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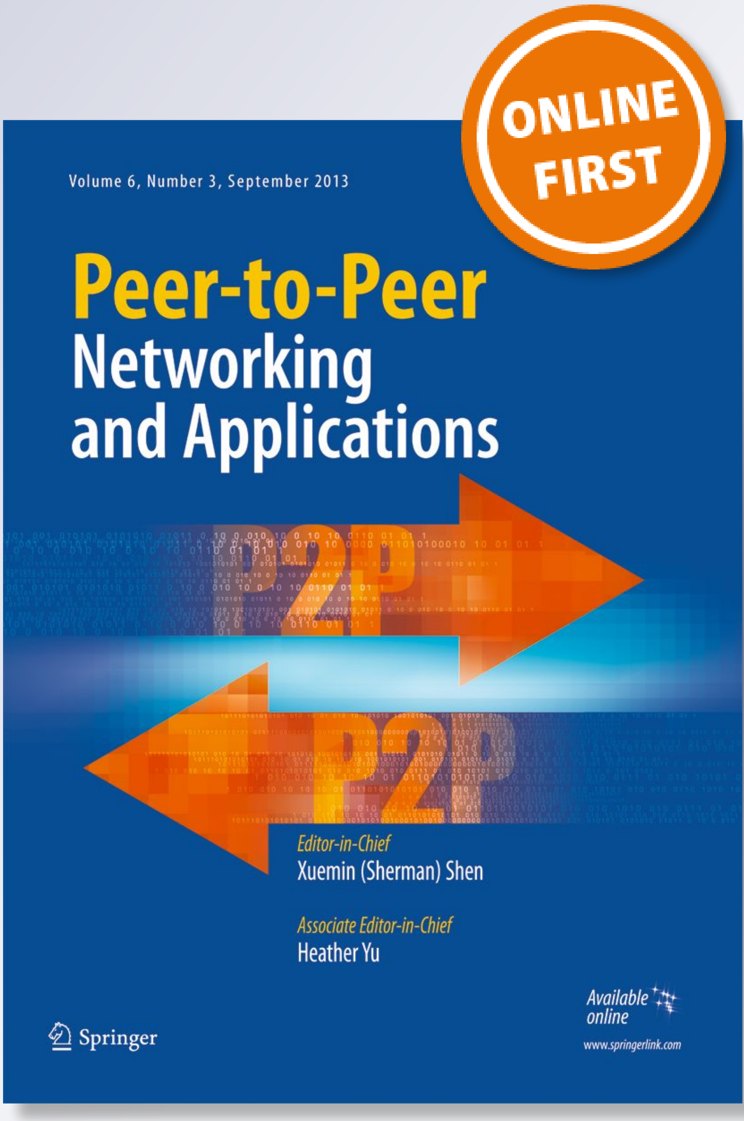

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Jia Xu [1] · Wei Lu [1] · Lijie Xu [1] · Dejun Yang [2] · Tao Li [1]

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Abstract
Mobile crowd sensing has become an efficient paradigm for performing large scale sensing tasks. An incentive mechanism is important for the mobile crowd sensing system to stimulate participants, and to achieve good service quality. In this paper, we design the incentive mechanisms for mobile crowd sensing, where the price and supply of the resource contributed by the smartphone users are determined by the supply-demand relationship of market. We present two models of mobile crowd sensing: the resource model and the budget model. In the resource model, each sensing task has the least resource demand. In the budget model, each task has a budget constraint. We design an incentive mechanism for each of the two models. Through both rigorous theoretical analysis and extensive simulations, we demonstrate that the proposed incentive mechanisms achieve computational efficiency, profitability, individual rationality, and truthfulness. Moreover, the designed mechanisms can satisfy the properties of non-monopoly and constant discount under certain conditions.

Keywords Mobile crowd sensing · Incentive mechanism · Supply-demand relationship

1 Introduction

Nowadays, smartphones are integrated with a variety of sensors such as camera, light sensor, GPS, accelerometer, digital compass, gyroscope, microphone, and proximity sensor. These sensors can collectively monitor a diverse range of human activities and surrounding environment. Compared with the traditional sensor network, mobile crowd sensing has a huge potential due to the prominent advantages [1], such as wide spatio-temporal coverage, low cost, good scalability, and pervasive application scenario. It will be an efficient approach to meet the demand in large scale sensing applications if we take advantage of pervasive smartphones to collect data.

Mobile crowd sensing can enable attractive sensing applications in various domains, such as BikeNet [2] for healthcare, CenceMe [3] for behavior and relationship discovery, PIER [4] for personalized environmental impact and exposure, Haze Watch [5] for pollution monitoring, Ear-Phone [6] for creating noise maps, SignalGuru [7] for providing traffic information, Frequent Trajectory Pattern Mining [8] for activity monitoring, LiFS [9]for indoor localization, crowd-participated system [10] for bus arrival time prediction, CCCN [11] for content delivery in content-centric network, etc.

The incentive mechanisms are crucial for mobile crowd sensing systems to compensate participants' resource consumption and potential privacy breach. The incentive mechanisms also help to achieve good service quality since sensing services are truly dependent on the quantity of users and the quality of sensed data. A lot of research effort has been focused on developing such incentive mechanisms to entice users to participate in mobile crowd sensing.

Unfortunately, existing studies in the literature have not yet considered the issue of pricing determination for mobile crowd sensing systems. In reverse auction based incentive mechanisms [12–17], the payments to the winners are determined by the reserve price and the mechanism adopted. In this

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model, the reserve price is self-determined by each user. However, it is difficult to find the reference to determine the reserve price, and the user usually submits it empirically. Thus there is a threat to each user by submitting the reserve price, which deviates from the market expectation. In Stackelberg game based incentive mechanisms [14, 18], the platform first announces her policy on rewards, and the users would then make decisions on their contribution levels. In this model, the cost (or the range of cost) of each user is assumed to be fixed and known in advance. Recently, some pricing mechanisms based on the quality of information (QoI) [19] have been proposed. However, it is difficult to set the *benchmark reward*. Thus, it is urgent to design the economic model of price determination for mobile crowd sensing systems.

