Market-Based Incentive Mechanism Design for Crowdsourcing

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对文章背景不是很懂，crowdsourcing？coverage hole?

***Abstract*—Participants coverage is an important role in the crowdsourcing-based applications. However most of the existing incentive mechanisms for the crowdsourcing has focused on how to allocate tasks to the participants to maximize the social welfare, and none of them consider the problem of participant coverage hole created by the uneven distribution of participants. In this paper, we propose a market-based incentive mechanism for crowdsourcing, where the platform motivates the participants to move to the coverage hole and complete the sensing tasks there from a market-based perspective. The market-based incentive mechanism is built on a novel reverse auction framework with reserve price, where the reserve price of a sensing task is the maximum payment for a participant to complete this task. The platform systematically reduces the reserve price of tasks in popular areas and participants are stimulated to complete the tasks in unpopular areas. Each round of reverse auction consists of a winning participant selection problem and a payment determination problem. Since the task allocation problem is NP-hard, we propose a greedy algorithm to solve it. We also design a critical payment policy to guarantee that participants declare their cost truthfully. Evaluation results show that the proposed mechanism outperforms existing solutions under various conditions.**

***Index Terms*—Crowdsourcing, incentive mechanism design, auction theory, mobility control.**

I. Introduction

The proliferation of smartphones embedded with multiple sensors has enabled crowdsourcing as a promising approach to collect and analyze distributed sensed data [1]. A typical crowdsourcing system consists of a platform residing in the cloud and many smartphone users (participants). Participants act as sensing service providers, and the platform recruits them to provide sensing data. By leveraging crowdsourcing, many applications are designed to achieve a wide variety of services [2], such as health care, environmental monitoring, noise pollution monitoring, 3D modeling of urban buildings [3], and radio frequency fingerprinting indoors [4].

The success of these crowdsourcing applications critically depends on the participation of a large number of smartphone users. However, users may not be willing to participate, considering the operational cost of sensing tasks, such as battery and computing power. Therefore, incentive mechanisms have attracted considerable attention from both academia and industry.

Some recent research has been devoted to incentive mechanism design for crowdsourcing, using pricing or auction [5, 6]. Most research focuses on how to allocate sensing tasks to participants so as to maximize social welfare, and none of them considers the coverage holes [7, 8] created by the uneven distribution of participants. In practice, most participants are clustered in some popular areas [9], and many of them may lose in the auction of sensing task. On the other hand, many tasks in the unpopular areas cannot be completed due to the lack of participants.

For many crowdsourcing services, their effectiveness depends on the coverage of the participants. For example, in order to build a noise pollution map of a city [10], the platform requires the noise measurements at specific times and places across the city [11]. However, due to the regularity of participants' mobility [12] [13] and uneven distribution of participants [9], some areas always suffer from poor coverage. Therefore, how to motivate participants to move to unpopular areas to complete the sensing tasks becomes an important problem for crowdsourcing.

In our previous work [14], we have proposed an movement-based incentive mechanism for crowdsourcing, where the platform leverages the movement-based incentive to motivate the participants to complete the sensing tasks in unpopular areas. Considering that most participants have destinations, and some of them may not follow the command from the platform. In this paper, we proposed a market-based incentive mechanism where the participants choose their destinations by themselves under the soft control of the platform.

The market-based incentive mechanism is built on a novel reverse auction framework with reserve price, where the reserve price of a sensing task is the maximum payment for a participant to complete the task. In the market-based incentive mechanism, the platform systematically reduces the reserve price of the tasks with more participants round by round and thus stimulates participants to bid for the tasks with less participants. Each round of the reverse auction consists of a winning participant selection problem and a payment determination problem. Since the winning participant selection problem is NP-hard, we propose a greedy algorithm to solve it. We also design a critical payment policy to guarantee that

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participants declare their cost truthfully. Evaluation results show that the market-based incentive mechanism outperforms existing solutions under various conditions.

The remainder of the paper is organized as follows. We present the system model and problem formulation in Section II. In Section III, we propose the market-based incentive mechanism. We present the evaluation results in Section IV. Section V concludes the paper.

