Group Buying based Incentive Mechanism for Mobile Crowd Sensing

Liqun Huang, Yanmin Zhu*, Jiadi Yu, Min-You Wu
Department of Computer Science and Engineering, Shanghai Jiao Tong University
*Corresponding Author
uliqun@sjtu.edu.cn, yzhu@cs.sjtu.edu.cn, {jiadiyu, mwu}@sjtu.edu.cn

***Abstract*—Mobile crowd sensing (MCS) has become a promising paradigm to perceive the environment with the help of smart phones. A monetary award is an effective method to incentivize participants to contribute good quality data. However, the reward for long-term data collection in the wide area could be unaffordable for a MCS requester. In this paper, we enable data requesters to recruit sensing workers in a group buying way. Requesters with similar data demand can form a group to share the payment and sensing data, which reduces cost and increases the coverage of sensing data. Agents from different groups compete in buying sensing data from sensing workers. We propose TGBA, a Two-phase Group Buying based Auction mechanism for MCS. In phase I, requesters submit bids to their group agent, the group agent decides the winners and clearing prices. In phase II, group agents attend the auction for recruiting workers. TGBA is computationally efficient and possesses good economic properties such as individual rationality, budget balance and truthfulness.**

***Index Terms*—Crowd sensing, group buying, smart phones, incentive mechanism.**

I. Introduction

Smart phones with various built-in sensors and powerful computational ability have become ubiquitous in our daily life. Smart phones are not only a communication handset, but also a set of sensors and chips that are capable of monitoring the activities of owners as well as the surrounding environment.

Mobile crowd sensing (MCS) is an innovative paradigm to perceive people's living environments with smart phones. Built-in sensors such as a camera, recorder, accelerometer, barometer and gyroscope, are utilized to collect sensing data, such as noise level, air pollution level and radio signal strength [1] [2] [3]. Subsequently, useful information is extracted from raw sensing data, and sent to a platform server located in the cloud, via wireless networks such as a cellular network or Wi-Fi. Leveraging people's mobility and the sensing ability of their smart phones, we can build a mobile sensing system. The platform aggregates and analyzes the data from a large number of users, and produces valuable information that closely links to our life. Stimulated by MCS, some pioneering projects have been carried out to monitor the environment, realize indoor localization [4], and improve people's living quality [5] [6] [7] [8].

Of central importance to mobile crowd sensing is to provide incentives to encourage active participation of smart phone users. From smart phone users' point of view, collecting sensing data would cause power consumption, bandwidth decrease, and even privacy exposures. Thus, a smart phone user is generally reluctant to contribute sensing data without being incentivized. The monetary award is a popular incentive mechanism for stimulating participation in MCS. In this incentive mechanism, smart phone users are data sellers and data requesters are buyers, and consequently a market of crowd sensing data is established.

Existing work. Auction-based mechanisms have been proposed for providing incentives in MCS. Some user-centric auction mechanisms focus on arousing enthusiasm of smart phone users by improving their utilities, such as [9] [10] [11] [12]. Center-centric auction mechanisms aim to increase the revenue of the platform, that is, acquire more valuable information with lower cost [13] [14].

Motivation. We observe that *the mismatch of small requester budget and high worker price* in practice may seriously impede the application of monetary incentives. A data requester in the real world often requests only several small pieces of sensing data and has only a small budget for collecting the sensing data. For example, a user may request only several photos of some point of interests to learn the crowdedness and then decide whether they would go there for sightseeing. Unfortunately, a smart phone worker may set a high price for performing such a sensing task. It takes the worker a considerable effort to complete the task, e.g., walking to the venue and taking a clear photo. It should be emphasised that average smart phone users cannot be motivated by small monetary rewards. As a consequence, small sensing tasks are pending without smart phone workers willing to work on them. On the other hand, we also observe that many different data requesters may share sensing data. Repeatedly performing sensing tasks for the same copy of sensing data would be a waste of both time and money. Instead, it would be helpful aggregating sensing tasks for similar sensing data.

Group buying is an effective win-win business paradigm which aggregates small demands and then gains a much higher bargaining power for buying at significantly lower prices. On one hand, buyers would enjoy a lower price for the service they request since the unit cost of sellers decreases as the total demand of services increases. On the other hand, the total profit of a seller would also increase thanks to the increased aggregate demand. The idea of group buying has been widely used on the web [15] and radio spectrum sharing [16]. Although many auction-based mechanisms have been proposed, none of them have considered the paradigm of group buying in MCS. Moreover, those auction-based mechanisms cannot be simply extended to deal with group buying because of the essential difference in the process of bidding and determining winning bids.

Our approach and contributions. Motivated by the advantages of group buying, we study the design of incentive mechanism that exploits the power of group buying for MCS. There are several key challenges. *First*, requesters are heterogeneous in MCS. Requesters have demand for various types of data, such as GPS data, RSS of Wi-Fi and the strength of noise. Each requester has his own strategy to measure the data quality. Consequently, requesters' budgets and valuations could be significantly divergent for the same worker. Requesters' utilities vary due to the different payments and valuations for the data. It is challenging to set fair prices for group members and achieve efficiency of making successful deals with workers. *Second*, workers are also heterogeneous. Workers might require different payments according to their condition, such as their locations, the percentage of battery remaining, and travelling costs. *Third*, it is critical for an auction to achieve truthfulness. In our scenario, we want to incentivize buyers to report their truthful valuations and budgets. The truthfulness for two-dimensional parameters in a two-phase auction mechanism is difficult to achieve and analyze.

In this paper, we propose a group buying based incentive mechanism for MCS. In *phase I*, data requesters submit their bids and a group agent decides winning members in his group. In *phase II*, a computationally efficient randomized matching algorithm is designed to allocate phone workers to each group and determine rewards for phone workers.

The remainder of this paper is organized as follows. We discuss related works in Section II. In Section III, we describe the system model of group buying in mobile crowd sensing and introduce key properties. We propose a two-phase group buying based auction in Section IV, and analyze it in Section V. The performance evaluation is presented in Section VI. We conclude the paper in Section VII.

II. Related Work

In recent years, incentive mechanisms have been explored with the growing applications of MCS. We classify the state-of-art related mechanisms into three categories in this section. The summarization is listed as follows.

