Profit Maximization in Mobile Crowdsourcing: A Truthful Auction Mechanism

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***Abstract*—In mobile crowdsourcing systems, smartphones can collectively monitor the surrounding environment and share data with the platform of the system. The platform manages the system and encourages smartphone users to contribute to the crowdsourcing system. To enable such sensing system, incentive mechanisms are necessary to motivate users to share the sensing capabilities of their smartphones. In this paper, we propose ProMoT, which is a Profit Maximizing Truthful auction mechanism for mobile crowdsourcing systems. In the proposed auction mechanism, the platform acts as an auctioneer. The smartphone users act as the sellers and submit their bids to the platform. The platform selects a subset of smartphone users and assigns the tasks to them. ProMoT aims to maximize the profit of the platform while providing satisfying rewards to the smartphone users. ProMoT consists of a winner determination algorithm, which is an approximate but close-to-optimal algorithm based on a greedy mechanism, and a payment scheme, which determines the payment to users. Both are computationally efficient with polynomial time complexity. We prove that ProMoT motivates smartphone users to rationally participate and truthfully reveals their bids. Simulation results show that ProMoT increases the profit of the platform in comparison with an existing scheme.**

I. Introduction

Mobile crowdsourcing is a collaborative and distributed sensing system, in which smartphones can collect and share sensory data. Nowadays, smartphones are equipped with a set of embedded sensors, such as camera, microphone, digital compass, gyroscope, and global positioning system. Mobile crowdsourcing system opportunistically takes advantage of smartphone sensing capabilities to relieve the cost of deploying wireless sensor networks.

A mobile crowdsourcing system typically consists of a platform and smartphone users [1]–[3], as illustrated in Fig. 1. The role of the platform is to provide sensing and monitoring services to platform users and encourage smartphone users to contribute to the system. Once receiving the requests from platform users, the platform recruits smartphone users to collect data. The largest sensor network in the world can be formed by using smartphones, which are widely distributed in the environment. Examples of mobile crowdsourcing applications include Earphone [4] for creating noise maps, Sensorly [5] for making cellular/WiFi network coverage maps, and Waze [6] as a community-based navigation application.

The smartphone users may not be interested to share their sensors with the platform unless they receive satisfying rewards which compensate their consumed resources such as battery. Although several mobile crowdsourcing applications have been proposed [4]–[7], most of them assume that smartphones share their sensors voluntarily. Incentive mechanisms encourage the smartphone users to contribute to the mobile crowdsourcing system. Such incentive mechanism must be immune against the strategic behavior of selfish users.

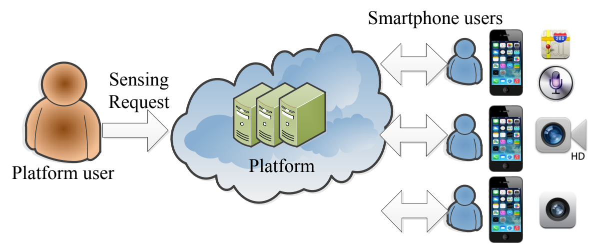

Fig. 1: A mobile crowdsourcing system consists of a platform residing in the cloud and the smartphone users, who are connected with the cloud.

Several auction-based incentive mechanisms have been developed for mobile crowdsourcing applications. Yang *et al.* [8] focus on the profit of the platform and propose a truthful auction mechanism for mobile crowdsourcing systems. In this work, which is called MSensing mechanism, tasks are assigned gradually to smartphone users by a greedy-based heuristic approach. The profit is sacrificed for the sake of computational efficiency in this mechanism. TRAC [9] is a truthful auction mechanism for location-aware sensing in mobile crowdsourcing. In TRAC, the platform assigns its sensing tasks to a set of smartphone users with the goal of minimizing the total payment to smartphone users. TRAC does not consider the profit of the crowdsourcing system. In [10], Koutsopoulos designs an optimal incentive mechanism to maximize the profit of the platform, in which the winner determination problem is NP-hard and cannot allocate the tasks in a computationally efficient manner. The works presented in [11]–[13] propose auction mechanisms for mobile crowdsourcing, when a limited budget is assigned for sensing tasks and the platform performs a subset of tasks according to its budget constraint. Although several auction mechanisms have been proposed for mobile crowdsourcing environment, the existing works suffer from several drawbacks. They either fail to allocate the tasks by a computationally efficient algorithm (e.g., [10]) or sacrifice the profit for the sake of efficiency (e.g., [8] sacrifices the profit to achieve truthfulness and low complexity solution at the same time). In addition, some of them do not consider the profit of the mobile crowdsourcing system (e.g., [9], [11]–[13]).

