2014 IEEE 34th International Conference on Distributed Computing Systems

Towards Truthful Mechanisms for Mobile Crowdsourcing with Dynamic Smartphones

Zhenni Feng[†], Yanmin Zhu[†,♮,*], Qian Zhang[‡], Hongzi Zhu[†], Jiadi Yu[†], Jian Cao[†], Lionel M. Ni [‡]
[†] Department of Computer Science and Engineering at Shanghai Jiao Tong University
[♮] Shanghai Key Lab of Scalable Computing and Systems
[‡] Hong Kong University of Science and Technology
[*] Corresponding Author
[†] {zhennifeng, yzhu, hongzi, jiadiyu, cao-jian}@sjtu.edu.cn; [‡] {qianzh, ni}@cse.ust.hk

***Abstract*—Stimulating participation from smartphone users is of paramount importance to mobile crowdsourcing systems and applications. A few incentive mechanisms have been proposed, but most of them have made the *impractical* assumption that smartphones remain static in the system and sensing tasks are known in advance. The existing mechanisms fail when being applied to the realistic scenario where smartphones dynamically arrive to the system and sensing tasks are submitted at random. It is particularly challenging to design an incentive mechanism for such a mobile crowdsourcing system, given dynamic smartphones, uncertain arrivals of tasks, strategic behaviors, and private information of smartphones. We propose two truthful auction mechanisms for two different cases of mobile crowdsourcing with dynamic smartphones. For the offline case, we design an optimal truthful mechanism with an optimal task allocation algorithm of polynomial-time computation complexity of $O(n+\gamma)^3$, where n is the number of smartphones and γ is the number of sensing tasks. For the online case, we design a near-optimal truthful mechanism with an online task allocation algorithm that achieves a constant competitive ratio of $\frac{1}{2}$. Rigorous theoretical analysis and extensive simulations have been performed, and the results demonstrate the proposed auction mechanisms achieve truthfulness, individual rationality, computational efficiency, and low overpayment.**

***Index Terms*—Crowdsourcing, Truthful mechanisms, Online mechanisms**

I. Introduction

These years have witnessed the rapid adoption of smartphones. It is reported that 1.5 billion smartphones will be shipped around the world in 2017 [1]. Being embedded with a variety of sensors such as accelerometer, gyroscope, camera, and digital compass, a smartphone is able to read various sensing data about its surroundings. As being attached to a user who may roam in different places, a smartphone collects sensing data that can be valuable to other users in the world.

Mobile crowdsourcing with smartphones, as illustrated in Fig. 1, has become a promising paradigm for collecting and sharing data, leveraging the unique advantage of distributed mobile smartphones. Within a mobile crowdsourcing system, there is a platform locating on the cloud and a pool of dynamically available smartphones. Those users who want to collect sensing data about a distributed phenomenon can send sensing queries to the platform which then recruits smartphones to provide the corresponding sensing services. A number of useful applications and systems have been investigated, such as noise mapping [2], cellular or WiFi coverage maps [3], and traffic information collection [4].

Stimulating smartphone participation is of paramount importance to the success of mobile crowdsourced sensing with smartphones. In general, smartphone users are reluctant to provide sensing services for others. *On the one hand*, performing sensing services consumes considerable resources on a resource-limited smartphone, such as energy and memory. *On the other hand*, as a smartphone shares sensing data, it may be subject to possible privacy breach. Without enough contributing smartphones, one is not able to receive desirable sensing services from the mobile crowdsourcing application. As a result, mobile crowdsourcing would not be practical for wide adoption. Although a number of exciting mobile crowdsourcing applications and systems [5] [2] have been developed, they usually assume that smartphones voluntarily contribute their resources to providing sensing services. This assumption does not hold in reality, suggesting such mobile crowdsourcing systems cannot be sustained in the long run.

A few truthful incentive mechanisms [6] [7] have been designed for mobile crowdsourcing applications. *However,*

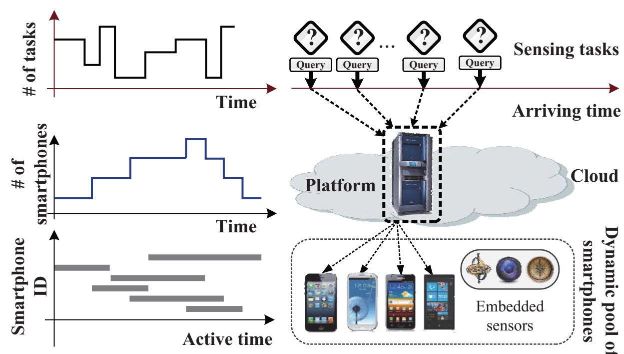


Fig. 1. Illustration of a mobile crowdsourcing system. The platform residing on the cloud receives sensing queries and assigns sensing tasks to smartphones. Both tasks and smartphones arrive to the system dynamically.

1063-6927/14 $31.00 © 2014 IEEE
DOI 10.1109/ICDCS.2014.10

most of them have made the impractical assumption that both smartphones and sensing tasks are static in the system. Clearly, such assumption is untrue in practice. In the real world, a smartphone may be opportunistically available for providing sensing services and hence may join the system for a certain duration of time, when, *e.g.*, the smartphone is idle. When the smartphone user returns to use the phone, it may leave the system. On the other hand, sensing tasks also arrive to the system dynamically, and arrivals of tasks can be unpredictable. As a result, existing incentive mechanisms may fail and become untruthful when being applied to crowdsourcing systems with dynamic smartphones and random arrivals of tasks.

It is particularly challenging to design incentive mechanisms given the unique characteristics of mobile crowdsourcing with dynamic smartphones. *First*, smartphones may dynamically join and leave the system, and sensing tasks may arrive to the system at random. Such uncertain and unpredictable behaviors further complicate the design of incentive mechanisms. *Second*, the key information about real cost, the begin and the end of active time are typically *private* and unknown to others. *Finally*, smartphone users are both rational and strategic. A smartphone takes actions solely for maximizing its own utility.

In response to the challenges, we propose two truthful auction mechanisms which include the new dimension of time in mechanism design. The proposed auction mechanisms explicitly take both dynamic smartphones and random arrivals of tasks into consideration. For the offline case, we design an efficient truthful mechanism with an optimal task allocation algorithm of polynomial-time computation complexity $O(n+\gamma)^3$, where n is the number of smartphones and γ is the number of sensing tasks. For the online case, we design a near-optimal truthful mechanism with an online task allocation algorithm that achieves a constant competitive ratio of $\frac{1}{2}$. Rigorous theoretical analysis and extensive simulations jointly demonstrate that our proposed auction mechanisms achieve truthfulness, individual rationality, and computational efficiency.

The major technical contributions made in this paper are as follows.

