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Truthful incentive mechanisms for mobile crowd sensing with dynamic smartphones

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ABSTRACT

The emergence of ubiquitous mobile devices has given rise to mobile crowd sensing, as a new data collection paradigm to potentially produce enormous economic value. Fully aware of the paramount importance to incentivize smartphone users' participation, a wide variety of incentive mechanisms have been proposed, however, most of which have made the *impractical* assumption that smartphones remain static in the system and sensing tasks are known in advance. Designing truthful incentive mechanisms for mobile crowd sensing system has to address four major challenges, *i.e.*, dynamic smartphones, uncertain arrivals of tasks, strategic behaviors, and private information of smartphones. To jointly address these four challenges, we propose two truthful auction mechanisms, *OT-OFMCS* and *NOT-ONMCS*, with respect to the offline and online case of mobile crowd sensing, aiming at selecting an optimal set of winning bids with low costs for maximizing the social welfare. The *OT-OFMCS* mechanism features an optimal task allocation algorithm with the polynomial-time computational complexity where the information of all smartphones and tasks are known a priori. The *NOT-ONMCS* mechanism is comprised of a critical payment scheme and an online allocation algorithm with a $\frac{1}{2}$-competitive ratio, where the real-time allocation decisions are made based on current active smartphones. To improve the theoretical competitive ratio, we investigate a modified online approximation algorithm *RWBD* with the ratio of $(1 - \frac{1}{e})$. Rigorous theoretical analysis and extensive simulations have been performed, and the results demonstrate our proposed auction mechanisms achieve truthfulness, individual rationality and computational efficiency.

1. Introduction

These years have witnessed the rapid adoption of mobile devices [1]. The proliferation of smartphones brings new opportunities to reinforce the impact of mobile crowd sensing application on global society. 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 crowd sensing 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 crowd sensing 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 tasks to the platform which then recruits smartphones to provide the desired sensing services. A number of useful applications and systems have been investigated, such as noise mapping [2,3], cellular/WiFi coverage maps [4], and traffic information collection [5].

Stimulating smartphone participation is of paramount importance to evaluate achieved service quality of mobile crowd sensing application. 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 the possible privacy breach. However, without enough contributing smartphones, one is not able to receive desirable sensing services from the mobile crowd sensing application. As a result, mobile crowd sensing would not be practical for wide adoption. Although a number of existing mobile crowd sensing applications and systems [2–

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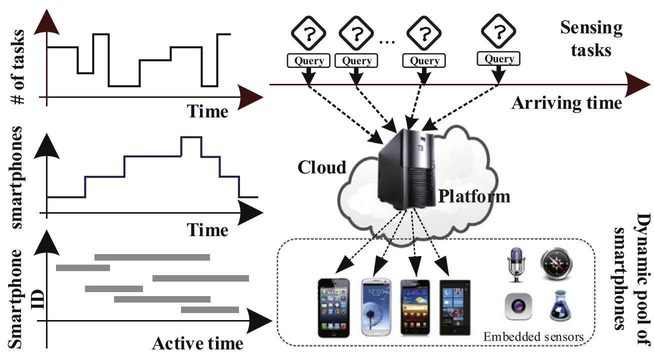


Fig. 1. Illustration of a mobile crowd sensing system. The platform residing on the cloud receives sensing tasks and assigns the tasks to smartphones. Both tasks and smartphones arrive to the system dynamically.

6] have been developed, they usually assume that smartphones voluntarily contribute their resources to provide sensing services. This assumption does not hold in reality, suggesting such mobile crowd sensing systems cannot be sustained in the long run. Thus, it is nontrivial to design reward-related incentive mechanisms for contributing smartphones as compensation.

A wide variety of truthful incentive mechanisms [7–13] has been designed for mobile crowd sensing. *However, 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 at the system dynamically, and arrivals of tasks can be busty and unpredictable. As a result, existing incentive mechanisms may fail and become untruthful when being applied to mobile crowd sensing systems with dynamic smartphones and random arrivals of tasks.

It is particularly challenging to design incentive mechanisms given the unique characteristics of mobile crowd sensing with dynamic smartphones. *First*, smartphones may dynamically join and leave the system, and sensing tasks may arrive at the system at random. Such uncertain and unpredictable behaviors further complicate the design of incentive mechanisms. *Second*, the key information about the real cost, arriving time and departure 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. Although existing mechanisms [14–17] investigate the design of online incentive mechanisms, they focus on diverse models or objectives, failing to be applied to solve our online assignment problem. For example, different from the existing works [14,17], the random arrivals of sensing tasks further increase the complexity of the online incentive mechanism design.

In response to the challenges, we propose two truthful auction mechanisms, *OT-OFMCS* and *NOT-ONMCS*, as well as a modified approximation algorithm. The *NOT-ONMCS* mechanism explicitly take both dynamic smartphones and random arrivals of tasks into consideration. *First*, as a benchmark of the online case, we design the *OT-OFMCS* mechanism in which the optimal maximum weighted matching algorithm produces the maximum social welfare with a polynomial complexity of $O((n+\gamma)^3)$. *Second*, we propose the suboptimal *NOT-ONMCS* mechanism, which is comprised of a winning bids decision algorithm and a critical payment scheme. Moreover, the near-optimal allocation algorithm can approximate the offline optimal solution within a factor of $\frac{1}{2}$. *As a complementary*, we further introduce a randomized winning bids decision algorithm *RWBD*, where the competitive ratio is increased to $(1-\frac{1}{e})$. Solid theoretical analysis and extensive simulations demonstrate that both *OT-OFMCS* and *NOT-ONMCS* mechanisms can achieve the desired properties of truthfulness, individual rationality and computational efficiency.

The preliminary result of this work was reported in 2014 IEEE ICDCS [18]. The rest of the paper proceeds as follows. The next section reviews related work. Section 3 presents the system model, the reverse auction model, and the mathematical formulation. We demonstrate the *OT-OFMCS* and *NOT-ONMCS* mechanism in Section 4 and Section 5 respectively. In Section 6, we propose a modified online algorithm *RWBD*. Section 7 presents evaluation results. Section 8 concludes the paper.

2. Related work

The related works about existing incentive mechanisms are demonstrated as the following two categories: *Offline Incentive Mechanisms* and *Online Incentive Mechanisms*. Especially, each category is divided into incentive mechanisms with strategic behaviors and without strategic behaviors.

2.1. Offline incentive mechanisms

A number of existing works [7,10,11,19,20] have made the impractical assumption on static smartphones and given tasks. All the information has been revealed before the task allocation is initially made.

2.1.1. Incentive mechanisms with strategic behaviors

Existing works [7,9–11,19–22] design auction-based incentive mechanisms to induce smartphones to disclose their real cost. Yang et al. [7] propose two incentive mechanisms for the user-centric model and platform-centric model, respectively. Li et al. [10] propose a randomized auction mechanism to increase the diversity of sensing devices and prevent the starvation of some users, however, only achieving the approximate truthfulness. Feng et al. [11] solve the location-aware sensing tasks allocation problem, modeled as the modified minimal weighted set cover problem, to minimize the social cost. Meanwhile, the critical payment scheme is proposed according to the work [23]. However, the mentioned works [7,10,11] only consider the smartphones with single-parameter bids, and the proposed mechanisms simply run in the offline settings. Especially, Koutsopoulos [9] aim to minimize the total expected payment under the known cost distribution of smartphones, where the prior distribution cannot be adapted to our setting.

In particular, Jin et al. [21] take it into consideration, that the quality of sensed data collected by the smartphones, aiming at maximizing the social welfare under the constraint of the task quality requirement. Based on the prior work, Jin et al. [24] further propose a payment mechanism, where a non-cooperative game is adopted to model the strategic behaviors of smartphones. Each smartphone can maximize its utility only when it determines to complete the assigned sensing task with the maximum effort. In addition to guarantee the truthfulness of smartphones, the existing work [25] further considers the probable misreporting of multiple task requesters. Jin et al. [25] adopt a double auction mechanism to stimulate the participation of both sides. However, none of the referred works [21,24,25] has considered dynamic arrivals of both smartphones and sensing tasks.