To address these issues, in this paper, we propose ProMoT, which is a Profit Maximizing Truthful auction mechanism in mobile crowdsourcing systems. ProMoT provides incentives to the users to share the capabilities of their smartphones with the platform. Each task has a value for the platform. The profit is defined as the summation of tasks' value minus the payments provided to the participating smartphone users. The platform publicizes its sensing tasks to the smartphone users. The users submit their bids to perform a subset of tasks. The platform selects a subset of users and provides proper payment to them. The goal of our mechanism is to maximize the profit of the platform, while it motivates the smartphone users to participate in the mechanism and reveal their bid truthfully. ProMoT consists of two components, which are the winner determination algorithm and the payment scheme. We use a similar system model as proposed by [8]. However, our winner determination algorithm and payment scheme are fundamentally different from [8]. The key contributions of our work are as follows:

- We first formulate the winner determination problem and show that it is NP-hard. We then convert the problem into a linear programming (LP) problem and propose a novel greedy mechanism. The mechanism selects those users who are most likely to increase the profit of the platform by using the solution of LP problem.
- We design a payment scheme, which incentivizes the smartphone users and provides satisfying rewards to them.
- Through theoretical analysis, we prove that ProMoT satisfies the main properties of an auction mechanism, namely the computational efficiency, individual rationality, and truthfulness.
- Through extensive simulations, we evaluate the performance of ProMoT in comparison with *MSensing* mechanism proposed in [8]. We further show that ProMoT significantly outperforms MSensing mechanism and improves the profit.

The rest of this paper is organized as follows. In Section II, we introduce the system model and formulate the problem. In Section III, we present the winner determination algorithm and the payment scheme in ProMoT. In Section IV, we evaluate the performance of ProMoT through extensive simulations. Conclusions are given in Section V.

II. System Model and Problem Formulation

Consider a mobile crowdsourcing system consisting of a *platform* and many *smartphone users*. The sensing tasks are submitted to the platform by platform users. The platform periodically advertises the sensing tasks to smartphone users. Let N denote the number of sensing tasks. The set of sensing tasks is denoted by $\mathcal{T} = \{\tau_1, \dots, \tau_N\}$. Each task $\tau_n \in \mathcal{T}$ represents a specific sensing service, which has a value $v_n > 0$ to the platform.

Let $\mathcal{M} = \{1, \dots, M\}$ denote the set of smartphone users who are participating in the mobile crowdsourcing system. Each user $m \in \mathcal{M}$ submits its bid to perform a subset of tasks

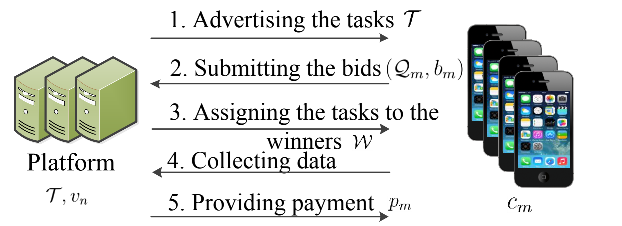

Fig. 2: The platform advertises the tasks to the smartphone users. Once receiving the sensing tasks, each smartphone user selects a subset of tasks and submits its bid to the platform. The platform then determines the winners and assigns the task to them. It also collects data and provides payments.

announced by the platform. Let the pair $(\mathcal{Q}_m, b_m)$ denote the tasks-bid of user m, where $\mathcal{Q}_m \subset \mathcal{T}$ is a subset of tasks selected by user m according to the sensing capabilities of its smartphone and its preference. Note that $\mathcal{Q}_m$ can be one or multiple tasks from the set $\mathcal{T}$, which are selected by user m. In addition, b_m is the price user m wants to receive, which beyond that it will not share its sensing devices. Let c_m denote the cost incurred on user m when performing tasks $\mathcal{Q}_m$. This cost is private and unknown to other users. In addition, let p_m denote the payment that user m receives. Smartphone users are also called *bidders* in this paper. Among these bidders, those who have positive payment (i.e., $p_m > 0$) are called winners. The utility of user m is

$$u_m = \begin{cases} p_m - c_m, & \text{if user } m \text{ wins} \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

Let $\mathcal{W}$ denote the set of winners. The profit of the platform is

$$\sum_{\tau_n \in \cup_{w \in \mathcal{W}} \mathcal{Q}_w} v_n - \sum_{w \in \mathcal{W}} p_w = v(\mathcal{W}) - \sum_{w \in \mathcal{W}} p_w. \quad (2)$$

A. Auction Mechanism

We introduce a reverse auction mechanism to model the interactions between the platform and smartphone users. In this model, the platform is the *buyer* and acts as an *auctioneer*, whereas the smartphone users are *sellers*. The platform selects a subset of bidders and assigns the tasks to them. The platform also provides rewards to the winners to compensate their shared resources and motivates them to participate truthfully in the system. Fig. 2 shows the steps of ProMoT.

