Participation and Reporting in Participatory Sensing

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***Abstract*—In participatory sensing (PS), users use smartphones to collect information related to a certain phenomenon of interest, and report their sensed data to the service provider through cellular or Wi-Fi networks. Previous studies on the incentive mechanism design for user participation often neglect the details of data reporting, which is non-trivial given the user mobility, location-dependent network availability, and transmission cost. In this paper, we study the decisions of the service provider and the users in PS applications that involve photo or video transmissions, where the reporting cost through the cellular network is non-negligible. The service provider uses a deadline reward scheme to motivate users to participate, and optimizes its reward to maximize its expected surplus. Users make their participation and reporting decisions based on the reward announced by the service provider. We jointly consider the user mobility and multiple access methods with different transmission costs and location heterogeneity in the problem formulation and analysis. For the general case with a time-discounted reward, we formulate a user's reporting decision problem as a sequential decision problem, and propose an optimal participation and reporting decisions (OPRD) algorithm using dynamic programming. For the special case with a fixed reward, we derive the *closed-form* participation and reporting decisions. Simulation results show that the OPRD algorithm improves the user payoff over the patient and impatient schemes by 9.8% and 13.2%, respectively.**

I. Introduction

Smartphones are becoming increasingly popular in our daily lives. According to Ericsson, the total smartphone subscriptions will reach 1.9 billion at the end of 2013, and are expected to grow to 5.6 billion in 2019 [1]. Most of the smartphones today include a rich set of *embedded sensors*, such as camera, microphone, global positioning system (GPS), and accelerometer, which enable smartphone owners to easily extract information from the surrounding environment [2]. Together with the popularity of App Stores for application distribution, and the development of mobile computing cloud for the processing of large-scale data, we are witnessing the rapid development of *mobile crowdsensing* [2], [3].

Mobile crowdsensing refers to a new sensing paradigm that involves a large number of individuals, who use their smartphones or mobile devices to collectively extract and share information related to a certain phenomenon of interest. Interesting applications include traffic jam alerts [4], citizen-journalism [5], tourist query [5], wireless indoor localization [6], and urban tomography [7]. We can classify the mobile crowdsensing applications into participatory sensing or opportunistic sensing according to the level of user involvement [2], [3]. In *participatory sensing* (PS), users need to actively engage in the data collection process (e.g., taking pictures and videos in citizen-journalism [5]). In *opportunistic sensing*, the data collection process is fully automated without any human intervention (e.g., building up the fingerprint database automatically in wireless indoor localization when a user turns on his smartphone [6]), users experience minimum burden during the data collection process. In this paper, we mainly focus on the *delay-sensitive* PS applications that involve the collection of photo or video data [4], [5], [7] within a given *deadline*. For example, in real-time tourist query [5], tourists may ask for the facility at a location and specify how long the query remains valid. People around the location can respond to the query with multimedia contents. In citizen-journalism [5], citizens can play the role of journalists, and report events in their everyday lives by sending audio and video information through mobile social networks as soon as possible, because the value of the data may degrade rapidly shortly after the events have happened.

In PS applications, the *service provider* (SP) usually needs to provide incentives to the users to encourage their participations. A number of results have focused on the incentive mechanism design in PS. Xie *et al.* in [8] proposed a stimulation mechanism to promote message tradings between a pair of mobile users. They modeled the message transaction between two users using the Nash bargaining framework. Lee *et al.* in [9] designed an incentive mechanism to stimulate user participations based on an iterative reverse auction. They aimed to stabilize the incentive cost and maintain a satisfactory level of user participation by giving losers of auctions some extra virtual credits. Jaimes *et al.* in [10] extended the incentive mechanism in [9] by taking into account the location of the users and considering the coverage and budget constraints of the SP during the participant selection. Duan *et al.* in [11] proposed a reward-based collaboration mechanism for data acquisition. They formulated the problem as a two-stage Stackelberg game, and considered both the cases with complete and incomplete information. Yang *et al.* in [12] considered two possible system operations to incentivize user participation. In the platform-centric model, the SP announces a total reward, and each user determines its level of participation accordingly. In the user-centric model, they considered an auction design, where a user selects the sensing tasks and submits the corresponding bids, while the SP selects the final

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participants. Koutsopoulos *et al.* in [13] considered the reverse auction design in participatory sensor network. The objective of the SP is to minimize the total payment to the users, subject to the quality of experience of its customers.

The related studies on incentive mechanism design for PS mentioned above mainly focus on the user participation in terms of performing the sensing task. However, most of the studies neglect the details of the data reporting process from the users to the SP, which may lead to overly-simplifying decisions for both the SP and users. First, these previous studies usually consider the sensing task at a particular location with static users. In practice, a single user can move around *multiple* locations to sense and report at different locations and different times. Second, these studies do not consider the difference in terms of the transmission cost and network availability when choosing between cellular or Wi-Fi networks for reporting. More specifically, for the cellular network with ubiquitous coverage, its usage cost is non-negligible, especially for PS applications that involve large amount of data transmissions in the form of photos or videos. For the Wi-Fi network, although the transmission cost can be lower, it typically has a smaller coverage and hence its availability depends on the user's mobility pattern. In fact, Liu *et al.* in [14] also studied the reporting issues related to the choices of cellular and Wi-Fi networks. However, [14] mainly studied the choice between cellular and Wi-Fi networks given some extra cellular budget without considering any incentive mechanism, while we focused on the incentive issue of reporting sensed data for a reward. Without considering the user mobility and network heterogeneity in terms of transmission cost and availability, the participation decisions of users may be suboptimal and the design of incentive mechanism for the SP may be ineffective.

