Sell Your Experiences: A Market Mechanism based Incentive for Participatory Sensing

Juong-Sik Lee
Nokia Research Center - Palo Alto
955 Page Mill Road, Palo Alto, CA 94304, USA
e-mail: juong-sik.lee@nokia.com

Baik Hoh
Nokia Research Center - Palo Alto
955 Page Mill Road, Palo Alto, CA 94304, USA
e-mail: baik.hoh@nokia.com

Abstract—This paper studies economic models of user participation incentive in participatory sensing applications. User participation is the most important element in participatory sensing applications for providing adequate level of service quality. However, incentive mechanism and its economic model for user participation have never been addressed so far in this research domain. In order to stimulate user participation, we design and evaluate a novel Reverse Auction based Dynamic Price (RADP) incentive mechanism, where users can sell their sensing data to a service provider with users' claimed bid prices. The proposed incentive mechanism focuses on minimizing and stabilizing incentive cost while maintaining adequate number of participants by preventing users from dropping out of participatory sensing applications. Compared with a Random Selection with Fixed Price (RSFP) incentive mechanism, the proposed mechanism not only reduces the incentive cost for retaining same number of participants by more than 60% but also improves the fairness of incentive distribution and social welfare. More importantly, RADP can remove burden of accurate pricing for user sensing data, the most difficult step in RSFP.

Keywords-component; Participatory Sensing; Economic Model; Incentive; Reverse Auction;

I. INTRODUCTION

There has been a growing body of studies on sensor networks; however commercialization of sensor network technologies has never been successfully deployed (or introduced) in the real world due to the expensive installation cost for sufficient number of sensors. Considering the issue, several groups [1, 13] have recently proposed to incorporate human carrying smartphones in a sensing data collecting loop. Such a novel approach is shortly called ***'Participatory Sensing'***. In participatory sensing, a large number of users carrying smart phones contribute to monitoring the environments with their sensing measurements (e.g., Mobile Millennium [2], Nokia Simple Context [14], Urban Atmosphere [3]). Smartphones carried by users transmit the sensing data to service providers, thereby replacing dedicated infrastructure and sensors. However, currently existing deployments have suffered from insufficient participants because participants who voluntarily submit their sensing data found no interest to remain actively in the system without being rewarded. From the viewpoints of service providers that collect and utilize user sensing data, an incentive scheme increases user participation for the service and helps address privacy concerns that arise in the data collection step. Participants may drop out of the collecting loop unless *Return on Investment (ROI)* is greater than their expectations. The expected ROI is dependent on true valuation of user's investment that includes all efforts for collecting data such as battery power consumption, device resources, and his privacy. However, such a true valuation dynamically changes among individuals, different types of sensing data, and user's contexts (e.g., spatial-temporal situations). In such environments, we observed that fixed price based incentive mechanisms cannot adapt to dynamic distributions of user's true valuations and lead users to dropping out of participatory sensing applications. Additionally, it is hard to infer optimal incentive price for user sensing data in the fixed price incentive mechanism. In this study, we address the problem of designing an incentive mechanism that removes the burden of accurate pricing for user sensing data, adapts itself to dynamic change of user's true valuation, and minimizes the user drop with minimal cost spent.

Motivated by several inherent advantages of dynamic pricing scheme such as its dynamic adaptation to market environments [18], we introduce a Reverse Auction based Dynamic Price (RADP) incentive mechanism in which users sell their sensing data to service provider with their claimed bids, and a service provider selects multiple users and purchases their sensing data. The selected users receive their bid prices as a reward for their sensing data. A reverse auction for participatory sensing application is a recurring one since a service provider recurrently and continuously requires users' sensing. In such a recurring reverse auction, we observe that the users with higher true valuations become starved frequently for being winners who sell their sensing data. Therefore the users with higher true valuations lost their interests in continuous participation and drop out of the reverse auction. The dropped participants weaken price competitions, thereby they cause incentive cost explosion because remaining participants constantly win and, as a result, increase their bid prices for selling their sensing data for the future auction rounds to maximize their expected profits. To overcome the challenge, we let the service provider give a virtual credit to the participants who lost in the previous reverse auction as a reward for their participation only. The virtual participant credit (VPC) can only be used for lowering bid price and the bid price after the deduction increases the wining probability of user for the future auction rounds. With this mechanism, the bidders who have higher true valuations can be winners by continuous participation and they can still remain active in the reverse auction. Such participation incentive maintains enough active bidders (i.e., desired level of participatory sensing service quality) and stabilizes the incentive cost by keeping the price competitions. We envision that the presented incentive mechanism effectively fits to commercial participatory sensing applications that will be popular soon upon many requests of environmental sensing. For its successful deployment in the real world, we have many issues to be resolved, but the incentive mechanism explored in this study plays an essential role as a cornerstone in achieving high level of service quality in participatory sensing applications.

