Enabling Crowd-Sourced Mobile Internet Access

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***Abstract*—Crowd-sourced mobile Internet access services enable mobile users to connect with each other and share their Internet connections. This is a promising solution for addressing users' increasing needs for ubiquitous connectivity and alleviating network congestion. The success of such services heavily depends on users' willingness to contribute their resources. In this paper, we consider a general model for such services, and design a distributed incentive mechanism for encouraging users' participation. This bargaining based scheme ensures that the contribution of user resources, in terms of Internet access bandwidths and battery energy, and the allocation of service capacity, measured in the delivered mobile data, are Pareto efficient and proportionally fair. The numerical results verify that the service always improves users' performance and that these benefits depend on the diversity of the users' resources.**

I. Introduction

Motivation. As the global mobile data traffic increases rapidly [1] and the cellular networks get congested much more frequently [2], it is important to design more flexible and innovative mechanisms to offer ubiquitous Internet connectivity to users by fully utilizing the resources of heterogeneous networks. In this context, user provided connectivity (UPC) services [3] offer a low cost solution for alleviating network congestion and satisfying users' communication needs. One of the first UPC services was FON [4], a community-based WiFi Internet access scheme, where roaming FON users can access Internet through the home WiFi connections of other nearby FON users. Several novel UPC schemes that leverage the capabilities of user-owned equipment to operate as mobile hotspots have also emerged recently, such as the ones by Karma [5] and Open Garden [6].

The award winning Open Garden solution[1] enables mobile devices to connect through Bluetooth or WiFi direct links in order to share their Internet connections. More specifically, the Open Garden mobile software creates a mesh network, where each user (device) may act as a *client* node (consuming data), a *relay* node (relaying data to other nodes), or a *gateway* node (connecting the mesh overlay with the Internet through a WiFi or a cellular connection). An example of the Open Garden operation is depicted in Fig. 1. Each user can concurrently consume data from multiple gateways (*channel bonding* [6]), over multiple and possibly multi-hop paths, and serve as a relay or even a gateway for others. The software identifies the best Internet connections, with the goal to increase the amount of data the participating users can consume.

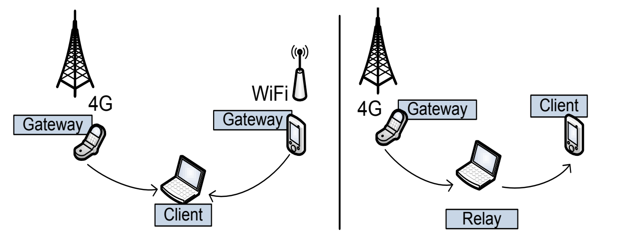

Fig. 1. An example of users interactions in the crowd-sourced mobile Internet access service. Left: concurrent downloading from two gateways. Right: multi-hop connection to Internet.

In a nutshell, Open Garden constitutes a *crowd-sourced Internet access* service, where users contribute resources in terms of Internet connections and battery energy. The key benefit is to turn the negative externality of network congestion to the positive network effect, by exploiting the diversity of connections and demands of different users. *However, the success of this service depends on the willingness of users to join the service and contribute their resources*. Clearly, a user with a low battery energy level and a fast Internet connection, may not be willing to participate and serve other users. Therefore, it is of paramount importance to design a proper *incentive mechanism* for inducing user participations, a mechanism that is currently missing from Open Garden.

Motivated by the Open Garden software, in this paper we propose a general model for the crowd-sourced mobile Internet access service, and design an incentive mechanism to guarantee its successful operation. Such an incentive scheme not only encourages mobile users to collaborate, but also leads to a proper data transmission and routing policy that balances efficiency and fairness. The efficiency is quantified in terms of the aggregate throughput, and can be maximized by having users with the highest Internet connection capacities serve as gateways, with other users serving as relays if necessary. The fairness criterion, on the other hand, concerns the relationship among data delivery, resource contribution, and economic gains/losses of each user. If a user experiences excessive unfair consumption of her resources by others, she will probably leave the service and hence deteriorate the performance experienced by other users.

Nevertheless, the design of this mechanism is very challenging. First of all, there is often no central entity controlling

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[1] On May 2012, Open Garden won the Most Innovative Startup Award at the TechCrunch Disrupt Conference.

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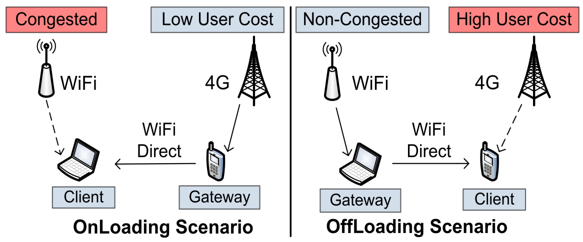

Fig. 2. The service can be used to *offload* cellular traffic to WiFi access points (AP), or *onload* WiFi traffic to cellular networks (downloading scenario). The offloading decisions depend mainly on the data usage (and energy) cost incurred by the users (user-initiated offloading), while the onloading decisions depend on the congestion of WiFi APs.

such a wireless mesh network with devices belonging to heterogeneous physical networks, and each user only has information regarding her own needs and resources. Therefore, the proposed scheme has to be distributed. Moreover, the fairness criterion should be carefully selected, so as to consider the fact that users have different needs and may contribute different resources with different costs. Also, a user will participate in the service, only if she expects to improve her performance compared to the one when acting independently (in *standalone* mode). Clearly, the incentive mechanism should also take into account this standalone performance.

Contributions. We introduce a new analytical framework for the UPC service, which is modeled as a multi-hop, multi-path mesh network that manages multiple unicast sessions from the Internet towards different users. Each user is parameterized by her Internet connection capacity, energy resources (e.g., battery level), monetary cost for downloading data (depending on the user's *data plan*), and her relaying capabilities. Users may have different communication needs, which are captured by different utility functions.

We employ game theory and specifically the Nash bargaining solution (NBS) concept [7] to characterize the efficient and fair contribution of the user resources and allocation of the service capacity to each user. The NBS yields an outcome which is Pareto efficient and proportionally fair [8], and is self-enforcing and acceptable by all users. Our proposed algorithm can compute the NBS of the system in a distributed fashion, thus enabling a decentralized implementation of the incentive mechanism. Achieving this is highly non-trivial mathematically, since the corresponding system optimization problem has both a coupled constraint set and a coupled objective function.

Moreover, we introduce a virtual currency system which facilitates the cooperation of users. Namely, users can cooperate not only by direct service exchange (e.g., relaying data for each other), but also by using this virtual currency to pay for the services they receive (e.g., exchange virtual money with relaying data). Additionally, it encourages users who currently do not have communication needs, to participate and serve other users so as to collect virtual money (that can use later when they have needs). Similarly, it enables users with poor Internet connections to utilize the service by paying other users. Clearly, this system increases the number of users who are willing to participate in the service and are able to cooperate with each other.