In this paper, we analyze the decisions of both users and the SP in two stages by modeling the details in data reporting. First, each user needs to make participation and reporting decisions based on its past mobility statistics, Wi-Fi availabilities at different locations, and the reward provided by the SP. We propose an *optimal* participation and reporting decision (OPRD) algorithm, which achieves the maximal user payoff in the general case with a time-discounted reward from the SP. We also derive *closed-form* decisions for the user in the special case of a fixed reward. The key challenges of the analysis are due to the location-dependent Wi-Fi availability and user mobility. For the SP, it needs to choose the reward to incentivize enough users to participate and report. We formulate the SP's problem as a discrete optimization problem that can be solved with an algorithm of linear complexity.

The main contributions of this paper are as follows:

- *Practical modeling*: To the best of our knowledge, this is the first paper that considers the joint participation and reporting decisions of the mobile users and the reward optimization of the SP under a common framework with *user mobility* and *network heterogeneity*.
- *Optimal user's participation and reporting decisions*: We show analytically that when the reward is small, a user will only report to the SP probabilistically due to the stochastic Wi-Fi availability. However, when the reward is larger than a threshold, we can guarantee a *sure* participation and reporting.
- *Service provider's reward optimization*: We analyze how the SP chooses an optimal reward that balances its utility and the total payment to the users.
- *Superior performance*: Simulation results show that the OPRD algorithm improves the user payoff over the patient and impatient benchmark schemes by 9.8% and 13.2%, respectively.

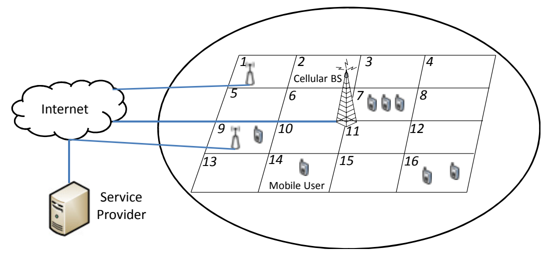

Fig. 1. An example of the network setting, where the users are moving within a set of $\mathcal{L} = \{1, \ldots, 16\}$ locations. The users are always under the coverage of a cellular base station, but Wi-Fi is only available at locations 1 and 9.

The rest of the paper is organized as follows. We describe our system model in Section II. Section III analyze users' decisions under both discounted and fixed rewards in stage two, and Section IV analyzes the reward optimization of the SP in stage one. Simulation results are given in Section V, and the paper is concluded in Section VI.

II. System Model

We consider a participatory sensing (PS) application that involves the real-time sensing and reporting of photo and video contents by a *deadline* T (e.g., citizen-journalism and real-time tourist query [5]). As shown in Fig. 1, the PS system consists of a service provider (SP) and a set of $\mathcal{I} = \{1, \ldots, I\}$ multiple mobile users (MUs) who may act as the participants. The SP aims to extract information from a set of locations $\mathcal{L} = \{1, \ldots, L\}$. Each MU makes its own decisions on whether or not to participate in the sensing task, and whether to report the information to the SP based on the reward and costs. For simplicity, we assume that the MUs are honest and will report their actual measurements to the server of the SP truthfully (once they have decided to report) [8].

Considering the location heterogeneity in terms of the availability of Wi-Fi, we let $\mathcal{L}^{(0)}$ and $\mathcal{L}^{(1)}$ be the set of locations without and with Wi-Fi, respectively. As an example, in Fig. 1, we have $\mathcal{L}^{(1)} = \{1, 9\}$.

We consider a Markovian user mobility model that has been widely used in the literature [15], [16]. Time is divided into a set of time slots $\mathcal{T} = \{1, \ldots, T\}$. Let $l_i(t) \in \mathcal{L}$ be the position of user $i \in \mathcal{I}$ at time t. The location transition matrix of user $i \in \mathcal{I}$ is $P_i = \left[p_i(l'|l)\right]_{L \times L}$, where $p_i(l'|l)$ is the probability that MU $i \in \mathcal{I}$ will move to $l' \in \mathcal{L}$ in the next time slot given that it is currently at location $l \in \mathcal{L}$.

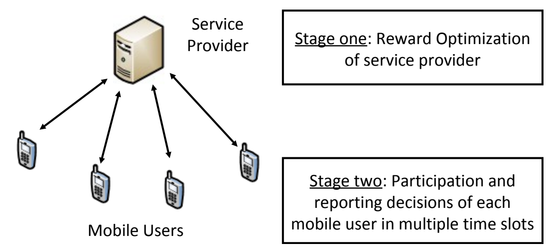

Fig. 2. The two stages that we consider in this paper.

Fig. 2 illustrates the two-stage decision process of the SP and users. In *stage one*, the SP announces the reward scheme to the potential participants. Specifically, we consider a deadline discounted reward scheme, where any participant who obtains measurement at its initial location $l_i(1)$ at time $t = 1$ and reports its data to the SP at time $t \in \mathcal{T}$ will be given a reward $r = \theta^{t-1}R$, where $R \geq 0$ is the initial reward and $0 < \theta \leq 1$ is the discount factor. The SP will not grant any reward for data reported after deadline T. This reward scheme is practical for delay-sensitive PS applications, such as real-time tourist query and citizen-journalism [5] mentioned above, where the value of data degrades with time.

In *stage two*, each user makes its participation and reporting decisions to maximize its expected payoff, by considering its sensing cost, transmission cost, and the reward scheme of the SP. Let σ_i be the sensing cost of MU $i \in \mathcal{I}$, which may be related to its privacy and energy costs in participation [11], [13]. Let c_i be the cost of using the cellular network for MU $i \in \mathcal{I}$ to report its sensed data to the SP. We assume that the users can use Wi-Fi networks free of charge. Moreover, we assume that the sensing and reporting tasks can be completed in one time slot. In this stage, user i needs to consider the following decisions:

- *Participation Decision*: User i decides whether it should perform sensing and obtain measurement at its initial location $l_i(1)$ at time $t = 1$, by comparing the *expected payoff* between participation and no participation.
- *Reporting Decision*: If user i has decided to participate in sensing, it should decide further on when to upload the data to the SP using what type of network, depending on the stochastic network availability in the future T time slots. That is, it is possible for a user to decide not to report its sensed data after it has decided to participate and has performed sensing. This is one of the key surprising results from our analysis.