2.1.2. Incentive mechanisms without strategic behaviors

Many related work [8,12,26] have assumed that smartphones are cooperative and participate in mobile crowd sensing system voluntarily. He et al. [12] offer an approximation algorithm *LRBA* to maximize total rewards of the platform in consideration of two constraints, *i.e.* smartphones with time budget and sensing tasks with specific locations. Jaimes et al. [26] propose an auction mechanism consisting of two components, the winning user selection algorithm and the price scheme. The main idea is to select smartphone users greedily according to their current locations to cover the largest area. However, they design the pricing scheme without considering smartphone users' strategic behavior. Similarly, Lee and Hoh [8] neglect that smartphones are self-interested, and they may misreport the real cost for higher utility. Other works [27,28] focus on the incentive mechanisms with reputation management system or equivalent service.

2.2. Online incentive mechanisms

Many online incentive mechanisms [14–17,29–32] have been proposed in consideration of dynamic smartphones or the random arrival of sensing tasks, which is more consistent with the realistic condition.

2.2.1. Incentive mechanisms with strategic behaviors

The existing work [14] proposes an online incentive mechanism to maximize the crowdsourcer's value under the budget constraint with respect to dynamic smartphones and fixed set of sensing tasks. Different from our work, in addition to dynamic smartphones, the future information about sensing tasks is also absent, which further increases the complexity of our mechanism design. Zhao et al. [17] aim to minimize the total payment while assigning the given group of tasks before deadline. Similarly, the full information of all sensing tasks is known in advance. In particular, the problem setting of Han et al.' work [31] is slightly close to our work. However, the implicit difference lies in the model of the sensing task, where they assume that each smartphone requires a period of sensing time to complete the assigned sensing task. Consequently, the authors propose a sensing-time schedule mechanism to determine the scheduled sensing time and associated reward for each winning smartphone. Different from their setting, we make an assumption that the sensing tasks can be completed in a single slot. In addition to the works [14,17], we either assume that the sensing cost of each smartphone is given, and is irrelevant to its sensing time. However, the sensing cost and payment of each smartphone in Han et al.' work [31] is proportional to its sensing time. Duan et al. [29] propose a distributed auction mechanism in consideration of sensing task assignment and scheduling. Han et al. [15] propose an online pricing mechanism regard to multi-minded users' random arrivals. Therefore, the models and problem definitions of existing works [14,15,17,29,31] differ from our work, and cannot be applied to our setting.

2.2.2. Incentive mechanisms without strategic behaviors

Boutsis et al. [30] design an efficient approximation algorithm, aiming at maximizing both two objectives of real-time demands and reliability, as well as achieving good performance compared to the Pareto optimal solution. Xu et al. [16] focus on maximizing the total expected profit subject to the budget and deadline constraints, however, neglecting the users' strategic behaviors.

3. System model and problem formulation

3.1. System model

In the mobile crowd sensing system, there are *tasks, smartphone users*, and a *cloud platform*. We divide the time into slots of the 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, *i.e.*,$N = \{1, 2, \cdots, n\}$. 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 at the platform. Let r_i denote the number of tasks arriving in slot t_i. The kth sensing task that arrives in slot t_j is denoted by $\tau_{j,k}$, $k \le r_j$. 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 into 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.*, the smartphones can provide all 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 dynamically arrives in and departs from the system. The period of time during which the smartphone is available to provide sensing services is called *active time*.

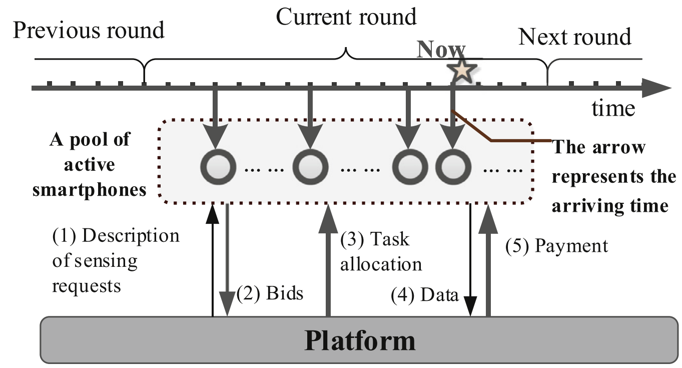


Fig. 2. The reverse auction framework for the mobile crowd sensing system with dynamic smartphones and random arrivals of tasks.

3.2. Reverse auction framework for mobile crowd sensing

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 crowd sensing system, the buyer is the platform buying sensing services, and the sellers are smartphones. The reverse auction framework is described as follows, which is also depicted in Fig. 2.

(i) At the start of each slot t_j, the platform advertises the set of available sensing tasks in this slot to each newly arriving smartphone.

(ii) Each new smartphone i submits a bid B_i, consisting of the arrvial time $\tilde{a}_i$, the departure time $\tilde{d}_i$ and the claimed cost b_i, to the platform.

(iii) The platform allocates a total of r_j sensing tasks in each slot t_j to the set of winning bids from current active smartphones.

(iv) Each smartphone i completes the assigned sensing task, and returns sensed data to the platform.

(v) Each smartphone i is paid the reward for its winning bid B_i before it departs.

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 $B_i = (\tilde{a}_i, \tilde{d}_i, b_i)$, $0 \le \tilde{a}_i \le \tilde{d}_i \le m$, $0 \le b_i < \infty$, to the platform, where a_i denotes the *arrival time* of *i*, d_i is the *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 decision rule is $\pi: \Gamma \mapsto B$, where the task $\tau_{j,k}$ is allocated to the bid $B_i = \pi(\tau_{j,k})$ which the smartphone i has submitted , *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 the bid B_i subject to the *payment rule*, $p : B \mapsto \mathbb{R}^n$. A smartphone that is not allocated a task in its active time according to the bid B_i would get no payment. Without loss of generality, we only consider a single round. The same design and analysis can be applied to other rounds. Note that the repeated auction [33] in two continuous rounds is omitted, and subject to our future research.

3.3. Auction model

Next, we discuss the characteristics of the rationality of smartphones. Since the real cost, the arriving time and the departure 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 arrival, an earlier 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 the 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 the strategy solely to maximize its own utility. Thus, it is possible for them to misreport their private information. This kind of misreporting is called *strategic behavior*.

Next, we define the utility of completing a sensing task for the platform, that for the system and social welfare. Suppose the sensing task $\tau_{j,k}$ is allocated to the smartphone i who has submitted the bid B_i. The platform (or the auctioneer) obtains a fixed value ν for a task being completed. Then, the formal definitions are as follows.

Definition 2 (Platform Utility of Sensing Task)**.** The utility of the sensing task $\tau_{j,k}$ for the platform is the difference between the value and the payment paid to the smartphone i.

$$u(\tau_{j,k})^p = \nu - p_i(B_i, B_{-i}). \tag{2}$$

Based on Definitions 1 and 2, the utility of single completed task for the system is the sum of the utility received by the platform and the utility of the assigned smartphone, given in Definition 3. Moreover, the social welfare is given in Definition 4.

Definition 3 (System Utility of Sensing Task)**.** The utility of the sensing task $\tau_{j,k}$ for the system is the difference between the value and the real cost of smartphone i.

$$u(\tau_{j,k})^s = \nu - p_i(B_i, B_{-i}) + p_i(B_i, B_{-i}) - c_i = \nu - c_i, \tag{3}$$

where the payment term is counteracted.

Table 1
Key notations.

Notation	Description
Γ, γ, τ_i	set of tasks, number of tasks and one task
N, i	set of user and one user
t_j, r_j	each time slot and number of tasks arriving in slot j
m	total slots in each round
n	maximum number of users in each slot
$\tau_{j,k}$, $\nu_{j,k}$	the kth task in slot j and its value
a_i, $\tilde{a}_i$	true and submitted arriving time of user i
d_i, $\tilde{d}_i$	true and submitted departure time of user i
c_i, b_i	true cost and bid price of user i
$\pi(\tau_{j,k})$	allocation result for task $\tau_{j,k}$
p_i, u_i	payment and utility of user i
$u(\tau_{j,k})^p$	platform utility of completed task $\tau_{j,k}$
$u(\tau_{j,k})^s$	system utility of completed task $\tau_{j,k}$
G, M	bipartite graph and maximum weighted matching result
$\hat{b}_i$, $\Phi(x)$	randomized cost and randomized function
ω, $\hat{w}$	social welfare and total loss of modified online algorithm

Definition 4 (Social Welfare)**.** The social welfare is the sum of the utilities of all completed sensing tasks for the system. It is computed as follows:

$$\omega = \sum_{\tau_{j,k} \in \Gamma} u(\tau_{j,k})^s. \tag{4}$$

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.

