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Delay-Sensitive Mobile Crowdsensing: Algorithm Design and Economics

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Abstract—In a *delay-sensitive* mobile crowdsensing (MCS) platform, a service provider offers monetary incentives to mobile users for *participating* in the data collection and *reporting* their obtained data by a *deadline*. One aspect missing from most prior literature in the incentive mechanism design is the consideration of the detailed data reporting process through cellular or Wi-Fi networks. In this paper, we consider the interactions between the service provider and the users in two stages. First, the service provider chooses a reward to maximize its expected profit under the incomplete information of the users' responses. Next, given the reward, each user makes his participation and reporting decisions, which are complicated due to his mobility and network heterogeneity. We propose an algorithm to compute the optimal user's decisions under the general setting using dynamic programming, and derive *closed-form* decision criteria for the special yet practical case of a non-discounted reward. We compute the optimal reward by characterizing the solution set and the discontinuity in the profit function. Simulation results show that our proposed algorithm achieves a significant gain in the user payoff over three benchmark heuristic schemes. In addition, a service provider's profit is sensitive to the estimation of the users' Wi-Fi availabilities.

Index Terms—Mobile crowdsensing, profit maximization, dynamic programming, cellular and Wi-Fi networks, service provider.

1 INTRODUCTION

1.1 Background

Mobile crowdsensing (MCS) refers to a new sensing paradigm, where a large number of individuals using their mobile devices (e.g., smartphones or wearable devices) to extract and share information related to a certain phenomenon of interest [2]–[4]. Recently, *delay-sensitive* MCS applications [5]–[7] have emerged involving the collection of time-sensitive and location-dependent data within a given *deadline*. For example, in commercial applications, such as Gigwalk [8] and Field Agent [9], the service provider utilizes MCS to provide their business customers (e.g., Coca-Cola and Johnson & Johnson) with critical *real-time* business information related to their stores and products, often in the form of photos, videos, audios, data, opinions, and feedbacks. Other examples include real-time tourist query [10], citizen-journalism [10], parking space identification [11], and data query [12], where the value of data may degrade rapidly shortly after the events have happened. To facilitate the deployment of these MCS applications, it is important to take into account the life cycle of the MCS process [13] and design *incentive mechanisms* [14]–[24] or *pricing mechanisms* [25]–[27] accordingly to motivate the users' participation, which are both open areas with active research.

Specifically, in this paper, we first investigate and analyze the *participation* (i.e., whether to perform the sensing task) and *reporting* (i.e., which wireless network to use to upload the sensed data) in the task execution phase [13] in delay-sensitive MCS applications. We then propose an incentive mechanism to efficiently collect the delay-sensitive and location-dependent data. In fact, the reporting process is an important user decision that cannot be overlooked, especially for delay-sensitive MCS applications. First, due to the *user mobility*, the users may sense and report at different locations and different times. Second, with the tighter network integration in 5G, users can choose between cellular or Wi-Fi networks more readily for data reporting. Due to the *network heterogeneity*, users would have different transmission costs and network availabilities in general. More specifically, for the cellular network with ubiquitous coverage, its usage cost is non-negligible, especially for MCS applications that involve a 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. Without considering the user mobility and network heterogeneity, the participation decisions of users may be suboptimal and the design of incentive mechanism for the service provider may be ineffective.

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In this paper, we would like to understand two sets of important questions: (i) *Algorithm design: Given a user's mobility and network availability, should he participate in MCS? If so, where, when, and through which network (e.g., cellular or Wi-Fi networks) should he upload his data?*[1] (ii) *Economics: Given the incomplete information of the users' costs and Wi-Fi availabilities, how should the service provider determine the optimal reward for profit maximization?*

1.2 Contributions

To answer these questions, we formulate the interactions between the service provider and mobile users as a two-stage Stackelberg game. In Stage I, the service provider optimizes its reward for profit maximization under the incomplete information of the users' responses. In Stage II, each user computes his participation and reporting decisions, given the reward, deadline, costs, and mobility. We formulate this multi-slot optimization problem using dynamic programming. The analysis in this two-stage problem is particularly challenging, as we need to characterize the service provider's profit by first computing the users' probability of reporting. Nevertheless, we design an algorithm to compute the optimal user's decision in Stage II, and propose a method to compute the optimal reward in Stage I by exploiting some special structures of the profit function and the users' responses. Overall, the main contributions of this paper are as follows:

- *Practical modeling*: Motivated by the practical delay-sensitive MCS applications, we consider the joint participation and reporting decisions of the mobile users and the reward optimization of the service provider, by taking into consideration the user mobility and network heterogeneity.
- *Algorithm design for user's optimal decisions*: Consider a general time-discounted reward, we propose an *optimal* participation and reporting decisions (OPRD) algorithm using dynamic programming. In the special yet practical case of a non-discounted reward, we derive the *closed-form* user decisions under various network scenarios. A counter-intuitive result is that it is possible for a user to participate and perform the sensing but eventually not to report the sensed data, if the transmission cost is high and he cannot meet a Wi-Fi network within the deadline.
- *Economics of delay-sensitive MCS*: We study the service provider's profit maximization problem under the incomplete information of the users. To characterize the profit, we derive the probability of reporting under *arbitrary* distributions of the users' costs and Wi-Fi availabilities. We elaborate the result further when the Wi-Fi availabilities follow the *truncated normal distribution*, which covers both the widely adopted normal and uniform distributions as special cases.
- *System insight*: Simulation result shows that underestimating the users' Wi-Fi availabilities may lead to a significant profit loss for the service provider, but overestimating it usually has a much milder effect.

The rest of the paper is organized as follows. We first review the related works in Section 2. We then describe our system model in Section 3. We analyze users' decisions with discounted reward and non-discounted reward in Section 4 and 5, respectively. We solve the service provider's reward optimization in Section 6. Numerical results are given in Section 7, and we conclude the paper in Section 8.

2 Related Works and Research Motivation

We can classify the literature on the incentive mechanism design in mobile crowdsensing [14]–[18] according to whether user mobility has been explicitly taken into account in the design. A number of incentive mechanisms [29]–[35] mainly focused on the users' static participation decisions and did not explicitly consider the *user mobility* in the participation decisions. However, in practice, users can move around multiple locations, and hence may sense and report at different locations and different times. On the other hand, some proposed incentive mechanisms [36]–[38] have explicitly considered the mobility of the users at multiple locations and time. However, none of [36]–[38] considered users' decisions and tradeoffs related to the data reporting process. In this paper, we jointly consider user participation and reporting, and take into account the network heterogeneity.

A particularly related paper to our work is [39], where Xu *et al.* studied the user reporting issues related to the choices of cellular and Wi-Fi networks. However, [39] mainly studied the choice between cellular and Wi-Fi networks given a fixed cellular budget from a user's perspective, and did not consider the service provider's incentive mechanism design. In contrast, we focused on the incentive issue of reporting the sensed data for a reward, and considered both the decisions of the users and service provider.

In this paper, we investigate and analyze a user's optimal participation and reporting decisions by taking into account his mobility, cellular cost, and Wi-Fi availability. Based on this result, we formulate the service provider's profit maximization problem and compute the optimal reward numerically.

3 System Model

We consider an MCS system shown in Fig. 1, where a *service provider* aims to collect *real-time* information (e.g., photos, videos, audios, and opinions) from certain locations of interest through the participation of the *mobile users* moving around (e.g., Gigwalk [8], Field

1. In practice, it is possible for a user to delay the upload of the sensed data. For example, Gigwalk releases an offline feature [28], where a user can perform sensing at a location with no Internet connectivity, and upload the sensed data at a later time.

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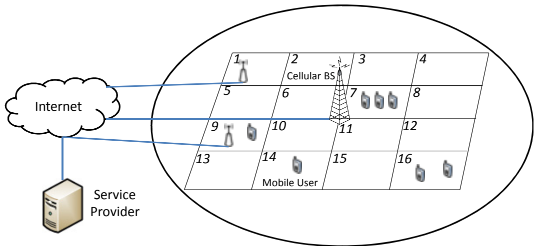

Fig. 1. An example of the mobile crowdsensing system, where the users are moving within a set of $\mathcal{L} = \{1, \ldots, 16\}$ locations. The users are always under the coverage of a cellular base station, but Wi-Fi is only available at locations 1 and 9.

Agent [9], and citizen-journalism [10]). In the following subsections, we describe how the service provider and the mobile users interact with each other.

3.1 Service Provider

The service provider aims to collect real-time information with the help of the mobile users by a given *deadline*. Specifically, we consider a time slotted system with a deadline T, which involves a set $\mathcal{T} = \{1, \ldots, T\}$ of time slots. Let $\mathcal{I} = \{1, \ldots, I\}$ be the set of mobile users and $\mathcal{L} = \{1, \ldots, L\}$ be the set of locations. We define $l_i(t) \in \mathcal{L}$ as the position of user $i \in \mathcal{I}$ at time $t \in \mathcal{T}$. The service provider wants users to help take measurements at the first time slot ($t = 1$) from a set of locations of interest $\mathcal{L}^{\text{sense}} \subseteq \mathcal{L}$. Any measurement taken at a later time slot will not be useful for the service provider. However, the service provider can tolerate a delay up to T time slots before the users report the measurements.