We use backward induction to analyze the sequential decisions of the SP and users. In Section III, we first study the participation and reporting decisions of user i given the reward scheme from the SP. In Section IV, based on the response of each user, we then study the reward optimization of the SP.

III. Stage Two: Participation and Reporting Decisions of Mobile Users

In this section, given the reward scheme of the SP parameterized by R, θ, and T, we study the participation and reporting decisions of each user in stage two. We first consider the general case with a discounted reward in III-A, and propose an optimal algorithm based on dynamic programming. Then, we consider the special case with a fixed reward in Section III-B, and derive the *closed-form* decisions.

A. General Case: Discounted Reward

Assuming that user i has chosen to participate in the sensing task, the optimal reporting decision of user i can be solved by using dynamic programming. Specifically, the *decision epochs* of user i are

$$t \in \mathcal{T} = \{1, \ldots, T\}, \tag{1}$$

where $\mathcal{T}$ is the set of all time slots.

The system *state* is defined as $\boldsymbol{s} = (k, l)$. The state element $k \in \mathcal{K} = \{0, 1\}$ keeps track of whether user i has reported the data to the server or not, where $k = 0$ means that user i has reported the data and $k = 1$ means that the data has not been reported. The state element $l \in \mathcal{L} = \{1, \ldots, L\}$ is the location index, where L is the total number of possible locations that the user may reach within the T time slots.

The *action* $a \in \mathcal{A}_k \subseteq \mathcal{A} = \{0, 1\}$ specifies the reporting decision of the user at a decision epoch, where $a = 0$ means that user i decides not to report, and $a = 1$ means that user i decides to report. As reporting through the Wi-Fi network has a zero cost, it is always optimal to choose action $a = 1$ whenever the data has not been reported (i.e., $k = 1$) and the current location has Wi-Fi (i.e., $l \in \mathcal{L}^{(1)}$). Since the user should report only if it has not done so, the feasible action set $\mathcal{A}_k$ depends on the state element k as follows:

$$\mathcal{A}_k = \begin{cases} \{0, 1\}, & \text{if } k = 1, \\ \{0\}, & \text{if } k = 0. \end{cases} \tag{2}$$

It should be noted that user i will only report (i.e., choose action $a = 1$) at most once within the T time slots.

We define the user *surplus* (i.e., reward minus transmission cost) at state $\boldsymbol{s} = (k, l)$ with action $a \in \mathcal{A}_k$ at time slot $t \in \mathcal{T}$ as

$$\phi_t(k, l, a) = \begin{cases} \theta^{t-1}R, & \text{if } a = 1, k = 1, \text{and } l \in \mathcal{L}^{(1)}, \\ \theta^{t-1}R - c_i, & \text{if } a = 1, k = 1, \text{and } l \in \mathcal{L}^{(0)}, \\ 0, & \text{if } a = 0. \end{cases} \tag{3}$$

The first and second rows refer to the surplus of reporting through Wi-Fi and cellular networks, respectively. The third row corresponds to the idle action, where there is no reward or transmission cost. As a result, the surplus is zero.

The *state transition probability* $p\big(\boldsymbol{s}' \mid \boldsymbol{s}, a\big) = p\big((k', l') \mid (k, l), a\big)$ is the probability that the system enters state $\boldsymbol{s}' = (k', l')$ if action $a \in \mathcal{A}_k$ is taken at state $\boldsymbol{s} = (k, l)$. Since the movement of the user from l to l' is independent of the value of k and action a, we have

$$p\big(\boldsymbol{s}' \mid \boldsymbol{s}, a\big) = p\big((k', l') \mid (k, l), a\big) = p(l' \mid l)\, p(k' \mid k, a), \tag{4}$$

where

$$p(k' \mid k, 1) = \begin{cases} 1, & \text{if } k' = 0, \\ 0, & \text{otherwise}, \end{cases} \tag{5}$$

and

$$p(k' \mid k, 0) = \begin{cases} 1, & \text{if } k' = k, \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Here, we assume that $p(l' \mid l)$ is defined according to an Markovian model estimated based on the past mobility pattern of the MU [15], [16].

Let $\delta_t : \mathcal{K} \times \mathcal{L} \rightarrow \mathcal{A}$ be the decision rule that specifies the reporting decision of user i at state $\boldsymbol{s} = (k, l)$ and time slot t. We define a *policy* $\boldsymbol{\pi} = (\delta_t(k, l), \forall\, k \in \mathcal{K}, l \in \mathcal{L}, t \in \mathcal{T})$ as the set of decision rules for all states and time slots. We denote $\boldsymbol{s}_t^{\boldsymbol{\pi}} = (k_t^{\boldsymbol{\pi}}, l_t^{\boldsymbol{\pi}})$ as the state at time slot t if policy $\boldsymbol{\pi}$ is used, and we let Π be the feasible set of $\boldsymbol{\pi}$. We consider that user i aims to find an optimal policy (i.e., *optimal reporting decisions*) $\boldsymbol{\pi}^*$ that maximizes its *expected* surplus as

$$\xi_i^* = \underset{\boldsymbol{\pi} \in \Pi}{\text{maximize}} \;\; E_{\boldsymbol{s}_1}^{\boldsymbol{\pi}} \left[\sum_{t=1}^{T} \phi_t\big(\boldsymbol{s}_t^{\boldsymbol{\pi}}, \delta_t(\boldsymbol{s}_t^{\boldsymbol{\pi}})\big) \right]. \tag{7}$$

$E_{\boldsymbol{s}_1}^{\boldsymbol{\pi}}$ denotes the expectation with respect user i's mobility pattern and policy $\boldsymbol{\pi}$ with an initial state $\boldsymbol{s}_1 = \big(1, l_i(1)\big)$, where $l_i(1)$ is the initial location of user i at time slot $t = 1$.