Finally, we discuss the impact of network congestion on the service. Interestingly, through the cooperation of users, this service can *offload* cellular traffic to WiFi networks [9], or *onload* WiFi traffic to cellular networks [10]. These scenarios are depicted in Fig. 2. The optimal strategy is determined by the NBS, and depends on congestion levels of users' Internet connections (which determine the effective capacity experienced by users), and the data plans of the users (i.e., the cost of cellular access).

Our main technical contributions are as follows:

- *Service Modeling*. We introduce a general crowd-sourced mobile Internet access service model that incorporates users' communication needs, monetary costs, and energy consumption costs, which are the key factors affecting users' participation and servicing decisions.
- *Incentive Mechanism*. We design an incentive mechanism, based on the Nash bargaining solution (NBS), that induces users' participation through fair allocation of the contributed resources. This is very crucial to maintain a good performance of the service.
- *Distributed Implementation*. We propose a distributed algorithm, which combines the concepts of consistency pricing [11] and primal-dual Lagrange relaxation [12], and achieves the unique NBS. This enables the decentralized implementation of the service without requiring central coordination or additional infrastructure.
- *Application Scenarios*. We discuss how the service can account for interference and congestion effects, and how it can be for used for mobile data offloading and onloading.
- *Performance Evaluation*. We evaluate the performance of the service for various system parameters and offloading/onloading scenarios. We find that the service benefits increase as users become more heterogeneous (diverse) in terms of their needs and available resources.

The rest of the paper is organized as follows. Sec. II introduces the system model and the Nash Bargaining problem formulation. In Sec. III we present the incentive mechanism for the service, and in Sec. IV we provide the algorithm for its distributed implementation. We present numerical results in Sec. V. Finally, we analyze related works in Sec. VI, and conclude in Sec. VII.

II. System Model and Problem Statement

A. System Model

We consider a set of mobile users $\mathcal{I} = \{1, 2, \ldots, I\}$, who are interested in providing a crowd-sourced Internet access service (hereafter referred to as *service*) to each other for a certain time period. The users can communicate with each other by forming a mesh network $G = (\mathcal{I}, \mathcal{E})$, where $\mathcal{E}$ is the set of directed links connecting them through WiFi Direct [13] or Bluetooth technology (IEEE 802.15.1). Some users may not be able to communicate directly, e.g., due to distance or incompatibility of their wireless interfaces. We focus on the downloading operation of the system, i.e., when users download data from the Internet and relay it to each other[2]. There are $|\mathcal{I}|$ data commodities in the system, where each commodity (n) corresponds to a (potentially multi-hop) unicast session originating from the Internet (e.g., a web/content server) and ending at a user $n \in \mathcal{I}$.

In every period, each user can serve one or more roles as follows: she can be a client node (consuming data), a relay node (routing data to other users), and/or a gateway node (downloading data from Internet). Specifically, let $C_{ij} \geq 0$ be the data amounts (in bytes) that can be transferred over link $(i, j) \in \mathcal{E}$ during the current period. Let $C_{0i} \geq 0$ be the amount of data that user $i \in \mathcal{I}$ can download (as a gateway) from the Internet through a cellular or a WiFi connection. For simplicity, we assume that each gateway only downloads data from the Internet using her best Internet connection. Clearly, wireless channel conditions may be affected by factors such as fading and shadowing and hence can be time-varying. Hence we will consider a time period length that is large enough comparing with the small-scale channel fluctuations such as fast fading, but small enough comparing with the large-scale channel fluctuations such as shadowing.

Each user $i \in \mathcal{I}$ has a maximum energy budget of $E_i \geq 0$ units (joules) that can be spent during the current time period. The user consumes energy during either downloading or relaying data. Let $e^s_{ij} > 0$ be the energy that user i consumes when she sends one byte to user j (over link $(i, j) \in \mathcal{E}$). Also, $e^r_{ij} > 0$ is the energy that user j consumes for receiving one byte from user i. Finally, $e_{0i} > 0$ is the energy consumption when node i downloads one byte from the Internet. Typically, energy consumption is higher with cellular than with WiFi connections [15].

Downloading data can induce certain monetary cost to the gateway users, depending on the type of Internet connection and pricing scheme (*data plan*). Let $p_i \geq 0$ be the price that each user i pays for each byte that she downloads (for herself or other users) from the Internet[3]. Each user perceives certain satisfaction (*utility*) for consuming data (not including relaying for other users). We introduce the utility function $U_i(\cdot)$ for user i, which is a positive, increasing, and concave function of the total bytes she directly downloads and receives from her neighbors. The concavity of the utility function models the user's diminishing marginal satisfaction of additional data consumption. Different users may have different utility functions [16], [17]. For example, the utility of a user browsing the web is initially proportional to the amount of data that she downloads, and saturates after the maximum intended data (or, equivalently time session) has been reached.

Each user downloads data to satisfy her own communication needs and/or the needs of other users. Let $y_i^{(n)} \geq 0$ be the data (bytes) that user i downloads from Internet for user $n \in \mathcal{I}$. We also define the data amount (in bytes) $x_{ij}^{(n)} \geq 0$ of commodity (n) that user i delivers (routes) to her one-hop neighbor user j. The operation of the system can be described by the *downloading* matrix $\boldsymbol{y} = (y_i^{(n)} \geq 0 : i \in \mathcal{I}, n \in \mathcal{I})$, and the *routing* matrix $\boldsymbol{x} = (x_{ij}^{(n)} \geq 0 : (i, j) \in \mathcal{E}, n \in \mathcal{I})$. These variables characterize the total amount of data of all commodities that are downloaded or routed by each user over each link, during the current time period. The routing and downloading decisions should satisfy the flow balance equations

$$\sum_{j \in In(i)} x_{ji}^{(n)} + y_i^{(n)} = \sum_{j \in Out(i)} x_{ij}^{(n)}, \; \forall\, i, n \in \mathcal{I}, \, i \neq n, \quad (1)$$

where $In(i) = \big(j : (j, i) \in \mathcal{E}\big)$ and $Out(i) = \big(j : (i, j) \in \mathcal{E}\big)$ are the sets of upstream and downstream one-hop neighbors of user i, respectively. Clearly, it holds $x_{ij}^{(i)} = 0, \forall\, i,\, j \in Out(i)$. Moreover, each link (i, j) cannot support more data than its maximum capacity. Hence:

$$\sum_{n \in \mathcal{I}} x_{ij}^{(n)} \leq C_{ij}, \, \forall\, (i, j) \in \mathcal{E}, \quad \sum_{n \in \mathcal{I}} y_i^{(n)} \leq C_{0i}, \, \forall\, i \in \mathcal{I}. \quad (2)$$

Finally, the total consumed energy e_i, $\forall\, i \in \mathcal{I}$ is:

$$e_i = \sum_{j \in Out(i)} e^s_{ij} \sum_{n \in \mathcal{I}} x_{ij}^{(n)} + \sum_{j \in In(i)} e^r_{ji} \sum_{n \in \mathcal{I}} x_{ji}^{(n)} + e_{0i} \sum_{n \in \mathcal{I}} y_i^{(n)}.$$

Clearly, we need to have $e_i \leq E_i$. For mobile devices, battery energy is an important concern [18], and different users may have different energy consumption preferences. For example, some users may be willing to consume almost their entire energy budgets for the current time period, while others may prefer a lower energy consumption. Thus, for each user i we introduce an energy consumption cost function $V_i(\cdot)$, which is strictly convex, positive, and increasing in e_i. Its value goes to infinity when the energy budget of the user is depleted. A function that satisfies these requirements is, for example, $V_i(e_i) = \delta_i / (E_i - e_i)$, where $\delta_i \in [0, 1]$ is a normalization parameter indicating user i's sensitivity in energy consumption.