- It is the *first* work, to the best of our knowledge, that considers dynamic smartphones and random arrivals of sensing tasks in designing truthful incentive mechanisms for mobile crowdsourcing systems. The dynamic behaviors of smartphones essentially increase the design complexity due to possible misreports on the active time.
- For the offline case, we design a truthful auction mechanism in which the optimal task allocation algorithm produces the maximum social welfare with a polynomial complexity of $O(n+\gamma)^3$. For the online case, we design a near-optimal truthful mechanism in which the online task allocation algorithm achieves a constant competitive ratio of $\frac{1}{2}$.
- We have provided both rigorous theoretical analysis and extensive simulations, and the results demonstrate that our proposed mechanisms achieve truthfulness, individual rationality, computational efficiency, and low overpayment.

The rest of the paper proceeds as follows. The next section reviews related work. Section III presents the system model, the reverse auction model, and the mathematical formulation. In Section IV, we describe the proposed mechanism for the offline case and in Section V, we describe the proposed mechanism for the online case. Section VI presents evaluation results. Section VII concludes the paper.

II. Related Work

In the section we review recent related work from the following three aspects.

Mobile crowdsourcing with cooperative smartphones. A number of existing applications and systems of mobile crowdsourcing have assumed voluntary participation. They usually regard crowdsourcing as an efficient way of collecting data, such as [5] [8]. In [5], the PEIR system first crowdsources sensing tasks to mobile handsets. Based on the sensory data sets, the PEIR performs system-wide processing and extracts statistical information to support interesting applications. Other studies [9] [10] focus on the issue of preserving privacy of users (data providers).

Incentive mechanisms based on auctions. Auctions have been widely used for providing incentives in mobile crowdsourcing. In [7] and [11], the authors design pricing schemes utilizing the auction framework to compensate the costs of smartphones. However, they neglect that smartphones are self-interested and they may misreport their private information to increase their benefit. In [6], two incentive mechanisms are proposed for the platform-centric model and the user-centric model, respectively. An optimal incentive mechanism is proposed in [12]. The mechanism aims to minimize the total payment to all the smartphones. In [12], the author assumes that the distribution of real costs of smartphones is known and then computes the expected payment upon the distribution. All of the existing auction mechanisms have made the impractical assumption on static smartphones and given tasks.

Incentive mechanisms without auctions. Some non-auction incentive mechanisms have also been proposed. In [13], reputation mechanisms are integrated into the existing pricing schemes of crowdsourcing websites, thus improving the performance of the noncooperative equilibria. In [14], an approach is proposed to motivate smartphones to join crowdsourcing applications. Instead of providing monetary rewards to smartphones, the approach requires a user should offer services to others if the user wants to receive services from others.

III. System Model and Problem Formulation

In the section we first describe the system model of the considered crowdsourcing scenario with smartphones. Then, we discuss the reverse auction framework which models the interaction between smartphones, sensing tasks and crowdsourcing system. Finally, the mathematical formation of our problem is discussed in detail.

A. System Model

In the mobile crowdsourcing system, there are *tasks*, *smartphone users*, and a *cloud platform*. We divide the time into slots of equal size. A time slot is denoted by t_i. There are in total n smartphones existing in the system during the whole time duration of interest. Let N denote the set of all smartphones, $N = \{1, 2, \cdots, n\}$. Note that the number of smartphones active in the system in any time slot is no more than n.

Tasks arise at random and dynamically arrive to the platform. Let r_i denote the number of tasks arriving in slot t_i. The k-th sensing task that arrives in slot j is denoted by $\tau_{j,k}, k \leqslant r_j$. Let Γ denote the set of all sensing tasks, $\gamma = |\Gamma|$. A task can be completed in a single slot. In the real world, a larger task can always be divided to tasks that can be completed in a single slot. A task is allocated to at most one smartphone for processing. In our work, a task can be processed by any smartphone in the system, *i.e.*, each smartphone can provide all kinds of sensing services.

A smartphone spends a certain cost when performing a sensing task, since it consumes resources, such as battery and bandwidth. Since each task can be completed in a single slot, we assume that the real cost for a given smartphone completing a task is the same. Let c_i denote the *real cost* (*i.e.*, the reserve price) of smartphone i for performing each sensing task. Each smartphone can process sensing tasks at certain periods when the user do not use it. Each time joining the participatory sensing market to compete for sensing tasks, a smartphone must determine the period of available time (called *active time*) within which it promises to complete a sensing task if it is assigned one.

B. Reverse Auction Framework for Mobile Crowdsourcing

We introduce the *reverse auction framework* to model the interactions between the platform and the smartphones. A reverse auction model is a kind of auction in which the role of *buyer* and *seller* are reverse. In the mobile crowdsourcing system, the buyer is the platform buying sensing services, and the sellers are smartphones.

The reverse auction framework is depicted in Fig. 2. We assume that the reverse auction is executed round by round. Within each round, smartphones dynamically join the system and tasks are submitted to the system at random. Each round is of equal size, containing m slots. Within each round, each smartphone i submits *at most one* bid $B_i = (\tilde{a}_i, \tilde{d}_i, b_i), 0 \leqslant \tilde{a}_i \leqslant \tilde{d}_i \leqslant m, 0 \leqslant b_i < \infty$, to the platform, where a_i denotes the begin of active time (*arrival time*) of i, d_i is the end of active time (*departure time*), b_i is the *claimed cost* for providing sensing service. Since a smartphone can only submit a single bid, the length of $[a_i, d_i]$ defines the maximum time that a smartphone is willing to wait for an allocation of a sensing task. The claimed cost b_i may be different from the real cost c_i and we would explain this later.

The platform determines the *allocation rule* π and the *payment rule* p. If $B = \{B_i | i = 1, 2, \cdots, n\}$, then the winning bids determination rule is $\pi : \Gamma \mapsto B$, where task $\tau_{j,k}$ is allocated to the smartphone which has submitted bid $B_i = \pi(\tau_{j,k})$, *i.e.*, B_i is a *winning bid*. After each smartphone with a winning bid finishes the sensing task, the platform pays a monetary reward to each smartphone i subject to the *payment rule*, $p : B \mapsto \mathbb{R}^n$. A smartphone that is not allocated a task during its active time would get no payment. Without lose of generality, we only consider a single round. The same design and analysis can be applied to other rounds.

Next, we discuss the characteristics of the rationality of smartphones. Since the real cost, the begin of active time and the end of active time of a smartphone are all *private*, each self-interested smartphone may manipulate the market by misreporting its private information, aiming at maximizing its benefit. For example, each smartphone may claim a delayed begin (arrival), an earlier end (departure) or a higher cost. However, it is clear that $\tilde{a}_i \geqslant a_i$ and $\tilde{d}_i \leqslant d_i$, which are called *no early-arrival* and *no late-departure* misreport, respectively. This is because no smartphones can offer sensing service beyond its active time. Next, we define the *utility* of smartphone i as the *net benefit* it receives from offering sensing service.