The reminder of this paper is organized as follows. In the next section, we briefly describe participatory sensing applications and motivations of our work. Section III analyzes participatory sensing in terms of market structure perspective and describes challenging problems that arise when applying traditional market mechanism into participatory sensing applications. Section IV illustrates the novel reverse auction based incentive mechanism for participatory sensing application. The proposed incentive mechanism is evaluated by various experimentations in Section V. Section VI discusses open challenges in real deployments and future works. Finally, in Section VII, we conclude with summary of our contributions.

II. BACKGROUNDS

A. Participation Sensing Applications

Traditional sensor networks require application-specific sensors deployed over a large area to monitor the environment such as air quality or automotive traffic jam. However, its performance heavily depends on the number of sensors. If sensor networks fail to lower the sensor cost, they cannot provide enough sensors to cover a wide area. As smart phones are getting prevalent in mobile industry, they are expected to replace application-specific sensors. Wireless connectivity, GPS-based localization capability, and OS can provide a platform for general-purpose sensors. Furthermore, smart phones carried by users add mobility to static sensors, covering a dynamic range. Each user transmits what he or she senses the environment through the phone to nearby wireless access points (e.g., cellular base stations or WLAN access points). Infrastructure service provider aggregates sensing measurements from a large number of users through access networks, and then delivers raw data or statistics to application service providers. Examples of participatory sensing applications can be categorized in two groups, an environment monitoring (e.g., traffic [8-12], air pollution [3], and noise [7]) and a personal monitoring (e.g., phone data [14], user activity [4], and context [6]). In the environment monitoring, the pre-defined number of user sensing data is required for a given geographic region at a given time in order to guarantee desired level of service quality. This paper focuses on environment monitoring participatory sensing applications in which a service provider collects the predefined number of user sensing data that includes geographical and temporal features.

B. Motivations

User participation is the most important element in participatory sensing application since application services (e.g. environmental sensing services) are truly dependent on users' sensing data. Additionally, user participation includes sending and transmitting the measurements to a service provider. During the participation, a user consumes his own private resource such as battery and computation power of his device. Also, he may expose himself to potential location privacy threats by sharing his sensing data tagged with location. Hence, without loss of generality, each user has 'true valuation' of the sensing data that denotes minimum price that the user wants to receive for their consumed resource and privacy. By monetizing and quantifying the true value, an incentive mechanism helps increase participation in the service and address privacy concerns that arise in the data collection step.

Designing incentive mechanisms requires knowing what value user place on their data and what factors this value depends on. Prior work [16] is limited to addressing the valuation of user data simply with a fixed price, and it does not distinguish different times of day, locations or various situations a user may be in. Moreover, user's true valuation differs among individuals and over different types of data, changes dynamically subject to contexts (e.g., spatial-temporal situations), and depends on the perceived useful of the returned service/application (e.g., many users ignore privacy while using Gmail, which is notorious for collecting user data). In such environments, without proper incentive or reward for user sensing data, we easily expect that users (with high true valuation) drop out of participatory sensing application, and it becomes very difficult to maintain adequate level of participants that are required for guaranteeing desired service quality.

To the best of our knowledge, it is a challenging question to design user participation incentive mechanism that removes the burden of accurate pricing for user sensing data and adapts itself to dynamic change of user's true valuation. It has never been addressed in the research domain of sensor networks. At the same time, minimizing the total cost of incentives while maintaining the required service quality gives us another challenge. Responding to these challenges, we propose a reverse auction based dynamic pricing incentive mechanism in which users can sell their sensing data to a service provider with their claimed bids and the price for user sensing data is determined not by a service provider but by users.

III. CHALLENGE IN TRADITIONAL REVERSE AUCTION

A. *Reverse Auction for Participatory Sensing*

Two types of market mechanisms can be applied to the participatory sensing applications from the pricing scheme perspective for rewarding user sensing data: Random Selection based Fixed Price (RSFP) incentive mechanism and Reverse Auction based Dynamic Price (RADP) incentive mechanism. In RSFP incentive mechanism, a service provider selects predefined number of users randomly and purchases their sensing data with a fixed price. Hence the selected users receive the fixed price equally. On the other hand, in RADP incentive mechanism, users bid for selling their sensing data, a service provider selects predefined number of lower bid price users, and the selected users receive their bid prices for their sensing data as a reward. Hence, the selling price in this mechanism dynamically changes based on bid prices of users. Compared to RSFP incentive mechanism, RADP incentive mechanism provides several inherent benefits. Since users decide their own prices for selling their sensing data, RADP incentive mechanism simplifies pricing decision of incentive cost from the service provider's point of view and users play more active roles in incentive negotiation in from the users point of view. User may enjoy and entertain the competition between other users in RADP incentive mechanism as if they play game. Additionally RADP incentive mechanism can adapt to dynamically changed data collection environments (e.g., geographic imbalance of collecting user sensing data) because when the number of participants decreases, the price increases to recruit more participants.

