

Towards a Sustainable Incentive Mechanism for Participatory Sensing

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Abstract—Participatory sensing plays an important role in Internet of Things (IoT) applications to collect large scale data via powerful sensors from ubiquitous devices. However, without a proper incentive mechanism to pay rewards to the users, the application provider (platform) cannot keep the motivation of users due to their costs during the data collection and uploading process. Moreover, conventional incentive mechanisms can hardly meet the requirements of data quality in various application scenarios in which the importance of data quality differs. In this paper, we present a novel incentive mechanism for sustainable participatory sensing considering the user selection and payment allocation in the long run. It takes data quality and historical participation information into account to prevent users from dropping out. It makes users report their costs truthfully and easily adjusts the adaptability to applications with different quality requirements. Extensive evaluation results demonstrate that our solution outperforms alternative state-of-the-art approaches and significantly improves system sustainability.

I. INTRODUCTION

In this paper, we develop a novel incentive mechanism for participatory sensing applications that successfully retains high-quality users to improve system sustainability. This work is motivated by the emergence of participatory sensing applications [1], where data are collected from smartphones, social networks, and other sensing devices, then offloaded to backend cloud servers. We assume that users will typically expect rewards from the application provider for contributing to the participatory sensing platform, otherwise lose momentum and finally quit. The application provider, on the other hand, aims to keep those who generate data with high quality stick to the platform, meanwhile minimize the total cost of rewards. This research challenge motivates the work described in this paper.

Participatory sensing plays an important role in the Internet of Things (IoT) field and allows a group of users to contribute sensory information to form a body of knowledge. A growth in mobile devices, such as the smartphones, which has rich and ubiquitous sensors, has made participatory sensing viable in large scales. Participatory sensing can be used to retrieve information about the environment, weather, urban mobility, congestion as well as any other sensory information that collectively forms knowledge [2]. Therefore, continuous collection of data with sufficiently good quality is the most critical factor for *sustainable* participatory sensing platforms.

To avoid users losing their interests and momentum in participating the service, the concept of *incentive mechanism* has been proposed in research community in recent years [3]. Typically, the platform claims several sensing tasks at first,

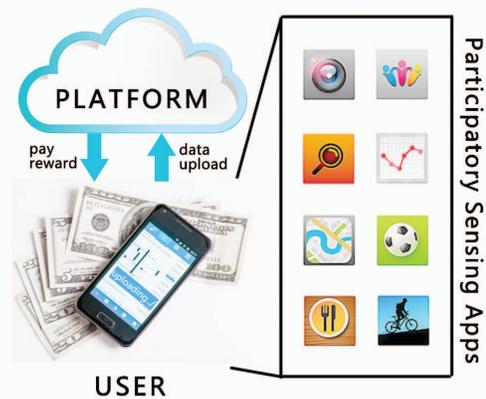


Fig. 1. Incentive mechanism in participatory sensing.

then each user asks the platform for a price (also called a bid) as the payment of the data they collected, finally the platform would make decisions on purchasing data from which users and the amount of their rewards based on the value of data, as illustrated in Figure 1. For instance, mechanisms based on Reverse Auction [4] allows users to bid for selling their sensing data, where the platform selects a certain number of users with lower bid price. The selected users are called winners, while the rest are losers. Then the platform allocates payments for the winners. As another example, Random Selection with Fixed Price (RSFP) [5] randomly selects winners from users and pay the same reward to all winners. However, all existing work aims to maximize the quantity of data or minimize the platform's cost, but ignores the quality of the data and the stickiness of users. We argue that this may significantly reduce the system sustainability in the long run.

The philosophy underlying our work is that we believe it is reasonable to increase the rewards to users who always contribute data with high quality, instead of paying just as much as the user's bid (zero profit) as in existing incentive mechanisms, to achieve a sustainable participatory sensing platform. The encouraging nature of this new approach helps control the whole bidding process and avoid the dropping out of high-quality users.

The main contribution in this paper lies in that we develop a novel incentive mechanism in participatory sensing applications, in which user historical information and data

quality are taken into account and a decision making algorithm is designed to exploit the trade-off between minimizing the platform's cost on rewards and keeping users active on participation. The biggest challenge behind this problem is that as the result of information asymmetry, the exact utility composed of quality of users is unknown, thus conventional incentive mechanisms are not applicable here. Instead, our solution predicts such information by taking advantage of users' historical data, and provides a decision making algorithm to decide the winner set and the payment to each winner.

Our solution is evaluated by results from extensive simulations with up to one thousand participants. Evaluation results demonstrate that our proposed solution successfully improves the sustainability of participatory sensing platform, more importantly, we achieve the goals of maintaining the platform utility at a high level and keeping the users active. In addition, the design of our incentive mechanism is general enough to be used in any long-term participatory sensing application.

The remainder of this paper is organized as follows. We compare our work with state of the art in Section II and present the system model and incentive algorithm in Section III and IV, respectively. The evaluation for our proposed solution is discussed in Section V. Finally, we conclude the paper in Section VI.

II. STATE OF THE ART

Thanks to the fast development of smartphones and social networks, participatory sensing receives more attention in various applications in recent years. People share their information about the point of interests (POIs) to social networks and special-purpose services, to help each other in health [6], [7], environmental monitoring [8], [9], transportation [10]–[12], disaster response [13], personal security [14] and so forth. For instance, [9] has presented the Personal Environmental Impact Report (PEIR) that uses location data sampled from everyday mobile phones to calculate personalized estimates of environmental impact and exposure. [12] predicts the fuel consumption for each segment of the road and recommend a fuel-efficient path to the driver by collecting consumption together with other information about moving vehicles. However, due to the opportunistic nature of participatory sensing, continuously collecting data with sufficient quality is the most critical factor for participatory sensing platforms. Our work takes advantage of these services, aiming to provide users with encouraging incentive to improve their stickiness.

The work proposed in this paper complements a large body of participatory sensing literature that focused on short-term data collection. For example, a platform-centric and a user-centric models are introduced in [15]. In the platform-centric model, the platform determines the payments to users by their sensing time following a Stackelberg Equilibrium, with the assumption that platform has the knowledge about unit costs of users. In the user-centric model, the user claims a task set to accomplish and the bid price. The aim of platform in both case is to maximize the total value of data completed subtracts the

payments to winners. A reward decision strategy is designed in [16] for client (platform) to maximize the utility. If the joined users are more than a certain number, the client will get a utility and pay each user the equally divided reward, otherwise the auction is failed. Complete and incomplete information scenarios are investigated under probabilistic framework. [17] designs a mechanism in a location based multi-task scenario. The users claim multiple tasks-bid pairs to the platform, then the platform choose some pairs to cover all the tasks while minimizing the total payments. An approximate algorithm is proposed for determining the winning bids, then a critical payment scheme is implemented to guarantee that submitted bids of users reflect their real costs. A payment allocation function under all-pay auction has been designed in [18] to maximize the platform's utility with a stochastic framework. In this work, all the users need to upload their data while only one user can be selected as the winner. This method is valid for risk-averse user and in information asymmetry condition. And the mechanism is proved to satisfy individual rationality.