To incentive the users to participate and report the measurements, the service provider will implement the following reward scheme.

Definition 1 (Service Provider's Reward Scheme): A reward scheme is characterized by the tuple $(R, \theta, T, \mathcal{L}^{\text{sense}})$, where $R \geq 0$ is the initial reward and $0 < \theta \leq 1$ is the discount factor. For a user who performs measurement at a location $l_i(1) \in \mathcal{L}^{\text{sense}}$ at time $t = 1$, and reports his data to the service provider at time $t \leq T$, the service provider will give him a reward $r = \theta^{t-1} R$.

In this reward scheme, the service provider will not grant any reward for data reported after deadline T. This discounted reward scheme with a deadline is valid for delay-sensitive MCS applications, where the value of data degrades with time.

We assume that the service provider cares about the total number of users, who have performed sensing at any locations in $\mathcal{L}^{\text{sense}}$ at time $t = 1$ and have reported the sensed data. Without loss of generality, we assume that all the users in $\mathcal{I}$ are at the locations of interest of the service provider at time $t = 1$, i.e., $l_i(1) \in \mathcal{L}^{\text{sense}}$, $\forall i \in \mathcal{I}$.

We assume that θ, $\mathcal{L}^{\text{sense}}$, and T are pre-defined reward parameters in the MCS applications. In Section 6, under the non-discounted reward (i.e., $\theta = 1$), we will discuss how the service provider optimizes the reward r to maximize its profit. In Section 7, we will study the impact of θ and T on the users' decisions.

3.2 Mobile Users

We define a user's attributes as follows.

Definition 2 (User Attributes): Each user $i \in \mathcal{I}$ is associated with:

- *Sensing cost* σ_i: The energy cost incurred by user i if performing the sensing task.
- *Cellular transmission cost* c_i: The payment[2] of user i to the cellular operator when reporting the sensed data to the service provider. We assume that the users can use Wi-Fi networks free of charge.
- *Mobility pattern*: User's mobility pattern determines the probability p_i of user i *not* meeting Wi-Fi before the deadline T, which will affect the user's decision on the reporting of sensed data.[3] We will discuss this point in more details in Section 5.

3.3 Wi-Fi Availability

The Wi-Fi deployment in the system affects the users' decisions. Let $\mathcal{L}^{(0)}$ and $\mathcal{L}^{(1)}$ be the set of locations without and with Wi-Fi, respectively, and we have $\mathcal{L}^{(0)} \cup \mathcal{L}^{(1)} = \mathcal{L}$. Fig. 1 illustrates an example with $\mathcal{L}^{(1)} = \{1, 9\}$, because only locations 1 and 9 have Wi-Fi deployed.

3.4 User's Participation and Reporting Decisions

Based on the reward scheme of the service provider in Definition 1, the user attributes in Definition 2, and the Wi-Fi deployment as characterized by sets $\mathcal{L}^{(0)}$ and $\mathcal{L}^{(1)}$, each user needs to make his *participation* and *reporting* decisions to maximize his expected payoff. A user i needs to make two decisions as follows:

- *Participation Decision*: User i needs to decide whether he should perform sensing at his initial location $l_i(1)$ at time $t = 1$ or not, by comparing the *expected payoffs* between participation and no participation.
- *Reporting Decision*: If user i has performed the sensing, he needs to further decide *where*, *when*, and using *which* type of network (i.e., cellular or Wi-Fi) to report his data to the service provider, depending on the stochastic network availability in the future T time slots.[4] Perhaps counter-intuitively, we will show that it can be optimal for a user to decide

2. It can be calculated as the product of the cellular data price and the amount of data upload.

3. In practice, p_i can be calculated as the number of time slots that user i cannot meet Wi-Fi divided by the total number of time slots T, so it can be estimated based on user i's mobility history.

4. We assume that a time slot is long enough such that the actions of sensing and data reporting can be completed together in one time slot (if needed).

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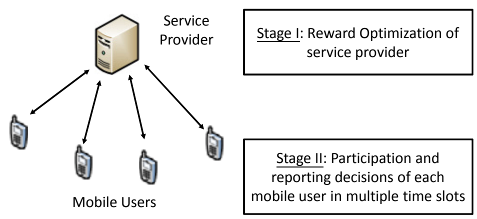

Fig. 2. The two stages that we consider in this paper.

not to report his sensed data after he has performed sensing.[5]

Later in Section 4, we will present a user's payoff function under different decisions in more details. For simplicity, we assume that the users are honest and will report their actual measurements to the service provider truthfully[6] (once they have decided to report) [38].

3.5 Two-Stage Model

Since the decisions of the service provider and the users are dependent of each other, we use a two-stage Stackelberg game to model their interactions. As shown in Fig. 2, we assume that the service provider first chooses its reward in Stage I, and each user then makes his participation and reporting decisions in Stage II.

By applying backward induction, we first consider the decisions of each user $i \in \mathcal{I}$ in Stage II given the reward scheme from the service provider, under discounted reward in Section 4 and under non-discounted reward in Section 5. In Section 6, we further study how the service provider makes decisions in Stage I by considering the potential response from the users.

A list of the key notations in this paper is given in Table 1.

TABLE 1
List of Key Notations

Notation	Meaning
i, $\mathcal{I}$	User index and the set of users
l, $\mathcal{L}$	Location index and the set of locations
$\mathcal{L}^{(0)}$, $\mathcal{L}^{(1)}$	Locations without Wi-Fi and with Wi-Fi
k	Data reporting status
t, $\mathcal{T}$	Time slot and the set of time slots
T	Deadline
θ	Discount factor of reward
r, R	Reward and maximum reward
s_i	Sensing cost of user i
c_i	Cellular transmission cost of user i
p_i	Probability of not meeting Wi-Fi by deadline of user i
a, $\mathcal{A}$, $\mathcal{A}_k$	Action, the set of actions, and the set of actions given k
$\delta_t(\cdot)$	Decision rule in time slot t
ξ_i^*	Maximal expected surplus for participation of user i
$\rho_i(r)$	Probability of reporting of user i given reward r
$\rho(r)$	Probability of reporting given reward r
$f(p)$	Probability density function of the probability p
μ, ϵ	Parameters of the truncated normal distribution

4 Users' Decisions Under Discounted Reward in Stage II

In this section, given the reward scheme announced by the service provider, we study the Stage II problem on the participation and reporting decisions of a user. As the participation and reporting decisions of the same user are coupled, it can be quite challenging to analyze. We consider the general case with a discounted reward in this section, and propose an optimal algorithm based on dynamic programming.

We consider the Markovian mobility model that has been widely used in the literature [43]–[45].[7] Let $Q_i = \left[q_i(l'|l)\right]_{L\times L}$ be the location transition matrix of user $i \in \mathcal{I}$, where $q_i(l'|l)$ is the probability that user $i \in \mathcal{I}$ will move to $l' \in \mathcal{L}$ in the next time slot given that he is currently at location $l \in \mathcal{L}$. We assume that Q_i is estimated based on the past mobility pattern of user i [43]–[45].[8]

As discussed in Section 3.2, since a user makes the participation decision before the reporting decision, we apply backward induction within Stage II to first analyze the reporting decision in Sections 4.1 and 4.2, and then study the participation decision in Section 4.3.

4.1 Dynamic Programming Formulation on Reporting Decision

Since there is no need to consider the reporting decision if a user does not participate, we assume 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, which consists of five components

5. If the user has decided not to participate, he will not need to further decide whether to report. Thus, we consider that he makes the participation decision before the reporting decision.

6. The issue of truthful bidding of agents in MCS has been discussed and analyzed in some recent papers, such as [33], [34], [36]. In terms of the particular problem that we study here, we can also use some verification methods to ensure the accuracy of the data. For example, in Field Agent [9], GPS markers, time-date stamps, photo / video verification, and human analysts are employed to ensure the data quality. In addition, it is possible to implement some quality control mechanisms [40], such as reputation [41], [42], to encourage the truthful reporting of the users, which are interesting topics for future work.

7. While there are other mobility models used in the MCS literature (e.g., the graph-based mobility model proposed in [46]), the Markovian model is shown to be accurate in predicting human mobility. For example, the work in [47] showed that the Markovian model can correctly predict 90% of daily human mobility in Ivory Coast.

8. We want to clarify that for the general case with discounted reward (as we consider in this section), we can only compute the optimal user's decision if his mobility pattern follows a Markovian model. However, for the special case with a non-discounted reward (as we will discuss in Section 5), as long as one can estimate the probability p_i (under any mobility model), we can compute the optimal user's decisions with Theorems 2 and 3 in closed-form.

in the modeling [48], namely decision epochs, states, actions, state transition probabilities, and surpluses.