In this paper, we regard the mobile crowd sensing as a resource market, where the resource price and contribution of users are determined by the supply-demand relationship. The supply-demand relationship based pricing has been studied for data trading in user provided networks [20] and bandwidth sharing in dynamic spectrum access networks [21]. In our models, the contribution of each user to the sensing system is considered as the resource consumed for the sensing. The resource supply of each user is determined by the resource pricing function.

However, it is very challenging to design incentive mechanisms for mobile crowd sensing based on supply-demand relationship. First, since the resource price is determined by the supply-demand relationship of market, we cannot incentivize the users by increasing the price which deviates from the market. We need to design the resource pricing function tactically to stimulate the users to contribute more to the system. Second, a user can take a strategic action by submitting a dishonest available resource to maximize its utility. Moreover, the sensing tasks are associated with some constraints, such as the least resource demand or budget.

The main contributions of this paper are as follows:

- We introduce a resource pricing function, which takes the resource supply-demand relationship into consideration. Moreover, the designed resource pricing function can always stimulate users to contribute more.
- We present two system models based on the supply-demand relationship: the resource model and the budget model. In the first one, the platform has the least resource demand for each task. While in the budget model, each task is with a budget. We design an incentive mechanism for each of two models.
- We show that the designed mechanisms always satisfy four desirable properties: computational efficiency, profitability, individual rationality, and truthfulness. Moreover, the designed mechanisms also satisfy the properties of non-monopoly and constant discount under certain conditions.

The rest of the paper is organized as follows. Section 2 formulates the two system models and lists some desirable properties. Section 3 and Section 4 present the detailed design of our assignment mechanisms for the two models, respectively. Performance evaluation is presented in Section 5. We review the state-of-art research in Section 6, and conclude this paper in Section 7.

2 System model and desirable properties

In this section, we model the mobile crowd sensing based on the supply-demand relationship. We present two models: the resource model and the budget model. In the resource model, each task has the least resource demand. This model is quite practical since many crowd sensing systems require the fused data over the fragmented data from participants, such as sampling the cell tower sequences on whole bus route [10], measuring the long-term equivalent noise levels [6], and gathering the air pollution readings all the time [5]. While in the budget model, there is a budget for each task. The crowd sensing systems with budget constraint have been widely studied [12, 22]. In both models, the platform wants to stimulate the users to contribute more resource. At the end of this section, we present some important economic properties.

2.1 The resource model

We consider a mobile crowd sensing system as shown in Fig. 1. It consists of a platform and a set of smartphone users $U = \{1, 2, \ldots, n\}$, who are interested in participating sensing tasks. The platform publicizes a set of tasks $T = \{1, 2, \ldots, m\}$ and the threshold resource demand $\mathbf{L} = (L_1, L_2, \ldots, L_m)$, where L_k, $k \in T$, is the least resource to complete task k. In other words, the sum of resource derived from multiple users should be not less than L_k for each $k \in T$. We assume that there are enough smartphone users who can satisfy the threshold resource demand. This assumption is reasonable for crowdsourcing systems as made in [14, 16, 23–25]. The resource means the comprehensive contribution of sensing, storage, transmission to the tasks. For the sake of simplicity, we assume that the resource contribution of user $i \in U$ for task k is only determined by the sensing time $st_i^k \in \mathbb{N}$.

Each task is dedicated to a specific area of interest (AoI). The users can perform a task if they are located

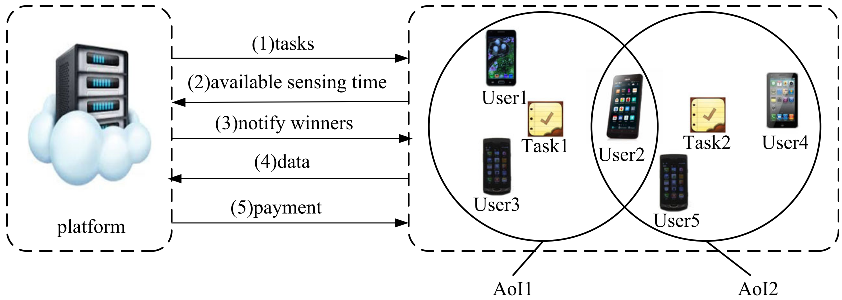


Fig. 1 System model of the smartphone sensing system

in the corresponding AoIs. To participate in the mobile crowd sensing, each user i can respond a finite available sensing time $at_i^k \in \mathbb{N}$ for task k according to the private future schedules, habits, preferences or behavior profiles [26]. We assume that each user can distribute its available sensing time freely among all tasks. Thus the response of users is an $n \times m$ available sensing time matrix **AT**.

We assume that the unit price of resource of user i for task k is $p\left(st_i^k\right)$, which is a function of sensing time. The resource demand and resource supply follow the basic supply-demand relationship [27]:

$$D_i^k = \alpha - \beta p\left(st_i^k\right) \tag{1}$$

$$S_i^k = a + bp\left(st_i^k\right) \tag{2}$$

where D_i^k is resource demand of task k for user i, S_i^k is resource supply of user i for task k, α, β, a and b are constants, $\alpha > a$, $b > 0$, $\beta > 0$, $st_i^k \in \mathbb{N}^+$. Specifically, the constants α and a embody the effects of all factors other than price that affect demand and supply, respectively. The constants β and b show how the price of the resource affects the quantity demanded and the quantity supplied.

It is easy to see that when $D_i^k = S_i^k$, the market achieves the supply-demand equilibrium with equilibrium price $p_e = \frac{\alpha - a}{\beta + b}$.

We define the utility of user i as the difference between its payment and cost. Then the utility of user i can be computed as follows:

$$u_i = \sum_{k=1}^{m} \left(p\left(st_i^k\right) - g\right)\left(a + bp\left(st_i^k\right)\right), st_i^k \in \mathbb{N}^+ \tag{3}$$

where $g \in (0, p_e)$ is the unit cost of resource.

Specially, the utility of the losers would be zero because they are paid nothing in our designed mechanisms and there is no cost for sensing.

Let A^k be the number of winners of task k. We define the utility of the platform as the difference between the value and payment:

$$u_0 = \sum_{i=1}^{A^k} \sum_{k=1}^{m} \left(r - p\left(st_i^k\right)\right)\left(a + bp\left(st_i^k\right)\right), st_i^k \in \mathbb{N}^+ \tag{4}$$

where $r \geq p_e$ is the unit value of resource.