Auction-based incentives aim to stimulate mobile crowd sensing workers with a monetary award, and the allocation of tasks is based on the result of the auction. Lee *et al.* [17] proposed a Reverse Auction based Dynamic Price mechanism. Sensing users bid prices for their own data, and some sensing data is sold to service provider with the claimed prices. Feng *et al.* [18] proposed TRAC, a truthful reverse auction framework which takes users' location information into account. Greedy strategy is adopted to solve the winning bids determination problem efficiently while maintaining the truthfulness in users' bidding behavior. Zhang *et al.* designed mechanisms to achieve improvement in recruiting opportunistically occurring participants, including a threshold-based auction (TBA), truthful online incentive mechanism (TOIM), and an arrival-departure model (TOIM-AD) based on TOIM [19]. Considering the dynamic availability of both smart phones and uncertain arrival tasks, Feng *et al.* [20] proposed two truthful auction mechanisms to solve the offline case and online case separately.

Cooperative incentive mechanisms try to model the cooperation between participants. Jaimes *et al.* [21] developed a repeated game model for a recurrent crowd sensing task. Participants compete and cooperate with each other in the long run with evolutionary behaviors. A reward-based collaboration mechanism was proposed by Duan *et al.* [22]. The total reward and the minimum number of collaborative users are announced firstly, and then the users' decisions are made according to his knowledge of the costs of other users.

Game-theoretic frameworks are also applied to analyze participants' behaviors or utilities in MCS. Yang *et al.* designed a Stackelberg game based incentive mechanism for the platform-centric model [10], where the users are followers and the platform is the leader. Luo *et al.* [14] introduced Bayesian game to model the all-pay auction, and the maximal profit of the service provider is achieved.

In cognitive radio network (CRN), several works adopt group buying based auction mechanism to share the considerable cost of spectrum among secondary users [16] [23]. But they cannot be directly applied to our work, due to the distinctions between spectrum and sensing data. Sharing sensing data has no impact on the interest of cooperators, because each buyer can get a copy with negligible transmission cost. In CRN, the spectrum is divided into channels, and the more cooperators, the narrower bandwidth one participant can obtain. As for sellers, the reserve price of spectrum is same for all group buying agents, while sensing workers might have different prices for different sensing tasks, due to their locations, preferences and so on.

None of the above works takes the similarity of sensing tasks into account, and the effective cooperation among MCS data requesters is neglected.

III. System model and problem formulation

In this section, we first describe the group buying scenario in crowd sensing. Then we formulate the problem of recruiting crowd sensing workers as a two-phase auction. Besides, the economic properties we hope to achieve are introduced.

A. System Model

In our scenario, there are multiple MCS data requesters who need to collect data in multiple regions. We assume that every request contains a location requirement, which describes the region where the sensing task should be performed. At the beginning, requests from all requesters are divided into groups according to their location requirements. Requests with the same location requirement are gathered in the same group.

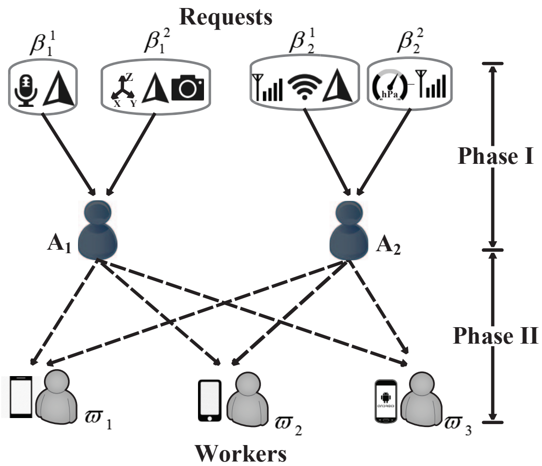

Figure 1. An example of group buying for 3 sensing workers and 2 groups which contains 2 requests respectively. In the first group, one request requires audio data from microphone and location information provided by GPS, the other request requires data from the accelerometer, GPS and camera. In the second group, the first request requires cell signal information, Wi-Fi signal strength and GPS data. The second request requires cell signal information and the value of the barometer.

After the division of requests, there are N groups of MCS requests. M sensing workers are available to handle these requests. We assume that there are K types of sensing data in the whole system, which form a type set $T = \{t_1, t_2, \cdots, t_K\}$. The recruited worker should collect the requested types of sensing data for his employer.

In the i-th group ($1 \leq i \leq N$), there are n_i requests which are regarded as group members denoted by $G_i = \{\beta_i^1, \beta_i^2, \cdots, \beta_i^{n_i}\}$. The k-th worker ($1 \leq k \leq M$) is denoted by ϖ_k. The request β_i^j ($1 \leq i \leq N$ and $1 \leq j \leq n_i$) has three private parameters for ϖ_k, demand $d_i^j(k) \subseteq T$ is the requirement of sensing data types, $v_i^j(k)$ is its valuation, and the budget $b_i^j(k)$ is the maximum payment amount for the desiring data. The demand could be different for different workers, because the sensors in workers' phones could be diverse. For example, few low-end handsets are equipped with a heart rate sensor.

In i-th group, an agent A_i is selected as the representative to participate in the auction of recruiting a sensing worker. Agents are heterogeneous and have different preferences for workers according to phone models, current locations and other information he could acquire. A_i's bid for worker ϖ_j is denoted by B_i^j, which indicates his group's preference for this worker. On the other hand, the workers can set different reserve prices on the basis of their current condition, such as travelling costs, battery consumption and so on. Here, r_i denotes the reserve price of worker ϖ_i, which is his truthful reward expectation for performing a task from one of the group agents. We assume that each group pays for at most one worker. Since tasks from different groups require different sensing locations, a worker cannot perform two tasks at the same time. One worker serving for multiple groups might cause considerable delays for data requesters, which cannot satisfy some real-time applications. Therefore, we also assume that each worker can simultaneously serve at most one group.

We design a truthful two-phase group buying based auction (TGBA) mechanism for MCS, as is illustrated in Figure 1. In phase I, the potential winners are selected by the group agents. In phase II, the group agents compete in recruiting workers.

In phase I, auctions among group members take place independently within every group. For worker ϖ_k, each member submit a triple $\left\langle \hat{b}_i^j(k), \hat{v}_i^j(k), d_i^j(k) \right\rangle$ as a bid to agent A_i. Notice that the valuation $\hat{v}_i^j(k)$ could be much higher than the reported budget $\hat{b}_i^j(k)$ or the actual budget $b_i^j(k)$.

The bids from group members are sealed-bids and we assume there is no collusion before bidding. The group agent A_i aggregate bids for ϖ_k from all members, and decides the set of winning bidders $S_i(k)$, a sub set of G_i. If β_i^j is in $S_i(k)$ and ϖ_k is hired by A_i, β_i^j is charged $p_i^j(k)$, which is decided by A_i; otherwise, β_i^j is not charged. At the end of phase I, each group agent has collected fund $F_i(k)$ for every $k \in \{1, 2, ..., M\}$ by processing this procedure.

