Economics of Peer-to-Peer Mobile Crowdsensing

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***Abstract*—Mobile crowdsensing is a new sensing paradigm relying on computation and storage capabilities of mobile devices. However, traditional server-client mobile crowdsensing models suffer from a high operational cost on the server, and hence a poor scalability. Peer-to-peer (P2P) mobile crowdsensing models can effectively reduce the server's operational cost, by leveraging the mobile devices' under-utilized computation and storage resources. In a P2P mobile crowdsensing model, the sensing data is saved and processed in mobile users' devices in a distributed fashion, and is shared among mobile users directly in a P2P manner. In this work, we focus on the incentive issue in such a P2P mobile crowdsensing model. Specifically, we propose a data market and a generic pricing scheme for the data sharing among data sensors and requesters. We analyze the user interactions in such a data market from a game theoretic perspective, and prove the existence and uniqueness of the market equilibrium. We further propose a generalized best response dynamics to reach the market equilibrium. Our theoretic analysis and numerical results indicate that the equilibrium social welfare decreases with the data transfer cost and data prices, while the ratio of the equilibrium social welfare to the maximum social welfare benchmark increases with the data transfer cost and data prices.**

I. Introduction

A. Background and Motivations

The proliferation of mobile devices with rich embedded sensors (e.g., smartphones, tablets, and sensor-equipped vehicles) has enabled a novel and fast-growing sensing paradigm known as *Mobile CrowdSensing (MCS)*, in which the target sensing data is collected by a large group of mobile users collectively using their mobile devices. Due to the low deploying cost and high sensing coverage, this new sensing paradigm has attracted a broad range of applications such as urban dynamic mining, public safety, and environment monitoring [1]–[3].

The existing mobile crowdsensing applications focused primarily on the centralized *server-client* architecture, where the participating users (clients) sense and report the data to a centralized server, who further processes the data and distributes to those users who require the data (e.g., [4]–[7]). However, the centralized architecture may not be suitable for all application scenarios, due to the high operational cost on the server (e.g., for data storage and processing).[1] On the other hand, mobile devices are becoming increasingly powerful, with their computation and storage capabilities often under-utilized.

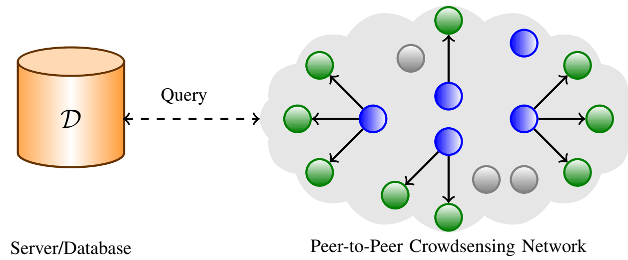

Fig. 1. P2P Mobile Crowdsensing Model. Blue Users: sensing data and sharing with others; Green Users: requesting data; Gray Users: doing nothing.

This motivates us to shift part or even all of the computation and storage burden on the server to the distributed mobile devices, giving rise to the *Peer-to-Peer (P2P)* crowdsensing architecture [8]–[11].

Specifically, in a P2P mobile crowdsensing system, the sensory data is no longer reported to the server; instead, it is saved and processed in mobile users' devices distributedly (via specific apps or dedicated middlewares, e.g., [9]), and is shared among multiple users directly in a P2P manner. The functionality of the server, like a traditional P2P system server (e.g., Homer Conferencing[2]), is mainly keeping track of each user's network access information (e.g., IP address) and data occupancy information (e.g., which data she has). Moreover, the data sharing among two users can be based on their local interactions (e.g., via WiFi or Bluetooth) when they are close enough, or social interactions (e.g., via Internet) when they are not locally connected. Fig. 1 illustrates such a P2P mobile crowdsensing model, where the sensory data is exchanged among users directly (from blue users to green users), and the server/database only needs to exchange the necessary control signals with users (e.g., establishing an Internet connection between two users for their data exchange).

Some recent studies of P2P mobile crowdsensing systems include MPSDataStore [8], SmartP2P [9], [10], and LL-Net [11]. However, these studies focused on the technical issues such as how to store data distributedly and how to search the distributed data efficiently, and none of them considered the *incentive* issue in such a system. Due to the data sensing cost and the data transfer cost (e.g., the data uploading and downloading cost during data sharing), incentive becomes extremely important in such a system. In this work, we will focus on the incentive issue in P2P mobile crowdsensing.