The platform selects a subset of users $W \subseteq U$ as winners and determines the sensing time st_i^k for each user, where $st_i^k \leq at_i^k$. Then the platform notifies winners. Each winner i performs task k with sensing time st_i^k, respectively, and sends data back to the platform. Each user i is paid p_i^k for task k, which is computed by the platform.

Since we consider the smartphone users are selfish individuals, each user i can behave strategically by submitting dishonest available sensing time, which is different from the real available sensing time rt_i^k, to maximize its utility u_i. We assume that each user i is required to log on the mobile crowd sensing application at least at_i^k time for performing task k. By this way, the user cannot submit $at_i^k > rt_i^k$. However, the user can adopt the strategic behavior by submitting $at_i^k < rt_i^k$. We also assume a, b and g are public information.

2.2 Budget model

The definitions of U, T, st_i^k, at_i^k, rt_i^k, $p\left(t_i^k\right)$, D_i^k, S_i^k, p_e, u_0, $u_i$are the same as those in the resource model. Different from the resource model, The tasks are with the budget$\mathbf{B} = (B_1, B_2, \ldots, B_m)$, where B_k, $1 \leq k \leq m$, is the budget of task $k \in T$. We assume the platform always tends to maximize its utility under the budget constraint.

2.3 Desirable properties for incentive mechanisms

Our objective is to design an incentive mechanism $\mathcal{M}$, which returns a winner set W, an $n \times m$ sensing time matrix **ST** and an

$n \times m$ payment matrix **P** for each model, satisfying the following desirable properties:

- **Computational efficiency:** An incentive mechanism $\mathcal{M}$ is computationally efficient if the winner set W, the sensing time matrix **ST** and the payment matrix **P** can be computed in polynomial time.
- **Profitability:** The platform should not incur a deficit. In other words, the value brought by the winners should be at least as large as the total payment paid to the winners.
- **Individual rationality:** Each user will have a non-negative utility while reporting true available sensing time, i.e., $u_i \geq 0, \forall i \in U$.
- **Truthfulness:** A mechanism is truthful if no user can improve its utility by submitting an available sensing time vector different from its real available sensing time vector, no matter what others submit. In other words, reporting the real available sensing time vector is a dominant strategy [28] for all users.
- **Non-monopoly:** The mechanism $\mathcal{M}$ is non-monopolistic if no user can complete any task $\mathrm{k} \in \mathrm{T}$ alone. In other words, each task needs at least two users to complete in mechanism $\mathcal{M}$.
- **Constant discount:** We define the discount as the ratio between the average unit price obtained by the mechanism $\mathcal{M}$ and the average unit price when the single user performs any task alone. If the upper bound of the discount is within a constant within (0, 1), we call that $\mathcal{M}$ satisfies the property of constant discount.

The importance of the first three properties is obvious, because they together assure the feasibility of the incentive mechanism. Being truthful, the incentive mechanisms can eliminate the fear of market manipulation and the overhead of strategizing over others for the users. Being non-monopolistic, the incentive mechanism can improve the variety and quality of sensing data. With constant discount, the platform is always economical when adopting the incentive mechanism to perform tasks through the paradigm of mobile crowd sensing, comparing with the monopoly case.

3 Incentive mechanism for the resource model

3.1 Pricing based on the supply-demand relationship

Generally, the unit price of resource will decrease if the supply of goods is larger than the demand, and it will increase otherwise. So the unit price of resource will shift around the equilibrium price as the time elapses. To incentivize the users, we introduce a simple price shift model, where the shift rate of unit price of resource $\frac{\mathrm{d}p\left(st_i^k\right)}{\mathrm{d}st_i^k}$ has the direct proportion with the excess demand $\left(D_i^k - S_i^k\right)$ at sensing time st_i^k:

$$\frac{\mathrm{d}p\left(st_i^k\right)}{\mathrm{d}st_i^k} = h\left(D_i^k - S_i^k\right), st_i^k \in \mathbb{N}^+ \tag{5}$$

where $h > 0$ is a constant.

Substituting (1) and (2) into (5), we obtain:

$$\frac{\mathrm{d}p\left(st_i^k\right)}{\mathrm{d}st_i^k} = \lambda\left(p_e - p\left(st_i^k\right)\right), st_i^k \in \mathbb{N}^+ \tag{6}$$

where $\lambda = (b + \beta)h > 0$.

Solving (6), we obtain the pricing function:

$$p\left(st_i^k\right) = p_e + (p_0 - p_e)e^{-\lambda st_i^k}, st_i^k \in \mathbb{N}^+ \tag{7}$$

where p_0 is the initial unit price of resource.

In order to stimulate users to contribute more, we set $p_0 < p_e$, making the unit price of resource be a strictly monotone increasing function with sensing time. Here we let

$$p_0 = \frac{g - p_e}{e^{-\lambda}} + p_e \tag{8}$$

3.2 Mechanism design

In this section, we present an incentive mechanism for mobile crowd sensing in the resource model, named IM-R. For each task $k \in T$, IM-R selects the winners iteratively based on their available sensing time in nonincreasing order until the contributed resource is not less than the threshold resource demand. We define $\widetilde{\mathbf{AT}}$ as the matrix of available sensing time, which is not considered so far, and define S_W as the contributed resource of winners for each task.

We first calculate the unit price of winner i for task k based on the available sensing time using (7). If the winner's resource contribution $a + bp\left(\widetilde{at_i^k}\right)$ does not exceed the remaining resource demand, we set the sensing time of winner i as its claimed available sensing time and the payment to i can be determined with unit price $p\left(st_i^k\right)$.

Otherwise, winner i is only required to contribute the remaining resource demand $L_k - S_W$, and the unit price $\frac{L_k - S_W - a}{b}$ can be obtained using (2). Then there are two cases: If the unit price is less than $p(1)$, which is the minimum value of the pricing function defined in (7), let the sensing time and unit price to be 1 and $p(1)$, respectively. Otherwise, we set the unit price $\frac{L_k - S_W - a}{b}$ and sensing time $\left\lceil -\frac{1}{\lambda}\ln\frac{L_k - S_W - a - bP_e}{b(p_0 - p_e)}\right\rceil$ through (2) and (7), respectively. The whole process is illustrated in Algorithm 1. Obviously, IM-R can stimulate users to contribute the resource as more as he has since IM-R selects the winners based on at_i^k in nonincreasing order.