The analysis on participatory sensing applications from the auction's point of view is one of essential elements in designing an efficient reverse auction based incentive mechanism. The sensing data collecting mechanism in participatory sensing applications can be regarded as a reverse auction in which there are many bidders (i.e., users) $i = 1,...,n$ who want to sell their sensing data and one auctioneer (i.e., a service provider) $i = 0$ who wants to purchase m number of sensing data. The traded goods are homogeneous sensing data (e.g. environmental data such as traffic speed, temperature, CO_2 level, etc.) on a certain geographic region for a specific time period. The user's sensing data have time sensitive perishable property because the sensing data become useless if it is not used at current time in targeted participatory sensing applications such as real time traffic or environmental monitoring services. After collecting sensing data for a specific time period, the service provider also requires new sensing data again for a next time period to provide real time services continuously. Hence the reverse auction for participatory sensing applications is performed at each round r recurrently. Therefore, the participatory sensing applications can be regarded as a recurring B2C (Business To Customers) reverse auction where users (i.e., customers) sell time sensitive perishable homogeneous resources (i.e., user sensing data) recurrently. In each auction round r, each bidder i bids her bid price b_i^r for selling her sensing data and the bid price is lower-bounded by the bidder's true valuation t_i since the true valuation denotes the minimum price at which the user wants to sell the sensing data. The auctioneer selects m number of lower bid price bidders and purchases their sensing data. The selected bidders receive their bid price as a reward for sensing data. Throughout the paper, let us assume that bidders are symmetric and risk-neutral [17]. Hence they always try to maximize the following utility $U_i(b_i^r)$ at each reverse auction round r:

$$U_i(b_i^r) = (c_i(b_i^r) - t_i) \cdot g_i(b_i^r), \tag{1}$$

where $c_i(b_i^r)$ and $g_i(b_i^r)$ denote received credit for sensing data as a reward and winning probability with bid price b_i^r at auction round r respectively. Hence, $(c_i(b_i^r) - t_i)$ represents expected gain of bidder i. Since bidders are risk-neutral, they always consider trade-off between expected gains $(c_i(b_i^r) - t_i)$ and winning probability $g_i(b_i^r)$. If bidder i increases her bid price, the expected gain is increased. Instead, the winning probability is decreased. Reversely, if bidder i decreases her bid price, the expected gain decreases and the winning probability increases. Therefore, the optimal bidding behaviors in the non-incentive compatible recurring auction is adaptive bidding behaviors where if a bidder lost in the last auction round, she decreases her bid price in order to increase winning probability. Reversely, if a bidder won in the previous auction round, she increases her bid price to increase expected gain [19].

B. *Incentive Cost Explosion*

Even if users receive rewards for selling sensing data in the market, users may lose their interest in future participation if the received rewards (i.e., Return on Investment) do not meet their expectations. In the long run, if the unsatisfied users conclude that they will not be satisfied in the future with the current reward, they will drop out of the market for participatory sensing applications. Such a user drop phenomenon is exacerbated in RADP incentive mechanism. To describe such a phenomenon, let us assume that the true valuations of n bidders that denote minimum prices of willingness to receive for their sensing data are distributed in the following way:

$$t_1 \leq ... \leq t_m \leq t_{m+1} \leq ... \leq t_n$$

Since m bidders are selected as winners for selling their sensing data, the m bidders with true valuations $t_1 \ldots t_m$ are selected as winners frequently in the recurring reverse auction, because the true valuations limit the lower bounds of bid prices of bidders and the rational bidders can learn that the bid price much greater than t_m cannot guarantee winning based on adaptive bidding behavior in the recurring reverse auction. Hence, as shown in Figure 1, the bidders are classified into two classes based on their true valuations distribution in recurring reverse auction: Winners Class (i.e., bidders with true valuations $t_1 \ldots t_m$) and Losers Class (i.e., bidder with true valuations $t_{m+1} \cdots t_n$). A frequent starvation of selling sensing data of bidders in Losers Class directly decreases their satisfaction and results in the bidders' drop-out of the reverse auction. In RADP incentive mechanism, such drops of participants decrease price competition, which in turn causes the explosion of incentive cost because the remaining bidders in Winner Class constantly win. As a result they may increase their bid prices for future reverse auction rounds to maximize their expected utility based on adaptive bidding behavior. For this reason, when the number of remaining users falls below a certain level, the incentive cost for paying user's sensing data explodes in RADP incentive mechanism. Lee and Szymanski explained and simulated market price collapse by bidder drop problem in general auction mechanism reversely [19, 20]. Therefore, although RADP incentive mechanism has several advantages for participatory sensing applications, the potential incentive cost explosion problem should be considered in applying it to various participatory sensing applications. To prevent the incentive cost explosion in the recurring reverse auction while keeping several inherent advantages of auction mechanism, we propose a novel Reverse Auction based Dynamic Price incentive mechanism with Virtual Participation Credit (RADP-VPC) that focuses on minimizing and stabilizing incentive cost while maintaining adequate number of participants by keeping price competition and preventing users from dropping out of the reverse auction for collecting user sensing data.