The incentive mechanisms in traditional P2P networks for content distributions (e.g., [12]–[14]), however, are not applicable to P2P mobile crowdsensing systems. The reason is summarized as follows. An important distinctive feature of such a P2P crowdsensing model is the joint consideration of

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[1] Niwa *et al.* in [8] reported that when 25 million smartphones sense data together, each collecting 1 Byte of data every minute and uploading to a storage server, the server requires 3Gbps of bandwidth and 1,350GB/h of storage (12PB per year), and needs to manage 36 billion sensor data each hour.

[2] http://www.homer-conferencing.com/en/index.php

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data generation (via sensing) and distribution (via sharing). Traditional studies on P2P networks usually assume that some peers are endowed with exogenous contents, and focus on the distribution of contents among users (e.g., [12]–[14]). Note that such a joint consideration of data generation and distribution will affect the incentive design in a P2P system, as users have multiple ways to obtain data, i.e., sensing by themselves and requesting from others.

B. Contributions

In a P2P mobile crowdsensing system, each user can choose to be a data *sensor*, sensing and sharing data with others with proper compensation, or a data *requester*, requesting data from a sensor with certain payment. This leads to a data *market* among the sensors (sellers) and the requesters (buyers). In this work, we seek to answer the following questions in such a data market: (i) *how to incentivize mobile users to participate in this crowdsensing and sharing system?* and (ii) *what is the equilibrium point of such a data market?* The first one is a mechanism design problem, i.e., designing the rule of the market. The second one is a game theoretical analysis problem, i.e., studying how the market would evolve under the proposed rules and what is the equilibrium point.

To solve the above questions, we first propose a generic *pricing* scheme for the data sharing among sensors and requesters, which combines both the revenue sharing scheme and the wholesale pricing scheme. Namely, with the proposed pricing scheme, a data sensor can obtain certain benefit from sharing data with a requester, which consists of two parts: a portion of the total benefit the requester achieves (from consuming the data), and a fixed wholesale price. Then, we model the user interactions in such a data market as a non-cooperative game, and analyze the game equilibrium systematically.

In summary, the key contributions are listed as follows.

- *Novel Model:* To our best knowledge, this is the first work that considers the incentive issue in a P2P mobile crowdsensing system, which is important for the large-scale commercial deployment of such a system.
- *Problem Formulation and Analysis:* We propose a data market and a generic pricing scheme for the data sharing among sensors and requesters. We analyze the user interactions in the data market from a game theoretic perspective, and prove the existence and uniqueness of the game equilibrium. We further propose a generalized best response dynamics to reach the equilibrium.
- *Performance Evaluation:* Our theoretic analysis and numerical results indicate that the equilibrium social welfare decreases with the data transfer cost and data prices, while the ratio of the equilibrium social welfare to the maximum social welfare benchmark increases with the data transfer cost and data prices. We further show that when the data price is smaller, the gap between the equilibrium social welfare and the maximum social welfare benchmark is also smaller.

The rest of the paper is organized as follows. In Section II, we present the system model and market formulation. In Section III, we analyzes the market equilibrium. In Section IV, we propose the best response algorithms. We present the numerical results in Section V, and conclude in Section VI. Due to space limitation, we leave most of the proofs in our online technical report [17].

II. System Model

A. Network Model

We consider a P2P mobile crowdsensing and sharing system with a set $\mathcal{N} = \{1, 2, \cdots, N\}$ of mobile users, who can sense data in a certain area and share data with each other. The total sensing area is divided into many grids/locations (e.g., squares with $100 \times 100\text{m}^2$), denoted by $\mathcal{I} = \{1, 2, \cdots, I\}$. Each user has the potential to sense a specific region consisting of one or multiple locations, depending on factors such as her mobility, device type, and energy budget. Each location $i \in \mathcal{I}$ is associated with a weight $w_{[i]}$ capturing the importance of the location.[3] Let $v_{n[i]}$ denote the user-dependent value of the data at location $i \in \mathcal{I}$ for user $n \in \mathcal{N}$. Then, the *utility* of the data at location i for user n is $w_{[i]} \cdot v_{n[i]}$.

In a P2P mobile crowdsensing system, each user can obtain the interested data by sensing the related locations directly, or by requesting from someone who has sensed the location already. The latter case may happen when the user is not able to sense the data by herself (e.g., due to the mobility or device capability constraint), or when the user's sensing cost is very large (e.g., due to the energy budget constraint). Such a data exchanging/sharing process can be based on the local WiFi or Bluetooth connection, or based on the Internet connections. To facilitate such data exchanges, the server needs to keep track of each user's network access information (e.g., IP address) and data occupancy information (e.g., which data she has), similar as most traditional P2P system servers did. The server, however, does not store and process any sensory data.