Definition 1 (Utility of Smartphone). *The utility of each smartphone i is the difference between the payment it receives from the platform and its real cost,* i.e.*,*

$$u_i = p_i(B_i, B_{-i}) - c_i, \tag{1}$$

where B_{-i} denotes the other bids in B except B_i.

Each self-interested smartphone selects strategy solely to maximize its own utility. Thus, it is possible for them to misreport its private information. This kind of misreporting is called *strategic behavior*.

We next define the utility for completing a sensing task and the social welfare. Suppose sensing task $\tau_{j,k}$ is allocated to smartphone i who has submitted bid B_i. The

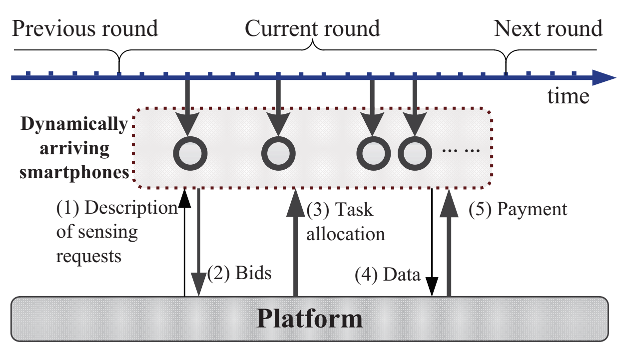


Fig. 2. The reverse auction framework for the mobile crowdsourcing system with dynamic smartphones and random arrivals of tasks.

system (or the auctioneer) obtains a fixed value ν for a task being completed. Then, the formal definitions are as follows.

Definition 2 (**Utility of Sensing Task**). *The utility of sensing task $\tau_{j,k}$ is the difference between the value and the real cost of smartphone i which is chosen to perform the sensing task,* i.e., $B_i = \pi(\tau_{j,k})$.

$$u(\tau_{j,k}) = u(\tau_{j,k}, B_i) = u(\tau_{j,k}, \pi(\tau_{j,k})) = \nu - c_i. \quad (2)$$

Definition 3 (**Social Welfare**). *The social welfare is the sum of the utilities of all completed sensing tasks. It is computed as follows:*

$$\omega = \sum_{\tau_{j,k} \in \Gamma} u(\tau_{j,k}). \quad (3)$$

Remarks: The social welfare is closely related to the allocation rule π and set B of submitted bids. When the allocation rule is fixed, the social welfare only changes with B. Thus, the social welfare can be denoted as $\omega(B)$ as well.

C. Problem Formulation

In the paper, we aim to design *auction mechanisms* for stimulating smartphone participation in mobile crowdsourcing. The objective of our design is to achieve the following important properties, such as, *truthfulness*, *individual rationality*, and *computational efficiency*. We give the formal definitions of these properties.

Definition 4 (**Truthfulness**). *An auction mechanism is truthful if and only if, for each smartphone i, it cannot increase its utility by misreporting its private information,* i.e., $u_i(\pi, \bar{B}_i, B_{-i}) \geqslant u_i(\pi, B_i, B_{-i})$ *whatever others report, where $\bar{B}_i = (a_i, d_i, c_i)$ denotes the private information, $B_i = (\tilde{a}_i, \tilde{d}_i, b_i)$ denotes a bid that is different from $\bar{B}_i$, B_{-i} is the set of bids submitted by all others except i.*

Definition 5 (**Individual Rationality**). *An auction mechanism satisfies the property of individual rationality if and only if each smartphone has a non-negative utility,* i.e., $u_i \geqslant 0$, *for each $i \in N$.*

Definition 6 (**Computational Efficiency**). *An auction mechanism is computationally efficient if and only if it terminates in polynomial time.*

To design truthful auction mechanisms possessing the properties listed above, we should address two key problems. The mathematical formulation of the two problems is as follows.

Definition 7 (**Winning Bids Determination Problem**). *For the mobile crowdsourcing system, its objective is a system-wide social welfare given in Definition 3. The mobile crowdsourcing system aims at maximizing the social welfare by selecting an optimal set of winning bids. The optimal set W^* of winning bids is selected by the optimal allocation rule,* i.e., $W^* = \{B_i | B_i = \pi^*(\tau_{j,k}), \tau_{j,k} \in \Gamma\}$. *The winning bids determination problem is*

$$\max_W \omega = \textstyle\sum_{\tau_{j,k} \in \Gamma} u(\tau_{j,k}, \pi(\tau_{j,k})), \quad (4)$$

$$s.t. \quad \textstyle\sum_{\tau_{j,k} \in \Gamma} I(\pi(\tau_{j,k}) = B_i) \leqslant 1, \forall i \in N, \quad (5)$$

$$a_i \leqslant j \leqslant d_i, \ if \ \pi(\tau_{j,k}) = B_i, \forall i \in N, \quad (6)$$

where $I(\pi(\tau_{j,k}) = B_i)$ is an indicator random variable which is 1 when the sensing task $\tau_{j,k}$ in slot j is allocated to smartphone i, and it equals to 0 otherwise.

Remarks: (4) gives the objective of maximizing the social welfare. The social welfare reflects the *efficiency* of the mobile crowdsourcing system. (5) indicates a smartphone is allocated no more than one sensing task or has at most one winning bid. (6) requires that a sensing task should be allocated to a smartphone within its active time.

Definition 8 (**Payment Determination Problem**). *The payment determination problem is to determine how much a participating smartphone should be paid and when the payment is executed.*

In the following two sections, we propose two auction mechanisms for two cases of mobile crowdsourcing.

- In *the offline case*, at the very beginning the platform receives the report of the active time of each smartphone, and the arrivals of each task. It is also at the beginning that the platform announces the set of all tasks together with their arrival times to all smartphones, each smartphone submits its bid, and the platform determines the winning bids after receiving all bids.
- In *the online case*, in the current time slot, the platform only knows the tasks that have already arrived in the current or the previous slots. It is also in the current slot that the platform announces the set of all the tasks that have arrived in the current slot, each smartphone newly joining in the system in the current slot submits its bid, and the platform determines the winning bids for the tasks announced in the current slot.

IV. Optimal and Truthful Auction Mechanism for Offline Mobile Crowdsourcing

We first consider the offline case. The offline case exists when the future tasks have been deterministically scheduled and the future availability of all smartphones can be known in advance. The offline case also serves as the benchmark for the online auction mechanism design.