In phase II, all agents participate in the auction of recruiting workers. Agent A_i ($1 \leq i \leq N$) submit a bid $\left\langle B_i^1, B_i^2, \cdots, B_i^M \right\rangle$ for all sensing workers, according to his knowledge about them. Then a matching is generated to decide the result of the auction. $w_i \in \{0, 1, 2, \cdots, M\}$ indicates the worker that A_i recruit, and the payment of A_i is P_i. If $w_i = 0$, A_i fails in the auction and does not hire a worker, therefore $P_i = 0$ and the winning members in $S_i(k)$ do not pay the agent. If $w_i > 0$, our mechanism ensures that A_i's payment P_i is not larger than his fund $F_i(w_i)$.

B. Problem Formulation

In one winning set, the workloads of members' sensing demand could be quite different. We introduce a workload function $f(d_i^j(k))$, which maps a subset of T to a non-negative real number. For simplicity, we assume that $f(d_i^j(k)) = \left|d_i^j(k)\right|$. Notice that other forms of workload function could be applied to our mechanism by simply replacing $\left|d_i^j(k)\right|$ with the new workload function.

To achieve fairness in our mechanism, payments of members should be proportional to the workloads of the demand. We assume a linear relation between payments and workloads. Thus the payment is formulated as

$$p_i^j(k) = p_i^0(k) \cdot \left|d_i^j(k)\right|, \tag{1}$$

where $p_i^0(k)$ is a positive real decided by agent A_i. Hereby, the utility of β_i^j is defined as

$$u_i^j = \begin{cases} v_i^j(w_i) - p_i^j(w_i) & w_i \neq 0 \text{ and } \beta_i^j \in S_i(w_i) \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Agent A_i sets the price $p_i^0(k)$ according to all of the bids for ϖ_k. It is guaranteed that the payment is not larger than the budget for all buyers in the winning set. Besides, our mechanism can assure that $p_i^j \leq v_i^j$ for all $\beta_i^j \in S_i$.

TABLE I
FREQUENTLY USED NOTATIONS

Symbol	Meaning
N, M	The number of groups and workers
T, K	Type set and number of sensing data types
G_i, A_i	The i-th group and its agent
β_i^j, n_i	The j-th member in G_i and size of G_i
$\hat{b}_i^j(k)$, $b_i^j(k)$	reported and actual budget of β_i^j
$\hat{v}_i^j(k)$, $v_i^j(k)$	reported and actual valuation of β_i^j
$d_i^j(k)$	β_i^j's demand of task types
$S_i(k)$	The winning set of G_i for k-th worker
$F_i(k)$	The collected fund of A_i for k-th worker
$p_i^j(k)$, P_i	The payment of β_i^j and A_i
B_i^j	A_i's bid for j-th worker
w_i	The index of worker whom A_i employs
ϖ_i, r_i	The i-th worker and his reserve price

Group agent A_i's budget for worker ϖ_k is

$$F_i(k) = \sum_{\beta_i^j \in S_i(k)} p_i^j(k). \tag{3}$$

Similarly, the utility of group agent A_i is defined as

$$U_i = \begin{cases} F_i(w_i) - P_i & w_i \neq 0 \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Workers also have non-negative utilities. The utility of ϖ_j is

$$V_j = \begin{cases} P_k - r_j & \varpi_j \text{ is hired by } A_k \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

Worker ϖ_j is hired by agent A_k, if and only if there exist an integer $k \in [1, N]$, such that $w_k = j$.

The employed worker should install the required applications on his smart phone, and run the applications in the requested locations while processing some simple operations according to the instructions if necessary.

C. Definitions of Properties

In this part, we present the definitions of properties which are achieved in our mechanism. Individual rationality, budget balance, and truthfulness are critical economic properties for an auction mechanism. Computational efficiency is an important criterion for practical application.

Definition 1. (Individual Rationality). *An auction is individual rational if the utility of each participant is non-negative.*

In order to satisfy rational buyers and sellers in our model, we should make sure that (2), (4) and (5) have non-negative results.

Definition 2. (Budget Balance). *An auction is budget balanced if the utility of the auctioneer is non-negative.*

In our mechanism, the auctioneer is the group buying platform. The auctioneer is nonprofit, and hence is transparent to the agents and workers in the auction. Notice that the platform may become for-profit by acting as group agents at the same time. To make a profit, the platform should design a module to process the task of a group agent.

Definition 3. (Truthfulness). *A mechanism is truthful, if it is a dominant strategy for the bidders to submit the bids with true valuation. A bidder cannot improve his utility by misreporting his bids, no matter what other players' strategies are.*

The group members and agents are bidders in phase I and II respectively. In truthful mechanism, the bidder β_i^j submits $\left\langle \hat{b}_i^j(k), \hat{v}_i^j(k), d_i^j(k) \right\rangle$, which could reveal β_i^j's true budget $b_i^j(k)$ and valuation $v_i^j(k)$ about the demand $d_i^j(k)$. There is no motive for a buyer to make false declaration of $d_i^j(k)$, since he can only get the types in $d_i^j(k)$ and redundant data type would cause higher cost. Agent A_i submits a bid $\langle B_i^1, B_i^2, \cdots, B_i^M \rangle$ to the auctioneer, which shows his valuation on each worker.

Definition 4. (Computational Efficiency). *An algorithm is computationally efficient if it generates the result and terminates in polynomial time.*

In this paper, our objective is to design an auction mechanism which satisfies individual rationality, budget balance, truthfulness and computational efficiency. The mechanism is illustrated in Section IV and its properties are proved in Section V.

IV. GROUP BUYING BASED AUCTION

In this section, we propose a truthful Two-phase Group Buying based Auction mechanism, which is called TGBA. TGBA satisfies these properties: individual rationality, budget balance, truthfulness and computational efficiency.

In phase I, the winners in a group are decided. The agent calculates payments for the winning group members, and calculates the fund he can collect. In phase II, agents from N groups bids for M workers. Their bids are set independently according to the fund they collect in phase I. If the agent successfully hires a worker, he will charge the winners in his group and send the required sensing data to the winners.

A. Phase I: Winning Set and Payments for Group Members

In phase I, the agent should make a decision on winning set and calculate the payment for each winner. We propose the Single Unit Clearing Price (SUCP) algorithm for winning set and payments decision, inspired by random n-th price auction in [24].

To achieve fairness, the payment is set to be proportional to the workload of the task demand. For simplicity, we assume that the workload of a demand $d_i^j(k)$ is defined as the number of tasks within, that is $\left| d_i^j(k) \right|$. Our algorithm remains effective when the workload function is modified to suit other scenarios.