An online mechanism is proposed in [19], in which the platform can decide whether to pay the user whenever she arrives. Conditions that users are with or without an arrival-departure time have been discussed. The user will be selected if the cost performance of this user is higher than a dynamically changing threshold. This mechanism also satisfies bid truthfulness. Another online mechanism is designed in [20], which applies a sequential all-pay auction to solve a multi-task utility optimization problem. The effect of extensive user participation and users' efforts into consideration. [21] designs an incentive negotiation mechanism, in which the platform will interact with the users by broadcasting prices for each subregion and collecting users' responses before selecting winners and allocating payments. A utility-based incentive mechanism with the concept of micro-economics via a third-party server is designed in [22], [23], in which the demand and supply influence the value of data. Three models in single-requester single-bid, single-requester multiple-bid and multiple-requester multiple-bid conditions are discussed in [24], where "requester" is the platform and "bid" means user. [25] designs three online incentive mechanisms, in which one method pursues utility maximum while the other two ensure bid truthfulness. Also, the mobile nature of users is discussed in this paper.

The IDF method is designed in [26], which studies the fairness of incentive distributions among participants in a specific scenario, where users are both data contributors and data consumers. The fairness was reflected on the relationship between data contribution and received service quota for future data consumption of the users. A mechanism considering amount and distribution of samples in data is designed in [27]. This mechanism uses a weighted entropy as quantitative metric to evaluate the distribution of samples and a greedy-based allocation strategy. [28] designs an optimal reverse auction mechanism considering the calculation of data value and payments to be allocated with bid truthfulness using a stochastic framework. A multi-attributive auction is designed in [29],

which considered many attributes of the sensing data. The platform measures the value of the data and gives the users the incentive through price negotiation. [30] designs two methods which consider optimizing the social welfare (subtracting the total costs of all users from platform’s utility), in which the former is based on the Lagrangian dual decomposition while the later can be converted to optimal pricing problem.

This paper is different from the above work in considering the long-term development of participatory sensing platforms and emphasize the stickiness of high-quality users to the platform.

More importantly, our work focuses on a new problem in participatory sensing. Namely, the problem of designing incentive mechanism to improve system sustainability. Past research on long-term incentive mechanism in participatory sensing describes how to prevent users from dropping out of the service, since the losers of the selection based on reverse auction take higher risks than the winners in each round due to several factors (e.g. higher costs than winners) which may lead to a reduction of number of users, and will eventually increase the cost of platform.

A winner selection strategy is proposed in [31] for selling e-services with a method to prevent bidder drop problem. The service provider allocates services to the bidders who bid higher than a threshold, and the rest of services are primarily sold to the bidders who bid less than the threshold but have higher probabilities to drop out in next round. A Reverse Auction based Dynamic Price with Virtual Participation Credit (RADP-VPC) mechanism using fixed payments is introduced in [5]. The service provider (platform) gives the virtual credits to the losers in reverse auction, which is used in winner selection stage as if the bidders’ bids are reduced by the credits. The credit keeps rising when the bidder continuously lose and will be reset to zero once she wins. Besides, the provider reveals the highest price of the winners in this round to the losers, to recruit them if this bid is higher than the losers’ expected bids. A location based data collection with budget constraints is discussed in [32]. It is assumed that each user has a coverage of sensing, and the valuable points covered by the user is the task set that the user has completed. The object is to select the cost-minimum set of the users who cover all the points. The authors use an approximate algorithm combined with the method the same in [31] to select users while preventing them from dropping out and recruiting them back. [33] provides a mechanism that maximize the social welfare, which is the total payments to users, and prevents users from dropping out by keeping all participated users’ winning probabilities higher than the dropping threshold of the users.

This paper complements that past work by taking a step further and looking at the important problem of how to prevent *high-quality* users dropping out. This unique challenge comes from the design of auction process in which users with high quality may be treated unfairly and lose interests to the platform gradually.

Finally, our system design is related to state of the art

auction algorithms in other application scenarios. For example, [34] considers the problem of spectrum sharing among primary (licensed) users (PUs) and secondary (unlicensed) users (SUs) based on bandwidth auction, in which each SU makes a bid for the amount of spectrum and each PU assigns the spectrum among the SUs according to the information from the SUs without degrading PS’s own performance. [35] presents a new algorithm of on-demand P2P streaming protocol design which deems streaming session as an auction where each peer participates locally by bidding for and selling media flows encoded with network coding. However, our paper is different from this existing work in that our mechanism is based on reverse auction while the above two are based on ordinary auction (where bidders pay money). Besides, our method uses single-buyer multi-seller framework while the other two methods are in multi-buyer multi-seller conditions.

To the best of our knowledge, no previous work has been applied to participatory sensing application scenarios where incentive mechanisms were investigated that (i) takes data quality and user historical information into consideration and that (ii) aims to improve system sustainability. Our paper fills in this gap by proposing a novel incentive mechanism in which user historical information and data quality are taken into account and a decision making algorithm is designed to exploit the trade-off between maximizing the platform’s utility and keeping users active on participation.

III. SYSTEM MODEL

In this section, we present the system model for incentive mechanisms to achieve sustainable participatory sensing. We first describe the model and assumptions, then illustrate the problem statement in detail.

A. Model and Assumptions

Our system is designed to operate in a participatory sensing platform of N users that can generate sensory data via smartphones or other mobile devices. The set of users is denoted by $U = \{1, 2, \dots, i, \dots, N\}$. The participatory sensing serves in a long-term scheme, i.e., it collects data from users in multiple rounds, denoted by a sequence of time slots $\{1, 2, \dots, t, \dots\}$. In each round t , user i can upload her data with quality $q_t^i \in (0, 1]$, and the quality is set to 0 if this user does not participate in this round. The platform pays the users for the uploaded data based on their quality.

We assume that the platform knows all historical information of all users. Ideally, if the platform knows all information about data quality from users, it can easily pick up the winners after negotiation. However, it is impractical for the platform to foresee the data quality as it is not a *priori* known information. In order to find a reasonable measurement to select winners, we leverage the historical information of the users, such as participation frequency (i.e., how many times this user has participated in) and average data quality in the past.

To represent the average data quality, we introduce a participation array \mathbf{h}^i for each user,

$$\mathbf{h}_t^i = \begin{cases} 1 & \text{if user } i \text{ participates in round } t \\ 0 & \text{otherwise} \end{cases}$$

to represent the participation information of a user, which contains $t'-1$ elements in round t' (the same as other arrays in rest of this paper), since all information about users updates after each round. In addition, we use \mathbf{q}^i to denote the data quality series of user i in past rounds. Therefore, the average data quality can be represented by $\bar{q}^i = \frac{\mathbf{h}^i \cdot \mathbf{q}^i}{|\mathbf{h}^i|}$, in which $|\cdot|$ indicates the $l-1$ norm of the array, and the average quality is set to a constant (for convenience) when the first time user i participates in the platform. Since there is no priori information about quality in the current round, the average data quality only considers historical information.