Given the optimal reporting decisions of user i above, we can obtain its *optimal sensing decision*. Specifically, user i chooses to participate in the sensing only if the maximal expected surplus is greater than its sensing cost (i.e., $\xi_i^* \geq \sigma_i$), and not to participate otherwise.

Let $v_t(\boldsymbol{s})$ be the maximal expected surplus of the MU from time slot t to time slot T, given that the system is in state $\boldsymbol{s}$ immediately before the decision at time slot t. The *optimality equation* [17, pp. 83] relating the maximal expected surplus at different states for $t \in \mathcal{T}$ is given by

$$v_t(\boldsymbol{s}) = v_t(k, l) = \max_{a \in \mathcal{A}_k} \{\psi_t(k, l, a)\}, \tag{8}$$

where for any $k \in \mathcal{K}$, $l \in \mathcal{L}$, and $a \in \mathcal{A}_k$, we have

$$\psi_t(k,l,a) = \phi_t(k,l,a) + \sum_{l' \in \mathcal{L}} \sum_{k' \in \mathcal{K}} p\big((k', l') | (k, l), a\big) v_{t+1}(k', l') \tag{9}$$

$$= \phi_t(k,l,a) + \sum_{l' \in \mathcal{L}} p(l' \mid l) \Big[a v_{t+1}(0, l') + (1-a) v_{t+1}(k, l') \Big]. \tag{10}$$

The first and second terms on the right hand side of (9) are the *immediate surplus* in time slot t and the *expected future surplus* in the remaining time slots for choosing action a, respectively. The derivation of (10) from (9) follows directly from (4), (5), and (6). Moreover, we set the boundary condition at $t = T + 1$ as

$$v_{T+1}(\boldsymbol{s}) = v_{T+1}(k, l) = 0, \quad \forall\, k \in \mathcal{K}, l \in \mathcal{L}. \tag{11}$$

With the optimality equation, we propose Algorithm 1 for user i to make its participation and reporting decisions under a discounted reward. First, in the planning phase, based on the optimality equation in (8) and the boundary condition in (11), we obtain the *optimal policy* $\boldsymbol{\pi}^*$ that solves problem (7) using *backward induction* [17, pp. 92]. Specifically, we first set $v_{T+1}(k, l)$ based on the boundary condition in (11) (line 2). Then, we obtain the values of $\delta_t^*(k, l)$ and $v_t(k, l)$ by updating them recursively backward from time slot $t = T$ to time slot $t = 1$ (lines 3 to 15). The complexity of Algorithm 1 is $\mathcal{O}(LT)$.

Algorithm 1 *Optimal Participation and Reporting Decisions (OPRD) Algorithm for user $i \in \mathcal{I}$.*

1: <u>Planning Phase:</u>
2: <u>Set $v_{T+1}(k, l)$</u> $:= 0$, $\forall\, k \in \mathcal{K}, l \in \mathcal{L}$
3: Set $t := T$
4: **while** $t \geq 1$
5:   **for** $l \in \mathcal{L}$
6:     Set $k := 0$
7:     **while** $k \leq 1$
8:       Calculate $\psi_t(k, l, a)$, $\forall\, a \in \mathcal{A}_k$ using (10)
9:       Set $\delta_t^*(k, l) := \arg\max_{a \in \mathcal{A}_k} \{\psi_t(k, l, a)\}$
10:       Set $v_t(k, l) := \psi_t\big(k, l, \delta_t^*(k, l)\big)$
11:       Set $k := k + 1$
12:     **end while**
13:   **end for**
14:   Set $t := t - 1$
15: **end while**
16: Output the optimal reporting policy $\boldsymbol{\pi}^*$
17: <u>Participation and Reporting Decisions</u>:
18: <u>Set $t := 1$ and $k := 1$</u>
19: Set $\xi_i^* = v_t\big(k, l_i(t)\big)$
20: **If** $\xi_i^* \geq \sigma_i$ (i.e., the participation decision)
21:   Obtain measurement at its current location $l_i(1)$ at $t = 1$
22:   **while** $t \leq T$ **and** $k = 1$
23:     Determine the location index $l := l_i(t)$ from GPS
24:     Set action $a := \delta_t^*(k, l)$ based on the optimal policy $\boldsymbol{\pi}^*$ (i.e., the reporting decision)
25:     **If** $a = 1$ and $l \in \mathcal{L}^{(0)}$
26:       Report through cellular network at time t
27:     **else if** $a = 1$ and $l \in \mathcal{L}^{(1)}$
28:       Report through Wi-Fi network at time t
29:     **end if**
30:     Set $t := t + 1$
31:   **end while**
32: **end if**

Theorem 1: The policy $\boldsymbol{\pi}^* = (\delta_t^*(k, l), \forall\, k \in \mathcal{K}, l \in \mathcal{L}, t \in \mathcal{T})$, where

$$\delta_t^*(k, l) = \underset{a \in \mathcal{A}_k}{\arg\max} \{\psi_t(k, l, a)\}, \tag{12}$$

is the optimal solution of problem (7).

Proof: The proof is based on the principle of optimality [18, pp. 18]. ■

Based on the optimal policy computed *offline* in the planning phase, user i decides to participate if $\xi_i^* \geq \sigma_i$, and not to participate otherwise (lines 19 and 20). If it decides to participate, it first obtains measurement at its current location (line 21), and carries out its reporting decision based on the optimal policy $\boldsymbol{\pi}^*$ through checking a table (lines 24 to 29). Notice that the optimal policy $\boldsymbol{\pi}^*$ is a *contingency plan* that contains information about the optimal reporting decision at *all* possible states (k, l) in any time slots $t \in \mathcal{T}$.

In fact, it is possible for user i to decide not to report its sensed data after it has decided to participate and has performed sensing. The intuition for this possibility is that user i may not be able to meet any Wi-Fi before the deadline as expected, and the reward is not enough for him to use cellular for reporting. We will show this insight more explicitly for the special case with a fixed reward in Section III-B.