B. User Type

For the data in each location, a user can choose to be a *sensor* (who senses the location directly and shares the data with others), a *requester* (who requests the data from a sensor), or an *alien* (who does nothing). Specifically,

- *Sensor*: As a sensor, the user senses data directly, which leads to some sensing cost (e.g., the energy cost). Meanwhile, the user can potentially share the sensory data with others, with certain monetary reward (see Section II-C);
- *Requester*: As a requester, the user requests data from a sensor, which leads to certain data transfer cost (e.g., data uploading cost for the sensor, and downloading cost for the requester). The requester not only needs to bear all of the transfer cost, but may also share certain benefit with the sensor as the reward (described in Section II-C);
- *Alien*: As an alien, the user neither senses the data, nor requests data from others. This may occur when the user is not interested in the data.

We consider a general scenario, where the same user may have different sensing costs for different locations (e.g., a larger cost for a far away location), and different users may have different sensing costs for the same location (e.g., a larger

[3] For example, a hotspot location may have a larger weight. Moreover, different users may have different personal preferences for the data at the same location, which is captured by a user-dependent data value.

cost for a far away user). Let $c_{n[i]}$ denote the sensing cost of user n at location i. Moreover, for analytical convenience, we assume that all users have the same average data uploading cost c_n^{UP}, and the same average data downloading cost c_n^{DL}. Hence, the total transfer cost for one data exchange between any two users is $s = c_n^{\text{DL}} + c_n^{\text{UP}}$.

C. Pricing Scheme

When a sensor shares the data with a requester, the requester needs to share certain benefit (that she achieves from consuming the data) with the sensor as the reward. Such a reward can be proportional to the total benefit (i.e., utility minus transfer cost) that the requester achieves from the data, or simply a fixed price. The former one is usually referred to as the *revenue sharing scheme*, and the second one is usually referred to as the *wholesale pricing scheme*, both widely used in reality (e.g., [15], [16]). In this work, we adopt a generic pricing scheme, which combines both revenue sharing and wholesale pricing schemes.

Definition 1 (Pricing Scheme): Suppose that a requester achieves a total benefit z from the data shared by a sensor. Then, the reward is $z \cdot (1 - \eta) + p$, where $\eta \in [0, 1]$ is the revenue sharing factor, and p is the wholesale price.

Obviously, our pricing scheme includes both the pure revenue sharing scheme (with $p = 0$) and the pure wholesale pricing scheme (with $\eta = 1$) as special cases.

D. User Payoff

Now we model the user behavior and define the user payoff. Without loss of generality, we consider an arbitrary user n and an arbitrary location i. For writing convenience, we omit the subscripts n and $[i]$ whenever there is no confusion caused, and hence write the sensing cost $c_{n[i]}$ and user-dependent data value $v_{n[i]}$ as c and v, respectively.

A user can be fully characterized by c and v, as we assume the identical data transfer cost and pricing scheme for all users. Note that different users may have different sensing cost c and data value v, which are independent and identically distributed (i.i.d.) according to the probability distribution functions $f_v(v)$ and $f_c(c)$, respectively. For simplicity, we assume the uniform distribution on $[0, 1]$ for both v and c in this work. Hence, the joint distribution of v and c is $f_{vc}(v, c) = 1$ if $v \in [0, 1], c \in [0, 1]$, and $f_{vc}(v, c) = 0$ otherwise.

A user will choose a decision $x \in \{\text{S}, \text{R}, \text{A}\}$, where

- $x = \text{S}$: Join the network as a *sensor*;
- $x = \text{R}$: Join the network as a *requester*;
- $x = \text{A}$: Do not join the network and remain as an *alien*.

Let $\pi_{vc}(x)$ denote the *payoff* of a type (v, c) user when choosing a decision x.[4] The objective of the user is to choose the proper decision x to maximize her payoff. Next, we define the user payoff $\pi_{vc}(x)$ under different decisions x.

[4]Notice that a user's payoff depends not only on her own choice, but also on other users' choices. We keep the notation $\pi_{vc}(x)$ for simplicity and present the detailed dependence relationship later in the paper.

1) Sensor: As a sensor, the user first achieves certain benefit directly for the data:

$$U_{vc}^{\text{S}} = w \cdot v - c.$$

Moreover, the sensor can also share the data with requesters with certain monetary reward (called sharing benefit), depending on the pricing scheme mentioned above. Let Φ denote the *average sharing benefit* of a sensor (which will be derived in Section III). Then, the payoff of a type (v, c) sensor is

$$\pi_{vc}(\text{S}) = U_{vc}^{\text{S}} + \Phi = w \cdot v - c + \Phi. \quad (1)$$