Specifically, the *decision epochs* of user i are

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

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 service or not, where $k = 1$ represents that user i has reported the sensed data so there is no backlogged data in the buffer, and $k = 0$ represent that user i has not reported the data. The state element $l \in \mathcal{L} = \{1, \dots, L\}$ is the location index, where L is the total number of possible locations that the user may reach within the T time slots.[9]

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., $k = 0$) and the current location has Wi-Fi (i.e., $l \in \mathcal{L}^{(1)}$). Since the user should report only if he has not done so, the feasible action set $\mathcal{A}_k$ depends on the state element k as follows:

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

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

The *state transition probability* $\mathbb{P}\big(\boldsymbol{s}' \,|\, \boldsymbol{s}, a\big) = \mathbb{P}\big((k', l') \,|\, (k, l), a\big)$ 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 user i from l to l' is independent of the value of k and action a, we have

$$\mathbb{P}\big(\boldsymbol{s}' \,|\, \boldsymbol{s}, a\big) = \mathbb{P}\big((k', l') \,|\, (k, l), a\big) = q_i(l' \,|\, l)\ \chi(k' \,|\, k, a), \tag{3}$$

where

$$\chi(k' \,|\, k, 1) = \begin{cases} 1, & \text{if } k' = 1, \\ 0, & \text{otherwise,} \end{cases} \tag{4}$$

and

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

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

$$\phi_t(k, l, a) = \begin{cases} \theta^{t-1} R, & \text{if } a = 1, k = 0, \text{and } l \in \mathcal{L}^{(1)}, \\ \theta^{t-1} R - c_i, & \text{if } a = 1, k = 0, \text{and } l \in \mathcal{L}^{(0)}, \\ 0, & \text{if } a = 0. \end{cases} \tag{6}$$

9. It is possible to consider a more general network coverage model, where the cellular network does not have ubiquitous coverage, and still formulate the user's decisions using dynamic programming. In this case, since there may be no available network at some locations, we need to define an additional state element to keep track of the network availability for the proper formulation of the reporting decision, which significantly increases the computational complexity of the proposed algorithm.

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 in this case.

After characterizing the five components in the dynamic programming model, we can define our reporting decision problem. Let $\delta_t : \mathcal{K} \times \mathcal{L} \to \mathcal{A}$ 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 the 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 his *expected* surplus as follows.

Optimal Reporting Decision Problem:

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

Here, $E_{\boldsymbol{s}_1}^{\boldsymbol{\pi}}$ denotes the expectation with respect to user i's mobility pattern and policy $\boldsymbol{\pi}$ with an initial state $\boldsymbol{s}_1 = \big(0, l_i(1)\big)$, where $l_i(1)$ is the initial location of user i at time slot $t = 1$.

4.2 Optimal Reporting Decision

Next, we discuss how to compute the optimal policy in problem (7). Let $v_t(\boldsymbol{s})$ be the maximal total expected surplus of user i 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* [48, pp. 83] relating the maximal expected surplus at different states for $t \in \mathcal{T}$ is given by

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

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

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

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

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 (from time slot $t + 1$ to time slot T) for choosing action a at time slot t, respectively. The derivation of (10) from (9) follows directly from (3), (4), and (5). Moreover, since there are no rewards, costs, and user's decisions after the deadline, we further define the boundary condition at an auxiliary time slot $t = T + 1$ as

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

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

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

With the optimality equation in (8) and the boundary condition in (11), we can obtain the optimal reporting policy $\boldsymbol{\pi}^*$ of problem (7) in Theorem 1. We will discuss the details of computing this optimal policy in Section 4.4.

Theorem 1: The optimal policy of problem (7) is $\boldsymbol{\pi}^* = (\delta_t^*(k,l), \forall k \in \mathcal{K}, l \in \mathcal{L}, t \in \mathcal{T})$, where

$$\delta_t^*(k,l) = \arg\max_{a \in \mathcal{A}_k} \{\lambda_t(k,l,a)\}. \tag{12}$$

Proof: The proof is based on the principle of optimality [49, pp. 18]. □

4.3 Optimal Participation Decision

Given the optimal reporting decisions of user i above, we can obtain his *optimal sensing decision* by comparing the optimal expected surplus with and without participation. First, by participating in sensing, his optimal expected surplus is equal to the optimal expected reward ξ_i^* in (7) minus the sensing cost σ_i. If not participating, user i's surplus is zero. This leads to the following result.

Proposition 1 (Optimal Participation Decision): A user i chooses to participate in sensing only if

$$\xi_i^* \geq \sigma_i. \tag{13}$$

4.4 Optimal Participation and Reporting Decisions Algorithm

From the results in Sections 4.2 and 4.3, we propose Algorithm 1 for user i to make his 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* [48, 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 13). The complexity of Algorithm 1 is $\mathcal{O}(LT)$.

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 17 and 18). If he decides to participate, he first obtains measurement at his current location (line 20), and carries out his reporting decision based on the optimal policy $\boldsymbol{\pi}^*$ through checking a table (lines 23 to 28). Notice that the optimal policy $\boldsymbol{\pi}^*$ obtained (line 14) in the planning phase is a *contingency plan* that contains information about the optimal reporting decisions at *all* the possible states (k,l) in any time slot $t \in \mathcal{T}$.

4.5 Insights

Since the participation decision is based on the expected reward, it is possible for user i to decide not to report his sensed data after he has participated and has performed sensing. This will happen when user i does not meet any Wi-Fi before the deadline, and the reward is not large enough to compensate the cost of reporting using the cellular network. We will show this insight more explicitly for the special case with a non-discounted reward in Section 5.

5 Users' Decisions Under Non-Discounted Reward in Stage II

Following the analysis on discounted reward in Section 4, we consider the special case of a non-discounted reward (i.e., $\theta = 1$) in this section.[10] We assume that any participant who can obtain a measurement at his initial location and report his data to the service provider by the deadline T will receive a reward $r \geq 0$. This

10. Although we have discussed the general case of the discounted reward in Section 4, the closed-form analysis of the participation and reporting decisions in this section enables us to obtain clear engineering insights about the connections between these two decisions. Moreover, due to the tractability of the non-discounted reward model, the analysis in this section serves as the basis for the reward optimization in Section 6.

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homogeneous reward scheme with a given deadline is widely used in practice, such as by Gigwalk and Field Agent.

We derive the *closed-form* expressions of users' participation and reporting decisions under small and large rewards in Sections 5.1 and 5.2, respectively. We summarize these results in the form of user i's probability of reporting in Section 5.3, which is useful for our later analysis.

5.1 Optimal Sensing and Reporting Decisions under a Small Reward

First, we consider user i's optimal decisions under a small reward $r \in [0, c_i)$. Let p_i be the probability of user i for *not* meeting Wi-Fi before the deadline, which is related to user i's mobility pattern and the Wi-Fi deployment in the network.[11]

We describe user i's closed-form decisions under a small reward in Theorem 2.

Theorem 2: For a small reward $r \in [0, c_i)$:

- *Participation Decision*: User i chooses to participate if and only if $r \geq \frac{\sigma_i}{1-p_i}$.
- *Reporting Decision*: If user i chooses to participate, then he will wait for a Wi-Fi network to report by deadline T. If no Wi-Fi network is available within T time slots, user i will *not* report.

Theorem 2 establishes a threshold $\frac{\sigma_i}{1-p_i}$ for user i's participation decision. We can see that when the sensing cost σ_i and the probability p_i of not meeting Wi-Fi increases, user i is less reluctant to participate. In addition, when the reward is small, user i will only report to the service provider probabilistically due to the stochastic Wi-Fi availability. The proof of Theorem 2 is given in Appendix B.

5.2 Optimal Sensing and Reporting Decisions under a Large Reward

Next, we derive user i's optimal decisions under a large reward $r \in [c_i, \infty)$.

Theorem 3: For a large reward $r \in [c_i, \infty)$:

- *Participation Decision*: User i chooses to participate if and only if $r \geq \sigma_i + p_i c_i$.
- *Reporting Decision*: If user i chooses to participate, then he 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 the cellular network in time slot T.

The proof of Theorem 3 is given in Appendix C. There are a few differences between the decisions in Theorems 2 and 3. First, the participation threshold $\sigma_i + p_i c_i$ in Theorem 3 depends on all three parameters σ_i, p_i, and c_i, while the participation threshold $\frac{\sigma_i}{1-p_i}$ in Theorem 2 does not depend on c_i. Second, in Theorem 3, since the reward r is large enough to cover the cellular cost c_i, user i will always report within the deadline, which is different from the case in Theorem 2.[12]

5.3 Probability of User i's Reporting

Since the ordering of the thresholds $\frac{\sigma_i}{1-p_i}$, $\sigma_i+p_i c_i$, and c_i in Theorems 2 and 3 varies under different values of σ_i, c_i, and p_i, in the following theorem, we summarize user i's decisions in the form of $\rho_i(r)$, which is the probability that user i will report his sensed data to the service provider given reward r.[13]

Theorem 4:

$$\rho_i(r) = \begin{cases} 0, & \text{if } r \in [0, \check{\gamma}_i), \\ 1 - p_i, & \text{if } r \in [\check{\gamma}_i, \hat{\gamma}_i), \\ 1, & \text{if } r \in [\hat{\gamma}_i, \infty), \end{cases} \quad (14)$$

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

- Case 1: $c_i < \sigma_i$: $\check{\gamma}_i = \hat{\gamma}_i = \sigma_i + p_i c_i$.
- Case 2: $c_i \geq \sigma_i$ and $p_i > 1 - \frac{\sigma_i}{c_i}$: $\check{\gamma}_i = \hat{\gamma}_i = \sigma_i + p_i c_i$.
- Case 3: $c_i \geq \sigma_i$ and $p_i \leq 1 - \frac{\sigma_i}{c_i}$: $\check{\gamma}_i = \frac{\sigma_i}{1-p_i}$ and $\hat{\gamma}_i = c_i$.