II. System Model and Problem Formulation

A. System Model

We consider a crowdsourcing system consisting of a platform residing in the cloud and many participants, as shown in Fig. 1. The platform accepts sensing requests from platform users and devises multiple sensing tasks based on the sensing requests. The platform publishes these sensing tasks to participants periodically. There are m sensing tasks. Let $T = \{t_1, t_2, \cdots, t_m\}$ denote the set of sensing tasks. A sensing task t_j specifies the desired sensing service, the corresponding location, and its reserve price. Let (x^t_j, y^t_j) denote the location of sensing task t_j, where the sensed data should be collected. Let ν_j denote the value of sensing task t_j to the platform and let γ_j denote the reserve price of task t_j, where the reserve price is used by the platform to withhold the sensing task if the bid is too high (higher than the reserve price). Initially, we assume $\gamma_j = \nu_j$ for each sensing task t_j. Similar to [15–17], we assume that each sensing task t_j has to be completed by k different participants to increase the sensing accuracy.

There are n participants in the crowdsourcing system and the set of participants is denoted by $N = \{1, 2, \cdots, n\}$. Each participant i is aware of its own location (x^b_i, y^b_i). Let ψ_i denote the capacity of participant i which is the maximum number of sensing tasks it can complete. Let $\mu'_{i,j}$ denote the cost for participant i to complete sensing task t_j within its sensing range. If i wants to complete t_j beyond its sensing range, i must move some distance so that t_j is within its sensing range. Generally, there will be some extra cost (eg., time, energy, dissatisfaction, etc.) for a participant to move from one place to another. Similar to [18], we use $f(d) = \exp^{\eta \cdot d} - 1$ to denote the cost for a participant to move distance d. If a sensing task is too far away from a participant, this participant may not want to move there. Let δ denote the upper bound of the moving distance. Then, the cost for a participant i to complete a task t_j is $\mu_{i,j} = \mu'_{i,j} + f(d_{i,j})$, where $f(d_{i,j}) = 0$ if t_j is within i's sensing range, $f(d_{i,j}) = \exp^{\eta \cdot d_{i,j}} - 1$ if t_j is beyond i's sensing range and the distance between task t_j and participant i is $d_{i,j}$. The notions are listed in Table I.

We use the reverse auction framework to model the interactions between the platform and the participants. The participants act as sellers to send bids. The platform then acts as the buyer to buy the sensed data from them. Fig. 1 illustrates the framework. First, the platform publishes the information about the set of sensing tasks T to participants. The information of each sensing task contains its location and the reserve price. Then, each participant i announces a bid b_i to apply for sensing tasks. The bid from a participant i is denoted as $b_i = \{s_i, \mu_{i,s_i}\}$, where s_i is the set of sensing tasks that participant i decides to bid for, and μ_{i,s_i} is the cost for completing a sensing task in s_i.[1] Upon receiving the set B of bids from the n participants, $B = \{b_1, b_2, \cdots, b_n\}$, the platform selects the winning participants and determines payment to each winning participant. Let B_0 denote the set of winning participants' bids, $b_i \in B_0$ if i wins and $b_i \notin B_0$ if i loses. Let P denote the payment determination results, $P = \{p_1, p_2, \cdots, p_n\}$, where $p_i > 0$ if i wins and $p_i = 0$ if i loses. Finally, each winning participant completes its sensing tasks and sends the sensing data back to the platform.

TABLE I: Notions about task and participant

Task	Description
x^t_j y^t_j	task t_j's location
ν_j	value of task t_j
γ_j	reserve price of task t_j
Participant	**Description**
x^b_i y^b_i	participant i's location
$\mu_{i,j}$	cost to complete sensing task t_j
ψ_i	capacity of participant i

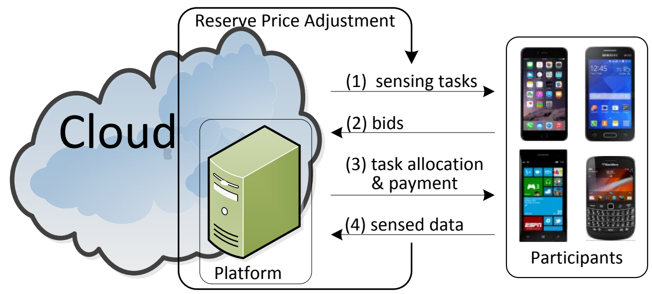


Fig. 1: An illustration of the crowdsourcing system.