2) Requester: As a requester, the user achieves certain benefit from the data, and meanwhile needs to share certain benefit with the sensor. Since the requester needs to bear all of the transfer cost, the benefit that the requester achieves is

$$U_{vc}^{\text{R}} = w \cdot v - s,$$

where $s = c_n^{\text{DL}} + c_n^{\text{UP}}$ is the data transfer cost. According to the pricing scheme defined in Definition 1, the requester needs to share a benefit β_{vc} with the sensor as reward, where

$$\beta_{vc} = U_{vc}^{\text{R}} \cdot (1 - \eta) + p = (1 - \eta) \cdot (w \cdot v - s) + p.$$

Hence, the payoff of a type (v, c) requester is

$$\pi_{vc}(\text{R}) = U_{vc}^{\text{R}} - \beta_{vc} = \eta \cdot (w \cdot v - s) - p. \quad (2)$$

3) Alien: As an alien, the user neither senses the data nor requests data from a sensor. Hence, her payoff is zero, i.e.,

$$\pi_{vc}(\text{A}) = 0. \quad (3)$$

E. Game Formulation

We model the sensing and sharing of sensors, requesters, and aliens as the following non-cooperative game:

- *Players*: A total of N users, each associated with a type (v, c);
- *Strategies*: A set of available actions (pure strategies) $\{\text{S}, \text{R}, \text{A}\}$ for each player (for each location);
- *Payoffs*: User payoffs under different strategies as defined in (1), (2), and (3), respectively.

For analytical convenience, we assume a large network with many users, e.g., $N \to \infty$, hence the impact of a single user's action on the whole population can be ignored. This assumption is mainly used for obtaining the closed form result, and our analysis holds for any finite number of users.

III. Game Equilibrium Analysis

In this section, we study the equilibrium of the proposed game. For clarity, we denote the strategy of a type (v, c) user as $x(v, c)$.[5] The equilibrium can be formally defined as follows.

Definition 2 (Game Equilibrium): A strategy profile $\{x^*(v, c),\ \forall v, c\}$ is an equilibrium, if and only if

$$\pi_{vc}(x^*(v, c)) \geq \pi_{vc}(x), \quad \forall x \in \{\text{S}, \text{R}, \text{A}\},$$

for any user with type (v, c).

Given a strategy profile $\{x(v, c),\ \forall v, c\}$, the market will be partitioned into three parts, each corresponding to one user

[5]Here, we focus on deriving the symmetric equilibrium, where the users with the same type will always choose the strategy.

choice, which we call the *market state*. Let $\mathcal{S}^{\text{S}}$, $\mathcal{S}^{\text{R}}$, and $\mathcal{S}^{\text{A}}$ denote the *market shares* of sensors, requesters, and aliens. That is,

$$\begin{aligned}\mathcal{S}^{\text{S}} &= \{(v,c) : x(v,c) = \text{S}\},\\ \mathcal{S}^{\text{R}} &= \{(v,c) : x(v,c) = \text{R}\},\\ \mathcal{S}^{\text{A}} &= \{(v,c) : x(v,c) = \text{A}\}.\end{aligned} \tag{4}$$

In what follows, we will first derive the average sharing benefit of a sensor, i.e., Φ. Then, we will analyze the user best response and characterize the game equilibrium.

A. Derivation of Average Sharing Benefit – Φ

Recall that the sharing benefit provided by a requester with type (v,c) is β_{vc}. Hence, given market shares $\mathcal{S}^{\text{S}}$, $\mathcal{S}^{\text{R}}$, and $\mathcal{S}^{\text{A}}$, the total sharing benefit provided by all requesters in $\mathcal{S}^{\text{R}}$ is

$$B^{\text{SE}} = N \iint_{\mathcal{S}^{\text{R}}} [(1-\eta)(w\cdot v - s) + p] f_{vc}(v,c)\mathrm{d}v\mathrm{d}c. \tag{5}$$

The total number of sensors in $\mathcal{S}^{\text{S}}$ is

$$N^{\text{SE}} = N \iint_{\mathcal{S}^{\text{S}}} f_{vc}(v,c)\mathrm{d}v\mathrm{d}c. \tag{6}$$

As the data transfer cost is identical between any pair of users, we will assume that a requester will request data from an arbitrary sensor randomly and uniformly. Hence, the *average* sharing benefit Φ of each sensor is

$$\Phi = \frac{B^{\text{SE}}}{N^{\text{SE}}} = \frac{\iint_{\mathcal{S}^{\text{R}}} [(1-\eta)(w\cdot v - s) + p] f_{vc}(v,c)\mathrm{d}v\mathrm{d}c}{\iint_{\mathcal{S}^{\text{S}}} f_{vc}(v,c)\mathrm{d}v\mathrm{d}c}. \tag{7}$$

B. Best Response Analysis

In the following, starting from an existing market share distribution $\mathcal{S}^{\text{S}}$, $\mathcal{S}^{\text{R}}$, and $\mathcal{S}^{\text{A}}$, we will derive how users update their actions according to their best responses.