The proof of Theorem 4 is given in Appendix D.

6 Stage I: Profit Maximization of Service Provider

Based on the users' decisions derived under a non-discounted reward[14] in Section 5, we consider the profit maximization of service provider in this section. Here, we assume that the service provider only has *incomplete information*[15] about the users' costs and Wi-Fi availabilities, as it is usually difficult for the service provider to know precisely each individual user's private information. In order to compute the profit, we first characterize the users' aggregate reporting response in terms of the probability of reporting in Section 6.1. More specifically, we derive it in the general case under *arbitrary* distributions of the users' costs and Wi-Fi availabilities in Section 6.1.1, and elaborate the result further under the special case of *truncated normal distribution* for the Wi-Fi availabilities in Section 6.1.2. In Section 6.2, we formulate the profit maximization problem and propose a method to compute the optimal reward by exploiting the special structure of the profit function.

11. We will discuss how to derive p_i in closed-form under a Markovian mobility model in Appendix A.

12. Note that as long as the Wi-Fi transmission cost is less than c_i, we can normalize it to zero and make proper changes of the other parameters, so that the rest of the analysis in this paper goes through. Please refer to Appendix E for the detailed discussion.

13. Later in Section 7, we will use this result to verify the accuracy of our analysis in Section 6.1.

14. For the general case with a discounted reward, since a user's decisions in Stage II do not have closed-form solutions, it is not possible to derive the closed-form solution for the service provider's decision in Stage I. We will leave the discussions of Stage I of this general case in the future work.

15. For "complete information", we refer to the case that the service provider knows the *exact values* of σ_i, c_i, and p_i of a *specific user* i. In contrast, for "incomplete information", we refer to the case that the service provider only knows the *probability distributions* of σ_i, c_i, and p_i in the *general user population*. Thus, we remove the subscript i in the notations in this section.

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6.1 Probability of Reporting

6.1.1 General Case

For the random variable σ on the sensing cost, we let $\mathcal{S}$ be its feasible set and $f(\sigma)$ be its probability mass function (pmf). For the random variable c on the cellular transmission cost, we let $\mathcal{C}$ be its feasible set and $f(c)$ be its pmf. For the probability p of not meeting Wi-Fi, we assume that it is a continuous random variable with probability density function (pdf) $f(p)$ for $p \in [p^{\min}, p^{\max}]$, where $0 \leq p^{\min} < p^{\max} \leq 1$.[16]

Let $\rho(r)$ be the probability of reporting data under reward r for a randomly chosen user. We derive it in closed-form for the general case with arbitrary distributions of σ, c, and p in the following theorem.

Theorem 5: The probability of reporting is

$$\rho(r) = \sum_{\sigma \in \mathcal{S}} \sum_{c \in \mathcal{C}} \rho(r|\sigma, c) f(\sigma) f(c), \tag{15}$$

where the conditional probability $\rho(r|\sigma, c)$ has different expressions under different cases. For the case $c < \sigma$, it is given by

$$\rho(r|\sigma, c) = \begin{cases} 0, & \text{if } r \in [0, \sigma + p^{\min} c), \\ \int_{p^{\min}}^{\frac{r-\sigma}{c}} f(p)dp, & \text{if } r \in [\sigma + p^{\min} c, \sigma + p^{\max} c), \\ 1, & \text{if } r \in [\sigma + p^{\max} c, \infty). \end{cases} \tag{16}$$

For the case $c \geq \sigma$, we need to further consider three subcases. First, for the subcase $1 - \frac{\sigma}{c} < p^{\min}$, same as (16), we have

$$\rho(r|\sigma, c) = \begin{cases} 0, & \text{if } r \in [0, \sigma + p^{\min} c), \\ \int_{p^{\min}}^{\frac{r-\sigma}{c}} f(p)dp, & \text{if } r \in [\sigma + p^{\min} c, \sigma + p^{\max} c), \\ 1, & \text{if } r \in [\sigma + p^{\max} c, \infty). \end{cases} \tag{17}$$

Second, for the subcase $1 - \frac{\sigma}{c} \geq p^{\max}$, we have

$$\rho(r|\sigma, c) = \begin{cases} 0, & \text{if } r \in [0, \frac{\sigma}{1-p^{\min}}), \\ \int_{p^{\min}}^{1-\frac{\sigma}{r}} (1-p) f(p)dp, & \text{if } r \in [\frac{\sigma}{1-p^{\min}}, \frac{\sigma}{1-p^{\max}}), \\ \int_{p^{\min}}^{p^{\max}} (1-p) f(p)dp, & \text{if } r \in [\frac{\sigma}{1-p^{\max}}, c), \\ 1, & \text{if } r \in [c, \infty). \end{cases} \tag{18}$$

Third, for the subcase $p^{\min} \leq 1 - \frac{\sigma}{c} < p^{\max}$, we have

$$\rho(r|\sigma, c) = \begin{cases} 0, & \text{if } r \in [0, \frac{\sigma}{1-p^{\min}}), \\ \int_{p^{\min}}^{1-\frac{\sigma}{r}} (1-p) f(p)dp, & \text{if } r \in [\frac{\sigma}{1-p^{\min}}, c), \\ \int_{p^{\min}}^{\frac{r-\sigma}{c}} f(p)dp, & \text{if } r \in [c, \sigma + p^{\max} c), \\ 1, & \text{if } r \in [\sigma + p^{\max} c, \infty). \end{cases} \tag{19}$$

It should be noted that $\rho(r|\sigma, c)$ is continuous, except at $r = c$ in (18) and (19). It is due to the change in users' behaviours at $r = c$ as stated in Theorems 2 and 3. The proof of Theorem 5 is given in Appendix F.

16. We can estimate the pmf $f(\sigma)$ based on the energy consumption required to perform the sensing. The pmf $f(c)$ can be estimated based on the amount of transmitted data during reporting and the cellular data pricing of the operator. We can estimate the pdf $f(p)$ based on users' mobility and the Wi-Fi deployment.

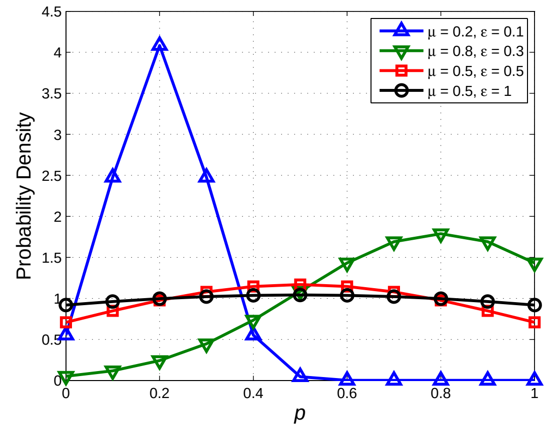

Fig. 3. The probability density functions of the truncated normal distributions with different μ and ϵ parameters.

6.1.2 Truncated Normal Distribution for Probability p

To elaborate the result further, we derive the probability of reporting when the probability p follows the *truncated normal distribution* [50], which in essence is the widely adopted normal distribution with upper or lower bounds. More specifically, for a truncated normal random variable $p \in [p^{\min}, p^{\max}]$, its pdf is

$$f(p) = \begin{cases} \frac{\frac{1}{\epsilon}\phi(\frac{p-\mu}{\epsilon})}{\Phi(\frac{p^{\max}-\mu}{\epsilon}) - \Phi(\frac{p^{\min}-\mu}{\epsilon})}, & \text{for } p \in [p^{\min}, p^{\max}], \\ 0, & \text{otherwise}, \end{cases} \tag{20}$$

where $\phi(w) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{w^2}{2})$ is the pdf of the standard normal distribution and $\Phi(x) = \int_{-\infty}^{x} \phi(w)dw$ is its cumulative distribution function (cdf). The pdfs of the truncated normal distributions are illustrated in Fig. 3. It should be noted that the truncated normal distribution is identical to the standard normal distribution with mean μ and standard deviation ϵ when $p^{\min} = -\infty$ and $p^{\max} = \infty$. Thus, the μ and ϵ parameters determine the position of the "peak" and the "flatness" in the pdf, respectively. For example, in Fig. 3, for the curve $\mu = 0.2$, $\epsilon = 0.1$, it means that its peak is at $p = 0.2$. Also, since its ϵ parameter is relatively small as compared to the other three curves, this curve has a higher peak. Moreover, the truncated normal distribution approaches the continuous uniform distribution in the interval $[p^{\min}, p^{\max}]$ when $\epsilon \to \infty$.

Let $F(p)$ be the cdf of random variable p, where $F(p) = \int_{-\infty}^{p} f(x)dx$. For the truncated normal distribution, its cdf is given by [50]

$$F(p) = \frac{\Phi(\frac{p-\mu}{\epsilon}) - \Phi(\frac{p^{\min}-\mu}{\epsilon})}{\Phi(\frac{p^{\max}-\mu}{\epsilon}) - \Phi(\frac{p^{\min}-\mu}{\epsilon})}. \tag{21}$$

Based on Theorem 5, we further derive $\rho(r)$ under the truncated normal distribution as follows.