ProMoT is composed of two major components denoted by the pair $(\mathcal{A}, \mathcal{P})$: a winner determination algorithm $\mathcal{A}$ and a payment scheme $\mathcal{P}$, which calculates the payment vector $\boldsymbol{p} = (p_1, \dots, p_M)$. ProMoT should achieve the main properties of an auction mechanism, defined as follows.

Definition 1 (Computational Efficiency): An auction mechanism is computationally efficient if both the winner determination algorithm $\mathcal{A}$ and payment scheme $\mathcal{P}$ terminate in polynomial time.

Definition 2 (Individual Rationality): The platform provides proper payments to the smartphone users to have non-negative utility. That is, $u_m \geq 0$, for all $m \in \mathcal{M}$.

Definition 3 (Truthfulness): An auction mechanism is truthful if reporting the true cost (i.e., $b_m = c_m$, $m \in \mathcal{M}$) is the dominant strategy of the bidders.

Proposition 1: An auction mechanism is truthful if and only if [14, p. 274]:

- The winner selection algorithm is monotone. In other words, if user m wins the auction by bidding $(\mathcal{Q}_m, b_m)$, it also wins by bidding $(\mathcal{Q}_m, b'_m)$, when $b'_m \leq b_m$.
- The payment scheme is based on the critical payment. The critical payment is the highest bid that the bidder can submit in order to win.

In Section III, we propose ProMoT by introducing the pair $(\mathcal{A}, \mathcal{P})$, which satisfies all mentioned properties.

B. Problem Formulation

In order to formulate the winner determination problem, we define binary variables $x_n, \forall \tau_n \in \mathcal{T}$ and $y_m, \forall m \in \mathcal{M}$. Let x_n indicate whether task τ_n is assigned to smartphone users. The binary variable x_n is equal to 1 if this task is performed by some smartphones and is equal to zero otherwise. In addition, we set $y_m = 1$ if user m wins the competition to perform a subset of tasks. We also define the vectors $\boldsymbol{x} = (x_n)_{\tau_n \in \mathcal{T}}$ and $\boldsymbol{y} = (y_m)_{m \in \mathcal{M}}$. The winner determination problem aims to maximize the social welfare, which is defined as the profit of the platform plus the utility of all bidders [15]. Assuming that all users reveal their cost truthfully (i.e., $b_m = c_m, \forall m \in \mathcal{M}$), the winner determination problem can be formulated as the following integer linear programming (ILP) problem.

$$\text{WD-ILP: } \underset{\boldsymbol{x},\boldsymbol{y}}{\text{maximize}} \sum_{\tau_n \in \mathcal{T}} v_n x_n - \sum_{m \in \mathcal{M}} b_m y_m \tag{3a}$$

$$\text{subject to } x_n \leq \sum_{m:\, \tau_n \in \mathcal{Q}_m} y_m, \;\; \forall \tau_n \in \mathcal{T} \tag{3b}$$

$$x_n, y_m \in \{0,1\}, \qquad \forall m \in \mathcal{M}, \tau_n \in \mathcal{T}, \tag{3c}$$

where the first constraint forces x_n to be zero if task τ_n is not assigned to any smartphone users. A task will be declined by the platform if it neither belongs to the tasks-bid of any smartphone users nor provides profit for the platform. The following theorem shows that it is not possible to find the optimal solution efficiently.

Theorem 1: The winner determination problem formulated in problem (3) is NP-hard.

Proof: We first show that problem (3) can be reduced to the knapsack problem. Therefore, if a polynomial algorithm can obtain the optimal solution of problem (3), then it can obtain the optimal solution of the knapsack problem as well. This is in contrast to NP-hardness of the knapsack problem [16, Ch. 8]. Given a set $S = \{s_1, \ldots, s_K\}$ of objects with specified profit a_k and weight w_k, as well as knapsack capacities B_i for different subsets $S_i \subset S$, $i \in \mathcal{I}$, the knapsack problem is

$$\begin{aligned} &\underset{\boldsymbol{z}}{\text{maximize}} \; \sum_{k=1}^{K} a_k z_k \\ &\text{subject to } \sum_{s \in S_i} w_s z_s \leq B_i, \;\; \forall i \in \mathcal{I} \\ &\qquad\qquad z_k \in \{0,1\}, \qquad k = 1, \ldots, K. \end{aligned}$$