A user with type (v,c) will choose to be a sensor (i.e., $x(v,c) = \text{S}$), if her payoff as a sensor is higher than the payoff as a requester or as an alien, i.e.,[6]

$$\pi_{vc}(\text{S}) > \max(\pi_{vc}(\text{A}), \pi_{vc}(\text{R})).$$

Solving the above two inequalities, we have

$$v > \max\left(\tfrac{c-\Phi}{w}, \tfrac{c-\Phi-\eta s-p}{w(1-\eta)}\right).$$

That is, a user with a type (v,c) that satisfies the above condition will choose to be a sensor. Hence, the newly derived market share of sensors is $\widetilde{\mathcal{S}^{\text{S}}} = \{(v,c) : v > \max(\frac{c-\Phi}{w}, \frac{c-\Phi-\eta s-p}{w(1-\eta)})\}$.

Similarly, a user with type (v,c) will choose to be a requester (i.e., $x(v,c) = \text{R}$), if

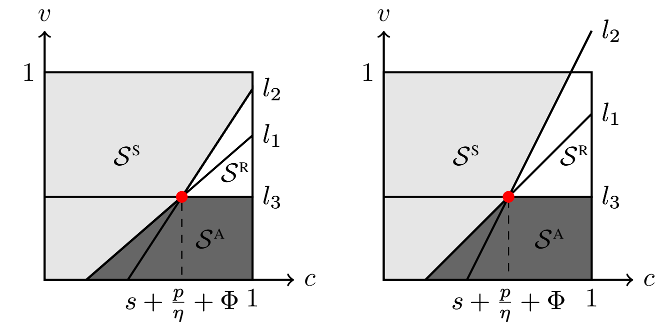
$$\pi_{vc}(\text{R}) > \max(\pi_{vc}(\text{A}), \pi_{vc}(\text{S})).$$

Solving the above two inequalities, we have

$$\tfrac{\eta s+p}{w\eta} < v < \tfrac{c-\Phi-\eta s-p}{w(1-\eta)}.$$

That is, the newly derived market share of requesters is $\widetilde{\mathcal{S}^{\text{R}}} = \{(v,c) : \frac{\eta s+p}{w\eta} < v < \frac{c-\Phi-\eta s-p}{w(1-\eta)}\}$.

[6]Notice that we ignore the equality case, as the probability having equalities is zero under the continuous distributions.



(a) Case 1

(b) Case 2

Fig. 2. Illustrations of lines l_1, l_2, and l_3. Gray region $\mathcal{S}^{\text{S}}$: Sensors; White region $\mathcal{S}^{\text{R}}$: Requesters; Black region $\mathcal{S}^{\text{A}}$: Aliens.

Similarly, a user with type (v,c) will choose to be an alien (i.e., $x(v,c) = \text{A}$), if

$$\pi_{vc}(\text{A}) > \max(\pi_{vc}(\text{S}), \pi_{vc}(\text{R})).$$

Solving the above two inequalities, we have

$$v < \min\left(\tfrac{c-\Phi}{w}, \tfrac{\eta s+p}{w\eta}\right).$$

That is, the newly derived market share of aliens is $\widetilde{\mathcal{S}^{\text{A}}} = \{(v,c) : v < \min(\frac{c-\Phi}{w}, \frac{\eta s+p}{w\eta})\}$.

Based on the above, we can find that the newly derived market shares can be characterized by the following three lines:

$$\begin{aligned} l_1: &\quad v = \tfrac{c-\Phi}{w},\\ l_2: &\quad v = \tfrac{c-\Phi-\eta s-p}{w(1-\eta)},\\ l_3: &\quad v = \tfrac{\eta s+p}{w\eta}.\end{aligned}$$

Specifically, as illustrated in Fig. 2, the users with types above lines l_1 and l_2 will choose to be sensors (gray region), the users with types below line l_2 and above line l_3 will choose to be requesters (white region), and the remaining users will choose to be aliens (black region).

