Behavior-Based Online Incentive Mechanism for Crowd Sensing with Budget Constraints

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Abstract—Crowd sensing is a new paradigm which leverages the ubiquity of sensor-equipped mobile devices to collect data. To achieve good quality for crowd sensing, incentive mechanisms are indispensable to attract more participants. Most of existing mechanisms focus on the expected utility prior to sensing, ignoring the risk of low quality solution and privacy leakage. Traditional incentive mechanisms such as the Vickrey-Clarke-Groves (VCG) mechanism and its variants are not applicable here. In this paper, to address these challenges, we propose a behavior based incentive mechanism for crowd sensing applications with budget constraints by applying sequential all-pay auctions in mobile social networks (MSNs), not only to consider the effects of extensive user participation, but also to maximize high quality of sensing data submission for the platform (crowd sensing organizer) under the budget constraints, where users arrive in a sequential order. Through an extensive simulation, results indicate that incentive mechanisms in our proposed framework outperform existing solutions.

I. INTRODUCTION

With the increasing ubiquity of sensor-embedded mobile devices (e.g., smartphones), mobile social networks (MSNs), which integrate data collection techniques and services into many kinds of social networks [1], [2], have received considerable research efforts in recent years due to two changes as follows. First, the terminal devices for social network applications change from PCs to mobile phones. Second, the interactive mode extends from the virtual space to the real physical world. MSNs provide a new opportunity for crowd sensing, which takes advantage of the pervasive mobile devices to solve complex sensing tasks. A typical example of crowd sensing applications is to provide the support for green traffic by sensing and reporting timely the measurements about traffic flows in some region. Different from existing crowdsourcing systems, crowd sensing exploits sensing and processing abilities of mobile devices to provide sensing data from the real physical world towards a specific goal or as part of a social or technical experiment [3], [4].

Extensive user participation and submission quality are two crucial factors determining whether crowd sensing applications in MSNs can achieve good service quality. Most of the current crowd sensing applications are based on a common hypothesis that all users voluntarily participate in submitting the sensing data. However, mobile devices are controlled by rational users, in order to conserve energy, storage and computing resources, so selfish users could be reluctant to participate in sensing data for crowd sensing applications. Thus, it is indispensable to provide some incentive schemes to stimulate selfish participants to cooperate in MSNs. Only a handful of works [5]–[8] focus on incentive mechanism for crowd sensing applications. All of these works apply a regular auction (e.g., a reverse auction) only for off-line crowd sensing applications with the ex-ante payment commonly known as “Free rider problem”.

The data submission quality issue from participants is also challenging in crowd sensing applications [9]. If the submission quality of participants is not well guaranteed, although the extensive user participation offers useful information, the service quality from participants is far from satisfactory to the requesters of crowd sensing applications. For example, on the one hand, the limit of the coverage constraint may make the participants with high quality data drop out of crowd sensing applications [10]; On the other hand, traditional incentive mechanisms such as the Vickrey-Clarke-Groves (VCG) mechanism [1] and its variants also will make the participants with higher true valuation become starved frequently to win, thereby drop out of crowd sensing applications [10]. Therefore, special mechanisms must be included to handle these challenges.

Although both extensive user participation and submission quality issues have been identified as two crucial human factors for crowd sensing applications, many recent research works [5]–[8] tend to separately study them in crowd sensing applications. The reason is that, if the extensive user participation and submission quality problems are addressed at the same time for crowd sensing applications, the issue would become more challenging. For example, some submission quality enhanced techniques [11], [12] stimulate participants to generate high quality sensing contents to achieve good service quality, but they could make some incentive strategies, especially the reputation-based incentive strategies under budget constraints, hard to implement extensive user participation coverage constraints for crowd sensing applications, since it is not practical to assume that the requester will always provide an unlimited budget to achieve good service quality. Therefore, how to simultaneously address both extensive user participation and submission quality issues becomes particularly challenging for crowd sensing applications with budget constraints.