A. Overview

We propose a truthful auction mechanism for the offline case, which consists of two components. The two components are designed in response to the two key problems in Section III-C. To solve the winning bids determination problem, we model the problem as the *maximum weighted matching in a bipartite graph* and find the optimal solution with polynomial-time computation complexity. For the payment determination problem, we leverage the traditional

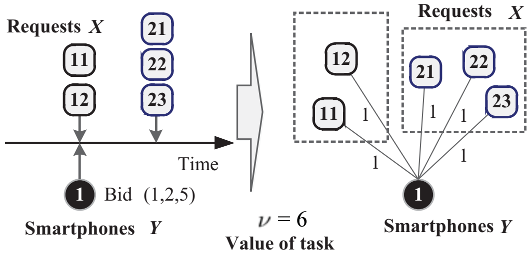


Fig. 3. An example of constructing the weighted bipartite graph. In the first slot, two sensing tasks and Smartphone 1 arrive and another three sensing tasks arrive in the second slot.

Vickrey-Clarke-Groves (VCG) mechanism and propose a payment scheme which guarantees that each smartphone discloses its private information truthfully. We also theoretically analyze the achieved properties of our proposed auction mechanism.

B. Optimal Algorithm for Winning Bids Determination Problem

We solve the winning bids determination problem in *three major steps*. In the first step, we transform the problem to a matching problem. In the second step, we employ the Hungarian algorithm to compute the maximum weighted matching. In the third step, we map the maximum weighted matching to the winning bids and the allocation of all the tasks.

Transforming to matching problem. For a bipartite graph $G = (X \cup Y, X \times Y)$, where X and Y ($X \cap Y = \emptyset$) are two sets of vertices, $X \times Y$ is the set of edges each of which connects two vertices in X and Y. Imagine that each task $\tau_{j,k}$ is a vertex $x_{j,k}$ ($k \leqslant r_i$) in X and each smartphone i is a vertex y_i in Y. For each pair of vertices $x_{j,k}$ and y_i, they share an edge $(x_{j,k}, y_i)$ with the weight $w(x_{j,k}, y_i) = \nu - b_i$ only if smartphone y_i is active in the j-th slot; otherwise, $w(x_{j,k}, y_i) = 0$. We give a simple example in Fig. 3 to illustrate the construction of the weighted bipartite graph.

Computing the maximum weighted matching. We employ the Hungarian algorithm [15] to find the maximum weighted matching in the bipartite graph $G = (X \cup Y, X \times Y)$ constructed in the previous step. The main idea of the algorithm is as follows. First, an arbitrary matching is selected. Then, for the current matching, an augmented path is computed, based on which the current matching can be improved. This process repeats until there exists no augmented path. The resulting matching is the maximum weighted matching for G.

Determining winning bids and task allocation. Let the resulting maximum weighted matching be denoted by M. Based on M, we can determine the winning bids and the corresponding task allocation as follows. For each edge $(x_{j,k}, y_i)$ in M, the connection means that task $\tau_{j,k}$ in the j-th slot is allocated to smartphone i.

C. Payment Scheme

It is critical to notice that social welfare calculated in Section IV-B is based on the claimed cost of smartphones. The payment determination problem for the auction mechanism design is to design a payment scheme that guarantees each smartphone truthfully discloses its real cost as well as the begin of active time and the end of active time. The payment scheme is dedicated to stimulate each smartphone to participate and furthermore truthfully report its private information. We design a payment scheme based on the VCG mechanism [16]. The main idea of the payment scheme is that each smartphone is paid an amount of money equal to its contribution to the social welfare of others in the mobile crowdsourcing system.

The payment of each smartphone i is computed as follows:

$$p_i(B) = (\omega^*(B) - (-b_i)) - \omega^*(B_{-i}) \quad (7)$$
$$= h(B_{-i}) - \omega^*(B_{-i}), \quad (8)$$

where $\omega^*(B)$ denotes the maximum social welfare when the set of submitted bids is B. $\omega^*(B_{-i})$ is similar to the $\omega^*(B)$. $h(B_{-i})$ is a function whose value depends on B_{-i} and is irrelevant to B_i.

Remarks: The payment scheme can be understood by amortizing the total social welfare to each element (*e.g.*, smartphone or sensing task) of the system. A sensing task $\tau_{j,k}$ has a social welfare of ν while the social welfare of a smartphone that is allocated a sensing task can be regarded as $-b_i$. The first part in (7) computes the social welfare of all others in the mobile crowdsourcing system when B_i is selected, and the second part in this equation computes the maximum social welfare of all others in the mobile crowdsourcing system without bid B_i. From the meaning of the first part, we can see that it is not relevant to the bid of smartphone i and thus we use function $h(B_{-i})$ to represent the first part.

Then, the utility of each smartphone i is,

$$u_i(B) = p_i(B) - c_i = h(B_{-i}) - \omega^*(B_{-i}) - c_i. \quad (9)$$

Obviously, for smartphone j that is not allocated in its active time according to the winning bids determination algorithm, the difference is zero.

D. Theoretical Analysis

Theorem 1. *The proposed auction mechanism for the offline case is truthful,* i.e.*, each smartphone truthfully reports its private information no matter what others report.*

Proof: To demonstrate the auction mechanism is truthful, we should guarantee that each smartphone i cannot increase its utility by misreporting any dimension of its private information whatever others report.

Firstly, we prove the proposed mechanism is *cost-truthful*, which means the smartphone cannot increase its utility by misreporting its real cost. Let $B_i = (\tilde{a}_i, \tilde{d}_i, b_i)$ denote the bid of smartphone i. When $\tilde{a}_i$ and $\tilde{d}_i$ are fixed, from (8), we can see that the two parts of computing payment are independent with the claimed cost b_i in bid B_i. Thus, each smartphone i cannot increase its utility by misreporting its real cost.

Then, we prove the proposed mechanism is *time-truthful*, which indicates each smartphone cannot increase its utility by delaying the begin of its active time and advancing its end of active time. For a smartphone that is not allocated a sensing task, it cannot receive a sensing task either, if it reports a *tighter* active time interval. For a smartphone that is allocated a sensing task by truthfully reporting its active time interval, it cannot benefit from reporting a tighter active time interval. The tighter active time interval may make the bid of the smartphone fail, leading to non-increasing utilities. Thus, a smartphone has no incentives to misreport the begin and the end of its active time. ■

Theorem 2. *The proposed auction mechanism achieves the property of individual rationality.*

Proof: For smartphone i that is not allocated any task in its active time, it would neither be paid nor incur sensing cost. Thus, its utility is zero.