Algorithm 1: IM-R

$W \leftarrow \emptyset$; $\mathbf{ST} \leftarrow 0$; $\mathbf{P} \leftarrow 0$; $\widetilde{\mathbf{AT}} \leftarrow \mathbf{AT}$;
foreach $k \in T$ **do**
  $S_W \leftarrow 0$;
  while $L_k > S_W$ **do**
    $i \leftarrow \arg max_{j\in U}\, \widetilde{at_j^k}$;
    if $\widetilde{at_i^k} > 0$ **then**
      $W \leftarrow W \cup \{i\}$;
      $p\left(\widetilde{at_i^k}\right) \leftarrow p_e + (p_0 - p_e)e^{-\lambda \widetilde{at_i^k}}$;
      if $L_k - S_W \geq a + bp\left(\widetilde{at_i^k}\right)$ **then**
        $st_i^k \leftarrow \widetilde{at_i^k}$;
        $p_i^k \leftarrow p\left(st_i^k\right)\left(a + bp\left(st_i^k\right)\right)$;
        $S_W \leftarrow S_W + \left(a + bp\left(st_i^k\right)\right)$;
      else if $\frac{L_k - S_W - a}{b} < p(1)$ **then**
        $st_i^k \leftarrow 1$;
        $p_i^k \leftarrow p(1)(a + bp(1))$;
        $S_W \leftarrow S_W + a + bp(1)$;
      else
        $st_i^k \leftarrow \left\lceil -\frac{1}{\lambda}\ln\frac{L_k - S_W - a - bP_e}{b(p_0 - p_e)}\right\rceil$;
        $p_i^k \leftarrow \frac{L_k - S_W - a}{b}(L_k - S_W)$;
        $S_W \leftarrow L_k$;
      end
      $\widetilde{at_i^k} \leftarrow 0$;
    end
  end
end
return$(W, \mathbf{ST}, \mathbf{P})$;

3.3 Mechanism analysis

In the following, we present the theoretical analysis, demonstrating that IM-R achieves the desired properties.

Lemma 1 *IM-R is computationally efficient.*

Proof There are at most n users that can be selected as winners. For each selection, IM-R selects the user with maximum available sensing time, which takes $O(n)$. The above selection process is performed for all m tasks. Thus the running time of IM-R is $O(mn^2)$.

Lemma 2 *IM-R is profitable.*

Proof It is not difficult to obtain $p\left(st_i^k\right) > 0$ from (7) and (8). Moreover, $p\left(st_i^k\right)$ is a strictly monotone increasing function with st_i^k, and $p\left(st_i^k\right) \to p_e$ when $st_i^k \to \infty$. So we have $0 < p\left(st_i^k\right) < p_e$. Note that $r \geq p_e$, we can obtain:

$$\left(r - p\left(st_i^k\right)\right)\left(a + bp\left(st_i^k\right)\right) > 0 \text{ for} \forall i \in U, \forall k \in T \tag{9}$$

Thus the utility of the platform defined in (4) is nonnegative.

Lemma 3 *IM-R is individual rational.*

Proof Based on (3), it suffices to prove that $p\left(st_i^k\right) \geq g$. The unit price is calculated through the following formula in IM-R:

$$p\left(st_i^k\right) = \begin{cases} p_e + (p_0 - p_e)e^{-\lambda \widetilde{at_i^k}} & , if\ L_k - S_W \geq a + bp\left(\widetilde{at_i^k}\right) \\ p(1) & , otherwise\ if\ \frac{L_k - S_W - a}{b} < p(1) \\ \frac{L_k - S_W - a}{b} & , otherwise \end{cases}$$

In the first case, it is not difficult to obtain that the minimum value of the pricing function is g when $\widetilde{at_i^k} = 1$. In the second case, $p\left(st_i^k\right) = p(1) = g$. In the third case, we have $p\left(st_i^k\right) = \frac{L_k - S_W - a}{b} \geq p(1) = g$. Thus, we have $u_i \geq 0$.

Lemma 4 *IM-R is truthful.*

Proof We can obtain the utility of arbitrary user i for performing arbitrary task k from (3):

$$u_i^k = \begin{cases} \left(p\left(st_i^k\right) - g\right)\left(a + bp\left(st_i^k\right)\right) & , st_i^k > 0 \\ 0 & , st_i^k = 0 \end{cases}$$

Note that we assume the strategic behavior by submitting $at_i^k > rt_i^k$ can be verified by the mobile crowd sensing application. We only prove that no user can improve its utility by submitting $at_i^k < rt_i^k$ below. If user i is a loser, submitting $at_i^k < rt_i^k$ cannot make i be the winner since IM-R selects the winners based on at_i^k in nonincreasing order, and the utility is still zero. If user i is the winner, submitting $at_i^k < rt_i^k$ cannot improve the sensing time of i. Since u_i^k is a strictly monotone increasing function with sensing time, IM-R is truthful.

The aforementioned four lemmas prove the following theorem.

Theorem 1 *IM-R is computationally efficient, profitable, individual rational and truthful.*

Note that L_k is the least resource to complete task k, then we have the following lemma.

Lemma 5 *IM-R is non-monopolistic if $L_k \geq \alpha - \beta p_e$ for all $k \in T$.*

Proof: $p\left(st_i^k\right)$ is a strictly monotone increasing function with st_i^k, and $p\left(st_i^k\right) \to p_e$ when $st_i^k \to \infty$. Accordingly, the resource supply $S_i^k = a + bp\left(st_i^k\right) \to a + bp_e = \alpha - \beta p_e$. Thus, when $L_k \geq \alpha - \beta p_e$, the task k cannot be completed by single user.