The joined users in one round form the active user set U_t . For each participant in active user set at round t , there is a cost c_t^i , and a bid b_t^i from this participant. The bid is no less than the cost $b_t^i \geq c_t^i$, as we assume that a rational user won't take the risk to get negative revenue. Some active users are chosen as winners at round t , and they compose the winner set S_t . The payments to active user i is p_t^i , $p_t^i \geq b_t^i$ if $i \in S_t$ to ensure the winners get a non-negative profit, otherwise the payment is set to 0. Since the formulation of processes in different rounds are the same to each other, we omit the subscript t in the rest of the paper unless otherwise specified.

The auction process in each round acts as follows: First, users bid prices to the platform to compensate the prediction costs generated in data collection. Then, the platform selects a subset of them, allocates payments and then receives the data. The decision making of selection and allocation processes are all based on the historical information of users as well as the remaining budget of the platform. In order to combine the participation information and average quality of the user, and to support a sustainable participatory sensing, we propose the concept of "fitness" to replace the conventional total utility the platform expects to obtain, so as to represent the trade-off between system gain and high-quality user stickiness. For each active user in a round, the fitness is defined as $f^i = g(\mathbf{h}^i) \cdot \bar{q}^i$, where $g(\cdot)$ measures the historical participation behaviors of the users. The total fitness of users in the winner set is $F = \sum_{i \in S} (g(\mathbf{h}^i) \cdot \bar{q}^i)$, which contains the historical participating information and data quality of users.

The platform allocates payments to all winners, the total cost of the platform in each round is denoted as $P = \sum_i p^i$, it is unnecessary to indicate whether i is in winner set S since for those who lose in that round, their payments are zeros. The platform has a finite budget R for each round, the total cost of platform cannot exceed the budget in each round, i.e. $P \leq R$. The total utility of the platform in one round should be the sum of real qualities of the winners. However, since we only know the average quality and the platform won't figure out qualities of this round before it ended, we cannot straightly maximize the utility but the expected-utility calculated by

average quality. Thus the utility is defined as $M = \sum_{i \in S} \bar{q}^i$, which means the expectation of the total qualities the platform can get from the winners in this round.

B. Problem Statement

Under this system model, we are interested in solving the following problem: which users should be chosen as winners in each round? Our goal is to find a winner set S to maximize the fitness in each round, thus the optimization function is:

$$\begin{aligned} & \max_S \sum_{i \in S} (g(\mathbf{h}^i) \cdot \bar{q}^i) \\ & \text{s.t. } \sum_{i \in S} p^i \leq R \end{aligned}$$

The biggest challenge lies in the information asymmetry, i.e., the platform has no priori knowledge about neither the qualities of the users, nor their real costs in performing data collection. Thus how to make decisions about payment to each user and the selection of the winners to optimally reduce this asymmetry is the most important and complex part of the designing. Next, we will describe the details of sustainable incentive mechanism.

IV. SUSTAINABLE INCENTIVE MECHANISM

In this section, we present our proposed incentive mechanism in detail. It consists of three main parts. First, we explain the reasons and advantages of using the concept of fitness. This concept is indivisible in our model since the platform aims at maximizing its long-term and short-term utilities under an asymmetry of information. Second, we discuss how to calculate the potential payments to users adopting a Vickrey Auction based approach to allow users to bid prices truthfully. Finally, we describe a winner selection method under the budget constraint in each round, and explain our algorithm which uses a dynamic programming solution of Knapsack problem.

A. Concept of Fitness

The usage of fitness helps us achieve the trade-off between platform's utility and users' participation. The asymmetry of information makes the platform to act blindly, to reduce the influence of this asymmetry, the platform expects the users to bid truthfully and leverage valid information from accumulated data (e.g., average quality) since the platform will not get the data before the winners get their payments. Thus the fitness contains two parts, one is about the participation array, and the other about the average quality. We first discuss the advantage of choosing average quality. Assume that there is an opportunistic user who has the highest average quality in this round, if the data quality is manipulated in order to lower cost and finally increase the net revenue, it is safe in this round since the platform cannot detect this cheat activity in advance. But after this round, this data will also reduce the average quality of this user, and the probability being selected as winner will be affected. Thus the best strategy of user is to upload data with relatively stable quality.

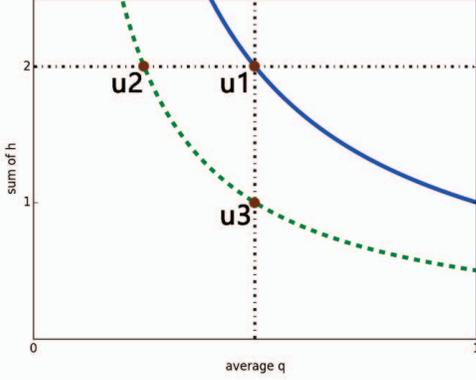


Fig. 2. An illustrating example with three users u_1 , u_2 and u_3 : all points in each curve have the same fitness value. u_1 has higher fitness while u_2 and u_3 are the same. With the same participation frequency, user with better average quality has higher fitness; while with the same average qualities, the user who participates more has higher fitness.

The explanation for participation function containing historical participation information is a little more complicated. In an extreme case that participation function $g(\cdot)$ is chosen to be a constant (e.g. $g(\cdot) = A$), it is obvious that fitness is proportional to platform's expected utility, $F = \sum_{i \in S} (A \cdot \bar{q}^i) = A \cdot \sum_{i \in S} \bar{q}^i = A \cdot M$, which implies that our model can be simply specialized to fit the methods that only consider platform's utility.

1) *Sustainable Utility of the Platform and Long-term User Participation*: The concept fitness is introduced to achieve a global concern about both long-term participation of users and the utility of the platform. The reason to consider long-term participation is that if the platform only aims at maximizing the short-term utility, where all users are treated without difference regardless of the historical contributions, long-term active users will feel unfair (i.e., the winning probability or reward of them are the same with brand new users), and may quit. Although this may not lead to a systematical user drop problem, the long-term utility is still influenced. As we explained above, the fitness can be transformed to platform's utility, but by a suitable historical participation function, we can maintain a high utility of platform and at the same time encourage users to contribute in the long run.

To attract users' attention, we need to use non-trivial participation function. The most important property of participation function is monotone increasing. For illustration, we simply use a function $g(\mathbf{h}^i) = |\mathbf{h}^i|$ (i.e., the number of rounds user i has participated in before this round). As shown in figure 2, the points on each of the two curves have the same fitness, assume that there are three active users u_1 , u_2 and u_3 : u_2 and u_3 are on the green dashed line, which means they share the same fitness while u_1 is on the blue solid one higher than the green one, this means u_1 's fitness is more than u_2 's or u_3 's. For the pair of u_1 and u_3 , the data qualities of them are the same, but u_1 has participated twice while u_3 only once.