In this paper, to address the fore-mentioned challenges, we...
propose a behavior-based incentive mechanism for practical crowd sensing applications with budget constraints. Specifically, our main contributions are summarized as follows:

- We explore a behavior-based incentive mechanism for crowd sensing applications with budget constraints in MSNs. In order to simultaneously satisfy the requirements of both extensive user participation and high quality sensing data submission, we combine the all-pay auction theory and a proportional share allocation rule to stimulate the participants to generate high efforts and adequate coverage constraints to achieve the better service for the requester of crowd sensing applications with budget constraints.
- We focus on a more real crowd sensing scenario where users arrive one by one online in a random order. We model the issue as a sequential all-pay auction, in which sensing data are submitted sequentially and the users with the high quality sensing data are selected as the winners. Further, after observing previous submissions, we derive every user best response effort bidding function for sequential crowd sensing applications with budget constraints, which influences user participation and sensing data submission quality.
- Extensive simulations show that our proposed incentive mechanism outperforms the existing solutions.

The rest of the paper is organized as follows. In Section II we briefly discuss the related work and motivation. In Section III we present our system model, related definitions and our design goals. In Section IV we design a behavior-based incentive strategy for sequential crowd sensing in MSNs, and present the performance evaluation in Section V. Finally, Section VI concludes the paper.

II. Background and Related Work

Extensive user participation and submission quality issues are two crucial human factors for crowd sensing applications in MSNs. The authors of [13] proposed recruitment frameworks to enable the platform to identify well-suited participants for sensing data collections. However, they only considered the users’ selection, rather than the incentive mechanism design. In recent years, most of reported studies have focused on how to stimulate selfish participants to enhance user participation levels. For instance, the authors of [7], [8], [10], [14] explored the extensive user participation to achieve a good sensing service for crowd sensing applications. Obviously, it is not practical to assume that the requester in their mechanisms will always have an unlimited budget. The authors of [5], [15]–[17] designed an incentive mechanism to enhance user participation levels under a budget constraint. Although they designed truthful mechanisms, which optimized the utility function of the platform under a fixed budget constraint, to.

\[2\] All-pay auction, is an auction in which every bidder must pay regardless of whether he wins the prize, which is awarded to the highest bidder as in a conventional auction.

Incentive extensive user participation, the effects of the online sequential manner, in which users arrive, were neglected. In practice, recently, there are a few works focusing on both budget constraints and the online sequential manner of users’ arrival to enhance user participating levels. For instance, the authors of [18], [19] exploited posted price mechanisms for stimulating the online arrival user participation. The authors of [20] leveraged threshold price mechanism for maximizing the number of tasks under budget constraints and task completion deadlines. However, they did not consider the submission quality issue of sensing data.

Compared with the extensive user participation issue, there are only a handful of research works [11], [12] focusing on the submission quality issue for crowd sensing applications in MSNs. These works stimulate participants to submit high quality sensing data to achieve good service quality, but do not support the extensive user participation issue. The authors of [21] study a problem about the low payment from a predefined number of participants. On the contrary, we focus on the utility maximum problem with a given budget. In our mechanism, in order to simultaneously satisfy the requirements of both extensive user participation and high quality sensing data submission, we combine the all-pay auction mechanism and a proportional share allocation rule to achieve the better service for crowd sensing applications with budget constraints. Furthermore, we account for the online arrival of users and model the issue as an online sequential all-pay auction. Simulations indicate that our proposed incentive mechanisms outperform existing solutions.

III. System Model and Problem Formulation

A. System Model

We consider the following crowd sensing system model illustrated in Fig. 1. The system consists of a crowd sensing application platform, to which a requester with a budget \( B > 0 \) posts a crowd sensing application that resides in the cloud and consists of multiple sensing servers, and many mobile device users, which are connected to the cloud by cellular networks (e.g., GSM/3G/4G) or WiFi connections. The crowd sensing application first publicizes a sequential sensing task in an Area of Interest (AoI), denoted by \( \Gamma = \{\tau_1, \tau_2, \cdots, \tau_m\} \). Assume that a set of users \( U = \{1, 2, \cdots, n\} \) interested in the crowd sensing service campaign register to the platform, and then arrive online in a sequential order.