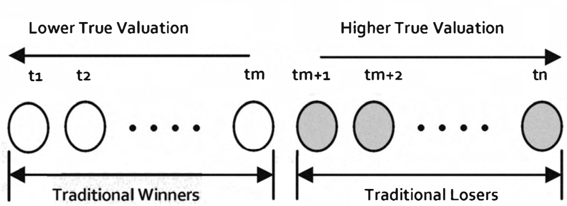

Figure 1. Winner and Loser class in reverse auction

IV. INCENTIVE MECHANISM DESIGN

RADP-VPC incentive mechanism is on the basis of discriminatory price, sealed bid reverse auction [18] for selecting m winners who can sell their sensing data. The design goals of RADP-VPC incentive mechanism focus on retaining participants during the recurring reverse auction and recruiting dropped users in order to achieve maintaining adequate number of participants for desired service quality while minimizing incentive cost by preventing incentive cost explosion.

A. Participant Retaining Mechanism

To maintain price competition and prevent incentive cost explosion, enough users in *Loser Class* of Figure 1 should participate continuously in the recurring reverse auction. For this purpose, the proposed incentive mechanism provides the following novel winner selection strategy using virtual credit as a reward for user participation itself. A user (i.e., bidder) i who lost in the previous auction round $r-1$, and participated in current auction round r receives virtual participation credit v_i^r as a reward for last participation itself. The virtual participation credit v_i^r can be defined as

$$\begin{aligned} &v_i^r = v_i^{r-1} + \alpha, \text{if user } i \text{ lost auction round } r-1 \\ &v_i^r = 0, \text{otherwise} \end{aligned} , \quad (2)$$

where α represents the amount of virtual participation credit. The virtual participation credit v_i^r has a cumulative property. Hence whenever a bidder loses in participating auction round consecutively, the amount of α is added to the virtual participation credit. The virtual participation credit v_i^r is set to zero whenever user i won or dropped out in the previous auction round. The virtual participation credit can only be used for decreasing bid price, thus increasing winning probability of user for current auction round. For this purpose, we define two types of bid prices: One is actual bid and the other is competition bid. The actual bid b_i^r is the bid price that is claimed by user and the competition bid price b_i^{r*} can be defined as

$$b_i^{r*} = b_i^r - v_i^r \quad (3)$$

In the proposed incentive mechanism, the auctioneer uses competition bid b_i^{r*} for selecting sellers (i.e., winners) in each auction round. Hence the virtual participation credit increases the winning probability of the bidder by decreasing competition bid. With this mechanism, bidders who have higher true valuation than bidders of Winner Class can be winners by participating continuously. Hence, the virtual participation credit encourages continuous participation of bidders in participatory sensing applications.

B. Participant Recruiting Mechanism

As we already discussed in Section III, users drop out of the auction if the received rewards do not meet their expectations. Hence recruiting dropped users is as important as retaining current active users in designing incentive mechanism for participatory sensing applications. In the reverse auction based incentive mechanism, the selling price of sensing data of each user dynamically changes based on price competition. If price competition is decreased by drop-out of bidders, the selling price increases. In this situation, the proposed mechanism reveals the highest selling price to the dropped users only. With this approach we can expect that the dropped users who have lower true valuations than revealed highest selling price may rejoin in the reverse auction for participatory sensing application because the dropped users have higher winning probability than the winner of the previous auction round with highest bid price.

Figure 2 illustrates the overall data collecting process using participant retaining and recruiting mechanisms of the proposed RADP-VPC incentive mechanism. The active participants register and download the mobile client application. The mobile clients send sensing measurements with bid prices to a service provider. The service provider checks the data quality, selects the winners based on their competition bid price of Eq. (3), and notifies to the selected winners. The selected winners receive their bid price and the dropped users receive the maximum bid price information for the participant recruiting mechanism.

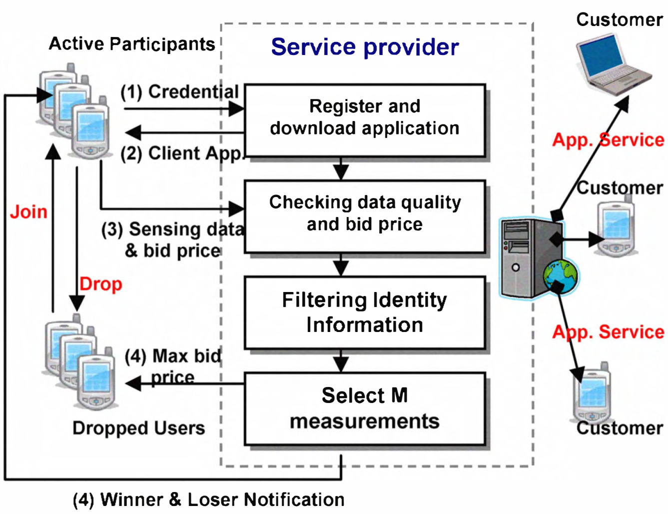

Figure 2. Data collection process using RADP-VPC

V. EXPERIMENTATION

In our experiments, we compare RADP-VPC incentive mechanism with RSFP that is widely used in rewarding mechanism [15] and identify pros and cons of each approach.