We map an instance of WD-ILP problem to the knapsack problem. Assume that $K = M + N$. We introduce binary variable $y'_m, m \in \mathcal{M}$ and replace y_m, $m \in \mathcal{M}$ of WD-ILP problem with $1 - y'_m$. Let $\boldsymbol{z} = (x_1, \ldots, x_N, y'_1, \ldots, y'_M)$, the objective function of WD-ILP problem, which is $\sum_{\tau_n \in \mathcal{T}} v_n x_n + \sum_{m \in \mathcal{M}} b_m y'_m + \sum_{m \in \mathcal{M}} b_m$, reduces to the objective function of the knapsack problem with profit vector $(v_1, \ldots, v_N, b_1, \ldots, b_M)$. In addition, constraint (3b) can be mapped to the knapsack capacity constraint assuming all weights w_k are 1. Therefore, we have constructed a reduction from the winner determination problem to the knapsack problem, which is known to be NP-hard [16, Ch. 8]. Consequently, WD-ILP problem is NP-hard and no polynomial time algorithm can obtain the optimal solution. ■

Theorem 1 shows that the winner determination problem is NP hard. This essentially prevents us to use the Vickrey-Clarke-Groves (VCG) mechanism in our auction mechanism. As a result, to propose a truthful auction mechanism which is computationally efficient, we introduce an approximate solution by adopting a novel greedy approach.

III. ProMoT

In this section, we first present our winner determination algorithm. As mentioned in Proposition 1, to design a truthful auction mechanism, the winner selection algorithm should be monotone. This algorithm is obtained by relaxing the binary variables of WD-ILP problem and introducing a greedy mechanism. We further present the payment scheme of the auction mechanism and prove that ProMoT achieves the main economic properties of an auction mechanism.

A. Winner Determination Algorithm

In order to overcome the computational complexity of the winner determination problem, we first relax the binary variables and formulate the following problem.

$$\text{WD-LP: } \underset{\boldsymbol{x},\boldsymbol{y}}{\text{maximize}} \sum_{\tau_n \in \mathcal{T}} v_n x_n - \sum_{m \in \mathcal{M}} b_m y_m \tag{4a}$$

$$\text{subject to } x_n \leq \sum_{m:\, \tau_n \in \mathcal{Q}_m} y_m, \quad \forall \tau_n \in \mathcal{T} \tag{4b}$$

$$0 \leq x_n, y_m \leq 1, \qquad \forall m \in \mathcal{M}, \tau_n \in \mathcal{T}. \tag{4c}$$

Problem (4) is an LP problem. Its optimal solution, denoted by $\boldsymbol{x}^*$ and $\boldsymbol{y}^*$, can be obtained in polynomial time. We introduce a novel greedy approach to determine the winners. Greedy mechanisms are based on a sorting method. We use the optimal solution of WD-LP problem to sort users and then gradually assign the tasks to them. This sorting implies that

$$y^*_{l_1} \geq y^*_{l_2} \geq \cdots \geq y^*_{l_M},$$

where $l_m \in \mathcal{M}$ and $\mathcal{M}^l = \{l_m \,|\, m = 1, \ldots, M\}$ indicates the index list. The optimal solution of WD-LP problem predicts which users are most likely to increase the profit of the platform. The larger value of y^*_m, the more contribution user m can provide. The winner determination algorithm is illustrated in Algorithm 1, where $\boldsymbol{v} = (v_1, \ldots, v_N)$ is the task valuation vector. Algorithm $\mathcal{A}$ first solves WD-LP problem and sorts the bidders based on the optimal solution of this problem as mentioned in Steps 3 and 4, respectively. It then selects the bidders consequently and checks whether each chosen bidder can increase the profit and make a progress towards finishing all tasks (Step 7). The selected bidder m wins the auction, if

$$\left(v\left(\mathcal{W} \cup \{m\}\right) - \sum_{w \in \mathcal{W} \cup \{m\}} b_w\right) - \left(v(\mathcal{W}) - \sum_{w \in \mathcal{W}} b_w\right) > 0. \quad (5)$$

In this case, user m, which can perform the tasks belonging to set $\mathcal{Q}_m$, will be added to the winner set $\mathcal{W}$ (Step 8).