B. User Model

We explore online auctions where each user arriving randomly has a chance to win the auction, and each offering sensing data such as location information for constructing network coverage maps, for which each user associate a private cost \( c_i \). The platform has a public (known to the mechanism designer and maybe known to all agents) budget \( B \in \mathbb{R}_+ \), and a public non-decreasing utility function \( U \) over the subsets of users. We assume that in each time step, a single user
appears and the platform makes a decision that is based on the information it has about the user and the history of the previous $i-1$ stages. Generally, there are three classes of user models: the i.i.d. model, the secretary model, and the adversarial model. The first model means that at each time step the costs and values of users are drawn from some unknown distributions. The second model means that the users’ costs are chosen by an adversary, however their arrival order is a permutation that is drawn uniformly at random from the set of all possible permutations. In the third model, the users’ costs and their arrival order are chosen by an adversary. Note that in the third model, although the adversary cannot observe the actions the mechanism takes, since it has full knowledge, the adversary chooses the worst arrival order and costs. Thereby, the mechanism cannot obtain the optimal solutions. Thus, in this paper, we only account for the two models with respect to the distribution of users, described in increasing order of generality: the i.i.d. model and the secretary model.

C. Problem Formulation

We model the above interactive process between the platform and users as an online sequential all-pay auction with the budget constraint, where the plethora of users with different preference and skill ability $\theta \in [\underline{\theta}, \overline{\theta}]$ ($\underline{\theta}$ and $\overline{\theta}$ denote the least skilled behavior ability and the most skilled behavior ability respectively) arrive and compete in a contest by their efforts in one period. User behavior abilities are described by the distribution function $F$. Assume that users are game-theoretic and seek to make strategy to maximize their individual utility in equilibrium. Receiving the crowd sensing campaign from the platform, each user $i$ provides its sensing profile $\Gamma_i$ to the platform according to its preference and skill ability so as to expect a prize allocation (i.e., payment) in return for its sensing data submission. The platform determines the payment $M_1, M_2, \cdots, M_n$ to the top $n$ (highest-ranked) submissions in one period ($M_1 \geq M_2 \geq \cdots \geq M_k = m > M_{k+1} = \cdots = M_n = 0, \sum_{i=1}^n M_i = B$): the user with the best submission receives $M_1$, the first runner-up receives $M_2$, and so forth. Note that different from traditional mechanisms, here $\Gamma_i$ is not fixed. Thereby, the contribution of user $i$, denoted by $e_i$, is uncertain and depends on user’s efforts. But when these sensing data are submitted to the platform, the platform can identify their contributions, i.e., their marginal utility (to be elaborated later).

More formally, an online mechanism $M = (f, p)$, which consists of an allocation function $f : \mathcal{R}_n^+ \rightarrow 2^{[n]}$ and a payment function $p : \mathcal{R}_n^+ \rightarrow \mathcal{R}_n^+$, is needed. That is, for any random arriving users’ strategy sequence, the allocation function computes an allocation of the budget for participatory users $S^{'} \subseteq \mathcal{U}$ and the payment function returns a payment vector to participatory users. Thus, the utility of user $i$ is $p_i = \frac{\theta_i}{\theta}$ if it is allocated, $-\frac{\theta_i}{\theta}$ otherwise. The platform expect to obtain the maximum value from the participatory users’ service quality under the budget constraint, i.e.,

$$\max U(S^{'}) \quad \text{Subject to} \sum_{i \in S^{'}} p_i \leq B$$

where $U(S^{'})$ is the monotone submodular value function of services from the participatory users $S^{'}$. More variables are given in Table I.

Putting the above online policy together, we design incentive mechanisms based on users’ behavior abilities to simultaneously satisfy the requirements of both extensive user participation and high quality sensing data submission. To stimulate users to produce endogenous maximal efforts, we introduce a sequential all-pay auction to the above online allocation strategies for our incentive mechanism design. Considering a risk-neutral budget constrained all-pay auctions, the above utility function $U(S^{'})$ indicates that $U(e_1, \cdots, e_L) = \sum_{i \in S^{'}} f(e_i)$, where the effort $f(e_i)$ is equal to the marginal utility of user $i$, i.e., $f(e_i) = U_i(S^{'}) = U(S^{'}) = U(S^{'}) = U(S^{'}) - U(S^{'})$ when the set of sampled users is $S^{'}$.

Generally speaking, the goal of the platform is to select a subset $S$ with the size $L$ that maximizes the total efforts of the users under the given budget. A utility-maximizing platform should select the number of prizes $L$, the total prize budget $B$ and the allocation of prizes $M_1 + M_2 + \cdots + M_k = B$ which maximizes the platform’s utility $U(e_1, \cdots, e_L, B)$. More generally, given a budget $B$ and a reserved effort $m$, finding a subset $S$, is equivalent to maximizing the above coverage issue of sensing data submitted by users.