The key notations are listed in Table 1.

3.4. Problem formulation

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

Definition 5 (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 6 (Individual Rationality)**.** An auction mechanism satisfies the property of individual rationality if and only if each smartphone has a non-negative utility, *i.e.*,$u_i \geq 0$, for each $i \in N$.

Definition 7 (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 8 (Winning Bids Decision Problem (WBDP))**.** For the mobile crowd sensing system, its objective is a system-wide social welfare given in Definition 4. The mobile crowd sensing system aims at maximizing the social welfare by selecting an optimal set of winning bids when each smartphone discloses its real cost. The winning bids decision problem is

$$\max \quad \omega = \textstyle\sum_{\tau_{j,k} \in \Gamma} u(\tau_{j,k})^s, \tag{5}$$

$$s.t. \sum_{\tau_{j,k} \in \Gamma} I(\pi(\tau_{j,k}) = B_i) \leqslant 1, \forall i \in N \tag{6}$$

$$a_i \leqslant j \leqslant d_i, \ if \ I(\pi(\tau_{j,k}) = B_i) = 1, \forall i \in N, \tag{7}$$

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:The first equation gives the objective of maximizing the social welfare. The social welfare reflects the *efficiency* of the mobile crowd sensing system. The second constraint indicates a smartphone is allocated no more than one sensing task or has at most one winning bid. And the second constraint requires that a sensing task should be allocated to a smartphone within its active time.

Definition 9 (payment decision Problem)**.** The payment decision problem is to determine how much a participating smartphone should be paid and when the payment is executed.

In the following two sections, we aim to propose two auction mechanisms for two cases of mobile crowd sensing, while addressing the above two key problems and achieving the desired properties of truthfulness, individual rationality and computational efficiency.

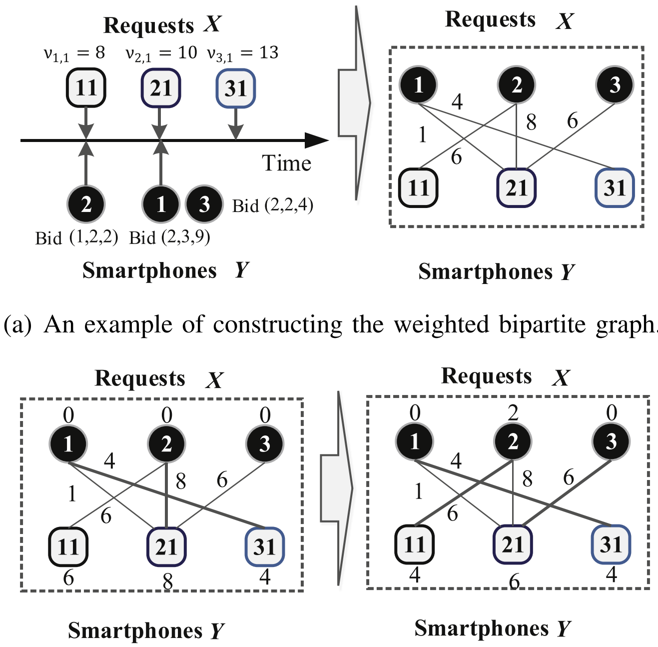
- In *the offline case*, at the very beginning the platform knows the arrival time and the departure time of each smartphone, and the arrival of each task. It is also at the beginning that the platform announces the set of all tasks together with the arrival time to all smartphones, each smartphone submits 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 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 irrevocably determines the winning bids for the tasks announced in the current slot.

4. Optimal and truthful auction mechanism for offline mobile crowd sensing (*OT-OFMCS*)

We first consider the offline case, which 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.

4.1. Overview

We propose a truthful auction mechanism, *OT-OFMCS*, for the offline case consisting of two components, which are designed in response to the two key problems in Section 3.4. To solve the winning bids decision problem, we model the problem as the *maximum weighted matching in a bipartite graph* and find the optimal solution with polynomial-time computational complexity. Since the proposed allocation algorithm can optimally determine the set of winning bids in polynomial time, for the payment decision problem, we naturally leverage the traditional VCG mechanism [23] to propose a payment scheme, which guarantees that each smartphone discloses its private information truthfully. We also theoretically analyze the achieved properties of the *OT-OFMCS* mechanism.



(a) An example of constructing the weighted bipartite graph.

(b) The maximum matching result based on the constructed bipartite graph.

Fig. 3. An example demonstrating the construction of the weighted bipartite graph and the running process of the maximum matching algorithm based on this construction. In Fig. 3(a), for the first three slots, only one sensing task arrive. In the first slot, Smartphone 2 arrives and another two smartphones 1, 3 arrive in the second slot. In Fig. 3(b), the deepened line is the final matching result.

4.2. Offline optimal algorithm for WBDP

We solve the winning bids decision 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.

4.2.1. 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 $x_{j,\,k}$ ($k \leq r_j$) 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 $w(x_{j,k}, y_i) = \nu_{j,k} - b_i$ only if smartphone y_i is active in the jth slot; otherwise, $w(x_{j,k}, y_i) = 0$. We give a simple example in Fig. 3(a) to illustrate the construction of the weighted bipartite graph.

4.2.2. Computing the maximum weighted matching

We employ the Hungarian algorithm [34] to find the maximum weighted matching from 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 does not exist an augmented path. The details are shown in Algorithm 1. The resulting matching is our maximum weighted matching for G.

4.2.3. 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 cor-

Algorithm 1 Maximum weighted matching.

Require: Bipartite weighted graph $G = (X \bigcup Y, X \times Y)$.
Ensure: Maximum weighted matching M.

1: Generate a feasible *labelling* ℓ and a *matching* M in E_ℓ, where $\ell : X \bigcup Y \to \mathcal{R}$ is a labelling function and $E_\ell = \{(x, y) : \ell(x) + \ell(y) = w(x, y)\}$ is the edge set of the *equality graph* $G = (X \bigcup Y, E_\ell)$.
2: Initially, a feasible labelling is $\forall y \in Y, \ell(y) = 0$ and $\forall x \in X, \ell(x) = \max_{y \in Y}\{w(x, y)\}$.
3: Let $S \subseteq X$ and $T \subseteq Y$ represent the candidate augmenting alternating path between the matching and edges not in the matching respectively.
4: **while** M is not perfect in E_ℓ **do**
5: pick free vertex $u \in X$. Set $S = \{u\}$, $T = \emptyset$.
6: Let $N_\ell(u) = \{v : (u, v) \in E_\ell\}$ and $N_\ell(S) = \bigcup_{u \in S} N_\ell(u)$ denote the *neighbors* of vertex u and set S, respectively.
7: **if** $N_\ell(S) = T$ **then**
8: update labels (forcing $N_\ell(S) \neq T$).
9: let $\alpha_\ell = min_{s \in S, y \notin T} \ell(x) + \ell(y) - w(x, y)$, where
$$\ell'(v) = \begin{cases} \ell(v) - \alpha_\ell & v \in S \\ \ell(v) + \alpha_\ell & v \in T \\ \ell(v) & otherwise \end{cases}.$$
10: **else**
11: pick $y \in N_\ell(S) - T$.
12: **if** y is free **then**
13: $u - y$ is a augmenting path. Augment M. Go to 4.
14: **end if**
15: **if** y is matched to a vertex z **then**
16: extend alternating tree: $S = S \bigcup \{z\}$, $T = T \bigcup \{y\}$. Go to 10.
17: **end if**
18: **end if**
19: **end while**
20: **return** M;

responding task allocation as follows. For each edge $(x_{j,\,k}, y_i)$ in M, the connection means that task $\tau_{j,\,k}$ in the jth slot is allocated to smartphone i.

4.2.4. Illustrating example

We use an example to demonstrate the construction of the weighted bipartite graph and the running process of Algorithm 1. In Fig. 3(a), suppose that only the first three slots are considered. The value of the sensing task in each slot is $\nu_{1,1} = 8, \nu_{2,1} = 10, \nu_{3,1} = 13$ respectively. Initially, the weighted bipartite graph is constructed in Fig. 3(a). According to line 1, we firstly generate a feasible matching in Fig. 3(b), *i.e.*, Smartphone 1 is matched to task $\tau_{3,\,1}$ and task $\tau_{2,\,1}$ is assigned to Smartphone 2. According to line 2, the labelling of each vertex from two sets X and Y is generated. Specifically, the labelling of Smartphone 1,2,3 is all zero and that of three sensing tasks arrving in each slot is respectively 6,8,4. Based on line 13, the new augmenting path is found. Specifically, Smartphone 3 is matched to task $\tau_{2,\,1}$. Finally, the final maximum matching result is obtained in Fig. 3(b).