At the beginning of phase I, the agent is responsible for distributing workers' information to his group members, which contains phone models, phone status (network condition, battery remaining, etc.), current locations, historical reputation and so on. Reviewing the information, each member makes decisions on the budget, valuation and demand for M workers and submit his bid to the agent. The bids are considered to be sealed and without collusion among bidders.

After receiving all bids from members, agent A_i executes algorithm SUCP to decide the winners $S_i(k)$ and their payments, for every $k \in \{1, 2, ..., M\}$. From agent A_i's point of view, β_i^j can be regarded as a buyer who wants to buy $\left|d_i^j(k)\right|$ same items with budget $\hat{b}_i^j(k)$. In other words, the acceptable unit price for β_i^j is not greater than the unit budget $\hat{b}_i^j(k)/\left|d_i^j(k)\right|$. The unit clearing price $p_i^0(k)$ is calculated according to these unit prices of all buyers.

Algorithm 1: Single Unit Clearing Price (SUCP), A_i calculates $F_i(k)$ and $S_i(k)$ for $k = 1, ..., M$

for $k \leftarrow 1$ to M **do**
  $m \leftarrow Random(1, n_i)$
  $p_i^0(k) \leftarrow \frac{\hat{b}_i^m(k)}{\left|d_i^m(k)\right|}$
  $S_i(k) \leftarrow \emptyset$
  $F_i(k) \leftarrow 0$
  for $j = 1$ to n_i **do**
    $p_i^j(k) \leftarrow p_i^0(k) \cdot \left|d_i^j(k)\right|$
    if $p_i^j(k) < \hat{b}_i^j(k)$ and $p_i^j(k) < \hat{v}_i^j(k)$ **then**
      $S_i(k) \leftarrow S_i(k) \cup \{\beta_i^j\}$
      $F_i(k) \leftarrow F_i(k) + p_i^j(k)$
    end if
  end for
end for

Group agent A_i randomly picks a member, and calculates the average budget per task as the unit clearing price $p_i^0(k)$. Selecting the unit clearing price randomly is the key step to ensure truthfulness in our mechanism, because the price is generated independent from the information in group members' bids. The payment for each group member is calculated with the unit clearing price. The member whose reported budget and valuation are both larger than the payment becomes a winner. In Section V, SUCP is proved to be a truthful mechanism, thus the bid can reveal the actual budget and valuation for a member. And the method of winner selection ensures that each member of the group has non-negative utility, no matter if A_i wins or loses in phase II.

The decision of winning set $S_i(k)$ and the calculation of $F_i(k)$ can be regarded as A_i's preparation for competing in hiring worker ϖ_k in phase II. The members in $S_i(k)$ will get sensing data of worker ϖ_k if and only if A_i wins ϖ_k in phase II.

Intuitively, the larger $F_i(k)$ will lead to a higher chance of recruiting ϖ_k as well as higher utility for A_i. However, the idea of maximizing $F_i(k)$ could result in untruthful bids from group members. This phenomenon is demonstrated by a simple example as follows:

TABLE II
AN EXAMPLE FOR SUCP

Buyer	Budget	Valuation	Demand
β_1^1	30	35	t_1
β_1^2	20	26	t_2
β_1^3	18	19	t_1
β_1^4	13	16	t_2
β_1^5	8	14	t_3

As is shown in Table II, in group G_1, there are 5 members with their reported budgets, valuations and demands. When β_1^5 is randomly selected, the unit clearing price is $8/1 = 8$, so all members are winners. The fund $F_1 = 8 \times 4 = 32$. Similarly, when β_1^1, β_1^2, β_1^3, or β_1^4 is selected, the fund would be 0, 20, 36 and 39 respectively. To maximize F_1, A_1 would select β_1^4 to calculate the unit clearing price. The utility of β_1^3 is $19 - 13 = 6$. Knowing A_1's maximization strategy, β_1^3 would report a false bid where budget is changed to 10. In this case, the fund is 0, 20, 26, 30, and 32, when β_1^1, β_1^2, β_1^3, β_1^4 or β_1^5 is selected. Hence β_1^5 is selected to achieve maximal fund for A_1 in this case. Consequently, β_1^3 improves his utility to $19 - 8 = 11$ by misreporting a lower budget.

In our mobile crowd sensing scenario, the maximization of utility for the agent is not achieved due to the requirement of truthfulness. However, the random selected unit price performs better than RSPE [25], which sacrifices more than half of the members in most cases. The comparison of SUCP with RSPE is thoroughly demonstrated in Section VI.

The drawback of SUCP is that false bids could happen in very rare cases. For example, when unit budgets of two bidders A and B are the same, and A is selected to calculate the clearing price, the other bidder B reports a false budget which is larger than the truthful budget. In this way, if bidder B has a valuation larger than the payment, bidder B gets positive utility by submitting the false bid. To reduce the possibility of this situation, we can require bidders to submit real number budgets. The budget can be assumed to be randomly distributed in a interval. When a unit clearing price is calculated, without collusion, the possibility that there exists another bidder that has the same unit budget is zero.

B. Phase II: Group Agents Attend the Auction of Sensing Workers

After phase I, each agent holds a tuple of funds for all workers. Fund $F_i(k)$ can be regarded as A_i's budget for worker ϖ_k, which will be collected from set $S_i(k)$ as soon as A_i wins ϖ_k. With the restriction on the budget, A_i has the right to express his own preference. But a truthful mechanism will oblige an agent to report his actual budget.

In phase II, an auction with multiple buyers and sellers is held. VCG auction is truthful but the running time is not polynomial. We want to achieve computational efficiency for our mechanism, and thus VCG auction is not adopted here. McAfee mechanism [26] provides a single clearing price and is computationally efficient. However, it is designed for a single type of goods. In our model, one buyer has different budgets for workers, thus the workers can be regarded as heterogeneous goods, which makes McAfee mechanism unsuitable for us.

To achieve truthfulness for group members, the allocation for agent A_i should be independent from his bid. Otherwise, the member β_i^j has the motive to misreport his bid to increase his own utility. Let's take the Algorithm 3 in [23] as an example, where agents' utilities are maximized. Assume that A_i wins ϖ_k when bids are truthful. In some cases, a winner β_i^j in $S_i(k)$ can report a lower bid to make $F_i(k)$ smaller, consequently the deal with ϖ_k will not bring the maximum utility for A_i, and then $\varpi_{k'}$, who brings the second largest utility in truthful bids, is allocated to A_i. If $\varpi_{k'}$ brings higher utility for β_i^j, β_i^j will prefer to submit the untruthful bid.