Lemma 6 *IM-R is constant discountable if $L_k < \alpha - \beta p_e$ and $A^k \geq 2$ for all $k \in T$.*

Proof Based on Lemma 5, the single user can complete any task k theoretically when $L_k < \alpha - \beta p_e$. Based on the resource supply function defined in (2), the unit price of resource for task k is $\frac{L_k - a}{b}$ if there is only one user. Thus the average unit price of resource for all tasks is $\overline{p} = \frac{\sum_{k\in T} L_k - ma}{mb}$.

On the other hand, by running IM-R, we have $\sum_{i=1}^{A^k}\left(a + bp\left(st_i^k\right)\right) < L_k + a + bp(1) = L_k + a + bg$. Then the average unit price of resource $\overline{p\left(st_i^k\right)} < \frac{L_k + a + bg - A^k a}{bA_k}$, for any $k \in T$. Thus we have $\overline{p\left(st_i^k\right)} < \frac{1}{mb}\sum_{k\in T}\left(\frac{L_k + a + bg}{A^k} - a\right)$ for $\forall k \in T$. So the discount $\frac{\overline{p\left(st_i^k\right)}}{\overline{p}} < \frac{\sum_{k\in T}\frac{L_{k}+a+bg}{A^k} - ma}{\sum_{k\in T} L_k - ma}$. Since $A^k \geq 2$ and $a + bg \ll L_k$, we obtain the strict upper bound of the discount $\frac{L_1 + a + bg - 2a}{2L_1 - 2a} = \frac{L_1 + a + bg - 2a}{2L_1 - 2a} < 1$ with $A^k = 2$, $m = 1$.

The above two lemmas prove the following theorem.

Theorem 2 *For all $k \in T$, IM-R is non-monopolistic if $L_k \geq \alpha - \beta p_e$ and constant discountable if $L_k < \alpha - \beta p_e$ and $A^k \geq 2$.*

4 Incentive mechanism for the budget model

4.1 Mechanism design

Algorithm 2: IM-B

$W \leftarrow \emptyset$; $\mathbf{ST} \leftarrow 0$; $\mathbf{P} \leftarrow 0$; $\widetilde{\mathbf{AT}} \leftarrow \mathbf{AT}$;
foreach $k \in T$ **do**
  $P_W \leftarrow 0$;
  while $B_k > P_W$ **do**
    $i \leftarrow \arg max_{j\in U} \widetilde{at_j^k}$;
    if $\widetilde{at_i^k} > 0$ **then**
      $p\left(\widetilde{at_i^k}\right) \leftarrow p_e + (p_0 - p_e)e^{-\lambda \widetilde{at_i^k}}$;
      if $B_k - P_W \geq p\left(\widetilde{at_i^k}\right)\left(a + bp\left(\widetilde{at_i^k}\right)\right)$ **then**
        $st_i^k \leftarrow \widetilde{at_i^k}$;
        $p_i^k \leftarrow p\left(st_i^k\right)\left(a + bp\left(st_i^k\right)\right)$;
        $P_W \leftarrow P_W + p_i^k$;
      else if $B_k - P_W \geq p(1)(a + bp(1))$ **then**
        $st_i^k \leftarrow \left\lceil -\frac{1}{\lambda}\ln\frac{-a+\sqrt{a^2-4b(P_W-B_k)}-2bp_e}{2b(p_0-p_e)}\right\rceil$;
        $p_i^k \leftarrow B_k - P_W$;
        $P_W \leftarrow B_k$;
      else
        break;
      end
      $W \leftarrow W \cup \{i\}$;
      $\widetilde{at_i^k} \leftarrow 0$;
    end
  end
end
return(W, **ST**, **P**);

In this section, we present an incentive mechanism for mobile crowd sensing in the budget model, named IM-B. The pricing mechanism is the same as that in Section 3.1.

Based on (9), each term of (4) is positive. This means the platform can always improve its utility through selecting more winners. Based on this observation, IM-B will keep selecting winners until the remaining budget cannot afford the new users.

The design rationale of IM-B is similar to that of IM-R. We define P_W as the total payment of winners for each task. For each task $k \in T$, IM-B selects the winners iteratively based on their available sensing time in nonincreasing order until the total payment is greater than or equal to the budget of the task.

We first calculate the unit price of winner i for task k using (7). If the winner's payment does not exceed the remaining budget, we set the sensing time of winner i as it's claimed available sensing time and the payment to i can be determined with unit price $p\left(st_i^k\right)$.

Otherwise, there are two cases: If the remaining budget is not less than $p(1)(a+bp(1))$ (this is the minimum payment when the sensing time is 1), the payment of winner i would be the remaining budget. In this case, the unit price can be obtained by solving $p\left(st_i^k\right)\left(a+bp\left(st_i^k\right)\right)=B_k-P_W$, and the sensing time can be obtained using (7). Otherwise, IM-B terminates the selection process for task k. The whole process is illustrated in Algorithm 2.

4.2 Mechanism analysis

We present the theoretical analysis, demonstrating that IM-B achieves the desired properties.

Theorem 3 *IM-B is computationally efficient, profitable, individual rational and truthful.*

Proof The computational efficiency, profitability and truthfulness are straightforward since IM-B adopts the same pricing mechanism and design rationale of IM-R. The proof is almost the same as that of Theorem 1.

For the individual rationality, it suffices to prove that $p\left(st_i^k\right)\geq g$ based on (3). In IM-B, if $B_k-P_W\geq p\left(\widetilde{at_i^k}\right)\left(a+bp\left(\widetilde{at_i^k}\right)\right)$, the unit price is calculated through the function $p_e+(p_0-p_e)e^{-\lambda\widetilde{at_i^k}}$. The minimum value of the function is g when $\widetilde{at_i^k}=1$. Otherwise, the unit price is calculated by solving $p\left(st_i^k\right)\left(a+bp\left(st_i^k\right)\right)=B_k-P_W$, where $B_k-P_W\geq p(1)(a+bp(1))$. Thus we have $p\left(st_i^k\right)\geq p(1)=g$ in this case.

Lemma 7 *IM-B is non-monopolistic if $B_k\geq p_e(\alpha-\beta p_e)$ for all $k\in T$.*

Proof: As discussed above, $p\left(st_i^k\right)$ is a strictly monotone increasing function with st_i^k, and $p\left(st_i^k\right)\rightarrow p_e$ when $st_i^k\rightarrow\infty$. Accordingly, the resource supply $S_i^k\rightarrow a+bp_e=\alpha-\beta p_e$. Thus for the single user i, the total payment would be less than $p_e(\alpha-\beta p_e)$, and IM-B would select the next user for the same task.