4.2.5. Discussion

Next, we discuss how to extend the solution if the tasks are heterogeneous, *i.e.*,a sensing task has a type and only some smartphones can accept such type of sensing tasks. When constructing the bipartite graph, the assignment of the weight of each edge between each pair of nodes $x_{j,\,k}$ and y_i is changed. Only when the smartphone y_i is active in the slot j and it has the capability to perform sensing task $\tau_{j,\,k}$, they share an edge with the weight of $\nu_{j,k} - b_i$. Thus, the algorithm can handle the model with heterogeneous tasks.

4.3. Offline payment scheme

It is critical to notice that social welfare calculated in Section 4.2 is based on the claimed cost of smartphones. The payment decision 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 arrival time and departure 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 [23]. 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 crowd sensing system.

The utility of each smartphone i is computed as follows:

$$p_i(B) = (\omega^*(B) - (-b_i)) - \omega^*(B_{-i}) \tag{8}$$

$$= \omega^*(B) - \omega^*(B_{-i}) + b_i \tag{9}$$

$$= h(B_{-i}) - \omega^*(B_{-i}), \tag{10}$$

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 $\nu_{j,\,k}$ while the social welfare of a smartphone that is allocated a sensing task can be regarded as $-b_i$. The first part of (8) computes the social welfare of all others in the mobile crowd sensing system when B_i is selected, and the second part of this equation computes the maximum social welfare of all others in the mobile crowd sensing 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,

$$u_i(B) = p_i(B) - c_i = h(B_{-i}) - \omega^*(B_{-i}) - c_i. \tag{11}$$

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

4.4. Theoretical analysis

Theorem 1. *The winning bids decision algorithm discussed in Section 4.2 is optimal.*

Proof. In the previous discussion, we generate a weighted bipartite graph from our problem in order to utilize the Hungarian algorithm. Then, we verify that the aforementioned algorithm is able to find the optimal maximum weighted matching by induction.

- In line 1, we can always take the trivial ℓ and empty matching $M = \emptyset$.
- In line 7, If $N_\ell(S) = T$, we can always update labels to create a new feasible matching ℓ'. The rule of updating labels in the line 9 guarantees that all edges in $S \times T$ and $\bar{S} \times \bar{T}$ that were in E_ℓ will be in $E_{\ell'}$. Particularly, this guarantees that the current matching M remains in $E_{\ell'}$ as does the alternating tree built so far.
- In line 10, if $N_\ell(S) \neq T$, there always exists augment alternating tree by choosing some $x \in S$ and some free point $y \notin T$ such that $(x,\ y) \in E_\ell$. In this case, we augment M.

- The algorithm always terminates and when it does terminate, M is a perfect matching in E_ℓ, and then it is optimal by the Kuhn-Munkres theorem [35].

□

Theorem 2. *The* OT-OFMCS *mechanism is truthful,* i.e.,*each smartphone truthfully reports its private information no matter what others report.*

Proof. To demonstrate the *OT-OFMCS* 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 *OT-OFMCS* mechanism is *cost-truthful*, which means for each smartphone, the misreporting of its real cost cannot increase its utility. Let $B_i = (\tilde{a}_i, \tilde{d}_i, b_i)$ denote the bid of smartphone i. Consider $\tilde{a}_i$ and $\tilde{d}_i$ are fixed. When the smartphone i submits its true bid, *i.e.*,$b_i = c_i$, we consider the following two cases. (i) The smartphone i is allocated some sensing task and has the utility $u_i(B) \geq 0$. Consider if it claims an untruthful bid, *i.e.*, $b_i \neq c_i$, it still wins. Since two parts of computing payment from the Eq. (9) are independent of the claimed cost b_i in the bid B_i, the payment never improves because of the misreporting. Consequently, its utility $u_i(B)$ remains the same. If it loses when it lies about the bid, its utility $u_i(B)$ is zero. That means the misreporting leads to the less utility than bidding truthfully. Therefore, it has no incentive to manipulate the cost. (ii) The smartphone i is not allocated any task and has the utility $u_i(B) = 0$. Consider if it still loses when bidding untruthfully, *i.e.*, $b_i \neq c_i$, its utility $u_i(B)$ is still zero. Let $\tilde{b}_i$ and b_i represent the untruthful and truthful bid, respectively. Next, we consider the condition where it wins with the untruthful bid $\tilde{b}_i$. That means it must claim a lower bid $\tilde{b}_i$, still lower than the payment $p_i(B)$ paid to it according to the Eq. (9), *i.e.*, $\tilde{b}_i \leq p_i(B)$. Obviously, its truthful bid b_i even has to be excessive than its contribution, *i.e.*, $p_i(B) \leq b_i$, because it loses when bidding truthfully. Consequently, its utility is now negative.

$$u_i(B) = p_i(B) - c_i \leq b_i - c_i = c_i - c_i = 0. \tag{12}$$

Thus, each smartphone i cannot increase its utility by misreporting its real cost.

Then, we prove the *OT-OFMCS* mechanism is *time-truthful*, which indicates each smartphone cannot increase its utility by delaying its arrival and advancing its departure. For a smartphone that is not allocated a sensing task, it cannot receive a sensing task either, if it reports a *tighter* arrival-departure interval. For a smartphone that is allocated a sensing task by truthfully reporting its arrival-departure interval, it cannot benefit from reporting a tighter arrival-departure interval. For example, a smartphone i submits a truthful bid (1,3,4), and the optimal allocation algorithm assigns the task $\tau_{2,1}$ to it. However, consider if it reports a tighter arrival and departure time, *i.e.*, (1,1,4). Next, we analyze the following two cases.

(i) The smartphone still wins. According to the utility function from the Eq. (11), its utility $u_i(B)$ remains the same. (ii) The smartphone loses and has the utility $u_i(B) = 0$. Therefore, the misreporting possibly makes its utility decrease to zero. Consequently, the tighter arrival-departure interval may fail the bid of the smartphone, leading to the non-increasing utilities. Thus, a smartphone has no incentives to misreport its arrival time and departure time. □

Theorem 3. *The* OT-OFMCS *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 (11). The utility can be computed in the following way:

$$\begin{aligned} u_i(B) &= \omega^*(B) - \omega^*(B_{-i}) + b_i - c_i, \\ &= \omega^*(B) - \omega^*(B_{-i}), \end{aligned} \tag{13}$$

$$\geqslant 0, \tag{14}$$

where (13) holds because we have demonstrated that smartphone i would truthfully report its private information. As $\omega^*(B)$ denotes the optimal solution, we get that $\omega^*(B) \geq \omega^*(B_i)$. □

Theorem 4. *The optimal algorithm for WBDP has polynomial-time computational complexity.*

The Hungarian algorithm can be modified to achieve an $O(n^3)$ running time [36,37], where n is the number of vertices in the graph. Thus, the optimal algorithm can be computed within $O((n+\gamma)^3)$.

5. Near-optimal truthful auction mechanism for online mobile crowd sensing (*NOT-ONMCS*)

We next consider the online case, which is for practical applications in the real world. We solve the two problems in Section 3.4 by proposing a near-optimal algorithm for winning bids decision and a payment scheme to induce truthfulness. Finally, we theoretically prove the *NOT-ONMCS* mechanism achieves the desired properties.

5.1. Overview

We propose an online auction mechanism, *NOT-ONMCS*, which is comprised of two components for solving the two problems stated in Section 3.4, respectively. For the online winning bids decision problem, however, it is hardly possible to find an optimal solution due to the uncertainty of future information about arrivals of tasks and arrivals and departures 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 [23]. We design a payment scheme that guarantees each smartphone disclose private information truthfully.

5.2. Online algorithm for WBDP

We propose an online greedy algorithm for solving the winning bids decision 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.