B. Problem Statement

Let $J_i^G(\cdot)$ denote the payoff that user i receives when she participates in the crowd-sourced Internet access service (superscript "G" stands for Open Garden). More specifically,

$$J_i^G(\boldsymbol{x}_i, \boldsymbol{x}_{-i}, \boldsymbol{y}_i) = U_i\big(y_i^{(i)} + \sum_{j \in In(i)} x_{ji}^{(i)}\big) - p_i \sum_{n \in \mathcal{I}} y_i^{(n)} - V_i(e_i),$$

where $\boldsymbol{y}_i = \big(y_i^{(n)} : n \in \mathcal{I}\big)$ is the downloading vector of user i, $\boldsymbol{x}_i = \big(x_{ij}^{(n)} : j \in Out(i),\, n \in \mathcal{I}\big)$ is the vector of her routing decisions, and $\boldsymbol{x}_{-i} = \big(x_{ji}^{(n)} : j \in In(i),\, n \in \mathcal{I}\big)$ the routing decisions of her upstream neighbors (delivering data to i).

As $y_i^{(i)}$ increases, user i's utility increases, as well as her monetary cost and energy cost. Hence the overall payoff J_i^G may not increase. On the other hand, the payoff J_i^G monotonically decreases with the amount of data that user i downloads for other users $n \in \mathcal{I}$, $n \neq i$, and routes to her downstream neighbors $j \in Out(i)$, due to the increase in the monetary and energy cost. Clearly, the user will have no incentive to perform these tasks unless she is compensated.

Moreover, we also need to consider the user payoff when she operates in standalone mode. Notice that a rational user will join the service only if this will improve her payoff. In the standalone operation, each user i does not receive or deliver data to her neighbors $\big(x_{ij}^{(n)} = 0, \forall\, j \in Out(i),\, x_{ji}^{(n)} =$

[2] For the uploading scenario there are slight changes, e.g., the amount of energy consumption is higher and uplink capacities are smaller [14], which however do not affect the design of our mechanism.

[3] For the time period of users interaction, and for the given value of C_{0i}, $\forall i \in \mathcal{I}$, price p_i is assumed fixed.

$0, \forall j \in In(i), \forall n \in \mathcal{I}\big)$ nor she downloads data for any other user $\big(y_i^{(n)} = 0, \forall n \neq i\big)$. Here the optimal downloading strategy can be obtained by simply solving the following *Standalone Operation Problem* (SOP):

$$\max_{0 \leq y_i^{(i)} \leq C_{0i}} U_i\big(y_i^{(i)}\big) - p_i y_i^{(i)} - V_i\big(y_i^{(i)}\big) \qquad (3)$$

This problem has a strictly concave objective, and a compact and convex non-empty constraint set. Hence it has a unique solution, denoted as J_i^s where s stands for Stand-alone. This will serve in the sequel as the performance benchmark for the comparison purpose.

We are interested in designing an incentive mechanism that determines which users should contribute how much resources (connectivity and/or battery energy), so as to maximize the service capacity (amount of data delivered within the current period). Accordingly, it should decide how this service capacity will be shared by the different users and how users should be compensated. These two tasks should be jointly designed so as to satisfy the fairness criterion.

There are two important notes here. First, a user being served by another user, may not be able to directly return the favor in the current period by offering similar relaying or downloading services. Hence, a resourceful user may be reluctant to help other less resourceful users. Second, some users may not have communication needs in a certain time period, and therefore may not be willing to participate in the service. This, in turn, may deteriorate the overall service performance. In order to address both issues, we introduce a virtual currency system, similar to the one for peer-to-peer or ad hoc networks [19], where users need to pay for receiving services. This enables the cooperation of users, even if they cannot directly exchange routing or downloading services, and encourages users to participate even if they currently have no communication needs themselves. As we will see in Sec. III, such a virtual currency exchange system allows users to "share" benefits of cooperation, in a flexible fashion, and achieve a good system operation point through a bargaining process.

Formally, the problem can be defined as follows:

Key Research Problem: *Given the graph $G = (\mathcal{I}, \mathcal{E})$, the capacity constraints, the energy consumption parameters, the pricing parameters, and the utility functions of the users, find the downloading, routing and payment decisions of the users, which ensure the fair and efficient performance of the crowd-sourced Internet access service.*

III. The Cooperative Servicing Game

In this section, we first explain how the virtual currency system works, and then formulate the operation of the service as an $|\mathcal{I}|$-person Nash bargaining problem based on the virtual currency system.

Virtual Currency. The currency system allows one-hop neighboring users to exchange (virtual) money for the services they offer to each other. Specifically, let $z_{ji}^{(n)} \geq 0$ denote the price paid by user i to j, for the data of commodity (n) that is delivered over link $(j,i) \in \mathcal{E}$. Similarly, $z_{ij}^{(n)} \geq 0$ denotes the payment by user $j \in Out(i)$ to user i for data commodity (n). We define the matrices $\boldsymbol{z}_i = \big(z_{ji}^{(n)} : j \in In(i), n \in \mathcal{I}\big)$, and, $\boldsymbol{z}_{-i} = \big(z_{ij}^{(n)} : j \in Out(i), n \in \mathcal{I}\big)$ for each user $i \in \mathcal{I}$. At the beginning of the period, each user i has a budget $D_i \geq 0$, and is rewarded with an additional amount $\gamma > 0$ of virtual money for her participation in the current period. This latter parameter is determined by the system, and it is the same for each user. However, γ is very small compared to the virtual money a user receives when she serve others. As it will become clear in the sequel, this parameter ensures that participation in the service is beneficial even for users who will not serve others, or receive service by others.