Lemma 8 *IM-B is constant discountable if $B_k<p_e(\alpha-\beta p_e)$ and $A^k\geq 2$ for all $k\in T$.*

Proof We first consider there is only one user i to perform task k. Based on Lemma 7, the single user can gain the payment with whole budget B_k and prevent IM-B from selecting the next user for the same task theoretically when $B_k<p_e(\alpha-\beta p_e)$. Thus $p\left(st_i^k\right)\left(a+bp\left(st_i^k\right)\right)=B_k$. Solving it, we get $p\left(st_i^k\right)=\frac{-a+\sqrt{a^2+4bB_k}}{2b}$. Thus, the average unit price of resource for all tasks is $\overline{p}=\frac{\sum_{k\in T}\sqrt{a^2+4bB_k}-ma}{2bm}$.

On the other hand, by running IM-B, we have $\sum_{i=1}^{A^k}p\left(st_i^k\right)\left(a+bp\left(st_i^k\right)\right)\leq B_k$. Then the average unit price of resource $\overline{p\left(st_i^k\right)}\leq\frac{-a+\sqrt{a^2+\frac{4bB_k}{A^k}}}{2b}$, for any $k\in T$. Thus we have $\overline{p\left(st_i^k\right)}\leq\frac{\sum_{k\in T}\sqrt{a^2+\frac{4bB_k}{A^k}}-ma}{2bm}$ for $\forall k\in T$. So the discount $\frac{\overline{p\left(st_i^k\right)}}{\overline{p}}\leq\frac{\sum_{k\in T}\sqrt{a^2+\frac{4bB_k}{A^k}}-ma}{\sum_{k\in T}\sqrt{a^2+4bB_k}-ma}$. Since $A^k\geq 2$, we obtain the largest discount $\frac{\sqrt{a^2+2bB_1}-a}{\sqrt{a^2+4bB_1}-a}<1$ with $A^k=2$, $m=1$.

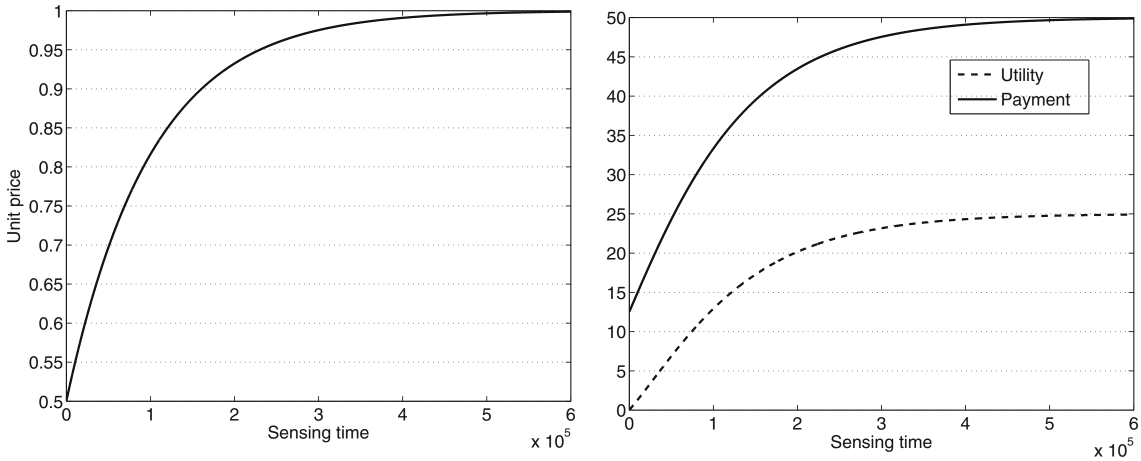
The above two lemmas prove the following theorem.

Theorem 4 *For all $k\in T$, IM-B is non-monopolistic if $B_k\geq p_e(\alpha-\beta p_e)$ and constant discountable if $B_k<p_e(\alpha-\beta p_e)$ and $A^k\geq 2$.*

5 Performance evaluation

5.1 Evaluation setup

We have conducted thorough simulations to investigate the properties of IM-R and IM-B, including pricing function, truthfulness, non-monopoly, and constant discount. We use the real mobility traces *WiFi Location* from *StudentLife* project [29]. The *StudentLife* continuous sensing app assesses the day-to-day and week-by-week impact of workload on stress, sleep, activity, mood, sociability, mental well-being and academic performance of a single class of 49 students across a 10 week term at Dartmouth College using Android phones. *WiFi Location* calculates the locations based on participants' WiFi scan log, and each item is recorded as (*unix_time*, *location*). There are 9069 different locations in the data set. Each location is viewed as an AoI in our simulations. We calculate the participant's available sensing time of certain AoI as the maximum duration from the time it is located first in the AoI to the first time it is located in another AoI. We set $\alpha=100$, $a=0$, $b=\beta=50$, $g=0.5$, $r=2$, $h=10^{-7}$. All the simulations were run on a Ubuntu 14.04.3 LTS machine with Intel Xeon CPU E5–2420 and 16 GB memory. Each measurement is averaged over 1000 instances.