5.2.1. Revealing equivalence

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

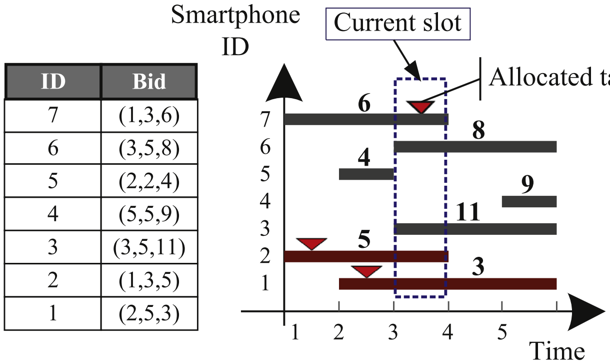


Fig. 4. An example illustrating the online winning bids decision algorithm. The dotted rectangle contains all active smartphones in the current time slot. The number above each line denotes the claimed cost.

5.2.2. Greedy strategy

The greedy winning bids decision 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 arrives, departs or obtains an allocation. In each slot, the platform greedily selects smartphones with the lowest costs and allocates sensing tasks to them. Algorithm 2 shows the details of selecting winning bids.

Algorithm 2 Winning bids decision algorithm.

Require: Set B of bids, vector $R = (r_1, r_2, \cdots, r_m)$.
Ensure: vector $\Pi = \{p_1, p_2, \cdots\}$.

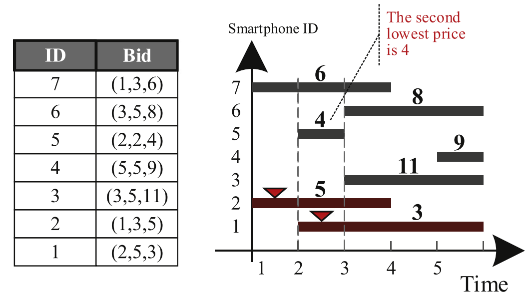
$S \leftarrow \emptyset$, $t \leftarrow 1$, $\Pi \leftarrow \vec{0}$;
while $t \leqslant m$ **do**
  Add each newly arriving smartphone to S and remove each smartphone that departs at slot t from S;
  Sort bids in S by its claimed cost in non-decreasing order.
  for k from 1 to r_t **do**
    Choose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

5.2.3. Illustrating example

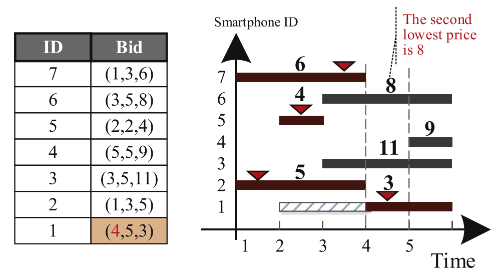
In Fig. 4, we give an example to illustrate the online algorithm. There are in total 7 smartphones, which arrives at and departs from the system in different time slots. For example, Smartphone 2 arrives to the system in the 1st slot and leaves in the 4th slot. It claims a cost of 5. The current slot is the 3rd slot. In this example, it is assumed that in each time slot only one new task arrives at 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 costs 11 and 8, respectively).

5.3. Online 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 decision algorithm is not optimal. In addition, simple payment schemes, *i.e.*,the scheme of *second price auction*, also fails 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 the idea of this payment scheme to our scenario assuming there is only one sensing task at each slot: *i.e.*,each winning smartphone is paid 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 in the following motivation example.



(a) Smartphone reports its bid truthfully.



(b) Smartphone misreports its begin of 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 its begin of active time while in Fig. 5(b) Smartphone 1 delays its begin of 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 its begin of active time.

5.3.1. Motivation example

The example is illustrated in Fig. 5(a) 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(b). 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 incentives to delay its begin of active time in order to increase its utility, which is shown in Fig. 5(b). When Smartphone 1 delays its begin of active time by 2 slots, *i.e.*, Smartphone 1 reports that its active time is [4,5], it obtains a payment of 8. It is obvious that Smartphone increases its utility by 4 when delaying its begin of active time by 2 slots. Thus, such payment scheme fails to ensure that each smartphone would truthfully report its private information.

We next explain the payment scheme. 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 departure 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.

5.3.2. Main steps of payment scheme

The main steps of computing the payment are listed as follows (Algorithm 3 shows the pseudo code of the payment scheme).

Algorithm 3 Payment scheme.

Require: Smartphone ID i, set B of bids of dynamic smartphones, slot t_i' in which B_i wins.
Ensure: payment p_i.

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

First, it removes B_i from B and allocates the sensing tasks to other smartphones utilizing the greedy rule in Algorithm 2 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.

5.3.3. Illustrating example

We give an example to show the computing of the payment for Smartphone 1 in Fig. 4. In Section 5.2, we know that Smartphone 1 is allocated a task in the 2nd slot. If the tasks are allocated to 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.

5.4. Theoretical analysis

According to [23], we can prove that the proposed *NOT-ONMCS* mechanism is truthful only if it satisfies the following two conditions: (1) The winning bids decision algorithm is *monotonic*, and (2) each smartphone is paid an amount that equals to the *critical value*.

Definition 10 (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 11 (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 decision 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 5. *The* NOT-ONMCS *mechanism is truthful.*

Proof. Firstly, we show that the winning bids decision algorithm is monotonic. For a smartphone that wins when submitting 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 decision algorithm is monotonic.

Then, we verify that the payment computed by Algorithm 3 is the critical value for smartphone i. Let p_i denote the payment computed by Algorithm 3. 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 3) 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 3 is the critical value. □

Theorem 6. *The* NOT-ONMCS *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. 3. 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 7. *The online algorithm for winning bids decision 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.*

Proof. We prove the competitive ratio by introducing a parameter a and $a = 0$ at the beginning. Set the value of a sensing task to ν. For any smartphone i that is allocated the sensing task $\tau_{j,k}$ offline in slot j but not online, increase a by $\nu - c_l$, where the sensing task $\tau_{j,k}$ is allocated to smartphone l for the online case. Since the smartphone i is not chosen in the online algorithm, its real cost is no smaller than the real cost of l, which also means $\nu - c_i \leqslant \nu - c_l$. For any smartphone i that is allocated in both the online and the offline cases, increase parameter a by $\nu - c_i$. It is obvious that a is no smaller than the solution of the offline algorithm, *i.e.,*$a \geq \omega_{opt}$. On the other hand, the utility of each sensing task in the online allocation is added to a at most twice. Thus, a is no more than twice of the approximate social welfare obtained by the online algorithm, *i.e.,*$a \leq 2\omega_{apx}$. Then, we get $2\omega_{apx} \geq \omega_{opt}$. □

Theorem 8. *The* NOT-ONMCS *mechanism has polynomial-time computational complexity.*

Proof. The online algorithm for the winning bids decision problem contains a loop with m iterations. In each loop, there is an operation of sorting with the computational complexity of $O(s_j \log s_j)$ in the slot j, where s_j is the number of smartphones that are active in the current slot. Thus, the computational complexity of each loop is $O(c) + O(n \log n) + O(1) = O(n \log n)$. Then, the computational complexity of the online algorithm is $O(mn\log(n))$.

The algorithm for computing the payment for each smartphone with the winning bid has the same computational complexity of $O(mn\log(n))$. In total, the computational complexity of computing the payment for all contributing smartphones is $O(\gamma mn\log(n))$, where γ is the total number of sensing tasks. □

6. $(1-\frac{1}{e})$-competitive approximation algorithm for online mobile crowd sensing

According to Gagan's work [38], we propose a modified approximation algorithm *RWBD* (randomized winning bids decision) with the competitive ratio of $(1-\frac{1}{e})$. Because the existing mechanism with the online task allocation algorithm *RWBD* cannot guarantee the truthfulness, we neglect the payment scheme and only analyze the theoretical competitive ratio in this section. Consequently, *RWBD* achieves a higher constant competitive ratio $(1-\frac{1}{e})$ while the online algorithm in Section 5.2 is only $\frac{1}{2}$-competitive. For the online winning bids decision problem, we design the online randomized algorithm *RWBD* to determinate the set of winning bids. Finally, we prove that *RWBD* is $(1-\frac{1}{e})$-competitive theoretically.

6.1. Online randomized algorithm for WBDP

We propose an online randomized-greedy algorithm *RWBD* to solve the winning bids decision problem. The main idea of *RWBD* is similar to the greedy online algorithm in Section 5.2. The key difference is that we randomize the cost b_i of each smartphone with a perturbed function $\Phi(x)$ completely independently of that of other smartphones [38]. Thus, once a new slot starts, *RWBD* updates the currently active and available smartphones, and allocates the sensing tasks to those with the lowest randomized cost $\hat{b}_i = b_i\Phi(x)$. Φ can be any randomized function. For the convenience of computation, we define $\Phi(x) = 1 - e^{-(1-x)}$. The key component of *RWBD* is to generate the randomized cost for all available smartphones once new slot starts. Next, we demonstrate this component.