At the end of the time period, user i's virtual currency is:

$$H_i(\boldsymbol{z}_i, \boldsymbol{z}_{-i}) = \beta_i\big(D_i + \gamma + \sum_{n \in \mathcal{I}} \sum_{j \in Out(i)} z_{ij}^{(n)} - \sum_{n \in \mathcal{I}} \sum_{j \in In(i)} z_{ji}^{(n)}\big),$$

where parameter $\beta_i > 0$ captures how important the virtual money is for user i, i.e., reflects her expectation for exploiting the virtual currency in the future. In game theoretic terms, β_i can be considered as the *discount rate* for each user. For example, a user that does not intent to participate in the service later, does not value the virtual currency much, and the corresponding β_i will be close to 0. The linear form of $H_i(\boldsymbol{z}_i, \boldsymbol{z}_{-i})$ implies that users are risk neutral [8]. Of course, after introducing the virtual currency system, the payoff of each user becomes the sum of J_i^G and the normalized currency $H_i(\cdot)$.

Bargaining Problem. The users are self-interested, and only participate in the crowd-sourced connectivity service if this ensures higher payoffs for them. In this work, we design the mechanism to achieve the Nash bargaining solution, which has the following desirable properties regarding the users' payoffs [20]: (i) Pareto optimal, (ii) proportionally fair, and (iii) considers the standalone performance of each user. The last point is especially important, as a fairness rule based on direct resource allocation only, e.g., an equal energy or bandwidth sharing scheme, may fail to incentivize all users to join the service.

We define an $|\mathcal{I}|$-person bargaining game and solve it using the NBS [7]. Due to the introduction of virtual currency, this is a game of transferrable utilities [8], which means that the produced welfare (service capacity and virtual money) can be divided in an arbitrary fashion among the users (through virtual currency transfers). Based on the Open Garden service architecture [6], we assume that when a user joins the service she may cooperates with any of the other nearby users, i.e., there is no option for selecting with whom to cooperate (no subgroups creation)[4]. Hence, this is a pure bargaining problem.

Next we formally introduce the Nash bargaining solution. Consider the bargaining game $\mathcal{G} = \langle \mathcal{I}, \boldsymbol{A}, \{u_i\} \rangle$, where $\mathcal{I} \triangleq \{1, 2, ..., I\}$ is the player set, and $\boldsymbol{A} \triangleq A_1 \times A_2 \times ... \times A_I$ is the strategy space where A_i is the set of strategies (actions) available to player i. The payoff of each player i, $u_i(\cdot)$, depends on the strategy profile of all players, $\boldsymbol{a} = (a_1, a_2, ..., a_I)$, with $a_i \in A_i$. The NBS for this game is [8]:

[4]This assumption holds also for other UPC services, e.g. FON [4]. A coalitional game theoretic analysis is required in case formation of subgroups is possible. However, it can be shown that also in this case the grand coalition will be formed since there is no cost for using the service and hence the game is superadditive [8] (this does not hold for FON).

Definition 1 (Nash Bargaining Solution–NBS). *A strategy profile $\boldsymbol{a}^* = (a_1^*, a_2^*, \ldots, a_I^*)$ is an NBS, if it solves the following problem:*

$$\begin{aligned} &\max_{\boldsymbol{a}\in\boldsymbol{A}} \Pi_{i\in\mathcal{I}}(u_i(\boldsymbol{a}) - u_i^d) \\ &\;\; s.t. \;\; u_i(\boldsymbol{a}) \geq u_i^d, \; \forall\, i \in \mathcal{I} \end{aligned} \tag{4}$$

where u_i^d is the disagreement point *of player i, i.e., her payoff when an agreement is not reached.*

In the sequel, we use the equivalent formulation where the product of terms in (4) is substituted by the sum of respective logarithmic terms [20]. Hence, we derive the NBS by solving the Bargaining Optimization Problem (BOP):

$$\max_{\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}} \sum_{i\in\mathcal{I}} \log\left(J_i^G(\boldsymbol{x}_i, \boldsymbol{x}_{-i}, \boldsymbol{y}_i) + H_i(\boldsymbol{z}_i, \boldsymbol{z}_{-i}) - J_i^s - \beta_i D_i\right)$$

s.t.

$$\sum_{j\in In(i)} x_{ji}^{(n)} + y_i^{(n)} = \sum_{j\in Out(i)} x_{ij}^{(n)}, \; \forall\, i, n \in \mathcal{I}, \, i \neq n, \tag{5}$$

$$\sum_{n\in\mathcal{I}} x_{ij}^{(n)} \leq C_{ij}, \; \forall\, (i,j) \in \mathcal{E} \tag{6}$$

$$\sum_{n\in\mathcal{I}} y_i^{(n)} \leq C_{0i}, \;\; \forall\, i \in \mathcal{I} \tag{7}$$

$$\sum_{n\in\mathcal{I}} \sum_{j\in In(i)} z_{ji}^{(n)} - \sum_{n\in\mathcal{I}} \sum_{j\in Out(i)} z_{ij}^{(n)} \leq D_i + \gamma, \forall i \in \mathcal{I} \tag{8}$$

$$J_i^G(\boldsymbol{x}_i, \boldsymbol{x}_{-i}, \boldsymbol{y}_i) + H_i(\boldsymbol{z}_i, \boldsymbol{z}_{-i}) \geq J_i^s + \beta_i D_i, \forall\, i \in \mathcal{I} \tag{9}$$

$$x_{ij}^{(n)} \geq 0, \, y_i^{(n)} \geq 0, \, 0 \leq z_{ij}^{(n)} \leq K, \forall\, i, j, n \in \mathcal{I} \tag{10}$$

where the *disagreement point* for each user is the sum of the standalone performance J_i^s she can achieve, and the normalized virtual currency $\beta_i D_i$ she has at the beginning of the period. Eq. (5), (6), and (7) are the flow balance and link capacity constraints respectively (defined in Sec. II). Eq. (8) states that users cannot have a virtual currency deficit, and (9) is the feasibility (individual-rationality) constraint, indicating that each user will agree to cooperate only if this does not make her payoff worse. Finally, notice that each payment decision $z_{ij}^{(n)}$ is also upper bounded by the total available virtual currency at the system $K = \sum_{i\in\mathcal{I}}(D_i + \gamma)$.

The BOP problem has always a non-empty feasible region. Therefore, due to constraint (9), there is no user of whom the payoff will decrease by participating in the service. This, in turn, implies that all users are incentivized to join the service in each time period. Technically, this is ensured due to the virtual currency system and specifically the rewarding parameter γ. In particular, the following lemma holds.