For smartphone i that is allocated a task in its active time, its utility is computed as shown in (9). The utility can be computed in the following way:

$$\begin{aligned} u_i(B) &= \omega^*(B) - \omega^*(B_{-i}) + b_i - c_i, , \\ &= \omega^*(B) - \omega^*(B_{-i}), && (10) \\ &\geqslant 0, && (11) \end{aligned}$$

where (10) holds because we have demonstrated that s-martphone i would truthfully report its private information. As $\omega^*(B)$ denotes the optimal solution, we get that $\omega^*(B) \geqslant \omega^*(B_{-i})$. ■

Theorem 3. *The optimal algorithm for winning bids determination problem has polynomial-time computation complexity.*

The Hungarian algorithm can be modified to achieve an $O(n^3)$ running time [17] [18], where n is the number of vertices in the graph. Thus, the optimal algorithm can be computed within $O(n+\gamma)^3$.

V. Near-optimal Truthful Auction Mechanism for Online Mobile Crowdsourcing

We next consider the online case, which is for practical applications in the real world. We solve the two problems in Section III-C by proposing a near-optimal algorithm for winning bids determination and a payment scheme to induce truthfulness. Finally, we theoretically prove the proposed auction mechanism achieves the desired properties.

A. Overview

We propose an online auction mechanism, which is comprised of two components for solving the two problems stated in Section III-C, respectively. For the online winning bids determination problem, however, it is almost impossible to find an optimal solution due to the uncertainty of future information about arrivals of tasks and active time of smartphones. Therefore, we design a near-optimal online algorithm to determine the set of winning bids. Furthermore, because the VCG-style payment scheme is no longer truthful when the allocation of sensing tasks is not optimal [16]. We design a payment scheme that guarantees each smartphone discloses its private information truthfully.

Algorithm 1: Winning Bids Determination

Input: Set B of bids, vector $R = (r_1, r_2, \cdots, r_m)$.
Output: vector Π={$p_1, p_2, \cdots$}.

$S \leftarrow \emptyset$, $t \leftarrow 1$, $\Pi \leftarrow \vec{0}$;
while $t \leqslant m$ **do**
  Add each newly arriving smartphone to S and remove each smartphone that departs at slot t from S;
  Sort bids in S by its claimed cost in non-decreasing order.
  for k from 1 to r_t **do**
    Choose the first smartphone B_j in S, $\Pi(j) \leftarrow t$;
    $S \leftarrow S - B_j$;
  end for
  $t \leftarrow t + 1$.
end while
return Π;

B. Online Algorithm for Winning Bids Determination

We propose an online greedy algorithm for solving the winning bids determination problem. The main idea of this greedy algorithm is to allocate the tasks to those smartphones with lowest costs which are currently active but have not been allocated a task. The algorithm is executed at the beginning of each slot. For example, if there are 3 newly arrived tasks in the current slot, then the algorithm will select three active smartphones for the three tasks. We proceed in two main steps to describe the algorithm. In the *first* step, we show that maximizing the social welfare is equivalent to minimizing the total cost of selected smartphones. In the *second* step, we explain the greedy strategy of the algorithm for selecting the smartphones in each time slot.

Revealing equivalence. Since all the sensing tasks are to be allocated and the sum of their values is fixed, the winning bids determination problem which maximizes the social welfare is equivalent to finding a subset of winning bids to minimize the total claimed cost in these bids.

Greedy strategy. The greedy winning bids determination algorithm is described in the following steps. Imagine that the algorithm maintains a set of all active smartphones that has not been allocated a sensing task. The set is updated at the beginning of each slot when any smartphone begins its active time, ends its active time or obtains an allocation. In each slot, the platform greedily selects smartphones with the lowest costs and allocates sensing tasks to them. Algorithm 1 shows the details of selecting winning bids.

Illustrating example. In Fig. 4, we give an example to illustrate the online algorithm. There are in total 7 smartphones, which has very different active time or claimed

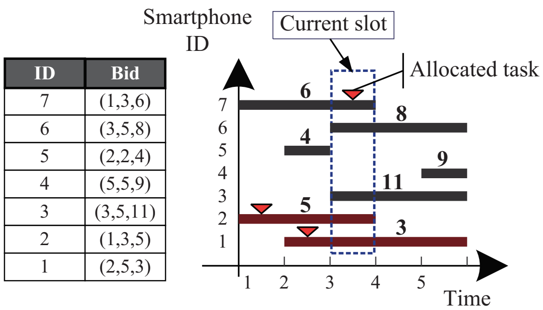


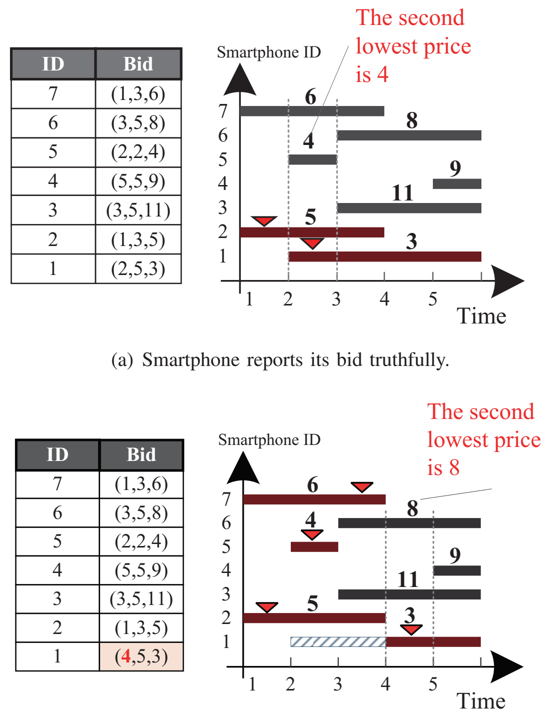
Fig. 4. An example illustrating the online winning bids determination algorithm. The dotted rectangle contains all active smartphones in the current time slot. The number above each line denotes the claimed cost.

costs. For example, Smartphone 2 begins its active time in the 1st slot and ends its active time in the 4th slot. It claims a cost of 5. The current slot is the 3rd slot. In this example, it is assumed that in each time slot only one new task arrives to the system. Previously, in the 1st slot, Smartphone 2 won a bid, and in the 2nd slot, Smartphone 1 won. In the current slot, the dynamic pool contains 3 smartphones, *i.e.*, 3, 6, and 7. According to the greedy strategy, Smartphone 7 wins a bid in the current slot since its cost 6 is smaller than those of Smartphones 3 and 6 (with a cost of 11 and 8, respectively).