B. Special Case: Fixed Reward

In this section, we consider a fixed reward, which is a special case of the discounted reward with $\theta = 1$. Any participant who can obtain measurement at its initial location and report their data to the SP by deadline T will receive a reward $r \geq 0$. We derive the *closed-form* expressions related to the participation and reporting decisions.

1) Four Scenarios of Rewards and Wi-Fi Availabilities: We consider the decisions of user i in the following four scenarios, for different values of reward r and different Wi-Fi availabilities at the initial location.

Scenario (i) $r \leq \sigma_i$: Since the reward is too small, user i will not participate in the sensing task.

Scenario (ii) $r \geq \sigma_i + c_i$: Since the reward is large enough, user i will definitely participate in the sensing. After sensing, user will report when it first meets a Wi-Fi network within the deadline. If it does not meet any Wi-Fi network within T time slots, it will use the cellular network for data reporting in time slot T.

Scenario (iii) $\sigma_i < r < \sigma_i + c_i$ and $l_i(1) \in \mathcal{L}^{(1)}$: The reward is medium and the Wi-Fi network is available to the user during the first time slot. User i will sense and report immediately using Wi-Fi in the first time slot.

Scenario (iv) $\sigma_i < r < \sigma_i + c_i$ and $l_i(1) \in \mathcal{L}^{(0)}$: This is the most challenging scenario, and will be discussed in details next.

2) Closed-Form Participation and Reporting Decisions: Let $p_i^{\text{nowifi}}(T)$ be the probability that user i will not meet any Wi-Fi by deadline T. We can compute the participation and reporting decisions of user i in *closed-form* in Theorem 2.

Theorem 2: (a) For a small reward $0 \leq r < c_i$:

- *Participation Decision*: User i chooses to participate if $r \geq \frac{\sigma_i}{1-p_i^{\text{nowifi}}(T)}$, and not to participate otherwise.
- *Reporting Decision*: If user i chooses to participate, then it will wait for a Wi-Fi network to report until deadline T. If no Wi-Fi network is available within T time slots, user i will choose *not* to report.

(b) For a large reward $r \geq c_i$:

- *Participation Decision*: User i chooses to participate if $r \geq \sigma_i + p_i^{\text{nowifi}}(T)c_i$, and not to participate otherwise.
- *Reporting Decision*: If user i chooses to participate, then it will wait for a Wi-Fi network to report until deadline T. If no Wi-Fi network is available within T time slots, user i will report through cellular network in time slot T.

Let $\gamma_i^{(1)} \triangleq \frac{\sigma_i}{1-p_i^{\text{nowifi}}(T)}$ and $\gamma_i^{(2)} \triangleq \sigma_i + p_i^{\text{nowifi}}(T)c_i$ be the two thresholds in Theorem 2(a) and (b), respectively. Theorem 2 confirms the intuition that when the reward is small, user i will only report to the SP probabilistically due to the stochastic Wi-Fi availability. When the reward is larger than the threshold $\gamma_i^{(2)}$, user i will always report within the deadline. The proof of Theorem 2 is given in Appendix A. Notice that Theorem 2 is general, and can be applied to any one of the four scenarios in Section III-B1.

Theorem 2 enables us to compute $p_i^{\text{report}}(r)$, which is the probability that user i will report its sensed data to the SP given reward r in the following theorem.

Theorem 3:

$$p_i^{\text{report}}(r) = \begin{cases} 0, & \text{if } r < \check{\gamma}_i, \\ 1 - p_i^{\text{nowifi}}(T), & \text{if } \check{\gamma}_i \leq r < \hat{\gamma}_i, \\ 1, & \text{if } r \geq \hat{\gamma}_i, \end{cases} \tag{13}$$

where the thresholds $\check{\gamma}_i$ and $\hat{\gamma}_i$ are defined in three cases:

- Case 1: $c_i < \sigma_i$: $\check{\gamma}_i = \hat{\gamma}_i = \gamma_i^{(2)}$.
- Case 2: $c_i \geq \sigma_i$ and $p_i^{\text{nowifi}}(T) > 1 - \frac{\sigma_i}{c_i}$: $\check{\gamma}_i = \hat{\gamma}_i = \gamma_i^{(2)}$.
- Case 3: $c_i \geq \sigma_i$ and $p_i^{\text{nowifi}}(T) \leq 1 - \frac{\sigma_i}{c_i}$: $\check{\gamma}_i = \gamma_i^{(1)}$ and $\hat{\gamma}_i = c_i$.

The proof of Theorem 3 is given in Appendix B.

IV. Stage One: Reward Optimization of SP

Given the response of user i under a fixed reward derived in Section III-B, we will discuss how the SP chooses a reward to maximize its expected surplus in this section. For the general case with a discounted reward, we will consider it in our future work.

Let $\mathcal{I}_l = \{1, \ldots, I_l\} \subseteq \mathcal{I}$ be the set of users with an initial location $l \in \mathcal{L}$, where the SP wants to obtain some measurements. Let $\mathbb{M}_l(n)$ be the set of all possible subsets of set $\mathcal{I}_l$ with n users, where $n = 0, 1, \ldots, I_l$. As an example, for $\mathcal{I}_l = \{1, 2, 3\}$, we have $\mathbb{M}_l(2) = \Big\{\{1,2\}, \{1,3\}, \{2,3\}\Big\}$ for $n = 2$. We define $P(n, r)$ as the probability that $n = 0, 1, \ldots, I_l$ users report their sensed data when the reward is equal to r. We can express it as

$$P(n,r) = \sum_{\mathcal{M} \in \mathbb{M}_l(n)} \Big(\prod_{m \in \mathcal{M}} p_m^{\text{report}}(r)\Big)\Big(\prod_{k \in \mathcal{I}_l \setminus \mathcal{M}} (1 - p_k^{\text{report}}(r))\Big). \tag{14}$$

Let $u(n)$ be the *utility function* of the SP when n users in set $\mathcal{I}_l$ report their measurements. We assume that $u(n)$ is a nondecreasing function in n with $u(0) = 0$. Overall, the SP aims to select reward r that maximizes its *expected* surplus (i.e., utility minus payment) as

$$\underset{r \geq 0}{\text{maximize}} \quad g(r) \triangleq \sum_{n=0}^{I_l} \Big(u(n) - rn\Big) P(n,r). \tag{15}$$

where rn is the total payment to the users.