Algorithm 1: Winner Determination Algorithm $\mathcal{A}$

1: Input: $\mathcal{T}, \boldsymbol{v}, \{(\mathcal{Q}_m, b_m)\}_{m \in \mathcal{M}}$
2: Initialize: $\mathcal{W} \leftarrow \emptyset$
3: Solve WD-LP problem (4), obtain optimal solutions $\boldsymbol{x}^*$ and $\boldsymbol{y}^*$
4: Sort y_m^* in the non increasing order, form the index list $\mathcal{M}^l$
5: **for** $m = 1$ to M
6: select user $l_m \in \mathcal{M}^l$
7: **if** $v\left(\mathcal{W} \cup \{l_m\}\right) - v(\mathcal{W}) - b_{l_m} > 0$
8: $\mathcal{W} \leftarrow \mathcal{W} \cup \{l_m\}$
9: **end if**
10: **end for**
11: Output: Winning users set $\mathcal{W}$

B. Payment Scheme

The payment scheme aims to ensure truthful bidding of smartphone users. As mentioned in Section II, the critical payment motivates the bidders to reveal their bid truthfully. We use the concept of critical payment to propose our payment scheme, denoted by $\mathcal{P}$. Each bidder is paid an amount of rewards which is the highest bid that the bidder can submit to win the auction. Let $\mathcal{M}_{-j}$ denote the set of smartphone users excluding user j. We execute the winner determination algorithm $\mathcal{A}$ with $\mathcal{M}_{-j}$ as input to find the winner set $\mathcal{W}_{-j}$. The critical value of bidder j is the highest value of b_j such that it can still win the auction and contribute to the profit of the platform. Therefore, the critical payment p_j is the maximum value of b_j such that the following inequality holds.

$$v\left(\mathcal{W}\right) - \sum_{i \in \mathcal{W} \setminus \{j\}} b_i - b_j \geq v\left(\mathcal{W}_{-j}\right) - \sum_{i \in \mathcal{W}_{-j}} b_i. \quad (6)$$

The payment scheme is shown in Algorithm 2.

C. Economic Properties

Through the following theorems, we prove that ProMoT achieves the main required properties of an auction mechanism, which are the computational efficiency, individual rationality, and truthfulness.

Theorem 2: (**Computational Efficiency**) Both winner determination algorithm $\mathcal{A}$ and payment scheme $\mathcal{P}$ terminate in polynomial time.

Proof: According to Algorithm 1, the winners are determined based on sorting the optimal solution of an LP problem. The optimal solution of LP problem can be obtained in at most $O((N+M)^2 N)$ steps using the interior-point method [17, Ch 1.2]. Therefore, the total complexity of algorithm $\mathcal{A}$ is $O((N+M)^2 N)$, which is polynomial in N and M. The payment scheme is obtained by running the algorithm $\mathcal{A}$ for each user. Consequently, the computational complexity of $\mathcal{P}$ is $O((N+M)^2 NM)$. ■

Algorithm 2: Payment Scheme $\mathcal{P}$

1: Input: $\mathcal{T}, \boldsymbol{v}, \{(\mathcal{Q}_m, b_m)\}_{m \in \mathcal{M}}$
2: Initialize $p_m \leftarrow 0, \quad \forall m \in \mathcal{M}$
3: Execute algorithm $\mathcal{A}$ with $(\mathcal{T}, \boldsymbol{v}, \{(\mathcal{Q}_m, b_m)\}_{m \in \mathcal{M}})$ as input, obtain $\mathcal{W}$
4: **for each** $j \in \mathcal{W}$
5: Execute algorithm $\mathcal{A}$ with $\left(\mathcal{T}, \boldsymbol{v}, \{(\mathcal{Q}_m, b_m)\}_{m \in \mathcal{M}_{-j}}\right)$ as input, obtain $\mathcal{W}_{-j}$
6: $p_j \leftarrow \left(v\left(\mathcal{W}\right) - \sum_{i \in \mathcal{W} \setminus \{j\}} b_i\right) - \left(v\left(\mathcal{W}_{-j}\right) - \sum_{i \in \mathcal{W}_{-j}} b_i\right)$
7: **end for**
8: Output: Payment vector $\boldsymbol{p} = (p_1, \ldots, p_M)$

Theorem 3: (**Individual rationality**) ProMoT is individually rational.

Proof: For each smartphone user j, p_j is the highest value of b_j such that inequality (6) still holds. So,

$$p_j - b_j = v\left(\mathcal{W}\right) - \sum_{i \in \mathcal{W}} b_i - \left(v\left(\mathcal{W}_{-j}\right) - \sum_{i \in \mathcal{W}_{-j}} b_i\right).$$

In the above equality, the right hand side is the social welfare when the set $\mathcal{W} \subseteq \mathcal{M}$ of users are selected as winners minus the social welfare obtained from the set $\mathcal{W}_{-j} \subseteq \mathcal{M}_{-j}$. Note that $\mathcal{M}_{-j} \subset \mathcal{M}$. According to Step 7 of Algorithm 1, if user j cannot increase the profit, then it will lose the auction. Therefore, this term is strictly positive if $j \in \mathcal{W}$, and we have $p_j - b_j > 0$. ■

To prove the truthfulness of ProMoT, we first need to show that the winner determination algorithm is monotone.