C. Payment Scheme

Next, we propose a payment scheme which guarantees that each smartphone discloses its private information truthfully. As mentioned before, a VCG-based payment scheme is inapplicable to our online mechanism because the winning bids determination algorithm is not optimal. In addition, simple payment schemes, e.g., the scheme of *second price auction*, also fail in our online scenario. We take the payment scheme of the second price auction as an example to illustrate how it fails. According to the second price auction, multiple bidders compete for a certain item. The bidder who claims the highest price wins. The winner only pays the price that the second highest bid claims. We could apply the idea of this payment scheme to our scenario assuming there is only sensing task at each slot: *i.e.*, each winning smartphone pays the price that is offered by the second lowest bid. However, we will use an example to demonstrate that this payment scheme fails to induce truthfulness, *i.e.*, a smartphone may misreport its private information.

The example is illustrated in Fig. 5, where the submitted bids and sensing tasks are the same as that of Fig. 4. The payment scheme which is derived from the idea of second price auction is explained in Fig. 5(a). In the first slot, Smartphone 2 is chosen to perform the sensing task and the second lowest price in the first slot is 6 which is reported by Smartphone 7, and then Smartphone 2 is paid 6. In the second slot the sensing task is allocated to Smartphone 1 and it is paid 4. However, Smartphone 1 has the incentive to postpone the begin of its active time in order to gain a higher utility, which is shown in Fig. 5(b). When Smartphone 1 delays the begin of its active time by 2 slots, *i.e.*, Smartphone 1 reports that its active time is [4,5], and then it obtains a payment of 8. It is obvious that this smartphone increases its utility by 4 when purposely delaying the begin of its active time by 2 slots. Thus, such payment scheme fails to ensure that each smartphone truthfully reports its private information.



(a) Smartphone reports its bid truthfully.

(b) Smartphone misreports the begin of its active time.

Fig. 5. An example illustrating that smartphones can benefit from misreporting when applying the idea of second price auction into the system at each slot. In Fig. 5(a), Smartphone 1 honestly report the begin of its active time while in Fig. 5(b) Smartphone 1 delays the begin of its active time by 2 slots. According to the second price rule, Smartphone 1 is paid 4 and 8 in the two situations, respectively. Thus, Smartphone 1 increases its utility by misreporting the begin of its active time.

We next explain the proposed payment scheme in detail. For a smartphone i whose bid wins, it is paid an amount of money that equals to the claimed cost of the first smartphone that makes the bid B_i fail. The smartphone is called the *critical player* of i, denoted by $c(i)$. Then, we discuss how to find the critical player $c(i)$ of i. If B_i wins in slot t'_i, the critical player $c(i)$ of i is the smartphone with the highest claimed cost and wins between t'_i and the end of active time d_i of smartphone i. For a smartphone that is not allocated a task, it would not be paid. In addition, each smartphone receives its payment in its reported departure slot.

Main steps of payment scheme. The main steps of computing the payment are listed as follows (Algorithm 2 shows the pseudo code of the payment scheme). First, it removes B_i from B and allocates the sensing tasks to

Algorithm 2: Payment Scheme

Input: Smartphone ID i, set B of bids of dynamic smartphones, slot t'_i in which B_i wins.
Output: payment p_i.

$t \leftarrow 1$, $\tilde{B} \leftarrow \emptyset$, $p_i \leftarrow b_i$, $B \leftarrow B - B_i$, $S \leftarrow \emptyset$;
while $t \leqslant \tilde{d}_i$ **do**
  add the bids of newly arriving smartphones to $\tilde{B}$ and remove the bids that has departed;
  sort the smartphone in $\tilde{B}$ according to its claimed cost in non-decreasing order;
  if $t \geqslant t'_i$ **then**
    select r_t-th smartphone j in the current slot;
    add the first r_t smartphones to S;
    if $b_j > p_i$ **then**
      $p_i \leftarrow b_j$;
    end if
  end if
  remove the first r_t smartphones from $\tilde{B}$;
  $t \leftarrow t + 1$;
end while
return p_i;

other smartphones utilizing the greedy rule in Algorithm 1 until slot $t'_i - 1$. Next, in each slot in $[t'_i, d_i]$, it allocates tasks to the smartphones according to the greedy rule and records the smartphone with the highest claimed cost that is allocated a task during these slots.

Illustrating example. We give an example to show the computing of the payment for Smartphone 1 in Fig. 4. In Section V-B, we know that Smartphone 1 is allocated a task in the 2nd slot. If the tasks are allocated among the rest smartphones, then the tasks would be allocated to smartphones $5, 7, 6, 4$ with claimed costs of $4, 6, 8, 9$, respectively. Then, the payment to Smartphone 1 is 9.

D. Theoretical Analysis

According to [16], we can prove that the proposed online auction mechanism is truthful if it satisfies the following two conditions: 1) The winning bids determination algorithm is *monotonic*, and 2) each smartphone is paid an amount that equals to the *critical value*.

Definition 9 (Critical Value). *Given the allocation rule, the critical value b_i^c for smartphone i is the minimum b'_i if smartphone i submits the bid $B_i = (a_i, d_i, b'_i)$ and its bid B_i wins.*

Remarks: This is called critical value because if smartphone i charges lower than b_i^c with bid $B_i = (a_i, d_i, b_i^c - \delta), \delta > 0$, it would win. Otherwise, it would lose for any bid $B_i = (a_i, d_i, b_i^c + \xi), \xi > 0$.

Definition 10 (Monotonicity). *For a smartphone i that wins with the bid $B_i = (\tilde{a}_i, \tilde{d}_i, b_i)$, it would still win if it reports a bid $B'_i = (a'_i, d'_i, b'_i)$, where $a'_i \leqslant \tilde{a}_i, d'_i \geqslant \tilde{d}_i, b'_i \leqslant \tilde{b}_i$.*

Remarks: The definition shows that a monotonic winning bids determination algorithm must guarantee that if a smartphone wins with a bid $B_i = (\tilde{a}_i, \tilde{d}_i, b_i)$, it would certainly win by reporting a lower claimed cost or weaker interval (*i.e.*, $a'_i \leqslant \tilde{a}_i, d'_i \geqslant \tilde{d}_i$).

Theorem 4. *The proposed auction mechanism for the online case is truthful.*

Proof: Firstly, we show that the winning bids determination algorithm is monotonic. For a smartphone that wins when submitting the bid $B_i = (\tilde{a}_i, \tilde{d}_i, b_i)$, we replace its bid B_i by $B'_i = (a'_i, d'_i, b'_i)$, where $a'_i \leqslant \tilde{a}_i, d'_i \geqslant \tilde{d}'_i, b'_i \leqslant b_i$. Assume that the smartphone i with bid B_i wins and is allocated a sensing task in slot $\tilde{t}_i$. It is obvious that bid B'_i would be allocated a task in slot $\tilde{t}_i$ or earlier slot. Thus, the winning bids determination algorithm is monotonic.