Moreover, under the newly derived market shares $\widetilde{\mathcal{S}^{\text{S}}}$, $\widetilde{\mathcal{S}^{\text{R}}}$, and $\widetilde{\mathcal{S}^{\text{A}}}$, we can compute the new average sharing benefit $\widetilde{\Phi}$ according to (7) directly, that is,

$$\widetilde{\Phi} = \frac{\iint_{\widetilde{\mathcal{S}^{\text{R}}}} [(1-\eta)(w\cdot v - s) + p] f_{vc}(v,c)\mathrm{d}v\mathrm{d}c}{\iint_{\widetilde{\mathcal{S}^{\text{S}}}} f_{vc}(v,c)\mathrm{d}v\mathrm{d}c}. \tag{8}$$

Note that $\widetilde{\Phi}$ is a function of the original average sharing benefit Φ, represented by $\widetilde{\Phi} = \varphi(\Phi)$, as the newly derived market shares $\widetilde{\mathcal{S}^{\text{S}}}$, $\widetilde{\mathcal{S}^{\text{R}}}$, and $\widetilde{\mathcal{S}^{\text{A}}}$ are functions of Φ. For convenience, we will write the newly derived B^{SE} and N^{SE} as functions of Φ as well, i.e., $B^{\text{SE}}(\Phi)$ and $N^{\text{SE}}(\Phi)$.

C. Game Equilibrium Analysis

If a strategy profile is an equilibrium, then none of the users has the incentive to change her strategy, which implies that the market shares and the average sharing benefit will no longer change. This leads to the following condition for the equilibrium.

Proposition 1: If a strategy profile $\{x^*(v,c),\ \forall v,c\}$ is an equilibrium, then the average sharing benefit $\Phi = \frac{B^{\text{SE}}(\Phi)}{N^{\text{SE}}(\Phi)}$.

Proposition 1 shows that finding the equilibrium $\{x^*(v,c),\ \forall v,c\}$ is equivalent to finding the equilibrium average sharing benefit Φ that satisfies $\Phi = \frac{B^{\text{SE}}(\Phi)}{N^{\text{SE}}(\Phi)}$.

Next, we analyze the existence and uniqueness of the equilibrium average sharing benefit Φ. Based on the above discussion, we can derive the equilibrium average sharing benefit Φ by solving $\Phi - \frac{B^{\text{SE}}(\Phi)}{N^{\text{SE}}(\Phi)} = 0$, i.e., $\Phi N^{\text{SE}}(\Phi) - B^{\text{SE}}(\Phi) = 0$. For convenience, we define the following function:

$$g(\Phi) = \Phi N^{\text{SE}}(\Phi) - B^{\text{SE}}(\Phi).$$

Then, the problem of finding the equilibrium can be transformed into the problem of finding the roots of $g(\Phi) = 0$.

As shown in Fig. 2, the lines l_1, l_2, l_3 may intersect in two different ways, depending on the value of average sharing benefit Φ. For example, in the left subfigure, the line l_2 intersects with the vertical boundary line $c = 1$, while in the right subfigure, the line l_2 intersects with the horizontal boundary line $v = 1$. This will further affect the derivations of $B^{\text{SE}}(\Phi)$ and $N^{\text{SE}}(\Phi)$. Hence, we consider these two cases separately.

1) Case 1 (High Average Sharing Benefit Regime): In this case, Φ is larger than a critical value Φ_0, i.e.,

$$\Phi \geq \Phi_0 \triangleq 1 - \eta s - p - w(1-\eta).$$

Intuitively, under the critical value $\Phi = \Phi_0$, the line l_2 will intersect at the cross point of lines $c = 1$ and $v = 1$ (i.e., the right upper corner).

In this case, the newly derived market shares $\widetilde{\mathcal{S}^{\text{S}}}$, $\widetilde{\mathcal{S}^{\text{R}}}$, and $\widetilde{\mathcal{S}^{\text{A}}}$ can be derived according to the left subfigure. For convenience, we denote the corresponding functions $g(\Phi)$, $N^{\text{SE}}(\Phi)$, $B^{\text{SE}}(\Phi)$ by $g_h(\Phi)$, $B_h^{\text{SE}}(\Phi)$, and $N_h^{\text{SE}}(\Phi)$, respectively.[7] Moreover, to simplify the notations, we normalize the location weight w to be $w = 1$.

It is easy to check that when $\Phi \geq \Phi_0$, the function $g(\Phi) = g_h(\Phi)$ is monotonically increasing in Φ (see our technical report [17] for details). We further notice that $g_h(\Phi) > 0$ when Φ is large enough. Hence, the root of $g_h(\Phi) = 0$ in the regime $\Phi \geq \Phi_0$ is determined by the value of $g_h(\Phi_0)$. Formally, we have the following proposition.

Proposition 2: If $g_h(\Phi_0) < 0$, then there is a unique equilibrium with respect to Φ in the regime $[\Phi_0, +\infty)$; otherwise there is no equilibrium in the regime $[\Phi_0, +\infty)$.