A case study: We consider the following scenario where the

| Variable | Description |
|----------|-------------|
| $\mathcal{U}$, $n$, $i$ | set of users, number of users, and some user |
| $B, B', e^*$ | budget constraint and stage-budget, the effort threshold |
| $T, T', t$ | deadline, end time step of each stage, and each step user $i$ sensing profile |
| $\Gamma, m, \tau_i$ | set of services, number of services, and some service |
| $\theta_i, e_i, U_i$ | behavior ability, effort bid and marginal utility of user $i$ |
| $S', J$ | set of sampled users and winners in sampled users |
| $L$ | number of users with allocated prizes larger than zero |
| $p_i, F_i$ | number of allocated prizes and ability distribution of user $i$ |
| $\underline{\theta}, \overline{\theta}$ | the least skilled and the most skilled behavior ability |
| $\Phi_j$ | order cumulative distribution function of the $j$-th best type |

Fig. 1. Our crowd sensing system framework with all-pay auctions.
platform expects to obtain the sensing data covering all roads in an AoI. For convenience of presentations and calculations, we divide each road in the AoI into multiple discrete points, and the objective of the platform is equivalent to receiving the submitted sensing data covering all points before \( T \). The set of all points in the AoI is denoted by \( \Gamma = \{ \tau_1, \tau_2, \ldots, \tau_m \} \). The set of points submitted by user \( i \) is denoted by \( \Gamma_i \) (called user \( i \)'s sensing profile), which are the result of users' efforts based on their behavior ability. For ease of presentation, assume that each point \( \tau_j \) needs to be sensed at most one time. The value of the sampled users to the platform is:

\[
U(S') = \sum_{j=1}^{m} \min \{ 1, \sum_{i \in S' \cap \Gamma_j} s_{i,j} \},
\]

where \( s_{i,j} \) equals to 1 if \( \tau_i \in \Gamma_i \), 0 otherwise.

### IV. Optimal Mechanism Design for the Sensing Contest

In this section, we present an online contest mechanism for achieving extensive user participation and stimulating users to submit high quality sensing data. To this end, we adopt a multiple-stage sampling-accepting process for guaranteeing extensive user participation. Then we introduce an online sequential all-pay auction for stimulating users to submit high quality sensing data.

#### A. Incentive Mechanism Design

An online contest mechanism needs to overcome several nontrivial challenges. First, the users' effort bids are unknown and need to be elicited in a truthful reporting manner. Second, the total prizes cannot exceed the platform's budget. Thirdly, the mechanism needs to balance the arrival of users and makes irrevocable decisions on whether to allocate the number of prizes; Finally, and most important, the mechanism needs to cope with strategic users' endogenous efforts. To achieve good service quality, previous online solutions and generalized secretary problems \cite{20,22,23} is via sampling: the first batch of the input is rejected and used as a sample which enables making an informed decision on the rest of the users. However, since users are likely to be discouraged to sense data knowing the pricing mechanism will automatically reject their effort bid. In other words, those users arriving early have no incentive to report their bids to the platform, which may delay the users’ completion or even lead to task starvation. On the other hand, the above mechanisms only apply for fixed services submitted by each user, thereby neglect users’ endogenous efforts.

To address the above challenges, we adopt a multiple-stage sampling-allocating process to design our online contest incentive mechanism. At each stage, based on the above submodularity, the mechanism maintains a effort threshold which is used to decide to allocate the number of the users’ prizes. The mechanism dynamically increases the sample size and learns a budget that are enough to allocate users for maximizing the total utility, then apply this density threshold for making further allocation decisions.

Specifically, given a distribution on the arrival of users, we can easily calculate every time step \( t \) s.t. the probability that a user arrives before \( t \) is 1/2\( t \). All of \( T \) time steps are divided into 2\( t \) quantiles: \( \{0, 1, \ldots, \lceil \log T \rceil \} \). We apply \( S' \) to denote the set of all sampled users until the time step \( t \). Our mechanism (see Algorithm 1) iterates over \( q_t \in \{0, 1, \ldots, \lceil \log T \rceil \} \) and at every time step \( q_t \), a budget of \( B/2^t \) is applied to allocate the number of prizes (illustrated in Fig. 2). Firstly, when a new user \( i \) arrives, with probability 1/3, our mechanism computes the best response effort bid of user \( i \) according to his current behavior ability, and thereby can submit its sensing data as a result of his efforts. Receiving user \( i \)'s sensing data \( \Gamma_i \), regardless of whether it is given prizes, it is added to the sample set \( S' \) due to the nature of the all-pay auction. Given a set of sampled users \( S' \), the platform computes the marginal utility of user \( i \), i.e.,

\[
U_i(S') = U(S' \cup \{i\}) - U(S'), \ i \notin S'.
\]