A. Experimentation Setup

This section describes user behaviors (i.e., bidding, dropping and rejoining), performance measures, and base experimentation scenarios. Without the loss of generality, we pick only one target area for environment monitoring to simplify our analysis on the result. A single target area can be extended to multiple target areas with different importance of monitoring in real world scenarios, where a service provider places different requirements on the minimum number of sensing data or different budget allowed for total incentive cost. Given the target area, a service provider picks the predetermined number of measurements at each time period. In our simulation model, we do not specify the unit of time period, but it can be viewed from a minute or a day according to various needs of applications. In this study, we measure the quality of monitoring by counting the number of active participants since the more number of measurements ensure higher confidence and make services robust against outliers.

In our user behavior model, participants drop when their efforts related to obtaining sensing data is undervalued than their expected true valuation of their efforts. (i.e., participant drops when the ROI (Return on Investment) is smaller than what they expected). Based on true valuation t_i of all the efforts for obtaining sensing data of user i, each user's ROI S_i^r at each reverse auction round r can be defined as following way:

$$S_i^r = \frac{e_i^r + \beta}{p_i^r \cdot t_i + \beta}, \tag{4}$$

where p_i^r denotes the number of participation of user i until current auction round r. Hence, $p_i^r \cdot t_i$ and e_i^r denote the expected minimum reward and the actual earned reward of user i until current reverse auction round, respectively. The β denotes user's tolerance period. A larger β makes the ROI value to decrease slower. Therefore, the ROI value is ratio of the earned reward (i.e. user's return) to expected minimum reward (i.e., user's investment). We use each user's ROI value to decide whether he drops out of the reverse auction for participatory sensing application. Each user drops when the ROI value goes below 0.5, which we set to satisfaction threshold. In the simulation we assign different tolerance period β so that each user has different minimum ROI threshold for dropping out of the reverse auction.

To model the rejoining behavior of dropped user, our recruitment mechanism broadcasts maximum bid value of winners only to the dropped users. Hence, the dropped users k can calculate the expected ROI value ES_i^{r+1} for the next auction round $r+1$ with the revealed maximum bid price of winners in the previous auction as shown in the below:

$$ES_k^{r+1} = \frac{e_k^r + \varphi_r + \beta}{(p_k^r + 1) \cdot t_k + \beta}, \tag{5}$$

where φ_r denotes the revealed maximum winning bid price at the previous reverse auction round r. If the computed expected ROI value of the user becomes larger than her minimum ROI threshold, the user rejoins the reverse auction in order to sell her sensing data. Note that the maximum winning bid price φ_r is only visible to dropped users so that we prohibit winners from increasing their bids close to the maximum bid. In the user behavior model, we assign to users a set of different tolerance periods β of Eq. (4) that is uniformly distributed in the range from 3 to 7. Hence each user has different minimum threshold for ROI value for dropping out of the reverse auction.

As we already explained in section III, the adaptive bidding behavior, known optimal for recurring discriminatory price sealed bid reverse auction, is used in this simulation. Hence, if a user loses in the previous auction round, she decreases the bid price by 20 % of current bid price for a next auction round. Reversely if a user wins in the last auction round, she increases bid price by 10 % of current bid price or stay at current bid price with probability of 0.5 for next auction round. For initial bids of users, we randomly generate the first bid of each user uniformly distributed between her true valuation and its 150%. To observe the effect of participant recruiting mechanism, when dropped user try to rejoin based on expected ROI value ES_k^{r+1} for next auction round $r+1$, a dropped user k tosses the coin and randomly decides to join or not if the expected satisfaction value of next reverse auction round is larger than her ROI threshold. We vary the percentage of actual rejoining in order to reflect the uncertainty in user reaction.

Based on these user behavior models, the service provider collects 20 measurements per a geographic area of interest every observation time period which we call round. Initially, 100 users participate in selling their sensing data and we visualize how many users the compared incentive mechanisms maintain in time. To see the dependency of incentive mechanisms on the distribution of true valuation, we simulate following three different true valuation distributions among users: Uniform distribution, Exponential distribution, and Gaussian distribution, all of which have 5 as a mean. We run 2000 rounds of the auction. We repeat the whole experiment trial 50 times with different random seeds and average out the number of active participants and the cost.