Due to the uneven distribution of the participants, some sensing tasks in popular areas are in *supply surplus* (i.e, the number of participants bidding for the sensing task is larger than the number of required participants), and some sensing tasks in unpopular areas are in *demand surplus* (i.e, the number of participants bidding for the sensing task is less than the number of required participants). In order to increase the coverage of the participants, the platform adjusts the reserve price based on the set B of bids and publishes the updated reserve price to the participants in the following auction round.

The platform's payoff, each participant i's payoff, and the social welfare of each auction result are defined as follows:

Definition 1. *The payoff of the platform is the total value of the sensing tasks completed by participants minors the total payment to the winning participants,*

$$u_0 = v(B_0) - \sum_{b_i \in B_0} p_i. \quad (1)$$

$v(B_0)$ is the total value of the sensing tasks completed by the

[1] In practice, the tasks in each participant's sensing range are similar (e.g., taking photos of a building from different angles at the same location), and a participant always bids for the tasks close to a common location (participant's current location or participant's intent destination), thus the cost for a participant i to complete a task in s_i is equal (denoted as μ_{i,s_i}).

winning participants, $v(B_0) = \sum_{t_j \in T} k_j \cdot \nu_j$, where $k_j = k$ if there are more than k winning participants completing sensing task t_j, and k_j is the number of winning participants completing sensing task t_j otherwise. $\sum_{b_i \in B_0} p_i$ is the total payment to the winning participants.

Definition 2. *The payoff of each participant i is*

$$u_i = \begin{cases} p_i - |s_i| \cdot \mu_{i,s_i} & \textit{if } b_i \in B_0 \\ 0 & \textit{if } b_i \notin B_0 \end{cases}, \tag{2}$$

where $|s_i| \cdot \mu_{i,s_i}$ is the cost for completing the set s_i of sensing tasks.

Definition 3. *The social welfare is the difference between the total value of the completed sensing tasks and the sensing cost [5],*

$$w_0 = v(B_0) - \sum_{b_i \in B_0} |s_i| \cdot \mu_{i,s_i}. \tag{3}$$

The social welfare is the aggregate payoffs of the platform and the participants, because the payment in the payoff of the platform and the payment in the payoffs of participants cancel each other from a social perspective.

B. Problem Formulation

The market-based incentive mechanism is built on the reverse auction framework with reserve price. The platform systematically reduces the reserve prices of the sensing tasks in supply surplus to motivate participants to bid for the sensing tasks in demand surplus. Each round of the reverse auction consists of a winning participant selection problem and a critical payment determination problem, which are formulated as follows:

Definition 4. ***Winning Participant Selection Problem.*** *Finding the set (B_0) of winning participants' bids such that*

$$\begin{aligned} \max\ & v(B_0) - \sum_{b_i \in B_0} |s_i| \cdot \mu_{i,s_i} \\ s.t.\quad & k_j \le k, j = 1, \cdots, m, \\ & |s_i| \le \psi_i, i = 1, \cdots, n. \end{aligned} \tag{4}$$

The objective of the winning participant selection problem is to maximize the *social welfare*. The first constraint shows that each sensing task needs at most k different participants to complete. The second constraint indicates that a participant i can complete at most ψ_i different sensing tasks.

Definition 5. ***Critical Payment Determination Problem.*** *For a participant i, let μ_{i,s_i} denote its truthful cost for completing a sensing task in s_i and let $\tilde{\mu}_{i,s_i}$ denote its untruthful cost. $u_i(\mu_{i,s_i})$ and $u_i(\tilde{\mu}_{i,s_i})$ are the payoffs of participant i by declaring the truthful cost μ_{i,s_i} and the untruthful cost $\tilde{\mu}_{i,s_i}$, respectively. The critical payment determination problem is to design a payment determination algorithm which satisfies*

$$u_i(\mu_{i,s_i}) \ge u_i(\tilde{\mu}_{i,s_i}). \tag{5}$$

A payment determination algorithm satisfying the critical payment determination problem can guarantee that participants declare their costs truthfully.