The mechanism allocates prizes to user \( i \) as long as the minimal prizes of the last offline sample stage is not larger than the result of effort threshold \( e \) (to be elaborated in the following subsection) multiplied by the marginal utility \( U_i(S) \), and the allocated stage-budget \( B' \) has not been exhausted. At the first stage, we set a small effort threshold and minimal prizes to start our mechanism. The randomization addresses extreme cases in which only a single user with the strongest behavior abilities can complete a large fraction of the crowd sensing application at the threshold efforts. This is the result that an incentive compatible variant of Dynkin’s celebrated algorithm \cite{22} to the issue of hiring the best secretary, is tailored to our setting.

To make the above mechanism to achieve our goal, in the following, we elaborate the computation methods of the effort threshold and the arrival user’s optimal sequential efforts.

#### B. Threshold Effort Decision

In this subsection, we first introduce a threshold effort to ensure the extensive participation. Then we apply all-pay auction to enhance users’ submission quality. We now turn to the following definition of nondecreasing submodular functions used in our pricing mechanisms.

**Definition 1 (Submodular Function):** Let \( \mathbb{N} \) be a finite set, a function \( U : 2^\mathbb{U} \rightarrow \mathbb{R} \) (the set of reals) is submodular if

\[
U(S \cup \{i\}) - U(S) \geq U(S' \cup \{i\}) - U(S'), \forall S \subseteq S' \subseteq \mathbb{U},
\]

where \( S, S' \), and \( \mathbb{U} \) are illustrated in Table I and \( i \) denotes some user.

**Background:** Submodularity, a discrete analog of convexity, has played an essential role in combinatorial optimization \cite{26}. It appears in many important settings and almost everywhere \cite{27} including cuts in graphs \cite{28,29,30}, rank function of
matroids [31], set covering problems and plant location problems [32]. In many settings such as set covering or matroid optimization, the relevant submodular functions are monotone, meaning that \( U(S) \leq U(S') \) whenever \( S \subseteq S' \). More recently submodular functions have become key concepts both in the machine learning and algorithmic game theory communities. For example, submodular functions have been used to model bidders’ valuation functions in combinatorial auctions [33–35], and for solving feature selection problems in graphical models [36] or for solving various clustering problems [37].

**Lemma 1:** The value function \( U(S) \) is monotone submodular.

The proof of Lemma 1 is given in the Appendix.

In a general submodular maximization problem, a proportional share allocation rule is a natural fit to compute the effort threshold (see Algorithm 2) due to its monotonicity when users are sorted according to their efforts relative to increasing marginal contributions. However, to enhance the sensing data quality (users’ efforts), we apply the optimal winning participant number \( L \) and the optimal prize amounts \( M_i(i \in \{1, \cdots, L\}) \) to calculate the effort threshold of the next time step. The optimal winning participant number \( L \) and the optimal prize amounts \( M_i(i \in \{1, \cdots, L\}) \) can be calculated according to the method in [38]. Then, these sampled users are sorted according to increasing marginal contributions relative to their prize amounts. This sorting implies:

\[
U_1/M_1 \geq U_2/M_2 \geq \cdots \geq U_L/M_L,
\]

where \( U_i \) denotes \( U_{i|S_{i-1}} = U(S_{i-1} \cup \{i\}) - U(S_{i-1}), \)

\( S'_{i-1} = \{1, 2, \cdots, i-1\}, \)

and \( S'_0 = \emptyset \). The specifical iteration process is illustrated in Algorithm 2 to guarantee the extensive user participation.