B. *Experimentation Results*

The following experiment results illustrate how the proposed incentive mechanism enhances the number of active participants in a cost effective way. We evaluate the effectiveness of our proposed mechanism in terms of following perspectives: incentive cost for maintaining desired service quality, social welfare, incentive mechanism stabilization, and fairness of incentive distribution. Table 1 summarizes the pros and cons of the compared two incentive mechanisms.

Table 1. Summary of incentive mechanism comparison

	Strengths	Weaknesses
RADP-VPC	- Eliminate complexity of incentive price decision. - Able to adapt to dynamic environments. - Minimize incentive cost. - Better fairness of incentive distribution. - Higher social welfare.	- Relatively harder to implement than RSFP
RSFP	- Simple to implement - Easy to predict total incentive cost	- Difficult optimal incentive price decision - Unable to adapt to dynamic environments.

1) Incentive Cost Reduction: Figure 3 shows the required incentive cost for maintaining 20 participants in the participatory sensing applications. Compared to RSFP incentive mechanism, the proposed RADP-VPC incentive mechanism can reduce the incentive cost by 45%, 28%, and 63% to maintain same number of participants for Uniform, Gaussian, and Exponential distribution of true values respectively. Thanks to price competition based winner selection strategy of the reverse auction, RADP-VPC incentive mechanism can select valuable user group who have lower true valuation than others. This means that the proposed incentive mechanism can select the users who can be retained by lower cost than others, and purchase from them. Such winner selection feature can decrease the required total incentive cost for purchasing user sensing data. Reversely, such phenomenon also means that the proposed RADP-VPC incentive mechanism can satisfy and retaining larger number of users than RSFP mechanism with equal incentive cost. Hence, the proposed mechanism can achieve better social welfare since more number of users can be satisfied in RADP-VPC mechanism.

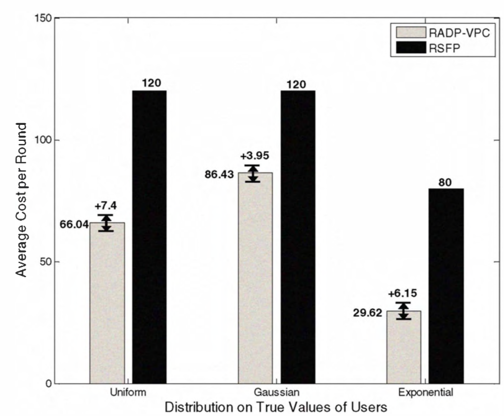

Figure 3. Incentive cost reduction by RADP-VPC

Additionally, the virtual participation credit can encourage and stimulate participation of user with higher true valuation. Hence the proposed incentive mechanism can keep the price competition and thereby prevent incentive cost explosion and stabilize the incentive cost in dynamic pricing environments. As you can see in Figure 4, using virtual participation credit can stabilize incentive cost by keeping price competitions via preventing higher true valuation users from dropping out of the reverse auction. However, random selection property of RSFP incentive mechanism selects some of higher true valuation users as winners for purchasing their sensing data with fixed price. Hence, even if the higher true valuation users receive fixed incentive cost, it is hard to satisfy the users with the incentive cost and requires higher incentive cost in order to retain the users with higher true valuation.

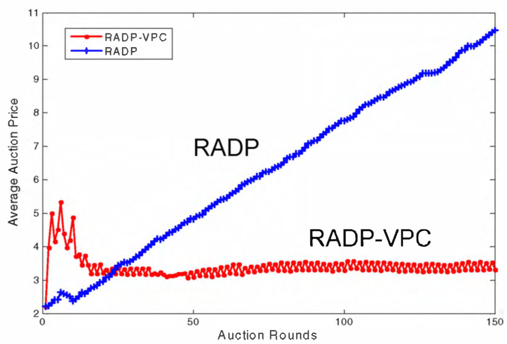

Figure 4. Stabilized incentive cost in RADP-VPC

2) Improved Fairness: RADP-VPC incentive mechanism improves the fairness of incentive cost distribution against users with different true valuations. Figure 5 illustrates the winning probability distribution of a user with a specific true valuation in two different incentive mechanisms, RADP-VPC and RSFP. The random selection strategy of RSFP incentive mechanism treats two groups of users with higher true valuations and lower true valuations equally. Hence, the winning probability (i.e. the probability of selling user sensing data) of users with higher true valuation becomes equal to that of users with lower true valuations. In contrast, the reverse auction based winner selection strategy of RADP-VPC treats users differently based on their true valuations. It allows users with lower true valuation to win more frequently than users with higher true valuations. Although it does not achieve the perfect fairness (where the winning probability is inversely proportional to true valuations of users), RADP-VPC still gains a considerable improvement on the fairness of incentive cost distributions, relatively compared to RSFP. If we dynamically change the virtual credit according to users with different true valuations and tolerance periods, the fairness can be more improved. The detail manipulation of the virtual participation credit remains an open question for future works.