2) Case 2 (Low Average Sharing Benefit Regime): In this case, Φ is smaller than the critical value Φ_0, i.e.,

$$\Phi \leq \Phi_0.$$

The newly derived market shares $\widetilde{\mathcal{S}^{\text{S}}}$, $\widetilde{\mathcal{S}^{\text{R}}}$, and $\widetilde{\mathcal{S}^{\text{A}}}$ can be derived according to the right subfigure. For convenience, we denote the corresponding functions $g(\Phi)$, $N^{\text{SE}}(\Phi)$, $B^{\text{SE}}(\Phi)$ by $g_l(\Phi)$, $B_l^{\text{SE}}(\Phi)$, and $N_l^{\text{SE}}(\Phi)$, respectively.

It is easy to check that when $\Phi \leq \Phi_0$, the function $g(\Phi) = g_l(\Phi)$ is either monotonically increasing with Φ, or first decreasing with Φ and then increasing with Φ (hence unimodal). We further notice that $g_l(0) < 0$. Hence, the root of $g_l(\Phi) = 0$ in the regime $\Phi \leq \Phi_0$ is determined by the value of $g_l(\Phi_0)$. Formally, we have the following proposition.

[7] The detailed derivations can be referred to our online technical report [17].

Proposition 3: If $g_l(\Phi_0) > 0$, then there is a unique equilibrium with respect to Φ in the regime $[0, \Phi_0]$; otherwise there is no equilibrium in the regime $[0, \Phi_0]$.

Combine Propositions 2 and 3, and notice that $g_h(\Phi_0) = g_l(\Phi_0) = g(\Phi_0)$, we have the following theorem for the existence and uniqueness of the equilibrium.

Theorem 1: There exists a unique equilibrium, and

- If $g(\Phi_0) < 0$, the equilibrium is located in $(\Phi_0, +\infty)$;
- If $g(\Phi_0) > 0$, the equilibrium is located in $(0, \Phi_0)$;
- If $g(\Phi_0) = 0$, the equilibrium is Φ_0.

In the next section, we will further study how to reach the equilibrium explicitly.

IV. Best Response Dynamics

In this section, we propose a best response dynamics to compute the above game equilibrium.

To describe the best response dynamics, we first define a *virtual* time-slotted system with slots $t = 1, 2, \cdots$ (each with a sufficiently small time period), and allow users to hypothetically change their decisions in every time slot based on the newly derived market shares. Let $\Phi(t)$ be the average sharing benefit at time slot t, and the corresponding $B^{\text{SE}}(\Phi)$ and $N^{\text{SE}}(\Phi)$ are denoted by $B^{\text{SE}}(\Phi(t))$ and $N^{\text{SE}}(\Phi(t))$, respectively. According to the analysis in Section III, we have

$$\Phi(t+1) = \frac{B^{\text{SE}}(\Phi(t))}{N^{\text{SE}}(\Phi(t))} = \begin{cases} \frac{B_h^{\text{SE}}(\Phi(t))}{N_h^{\text{SE}}(\Phi(t))}, & \text{if } \Phi(t) \leq \Phi_0, \\ \frac{B_l^{\text{SE}}(\Phi(t))}{N_l^{\text{SE}}(\Phi(t))}, & \text{if } \Phi(t) \geq \Phi_0. \end{cases}$$

However, under the pure best response update mentioned above, the system may not converge. To this end, we propose a generalized best response dynamics, where each user updates her decision with probability $1 - \lambda$ in each time slot. Then,

$$\Phi(t+1) = \lambda \cdot \Phi(t) + (1-\lambda) \cdot \frac{B^{\text{SE}}(\Phi(t))}{N^{\text{SE}}(\Phi(t))}. \tag{9}$$

Clearly, $\lambda = 0$ corresponds to the pure best response dynamics, while $\lambda = 1$ corresponds to a fixed network without dynamics.

Next, we show the convergence of the above generalized best response dynamics. For notational convenience, we define

$$\psi_l(\Phi) = \frac{\mathrm{d}\frac{B_l^{\text{SE}}(\Phi)}{N_l^{\text{SE}}(\Phi)}}{\mathrm{d}\Phi} \text{ and } \psi_h(\Phi) = \frac{\mathrm{d}\frac{B_h^{\text{SE}}(\Phi)}{N_h^{\text{SE}}(\Phi)}}{\mathrm{d}\Phi}.$$

Proposition 4: The generalized best response dynamics in (9) converges to the unique equilibrium Φ, if λ is larger than a threshold λ_0, where

$$\lambda_0 = \begin{cases} \max\left(\frac{\psi_h(\Phi_0)-1}{\psi_h(\Phi_0)+1},\ 0\right), & \text{if } g(\Phi_0) < 0, \\ \max\left(\frac{\psi_l(0)-1}{\psi_l(0)+1},\ 0\right), & \text{if } g(\Phi_0) > 0. \end{cases} \tag{10}$$

Intuitively, a smoothed enough dynamics (by setting a large λ) will guarantee that the dynamics (9) converges to the unique equilibrium, at the cost of a slower convergence speed.