Lemma 1: Algorithm $\mathcal{A}$ is monotone.

Proof: Let $\boldsymbol{b}_{-j} = (b_1, \ldots, b_{j-1}, b_{j+1}, \ldots, b_M)$ denote the vector of bids excluding b_j, and $\boldsymbol{b} = (\boldsymbol{b}_{-j}, b_j)$ is the bid vector. We show that for all vectors $\boldsymbol{b}_{-j}$, y_j^* is a non increasing function of b_j. Let $(\boldsymbol{x}^*, \boldsymbol{y}^*)$ and $(\boldsymbol{x}^{'*}, \boldsymbol{y}^{'*})$ denote the optimal solutions of WD-LP problem for $\boldsymbol{b} = (\boldsymbol{b}_{-j}, b_j)$ and $\boldsymbol{b}' = (\boldsymbol{b}_{-j}, b_j')$, respectively, where $b_j' \leq b_j$. We denote these problems as $LP(\boldsymbol{b})$ and $LP(\boldsymbol{b}')$, respectively. Since $(\boldsymbol{x}^{'*}, \boldsymbol{y}^{'*})$ is a feasible solution for $LP(\boldsymbol{b})$,

$$\sum_{\tau_n \in \mathcal{T}} v_n x_n^* - \sum_{m \in \mathcal{M}} b_m y_m^* \geq \sum_{\tau_n \in \mathcal{T}} v_n x_n^{'*} - \sum_{m \in \mathcal{M}} b_m y_m^{'*}. \quad (7)$$

Thus

$$\sum_{\tau_n \in \mathcal{T}} v_n x_n^* - \sum_{m \in \mathcal{M}_{-j}} b_m y_m^* - b_j y_j^* \geq \sum_{\tau_n \in \mathcal{T}} v_n x_n^{'*} - \sum_{m \in \mathcal{M}_{-j}} b_m y_m^{'*} - b_j y_j^{'*}. \quad (8)$$

If we define $\phi_1 \triangleq \sum_{\tau_n \in \mathcal{T}} v_n x_n^* - \sum_{m \in \mathcal{M}_{-j}} b_m y_m^*$ and $\phi_2 \triangleq \sum_{\tau_n \in \mathcal{T}} v_n x_n^{'*} - \sum_{m \in \mathcal{M}_{-j}} b_m y_m^{'*}$, we can rewrite (8) as:

$$\phi_1 - \phi_2 \geq b_j(y_j^* - y_j^{'*}). \quad (9)$$

Since $(\boldsymbol{x}^*, \boldsymbol{y}^*)$ is a feasible solution for $LP(\boldsymbol{b}')$,

$$\sum_{\tau_n \in \mathcal{T}} v_n x_n^{'*} - \sum_{m \in \mathcal{M}} b'_m y_m^{'*} \geq \sum_{\tau_n \in \mathcal{T}} v_n x_n^* - \sum_{m \in \mathcal{M}} b'_m y_m^* \quad (10)$$

By substituting $\boldsymbol{b}' = (\boldsymbol{b}_{-j}, b'_j)$, we similarly have

$$\phi_1 - \phi_2 \leq b'_j(y_j^* - y_j^{'*}). \quad (11)$$

From (9) and (11), we obtain

$$b'_j(y_j^* - y_j^{'*}) \geq \phi_1 - \phi_2 \geq b_j(y_j^* - y_j^{'*}). \quad (12)$$

So

$$(b_j - b'_j)(y_j^* - y_j^{'*}) \leq 0. \quad (13)$$

Since $b'_j \leq b_j$, we have $y_j^{'*} \geq y_j^*$. Algorithm $\mathcal{A}$ sorts the users according to $\boldsymbol{y}^*$ in a non increasing order, and each y_m^* is a non increasing function of b_m. Thus, the winner determination algorithm is monotone. ■

Theorem 4: (**Truthfulness**) ProMoT is truthful.