6.1.1. Generating the randomized cost

When new slot starts, the claimed costs of all available bids are replaced by the randomized costs. The key algorithm is shown in Algorithm 4. Combined with Algorithm 2, the randomized cost generation algorithm forms the online randomized-greedy algorithm *RWBD*.

Algorithm 4 Randomized cost generation.

Require: Any available Bid B_i, randomized function $\Phi(x) = 1 - e^{-(1-x)}$.
Ensure: Randomized cost $\hat{b}_i$ of B_i.
1: Generate a random number x_i uniformly for any available bid B_i, where $x_i \in [0, 1]$.
2: Obtain the perturbed weight $\Phi(x_i) = 1 - e^{-(1-x_i)}$.
3: $\hat{b}_i \leftarrow b_i \cdot \Phi(x_i)$.
4: **return** $\hat{b}_i$;

6.1.2. Illustrating example

Return to Fig. 4, the randomized-greedy algorithm *RWBD* works as follows. Suppose that only one new task arrives in each time slot. The current slot is the 3rd slot. In the 1st slot, only Smartphone 2 and 7 were active and available. Suppose that their separate perturbed weights were generated as 0.2 and 0.7. Thus, each randomized cost for Smartphone 2 and 7 was 1 and 4.2. So Smartphone 2 won. Similarly, In the 2nd slot, assume that the perturbed weights for Smartphone 1, 5 and 7 were 0.1, 0.6 and 0.4 respectively. So Smartphone 1 won because of the lowest randomized cost 0.3. In the current slot, another two Smartphones 3 and 6 arrive. Suppose that the separate randomized cost of available smartphones is 0.88, 7.2 and 0.7 respectively. According to the randomized-greedy strategy, Smartphones 7 wins since it has the lowest randomized cost 0.7 within all active Smartphones 3,6,7.

6.2. Theoretical analysis

Inspired by Gagan's work [38], we give a simplified analysis of the competitive ratio for the online randomized-greedy algorithm *RWBD*. First, we transfer our primal algorithm to the discrete version. Second, we give the essential definitions for the convenience of proof. Finally, the process of concrete theoretical derivation is given.

Theorem 9. *The online randomized-greedy algorithm* RWBD *for winning bids decision problem has the competitive ratio of $(1-\frac{1}{e})$, for each input, $\omega_{RWBD}/\omega_{opt} \geqslant (1-\frac{1}{e})$, where ω_{RWBD} and ω_{opt} denote the resulting social welfare of the randomized-greedy online algorithm and the optimal offline algorithm, respectively.*

Proof. For the discrete version, we replace the original perturbed function with $\Phi(x) = 1 - (1-\frac{1}{k})^{-(k-x+1)}$, where $x \in \{1, 2, \ldots, k\}$ and k is the parameter. Let u denote one from the set of smartphones N. Thus, our discrete algorithm matches each incoming task to the smartphone with the lowest randomized cost $b_u\Phi(x)$, where b_u is the claimed price of u. Since $\Phi(x)$ is a decreasing function, the discrete version converges to our original algorithm when k tends to infinity.

Next, we give some essential notations. First, let w_u be the expected social welfare when u wins. According to the construction of the weighted bipartite graph in Section 5.2, we have $w_u = \nu - b_u$. Second, let $\sigma \in [k]^n$ represent the permulation of smartphones sorted by the expected welfare in the descending order. Furthermore, for any smartphone u, $\sigma(u) = t$ means u is the t-th position of σ. P_t is defined as the set of the cases where u is matched in σ and $\sigma(u) = t$. Conversely, Q_t is the opposite set of P_t. Let O_t denote the set of cases where u cannot be matched at postion t but matched at $t-1$. Furthermore, the marginal loss β_t at position t is defined as:

$$\beta_t = \frac{\sum_{(\sigma,t,u)\in O_t} w_u}{k^n}, \tag{15}$$

indicating the implicit loss of social welfare when u at postion t belongs to the set O_t. For any smartphone u, let x_t denote the expected social welfare at postion t under the random permutation σ. Thus, x_t is defined as follows:

$$x_t = \frac{\sum_{(\sigma,t,u)\in P_t} w_u}{k^n}, \tag{16}$$

Meanwhile, the optimal welfare at any position t is defined as $B = \frac{\omega_{opt}}{k}$, since any smartphone u is matched with the probability of $\frac{1}{k}$. Thus, the expected social welfare x_t at position t also has the following equation:

$$x_t = B - \sum_{s\le t} \beta_s. \tag{17}$$

Furthermore, we have the total loss $\hat{\omega} = \sum_t B - x_t = \sum_t (k-t+1)\beta_t$. The detailed proof is shown in the work [38]. Thus, the expected social welfare of *RWBD* is $\omega_{RWBD} = \sum_t x_t$. Therefore, we should prove that $\sum_t x_t \geq (1-\frac{1}{e})\omega_{opt}$.

For the page limit, we omit some details. According to the lemma 3.1. and observation 3 of work [38], for any smartphone u at position t under the permutation σ, its randomized cost $b_u\Phi(t)$ is no less than the average value of randomized costs over rematched smartphones. Therefore, based on the known lemma, the deduction is given as follows:

$$\sum_t \Phi(t)\frac{\sum_{(\sigma,t,u)\in O_t} w_u}{k^n} \le \frac{1}{k}\sum_t \Phi(t)\frac{\sum_{(\sigma,t,u)\in P_t} w_u}{k^n} \tag{18}$$

$$\sum_t \Phi(t)\beta_t \le \frac{1}{k}\sum_t \Phi(t)x_t \tag{19}$$

$$= \frac{1}{k}\sum_t \Phi(t)(B - \sum_{s\le t}\beta_s) \tag{20}$$

The inEq. (18) is true because of $w_u = \nu - b_u$. According to Eqs. 15 and (16), the inEq. (19) holds. Based on the derivation (17), Eq. (20) holds. Furthermore, we reorder the Eq. (20) to reach the following conclusion:

$$\sum_t \beta_t(\Phi(t) + \frac{\sum_{s\ge t}\Phi(s)}{k}) \le \frac{B}{k}\sum_t \Phi(t), \tag{21}$$

Recall that $\Phi(t) = 1 - (1-\frac{1}{k})^{-(k-x+1)}$. Finally, for our online algorithm *RWBD*, the total loss $\hat{\omega}$ has the following derivation:

$$\hat{\omega} = \sum_t B - x_t = \sum_t (k-t+1)\beta_t \tag{22}$$

$$\le k\sum_t \beta_t(\Phi(t) + \frac{\sum_{s\ge t}\Phi(s)}{k}) \tag{23}$$

$$\le B\sum_t \Phi(t) \tag{24}$$

$$= \frac{kB}{e} \tag{25}$$

$$= \frac{w_{opt}}{e} \tag{26}$$

where Eq. (23) holds since we observe $\Phi(t) + \frac{\sum_{s\ge t}\Phi(s)}{k} \ge \frac{k-t+1}{k}$. And Eq. (24) holds according to Eq. (21). Eq. (25) holds because $\sum_t \Phi(t) = \frac{k}{e}$ when $k \to \infty$. Recall that $B = \frac{\omega_{opt}}{k}$, Eq. (26) holds.

Therefore, the total social welfare w_{RWBD} is given as:

$$w_{RWBD} = w_{opt} - \hat{\omega} \ge (1-\frac{1}{e})w_{opt}. \tag{27}$$

□

7. Evaluation

7.1. Methodology and simulation settings

7.1.1. Methodology

We evaluate the performance of two proposed online algorithms, *i.e.*, winning bids decision *WBD* and *RWBD* algorithm against the following two benchmarks. The first benchmark is the optimal solution with the maximum weighted matching algorithm *OSMA* demonstrated in Section 4, which has full knowledge about the arrival of smartphones and sensing tasks. The second benchmark is random assignment algorithm *RAS*, which allocates the incoming tasks to current qualified smartphones at random and is regarded as a naive strategy.

7.1.2. Settings

Extensive simulations are conducted based on the following metrics: *social welfare, overpayment ratio, running time and competitive 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:

Table 2
Summary of default settings.