Algorithm 2: Random Assignments and Differential Prices (RADP), the auctioneer decides assignments and payments

```
Generate a matching Λ between workers and bidders,
  and record the matching with vector {λ_i}
for i ← 1 to N do
  x ← λ_i
  if x = 0 or B_i^x < r_x then
    continue
  end if
  c ← +∞
  for j ← 1 to N do
    if j = i then
      continue
    end if
    for k ← 1 to M do
      if B_j^k ≥ r_x and B_j^k ≤ B_i^x and B_j^k ≤ c then
        c ← B_j^k
      end if
    end for
  end for
  if c ≤ B_i^x then
    P_i ← c
    w_i ← x
  else
    P_i ← 0
    w_i ← 0
  end if
end for
```

In phase II, we propose an algorithm, which is called Random Assignments and Differential Prices (RADP), to determine a matching and payments. RADP achieves budget balance, as well as truthfulness and computational efficiency.

The auctioneer executes algorithm RADP when he receives bids vector $\left\langle B_i^1, B_i^2, \cdots, B_i^M \right\rangle$ for all $i \in [1, N]$. First of all, a random matching Λ between bidders and sellers is generated. The matching Λ ensures that one bidder can win less than 2 worker and one worker can be assigned to at most 1 bidder. We use a vector $\{\lambda_i\}$, where $i \in \{1, 2, ..., N\}$, to indicate the results of Λ. For agent A_i, λ_i is in $\{0, 1, ..., M\}$, which means the λ_i-th worker is assigned to A_i. When λ_i equals 0, no worker is assigned to A_i.

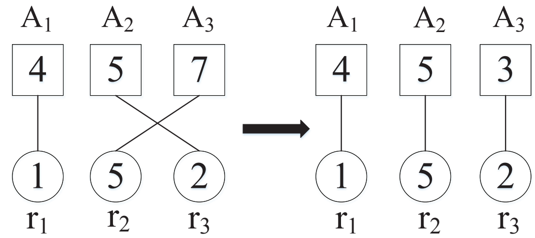

Figure 2. An example of untruthful bidding when auctioneer maximizes the number of matching pairs

For the agent A_i with non-zero λ_i, if the reserve price of λ_i-th worker is not greater than A_i's budget for him, the auctioneer will decide the clearing price c according to the bids from other agents. It is necessary that the clearing price should be within $[r_{\lambda_i}, B_i^{\lambda_i}]$, which satisfies both the worker and the agent. To achieve truthfulness for agents, the clearing price is the lowest B_j^k in $[r_{\lambda_i}, B_i^{\lambda_i}]$, where $j \neq i$ and $1 \leq k \leq M$. If no such bid is found, the deal between A_i and the λ_i-th worker will fall through. In this case, the worker, the agent A_i and all members in G_i has zero utility.

Considering efficiency of the auction, maximizing the number of successful agents or maximizing the total welfare of agents seems attractive. There exists a polynomial algorithm to solve this problem by modeling it as a maximum weighted bipartite matching. But the intent on maximization may lead to untruthful bids. A simple example shown in Figure 2 is demonstrated as follows:

There are 3 workers with reserve price 1, 5, and 2. Without loss of generality, we assume A_1's budgets for 3 workers are the same, that is $F_1(1) = F_1(2) = F_1(3) = 4$. Furthermore, we assume $F_2(k) = 4$ and $F_3(k) = 7$, for any $k \in [1, 3]$.

To achieve maximum matching pairs or maximum total welfare of agents, one possible solution is that A_1 hires worker 1, A_2 hires worker 3 and A_3 hires worker 2. Here we focus on the action of A_2. A_2 knows the auctioneer's intent of maximizing matching pairs, he hereby misreports a false budget 3 for all workers in order to improve his utility. In this way, A_2's utility increases from $(7-5)$ to $(7-2)$, according to the solution in Figure 2. Likewise, maximizing the number of successful agents could result in untruthfulness among bidders.

V. Theoretical Analysis

In this section, we prove the economic properties of our mechanism TGBA and analyze the time complexity of SUCP and RADP.

A. Proof of Economic Properties

Theorem 1. *TGBA has the property of individual rationality and budget balance.*

Proof: Line 8 and 9 in Algorithm 1 show that β_i^j is in the winning set $S_i(k)$ if and only if the payment is smaller than its budget and valuation of worker ϖ_k. According to equation (2), if agent A_i hires the w_i-th worker, the utility of β_i^j will be positive; otherwise, the utility will be zero.

Similarly, it can be seen from line 18 in Algorithm 2 and equation (4) that the utility of an agent is non-negative. The auctioneer is assumed to attend the auction voluntarily, and thus always has zero utility. Hence the mechanism satisfies individual rationality and budget balance. ∎

Theorem 2. *TGBA is truthful for requests.*

Proof: For request β_i^j with a bid $\left\langle \hat{b}_i^j(k), \hat{v}_i^j(k), d_i^j(k) \right\rangle$, we will prove that the dominant strategy is to submit the bid where $\hat{b}_i^j(k) = b_i^j(k)$ and $\hat{v}_i^j(k) = v_i^j(k)$. Notice that the demand $d_i^j(k)$ is considered to be truthful, because β_i^j can merely get the data described in $d_i^j(k)$. Misreporting a smaller size of demand causes deficiency in sensing data, and a larger size leads to higher price. For simplicity, we denote the truthful bid by $\phi = \left\langle b_i^j(k), v_i^j(k), d_i^j(k) \right\rangle$, and the untruthful bid by $\tilde{\phi} = \left\langle \tilde{b}_i^j(k), \tilde{v}_i^j(k), \tilde{d}_i^j(k) \right\rangle$. Assume that A_i is assigned with ϖ_k. The truthfulness for β_i^j is analyzed in the following four cases:

1) β_i^j wins by submitting ϕ and $\tilde{\phi}$. Since β_i^j is not selected to calculate the unit clearing price (otherwise β_i^j loses), $p_i^0(k)$ is the same for both bids. From line 8 in Algorithm 1, it can be deduced that $p_i^0(k)$ is smaller than $\min\{b_i^j(k), v_i^j(k), \tilde{b}_i^j(k), \tilde{v}_i^j(k)\}$. According to equation (1), the payment is same for both bids. The utility of β_i^j hereby remains the same when β_i^j replaces ϕ with $\tilde{\phi}$.
2) β_i^j wins by submitting ϕ and loses by submitting $\tilde{\phi}$. According to individual rationality, the utility of a winner is non-negative, which is not smaller than a loser's zero utility.
3) β_i^j loses by submitting ϕ and wins by submitting $\tilde{\phi}$. The reason why β_i^j loses with ϕ is that $b_i^j(k) < p_i^0(k) \left| d_i^j(k) \right|$ (lacking budget) or $v_i^j(k) \le p_i^0(k) \left| d_i^j(k) \right|$ (low valuation). The false bid $\tilde{\phi}$ cannot change the unit clearing price $p_i^0(k)$. If the reason of failure is lacking budget, then β_i^j has to report a larger budget $\tilde{b}_i^j(k)$, which β_i^j cannot afford. The deal with ϖ_k is canceled and all members in G_i gains nothing. If the failure is caused by low valuation, β_i^j has to report a larger valuation $\tilde{v}_i^j(k)$, and hence $u_i^j = v_i^j(k) - p_i^0(k) \left| d_i^j(k) \right| \le 0$. In both situations, untruthful bid can not bring positive utility.
4) β_i^j loses by submitting ϕ and $\tilde{\phi}$. For losers in G_i, the utilities are all zero.

∎

We analyze the truthfulness for group members, and prove that a member cannot improve its utility unilaterally. For a randomized auction, it is a common method to prove truthfulness by calculating the expected utility for truthful bid and false bid respectively. We prove ex post truthfulness, a stronger notion of truthfulness. For every random case, after all unit clearing prices are calculated and the random matching is generated, the untruthful bid never brings higher utility. Consequently, it is evident that the expected utility of false bid is not larger than that of the truthful bid.

Theorem 3. *TGBA is truthful for agents.*

Proof: For agent A_i, his budget is decided in phase I, and his bid works in phase II. To prove truthfulness for agents, we only need to prove that RADP is a truthful algorithm for agents. Assume that A_i is assigned with ϖ_k. His untruthful bid for ϖ_k is denoted by $\tilde{B}_i^k$, and the truthful bid is $F_i(k)$. The truthfulness is analyzed in the following four cases:

1) A_i wins by submitting $F_i(k)$ and $\tilde{B}_i^k$. The clearing price is the minimum bid B_j^l $(j \neq i)$ which is greater than or equal to the reserve price r_k. No matter how A_i wins, his payment is always B_j^l. And his utility remains unchanged with untruthful bid.
2) A_i wins by submitting $F_i(k)$ and loses by submitting $\tilde{B}_i^k$. According to the property of budget balance, the agent's utility is non-negative when he wins a worker. But when A_i loses, he has zero utility.
3) A_i loses by submitting $F_i(k)$ and wins by submitting $\tilde{B}_i^k$. When $r_k \le F_i(k)$, A_i loses with $F_i(k)$ because there is no B_j^l $(j \neq i)$ in $[r_k, F_i(k)]$. If A_i wins with $\tilde{B}_i^k$, the clearing price is in $\left(\mathrm{F}_i(\mathrm{k}), \tilde{B}_i^k\right]$, which brings negative profit for A_i. When $r_k > F_i(k)$, it can be deduced that $\tilde{B}_i^k \ge P_i \ge r_k > F_i(k)$, thus the utility for false bid $(F_i(k) - P_i)$ is negative.
4) A_i loses by submitting $F_i(k)$ and $\tilde{B}_i^k$. The utility is zero in both situations.

∎

B. Time Complexity

In crowd sensing, computational efficiency of the incentive mechanism is important. Quick feedback from the auction system can improve participants' experience by reducing the waiting time.

Theorem 4. *TGBA is computationally efficient. The time complexity of SUCP is $O(Mn_i)$ for A_i, and time complexity of RADP is $O(MN^2)$.*

Proof: For SUCP, the unit clearing price is randomly selected in $O(1)$ time, and the inner for-loop is done in $O(n_i)$ time. For RADP, random matching can be generated in $O(N)$ time. At most $M(N-1)$ bids are checked for A_i, where $i \in [1, N]$.

Thus, TGBA has the property of computational efficiency. ∎

Notice that in phase I, we randomly pick a price as clearing price rather than sacrificing m users whose budgets are the smallest among all members. SUCP does not require sorted bids, and thus the running time is lower than that of SAMU [16] or RSPE adopted in [23]. The requirement of decreasing budget will increase time complexity to $O(Mn_i \log n_i)$.

VI. Performance Evaluation

In this section, we evaluate the performance of TGBA and make some comparisons between TGBA and the mechanism based on RSPE. The simulation is run by MATLAB.

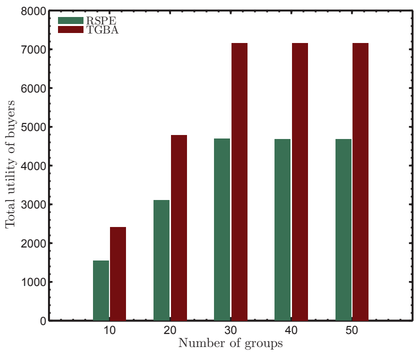

Figure 3. Total utility of buyers with different N

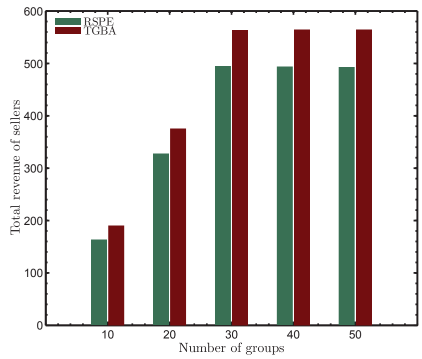

Figure 4. Total revenue of sellers with different N

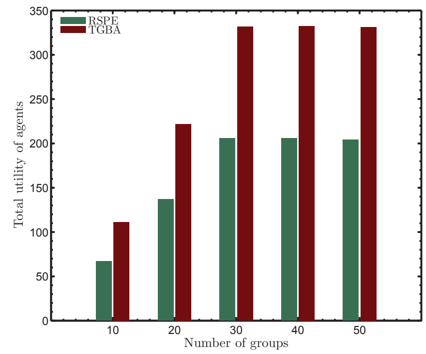

Figure 5. Total utility of agents with different N

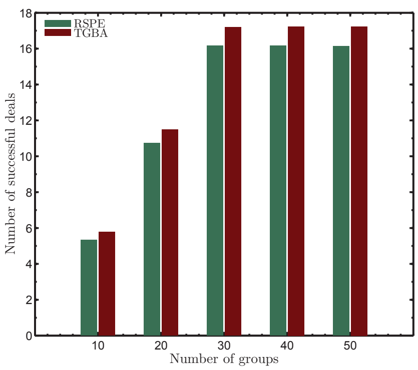

Figure 6. The number of successful deals between agents and workers with different N