Proof: According to Proposition 1, auction mechanism $(\mathcal{A}, \mathcal{P})$ is truthful if algorithm $\mathcal{A}$ is monotone and $\mathcal{P}$ selects the critical payment. Lemma 1 shows that algorithm $\mathcal{A}$ determines the winners in a monotone manner. In addition, payment scheme $\mathcal{P}$ calculates the critical values and sets them as payment. To prove this fact, we show that if smartphone user m submits a bid higher than p_m, it will lose the auction. In this case, according to (6), the social welfare is less than what is obtained without participating user m. Therefore, the platform declines the bid of user m to maximize the social welfare and we can conclude that p_m is the critical payment. ■

IV. Performance Evaluation

To evaluate the performance of ProMoT, we run both algorithm $\mathcal{A}$ and payment scheme $\mathcal{P}$ for a mobile crowdsourcing system with N tasks and M smartphone users. In order to compare our mechanism with MSensing mechanism [8], we use a similar simulation setup. We assume that tasks and users are randomly distributed in a 1000 m $\times$ 1000 m region. Each user submits a bid to perform a subset of tasks located within a distance of r (sensing coverage radius) from it. The value of each task v_n is uniformly distributed over $[1, 10]$. The cost of user m is $\rho|\mathcal{Q}_m|$, where ρ is uniformly distributed over $[1, 5]$.

We first evaluate the profit of the platform when there are 100 tasks announced to the smartphone users. We set the sensing coverage radius r to 80 m and vary the number of smartphone users M from 1000 to 5000. Fig. 3 shows the profit, when ProMoT is compared with MSensing mechanism. Results show that a higher profit is obtained by using ProMoT. In addition, the profit increases when the number of smartphone users becomes larger. In this case, more smartphone users compete with each other to perform the tasks. The platform selects those users with lower cost resulting in more profit. In Fig. 4, we fix the number of smartphone users to 1000

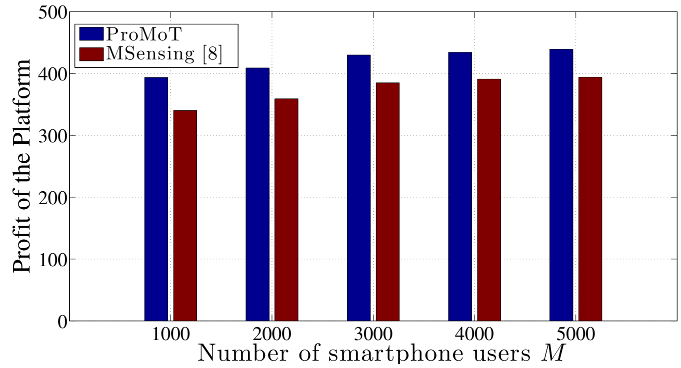

Fig. 3: Profit of the platform for different number of smartphone users competing for $N = 100$ tasks. The higher profit is obtained when the number of smartphone users M becomes larger. ($r = 80$ m)

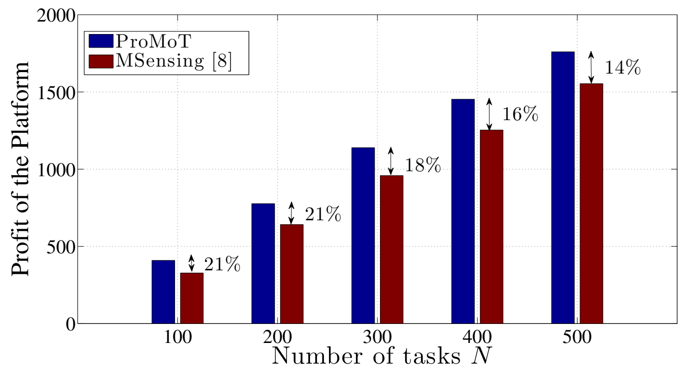

Fig. 4: Profit of the platform for different number of tasks with fixed $M =$ 1000 smartphone users. ($r = 80$ m)

and evaluate the profit for different number of sensing tasks. The profit increases when the platform announces more tasks. ProMoT outperforms MSensing, especially when the platform announces fewer number of tasks. This is obtained due to our novel greedy-based winner determination algorithm.

We also evaluate the profit obtained from ProMoT for different sensing coverage radii r. The number of users bidding to perform a specified task becomes larger, when r increases. As shown in Fig. 5, our mechanism outperforms MSensing especially in the case of large sensing coverage radius. ProMoT improves the obtained profit by up to 25% in comparison with MSensing.

We investigate another important metric of auction mechanisms, which is the bidder's satisfaction. It is defined as the ratio between the number of winners and the total number of bidders and calculated as

$$\frac{|\mathcal{W}|}{M} \times 100\%.$$

Fig. 6 shows the bidders' satisfaction for different number of tasks. The bidders' satisfaction increases gradually with increasing N. According to this figure, although ProMoT selects approximately the same number of smartphones as MSensing does (55 smartphone users v.s. 53, when $N = 300$), they provide a higher profit for the platform. This is obtained by our different winner determination algorithm, which selects users based on the solution of WD-LP problem.