Our objective is to design an incentive mechanism that solves the above two problems.

III. Market-Based Incentive Mechanism

In this section, we propose the market-based incentive mechanism. First, we analyze the reserve price adjustment. Then, we prove that the winning participant selection problem is NP-hard and design a polynomial algorithm for winning participant selection to obtain a near-optimal solution. Finally, we present the critical payment determination algorithm.

A. Reserve Price Adjustment

We assume that the participants are self-interested which means they always want to maximize their own payoff. Thus each participant i bids for the set s_i of sensing tasks to maximize its maximal payoff. The maximal payoff of participant i for bidding a set s_i^* of sensing tasks is as follows:

$$u_i^*(s_i^*) = \sum_{t_j \in s_i^*} (\gamma_j - \mu_{i,s_i^*}). \tag{6}$$

In order to maximize its maximal payoff, the set of sensing tasks in bid b_i is

$$s_i = \arg \max_{|s_i^*| < \psi_i} \sum_{t_j \in s_i^*} (\gamma_j - \mu_{i,s_i^*}). \tag{7}$$

Before presenting the reserve price adjustment, we define the supply for sensing task and demand of sensing task, supply surplus and demand surplus, respectively.

Definition 6. *The supply for sensing task t_j, denoted by h_j, is the number of participants bidding for sensing task t_j. Formally,*

$$h_j = \sum_{b_i \in B} y_{i,j}, \tag{8}$$

where $y_{i,j} = 1$ if participant i bids for sensing task t_j and $y_{i,j} = 0$ otherwise. The demand of a sensing task t_j is defined as the number of participants that task t_j requires to be completed by, i.e., the demand of a sensing task t_j is k.

Definition 7. *Task t_j is in supply surplus if the supply for t_j exceeds the demand of t_j, i.e., $h_j > k$, and task t_j is in demand surplus otherwise.*

After receiving the bids of participants, the platform analyzes the supply for each sensing task. The platform reduces the reserve price of the sensing tasks in supply surplus by a given step ϵ, and announces the new reserve price to all participants in the following auction round as shown in Fig. 1. The purpose of the reserve price adjustment is to motivate participants to bid for the sensing tasks in demand surplus to increase the coverage of the participants. The pseudo-code is shown in Algorithm 1.

B. Winning Participant Selection

In this subsection, we first prove that the winning participant selection problem is NP-hard. Then, we propose a greedy algorithm to solve this problem.

Algorithm 1 : Reserve Price Adjustment

Input: set $T = \{t_1, t_2, \cdots, t_m\}$ of m sensing tasks, set $B = \{b_1, b_2 \cdots, b_n\}$ of n bids.

Output: reserve price γ_j of each task t_j.

for all $t_j \in T$ **do**
  $h_j = \sum_{b_i \in B} y_{i,j}$;
  if $h_j > k$ **then**
    $\gamma_j = \gamma_j - \epsilon$;
  end if
end for

Algorithm 2 : Winning Participant Selection

Input: set $T = \{t_1, t_2, \cdots, t_m\}$ of m sensing tasks, set $B = \{b_1, b_2 \cdots, b_n\}$ of n bids.

Output: set B_0 of winning participants.

$B_0 \leftarrow \emptyset$;
$i = \arg\ \max_{b_i \in B} w_i(B_0)$
while $w_i(B_0) > 0$ **do**
  $B_0 \leftarrow B_0 \cup \{b_i\}$;
  $B \leftarrow B \setminus \{b_i\}$;
  $i = \arg\ \max_{b_i \in B} w_i(B_0)$;
end while

Theorem 1. *The winning participants selection problem is NP-hard.*

Proof: We prove the NP-hardness of the winning participant selection problem by giving a polynomial time reduction from the `SET COVER` problem. First, we present the `SET COVER` problem. Then, we construct corresponding `INSTANCE A` of the winning participant selection problem. Finally, we prove `INSTANCE A` is NP-hard by giving a polynomial time reduction from the `SET COVER` problem.