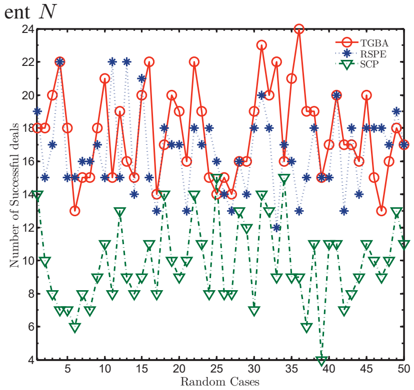

Figure 7. Comparison of TGBA, RSPE and SCP

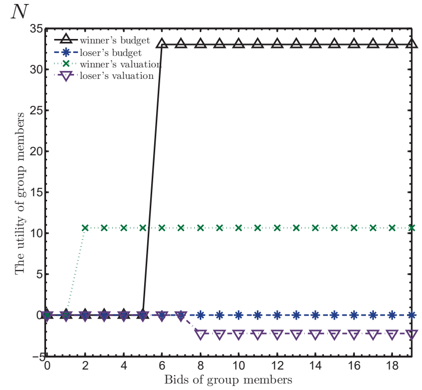

Figure 8. Truthfulness of group members

A. Simulation Setup

The default parameters are set as follows: $M = 30$ and $n_i = 30$ for $i = 1, ..., n$. In phase I, for request β_i^j, $\left|d_i^j(k)\right|$ is uniformly distributed in $[1, 5]$, $b_i^j(k)$ is uniformly distributed within $[1, 10]$, and $v_i^j(k)$ is uniformly distributed within $[5, 50]$. In phase II, r_i is uniformly distributed in $[20, 50]$, which is larger than the budget of any single request. We vary N from 10 to 50 with an increment of 10. For each N, we randomly generate 5000 cases with the setup of parameters mentioned above.

In RSPE, a vector of descending bids $\mathbf{b} = \{b_1, b_2, ..., b_x\}$ is randomly divided into two descending bids $\tilde{\mathbf{b}} = \{\tilde{b}_1, \tilde{b}_2, ..., \tilde{b}_y\}$ and $\hat{\mathbf{b}} = \{\hat{b}_1, \hat{b}_2, ..., \hat{b}_z\}$. $\tilde{F} = \max_{1 \le i \le y} i \cdot \tilde{b}_i$ and $\hat{F} = \max_{1 \le i \le z} i \cdot \hat{b}_i$. Then we find the largest j that satisfies $j\tilde{b}_j \ge \hat{F}$, and the first j bidders in $\tilde{b}$ are winners and the payment is $\hat{F}/j$ each. Similarly, we find the largest k that satisfies $k\hat{b}_k \ge \tilde{F}$, and the first k bidders in $\hat{b}$ are also winners and the payment is $\tilde{F}/k$ each. If the buyer's valuation is lower than the payment, he is deleted from the winning set. Notice that in our simulation, RSPE is applied in phase I to calculate the unit clearing price.

We adapt the VCG mechanism in the double auction for a single clearing price algorithm (SCP). In SCP, the auctioneer decides one clearing price for all winning agents and workers. The sellers' prices are sorted in increasing order and buyers' bids are sorted in decreasing order. The auctioneer finds the breakeven index k and the clearing price is $\max\{s_k, b_{k+1}\}$, where s_k is the k-th seller's price and b_{k+1} is the $(k+1)$-th buyer's bid. In our comparison, SCP is applied to determine the payments for winning group agents.

We focus on the total utility for buyers (group members), agents and sellers (workers). As the platform runs for a long period of time, auctions are held many times. Therefore we adopt the average performance to evaluate our mechanism. The total utility for buyers is defined as $\sum_{i=1}^{N}\sum_{j=1}^{n_i} u_i^j$, the total utility for agents is $\sum_{i=1}^{N} U_i$ and total revenue for sellers is $\sum_{i=1}^{N} P_i$. The data presented in Section VI-B is the average values over 5000 cases.

B. Simulation Results

Figure 3 shows the total utility of buyers with different N, number of groups. Our mechanism TGBA outperforms RSPE by over 50% for each N. Figure 4 shows the total revenue of buyers. The improvements which are made by TGBA is about 14%. The total utility of agents is shown in Figure 5. TGBA increases the utility by more than 60%.

For TGBA, we can observe that the total utility increases with N, when N does not exceed M. But when N is larger than M, the utility maintains at the same level.

The average number of successful deals between agents and workers is shown in Figure 6. TGBA has more successful deals than RSPE. When $N \le M$, over 57% of agents are assigned with a worker. And when $N > M$, over 57% of workers are hired by agents. Figure 7 shows that TGBA performs better than SCP obviously, which reveals that RADP is more suitable for the group buying market with heterogeneous goods.

We randomly select cases to study the truthfulness of TGBA. We choose a winner or a loser to submit false bid unilaterally. Figure 8 shows that a group member cannot improve his utility unilaterally by submitting a false bid, no matter he is a winner or a loser. Sometimes the utility will be negative if a loser misreports a high valuation.

In a word, our mechanism TGBA satisfies good economic properties and improves the number of successful deals between workers and agents, as well as achieving higher utility for buyers and agents.

VII. Conclusion

This paper is motivated by the situation where mobile crowd sensing researchers cannot afford abundant data for long-term applications. We model the group buying behavior among crowd sensing requesters, and propose a two-phase auction mechanism TGBA. In phase I, auctions take place in each group. The group members submit bids to their group agent and the group agent decides the clearing price and the winning set according to the algorithm SUCP. In phase II, agents attend auction to hire workers. We propose RADP to solve this multi-buyer, heterogeneous item auction. TGBA is computationally efficient, and satisfies some economic properties such as individual rationality, budget balance and truthfulness. The simulation results show that TGBA achieves high total utility for buyers, sellers and agents.

Acknowledgements

This research is supported in part by 973 Program (2014CB340303), NSFC (No. 61472254, 61170238 and 61420106010), the Science and Technology Commission of Shanghai (Grant No.14511107500) and Singapore NRF (CREATE E2S2). This work is also supported by the Program for New Century Excellent Talents in University and the Program for Changjiang Scholars and Innovative Research Team in University, China.

References

[1] Kaishun Wu, Haochao Li, Lu Wang, Youwen Yi, Yunhuai Liu, Dihu Chen, Xiaonan Luo, Qian Zhang, and Lionel M Ni, “hjam: Attachment transmission in wlans”, *Mobile Computing, IEEE Transactions on*, vol. 12, no. 12, pp. 2334–2345, 2013.