(a) Pricing curve

(b) utility curve and payment curve

Fig. 2 Pricing curve, utility curve and payment curve changing in the sensing time

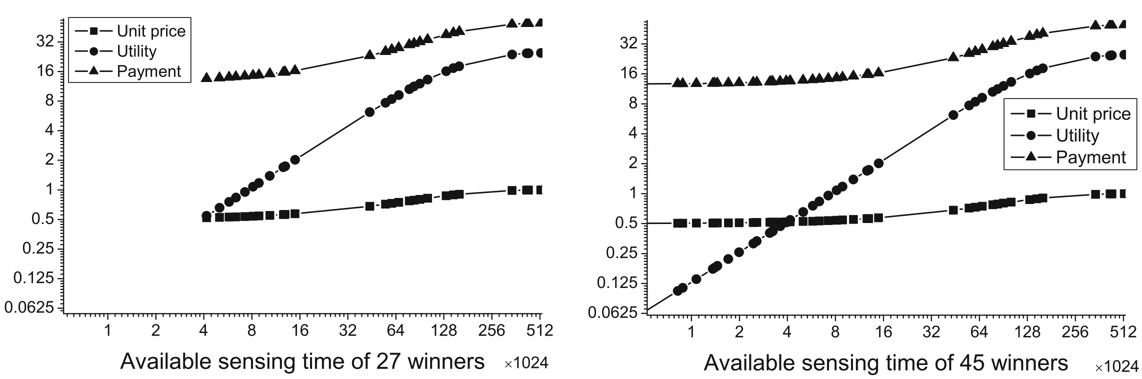
5.2 Pricing function

We first investigate the property of the pricing function in theory. Figure 2 plots the pricing curve, utility curve and payment curve along with the sensing time. We can see that the unit price increases with the sensing time. Based on (7) and the settings in Section 5.1, the unit price distributes in [0.5, 1), and it approaches to 1 when the sensing time approaches to infinite. As shown in Fig. 2(b), the utility and payment of the user are also increases with the sensing time. This is because the utility function given in (3) is strictly monotone increasing with the unit price when $p\left(st_i^k\right) \geq g$. It is not difficult to get that the utility distributes in [0, 25), and it approaches to 25 when the sensing time approaches to infinite (i.e. $p\left(st_i^k\right) \rightarrow 1$) under our settings. Similarly, the payment function$p_i = p\left(t_i^k\right)\left(a + bp\left(t_i^k\right)\right)$ is also monotone increasing with the unit price, and it approaches to 50 when the sensing time approaches to infinite. From the investigation, we can demonstrate that our pricing function can stimulate users to contribute more.

Then we investigate the property of pricing function through the real data set. Due to the space limitation, We choose the location of *in[sudikoff]* in *WiFi Location*. We set the threshold resource demand of IM-R as 1000, and set the budget of IM-B as 1000. Figure 3(a) and (b) plot the unit price, utility and payment of winners in IM-R and IM-B, respectively. The number of winners in IM-R and IM-B are 27 and 45, respectively. This is because the unit price is always less than 1 in our settings, and IM-B could recruit more users than that of IM-R. As shown in Fig. 3, the winner with more available sensing time would obtain higher unit price, utility and payment. However, the increase rate of all unit price, utility and payment tends to decrease. In fact, the unit price, utility and payment have the strict upper bound 1, 25 and 50 under our settings, respectively.

5.3 Truthfulness

To investigate the truthfulness of our incentive mechanisms, we set a new available sensing time $at_i^{k'} = \gamma at_i^k$, which is a fraction of at_i^k for each winner i. When the winner i adopts new available sensing time, we keep other users' available sensing time unchanged. The new utility of any winner i is



(a) IM-R with L=1000

(b) IM-B with B=1000

Fig. 3 Unit price, utility and payment of winners in the location of *in[sudikoff]* denoted as $u_i^{'}$. We assume that each task is dedicated to a specific location in the data set *WiFi Location*. There are averagely 4.90 and 4.93 winners for each location in IM-R and IM-B, respectively. We set $L = 1000$ for IM-R and $B = 1000$ for IM-B. We calculate the average utility ratio $r_u = \frac{\sum_{i\in W}\frac{u_i^{'}}{u_i}}{|W|}$. Figure 4 depicts the average utility ratio of IM-R and IM-B with γ being varied from 0.1 to 0.9. In our simulation, no winner can improve its utility by decreasing available sensing time. Moreover, as shown in Fig. 4, the utility will decrease accordingly when the available sensing time decreases. The average utility ratio of IM-R and IM-B are very close since IM-R and IM-B use the same utility function, which only determined by the sensing time.

5.4 Non-monopoly

Further, we investigate the property of non-monopoly. Due to the space limitation, We choose the location of *in[burke]* in *WiFi Location*. Both the threshold resource demand of IM-R and the budget of IM-B are uniformly distributed in $(\delta, \delta + 100)$. Figure 5 plots the average number of winners of IM-R and IM-B with different δ. As shown in Fig. 5, the average number of winners of IM-R increases with the threshold resource demand. This is because IM-R needs to select more users to meet the threshold resource demand. The average number of winners of IM-B also increases with the budget since IM-B could select more users under the large budget. When $\delta \geq 50$, the task cannot be completed by any single user. The average number of winners of IM-R and IM-B reaches the minimum of 4.54 and 7.41, respectively, when $\delta = 50$.

5.5 Constant discount

Finally, we investigate the property of constant discount. Let A_i be the set of tasks that are assigned to the user i. We choose m locations of *WiFi Location* randomly. The threshold resource demand for each location of IM-R is uniformly

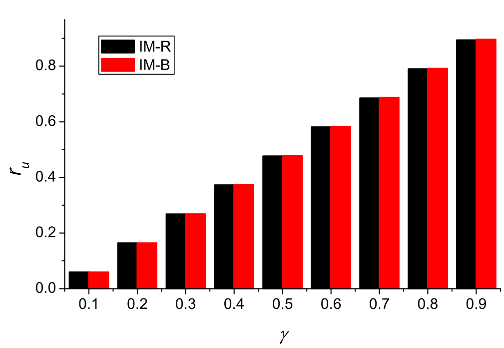


Fig. 4 Average utility ratio when using a fraction of available sensing time

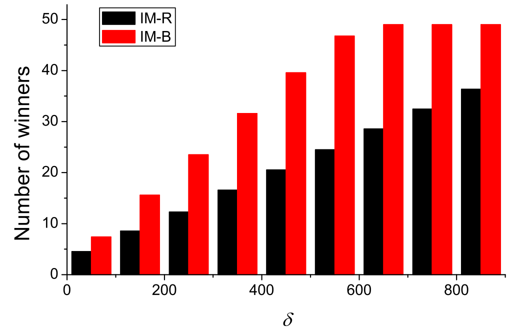


Fig. 5 Number of winners with different threshold resource demand and budget

distributed in (25, 50). The average discount of IM-R, denoted by d_R, is defined as the ratio between the average unit price obtained by IM-R and the unit price when there is only one user to perform each task, i.e.,

$$d_R = \frac{\overline{p(st_i^k)}}{\bar{p}} = \frac{\frac{\sum_{i\in W}\sum_{k\in A_i} p\left(st_i^k\right)}{\sum_{i\in W}|A_i|}}{\frac{\sum_{k\in T}L_k - ma}{mb}}$$