Corollary 1: If the probability p of not meeting Wi-Fi follows the truncated normal distribution with pdf given by $f(p)$ in (20), then the probability of reporting $\rho(r)$ is

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given by (15), where the conditional probability $\rho(r|\sigma,c)$ has different expressions under different cases. For the case $c<\sigma$, it is given by

$$\rho(r|\sigma,c)=\begin{cases}0, & \text{if } r\in[0,\sigma+p^{\min}c),\\ F(\frac{r-\sigma}{c}), & \text{if } r\in[\sigma+p^{\min}c,\sigma+p^{\max}c),\\ 1, & \text{if } r\in[\sigma+p^{\max}c,\infty),\end{cases} \tag{22}$$

where $F(p)$ is the cdf defined in (21). For the case $c\geq\sigma$, we need to further consider three subcases. First, for the subcase $1-\frac{\sigma}{c}<p^{\min}$, same as (22), we have

$$\rho(r|\sigma,c)=\begin{cases}0, & \text{if } r\in[0,\sigma+p^{\min}c),\\ F(\frac{r-\sigma}{c}), & \text{if } r\in[\sigma+p^{\min}c,\sigma+p^{\max}c),\\ 1, & \text{if } r\in[\sigma+p^{\max}c,\infty).\end{cases} \tag{23}$$

Second, for the subcase $1-\frac{\sigma}{c}\geq p^{\max}$, we have

$$\rho(r|\sigma,c)=\begin{cases}0, & \text{if } r\in[0,\frac{\sigma}{1-p^{\min}}),\\ F(1-\frac{\sigma}{r})-g(p^{\min},1-\frac{\sigma}{r}), & \text{if } r\in[\frac{\sigma}{1-p^{\min}},\frac{\sigma}{1-p^{\max}}),\\ F(p^{\max})-g(p^{\min},p^{\max}), & \text{if } r\in[\frac{\sigma}{1-p^{\max}},c),\\ 1, & \text{if } r\in[c,\infty),\end{cases} \tag{24}$$

where we define the function

$$g(c,d)\triangleq\frac{\epsilon}{Z\sqrt{2\pi}}\Big(\exp\Big(-\frac{(c-\mu)^2}{2\epsilon^2}\Big)-\exp\Big(-\frac{(d-\mu)^2}{2\epsilon^2}\Big)\Big)+\frac{\mu}{2Z}\Big(\operatorname{erf}\Big(\frac{d-\mu}{\sqrt{2}\epsilon}\Big)-\operatorname{erf}\Big(\frac{c-\mu}{\sqrt{2}\epsilon}\Big)\Big) \tag{25}$$

with $Z\triangleq\Phi(\frac{p^{\max}-\mu}{\epsilon})-\Phi(\frac{p^{\min}-\mu}{\epsilon})$ and the error function $\operatorname{erf}(x)\triangleq\frac{2}{\sqrt{\pi}}\int_0^x\exp(-\frac{w^2}{2})dw$. Third, for the subcase $p^{\min}\leq 1-\frac{\sigma}{c}<p^{\max}$, we have

$$\rho(r|\sigma,c)=\begin{cases}0, & \text{if } r\in[0,\frac{\sigma}{1-p^{\min}}),\\ F(1-\frac{\sigma}{r})-g(p^{\min},1-\frac{\sigma}{r}), & \text{if } r\in[\frac{\sigma}{1-p^{\min}},c),\\ F(\frac{r-\sigma}{c}), & \text{if } r\in[c,\sigma+p^{\max}c),\\ 1, & \text{if } r\in[\sigma+p^{\max}c,\infty).\end{cases} \tag{26}$$

The proof of Corollary 1 is given in Appendix G.

6.2 Profit Maximization of Service Provider

We define $\mathbb{P}(n,r)$ as the probability that $n\in\{0,1,\dots,I\}$ users report their sensed data when the reward is equal to r. Here, we consider the incomplete information case that the service provider assumes the same $\rho(r)$ for all the users.[17] Thus, $\mathbb{P}(n,r)$ follows a binomial distribution given by

$$\mathbb{P}(n,r)=\binom{I}{n}\rho(r)^n\big(1-\rho(r)\big)^{I-n}. \tag{27}$$

17. The reward optimization under the complete information case, where the service provider knows $\rho_i(r)$ of each user $i\in\mathcal{I}$, has been discussed in our conference version in [1].

Let $u(n)$ be the *utility function* of the service provider when $n\in\{0,1,\dots,I\}$ users in set $\mathcal{I}$ report their measurements. We assume that $u(n)$ is a nondecreasing function in n with $u(0)=0$. Overall, the service provider aims to select reward r that maximizes its *expected* profit (i.e., utility minus payment) as

$$\underset{r\geq 0}{\text{maximize}}\quad \phi(r)\triangleq\sum_{n=0}^{I}\Big(u(n)-rn\Big)\mathbb{P}(n,r), \tag{28}$$

where the product rn is the total payment to the users.[18]

The naive approach to solve problem (28) numerically is to directly apply a line search method for one-dimensional optimization [51, pp. 741]. However, this approach may be inefficient due to the large search space of $r\geq 0$. Let r^* be the optimal solution of problem (28). Let $\sigma^{\min}=\min(\mathcal{S})$, $\sigma^{\max}=\max(\mathcal{S})$, and $c^{\max}=\max(\mathcal{C})$. We have the following theorem that reduces the search space of the optimal solution r^*.

Theorem 6: $r^*\in\{0\}\cup[\sigma^{\min},\sigma^{\max}+c^{\max}]$.

From Theorem 6, we obtain

$$\max_{r\geq 0}\phi(r)=\max\big\{0,\max_{\sigma^{\min}\leq r\leq\sigma^{\max}+c^{\max}}\phi(r)\big\}, \tag{29}$$

since $\phi(0)=0$. Thus, if $\phi(r)$ is continuous for $\sigma^{\min}\leq r\leq\sigma^{\max}+c^{\max}$, then we can solve problem (29) numerically by applying a line search [51, pp. 741] for a single-variable continuous function on a fixed interval $r\in[\sigma^{\min},\sigma^{\max}+c^{\max}]$ once. The proof of Theorem 6 is given in Appendix H.

However, as mentioned in Section 6.1.1, when $c\geq\sigma$, from (18) and (19), there is a discontinuous point at $r=c$ for $\rho(r|\sigma,c)$ and thus for the probability $\rho(r)$ and the objective function $\phi(r)$. As a result, directly applying a line search method for one-dimensional continuous optimization may return with an inaccurate solution, as the objective function $\phi(r)$ may be discontinuous at some r. To address this problem, we first define the set of discontinuous points for $\phi(r)$ as

$$\tilde{\mathcal{R}}\triangleq\{c\in\mathcal{C}:\exists\,\sigma\in\mathcal{S}\text{ such that } c\geq\sigma\}. \tag{30}$$

If $\tilde{\mathcal{R}}$ is non-empty, we can let $V=|\tilde{\mathcal{R}}|>0$ and $\tilde{\mathcal{R}}=\{r^{(1)},r^{(2)},\dots,r^{(V-1)},r^{(V)}\}$. Then, we define some intervals

$$\mathcal{R}^{(v)}\triangleq\begin{cases}[\sigma^{\min},r^{(1)}], & \text{if } v=0,\\ [r^{(v)},r^{(v+1)}], & \text{if } v=1,\dots,V-1,\\ [r^{(V)},\sigma^{\max}+c^{\max}], & \text{if } v=V.\end{cases} \tag{31}$$

In this way, the interval $[\sigma^{\min},\sigma^{\max}+c^{\max}]$ can be expressed as the union of the non-overlapping intervals $\mathcal{R}^{(v)}$ for $v=0,1,\dots,V$ as

$$[\sigma^{\min},\sigma^{\max}+c^{\max}]=\mathcal{R}^{(0)}\cup\mathcal{R}^{(1)}\cup\ldots\cup\mathcal{R}^{(V-1)}\cup\mathcal{R}^{(V)}. \tag{32}$$

18. Note that the profit maximization problem in (28) is for one sensing task only. If there are multiple sensing tasks with different delay requirements, since their optimization problems are decoupled, we can treat each sensing task separately with a different discount factor θ.

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Thus, problem (29) can be expressed as

$$\max_{r\geq 0}\phi(r)=\max\Big\{0,\max_{v\in\{0,\ldots,V\}}\big\{\max_{r\in\mathcal{R}^{(v)}}\phi(r)\big\}\Big\}. \tag{33}$$

Since $\mathcal{R}^{(v)}$ is a continuous interval, we can apply a line search method for one-dimensional continuous optimization to solve $\max_{r\in\mathcal{R}^{(v)}}\phi(r)$, and eventually solve $\max_{r\geq 0}\phi(r)$.[19]

7 Numerical Results

In this section, we provide numerical results to illustrate the users' decisions in Stage II and the service provider's choice of reward in Stage I. Specifically, in Section 7.1, we evaluate the performance of our proposed OPRD algorithm in Stage II against three benchmark schemes. In Section 7.2, we verify the accuracy of the probability of reporting derivation in Section 6.1 as the aggregate reporting decision of each individual user i in Section 5.3. Finally, we show the impact of the service provider's valuation and users' Wi-Fi availabilities on the optimal reward and profit in Stage I. Interestingly, we find that by underestimating the users' Wi-Fi availabilities, the service provider may offer a very high reward, which may lead to a significant profit loss. On the other hand, overestimating the users' Wi-Fi availabilities has a much milder effect.