[2] Kaishun Wu, Haoyu Tan, Yunhuai Liu, Jin Zhang, Qian Zhang, and Lionel M Ni, “Side channel: bits over interference”, *Mobile Computing, IEEE Transactions on*, vol. 11, no. 8, pp. 1317–1330, 2012.

[3] Kaishun Wu, Haoyu Tan, Hoi-Lun Ngan, Yunhuai Liu, and Lionel M Ni, “Chip error pattern analysis in ieee 802.15. 4”, *Mobile Computing, IEEE Transactions on*, vol. 11, no. 4, pp. 543–552, 2012.

[4] Kaishun Wu, Jiang Xiao, Youwen Yi, Dihu Chen, Xiaonan Luo, and Lionel M Ni, “Csi-based indoor localization”, *Parallel and Distributed Systems, IEEE Transactions on*, vol. 24, no. 7, pp. 1300–1309, 2013.

[5] Rajib Kumar Rana, Chun Tung Chou, Salil S Kanhere, Nirupama Bulusu, and Wen Hu, “Ear-phone: an end-to-end participatory urban noise mapping system”, in *Proceedings of the 9th ACM/IEEE International Conference on Information Processing in Sensor Networks*. ACM, 2010, pp. 105–116.

[6] Emmanouil Koukoumidis, Li-Shiuan Peh, and Margaret Rose Martonosi, “Signalguru: leveraging mobile phones for collaborative traffic signal schedule advisory”, in *Proceedings of the 9th international conference on Mobile systems, applications, and services*. ACM, 2011, pp. 127–140.

[7] Linda Deng and Landon P Cox, “Livecompare: grocery bargain hunting through participatory sensing”, in *Proceedings of the 10th workshop on Mobile Computing Systems and Applications*. ACM, 2009, p. 4.

[8] Zheng Yang, Chenshu Wu, and Yunhao Liu, “Locating in fingerprint space: wireless indoor localization with little human intervention”, in *Proceedings of the 18th annual international conference on Mobile computing and networking*. ACM, 2012, pp. 269–280.

[9] Juong-Sik Lee and Baik Hoh, “Dynamic pricing incentive for participatory sensing”, *Pervasive and Mobile Computing*, vol. 6, no. 6, pp. 693–708, 2010.

[10] Dejun Yang, Guoliang Xue, Xi Fang, and Jian Tang, “Crowdsourcing to smartphones: incentive mechanism design for mobile phone sensing”, in *Proceedings of the 18th annual international conference on Mobile computing and networking*. ACM, 2012, pp. 173–184.

[11] Haifeng Xu and Kate Larson, “Improving the efficiency of crowdsourcing contests”, in *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*. International Foundation for Autonomous Agents and Multiagent Systems, 2014, pp. 461–468.

[12] Iordanis Koutsopoulos, “Optimal incentive-driven design of participatory sensing systems”, in *Infocom, 2013 proceedings ieee*. IEEE, 2013, pp. 1402–1410.

[13] Luis G Jaimes, Idalides Vergara-Laurens, Miguel Labrador, et al., “A location-based incentive mechanism for participatory sensing systems with budget constraints”, in *Pervasive Computing and Communications (PerCom), 2012 IEEE International Conference on*. IEEE, 2012, pp. 103–108.

[14] Tie Luo, Hwee-Pink Tan, and Lirong Xia, “Profit-maximizing incentive for participatory sensing”, in *INFOCOM, 2014 Proceedings IEEE*. IEEE, 2014, pp. 127–135.

[15] “Groupon inc”, http://www.groupon.com.

[16] P. Lin, X. Feng, Q. Zhang, and M. Hamdi, “Groupon in the air: A three-stage auction framework for spectrum group-buying”, in *INFOCOM, 2013 Proceedings IEEE*, April 2013, pp. 2013–2021.

[17] Juong-Sik Lee and Baik Hoh, “Sell your experiences: a market mechanism based incentive for participatory sensing”, in *Pervasive Computing and Communications (PerCom), 2010 IEEE International Conference on*. IEEE, 2010, pp. 60–68.

[18] Zhenni Feng, Yanmin Zhu, Qian Zhang, Lionel M Ni, and Athanasios V Vasilakos, “Trac: Truthful auction for location-aware collaborative sensing in mobile crowdsourcing”, in *INFOCOM, 2014 Proceedings IEEE*. IEEE, 2014, pp. 1231–1239.

[19] Xinglin Zhang, Zheng Yang, Zimu Zhou, Haibin Cai, Lei Chen, and Xiangyang Li, “Free market of crowdsourcing: Incentive mechanism design for mobile sensing”, *Parallel and Distributed Systems, IEEE Transactions on*, vol. 25, no. 12, pp. 3190–3200, 2014.

[20] Zhenni Feng, Yanmin Zhu, Qian Zhang, Hongzi Zhu, Jiadi Yu, Jian Cao, and Lionel M Ni, “Towards truthful mechanisms for mobile crowdsourcing with dynamic smartphones”, in *Distributed Computing Systems (ICDCS), 2014 IEEE 34th International Conference on*. IEEE, 2014, pp. 11–20.

[21] Luis G Jaimes, Alireza Chakeri, Juan Lopez, and Andrew Raij, “A cooperative incentive mechanism for recurrent crowd sensing”, in *SoutheastCon 2015*. IEEE, 2015, pp. 1–5.

[22] Lingjie Duan, Takeshi Kubo, Kohei Sugiyama, Jianwei Huang, Teruyuki Hasegawa, and Jean Walrand, “Incentive mechanisms for smartphone collaboration in data acquisition and distributed computing”, in *INFOCOM, 2012 Proceedings IEEE*. IEEE, 2012, pp. 1701–1709.

[23] Dejun Yang, Guoliang Xue, and Xiang Zhang, “Truthful group buying-based spectrum auction design for cognitive radio networks”, in *Communications (ICC), 2014 IEEE International Conference on*. IEEE, 2014, pp. 2295–2300.

[24] Jason F Shogren, Michael Margolis, Cannon Koo, and John A List, “A random nth-price auction”, *Journal of economic behavior & organization*, vol. 46, no. 4, pp. 409–421, 2001.

[25] Andrew V Goldberg, Jason D Hartline, Anna R Karlin, Michael Saks, and Andrew Wright, “Competitive auctions”, *Games and Economic Behavior*, vol. 55, no. 2, pp. 242–269, 2006.

[26] Preston McAfee, “A dominant strategy double auction”, *Journal of Economic Theory*, vol. 56, no. 2, pp. 434 – 450, 1992.