`SET COVER`: *A set $C = \{c_1, c_2, \cdots, c_n\}$, where c_i is the set of some elements in the universe set $V = \bigcup_{c_i \in C} c_i$. The question is whether a subset $C_0 \subseteq C$ of size s exists such that every element in V belongs to at least one member in C_0.*

In the `SET COVER` problem, each element in the universe set V only needs to be covered by one subset. However, in the winning participant selection problem, each sensing task needs to be completed by k different participants. Thus, it is necessary to make some change to the original optimization problem. We replace each sensing task t_j by k sensing tasks $\{t_{j,1}, t_{j,2}, \cdots, t_{j,k}\}$. If s_i covers sensing task t_j, we define s_i covers one uncovered sensing task in $\{t_{j,1}, t_{j,2}, \cdots, t_{j,k}\}$ (if all of the k sensing tasks have been covered, we define s_i covers a random sensing task in $\{t_{j,1}, t_{j,2}, \cdots, t_{j,k}\}$).

`INSTANCE A`: *A set $S = \{s_1, s_2, \cdots, s_n\}$, where s_i is in the bid b_i of participant i. The universe set of sensing tasks is $U = \bigcup_{s_i \in S} s_i$. We assume that the value of each task is $\nu_j = n$, and the cost for participant i to complete the set s_i of sensing tasks is $|s_i| \cdot \mu_{i,s_i} = 1$. The question is whether there exists a subset $S_0 \subseteq S$ such that $w_0 \geq n \cdot |U| - s$, where w_0 is the social welfare, and s is the size of S_0.*

We prove that there is a solution to the `SET COVER` problem if and only if there is a solution to `INSTANCE A`. We first prove the forward direction. Let C_0 be a solution to the `SET COVER` instance. We can select the corresponding set S_0 as the solution to `INSTANCE A`. Clearly, $w_0 = n \cdot |U| - |S_0| \geq n \cdot |U| - s$. Next we prove the backward direction. Let S_0 be a solution to `INSTANCE A`, $w_0 \geq n \cdot |U| - s$. Since $s \leq n$, the only possibility that we have such a social welfare is when the set S_0 covers all the sensing tasks. Therefore the corresponding set C_0 is a solution to the `SET COVER` problem. Hence, the winning participant selection problem (the optimization problem of INSTANCE A) in Eq. (4) is NP-hard. ■

To achieve the desired property of computational efficiency, we propose a greedy algorithm to solve the winning participant selection problem. The idea is to pick the participant who has the highest marginal social welfare, until the social welfare cannot benefit from the unselected participants. More specifically, the marginal social welfare of participant i is:

$$w_i(B_0) = v(B_0 \cup \{b_i\}) - v(B_0) - |s_i| \cdot \mu_{i,s_i}, \tag{9}$$

where B_0 is the set of selected winning participants' bids, $B_0 = \emptyset$ initially. $v(B_0 \cup \{b_i\}) - v(B_0)$ is the marginal value of participant i after the platform has selected the set B_0 of winning participants. $|s_i| \cdot \mu_{i,s_i}$ is the cost for participant i to complete the set s_i of sensing tasks. In each iteration, B_0 is updated, and deleted from the set B of bids. The pseudo-code is shown in Algorithm 2.

C. Critical Payment Determination Algorithm

The payment determination should guarantee that each participant honestly reports its real cost. We propose a critical payment determination algorithm based on the critical payment in [19]. If participant i wins by declaring a bid $b_i = \{s_i, \mu_{i,s_i}\}$, it is paid some amount of monetary reward. The amount is determined according to a critical bid $b_i^c = \{s_i, \mu_{i,s_i}^c\}$, where μ_{i,s_i}^c is determined as follows. If $\mu_{i,s_i} < \mu_{i,s_i}^c$, participant i wins; if $\mu_{i,s_i} > \mu_{i,s_i}^c$, i loses. Participant i loses when it cannot make any contribution to the social welfare, i.e., $w_i(B_0) \leq 0$.