And for the pair of u_1 and u_2 , they both participated twice, however, the data quality of u_1 is higher than u_2 's. In both of the cases, if the platform can only choose one user as winner, due to the high fitness u_1 will be the winner.

Though with a simplest form of $g(\cdot)$, this example properly shows that we address the two concerns of the platform. When the users have the similar qualities, who participated more (more active) are likely to win, this attracts users to continually contribute. On the other hand, if all users have nearly the same participation rates, those with higher quality are likely to win, this ensures the platform's short-term utility and encourage users to upload data with high quality. These two property together ensure the platform's long-term utility since users are attracted to participate permanently and more likely to provide high quality data.

2) *Solve the User Dropping Problem*: The bidders with high costs or low qualities will struggle in winning the auction, since their marginal utility to the platform is lower than others'. Some of them may lose repeatedly due to their relatively high costs and mediocre qualities. As a result of lack of revenue, they will possibly quit the reverse auction and never participate again. In a long-term scenario, this effect will gradually decrease the number of users, and after a considerable part of users quit, the competition level will be significantly influenced and the price level of the rest users will increase rapidly.

In our work, the participation function $g(\mathbf{h})$ is used to solve this problem in our mechanism. Before we select the winners, all active users will be related to fitness scores, and these scores are relevant to the users' historical participation information. The function $g(\mathbf{h})$ is a strictly increasing monotonic function of the historical participation, therefore, even without efforts to increase the data quality, the fitness of the users still increases as long as they keep participating thus the winning chance also improves. As a result, our mechanism can still attract users to participate even after they lose for several rounds. The choice of $g(\mathbf{h})$ is out of the scope of this paper, and a more sophisticated test function for $g(\mathbf{h})$ is used in Section V.

3) *Adjust the Importance of Quality*: We introduce another function $w(q)$ to adapt to various scenarios with different quality requirements. Actually, this function is set to $w(q) = q$ by default as appeared in Section III. After replacing q by $w(q)$, the objective function becomes $\max \sum_{i \in S} (g(\mathbf{h}^i) \cdot w(\bar{q}^i))$, while the constraints stay unchanged. For simplicity, we omit the average symbol and only focus on one round scenario in this part, but the results also apply to multi-round scenarios. In the aforementioned formula of fitness, we use the average quality directly, while in different sensing scenarios, the importance of the quality may differ. For example, some applications predict the occurrence of some events, the results are highly depended on the data quality. While for other applications recording daily information, the quantity of data is more important than the quality. Thus we can use the non-linear function $w(q)$ to change the distribution of data utility evaluated by the platform. Here we assume that the cost-

quality curve is monotone increasing for all users. We will illustrate different choices of $w(q)$ in place of q .

First we set $c = \alpha \cdot q$ (the parameters in this part are always positive constant) as the simplest case to explain the usage of $w(q)$. Now we assume bids are equal to costs. If $w(q) \propto q$, e.g. $w(q) = \beta \cdot q$ (β is also a constant), the marginal ratio of fitness is $\frac{dw}{dc} = \frac{\beta dq}{\alpha dq} = \frac{\beta}{\alpha}$ for all possible q , thus $\frac{w(q_2) - w(q_1)}{c_2 - c_1} = \frac{\beta(q_2 - q_1)}{c_2 - c_1} = \frac{w(q_2 - q_1)}{c_2 - c_1}$ (assume $q_2 > q_1$), this means that two users with profile (q_1, c_1) and $(q_2 - q_1, c_2 - c_1)$ together take the same reward and also provide the same fitness with another user with (q_2, c_2) , thus the platform cannot achieve a certain fitness using a lower total payment. However, if $w(q)$ is monotone increasing and convex, for example, $w(q) = \frac{1}{2}\beta \cdot q^2$, the marginal ratio of fitness is $\frac{dw}{dc} = \frac{\beta}{\alpha} \cdot q$ for all possible q . Still use the two users case, now

$$\begin{aligned} \frac{w(q_2) - w(q_1)}{c_2 - c_1} &= \frac{\beta q_2^2 - \beta q_1^2}{2 c_2 - c_1} = (q_2 + q_1) \cdot \frac{\beta (q_2 - q_1)}{2 c_2 - c_1} \\ &> (q_2 - q_1) \cdot \frac{\beta (q_2 - q_1)}{2 c_2 - c_1} \\ &> \frac{w(q_2 - q_1)}{c_2 - c_1} \end{aligned}$$

thus two users with (q_1, c_1) and $(q_2 - q_1, c_2 - c_1)$ will together get the same reward as another user with (q_2, c_2) but provide a lower total fitness, this means that the platform can achieve the same fitness with lower total payments by choosing users with high quality as much as possible. As the result, with the same goal of trying to maximizing the fitness of all winners, if we convert the function $w(q)$ to another form, the distribution of the final quality the platform get will also change. The following theorem shows that as long as the cost is an increasing function of the true quality q , we can always choose a $w(q)$ to achieve higher fitness with fewer users given a fixed total cost.

Theorem 1: If $c = c(q)$ is strictly monotone increasing, there exists $w(q)$, s.t., dw/dc is an increasing function of q .

Proof: We have $c'(q) > 0$, then the marginal ratio of fitness is $\frac{dw}{dc} = \frac{w'(q)}{c'(q)}$, and $\frac{d^2w}{dc^2} = \frac{w''(q)c'(q) - c''(q)w'(q)}{c'(q)^3}$. First we prove the positive marginal ratio is achievable. Since $c = c(q)$ is fixed, $c'(q)$ and $c''(q)$ are known, we only need to find a proper $w(q)$ to satisfy $w''(q)c'(q) - c''(q)w'(q) > 0$, let $m > \max(|\frac{c''(q)}{c'(q)}|)$ (m is a constant larger than $|\frac{c''(q)}{c'(q)}|$ for all possible q) and $\gamma = \max\{2, m\}$, $w(q) = q^{\gamma+1}$ is one of the candidate functions,

$$\begin{aligned} w''(q)c'(q) - c''(q)w'(q) &= \eta(q)[\gamma - q \frac{c''(q)}{c'(q)}] \\ &\geq \eta(q)[\gamma - |\frac{c''(q)}{c'(q)}|] \\ &> \eta(q)[\max(|\frac{c''(q)}{c'(q)}|) - \frac{c''(q)}{c'(q)}] \\ &> 0 \end{aligned}$$

where $\eta(q) = (\gamma+1)q^{\gamma-1}c'(q) > 0$. Which means $\frac{d^2w}{dc^2} > 0$. As the quality increases, the marginal ratio of fitness also grows, i.e. $w(c_1 + c_2) > w(c_1) + w(c_2)$, this property makes platform

to select fewer users with high data quality to achieve the maximum fitness. ■

Here we only discuss the increasing monotone condition, otherwise the users can increase their quality while maintaining or even reducing the sensing cost, which hardly happens in a real-world scenario. This theorem shows that if the main interest of an application is quality, it should select those users with higher quality than others by choosing a proper function of $w(q)$ to replace the quality in fitness. This means that our method has the capability to meet different quality requirements in various application scenarios. Note that for an application with high-quality requirement, function $w(q)$ amplifies the differences of fitness between high-quality (HQ) users with low-quality (LQ) users, combined with function $g(\mathbf{h})$, the effect of preventing bidder drop problem will be better for HQ users than LQ users, thus our method can be applied in such applications to ensure the stickiness of high-quality users.