Lemma 1. *The BOP problem has a unique optimal solution.*

Proof: The objective function is strictly concave since it is a composition of (strictly) concave functions. Additionally, the constraint set is compact, convex and non-empty. Notice that constraint (9) can be always strictly satisfied by some solution point. For example, each user i can choose not to route any traffic, i.e., $x_{ij}^{(n)} = x_{ji}^{(n)} = 0, \forall i, j, n \in \mathcal{I}$, and only download data for herself. This way, she achieves her standalone performance, but still improves her payoff due to the participation reward γ. This also ensures that the logarithmic arguments are non-zero. Therefore, the problem has always a unique solution $(\boldsymbol{x}^*, \boldsymbol{y}^*, \boldsymbol{z}^*)$ [12]. ■

We can derive the solution of the BOP problem by solving the necessary and sufficient KKT conditions [12]. This will yield the efficient and fair downloading and routing policy, as well as the necessary virtual currency transfers among the users. Based on the system parameters, i.e., the users' connection capacities, battery energy, and pricing plans, the service can offload data to WiFi networks or even onload data to cellular networks.

However, in all these cases, the critical question is whether we can find this solution in a distributed fashion. This will enable the distributed execution of the incentive mechanism, which is a prerequisite for crowd-sourced mobile Internet access services.

IV. Distributed Algorithm Design for BOP

The difficulties to solve the BOP problem in a decentralized fashion are twofold. First, the decision variables of different users are coupled in the constraints. That is, the routing decisions of each user should take into account the capacity constraints of her neighboring nodes. Second, there is coupling in the objective functions. Namely, the logarithmic component of the BOP objective that corresponds to each user i is dependent on the decision variables of her neighbors. We address these issues by introducing new auxiliary local variables for each user and *consistency* constraints for each pair of neighboring users (for the coupled objectives) [11]. The transformed problem then has coupling only in the constraints, and can be solved using a primal-dual Lagrange decomposition method [11].

Let us focus on user $i \in \mathcal{I}$, whose payoff and virtual currency functions depend on her own decisions $(\boldsymbol{x}_i, \boldsymbol{y}_i, \boldsymbol{z}_i)$ and the decisions $\boldsymbol{x}_{-i}$, and $\boldsymbol{z}_{-i}$ of her one-hop upstream and downstream neighbors, $j \in In(i)$ and $j \in Out(i)$, respectively. To deal with this coupling, we introduce the matrices of auxiliary variables $\boldsymbol{\xi}_i = \left(\xi_{ji}^{(n)} \geq 0 : j \in In(i), n \in \mathcal{I}\right)$, and $\boldsymbol{\sigma}_i = \left(\sigma_{ij}^{(n)} : j \in Out(i), n \in \mathcal{I}\right)$, and the respective component-wise equality constraints:

$$\xi_{ji}^{(n)} = x_{ji}^{(n)}, \forall\, i \in \mathcal{I}, \, j \in In(i), \, n \in \mathcal{I}, \tag{11}$$

$$\sigma_{ij}^{(n)} = z_{ij}^{(n)}, \forall\, i \in \mathcal{I}, \, j \in Out(i), \, n \in \mathcal{I}. \tag{12}$$

This means that each user can independently determine her downloading, routing, and payment variables, subject to the (iterative) coordination with her one-hop neighbors about their (common) routing and payment decisions (through the auxiliary variables). Accordingly, we can group the variables per user so that each user only needs to take local decisions.

Specifically, we relax constraints (5), (8), (11), and (12), and introduce the respective Lagrange multipliers $\boldsymbol{\lambda} = (\lambda_i^{(n)} : i, n \in \mathcal{I})$, $\boldsymbol{\rho} = (\rho_i \geq 0 : i \in \mathcal{I})$, $\boldsymbol{\tau} = \left(\tau_{ji}^{(n)} : i, n \in \mathcal{I}, j \in In(i)\right)$, and $\boldsymbol{\pi} = \left(\pi_{ij}^{(n)} : i, n \in \mathcal{I}, j \in Out(i)\right)$. Then, we define the (partial) Lagrangian:

$$
\begin{aligned}
L \; = \; & \sum_{i\in\mathcal{I}} \Big(\log\big(J_i^G(\boldsymbol{x}_i,\boldsymbol{\xi}_i,\boldsymbol{y}_i) + H_i(\boldsymbol{z}_i,\boldsymbol{\sigma}_i) - J_i^s - \beta_i D_i\big) \\
+ & \sum_{n\in\mathcal{I}} \lambda_i^{(n)} \big(\sum_{j\in In(i)} x_{ji}^{(n)} + y_i^{(n)} - \sum_{j\in Out(i)} x_{ij}^{(n)} \big) \\
+ & \sum_{n\in\mathcal{I}} \sum_{j\in In(i)} \tau_{ji}^{(n)} (\xi_{ji}^{(n)} - x_{ji}^{(n)}) \\
+ & \sum_{n\in\mathcal{I}} \sum_{j\in Out(i)} \pi_{ij}^{(n)} (\sigma_{ij}^{(n)} - z_{ij}^{(n)}) \\
- & \rho_i \big(\sum_{n\in\mathcal{I}} \sum_{j\in In(i)} z_{ji}^{(n)} - D_i - \sum_{n\in\mathcal{I}} \sum_{j\in Out(i)} z_{ij}^{(n)} \big) \Big),
\end{aligned}
$$

which is separable in user-specific components $L_i(\cdot)$, $i\in\mathcal{I}$.

In each iteration t, the user maximizes the Lagrange function in terms of the primal variables, and uses the obtained values to update the dual variables. More specifically, each user $i\in\mathcal{I}$, in each iteration, solves the following problem to optimize her primal variables:

$$\max_{\boldsymbol{x}_i,\boldsymbol{y}_i,\boldsymbol{z}_i,\boldsymbol{\xi}_i,\boldsymbol{\sigma}_i} L_i\big(\boldsymbol{x}_i,\boldsymbol{\xi}_i,\boldsymbol{y}_i,\boldsymbol{z}_i,\boldsymbol{\sigma}_i\big) \tag{13}$$

s.t.

$$\sum_{n\in\mathcal{I}} x_{ij}^{(n)} \le C_{ij},\ (i,j)\in\mathcal{E},\ \ \sum_{n\in\mathcal{I}} y_i^{(n)} \le C_{0i} \tag{14}$$

$$J_i^G(\boldsymbol{x}_i,\boldsymbol{\xi}_i,\boldsymbol{y}_i) + H_i(\boldsymbol{z}_i,\boldsymbol{\sigma}_i) - J_i^s - \beta_i D_i > 0 \tag{15}$$

$$x_{ij}^{(n)}, y_i^{(n)}, \xi_{ij}^{(n)}, \sigma_{ij}^{(n)} \ \ge 0,\ 0\le z_{ij}^{(n)} \le K,\ n\in\mathcal{I},\ j\in\mathcal{N}_i \tag{16}$$

where $\mathcal{N}_i = In(i)\cup Out(i)$, and the objective $L_i(\cdot)$ is:

$$
\begin{aligned}
L_i \; & = \log\big(J_i^G(\boldsymbol{x}_i,\boldsymbol{\xi}_i,\boldsymbol{y}_i) + H_i(\boldsymbol{z}_i,\boldsymbol{\sigma}_i) - J_i^s - \beta_i D_i\big) \\
+ \; & \sum_{n\in\mathcal{I}} \big(\lambda_i^{(n)} y_i^{(n)} - \sum_{j\in Out(i)} x_{ij}^{(n)} \big(\lambda_i^{(n)} - \lambda_j^{(n)}\big)\big) \\
- \; & \rho_i \sum_{n\in\mathcal{I}} \sum_{j\in In(i)} z_{ji}^{(n)} + \sum_{j\in In(i)} \rho_j \sum_{n\in\mathcal{I}} z_{ji}^{(n)} + \sum_{n\in\mathcal{I}} \tau_{ji}^{(n)} \xi_{ji}^{(n)} \\
- \; & \sum_{n\in\mathcal{I}} \Big[\sum_{j\in Out(i)} \big(x_{ij}^{(n)} \tau_{ij}^{(n)} - \pi_{ij}^{(n)} \sigma_{ij}^{(n)} \big) + \sum_{j\in In(i)} \pi_{ji}^{(n)} z_{ji}^{(n)} \Big].
\end{aligned}
$$

The user then uses the primal variables to calculate the gradients and update the dual variables [12]:

$$
\begin{aligned}
\lambda_i^{(n)\,(t+1)} \; = \; & \lambda_i^{(n)\,(t)} + s^{(t)} \big(\sum_{j\in In(i)} x_{ji}^{(n)\,(t)} + y_i^{(n)\,(t)} \\
& - \sum_{j\in Out(i)} x_{ij}^{(n)\,(t)} \big)
\end{aligned}
\tag{17}
$$

$$\tau_{ji}^{(n)\,(t+1)} = \tau_{ji}^{(n)\,(t)} + s^{(t)} \cdot \big(\xi_{ji}^{(n)\,(t)} - x_{ji}^{(n)\,(t)}\big) \tag{18}$$

$$\pi_{ij}^{(n)\,(t+1)} = \pi_{ij}^{(n)\,(t)} + s^{(t)} \cdot \big(\sigma_{ij}^{(n)\,(t)} - z_{ij}^{(n)\,(t)}\big) \tag{19}$$

$$\rho_i^{(t+1)} = \big[\rho_i + s^{(t)} \big(\sum_{n\in\mathcal{I}} \big(\sum_{j\in In(i)} z_{ji}^{(n)\,(t)} - \sum_{j\in Out(i)} z_{ij}^{(n)\,(t)} \big) - D_i \big)\big]^+ \tag{20}$$

where $[\cdot]^+$ denotes the projection onto the non-negative orthant and $s^{(t)}\ge 0$ is a properly selected step during iteration t [12]. Finally, each user passes the updated dual variables to her one-hop neighbors, who will use them to optimize the primal variables in the next iteration.

The Algorithm is executed in a synchronous fashion, which requires a common clock of all users and a small delay for message passing (circulation of the dual and primal variables). This is a reasonable assumption for small-scale crowd-sourced connectivity networks in a small neighborhood. The complete algorithm is summarized in Algorithm 1 and provably converges to the optimal solution.

Algorithm 1: Distributed Solution of BOP

```
output: x*, y*, z*
t ← 0;
Set x^(0), y^(0), z^(0), ξ^(0), σ^(0), λ^(0), τ^(0), π^(0), ρ^(0), ϵ;
conv_flag ← 0; # initialize the convergence flag
while conv_flag = 0 do
    t ← t + 1;
    for i = 1 : I do
        Solve (13) - (16) to get x_i^(t), y_i^(t), z_i^(t), ξ_i^(t), σ_i^(t) ;
        Send x_ij^(n)(t), ∀n ∈ I \ {i}, to j ∈ Out(i);
        Send z_ji^(n)(t), ∀n ∈ I \ {i}, to j ∈ In(i);
        for j = 1 : I, n = 1 : I do
            Calculate
            λ_i^(n)(t+1), ρ_i^(t+1), τ_ji^(n)(t+1), π_ij^(n)(t+1) using
            (17) - (20);
        end
        Send λ_i^(n)(t+1), τ_ji^(n)(t+1), ∀n ∈ I \ {i}, to
        j ∈ In(i);
        Send ρ_i^(t+1) and π_ij^(n)(t+1), ∀n ∈ I \ {i}, to
        j ∈ Out(i);
    end
    if |λ_i^(n)(t+1) − λ_i^(n)(t)| < ϵ and |ρ_i^(t+1) − ρ_i^(t)| < ϵ
    and |π_ij^(n)(t+1) − π_ij^(n)(t)| < ϵ and
    |τ_ji^(n)(t+1) − τ_ji^(n)(t)| < ϵ ∀i, n ∈ I, j ∈ Out(i) then
        conv_flag ← 1;
    end
end
```

Lemma 2. *Algorithm 1 converges to the optimal solution ($\boldsymbol{x}^*,\boldsymbol{y}^*,\boldsymbol{z}^*$) of the BOP problem, under properly chosen step sizes $s^{(t)}$ for each iteration t.*

Proof: BOP has a strictly concave objective and a closed, non-empty and convex constraint set. Thus, Algorithm 1 converges to optimal solution [12] if (i) the step sequence $s^{(t)}$, $t=1,2,\ldots$, is properly selected, and (ii) the gradients used in (17)-(20), are bounded. Consider user i, and we see that $x_{ij}^{(n)}, y_i^{(n)}, n\in\mathcal{I}, j\in Out(i)$ are bounded by (14), $\xi_{ji}^{(n)}, n\in\mathcal{I}, j\in Out(i)$ are also bounded due to the energy cost function, and $z_{ji}^{(n)}, n\in\mathcal{I}, j\in Out(i)$ are positive and upper bounded by K. Hence, if we employ a diminishing step size, e.g. $s^{(t)} = (1+m)/(t+m)$ with $m\ge 0$, then the convergence is guaranteed [11], [12]. ∎

Notice that each user passes messages for each commodity $n\in\mathcal{I}$, only to her one-hop neighbors. Hence, the message passing overhead of the algorithm is $O(\bar{d}N^2)$, where $\bar{d}$ is the average degree of the graph G. However, we expect that the number of users in the group will be small (due to the need to be in proximity), hence even a complexity of $O(N^3)$

(assuming a fully connected graph) is affordable.

V. Numerical Study

We consider a basic system setup and demonstrate how the crowd-sourced connectivity service performs in certain representative scenarios. The system parameters follow related experimental studies [14], [15], [21], [22], [23]. More numerical results can be found in our technical report [24].

Simulation Setup. We consider a set of $|\mathcal{I}| = 6$ users, randomly placed in a geographic area[5], and study their interactions for a time period of $T = 120$ seconds. The Internet access capacity of each user depends on whether she uses a cellular 4G, 3G, or a WiFi connection. Moreover, in practice, the effective capacity is affected by the network conditions such as interference and congestion. Field experiments have measured the actual average speed to be 12.74 Mbps for LTE, 4.12 Mbps for WiFi, and 1 Mbps for 3G networks [14], [21], [22].