7.1 User's Participation and Reporting Decisions

In the simulation study with Matlab, we generate 10000 random scenarios with different network settings and user mobility patterns, and show the average value as one point in the figure. We assume the following default system parameters unless specified otherwise. We consider that there are $L=16$ possible locations in a four by four grid (similar to that in Fig. 1). The length of each time slot is $\Delta t=10$ seconds. For each network setting, we randomly generate the locations of Wi-Fi networks by assuming the probability that a Wi-Fi connection is available at a particular location to be $p^{\text{wifi}}=0.4$. We consider a Markovian mobility model characterized by the location transition matrix $Q_i=\big[q_i(l'|l)\big]_{L\times L}$. The probability of user i in staying at a location is given by $q_i(l\,|\,l)=p^{stay}=0.5$ for each location $l\in\mathcal{L}$. Moreover, the user is equally likely to move to any of the neighbouring locations from his current location. Let us take location 7 in Fig. 1 as an example. The probability that the user moves to one of the locations 3, 6, 8, or 11 in the next time slot is $(1-0.5)/4=0.125$. As another example, at location 4, the user will move to one of his neighbouring locations 3 or 8 in the next time slot with probability $(1-0.5)/2=0.25$. To generate a mobility pattern, we first randomly pick an initial location among the L possible locations, and then determine his subsequent locations in the remaining time slots based on the Markovian mobility model that we just described.

First, we compare the expected user payoff, which is the reward minus the total sensing and transmission costs, under the OPRD scheme (i.e., Algorithm 1, denoted as optimal) and three 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, he 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. He will use a Wi-Fi network to report if $l_i(1)\in\mathcal{L}^{(1)}$, otherwise he will use the cellular network to report if $l_i(1)\in\mathcal{L}^{(0)}$.
- *Heuristic scheme inspired by effSense [52]*: effSense is a data uploading scheme that aims to reduce the energy consumption of data-plan users. To save energy, it uploads data through Wi-Fi if the user can meet any Wi-Fi networks by the deadline, but through the cellular network otherwise. effSense is a predictive scheme that leverages the predictability of the Wi-Fi availability in determining the data uploading decision, but it does not take into account the detailed user mobility and the Wi-Fi locations as in our proposed OPRD scheme. More specifically, effSense treats the events of meeting Wi-Fi in each time slot as independent random variables, so the probability of meeting Wi-Fi in each time slot is p^{wifi}. Thus, inspired by effSense, we propose a heuristic scheme that the user decides to participate if $r\geq\sigma_i+(1-p^{\text{wifi}})^T c_i$, where $(1-p^{\text{wifi}})^T c_i$ represents user i's expected data reporting cost. The reporting decisions through cellular or Wi-Fi networks are the same as the effSense operations described above.

Impact of deadline on user payoff: In Fig. 4, we plot the expected user payoff under the four schemes for different values of deadline D (measured in minutes, so $T=60D/\Delta t$). We assume that the discounted factor $\theta=0.9$, initial reward $R=25$, sensing cost $\sigma_i=10$, and cellular transmission cost $c_i=11$. As we can see, our proposed OPRD scheme achieves the maximal expected user payoff compared with the three heuristic schemes under different deadlines. As the user under the impatient scheme will always report in the first time slot, his expected payoff is independent of D. In contrast, for the OPRD, patient, and effSense schemes, the longer the deadline, the higher the chance of meeting Wi-Fi, so the expected payoffs under these schemes increase with D initially. As the deadline D increases beyond 5 minutes, the chance of meeting Wi-Fi is already very high, so the expected payoffs saturate.

Impact of sensing cost on user payoff: In Fig. 5, we plot the expected user payoff against the sensing cost σ_i for $\theta=0.9$, $R=25$, $c_i=15$, and $D=5$ minute. When $\sigma_i\leq 20$, we observe that the expected

19. We remark that since we do not impose any restriction on the structure of the objective function, the linear search algorithm can only compute the locally optimal solution.

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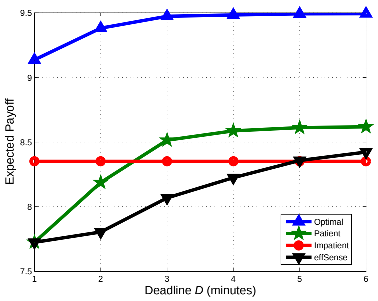

Fig. 4. The expected payoff versus the deadline for $\theta = 0.9$, $R = 25$, $\sigma_i = 10$, and $c_i = 11$.

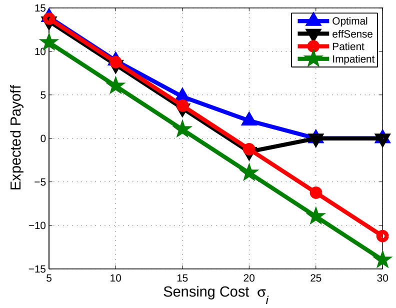

Fig. 5. The expected payoff versus the sensing cost for $\theta = 0.9$, $R = 25$, $c_i = 15$, and $D = 5$ min.

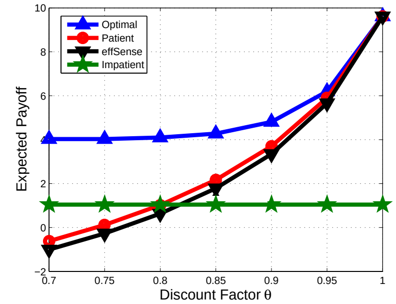

Fig. 6. The expected payoff versus the discount factor for $R = 25$, $c_i = 15$, $\sigma_i = 15$, and $D = 5$ min.

payoffs under all the schemes decrease with σ_i. When $\sigma_i > 20$, the payoffs under the patient and impatient schemes continue to drop, because both schemes always participate despite the high sensing cost. However, the payoff under the OPRD scheme is always non-negative, as the user can decide not to participate when σ_i is too high. A similar observation applies to the effSense scheme, except that its participation decision is not fully optimal, as it does not take advantage of the user's accurate mobility information. Thus, it usually results in a non-negative payoff, except at $\sigma_i = 20$ with a slightly negative payoff. Notice that although effSense performs well under this setting, there are other settings (e.g., in Fig. 4) that it deviates from the optimal scheme.

Impact of discount factor on user payoff: In Fig. 6, we plot the expected user payoff against the discount factor θ for $R = 25$, $c_i = 15$, $\sigma_i = 15$, 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 first time slot, as the reward reduces at a faster rate. As a user under the impatient scheme reports in the first time slot, his payoff is independent of θ. When θ is close to 1, we are considering the delay-insensitive applications, where the reward is not time-discounted. In this case, it is optimal for a user to be patient and wait for Wi-Fi to report his sensed data until the deadline. Since the optimal, patient, and effSense schemes adopt this same reporting strategy, their performances are similar.

Impact of cellular transmission cost on user payoff: In Fig. 7, we plot the expected user payoff against the cellular transmission cost c_i, where we assume that $\theta = 0.9$, $R = 25$, $\sigma_i = 10$, and $D = 1$ minute. As we can see, as c_i increases, the expected user payoffs under all the four schemes decrease. 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.

7.2 Accuracy of Analysis

In order to verify the derivation of the probability of reporting $\rho(r)$ in Corollary 1, in Fig. 8, we plot $\rho(r)$ obtained from the analysis and simulation against reward r for $p^{\min} = 0$ and $p^{\max} = 1$ under different discrete uniform distributions $f(\sigma)$ and $f(c)$ of the sensing cost σ and cellular transmission cost c, respectively. In particular, we consider different scenarios[20] of the feasible sets of σ and c: (a) Scenario 1: $\mathcal{S} = \{2\}$ and $\mathcal{C} = \{9\}$. (b) Scenario 2: $\mathcal{S} = \{2, 5, 10\}$ and $\mathcal{C} = \{9, 10, 15\}$. (c) Scenario 3: $\mathcal{S} = \{2, 5, 10, 15, 17\}$ and $\mathcal{C} = \{9, 10, 15, 18, 20\}$. For the analysis, we plot $\rho(r)$ in (15) under the truncated normal distribution of p in Corollary 1 with $\mu = (p^{\min} + p^{\max})/2$ and $\epsilon = 1$. For the Monte Carlo simulation, we generate $p_i \in [p^{\min}, p^{\max}]$ from a uniform distribution, obtain $\rho_i(r)$ from (14), and plot $\rho(r)$ by averaging over 100000 samples of $\rho_i(r)$. We can see in Fig. 8 that the simulation results perfectly match with the analysis in Corollary 1. It happens when the truncated normal distribution of the analysis approaches the uniform distribution of the simulation, where the parameter $\mu = (p^{\min} + p^{\max})/2$ is equal to the mean of the uniform distribution and $\epsilon = 1$ is large with respect to the scale of the probability measure.