B. Potential Payments to Users

Before we introduce the winner selection method, we propose an algorithm to calculate the potential payments to each active user in this round. This is because the winner selection is processed under a constant budget, and to maximize the total fitness under this budget, the fitness and payment of each user are both indispensable. If the active user finally wins, this potential payment then becomes the real reward of this user.

The method we use here is similar to a Vickrey Auction. In a single winner Vickrey Auction, the winner who has claimed the highest price only need to pay the second highest price. Since in an ordinary auction (e.g. English Auction), in order to ensure a positive net profit after winning, the bidders will bid slightly lower than their expected values of the good. While in Vickrey Auction, the net profit is the difference between the highest two bids (all bids are distinct) and is positive, thus bidders don't struggle considering a lower price than their assessments of the good. More detailed, if a bidder bids higher than her expected value, she may have to pay more than this value with a negative net profit, this will not happen to a rational bidder. On the other hand, since the bidder with highest bid wins, if the bidder bids lower than that value, she will take a higher risk to lose, and any winner gets a positive net profit naturally, thus the best strategy for bidders is to bid exactly the same as the assessment values, which is called the bid truthfulness property.

On the contrary, in the reverse auction, bidders with lower bids are more likely to win but usually will bid prices higher than their true costs for receiving a positive profit. Since the platform wants to grasp the real profiles of information about users, it expects the users to bid their true costs. However, if the platform pay winners as much as their costs respectively after they bid truthfully, the net profit will be zero to any of winner, this lead to unwillingness of the users to keep participating in. But if the platform allocates higher payment to a user than her bid (e.g. take a higher bid as the reward of this user), then she can feel free to bid truthfully since she

will always get a positive net profit after winning. The essence that winner's net profit is ensured to be positive is the same as Vickrey Auction.

In our method, we guarantee the net profit of users to be positive by allocating payments a little bit more than the winners' bids. More specifically, the payment of one winner depends on her bid, other users' bids and other information. Once we get the bid prices of all active users, the cost performance ratio of each user's data $r = \frac{\bar{q}}{b}$ will be calculated, and then sorted in non-decreasing order, as

$$\frac{\bar{q}^{i_1}}{b_{i_1}} \geq \frac{\bar{q}^{i_2}}{b_{i_2}} \geq \frac{\bar{q}^{i_3}}{b_{i_3}} \geq \dots \Leftrightarrow r^{i_1} \geq r^{i_2} \geq r^{i_3} \geq \dots$$

For user i , we use the largest r that strictly less than r^i to calculate the payment, which is $p^i = \frac{\bar{q}^i}{r^j}$, $r^j = \max\{r^k | k \in U_t, r^k < r^i\}$. Thus $p^i = \frac{\bar{q}^i}{r^j} > \frac{\bar{q}^i}{r^i} = b^i$. Note that for the users with the lowest r , there do not exist a lower r to calculate the payments, in this condition, we slightly increase their bids as payments to them. If a user bids more than the real cost, the probability to lose is increased, while if she bids less than the real cost, she may obtain a negative revenue. Since bidding with truthfulness will get the winner a price more than her bid, the best strategy is to claim a bid exactly the same as the cost. Hence our mechanism satisfies the bid truthfulness.

C. Optimal Winner Set Selection

Winner selection is an important part of the incentive mechanism whatever the mechanism does, since the platform always needs to choose a set of users to achieve its goal. In our framework of model, the optimization problem shares the same essential elements with the optimization of well-known Knapsack problem and is NP-hard [36]. To explain the equivalence of the two problem, we take each active user as an item, the fitness and cost of this user as value and weight of the item, and the budget as the capacity of the knapsack. Now we need to maximize the total value (fitness) of items (users) subjected to the total weight (costs) not exceeding the capacity (budget). Since each user can at most be selected once, our optimization problem is equivalent to a 0/1 Knapsack problem.

A 0/1 Knapsack problem can be solved by a dynamic programming algorithm in pseudo-polynomial time [37]. The restriction of Knapsack problem is that the weights of items and capacity of the knapsack are all integers. In our condition, since a bid is supposed to have a monetary minimum unit, and the number before that unit should be integer, if we multiply a large integer to both budget and bids of whatever unit, the final numbers all will become integers, thus the restriction can be easily satisfied.

Since the value in our algorithm is exactly fitness, the selection result is highly dependent on the fitness of all users, our method is called Fitness Determined Selection (FDS). The algorithm is shown in Algorithm 1. This algorithm is the combination of two parts, one is potential payments calculation, the other is winner selection, as mentioned before. The time complexity mainly concerns on two parts, finding the largest r less than each user (Lines 15-21) takes $O(n^2)$ time,

input : An integer budget R of the platform
output: The set of winners in this round

```

1 initialization;
2 for  $j$  from 1 to  $R$  do
3    $l_j \leftarrow 0$ ;
4    $V_j \leftarrow \emptyset$ ;
5 end
6 if some users participate in round  $t$  then
7    $U_t$  contains all these users;
8    $b^i$  is the uploaded bid of user  $i \in U_t$ ;
9 else
10  return:  $\emptyset$ 
11 end
12 for each user  $i$  in  $U_t$  do
13   calculate  $\bar{q}^i, f^i$ ;
14    $r^i = \bar{q}^i / b^i$ ;
15 end
16 for each user  $i$  in  $U_t$  do
17   if  $\exists r^j = \max\{r^k | k \in U_t, r^k < r^i\}$  then
18      $p^i = \bar{q}^i / r^j$ ;
19   else
20      $p^i = b^i + \epsilon, \epsilon > 0$ ;
21   end
22 end
23 for each user  $i \in U_t$  do
24    $j \leftarrow R$ ;
25   while  $p^i \leq j$  do
26     if  $l_j < l_{j-p^i} + f^i$  then
27        $l_j \leftarrow l_{j-p^i} + f^i$ ;
28        $V_j \leftarrow V_{j-p^i} \cup i$ ;
29     end
30      $j \leftarrow j - 1$ ;
31   end
32 return:  $V_R$ 

```

Algorithm 1: Fitness Determined Selection (FDS)

selecting winners using in dynamic programming part (Lines 22-31) takes $O(nR)$ time. For a large n , the time complexity is dominated by $O(n^2)$, thus our algorithm is scalable to large user sets.