Then, we verify that the payment computed by Algorithm 2 is the critical value for smartphone i. Let p_i denote the payment computed by Algorithm 2. If the smartphone i submits a bid $\bar{B}_i = (a_i, d_i, p_i - \xi), \xi > 0$, there exist at least one smartphone j in the set S (obtained by Algorithm 2) that charges higher than i. Thus, i would be allocated a task instead of j. On the contrary, if the smartphone i reports bid $\bar{B}_i = (a_i, d_i, p_i + \zeta), \zeta > 0$, smartphone i cannot win when competing with smartphones in set S in its active time. Thus, we prove that the payment calculated by Algorithm 2 is the critical value. ■

Theorem 5. *The proposed auction mechanism satisfies the property of individual rationality.*

Proof: For a smartphone that whose bid fails, its utility is zero. For a smartphone with a winning bid, its payment is calculated in Algorithm. 2. Next, we demonstrate that the payment of smartphone i is no smaller than its real cost. For the smartphones in the set S, there is at least one smartphone j chosen in the slot t'_i that reports a cost no smaller than the claimed cost of i; otherwise, the smartphone j would be allocated a task instead of i in the greedy online algorithm. Since we have demonstrated that each smartphone would report its real cost, we conclude that the payment is no less than the real cost. Thus, the utility of i is nonnegative. ■

Theorem 6. *The online algorithm for winning bids determination problem is $\frac{1}{2}$-competitive, for each input, $\omega_{apx}/\omega_{opt} \geqslant \frac{1}{2}$, where ω_{apx} and ω_{opt} denote the resulting social welfare of the approximate online algorithm and the optimal offline algorithm, respectively.*

Theorem 7. *The auction mechanism for the online case has polynomial-time computation complexity.*

Due to space limit, we omit the proof details of Theorem 6 and Theorem 7.

VI. Evaluation

In this section, we report simulation results and study the performance of the proposed algorithms for mobile crowdsourcing with dynamic smartphones.

A. Methodology and Simulation Settings

We evaluate the performance of two auction mechanisms with extensive simulations based on the following metrics:

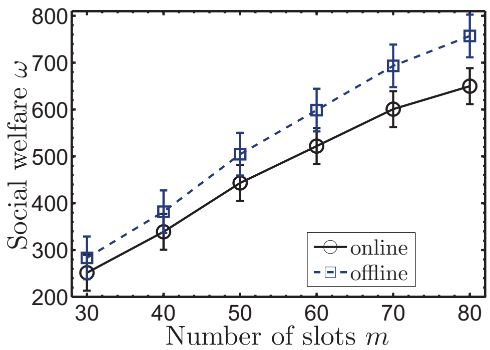


Fig. 6. Social welfare ω vs. Number of slots m.

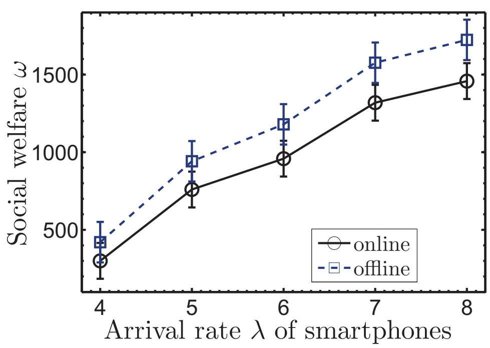


Fig. 7. Social welfare ω vs. Arrival rate λ of smartphones.

social welfare, overpayment ratio. We give the definition of overpayment ratio. The overpayment is the difference between the total payment to smartphones and the sum of real costs of each contributing smartphone. Then, the overpayment ratio is defined as follows.

Definition 11 (**Overpayment Ratio**). *The overpayment ratio characterizes the relative overpayment. It is computed as follows.*

$$\sigma = \frac{\sum_{B_i \in \{\pi(\tau_{j,k}) | \tau_{j,k} \in \Gamma\}} (p_i - c_i)}{\sum_{B_i \in \{\pi(\tau_{j,k}) | \tau_{j,k} \in \Gamma\}} c_i}. \quad (12)$$

The arrivals of dynamic smartphones and sensing requests are generated with Poisson distributions. The length of active time of each smartphone is uniformly selected and its average is set to ten percents of the default number of total time slots in a round. The length of active time characterizes the average time that a smartphone is willing to wait in a round. The default setting is listed in Table I.

TABLE I
SUMMARY OF DEFAULT SETTINGS

Parameter	Default value
Arrival rate λ of smartphones	6
Arrival rate λ_t of sensing tasks	3
Average of real costs $\bar{c}$	25
Number of slots m	50
Average length of active time	5

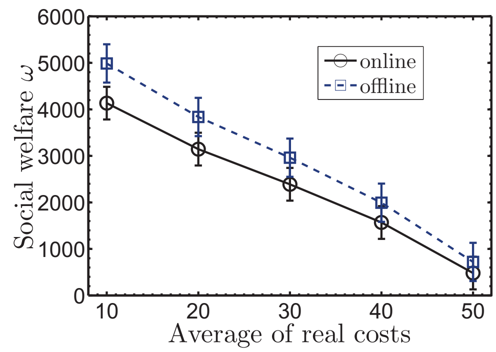


Fig. 8. Social welfare ω vs. Average of real costs.

B. Evaluation Results

Evaluation of social welfare. In Fig. 6, we can find that the social welfare increases with the increasing number of time slots. It is easy to understand since a higher social welfare can be obtained when more sensing tasks are processed in longer time. The offline auction mechanism offers a larger social welfare than the online auction mechanism does. The gap between them expands as the number of slots increases. From Fig. 7, we can see that the social welfare increases when the arrival rate of smartphones goes up. This is because a larger arrival rate indicates there are more smartphones existing in the system and it is more likely to hire smartphones with lower costs. In Fig. 8, we find that the social welfare decreases with the average of real costs increasing. This is because when the average of real costs becomes larger, the system needs to pay more to get these tasks processed.

Evaluation of overpayment ratio. Fig. 9 shows that overpayment ratio stays slow with the increasing number of time slots. The modest and stable overpayment ratio reflects that the mobile crowdsourcing system is stable even in the long run. The overpayment ratio of the offline mechanism is larger than that of the online mechanism. This suggests that the offline mechanism must pay more in order to induce cooperation from selfish smartphones. Fig. 10 shows that the overpayment ratio keeps stable with the increasing number of smartphones. The overpayment ratio for the online mechanism decreases slightly since

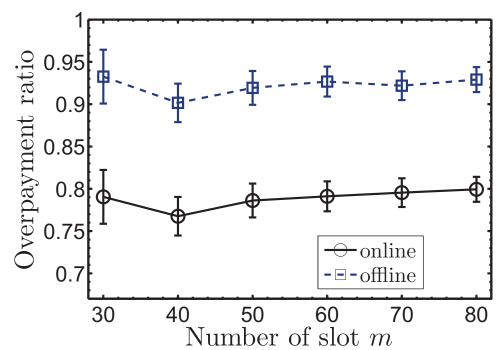


Fig. 9. Overpayment ratio σ vs. Number of slots m.