Let $\mathcal{R} = \{\check{\gamma}_1, \hat{\gamma}_1, \ldots, \check{\gamma}_{I_l}, \hat{\gamma}_{I_l}\}$ be the thresholds of all users in set $\mathcal{I}_l$. Let r^* be the optimal solution in problem (15). We can prove that the SP should choose $r^* \in \mathcal{R} \cup \{0\}$ to maximize its expected surplus.

Theorem 4: $r^* \in \mathcal{R} \cup \{0\}$.

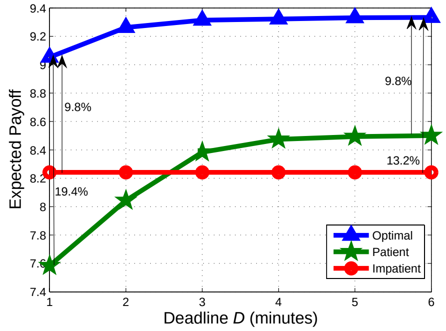

Fig. 3. The expected user payoff versus the deadline for $\theta = 0.9$, $R = 25$, $\sigma_i = 10$, $c_i = 11$, and $p^{stay} = 0.5$.

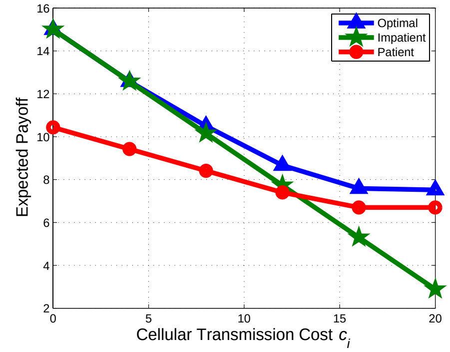

Fig. 4. The expected user payoff versus the cellular transmission cost c_i for $\theta = 0.9$, $R = 25$, $\sigma_i = 10$, $p^{stay} = 0.5$, and $D = 1$ minute.

The proof of Theorem 4 is given in Appendix C. As a result, we can simplify the reward optimization problem in (15) as

$$\underset{r \in \mathcal{R} \cup \{0\}}{\text{maximize}} \quad \sum_{n=0}^{I_l} \Big(u(n) - rn \Big) P(n, r), \tag{16}$$

which is a discrete optimization problem with a linear complexity. Since there are at most $2I_l + 1$ values of r to consider in (16), we can apply the exhaustive search to solve it.

V. Performance Evaluations

In this section, we evaluate the performance of our proposed OPRD algorithm (i.e., Algorithm 1) by comparing it with two heuristic benchmark schemes in terms of the expected payoff achieved by a user. We also show the simulation result related to the reward optimization of the SP for the fixed reward case.

Each data point in the plots represents the average value based on 1000 randomly generated scenarios with different network availabilities and user mobility patterns. Unless specified otherwise, we assume that the probability that a Wi-Fi connection is available at a particular location is 0.4. Each time slot corresponds to $\Delta t = 10$ seconds. Each user is moving around $L = 16$ possible locations in a four by four grid (similar to that in Fig. 1). For the state transition probabilities $p_i(l' \,|\, l)$, we assume that probability that user i stays at a location is given by $p_i(l \,|\, l) = p^{stay}$, $\forall\, l \in \mathcal{L}$. Moreover, the user is equally likely to move to any of the neighbouring locations. Take location 7 in Fig. 1 as an example, if $p^{stay} = 0.5$, then the probability that the user will move to one of the locations 3, 6, 8, or 11 is equal to $(1 - 0.5)/4 = 0.125$.

A. Performance Evaluation of the OPRD scheme

First, we compare the expected user payoff, which is the reward minus the total sensing and transmission costs, under the OPRD scheme (denoted as optimal) with two benchmark schemes:

- *Patient* scheme: A user will always participate in sensing, and wait for a Wi-Fi network for reporting. If no Wi-Fi network is available within T time slots, it will use cellular to report in time slot T if $\theta^{T-1} R \geq c_i$, and not to report otherwise.
- *Impatient* scheme: The user will always participate and report in the first time slot. It will use a Wi-Fi network to report if $l_i(1) \in \mathcal{L}^{(1)}$, otherwise it will use the cellular network to report if $l_i(1) \in \mathcal{L}^{(0)}$.

In Fig. 3, we plot the expected user payoff under the three schemes for different values of deadline D (in minutes, so $T = 60D/\Delta t$). We assume that the discounted factor $\theta = 0.9$, initial reward $R = 25$, sensing cost $\sigma_i = 10$, cellular transmission cost $c_i = 11$, and probability of staying at a location $p^{stay} = 0.5$. As we can see, our proposed OPRD scheme results in the maximal expected user payoff as compared with the two heuristic schemes under different deadlines. Specifically, it improves the user payoff over the impatient scheme by 9.8% and 13.2% for $D = 1$ minute and $D = 6$ minutes, respectively. Also, the payoff improvements over the patient scheme are 19.4% and 9.8% for $D = 1$ minute and $D = 6$ minutes, respectively. As the user under the impatient scheme will report in the first time slot anyway, its expected payoff is independent of D. In contrast, for the OPRD scheme and the patient scheme, the longer the deadline, the higher the chance in meeting Wi-Fi, so the expected payoff increases with D initially. As the deadline D increases beyond 5 minutes, the chance of meeting Wi-Fi is already very high, so the expected payoff saturates.