Parameter name	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

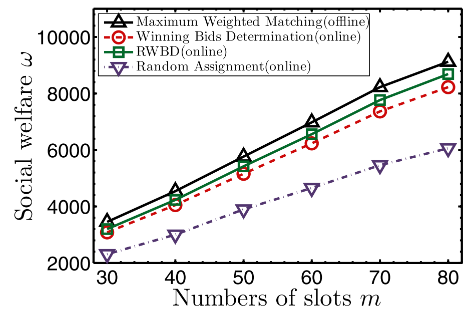


Fig. 6. Social welfare ω vs. Number of slots m.

Definition 12 (Overpayment Ratio)**.** The overpayment ratio characterizes the relative overpayment. It is computed as

$$\rho = \frac{\sum_{B_i\in\{\pi(\tau_{j,k})|\tau_{j,k}\in\Gamma\}}(p_i - c_i)}{\sum_{B_i\in\{\pi(\tau_{j,k})|\tau_{j,k}\in\Gamma\}} c_i}. \tag{28}$$

We simulate the arrivals of dynamic smartphones and sensing requests with Poisson distributions. Meanwhile, the real costs of bids are generated according to the normal distribution. In a simulation, the mean μ is varied from 10 to 60. We set such a standard deviation σ that 99.73% samples fall within $[\mu-\sigma, \mu+\sigma]$, *i.e.*, $\sigma = \frac{50-\mu}{3}$. Suppose that each sensing task has a fixed value $\nu = 55$. Furthermore, the length of active time of each smartphone is uniformly selected and its average is set to the ten percents of the default number of total time slots in a round. The length of the active time characterizes the average time that a smartphone is willing to wait for in a round. The default setting is listed in Table 2. Each experiment is conducted under four comparable methods and each data point is the average value of 20 iterates which run in the same setting.

7.2. Evaluation results

7.2.1. Evaluation of social welfare

In Fig. 6, we can observe that the social welfare increases when the number of total slots increases from 30 to 80. It is easy to understand since a higher social welfare can be obtained when more sensing tasks are processed in the increased length of time. The two online algorithms, *i.e.*, both winning bids decision and randomized-greedy algorithm have comparable performance to the offline optimal algorithm *OSMA*. Furthermore, *RWBD* obtains slightly larger social welfare compared to the naive greedy method *WBD*. As a baseline, the random assignment algorithm *RAS* has the lowest social welfare since arbitrary allocation may lead to higher costs. Meanwhile, the gap between *WBD* and *OSMA* is slightly expanded as the number of slots increases.

From Fig. 7, we can find 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. *RWBD* offers a larger social welfare than *WBD* but less than *OSMA* due to the lack of future information. However, the social welfare of *RAS* never promotes since the random assignment never works even with more smartphones.

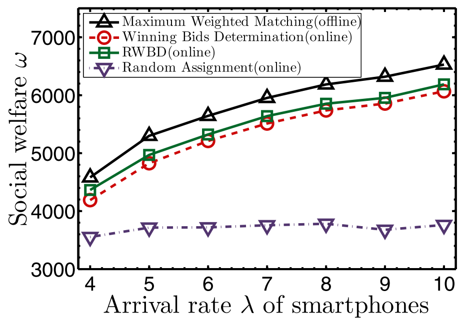


Fig. 7. Social welfare ω vs. Arrival rate λ of smartphones.

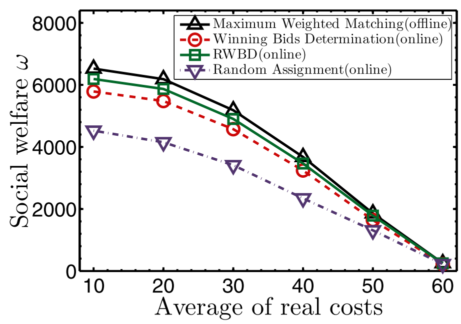


Fig. 8. Social welfare ω vs. Average of real costs.

In Fig. 8, we can see that the social welfare decreases when the average of real costs increases from 10 to 60. This is because when the average of real costs becomes larger, the system needs to pay more to get the tasks processed. Furthermore, the social welfare under four methods decreases rapidly to zero when the average increases to the largest value 60. Considering that the fixed value of each task is less than 60, almost no smartphones can be selected as the winners when the average is up to 60.

7.2.2. Evaluation of overpayment ratio

Fig. 10shows that overpayment ratio stays slow with the increasing number of time slots. With a longer time, the modest and stable overpayment ratio reflects that the mobile crowd sensing 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. 11shows that the overpayment ratio decreases with the increasing number of smartphones under the proposed online and offline mechanisms. Since more smartphones arrive in each slot, more cheap smartphones can be hired as winners. Meanwhile, for each winning smartphone, we can find the corresponding critical player with the low cost more easily, leading to reduced overpayment ratio.

Fig. 12depicts the change of overpayment ratio when the average of real costs of smartphones increases from 10 to 60. It can be observed that the overpayment ratio decreases under two mechanisms and the offline mechanism is larger than that of the online mechanism. Because the lower average cost produces higher standard deviation σ according to $\sigma = \frac{50-\mu}{3}$, the real costs of bids with the high deviation are generated, which leads to the gap between each winning smartphone and its critical player's claimed price. Therefore, it induces the higher overpayment ratio when the average cost is low. Furthermore, the overpayment ratio decreases rapidly to zero when the average is up to 60. Since almost no smartphones win, the ratio with the near-zero value is generated.

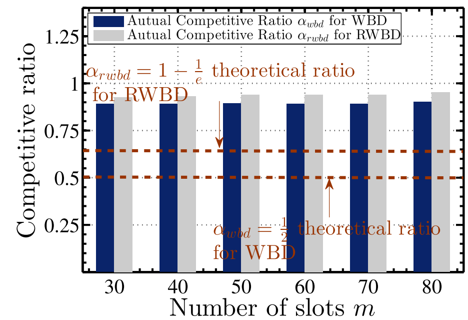


Fig. 9. Evaluation of competitive analysis.

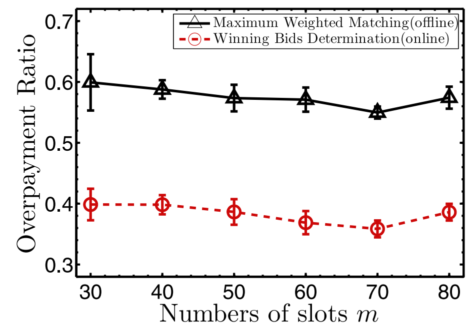


Fig. 10. Overpayment ratio ρ vs. Number of slots m.

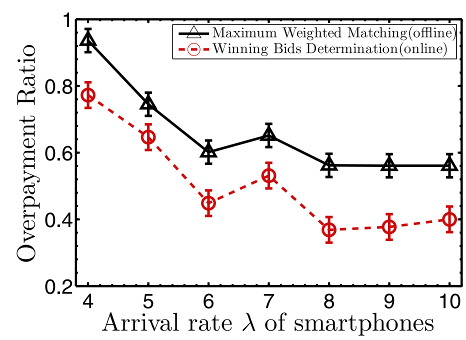


Fig. 11. Overpayment ratio ρ vs. Arrival rate λ of smartphones m.

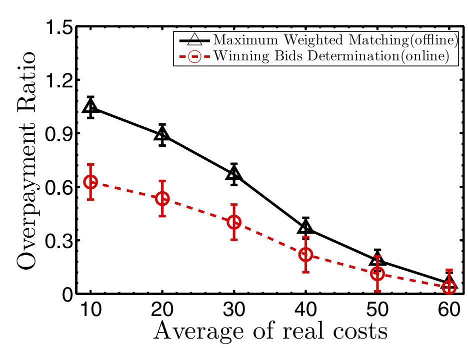


Fig. 12. Overpayment ratio ρ vs. Average of real costs.

7.2.3. Evaluation of competitive ratio

We report the competitive ratio in Fig. 9. The actual experiment values are demonstrated under two online assignment algorithms with the increasing number of time slots. Meanwhile, each theoretical competitive ratio of *RWBD* and *WBD* is plotted with the red dotted line. It can be observed that the actual competitive ratio of two online algorithms is consistently higher than 0.75 and the ratio of *RWBD* is slightly larger than that of *WBD*. However, both fail

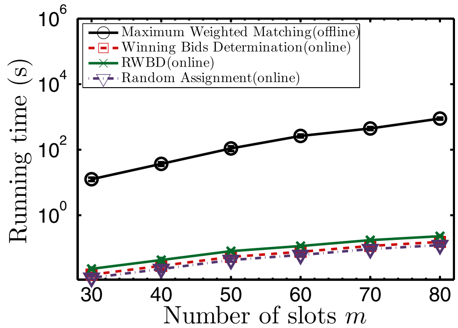


Fig. 13. Evaluation of computational efficiency (y-axis in log scale).

