mathcal{P}, i \in \mathcal{I}^c. \tag{15}$$

Note that according to Algorithm 1, $\tilde{y}_i^{c*} > 0$ for $i = c$ and only one $i \in \mathcal{H}$. Each application can download its data through at most one interface. Therefore,

$$\sum_{i\in\mathcal{I}^c} \alpha_{i,p}^c \le \sum_{i\in\mathcal{I}^c} \tilde{\gamma}_i^{c*}, \quad \forall p \in \mathcal{P}. \tag{16}$$

It should be mentioned that we always have $\sum_{i\in\mathcal{I}^c} \tilde{\gamma}_i^{c*} \le 1$.

The following constraints are required to restrict the total bandwidth of cellular and WiFi interfaces to the values obtained from Algorithm 1.

$$\sum_{p\in\mathcal{P}} x_{c,p}^c \le \tilde{y}_c^{c*}, \tag{17}$$

$$\sum_{p\in\mathcal{P}} \sum_{h\in\mathcal{H}} x_{h,p}^c \le \sum_{h\in\mathcal{H}} \tilde{y}_h^{c*}. \tag{18}$$

Note that the terms in the right hand side of (17)-(18) are constants obtained from Algorithm 1 and we have $\tilde{y}_h^{c*} > 0$ at most for one $h \in \mathcal{H}$. The optimization problem for user $c \in \mathcal{C}$ is formulated as follows for $\mathbf{X}^c = (x_{i,p}^c)_{i\in\mathcal{I}^c,\, p\in\mathcal{P}}$ and $\mathbf{A}^c = (\alpha_{i,p}^c)_{i\in\mathcal{I}^c,\, p\in\mathcal{P}}$

$$\begin{aligned} &\underset{\mathbf{X}^c, \mathbf{A}^c}{\text{maximize}} \sum_{p \in \mathcal{P}} \sum_{i \in \mathcal{I}^c} x_{i,p}^c \\ &\text{subject to } \alpha_{i,p}^c \in \{0,1\}, \quad \forall p \in \mathcal{P}, i \in \mathcal{I}^c, \\ &\qquad\qquad \text{constraints } (2), (15)-(18). \end{aligned} \tag{19}$$

The solution of problem (19) for each device c is denoted by $(\mathbf{X}^{c*}, \mathbf{A}^{c*})$. Problem (19) is still an integer linear programming problem. However, its complexity is much less than Algorithm 1 because we have $|\mathcal{C}|$ optimization problems of size $2P$ running over different mobile devices. By substituting the results of problem (19) in (1), the revenue of the service provider generated by iCoMe will be obtained. It should be noted that since our main focus is on maximizing the revenue of the service provider and wireless resource management, considering priority and fairness in serving different applications in mobile devices is beyond the scope of this work.

C. Computational Complexity

The following theorem discusses the computation complexity of iCoMe and shows that it has a polynomial time complexity. It is worth mentioning that the complexity of problem (19) is much less than Algorithm 1 and we only consider the complexity of Algorithm 1, which is running in the service provider.

Theorem 1: The computational complexity of Algorithm 1 is $O(M^2)$.

Proof: During each iteration of Algorithm 1, we search for the maximum value over vectors Λ and $\mathcal{D}$ with computing complexity of $|\mathcal{H}| < M$ and $|\mathcal{C}| < M$ at most, respectively. The algorithm terminates after allocating the resources for all device $c \in \mathcal{C}$. Therefore, the running time of the algorithm is less than $O(M^2)$. ■

IV. Performance Evaluation

In this section, we conduct simulations to evaluate the performance of our proposed mechanism in comparison with the non-cooperative scheme. Furthermore, comparisons between the optimal resource management framework and iCoMe confirm the performance of our proposed mechanism.

We consider a wireless system as shown in Fig. 1. We assume that mobile devices are distributed in an area of radius 1 km associated with a base station and their available cellular bandwidth is taken from the scenario set 100 Mbps×{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9} with the corresponding probability distribution {0.2, 0.2, 0.2, 0.1, 0.1, 0.05, 0.05, 0.05, 0.03, 0.02}. The maximum data rate of WiFi links is assumed to be 150 Mbps according to IEEE 802.11n standard [16] while their approximate outdoor range is about 250 m. We adopt a model similar to the one used in [7] for the data traffic generation. We consider $P = 10$ applications running in the cloud servers whose data arrivals are according to a Poisson process with average rate of 2 packets/sec where the size of each packet is 100 KB. We assume that the cost of using 1 Mbps of bandwidth in a unit of time is 1 monetary unit (MU) for mobile devices ($v = 1$). In addition, the reward that each device receives by sharing 1 Mbps of its bandwidth in a unit of time is 0.3 MU ($r = 0.3$) .

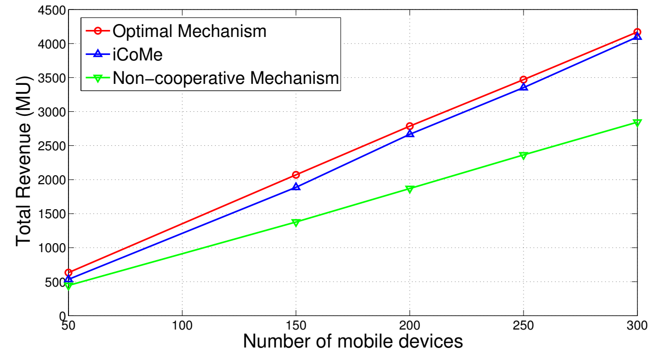

Fig. 2. The total revenue that the service provider gains in a unit of time. The performance of iCoMe is compared with the optimal resource management mechanism and the non-cooperative scheme.