In Fig. 4, we plot the expected user payoff against the cellular transmission cost c_i, where we assume that $\theta = 0.9$, $R = 25$, $\sigma_i = 10$, $p^{stay} = 0.5$, and $D = 1$ minute. As we can see, as c_i increases, the expected user payoff under all the three schemes decreases. Also, we observe that our proposed OPRD scheme results in the maximal expected user payoff as compared with the two heuristic schemes for different values of c_i. When the cellular transmission cost c_i is small, the impatient scheme performs similarly as the optimal scheme. However, as c_i increases, it is better for the user to be patient and wait longer for the availability of Wi-Fi.

In Fig. 5, we plot the expected user payoff against the discount factor θ for $R = 30$, $c_i = 11$, $\sigma_i = 10$, $p^{stay} = 0.5$, and $D = 5$ minutes. When θ is close to 1, it is a good decision for the user to be patient and wait for Wi-Fi to report. However, when θ is smaller, it is better to be impatient and report in the

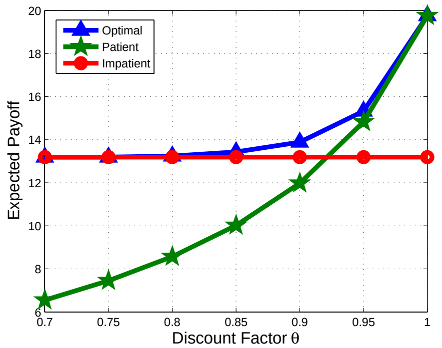

Fig. 5. The expected user payoff versus the discount factor θ for $R = 30$, $c_i = 11$, $\sigma_i = 10$, $p^{stay} = 0.5$, and $D = 5$ minutes.

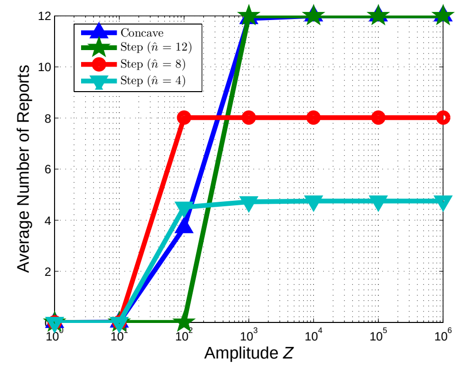

Fig. 6. The average number of reports received by the SP versus amplitude Z in different utility functions. We assume that $I_l = 12$, $c_i = 8$, $\sigma_i \in \mathcal{N}(5, 1)$, and $p_i^{\text{nowifi}}(T) \in U[0.1, 0.9]$.

first time slot, as the reward reduces at a faster rate. As a user under the impatient scheme reports in the first time slot, its achieved payoff is independent of θ.

B. Reward Optimization of the Service Provider

We consider that the SP is interested to collect measurements at location l with $I_l = 12$ users. Since all the users are responsible for sensing the same phenomenon of interest at the same initial location, we assume that the sizes of the sensed data are the same and the cellular prices for all users are the same. Therefore, we assume that the cellular transmission cost is $c_i = 8, \forall i \in \mathcal{I}_l$. We assume that the sensing cost σ_i is a Gaussian random variable with mean equal to 5 and a unit variance (i.e., $\mathcal{N}(5, 1)$), and $p_i^{\text{nowifi}}(T)$ is a uniformly distributed random variable in $(0.1, 0.9)$ (i.e., $U(0.1, 0.9)$). In the reward optimization, we consider the step utility function of the SP in the form $u(n) = Z$ if $n \geq \hat{n}$ and $u(n) = 0$ otherwise, where Z is the amplitude of the utility function. It is related to PS applications that require at least $\hat{n}$ users to participate in order to reach its full functionality [11]. We also consider a concave utility function in the form $u(n) = Z \log(1 + n)$ with $u(0) = 0$. It is related to PS applications that exhibit a diminishing marginal utility for every extra report received.

In Fig. 6, we plot the average number of reports received by the SP with the optimal reward r^* in problem (16) against the amplitude Z in the utility function. For the step functions, when Z increases, we notice that the number of received reports first increases, and then stays constant. On the other hand, for the concave function, the number of received reports increases until it reaches I_l.

In Fig. 7, we show an example of $P(n, r)$, which is the probability of receiving n reports given reward r, by plotting it against $n \in \{0, 1, \ldots, I_l\}$ and the reward thresholds $r \in \mathcal{R}$. It can be seen that for $r < c_i = 8$, the non-zero probabilities of $P(n, r)$ are usually less than one, which is due to the probabilistic reporting decision using Wi-Fi as stated in Theorem 2(a). On the other hand, for $r \geq c_i$, the non-zero probabilities of $P(n, r)$ are always equal to one, which is due to the sure reporting decision as stated in Theorem 2(b).

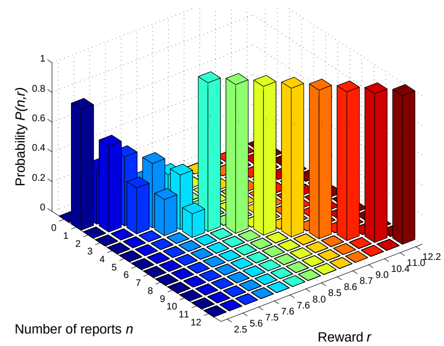

Fig. 7. An example of $P(n, r)$ against $n \in \{0, 1, \ldots, I_l\}$ and $r \in \mathcal{R}$, where $I_l = 12$, $c_i = 8$, $\sigma_i \in \mathcal{N}(5, 1)$ and $p_i^{\text{nowifi}}(T) \in U(0.1, 0.9)$.

VI. Conclusion

In this paper, we studied the decisions of both the mobile users and service provider (SP) in a participatory sensing system. We first considered the participation and reporting decisions of users under a deadline reward scheme. For the general case with a time-discounted reward, we proposed an optimal participation and reporting decision (OPRD) algorithm that achieves the maximal expected surplus for each user. For the special case with a fixed reward, we derived the user's participation and reporting decisions in closed-form. Next, given the responses from the users, we considered the reward optimization of the SP, who aims to choose an optimal reward to maximize its expected surplus. Simulation results showed that our proposed OPRD algorithm achieves the highest expected user payoff as compared with the patient and impatient benchmark schemes. For future work, we will consider the reward optimization of the SP under incomplete user information and the general case with a discounted reward.