**Algorithm 2 GetEffortThreshold**

**Input:** Sample set \( S' \), stage budget constraint \( B' \)

**Output:** Effort threshold and minimal prizes, i.e., \( (e, M_L) \)

1. Compute the optimal winners’ number and the optimal prize amounts \( M_i(i \in \{1, \cdots, L\}) \);
2. Sort their marginal utility relative to their prize amounts, s.t. \( U_j/M_j \geq U_2/M_2 \geq \cdots \geq U_L/M_L \); set \( k = 1 \);
3. The winner set \( J \leftarrow \emptyset \); \( i \leftarrow \arg \max_{j \in X'} (U_j(J)/M_j) \);
4. while \( k \leq L \) and \( M_i \leq U_i/B'/U(J \cup i) \) do
5. \( J \leftarrow J \cup i \);
6. \( i \leftarrow \arg \max_{j \in S' \setminus J} (U_j(J))/M_j ; \)
7. \( k \leftarrow k + 1 \);
8. end while;
9. \( e \leftarrow B'/U(J) ; \)
10. return \( (e, M_L) \);

In the following subsection, due to space limitations, assuming that the reserved value \( m \) is zero, i.e., \( e_0 = 0 \), we derive the equilibrium effort bidding function for sequential all-pay auction arrival users. For the positive reserve case, \( e_0 > 0 \), the similar results can also be derived, which will be discussed in our future work.

For technical reasons, we assume that ties are broken in favor of the late entrant so as to illicit the truthful effort bid of the current user. For user \( i \), a submission of quality \( e_i \) costs \( e_i/\theta_i \), indicating that it is less costly for a high ability user to submit a sensing data of a given quality than a low ability user. Assume that \( \Phi_j \) is the cumulative distribution function of the \( j \)-th best type out of \( n-1 \) users. According to equation (2.1.3) of [39], we have

\[
\Phi_j(e) = \sum_{i=1}^{n-1} \left( \begin{array}{c} n-1 \\vdash i \\ i \end{array} \right) \Phi(e)^i(1-\Phi(e))^{n-1-i}.
\]

Moreover, the expected utility \( \nabla \) of the user of ability type \( \theta \) bidding with quality \( e \) is \( \nabla = \sum_{i=1}^{L} \Phi_j(e)(M_i - M_{i+1}) \).

Thus, applying backward induction iteratively for user \( n, n-1, \cdots, i+1 \), we can obtain the following maximization problem of the just arrival user \( i \):

\[3\]This is a technical assumption to derive strict subgame perfect equilibria instead of \( \varepsilon \)-equilibria.
\[
\begin{align*}
\max_{e_i} & \left\{ \sum_{j=1}^{n} F_j(e_j = 0) - \frac{c}{d} \right\} \\
\text{s.t.} & \quad e_i \geq e_{L-th}(\theta_{L-th}),
\end{align*}
\]  

(1)

where \(e_{L-th}(\theta_{L-th})\) denotes the L-th largest effort bids observed by user i.

Therefore, in the following, we derive user i’s best response effort bidding function based on the assumption that the behavior ability distribution function is \(F(x) = x^c\), where \(0 < c < 1\) like [9, 40]. To derive a closed-form solution, we therefore restrict attention to the specific family of concave distribution functions, for which we are able to explicitly calculate the subgame perfect equilibrium e of each contestant. This will allow us to derive some general optimal results on multi-stage sequential all pay auctions. If we let \(\bar{\theta}_i = \left((1 - d_{L-th})\theta_{L-th}\right)^{d_i/d_{L-th}}\), and \(\bar{\theta}_i^* = \left((1 - d_{1-th})\theta_{1-th}\right)^{d_i/d_{1-th}}\), given \(e_1, e_2, \ldots, e_{i-1}\), user i’s best response effort bidding function is obtained as follows (the complete calculation process given in the Appendix):

\[
e_i = \begin{cases} 
0 & 0 < \theta_i < \bar{\theta}_i \\
\{e_{j-th}(\theta_{j-th})\}_{j \in \{1, 2, \ldots, L\}} & \bar{\theta}_i \leq \theta_i < \bar{\theta}_i \\
\nabla[\theta_i(1 - d_i)]^{1/d_i} & \bar{\theta}_i^* \leq \theta_i \leq 1
\end{cases}
\]

(2)

V. PERFORMANCE EVALUATION

To evaluate the performance of our BBS mechanism, and explore the effects of extensive user participation and high quality sensing data submission for real crowd sensing applications, we implement the mechanism by applying the well-known Manhattan model obtained from the Google Map, which is the same as [41].