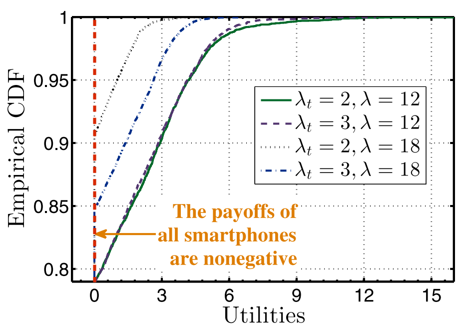


Fig. 14. Empirical CDF of utilities for all smartphones in the offline case.

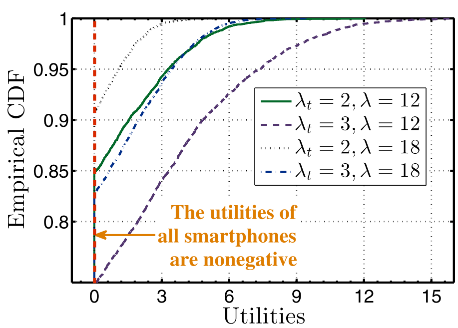


Fig. 15. Empirical CDF of utilities for all smartphones in the online case.

to approach one because two online assignment algorithms have no knowledge about future arrivals of tasks and smartphones. The competitive ratio decreases slightly with a longer time. This is because it is more difficult for the online assignment algorithms to make near-optimal task allocations in the long run.

7.2.4. Evaluation of computational efficiency

Fig. 13plots the computational efficiency of four methods. It is clear that *OSMA* takes much more time than other three online assignment algorithms. Specifically, *RWBD* consumes slightly more time than that of *WBD*. For example, when the number of slots $m = 80$, *WBD* terminates within less than 0.1 s while *OSMA* takes more than 10 min.

7.2.5. Evaluation of individual rationality

We further verify that both the proposed offline and online algorithm have the property of individual rationality. From the Figs. 14 and 15, we can observe that no smartphones have the negative utilities. Specifically, we can find that the utilities of nearly 80% and 75% of smartphones are equal to zero, indicating that only a few smartphones with slightly low costs can win. Moreover, we can see that more smartphones are assigned sensing tasks in the offline case, compared to the online case, which implies the fact

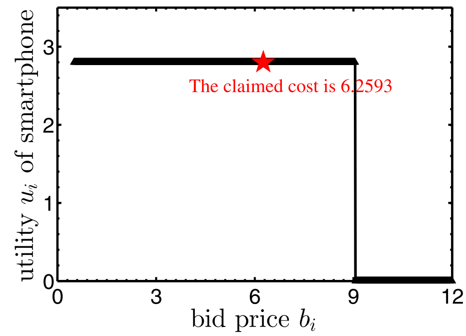


Fig. 16. Online truthfulness for the smartphone s_1 who is assigned a sensing task.

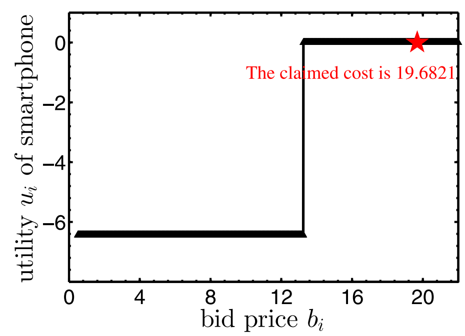


Fig. 17. Online truthfulness of the smartphone s_{120} who initially loses.

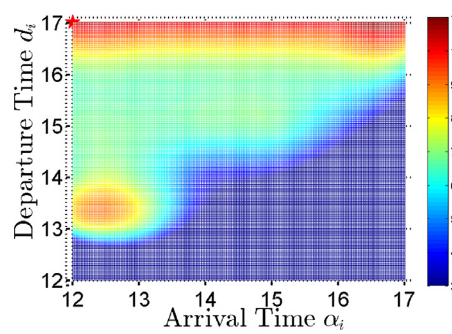


Fig. 18. Cost truthfulness for the smartphone s_{59}.

that *OSMA* offers a larger social welfare than *WBD* under the same setting. Furthermore, Fig. 15 shows that there are more winning smartphones when the arrival rate λ_t of sensing tasks increases to 3 from 2, and that of smartphones λ remains the same.

7.2.6. Evaluation of truthfulness

To prove the truthfulness of both the offline and online mechanisms, we pick a few smartphones arbitrarily, and record their utilities under the varying bid prices or active time.

First, we show the truthfulness of the online case in Figs. 16 and 17. We arbitrarily pick a smartphone who has the real cost $c_1 = 6.2593$ and is assigned a sensing task τ_2. Next, we change its bid on the sensing cost and fix other bids, while recording the change of its utility. In Fig. 16, we can observe that its utility on the sensing cost never improves its utility. Thus, we verify that the smartphone 1 has no incentive to deviate from bidding its real cost. In Fig. 17, we pick the second smartphone who has the real cost $c_{120} = 19.6821$ and fails to be assigned any sensing task. Fig. 17 shows that it would get the negative utility when it claims a lower cost less than 13.2463. Therefore, its utility is maximized only when it reports its real cost.

Similarly, we verify the truthfulness of the offline case in Figs. 18 and 19. We select another smartphone whose real bid is

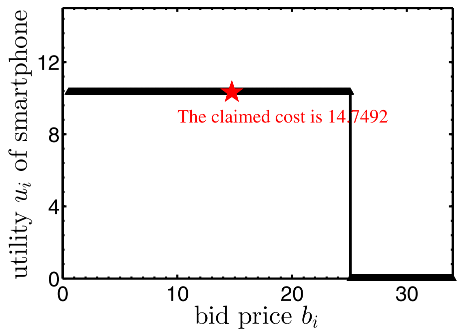


Fig. 19. Time truthfulness for the smartphone s_{59}.

$c_{59} = 14.7492$, $a_{59} = 12$ and $d_{59} = 17$. In Fig. 18, we fix its bid on the sensing cost as 14.7492, and vary its bid on the arrival time and departure time from 12 to 17. As a result, we can find that its utility is maximized only when it reports its real active time. The misreporting of the arrival time and departure time never improves its utility. For Fig. 19, its bid on the active time is fixed as [12,17], and the bid on the sensing cost is increased with the step of 0.01. Consequently, we observe that only reporting the real cost maximizes its utility.

8. Conclusion and future work

In this paper we have studied the crucial problem of incentive mechanism design for mobile crowd sensing systems with dynamic smartphones. Although a wide variety of incentive mechanisms have been investigated for mobile crowd sensing, most of them have impractically assumed that the smartphones are static and the sensing requests are given. This paper has presented two truthful auction mechanisms, *OT-OFMCS* and *NOT-ONMCS*. *First*, as a benchmark of the online case, we have designed the *OT-OFMCS* mechanism which features an offline optimal task allocation algorithm and a VCG-based payment scheme. Moreover, the optimal algorithm is in polynomial time complexity. *Second*, we have proposed a suboptimal *NOT-ONMCS* mechanism which features an online allocation algorithm and a novel payment scheme. Especially, we have investigated a modified online approximation algorithm *RWBD*, where the theoretical competitive ratio is increased to $(1 - \frac{1}{e})$ from $\frac{1}{2}$. Both analytical and simulation results have demonstrated both *OT-OFMCS* and *NOT-ONMCS* mechanisms are truthful, also achieving individual rationality and computational efficiency.

Meanwhile, we intend to extend current mechanism design from the following two aspects. First, the proposed auction mechanisms simply model the private information, such as the cost and active time. Another important metric, *i.e.*,the quality of service of each smartphone, fails to be taken into consideration. Generally, the smartphone with a higher quality of service is inclined to provide more accurate sensed data, leading to the increase of the expected value. The possible effect on the social welfare should be further studied in mobile crowd sensing with dynamic smartphones. Second, our current work only considers a single round. Each smartphone probably alters its strategy in several continuous rounds for a higher overall utility. Therefore, we will extend the current work to investigate the truthful mechanism design in a repeated auction.

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