We assume that users communicate with each other using WiFi Direct. The achievable rate among two users i and j decreases with their Euclidian distance d_{ij} (in meters). In order to account for a representative setting with average interference and channel conditions, we assume that two users separated by 1 meter achieve a communication speed of 64Mbps, and the speed drops to 0.1 Mbps when the distance increases to 30 meters. The rate will be zero when the distance is larger than 30 meters. For within range transmissions, the maximum amount C_{ij} of data that can be transferred over each link (i, j) satisfies $C_{ij} = T \cdot 100 \log(1 + 0.9/d_{ij}^2)$.

For mobile devices, the energy consumed by a data transfer is proportional to the size of the data and the transmission power level [15]. Moreover, the energy consumption is affected by other parameters, such as the channel conditions (e.g., due to packet retransmissions) and the transmission rate [14], [23]. Typically, the energy consumption (per MByte) of WiFi transmissions is smaller compared to LTE transmissions, which, in turn, is smaller than 3G transmissions. We consider here an average energy consumption of $e_{0i} = 100$J/MByte when user i has a 3G Internet access connection, $e_{0i} = 4.65$J/MByte for an LTE connection, and $e_{0i} = 2.85$J/MByte for a WiFi connection [15], [23], [25]. For WiFi direct links, we assume that the energy consumption per MByte increases with the distance (since the achievable rate decreases with the distance), in the form of[6] $e_{ij}^s = (0.36 + 0.001 d_{ij}^2)$Joules/Mbit.

Every user $i \in \mathcal{I}$ has a logarithmic utility function $U_i = \alpha_i \log\left(1 + y_i^{(i)} + \sum_{j \in In(i)} x_{ji}^{(i)}\right)$, which satisfies the principle of diminishing marginal returns [26]. Parameter $\alpha_i \in [0, 1]$ captures the different communication needs of the different users. Also, the virtual currency parameters β_i, $\forall i \in \mathcal{I}$, are uniformly distributed in $(0, 1]$. Finally, the data usage prices depend on the country, the data plan of each user, and the service provider. In a recent publication, ITU reports an average price of 0.021\$/Mbit in US, 0.006\$/Mbit in China, and 0.002\$/Mbit in UK [27]. We select the prices according to these findings, and we set $p_i = 0$ for users who have an unlimited cellular data plan or using WiFi connections.

[5]We expect to see such small groups in practical networks, since each user should be in communication range with at least one more user.

[6]The parameters of e_{ij}^s have been selected so as to have $e_{ij}^s = e_{0i} = 2.85$J/MByte when $d_{ij} = 1$.

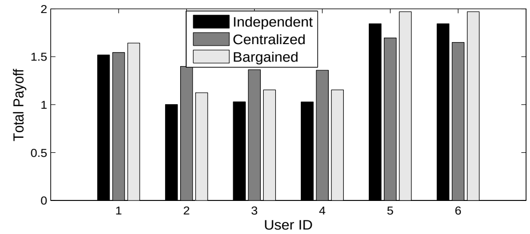

Fig. 3. Comparison of centralized, independent, and bargained solution. System basic parameters are: $\{C_{0i}\}_i = \{12.7, 0.0, 1.0, 1.0, 4.12, 2.1\}$ Mbps, $\{e_{0i}\}_i = \{0.58, 0.0, 12.5, 12.5, 0.36, 0.36\}$Joule/Mbit, and $\{p_i\}_i = \{0.02, 0, 0.008, 0.001, 0.0, 0.0\}$ \$/Mbit. The aggregate total payoff improvement of the bargained solution (compared to the independent solution) is approximately 10%.

Numerical Results. First, we consider a setting where user 1 has an LTE connection, user 2 does not have any Internet access, users 3 and 4 have 3G connections, and users 5 and 6 have WiFi connections. The Internet access capacity, energy, and price values for all users are shown in the caption of Fig. 3. For simplicity, all other system parameters have been set equal for all users. In this experiment, we compare the "bargained" payoff J_i^G for each user i (under the *bargaining solution*), with the "independent" payoff J_i^s that she achieves in the standalone operation. We also compute the user's "centralized" payoff J_i^c that corresponds to a benchmark case where the system maximizes the aggregate welfare. For each case, we plot the total payoff which has also accounted for the virtual currency benefit. The results represent the average obtained over 100 experiments for different user locations and hence user distances[7]. We observe that the bargained solution always improves upon the independent payoff. However, a centralized solution might lead to a lower total payoff for some user comparing with the independent solution. This illustrates the fair allocation of the proposed bargained solution.

The performance benefits of the crowd-sourced service depend on the diversity of the users's resources. In Fig. 4 we investigate this aspect regarding the difference of Internet capacities among users. Namely, we assume that 2 users have high Internet access capacities, while the other 4 have equal but much lower Internet access capacities. We run the experiment 30 times and average the results for different user locations and distances. We calculate the aggregate downloaded data in a single period, when users participate in the service and when they operate in standalone mode. All the other system parameters are equal for all users and remain unchanged across the different experiments. We see that as users become less diverse (i.e., the 4 users' capacity increases) the gap of total downloaded data for the bargained solution (compared to the standalone solution) decreases from 29.36% to almost 0%. Similar results hold when users are diverse in terms of their energy consumption [24]. This reveals that the service benefits are larger for users with different Internet access capacities and/or energy consumption parameters.

[7]Specifically, users are placed in the $[0, 100m] \times [0, 100m]$ plane randomly, with a uniform distribution.

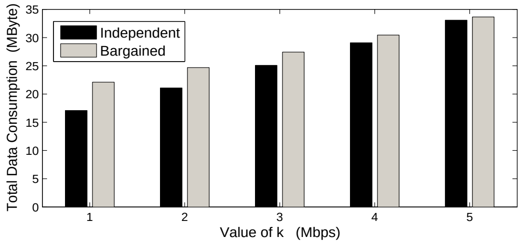

Fig. 4. Service performance for users with diverse Internet access capacities. $C_{01} = C_{02} = 12.7$ Mbps, $C_{03} = C_{04} = C_{05} = C_{06} = k$ Mbps. Internet access prices are identical and equal to $p = 0.01$. Similarly, energy consumption for downloading is $e_{0i} = 0.158$ for each user i. Results are averaged over 30 runs with uniformly distributed user locations in $[0, 100m] \times [0, 100m]$.