A. Experimental Setup

In the simulation, the sensing range of each mobile phone is set to 7 meters. The AoI obtained from the Google Map is located at Manhattan, NY, which spans 4 blocks from west to east with a total length of 1.135km and 4 blocks from south to north with a total width of 0.319km, and includes 3 Avenues and 3 Streets. We divide each road in the AoI into multiple discrete Alos with a uniform spacing of 1 meter, so the AoI consists of 1135 + 3 + 319 + 3 - 9 = 4353 PoIs in total, where each Avenue has 1135 points and each Street has 319 points, and the crossing of Avenues and Streets includes 9 points. Data sensing area sizes are set at random. In summary, we used 1887 sensing data packets from different locations via 200 different users [41]. The sensing range (behavior ability) of different users’ sensor changes from 3 meters to 10 meters. To start the mechanism, we initially set the effort threshold \(e^*\) and the number of minimal prizes \(M^*\) of Algorithm 1 are set to 0.1. Users arrive according to a Poisson process in time with arrival rate \(\lambda\), which varies from 0.3 to 8 with the increment of 0.1. Arriving at our scenario, some user is placed randomly at some location on the AoI’s roads. All measurements are averaged over 30 sensing tasks. Our primary goals are to evaluate the performance of the online mechanism on real effort bids as well as to test users’ participating response to different mechanisms.

B. Threshold Evolution of Different Mechanisms

To test the performance of our BBS mechanism, we use the users’ effort bids from all-pay auctions and compare our mechanism against several benchmarks. Note that in order to show how many users can be accepted to participate in the crowd sensing given a specified budget, we only need to computing the values of users’ best response effort bidding function, which is practically obtained according to the users’ arrival sequence. We compare our BBS mechanism against two benchmarks. One has full knowledge about users’ costs, and the other is the GetEffortThreshold procedure applied offline. We simulate these algorithms on different budgets to examine the change in the threshold efforts as the number of users increases in the sample. In all simulations, we observe that the threshold efforts converged quickly. Fig. 3(a) shows that the value of the threshold efforts changes with the stage of the mechanism (the number of users that submitted their effort bids) on the logarithmic scale. As we can see, the threshold efforts quickly stabilize and remain almost constant throughout the running.

C. Effects of User Participation

To examine whether users perform strategic considerations in their prizing mechanisms, we can observe the distinct difference between the plots of the different total efforts (bids) in Fig. 3(b) based on different mechanisms. Most of users in the Winner-Take-All scheme, where a single winner gets all prizes, drop out of the contest, since the probability of winning the crowd sensing contest decreased with number of participants. Users in the Multiple-Winners scheme, where multiple winners get the same prizes, exert lower effort when there are larger number of participants. In the reverse auction, bidders accepted in the best possible scheme increase their bids. (The following drops off since we enforce the budget constraint). In the best incentive compatible schemes, bids are lowered, since users bids are rejected. We believe that this is a strong support for persisting in incentive compatible mechanisms, since they think that this will increase their profit. Interestingly, our BBS scheme solves both incentive compatibility and individual rationality problems.

D. Effects of Submission Quality

To examine the quality of submission sensing data quality, we plot the total utility value as a function of different budgets in Fig. 3(c). In the Winner-Take-All scheme, most of users drop out of the contest, since the probability of winning the crowd sensing contest decreases with the number of participants increasing. Thus, the total utility value would decreased from its maximum. Users in the Multiple-Winners scheme, where multiple winners get the same prizes, exert lower effort and obtain more total utility values when there are
larger numbers of participants as more budgets are provided. In the reverse auction, bidders accepted in the best possible scheme increased their bids. In the following, they drop off since we enforced the budget constraint. In the best incentive compatible schemes, bids are lowered, since users bids are rejected. We believe that this is a strong support for persisting in incentive compatible mechanisms, since they think that this will increase their total utilities. Interestingly, our BBS scheme solves both IR and IC problems, therefore, it ensures extensive user participation and high quality sensing data submission, just as illustrated in Fig. 3(a) and Fig. 3(b).

Furthermore, we also quantify submission quality by considering users’ mean differences from true on-site data over their effort bids. Fig. 3(d) indicates that our BBS mechanism has a lower mean errors than the proportional share allocation rule.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we present a behavior based incentive strategy to motivate users to exert the most sensing effort according to their behavior abilities and willingness for practical crowd sensing applications. We assess the participants’ efforts according to their context situation (e.g., sensing location and submission quality). A natural extension of this scheme may be desirable to have submissions privacy protected and to hide user experience level or identity.