7.3 Reward Optimization of Service Provider

Unless specified otherwise, for the service provider's reward optimization, we consider an increasing concave utility function $u(n) = \alpha \ln(1 + \kappa n)$, where $u(0) = 0$.[21] Here, $\kappa > 0$ represents the service provider's valuation of the participation level n, where a larger κ means a higher valuation. We choose the amplitude parameter $\alpha = 5$ in the simulations. We consider a discrete uniform distribution $f(\sigma)$ of the sensing cost $\sigma \in \mathcal{S} = \{2, 5, 10\}$

20. In fact, we can choose these scenarios arbitrarily because we should be able to show that our mathematical analysis matches well with the simulation result. Instead, we choose these scenarios systematically (in the increasing order of the sensing and cellular transmission costs) to further show the impact of these scenarios on $\rho(r)$.

21. It should be noted that the logarithmic utility function has been widely used in the networking literature to model elastic applications [53].

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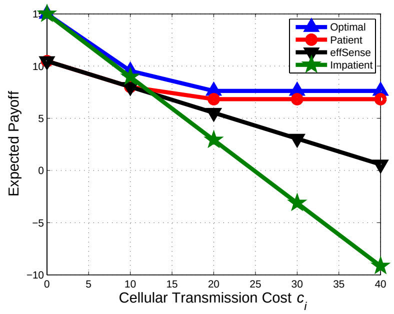

Fig. 7. The expected payoff versus the cellular transmission cost c_i for $\theta = 0.9$, $R = 25$, $\sigma_i = 10$, and $D = 1$ min.

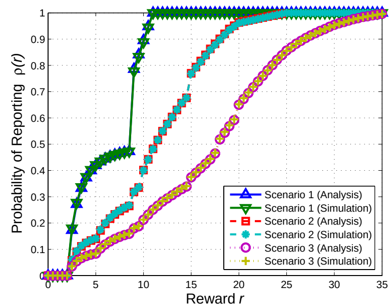

Fig. 8. The probability of reporting $\rho(r)$ versus reward r under different distributions of sensing and cellular transmission costs.

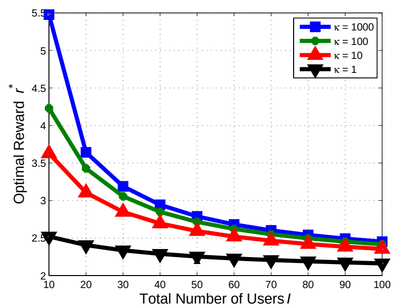

Fig. 9. The optimal reward r^* versus the number of users I under different parameter κ for $\mu = 0.5$ and $\epsilon = 0.3$.

and $f(c)$ of the cellular transmission cost $c \in \{8, 15, 18\}$. We consider that the probability of not meeting Wi-Fi $p \in [0, 1]$ follows a truncated normal distribution in (20) with parameters μ and ϵ.

7.3.1 Impact of Service Provider's Valuation on Participation Level

In Fig. 9, we plot the optimal reward r^* against the number of users I under different valuation parameter κ for $\mu = 0.5$ and $\epsilon = 0.3$. As we can see, when κ increases, the service provider has a higher valuation of the participation level, so r^* increases. Interestingly, when I is large, the service provider does not need to give a high reward, even though it has a large valuation parameter κ, because the number of potential participants is large enough for the MCS campaign.

7.3.2 Impact of Users' Wi-Fi Availability

In Fig. 10, we plot the optimal reward r^* against the parameter μ for $I = 30$ and $\kappa = 10$. We can see that r^* increases with μ. It is because when μ increases, it is less likely for the users to meet Wi-Fi before the deadline, so the service provider needs to offer a larger reward to incentivize the users' data reporting. Moreover, for $\mu \geq 0.3$, we observe that r^* decreases significantly with ϵ. The reason is that with a small ϵ and a large μ, there is a large proportion of users with a high probability p of not meeting Wi-Fi (as illustrated in Fig. 3), so the service provider needs to give a large r^* to encourage the users to participate. On the other hand, for $\mu < 0.3$, we observe that r^* decreases slowly with ϵ. It is because with a small ϵ and a small μ, there are a lot of users with high Wi-Fi availabilities, so the service provider can give a smaller r^*.

In Fig. 11, we plot the optimal profit $\phi(r^*)$ against the parameter μ for $I = 30$ and $\kappa = 10$. We can see that the optimal profit decreases with μ when the chance of meeting Wi-Fi diminishes. Interestingly, when ϵ is small, it results in a larger profit when $\mu < 0.3$, but a smaller profit when $\mu \geq 0.3$. It is because when $\mu < 0.3$, a smaller ϵ results in a larger proportion of users with higher Wi-Fi availabilities (as illustrated in Fig. 3), so the optimal profit increases. On the contrary, when $\mu \geq 0.3$, as shown in Fig. 10, a small ϵ results in a significant increase in the optimal reward and thus the total payment to the users, which reduces the optimal profit substantially.

7.3.3 Impact of Inaccurate Information of Users' Wi-Fi availabilities

Next, we study the impact of the μ parameter on the service provider's profit. We assume that the actual distribution of p is a truncated normal distribution with parameters $\mu = 0.5$ and $\epsilon = 0.3$. However, the service provider may have inaccurate knowledge of μ. In Fig. 12, we plot the profit against the total number of users I under different knowledge of μ for $\kappa = 10$. As we can see, the inaccurate μ information leads to a reduction in the service provider's profit. Interestingly, for the case of $\mu = 0.9$, it leads to a significant under-estimation of the users' participation level, especially when I is large. As a result, the service provider gives a large reward to incentivize the users' participation, which results in a huge amount of payment to the users, and thus a sharp drop in profit. On the other hand, for the case of over-estimating the users' Wi-Fi availabilities (i.e., $\mu = 0.1$ and $\mu = 0.3$), it leads to an over-estimation of the users' participation level, which results in a small reward that cannot attract enough participants. Although it reduces the profit, it does not lead to a huge profit loss as in the case of $\mu = 0.9$. In other words, the inaccurate μ information may result in a significant profit loss only when μ is over-estimated. As a result of the sensitivity of μ on the profit, a service provider should estimate the users' Wi-Fi availabilities precisely.

8 Conclusion

In this paper, we studied the algorithm design and economics in a delay-sensitive mobile crowdsensing system. First, for a mobile user, we proposed the OPRD algorithm to compute his optimal participation and reporting decisions in the general case. We derived closed-form expressions in the special case of non-discounted reward and showed that his behaviour exhibits some threshold

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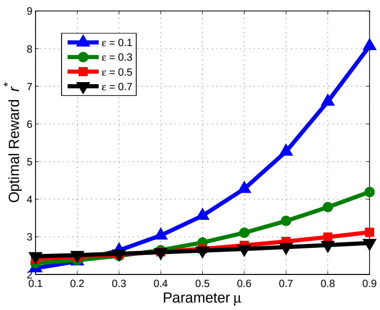

Fig. 10. The optimal reward r^* versus the μ parameter for $I = 30$ and $\kappa = 10$.

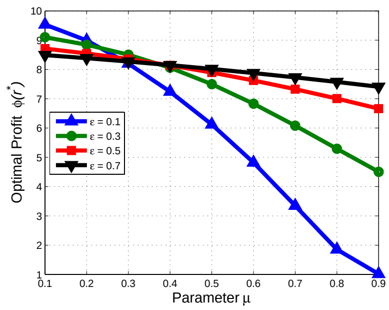

Fig. 11. The optimal profit $\phi(r^*)$ versus the μ parameter for $I = 30$ and $\kappa = 10$.

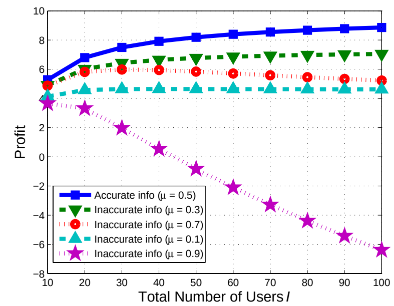

Fig. 12. The profit obtained versus I under different knowledge of μ parameter for $\kappa = 10$ and $\epsilon = 0.3$.

structures. Next, given these users' responses, we considered the service provider's profit maximization under the incomplete information of the users. To this end, we derived the probability of reporting in closed-form under arbitrary distributions of the users' costs and Wi-Fi availabilities, and elaborated the results further when the Wi-Fi availabilities follow the truncated normal distribution. We proposed a method to compute the optimal reward in a non-convex problem efficiently by bounding the solution set and characterizing the discontinuity in the profit function. Simulation results showed that a service provider may suffer from a significant profit loss if it underestimates the users' Wi-Fi availabilities.

In this work, we have only considered the reward optimization under the non-discounted reward case. For future work, we will consider the reward optimization under the general case with discounted reward. Moreover, we will study the use of quality control mechanisms [40], such as reputation [41], [54], to encourage the users' truthful reporting in our future work. In addition, we assume that all the users are initially at the locations of interest in this paper. The incorporation of the task selections [55], [56] into the problem, where the users need to move to the locations and work on the tasks, is an interesting topic for future study.

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Delay-Sensitive Mobile Crowdsensing: Algorithm Design and Economics

Man Hon Cheung, Fen Hou, and Jianwei Huang

Appendix A
Derivation of closed-form p_i under the Markovian Mobility Model

As shown in Theorems 2, 3, and 4, the probability p_i of not meeting Wi-Fi by deadline is a key factor on user i's participation and reporting decisions. Here, we show an example on how to compute the *closed-form* expression on p_i with information regarding the initial location of user i and the deadline under the Markovian mobility model used in Section 4.