The critical bid of participant i is related to the bid of the first participant x that makes participant i useless, i.e., when $B_0 = \{b_1, b_2, \cdots, b_{x-1}\}$, $w_i(B_0) > 0$; when $B_0 = \{b_1, b_2, \cdots, b_{x-1}, b_x\}$, $w_i(B_0) \leq 0$. We assume that a participant is replaceable in order to prevent the monopoly. The basic idea of finding the critical bid of participant i is to delete b_i and greedily select other participants until $w_i(B_0) \leq 0$. Suppose the bid of the first participant x which makes participant i useless is $b_x = \{s_x, \mu_{x,s_x}\}$. The critical bid of participant i is $b_i^c = \{s_i, \mu_{x,s_x}\}$, i.e., $\mu_{i,s_i}^c = \mu_{x,s_x}$. Then, the critical payment to participant i is

$$p_i^c = |s_i| \cdot \mu_{i,s_i}^c, \tag{10}$$

The pseudo-code of the algorithm is shown in Algorithm 3.

Theoretical analysis shows that our proposed mechanism satisfies the desired properties of truthfulness, individual rationality, platform profitability, and computational efficiency. And these theoretical analysis is omitted due to space limitation.

Algorithm 3 Critical Payment Determination

Input: set $T = \{t_1, t_2, \cdots, t_m\}$ of m sensing tasks, set $B = \{b_1, b_2 \cdots, b_n\}$ of n bids, set B_0 of winning participants' bids.

Output: critical payment p_i^c.

$B_1 \leftarrow B \setminus \{b_i\}$, $B_2 \leftarrow \emptyset$;
while $w_i(B_2) < 0$ **do**
  $x = \arg\ \max_{b_x \in B_1} w_x(B_2)$;
  $B_1 \leftarrow B_1 \setminus \{b_x\}$;
  $B_2 \leftarrow B_2 \cup \{b_x\}$;
  if $w_i(B_2) > 0$ **then**
    CONTINUE;
  end if
  if $w_i(B_2) \leq 0$ **then**
    $\mu^c_{i,s_i} = \mu_{x,s_x}$;
    $p_i^c = |s_i| \cdot \mu^c_{i,s_i}$;
    QUIT;
  end if
end while

IV. Simulation Results

We evaluate the performance of the proposed market-based incentive mechanism by various simulations. Although there are many existing work about incentive mechanism design for crowdsourcing, most of them considers mobility control to enlarge the coverage of participants and most of them are based on the greedy algorithm similar to the MSensing incentive mechanism in [20]. Thus, we mainly compare our mechanism with MSensing.

In our simulations, we launch a crowdsourcing application in a square of $200m \times 200m$. The whole area is divided into 100 grids, each of which is a square of $20m \times 20m$. 100 sensing tasks are uniformly distributed across the whole areas, i.e., there is one sensing task in each grid. Each sensing task requires to be completed by $k = 4$ different participants in order to increase the accuracy. 500 participants are clustered in the popular areas. The capacity of each participant is 1. We assume the middle of the sensing area is popular, i.e., the X-position of each participant follows normal distribution with mean $\mu = 100m$ and standard deviation $\sigma = 10m$.

The value of each sensing task to the platform is $\nu = 10$. Participants set their cost μ' for completing one sensing task within its sensing range according to uniform distribution between $[1, 3]$. We assume that the parameter η in moving cost function $f(d)$ is $\eta = 0.005$, and the moving distance upper bound is $\delta = 100m$.

Initially, the reserve price of each sensing task is $\gamma = 10$. In order to motivate participants to bid for the sensing tasks in demand surplus, the platform decreases the reserve price of the sensing tasks in supply surplus in each round by step ϵ. We run 2000 rounds of the auction. We repeat the whole experiment trial 50 times with different random seeds and average out the simulation results.

The following three metrics are used for evaluating the performance of the incentive mechanism.

- **Task Completion Ratio**, the ratio of sensing tasks being completed.
- **Participant Winning Ratio**, the ratio of participants winning in auction.
- **Social Welfare**, the difference between the total value of the completed sensing tasks and the total sensing cost [5].

Fig. 2 shows how the number of participant (n) affects the performance. Generally speaking, the task completion ratio and social welfare increase when n increases as shown in Fig. 2(a) and 2(c). This is because more sensing tasks can be completed and higher social welfare can be achieved with more participants.