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we have
\[ U(S \cup \{k\}) - U(S) = \sum_{j=1}^{m} \min \left\{ \max\{0, 1 - \sum_{i \in S} s_{i,j}\}, s_{k,j} \right\} \]
\[ \geq \sum_{j=1}^{m} \min \left\{ \max\{0, 1 - \sum_{i \in S'} s_{i,j}\}, s_{k,j} \right\} = U(S' \cup \{k\}) - U(S') \]
Besides, for all \( S \subseteq U \) and \( k \in U \setminus S \), we have \( U(S \cup \{k\}) - U(S) \geq 0 \). Thus, \( U(S) \) is monotone submodular. Therefore the Lemma [1] holds.

**Proof of User \( i \)'s Bidding Function:**
In the following, we derive user \( i \)'s best response effort bidding function based on the assumption that the behavior ability distribution function is \( F(x) = x^n \), where \( 0 < c < 1 \) like [9].

Applying backward induction, we expect that user \( n \) will win the auction if the quality of her submission is higher than or equal to the best quality submission among all previous submissions, \( \max \{ e_j(\theta_j) \}_{j < n} \), and if her ability is sufficiently high, \( \theta_n \geq \frac{1}{d} \max \{ e_j(\theta_j) \}_{j < n} \). If her ability is not high enough, i.e., \( \theta_n < \frac{1}{d} \max \{ e_j(\theta_j) \}_{j < n} \), then her benefit from winning (\( \nabla \)) is less than her bidding cost. In this case, she should bid zero. Likewise, if he bids zero, indicating that his ability is not high enough, i.e., \( \theta_n < \frac{1}{d} \max \{ e_j(\theta_j) \}_{j < n} \). On the other hand, user \( n - 1 \) wins the all-pay auction conditional on her submitting sensing data with quality at least as high as the best previous submission. Thus, \( \max \{ e_j(\theta_j) \}_{j < n} = e_{n-1} \) holds. Putting these together, we have: if user \( n \) bids zero, his ability must be not high enough, i.e., \( \theta_n < \frac{e_{n-1}}{c} \). In other words, \( F_n(e_n = 0) = F_n(\theta_n < \frac{e_{n-1}}{c}) = (\frac{e_{n-1}}{c})^c \). Likewise, for user \( i < n - 1 \), we have \( F_{i+1}(e_{i+1} = 0) = (\frac{e_i}{c})^c \). Applying backward induction, iteratively for user \( n, n - 1, \ldots, i + 1 \), we can obtain the following equation.

\[ \prod_{j=i+1}^{n} F_j(e_j = 0) = \left[ \frac{e_i}{c} \right]^{(1 - c)^n} \left[ \frac{e_{i-1}}{c} \right]^{(1 - c)^{(n-1)i}} \cdots \left[ \frac{e_1}{c} \right]^{(1 - c)^{n-1}} \]

Since the constraint is not binding, the above equation is fed into equation [1] to compute the first-order condition, thereby, \( e_{i} \) is obtained by:

\[ [1 - (1 - c)^{n-i}] \frac{e_{i-1}}{c} - (1 - c)^{n-i} \frac{1}{e_{i}} = 0. \]

The second-order condition is obtained by:

\[ -\frac{1}{c} \left( (1 - c)^{n-i} - (1 - c)^{n-i-1} \right) \frac{e_{i-1}}{c} \frac{e_{i-1}}{c} \frac{1}{e_{i}} < 0. \]

Thus, the interior solution is \( e_i(\theta_i) = \nabla^{\theta_i} (1 - (1 - c)^{n-i}) \). Let \( d_i = (1 - c)^{n-i} \). The interior solution is rewritten as \( e_i(\theta_i) = \nabla^{\theta_i} (1 - d_i) \). Therefore, if we let \( \theta_i = [(1 - d_i)(1 - \theta_i)]^{d_i}/d_i, \) and \( \theta_i' = [(1 - d_i)(1 - \theta_i)]^{d_i}/d_i, \) user \( i \)'s best response effort bidding function, i.e. the previous expression [2] holds evidently.