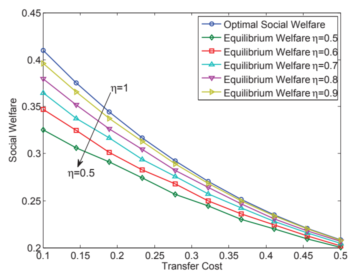


Fig. 3. Social welfare under different revenue sharing factors η (wholesale price $p = 0$).

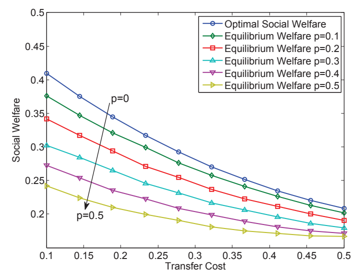


Fig. 4. Social welfare comparison under different wholesale prices p (revenue sharing factor $\eta = 1$).

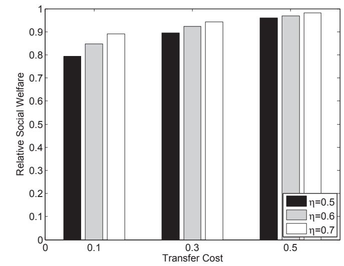


Fig. 5. Ratio of the equilibrium welfare to the optimal social welfare under different factors η.

V. Simulations and Efficiency Evaluation

Now we provide simulation results to illustrate the efficiency of the equilibrium, i.e., the ratio of the equilibrium social welfare to the maximum social welfare benchmark (in a centralized optimization). Here, social welfare is the sum of all users' payoffs. We will illustrate the absolute and relative equilibrium social welfares under different system parameters.

The social welfare is defined as the sum of all users' payoffs. Hence, given a particular market partition $\mathcal{S}^{\mathrm{S}}$, $\mathcal{S}^{\mathrm{R}}$, and $\mathcal{S}^{\mathrm{A}}$, the social welfare is

$$W = \iint_{\mathcal{S}^{\mathrm{S}}} (v - c) \mathrm{d}v \mathrm{d}c + \iint_{\mathcal{S}^{\mathrm{R}}} (v - s) \mathrm{d}v \mathrm{d}c,$$

where the social welfare generated by a sensor is $v - c$, and the social welfare generated by a requester is $v - s$. From a centralized optimization perspective, those users with type (v, c) that satisfies $v > c$ and $c < s$ should choose to be sensors, those users with type (v, c) that satisfies $v > s$ and $c > s$ should choose to be requesters, and all other users should choose to be aliens. Accordingly, we can compute the maximum social welfare benchmark. For more details, please refer to our online technical report [17].

We numerically compare the social welfare of the equilibrium with the optimal social welfare. Figs. 3, 4, and 5 show the social welfare of the equilibrium under different system parameters η, p, and s. We choose a large range of the transfer cost $s \in [0.1, 0.5]$ and compute the equilibrium social welfare. We have three observations.

(i) The social welfare is decreasing in the transfer cost s in Figs. 3 and 4. This is because the generated sharing benefit is reduced when increasing the transfer cost. On the other hand, the larger transfer cost, the smaller gap between the achieved social welfare and the optimal social welfare benchmark. This is because a larger transfer cost reduces the sharing benefit for sensors, hence weakens the competition among sensors. This is a tradeoff for the system designers to balance.

(ii) Given the transfer cost s, the social welfare is increasing in the revenue sharing factor η and is decreasing in the wholesale price p in Figs. 3 and 4. This is because a larger η or a smaller p decreases the revenue sharing for the sensing users, thus weakens the competition of the sensing users. In the extreme case with $\eta = 1$ and $p = 0$, the social welfare will achieve the maximum value.

(iii) The ratio of the equilibrium social welfare to the optimal social welfare is increasing in the transfer cost in Fig. 5. It demonstrates that a larger transfer cost weakens the sharing effect among users.

VI. Conclusion

We present a novel P2P mobile crowdsensing architecture that can effectively reduce the operational cost in the centralized server. We study the incentive mechanisms and market behaviors of such a system. In particular, we propose a non-cooperative game under a generic pricing scheme, and analyze the existence and uniqueness of the equilibrium systematically. We also propose an evolution dynamics that is guaranteed to converge to the unique equilibrium. Our numerical results confirm the feasibility of the model and quantify the efficiency loss under different system parameters and pricing parameters. There are several important extensions for the model in this work. It is important to study the coupling of different locations when conducting the sensing and sharing decisions. It is also meaningful to consider a dynamic system in a long period of time.

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