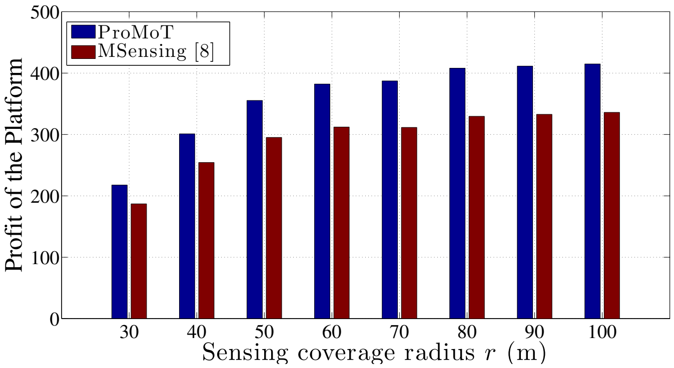

Fig. 5: Profit of the platform for different sensing coverage radii r. ProMoT outperforms MSensing, especially in large sensing coverage radius. ($N = 100, M = 1000$)

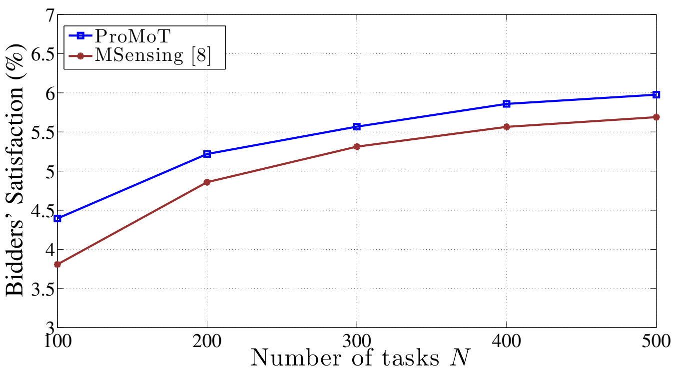

Fig. 6: Bidder's satisfaction for different number of tasks N. ($M = 1000, r = 80$ m)

In order to investigate the trade-off between optimal and computationally efficient approaches, we evaluate the social welfare. We compare the optimal solution of NP-hard problem (3) with our winner determination algorithm $\mathcal{A}$. Fig. 7 shows that algorithm $\mathcal{A}$ results in close-to-optimal solutions for different number of smartphone users and tasks, while the gap is less than 0.3%. This confirms that algorithm $\mathcal{A}$ selects almost the same winners as problem (3) does.

V. Conclusion

In this paper, we proposed ProMoT, a truthful auction mechanism for mobile crowdsourcing systems. ProMoT motivates the smartphone users to contribute to the mobile crowdsourcing system by providing proper rewards to them. The goal of the mechanism is to maximize the profit of the platform of the mobile crowdsourcing system, while motivating smartphone users to participate in the auction mechanism truthfully. ProMoT consists of a winner determination algorithm and a payment scheme. We first proved that determining the winners of the auction mechanism optimally is NP-hard. To overcome the computational complexity of the winner determination algorithm, we then introduced a greedy-based mechanism. We further proposed a payment scheme. Both winner determination algorithm and payment scheme have polynomial time computation complexity. We also proved that ProMoT achieves the individual rationality and truthfulness,

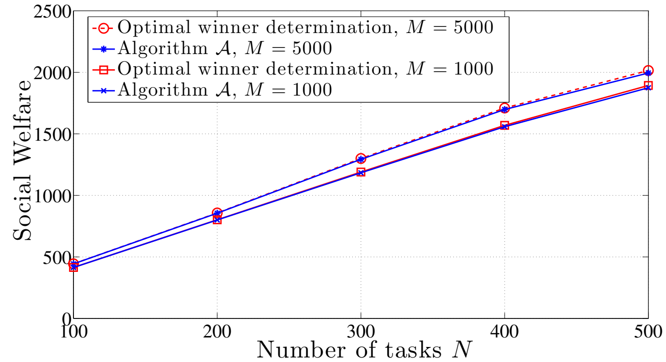

Fig. 7: Comparing the computationaly efficient winner determination algorithm $\mathcal{A}$ with NP-hard optimal winner determination problem. ($r = 80$ m)

as the main economic properties of an auction mechanism. Through extensive simulations, we evaluated the performance of ProMoT. Results show that ProMoT considerably increases the profit of the platform in comparison with MSensing mechanism [8]. For future work, we will consider the case of multiple crowdsourcing systems with multiple platforms and propose a double auction mechanism.

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