V. EVALUATION

In this section, we evaluate the performance of our solution FDS in terms of system sustainability based on extensive simulation experiments. For better understanding of the impact of the fitness, we investigate the performance trend with regard to varying amount of users.

A. Experimental Setting

We now give detailed information on the simulation we conduct. We set number of time slots to 100. The number of users (N) ranges from 300 to 1100, stepping by 100, and set to 300 by default. We assume that the cost and data quality of each active user is approximately (since $c, p \in (0, 1]$ and c

has a minimum unit) normal distributed $\mathcal{N}(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho)$, in which $\mu_1 \in [0.3, 0.7]$, $\mu_2 \in [0.3, 0.7]$ and $\rho \in [0.3, 0.6]$ are uniform distributed respectively, and $\sigma_1 = 0.1$, $\sigma_2 = 0.1$. Moreover, we allocate each user a participating probability subjected to uniform distribution $\mathcal{U}(0.3, 0.7)$. The budget in each round is set to 12. The function $g(\mathbf{h})$, $w(q)$ are set to $g(\mathbf{h}) = 1 + 0.1 \times \ln(1 + 10|\mathbf{h}|)$ and $w(q) = q$ if not explicitly mentioned. Each measurement is repeated for at least 100 times to eliminate the noise of randomness.

B. Methodology

We proceed to describe the methodology adopted in our evaluation. In each experiment, we repeat at least 100 implementations. In each implementation, we initiate the users and repeat for 100 rounds with storing the results of each round as historical information. And in each round, the payments and optimal winner set are calculated using our algorithm.

We compare the system performance of three candidate solutions: *Baseline*, *PFHQ*, and *OPT*. *Baseline* represents the default random selection method to select winners from active user sets, which is popular in participatory sensing applications. It picks up a user randomly, and selects this user to be winner if the platform still has sufficient budget to pay this user. The process is repeated until the remaining budget cannot afford anyone left in current active user set. *PFHQ* stands for Pick From Highest Quality method, which means the active users are sorted in non-increasing order of their average qualities, then each user in the sorted user set will be visited, and then be selected as winner if with sufficient budget. Because our mechanism is intended to increase the platform's utility which is composed by users' qualities, comparing with this quality-oriented method is meaningful. *OPT* is a powerful but impractical method, in which user's quality and real cost assume to be known by the platform, thus the platform can choose the optimal winner set which can maximize the total utility of the platform, which means it can get the optimal utility none of any other possible method can achieve, thus is named optimal method. Since this is also a quality-oriented method, we choose this alternative approach to illustrate the performance in partially maximizing the total utility.

C. Results

Figure 3 presents the results of total fitness of the winners in each round when four candidate solutions are adopted. We observe that the total fitness slowly increases as the number of round increases in all cases, for instance, the total fitness is 23 at round 1 and goes up to 33.3 at round 100 for FDS, and 21 at round 1 and increases to 31.6 at round 100 for OPT. This is mainly because as the number of round increases, the participation times of all users also increase, so does the fitness of each user since the average quality is relatively steady, and finally the total fitness of winner set grows. We can also see that our FDS mechanism outperforms the other candidates, for example, the fitness is 31, 29.5, 22, and 18 on average for FDS, OPT, PFHQ, and Baseline respectively, which implies an 5.08%, 40.9%, and 72.2% increase. This indicates that our

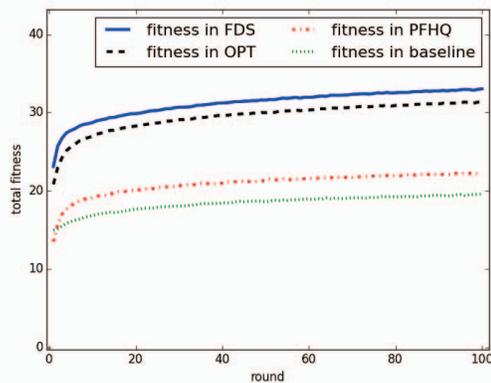


Fig. 3. Total fitness of the winners in each round.

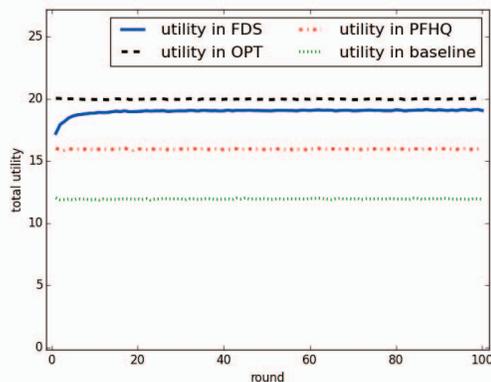


Fig. 4. Total utility the platform obtains in each round.

solution manages to increase the total fitness by considering the historical information which other methods do not use. Especially, FDS performs better than OPT because the later aims only at the total utility and ignores other information of the users. And since the fitness of each round grows slowly and steadily, we can take the average value of all rounds to illustrate the dependency of fitness on other parameters.

Figure 4 shows the total utility the platform obtains in each round of the four candidate algorithms. Firstly, we note that the values of OPT, PFHQ, and Baseline almost remain at 20, 16, and 12, respectively. The main reason is that the patterns of user profiles maintain mostly the same in each round. Secondly, we observe that with FDS, there is a slowly increases in total utility from 17 at Round 1 to 19 at around Round 10, and then keeps almost unchanged. This is because as number of rounds grows, the platform has gradually grasp the pattern of profiles of users by collecting information, thus the prediction of the final utility becomes more stable. Finally, OPT performs the best since it has all information to get the maximum utility of each round and has the optimal selection. The average utility of FDS is 18.7% and 58.3%

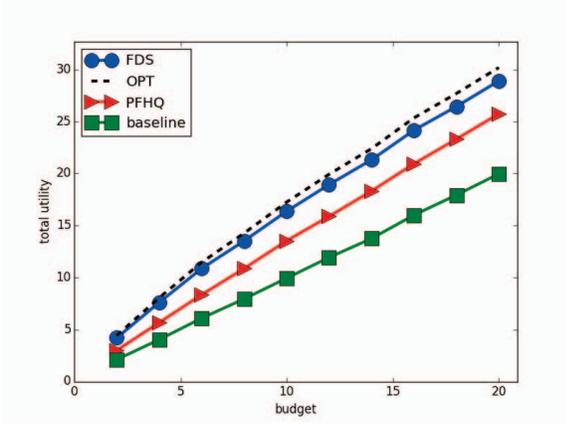


Fig. 5. Total utility under varying budgets.