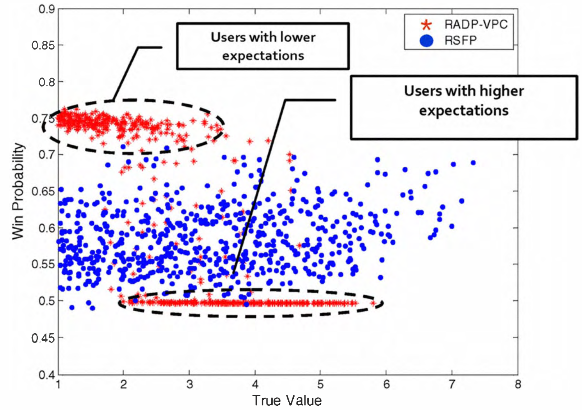

Figure 5. Fairness against true valuation

3) Service Quality Guarantee: RADP-VPC incentive mechanism guarantees the participatory sensing service in operation. In other words, it always achieves the desired minimum number of active participants for providing adequate level of service quality, thereby preventing the service from breaking down. The price competition based winner selection in the reverse auction mechanism can guarantee at least desired minimum number of participants (i.e., 20 participants) for guaranteeing service quality. Additionally, the virtual participation credit can retain additional participants from the traditional loser class. Therefore, as shown in Figure 6, RADP-VPC incentive mechanism can guarantee the desired service quality because it can adapt to various distributions of user's true valuation dynamically. Furthermore, it motivates users to moving to uncongested geographic areas to maximize their ROI which helps geographic balance of sensing data collection.

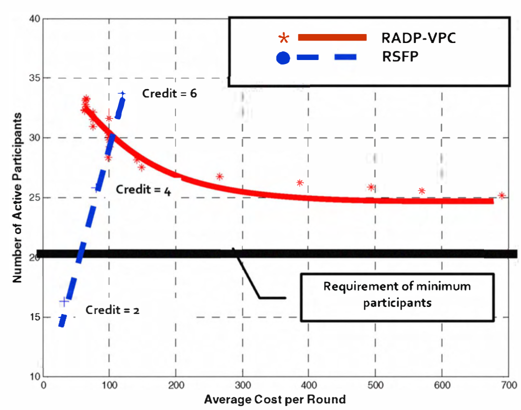

Figure 6. Service quality guarantee

On the other hand, RSFP fails to achieve minimum number of active participants (i.e., 20 participants) if the value of fixed credit is not properly chosen, as depicted in Figure 6 (see the case when credit=2). This is caused by the fact that the static property of fixed pricing cannot adapt to dynamic distributions of user's true valuations. Therefore, the service breakdown can happen often in the real world deployments since the system designer does not have the prior knowledge on the distribution of true values of participants.

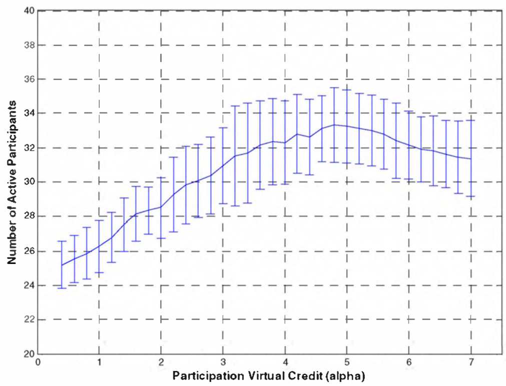

Figure 7. Dependency of active participants on VPC

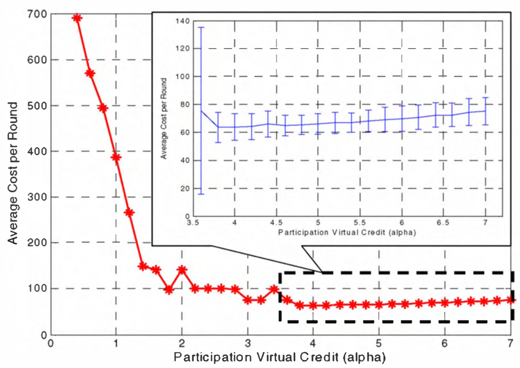

Figure 8. Dependency of average incentive cost on VPC

4) Optimal Virtual Participation Credit: The optimal Virtual Participant Credit (VPC) of the proposed mechanism can stimulate participations of users with higher true valuations and minimize the incentive cost for maintaining adequate level of user participations (i.e., service quality) in participatory sensing applications. As you can see in Figure 7, if the VPC is increased, the number of active participant is also increased because higher VPC can encourage higher true valuation users to participate in selling their sensing data in the reverse auction. However, if the VPC goes beyond the certain point (i.e., optimal value), the number of active participants starts to decrease because the increased VPC can select users with quite high true valuation as winners for selling their sensing data, and the selected user will drop out in the end because the return from selling their sensing data cannot meet their high expectations. In terms of incentive cost perspective, the optimal VPC can minimize the incentive cost because it keeps the price competition and prevents the incentive cost explosion. However, a quite high VPC increases incentive cost slightly because the participation incentive is paid to users based on their original bid price (not competition bid price in Eq. (3)). The Figure 8 illustrates such phenomenon. Therefore, the optimal VPC should be selected by considering distribution of users' true valuations and minimum number of active participants. The algorithm for choosing the optimal VPC remains for future works.