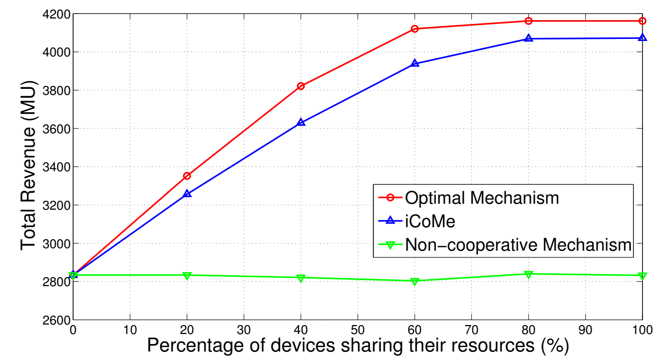

Fig. 3. The total revenue in a unit of time for different percentage of users contributing in the cooperative framework. Motivating more devices increases the total revenue that the service provider can gain. ($M = 300$)

We first evaluate the performance of our mechanism by considering the total revenue that service provider gains in a unit of time for different number of mobile devices (M) associated with the base station assuming that all devices are interested in the cooperative framework. We compare the performance of iCoMe with the optimal resource management mechanism presented in Section II and with the non-cooperative scheme. It should be mentioned that in the non-cooperative scheme, each device uses only its own cellular interface to download its data and the total traffic of each user $m \in \mathcal{M}$ downloaded in a unit of time is $\min\{d^m, w^m\}$. According to Fig. 2, the service provider gains more revenue by using iCoMe in comparison with the non-cooperative scheme especially for the dense areas. For example, iCoMe increases the total revenue by 10% in the case of $M = 50$ while the revenue increment is approximately 46% when $M = 300$.

Fig. 3 shows the revenue that service provider gains for different percentage of mobile devices which are contributing to the cooperative framework when 300 mobile devices are distributed in the coverage area of the base station. The total revenue will be increased by 40% approximately in comparison with the non-cooperative scheme when all users are interested in the cooperative framework. Furthermore, the revenue of the service provider will be increased by motivating more devices to share their resources.

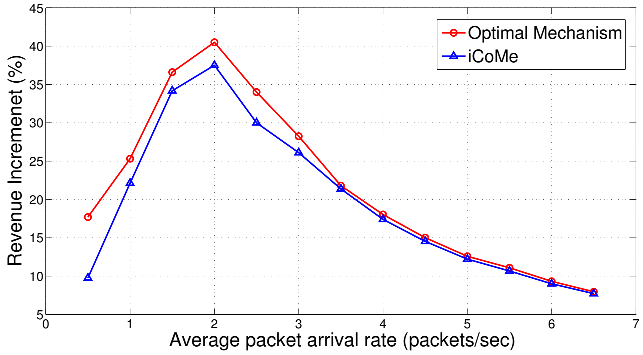

Fig. 4. The percentage of revenue increment for different packet arrival rates to evaluate the performance of iCoMe in low load and high load traffic conditions. ($M = 300$)

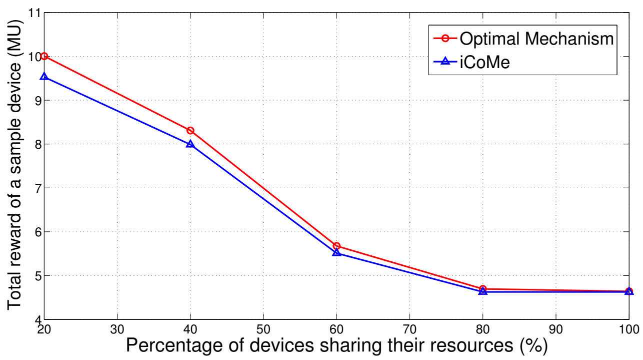

Fig. 5. The total reward that a mobile device obtains by sharing its available resources for different percentage of users contributing in the cooperative framework. ($M = 300$)

In order to determine the performance of our mechanism for different data traffic conditions, Fig. 4 illustrates the percentage of revenue increment. It is assumed that $M = 300$ and 50% of devices are interested in contributing to the cooperative framework and the average data arrival rate changes from 0.5 to 6.5 packets/sec. In low load conditions, a few number of devices needs to use the other devices' resources while in high load cases, a few number of mobile devices can share their available resources with other devices. Therefore, in such conditions, the increase in the revenue generated by our mechanism is less than other cases.

Fig. 5 shows the reward that a mobile device obtains by sharing its available bandwidth. We select a mobile device $h \in \mathcal{H}$ randomly and evaluate the obtained reward for the different percentage of mobile devices sharing their resources. The reward of each mobile device will be decreased when more devices are contributing to the cooperative framework while the total revenue of the service provider will be increased in such cases.

In addition, it can be concluded from the obtained results that iCoMe is almost as good as optimal resource management mechanism in terms of generated revenue. Such conclusion can be drawn from the comparison of the iCoMe performance and the optimal solution. Therefore, the performance of our proposed mechanism with acceptable polynomial time computational complexity is close to the optimal solution.

V. Conclusion

In this paper, we proposed iCoMe, a cooperative mobile resource management mechanism which creates ubiquitous access to the service provider for mobile users with the goal of maximizing the revenue of the service provider. In iCoMe, mobile devices share their cellular resources with each other and form a cooperative framework using local connections. With polynomial time computational complexity, iCoMe performs close to the optimal resource management mechanism. Simulation results validated the performance of iCoMe by comparing the revenue generated by iCoMe with the non-cooperative schemes. As a future direction, we will introduce a game theoretic framework for sharing revenue between mobile users to maximize social welfare and motivate users to share their resources. It is also interesting to consider the uncertainty of links bandwidth with robust optimization techniques which will be considered in future works.

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