For IM-B, the budget for each location of IM-B is uniformly distributed in (12.5, 50). The average discount of IM-B, denoted by d_B, is defined as the ratio between the average unit price obtained by IM-B and the unit price when there is only one user to perform each task, i.e.,

$$d_B = \frac{\overline{p(st_i^k)}}{\bar{p}} = \frac{\frac{\sum_{i\in W}\sum_{k\in A_i} p\left(st_i^k\right)}{\sum_{i\in W}|A_i|}}{\frac{\sum_{k\in T}\sqrt{a^2 + 4bB_k} - ma}{2bm}}$$

Figure 6 plots the average discount with different number of locations. The average discount of both IM-R and IM-B decrease with the number of locations. This is consistent with our theoretical result of Lemma 6 and Lemma 8. In our tests, the average discount of IM-R and IM-B reach the maximum of 0.83 and 0.78, respectively, when $m = 1$.

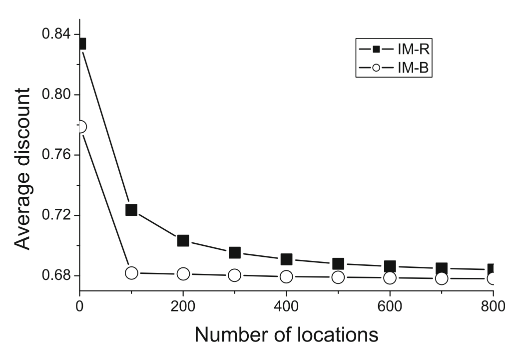


Fig. 6 The average discount with different number of locations

6 Related work

Many reverse auction based incentive mechanisms for mobile crowd sensing have been proposed thus far. Singer proposed a truthful budget feasible mechanism [12] based on the proportional share allocation rule. However, the designed mechanism was not established on any crowdsensing system model and only valid for submodular functions. Pricing mechanisms were also developed in [13] for the budget feasible maximizing task problem and the budget feasible minimizing payment problem based on the method proposed in [12]. Koutsopoulos designed an optimal reverse auction [30], considering the data quality as *user participation level*. However, the *quality indicator*, which essentially measures the relevance or usefulness of information, is empirical and relies on user's historical information. Wen et al. proposed an incentive mechanism [31] based on *quality-driven auction*, and incorporated the incentive mechanism into a Wi-Fi fingerprint-based indoor localization system. Yang et al. proposed two different models for smartphone crowdsourcing [14]: the platform-centric model where the platform provides a reward shared by participating users, and the user-centric model where users have more control over the payment they will receive. They further proposed IMC [15], which consider the competition among the requesters in crowdsourcing. Xu et al. proposed truthful incentive mechanisms for the mobile crowdsensing system where the tasks are time window dependent, and the platform has strong requirement of data integrity [23]. Furthermore, they studied the budget feasible mechanisms for the same crowdsensing system [22]. In [16], Feng et al. formulated the location-aware collaborative sensing problem as the *winning bids determination problem*, and presented a truthful auction using the proportional share allocation rule proposed in [12]. However the mechanism is only effective to perform location-aware tasks. In [17], Zhao et al. investigated the online crowdsourcing scenario where the users submit their profiles to the crowdsourcer when they arrive. They designed two online mechanisms, *OMZ*, *OMG* for different user models. In [32], a reputation-based auction mechanism is incorporated into crowdsourcing by evaluating the reliability of crowdsourcing participants. The incentive mechanisms for the crowdsourcing system with biased requesters were proposed in [33]. However, none of the above work considered the influence of supply-demand relationship of market, and the submitted reserve price of each user is baseless in above work.

In Stackelberg game based incentive mechanisms [14, 18], the cost (or the range of cost) of each user is assumed to be fixed and known by the platform. The QoI based incentive mechanism [19] can measure the quality of the contributions, and reward the participants proportionally to their quantified contributions. However, it cannot give the ultimate price. In [34], a linear decreasing function is used to characterize the relationship between the reward of a task and the number of received measurements in order to achieve the *participation balance* among tasks. The quality based pricing is also applied to solve other pricing problems, such as message forwarding problem [35]. In [35], the payment of the any *intermediate node* is determined by the *contribution time*, which is a specific criterion to measure the contribution to the quality of the selected path.

The Bargaining theory [36, 37] is also adopted for to determine the price of sensing task for mobile users. However, the reward of the platform and the cost of each mobile user should be known in order to calculate the Nash bargaining solution.

In [38], Tham et al. proposed a market-based approach for crowdsensing taking data quality into account, and proved the existence of the market equilibrium. In [39], appealing to exchange economy theory, He et al. employed the notion of "Walrasian Equilibrium" as a comprehensive metric, at which there exists a price vector for mobile users and an allocation for task initiators such that the allocation is Pareto optimal and the market gets cleared. However, neither of them considers the specific resource demand of tasks.

7 Conclusion

In this paper, we have investigated the incentive mechanisms for mobile crowd sensing based on the supply-demand relationship. We studied two models: the resource model and the budget model, where the price and supply of the resource are determined by the supply-demand relationship of the resource market. We designed a supply-demand relationship based pricing function to stimulate users to contribute more. We presented incentive mechanisms for both models, and proved that they are computationally efficient, profitable, individual rational and truthful. We further showed that they are non-monopolistic and constant discountable under certain conditions. In the future work, we will further explore the method for setting the parameters of proposed incentive mechanisms and reveal the impacts of the parameters on the performance.

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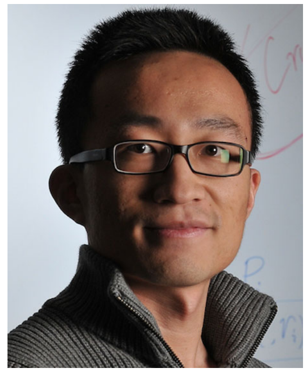

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