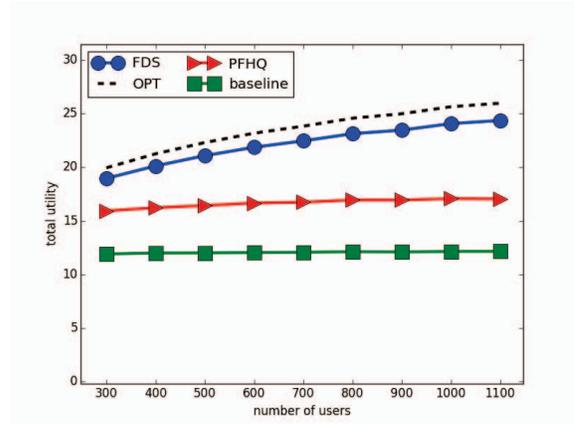


Fig. 6. Total utility under varying number of users.

better than PFHQ and Baseline, respectively. Although FPHQ sorts the users in order of qualities, the costs of the top users still have uncertainty to some extent, thus will increase the platform's cost and limit the total utility the platform can get. As for Baseline, this method selects users completely at random, thus the utility is similar to an average condition. The slight difference between FDS and OPT is because of the information asymmetry, FDS can only predict the optimal selection while the OPT can find that selection with excessive assumption.

Figure 5 presents the total utilities under varying number of budgets, ranging from 2 to 20. We can see that the total utility increases linearly with the budget in all cases. This is because the platform can select more users with more budget and the number of users are nearly proportional to the budget. In addition, we notice that the OPT results with the largest increase ratio, due to that it can utilize the budget optimally at any condition. FDS has larger increase ratio than PFHQ and Baseline, which implies that as more budget can be used, the marginal utility increase of FDS is higher than PFHQ and Baseline, and thus the budget is well (though not optimally) leveraged.

Figure 6 shows the total utilities under varying number of users, ranging from 300 to 1100. We can see that the total utility increases linearly with the number of users for OPT and FDS, and remains unchanged for PFHQ and Baseline, this is because as more users join in, the selection of the former two methods can pick up more top users with higher qualities and lower costs, while the later two either ignore the cost or don't take cost and quality into consideration. In addition, we notice that OPT has the largest total utility, and FDS performs better than PFHQ and Baseline, which indicates that FDS is more suitable in large scale scenarios while also performing well in small scale and thus is scalable in real applications.

Figure 7 presents the total fitness under varying number of budgets, ranging from 2 to 20. We can see that the total fitness increases linearly with the budget in all case, this is also because the platform can take more winners with more

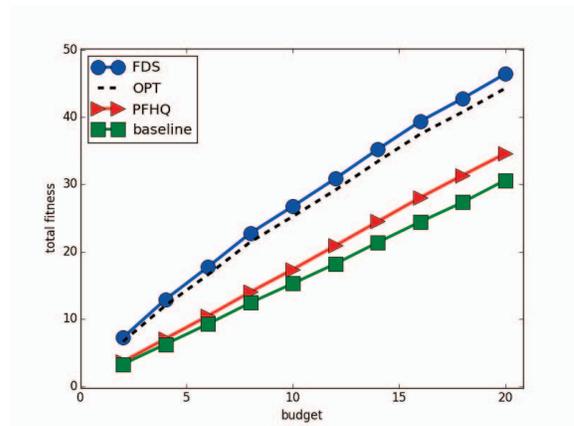


Fig. 7. Total fitness under varying budgets.

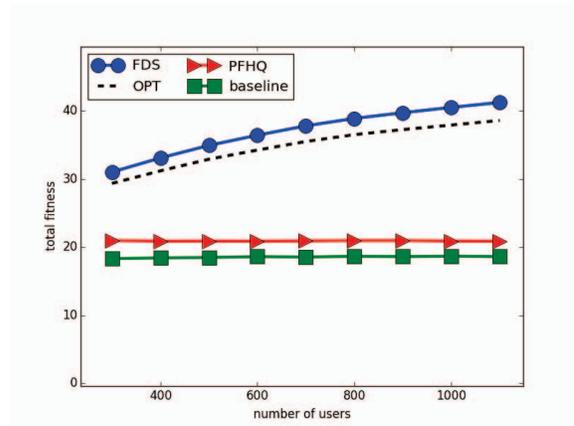


Fig. 8. Total fitness under varying number of users.

budget. In addition, we notice that the FDS results in the largest increase ratio, which means that the consideration of combining both participation and quality performs the best in all methods.

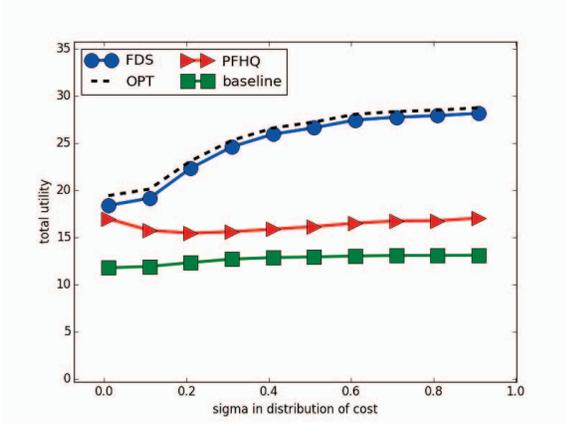


Fig. 9. Total utility under different σ of cost in the normal distribution

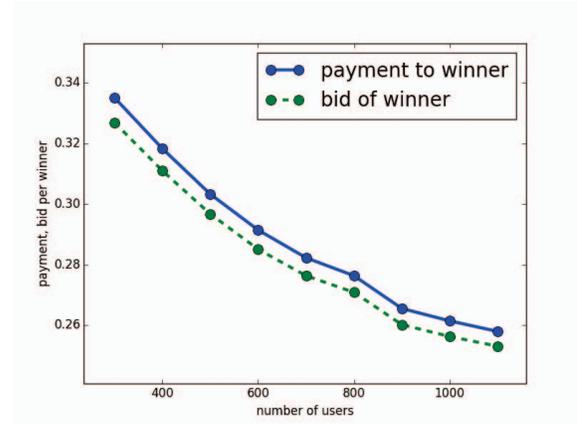


Fig. 11. Average payment and bid of winners under varying number of users.

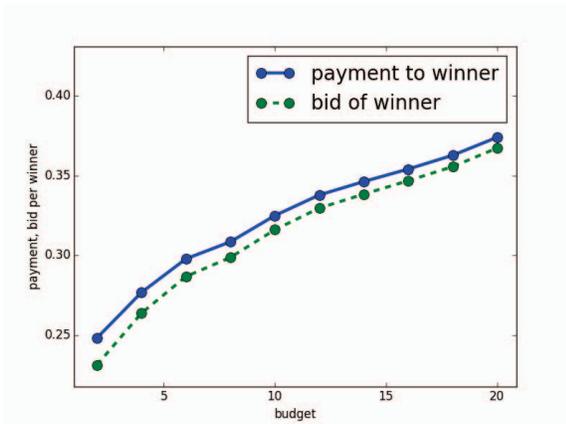


Fig. 10. Average payment and bid of winners under varying budgets.