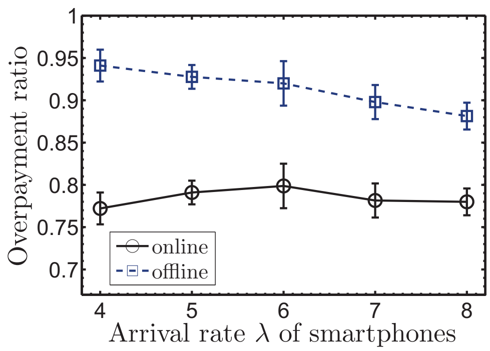


Fig. 10. Overpayment ratio σ vs. Arrival rate λ of smartphones m.

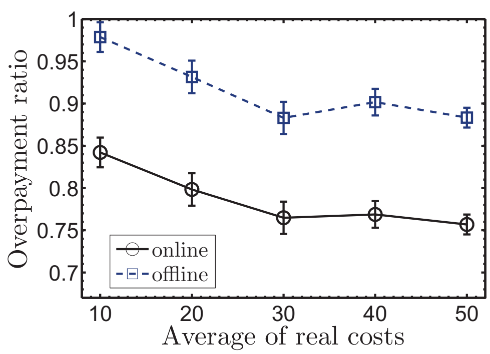


Fig. 11. Overpayment ratio σ vs. Average of real costs.

the system is more likely to hire smartphones with lower costs when there are more smartphones. Fig. 11 depicts the change of overpayment ratio when the average of real costs of smartphones increases. It can be observed that the overpayment ratio of the offline mechanism is larger than that of the online mechanism .

VII. Conclusion

In this paper we have studied the crucial problem of incentive mechanism design for mobile crowdsourcing systems with dynamic smartphones. Although there have been several incentive mechanisms for mobile crowdsourcing, most of them have impractically assumed that the smartphones are static and the tasks to be allocated are given. This paper has presented two truthful auction mechanisms. For the offline case, we have designed an efficient truthful mechanism which features an optimal task allocation algorithm of polynomial-time computation complexity of $O((n+\gamma)^3)$. For the online case, we have designed a near-optimal truthful online mechanism which features an online task allocation algorithm achieving a constant competitive ratio of $\frac{1}{2}$. Both analytical and simulation results have demonstrated our proposed auction mechanisms are truthful, also achieving individual rationality, computational efficiency, and low overpayment.

Acknowledgements

This research is supported by China 973 Program (2014CB340303 and 2013CB329006), NSFC (No. 61170238, 61173156, 61202375, 61272438), National 863 Program (2013AA01A601), STCSM (12ZR1414900, 12511502704), Singapore NRF (CREATE E2S2), HK RGC (CERG 622410, 622613 and HKUST6/CRF/12R) and M-SRA funding for Urban Computing and for Star Track program. This work is also supported by Program for Changjiang Scholars and Innovative Research Team in University (IRT1158, PCSIRT), China.

References

[1] “Canalys: 1.5bn smartphones to be shipped worldwide in 2017, android dominates with 67.1%”, http://thenextweb.com/.

[2] Rajib Kumar Rana, Chun Tung Chou, Salil S. Kanhere, Nirupama Bulusu, and Wen Hu, “Ear-phone: an end-to-end participatory urban noise mapping system”, in *ACM/IEEE IPSN*, 2010.

[3] “Sensorly”, http://www.sensorly.com/.

[4] Arvind Thiagarajan, Lenin Ravindranath, Katrina LaCurts, Samuel Madden, Hari Balakrishnan, Sivan Toledo, and Jakob Eriksson, “Vtrack: accurate, energy-aware road traffic delay estimation using mobile phones”, in *ACM SenSys*, 2009.

[5] Min Mun, Sasank Reddy, Katie Shilton, Nathan Yau, Jeff Burke, Deborah Estrin, Mark Hansen, Eric Howard, Ruth West, and Pter Boda, “Peir: the personal environmental impact report, as a platform for participatory sensing systems research”, in *ACM MobiSys*, 2009.

[6] Dejun Yang, Guoliang Xue, Xi Fang, and Jian Tang, “Crowdsourcing to smartphones:incentive mechanism design for mobile phone sensing”, in *ACM MOBICOM*, 2012.

[7] Juong-Sik Lee and Baik Hoh, “Sell your experiences:a market mechanism based incentive for participatory sensing”, in *IEEE percom*, 2009.

[8] Anshul Rai, Krishna Kant Chintalapudi, Venkata N.Padmanabhan, and Rijurekha Sen, “Zee: Zero-effort crowdingsourcing for indoor localization”, in *ACM SIGCOMM*, 2012.

[9] Xielei(Oscar) Wang, Wei Cheng, Prasant Mohapatra, and Tarek Abdelzaher, “Artsense: Anonymous reputation and trust in participatory sensing”, in *IEEE INFOCOM*, 2013.

[10] Khuong Vu, Rong Zheng, and Jie Gao, “Efficient algorithms for k-anonymous location privacy in participatory sensing”, in *IEEE INFOCOM*, 2012.

[11] Luis G.Jaimes, Idalides Vergara-Laurens, and Miguel A.Labrador, “A location-based incentive mechanism for participatory sensing systems with budget constraints”, in *IEEE percom*, 2012.

[12] Iordanis Koutsopoulos, “Optimal incentive-driven design of participatory sensing systems”, in *IEEE INFOCOM*, 2013.

[13] Yu Zhang and Mihacla van der Schaar, “Reputation-based incentive protocols in crowdsourcing applications”, in *IEEE INFOCOM*, 2012.

[14] Afra J. Mashhadi, Sonia Ben Mokhtar, and Licia Capra, “Fair content dissemination in participatory DTNs”, *Ad Hoc Networks*, vol. 10, no. 8, pp. 1633–1645, 2012.

[15] H. W. Kuhn, “The hungarian method for the assignment problem”, *Naval Research Logistics Quarterly*, vol. 2, no. 1-2, pp. 83–97, 1955.

[16] Noam Nisan, Tim Roughgarden, Eva Tardos, and Vijay V Vazirani, *Algorithmic game theory*, Cambridge University Press, 2007.

[17] Jack Edmonds and Richard M. Karp, “Theoretical improvements in algorithmic efficiency for network flow problems”, *J. ACM*, vol. 19, no. 2, pp. 248–264, Apr. 1972.

[18] N. Tomizawa, “On some techniques useful for solution of transportation network problems”, *Networks*, vol. 1, no. 2, 1971.