Appendix

A. Proof of Theorem 2

Let ρ_i be the payoff (i.e., the reward minus the total sensing and transmission costs) of user i. Assume that user i has already performed sensing.

(a) In this case, with probability $p_i^{\text{nowifi}}(T)$, user i will not meet any Wi-Fi, and it will not report to the SP, so $\rho_i = -\sigma_i < 0$. With probability $1 - p_i^{\text{nowifi}}(T)$, user i will report by Wi-Fi, so $\rho_i = r - \sigma_i$. User i chooses to participate if and only if its expected payoff $E[\rho_i] = p_i^{\text{nowifi}}(T)(-\sigma_i) + \big(1 - p_i^{\text{nowifi}}(T)\big)(r - \sigma_i) \geq 0$.

(b) In this case, with probability $p_i^{\text{nowifi}}(T)$, user i will not meet any Wi-Fi, but it will report by cellular at deadline T to obtain the reward, so $\rho_i = r - \sigma_i - c_i$. With probability $1 - p_i^{\text{nowifi}}(T)$, user i will report by Wi-Fi, so $\rho_i = r - \sigma_i$. User i chooses to participate if and only if its expected payoff $E[\rho_i] = p_i^{\text{nowifi}}(T)(r - \sigma_i - c_i) + \big(1 - p_i^{\text{nowifi}}(T)\big)(r - \sigma_i) \geq 0$.

For the *reporting decisions*, with a fixed reward before the deadline, there is no harm for user i to wait for Wi-Fi until deadline T under both cases (a) and (b). However, the difference in reporting decisions for these two cases at time T is due to the fact that user i can recover the cellular cost in (b) with a larger reward r (i.e., $r \geq c_i$), but not in (a). ■

B. Proof of Theorem 3

The participation and reporting decisions under a fixed reward for different values of σ_i, c_i, and $p_i^{\text{nowifi}}(T)$ are summarized in the three cases in Fig. 8. The decisions for $r \leq \sigma_i$ and $r \geq \sigma_i + c_i$ have been described in scenarios (i) and (ii) in Section III-B1. Here, we consider the decisions for $\sigma_i < r < \sigma_i + c_i$.

• Case 1: $c_i < \sigma_i$. In this case, $\sigma_i < r < \sigma_i + c_i$ implies that $r > c_i$. The result in Theorem 2(b) applies.

• Case 2: $c_i \geq \sigma_i$ and $p_i^{\text{nowifi}}(T) > 1 - \frac{\sigma_i}{c_i}$. For the first interval $\sigma_i < r < c_i$, since $\gamma_i^{(1)} = \frac{\sigma_i}{1 - p_i^{\text{nowifi}}(T)} > \frac{\sigma_i}{1-(1-\frac{\sigma_i}{c_i})} = c_i$, we conclude from Theorem 2(a) that user i will not participate. For the second interval $c_i \leq r < \sigma_i + c_i$, since $\gamma_i^{(2)} = \sigma_i + p_i^{\text{nowifi}}(T)c_i > \sigma_i + (1 - \frac{\sigma_i}{c_i})c_i = c_i$, the result in Theorem 2(b) applies.

• Case 3: $c_i \geq \sigma_i$ and $p_i^{\text{nowifi}}(T) \leq 1 - \frac{\sigma_i}{c_i}$. For the first interval $\sigma_i < r < c_i$, as $\gamma_i^{(1)} \leq c_i$, the result in Theorem 2(a) applies. Since $\gamma_i^{(2)} \leq c_i$, we conclude from Theorem 2(b) that user i will participate in the second interval $c_i \leq r < \sigma_i + c_i$.

From Fig. 8, we observe the distinct responses of user i in three ranges characterized by the thresholds $\check{\gamma}_i$ and $\hat{\gamma}_i$ defined in Theorem 3: User i decides not to participate if $r < \check{\gamma}_i$, participate and report with Wi-Fi with probability $1 - p_i^{\text{nowifi}}(T)$ (i.e., the probability of meeting Wi-Fi by deadline) if $\check{\gamma}_i \leq r < \hat{\gamma}_i$, and participate and report for sure if $r \geq \hat{\gamma}_i$. ■

C. Proof of Theorem 4

Assume on the contrary that $r^* \notin \mathcal{R} \cup \{0\}$. From (14) and the threshold descriptions of $p_i^{\text{report}}(r)$ in (13), we can always find $\bar{r} \in \mathcal{R} \cup \{0\}$ such that $\bar{r} < r^*$ and $P(n, r^*) = P(n, \bar{r})$. As a result, we have $g(r^*) < g(\bar{r})$, which contradicts that r^* is the optimal solution in problem (15). ■

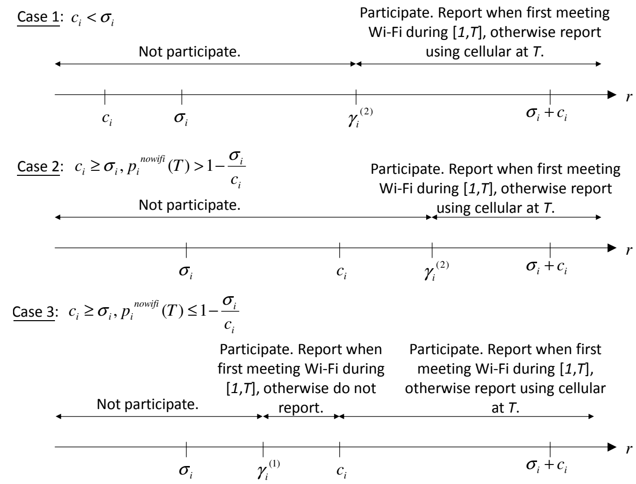

Fig. 8. Participation and reporting decisions of user i under different r.

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