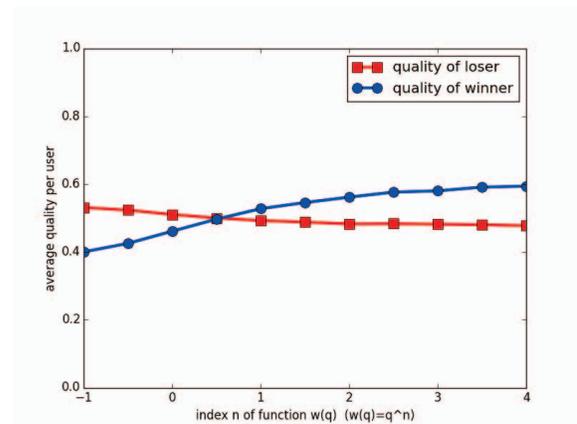


Fig. 12. Average quality of winners and losers with different index of w

Figure 8 shows the total fitness under varying number of users, ranging from 300 to 1100. We can see that the total fitness increases linearly with the number of users for OPT and FDS, and remains unchanged for PFHQ and Baseline. This is because the selection of OPT and FDS can leverage more information of the user set (although OPT only use the quality part), and the other two cannot achieve this. In addition, we notice that FDS has the largest total fitness, which indicates that it can work well in various scales of user sets.

Figure 9 shows the total utility under different variances (σ) of the cost. We can see that as the variance of cost grows, the total utility of OPT and FDS increases while PFHQ and Baseline maintain nearly unchanged. This is because the former two method can utilize the information both high qualities and lower costs while the later two barely concern the costs change in users. A higher variance in cost is more likely to generate users with lower cost thus enables the platform to potentially take more winners. This indicates that our method works well for both applications with high or low cost variance.

Figure 10 and 11 presents the average payment to and bid

from winners under varying budgets and number of users. First, both the payments and bids increase as the budget goes up. This is reasonable because as budget grows with other parameters unchanged (especially the number of users), the platform will choose more high cost users since each user can be selected at most once and thus the average of payments and bids are increased by this part of winners. Second, both the payments and bids decrease as the number of users increases. This indicates that as the user set grows, the platform can replace a part of users by those with higher cost performance, and thus rise the utility of platform with the same budget. Finally we observe in both figures that the average payment is always slightly higher than the bid, which exactly shows the fact that our method offers the winners higher payments than their bids and the payments decision based on Vickrey Auction works as intended.

Figure 12 shows the average quality of winners and losers respectively under varying index n of q in $w(q) = q^n$. Here we use this form of function $w(q)$ to show the effect of changing distribution of received quality by this function. We can see that as the index n grows, the average quality of winners also

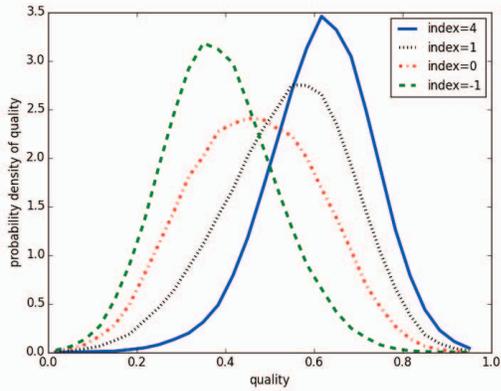


Fig. 13. Distribution of winners' quality with different index of w

grows while quality of losers declines. Also, before $n = 0.5$ \bar{q} of losers is higher than \bar{q} of winners while for $n > 0.5$ the rank reverse. This is because that for a lower index, the fitness of lower quality is enhanced since $q \leq 1$, but for an index greater than 1, the fitness of higher quality is amplified. This indicates that even without a constraint of strict relation between quality and cost, the function $w(q)$ can still filter out higher or lower quality users, which can be utilized in various scenarios with different quality requirements.

Figure 13 shows the actual distribution of qualities of the winners under varying index of $w(q) = q^n$. We can see that for larger index, the distribution curve moves to the right and has a higher maximum value, which implies that the effect of $w(q)$ has a limit in changing received quality distribution, this is because the qualities of users have an inherent distribution, the force of this distribution interact with $w(q)$ forms the final curve.

Figure 14 shows the total fitness and utility under varying index of $w(q) = q^n$. We can see that as the index increases, the utility changes a little bit and stays around 20, while the fitness rapidly decreases at first. This is because the utility does not directly depended on the index in $w(q)$ but fitness does, also the quality is between 0 and 1, thus the higher the index is, the less $w(q)$ and fitness are. The stable utility tells that though the total fitness changes, the utility of the platform is barely influenced. Besides, together with Figure 12, these two graphs indicate that the total number of winners varies under different index (dividing the total utility by the average utility per user), more specifically, when the index is higher, the average quality of each winner increases while the total utility stays nearly unchanged and the number of winners decreases. This implies that our method indeed select fewer but higher quality users when the index is high even without a strict constraint on relation between quality and cost.

D. Discussions

Simulation results show that our proposed solution achieves better system performance in terms of system sustainability,

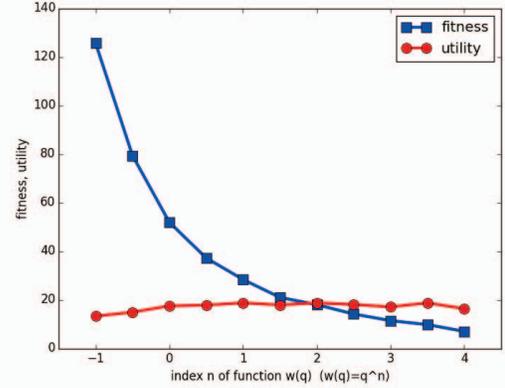


Fig. 14. Total fitness and utility under different index of w

and exploits the trade-off between system gain and high-quality user stickiness. In addition, the design of the incentive mechanism is general enough to be used in any long-term participatory sensing application.

Possible future improvements of our work include considering more complicated factors in general or specific participatory sensing scenarios, designing a proper function of $g(h)$ and $w(q)$ for various scenarios, and applying our solution into real world participatory sensing applications.

VI. CONCLUSION

In this paper, we presented the design and evaluation of a novel incentive mechanism for participatory sensing that leverages the historical information of users to improve system sustainability. Our proposed solution incorporates a new decision making algorithm designed to exploit the trade-off between maximizing the platform's utility and keeping users active on participation. Extensive simulation results show that our solution outperforms three alternative approaches in terms of total fitness. Given the popularity and stronger power of sensing devices and importance of Internet of Things, we hope that this work will motivate further research on achieving sustainable participatory sensing applications.

VII. ACKNOWLEDGEMENT

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