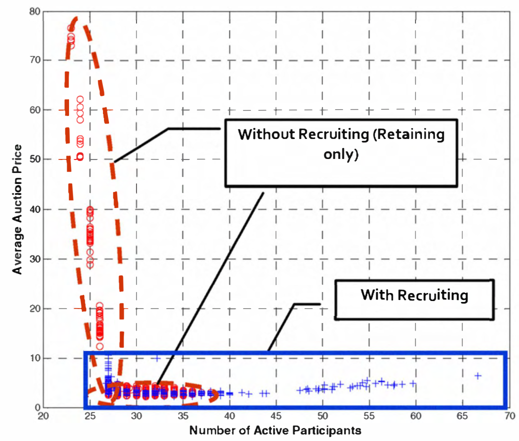

Figure 9. Retaining and recruiting

5) Recruiting meets retaining: We also simulated the dropped user's rejoining case in the proposed RADP-VPC incentive mechanism. The recruiting mechanism helps increasing active participants and reduces the incentive costs. Specifically, recruiting dropped users increases the bid price competition, which in turn leads to stabilize and minimize incentive costs. To compare RADP-VPC and RADP-VPC with recruiting, we randomly select the virtual credit, alpha between 0.5 and 7, run two schemes, and measure the incentive cost and the number of active participants of each experiment trial. Figure 9 shows that RADP-VPC with recruiting dramatically suppresses the auction price, thereby alleviating the pressure on choosing the right value of Virtual participant Credit (i.e., alpha in Eq. (2)). To recruit users who once dropped out, we broadcast a current max bid to them like an invitation. As a broadcasting method, either SMS or Email can be used to spread out historical change of max bids in previous auction rounds. However, note that the information on the max bid should be kept hidden from active participants.

VI. DISCUSSIONS

We address the limitations and possible enhancements of the proposed incentive mechanism.

Our proposed incentive mechanism reveals user locations to a service provider regardless of winning or losing. Although winners are paid back with earned credit that compensates their privacy infringements, losers not only waste their efforts related to data gathering but also let their own privacy threatened even if they receive virtual participant credit. To alleviate the privacy concern, one potential solution is to keep data encrypted while auction is being performed. Then, only the selected data will be decrypted by a service provider who accesses the proper decryption key through communicating with the owners of data. However, this approach makes it impossible for a service provider to consider data quality as well as bid price in selecting data. Furthermore, even encrypted measurement cannot provide guaranteed privacy because the encrypted measurement should be tagged with the ID of geographic area to perform a reverse-auction per geographic area. Then the ID of geographic area can be still mapped to the proximity of user location.

Instead of deploying the proposed market mechanism based data collection on service providers, it can also be deployed as a middleware of a data broker for participatory sensing application. A data broker is located between data providers and data consumers. Roles of a data broker can be limited or extended according to different business models. It provides the following services to data consumers: (i) data collection infrastructure including client software, servers, and databases, (ii) maintenance and management on databases and APIs, (iii) data mining on collected raw data, and (iv) protection against user privacy and security. In the proposed scheme, service providers set up the incentive cost function only with user's bid values. However, some service providers prefer measurement accuracy to the incentive cost. In such environments, we expect that the main job of a data broker is to match the user selling price and data quality to service providers with different requirements. Some of users' measurements and price are not acceptable to a certain service provider, but they may be acceptable to other service providers. This extension gives higher chance of being winners to users and at the same time it helps achieve a higher penetration rate.

Designing optimal reverse auction mechanisms for participatory sensing applications is another challenge because traditional incentive compatible auctions, such as Vickrey auction, can exacerbate incentive cost explosion in the recurring reverse auction environments [20, 21].

VII. CONCLUDING REMARKS

User participation is one of the most important elements in participatory sensing applications. In this paper, we study the economic model of user participation incentive. We address the problem of retaining the desired number of active participants in the participatory sensing applications to provide adequate level of service quality with minimal incentive cost. To tackle this problem, we propose Reverse Auction Dynamic Price with Virtual Participation Credit (RADP-VPC) incentive mechanism where users can sell their sensing data to a service provider. Compared to Random Selection Fixed Price incentive mechanism, the proposed incentive mechanism not only reduces the incentive cost by 60% (at best) but also stabilizes the incentive cost while maintaining the desired number of active participants by preventing users dropping and keeping the bid price competition. The proposed incentive mechanism improves the fairness of incentive distribution and social welfare. For future study, we plan to extend our study based on the discussions of section VI, and design advanced algorithm for finding optimal virtual participant credit and more efficient reverse auction mechanism.

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