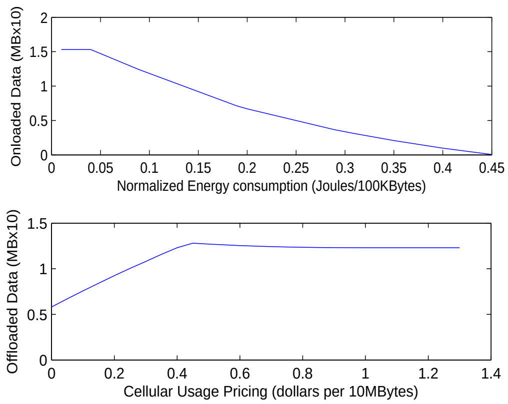

Fig. 5. Upper subfigure (Onloading): 4G capacity (10 Mbps) is 5 times larger than the WiFi capacity (2 Mbps), mobile data price is $p = 0.01$ \$/Mbit, and the 4G link energy consumption 3-times larger than the WiFi link energy consumption ($e_{0i} = 2.85$ J/MB). Lower subfigure (Offloading): 4G capacity (4 Mbps) is twice the WiFi capacity, and data usage price increases.

In Fig. 5 we simulate the offloading - onloading scenario illustrated in Fig. 2. Onloading becomes an attractive option when WiFi links are congested and cellular access is of a low cost for each user i. The upper subfigure in Fig. 5 shows that the amount of onloaded data decreases when the energy consumption (e_{ij}) of the cellular user for delivering data to the WiFi user increases. On the other hand, offloading becomes attractive when the WiFi connection is resourceful. The lower subfigure in Fig. 5 shows that the amount of offloaded data increases with the price per byte paid by the 4G user. Interestingly, after a certain point (about cellular pricing equal to 0.44 in the figure), the offloading data amount slightly decreases and then remains constant despite the further cellular price increase. This is due to the fairness criterion imposed by the proposed mechanism, which compares the standalone performance of each user. In particular, as the data price increases, the cost of the 4G user for offloading more traffic increases significantly, and hence it cannot be compensated with the virtual currency payment by the WiFi user (due to the total virtual currency constraint). Therefore, the 4G user does not deliver any more data to the WiFi user.

Next, we study the impact of the energy parameters on the onloading - offloading decisions for the system in Fig. 2. Assume that both users have zero data usage cost[8]. Also, assume that the 4G user (user 1) has an Internet access connection with a capacity twice as the capacity of the WiFi user (2Mbps) (user 2). In Fig. 6 we plot the amount of offloaded data (negative values represent onloading decisions) versus the ratio of the energy consumption of the two users, e_{01}/e_{02}. We observe that when this energy cost ratio is between (approximately) 1.5 and 2.5, there is neither offloaded nor onloaded data, i.e., each user serves her own traffic needs. However, when the cellular link becomes more expensive in terms of energy consumption, the WiFi user begins to serve and deliver data for the 4G user. The amount of offloaded data increases as the ratio increases, but follows a concave curve due to the imposed fairness rule (as it would be unfair for the WiFi user to deliver too much traffic for the cellular user). On the other hand, when the cellular link has almost equal or lower energy consumption than the WiFi connection (e.g., due to interference in the WiFi channels), our scheme will onload data from the WiFi link to the cellular link. Notice that when the ratio of the energy consumption is 1, the proposed scheme will onload traffic since the cellular connection has a higher capacity.

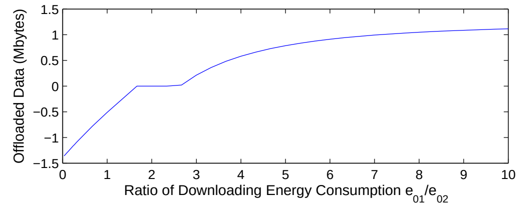

Fig. 6. Offloading - onloading decisions based on the energy consumption ration e_{01}/e_{02} for the 4G user (user 1) and the WiFi user (user 2). Cellular data usage is free of charge, and 4G capacity is twice the WiFi capacity (2Mbps).

VI. Related Work

One main example of UPC services is the WiFi community network, where residential users share their WiFi connections with roaming users [4], [28]. The key challenges for these services include security issues[9] [29] and incentive issues of user participation [30]. One popular approach for addressing the incentive issues is to design reciprocity schemes (reputation-based or credit-based), which deter free riding by rewarding the users who contribute more resources. References [19], [31], and [32] studied similar mechanisms for other classes of autonomous networks, such as peer-to-peer (P2P) or ad hoc networks. However, these results are not directly applicable to our model, since the proposed mechanisms did not account for users' different types of resources, or for their mobile data usage cost. Also, most users in our model can access the Internet without relying on other users' help, while this is typically not the case for ad hoc networks. The characterization of such standalone operations is critical in

[8]This can be the case when, for example, the 4G user has an unlimited data plan. Similar results and conclusions hold for the case the users have non-zero but equal data usage cost.

[9]Recent technological advances, such as the HotSpot 2.0 protocol, address many of the initial security issues in this type of services [33].

determining whether a user will agree to join the service or not. To address both challenges, we consider a utility-based criterion and employ the Nash bargaining solution [7], [20].

UPC services can be centralized (as in FON), or decentralized where users negotiate directly with each other. For the centralized case, [34] studied a pricing rule for inducing service adoption, and [35] analyzed the price competition among FON-like operators and conventional operators. For decentralized services, [17] and [16] performed game-theoretic analysis to predict the prices that users charge to each other. Also, in [36] a UPC model was considered with mobile WiFi hotspots. Our scheme differs in that each user can concurrently provide service (as a gateway or a relay), and consume service (as a client), and the data transmissions to a single user can be multi-hop and multi-path. Besides, mobile users often have tight pricing constraints and are limited by battery energy, both of which affect their decisions.

Another cluster of literature that is closely related to our work focuses on the incentive schemes for wireless mesh networks [37] and cooperative wireless networks [38]. However, these results often do not account for the users' monetary cost due to mobile data usage. Another unique aspect of our model is the interactions between users from heterogeneous networks (cellular and WiFi). Hence the distributed cooperation of users may lead to either offloading cellular traffic to WiFi APs [9], or *onloading* WiFi traffic to cellular networks [10] as was illustrated in Fig. 2. Such flexible cooperation framework differs from previous offloading-only architectures [39].

VII. Conclusions

UPC services for mobile Internet constitute a paradigm shift in wireless communications, which many compare to the advent of P2P overlays for wired networks. In this work, we proposed a distributed incentive mechanism for a crowd-sourced mobile Internet access service, which improves the performance of the participating users. The more diverse the needs and resources of the users are, the higher the performance benefits of the service is.

There are many directions for future work. First, we will investigate the impact of the virtual currency parameters, such as the budget D_i and the reward γ, on the service performance. There are several related studies for P2P systems, but we need to take into account the specific characteristics of our new services. Moreover, it would be exciting to study the impact of this ad hoc offloading-onloading service on the cellular network congestion and operator's cost. Operators and users may have conflicting interests, regarding the crowd-sourced service, and it would be interesting to try to reconcile them by properly extending the incentive mechanism.

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