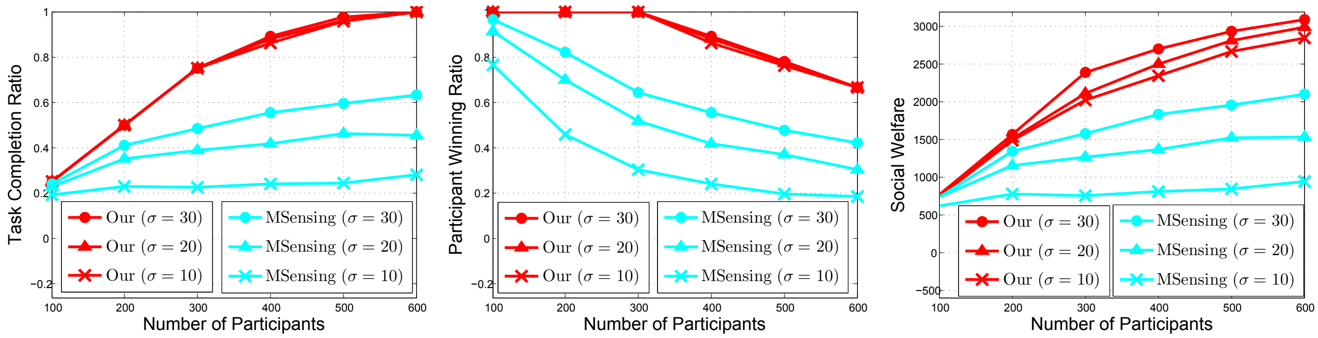
Our mechanism outperforms MSensing in terms of task completion ratio, participant winning ratio, and social welfare, and the performance improvement is larger when there are more participants. For example, when $n = 200$ and $\sigma = 10$, compared to MSensing, our mechanism increases the task completion ratio by 117.39%, the participant winning ratio by 117.39%, and the social welfare by 94.38%. When $n = 500$ and $\sigma = 10$, compared to MSensing, our mechanism increases the task completion ratio by 294.9%, the participant winning ratio by 294.9%, and the social welfare by 246.02%. The reason is as follows. In our mechanism, the platform stimulates participants to complete the sensing tasks in the unpopular areas by adjusting the reserve prices. For MSensing, many of the participants are clustered in the popular areas and will lose in the auction. Thus our incentive mechanism performs better.

The performance improvement of our mechanism is much larger when the concentration of participants is higher. For example, when $n = 500$, compared to MSensing, our mechanism can increase the task completion ratio by 294.9% with $\sigma = 10$, 106.53% with $\sigma = 20$, and 63.52% with $\sigma = 30$, as shown in Fig. 2(a); Similar trend can be found in Fig. 2(b) and Fig. 2(c). This is because when more participants are clustered in the popular areas, more participants will lose auction in MSensing.

The simulation results show that the market-based incentive mechanism outperforms MSensing in terms of task completion ratio, participant winning ratio, and social welfare. Both of the platform and the participants can benefit from our mechanism. From the platform perspective, it achieves better coverage by motivating participants in popular areas to move to unpopular areas. From the participants perspective, more participants are winning in auction and getting remuneration.

V. Conclusions

In this paper, we designed a novel market-based incentive mechanism for crowdsourcing, where the platform stimulates participants to bid for the sensing tasks in unpopular areas to enlarge the coverage of the participants. A reverse auction framework with reserve price is used to model the interactions between the platform and the participants. The platform systematically reduces the reserve price of the sensing tasks in supply surplus to motivate participants to bid for sensing tasks in demand surplus. We formulated the task allocation problem and proposed a greedy-based approximate algorithm to solve it. We also designed a critical payment policy to guarantee that participants declare their cost truthfully. Evaluation results



(a) Task Completion Ratio (b) Participant Winning Ratio (c) Social Welfare

Fig. 2: The effects of the number of participants. ($\delta = 100$, $\epsilon = 0.05$, $\eta = 0.005$.)

show that the proposed market-based incentive mechanism outperforms existing solution in terms of task completion ration, participant winning ratio, and social welfare.

To the best of our knowledge, we are the first to consider controlling the mobility of participants to overcome the coverage hole of participants from a market perspective. As the initial work, we do not expect to solve all the problems. In the future, we will consider more practical moving cost functions and study how such cost function affects the incentive mechanism design.

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