For the computation of p_i, given the location transition matrix $Q_i = \big[q_i(l'|l)\big]_{L\times L}$ of user i, we first define a matrix $\tilde{Q}_i$ based on matrix Q_i as:

$$\tilde{Q}_i(l_1,l_2) = \begin{cases} 0, & \text{if } l_1 \in \mathcal{L}^{(1)} \text{ or } l_2 \in \mathcal{L}^{(1)}, \\ q_i(l_2 \,|\, l_1), & \text{otherwise}, \end{cases} \quad (34)$$

where $\tilde{Q}_i(l_1,l_2)$ is the (l_1,l_2)-th entry of matrix $\tilde{Q}_i$. Notice that we set $\tilde{Q}_i(l_1,l_2)=0$ in the first line of (34), so that we do not count any user movement path that includes at least one location with Wi-Fi available.

The *closed-form* expression on p_i is given by the following proposition.

Proposition 2: Given the location transition matrix $Q_i = \big[q_i(l'|l)\big]_{L\times L}$ of user i, the probability of not meeting Wi-Fi within the T time slots is given by

$$p_i = \begin{cases} \sum_{l\in\mathcal{L}^{(0)}} \tilde{Q}_i^{T-1}\big(l_i(1),l\big), & \text{if } l_i(1) \in \mathcal{L}^{(0)}, \\ 0, & \text{if } l_i(1) \in \mathcal{L}^{(1)}, \end{cases} \quad (35)$$

where $\tilde{Q}_i^{T-1}$ is the $(T-1)$-step transition matrix obtained by multiplying the matrix $\tilde{Q}_i$ by itself for $T-1$ times.

Proof: For an initial location $l_i(1) \in \mathcal{L}^{(1)}$ with Wi-Fi, we have $p_i = 0$. For an initial location $l_i(1) \in \mathcal{L}^{(0)}$ without Wi-Fi, we can define matrix $\tilde{Q}_i$ as in (34), and obtain p_i in (35), which ignores all the user paths that pass through one or more locations with Wi-Fi.

More specifically, given $\tau \geq 0$ and $l_1, l_2 \in \mathcal{L}$, let

$$q^{\tau}_{l_1,l_2} \triangleq \mathbb{P}\big\{l_i(t+\tau)=l_2 \big| l_i(t)=l_1\big\} \quad (36)$$

be the probability that user i moves from location l_1 to location l_2 in τ time steps. From the *Chapman-Kolmogorov equations* [57, pp. 185], we have

$$q^{\tau_1+\tau_2}_{l_1,l_2} = \sum_{l\in\mathcal{L}} q^{\tau_1}_{l_1,l}\, q^{\tau_2}_{l,l_2}, \quad \forall\, \tau_1,\tau_2 \geq 0,\ l_1,l_2 \in \mathcal{L}. \quad (37)$$

Through matrix manipulation, we have

$$q^{\tau}_{l_1,l_2} = Q_i^{\tau}(l_1,l_2). \quad (38)$$

By defining matrix $\tilde{Q}_i$ in (34), we obtain p_i in (35), which ignores all the user paths that pass through locations with Wi-Fi. □

Appendix B
Proof of Theorem 2

Let ν_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. In this case, with a probability p_i, user i will not meet any Wi-Fi, and he will not report to the service provider, so $\nu_i = -\sigma_i < 0$. With a probability $1-p_i$, user i will report by Wi-Fi, so $\nu_i = r - \sigma_i$. User i chooses to participate if and only if his expected payoff $E[\nu_i] = p_i(-\sigma_i) + \big(1-p_i\big)(r-\sigma_i) \geq 0$, i.e., $r \geq \frac{\sigma_i}{1-p_i}$. It should be noted that user i would not report through the cellular network anywhere, because it will result in an even smaller payoff under this small reward $r \in [0, c_i)$.

For the *reporting decision*, with a non-discounted reward before the deadline, there is no harm for user i to wait for Wi-Fi until deadline T. However, user i will not report if Wi-Fi network is still not available by time slot T, because user i's reward r is not large enough for him to cover the cellular cost c_i. ■

Appendix C
Proof of Theorem 3

Let ν_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. In this case, with a probability p_i, user i will not meet any Wi-Fi, but he will report by cellular at deadline T to obtain the reward, so $\nu_i = r - \sigma_i - c_i$. With a probability $1-p_i$, user i will report by Wi-Fi, so $\nu_i = r - \sigma_i$. User i chooses to participate if and only if his expected payoff $E[\nu_i] = p_i(r-\sigma_i-c_i) + \big(1-p_i\big)(r-\sigma_i) \geq 0$, i.e., $r \geq \sigma_i + p_i c_i$.

For the *reporting decision*, with a non-discounted reward before the deadline, there is no harm for user i to wait for Wi-Fi until deadline T. However, user i will report even if Wi-Fi network is still not available by time slot T, because user i's reward r is large enough for him to cover the cellular cost c_i. ■

Appendix D
Proof of Theorem 4

We divide the analysis into three ranges: (a) $r \leq \sigma_i$, (b) $r \geq \sigma_i + c_i$, and (c) $\sigma_i < r < \sigma_i + c_i$.

(a) First, for the range $r \leq \sigma_i$, from Theorem 2, user i will not participate in the sensing task, since the reward is too small (not even enough to cover the sensing cost).

(b) Second, for the range $r \geq \sigma_i + c_i$, from Theorem 3, since the reward is large enough, user i will definitely participate in the sensing. After sensing, he will upload the data with Wi-Fi when he first meets a Wi-Fi network within the deadline. Otherwise, he will use the cellular network for data reporting in time slot T.

(c) Third, 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 3 applies.

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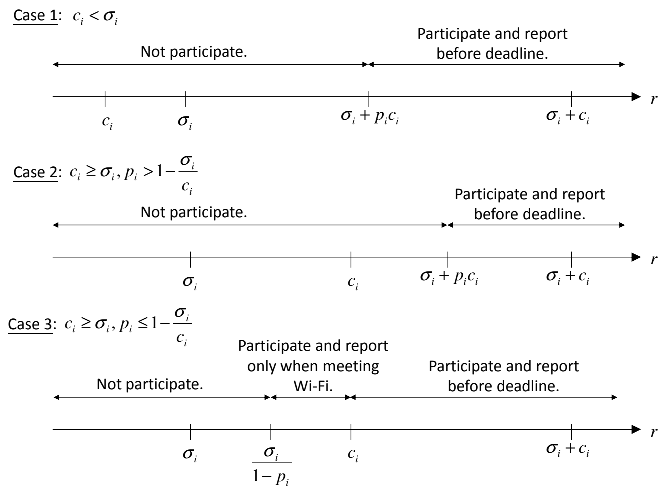

Fig. 13. Participation and reporting decisions of user i under different values of σ_i, c_i, p_i, and r. The label "report before deadline" in Cases 1, 2, and 3 means user i should report when first meeting Wi-Fi during $[1, T]$, otherwise he should report using cellular at T. The label "report only when meeting Wi-Fi" in Case 3 means user i should report when first meeting Wi-Fi during $[1, T]$, otherwise he should not report.

- Case 2: $c_i \geq \sigma_i$ and $p_i > 1 - \frac{\sigma_i}{c_i}$. We consider two intervals of r. For the first interval $\sigma_i < r < c_i$, since the participation threshold $\frac{\sigma_i}{1-p_i} > \frac{\sigma_i}{1-(1-\frac{\sigma_i}{c_i})} = c_i$, we conclude from Theorem 2 that user i will not participate. For the second interval $c_i \leq r < \sigma_i + c_i$, since the participation threshold $\sigma_i + p_i c_i > \sigma_i + (1 - \frac{\sigma_i}{c_i})c_i = c_i$, the result in Theorem 3 applies.
- Case 3: $c_i \geq \sigma_i$ and $p_i \leq 1 - \frac{\sigma_i}{c_i}$. We also consider two intervals of r. For the first interval $\sigma_i < r < c_i$, as the participation threshold $\frac{\sigma_i}{1-p_i} \leq c_i$, the result in Theorem 2 applies. Since the participation threshold $\sigma_i + p_i c_i \leq c_i$, we conclude from Theorem 3 that user i will participate in the second interval $c_i \leq r < \sigma_i + c_i$.

In Fig. 13, we illustrate the detailed participation and reporting decisions in the three cases in Theorem 4. 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 4: User i decides not to participate if $r < \check{\gamma}_i$, participate and report through Wi-Fi with probability $1 - p_i$ (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 $r \geq \hat{\gamma}_i$. ■

Appendix E
Generalization of Non-negative Wi-Fi Transmission Cost

It is possible to consider a more general transmission cost model, where the transmission cost w_i of Wi-Fi is $0 \leq w_i < c_i$ instead of zero.[22] Define $\sigma_i^{\text{new}} \triangleq \sigma_i + (1 - p_i)w_i$. In this case, we have the following theorems on the users' optimal participation and reporting decisions under the small and large reward cases, which generalize Theorems 2 and 3.

Theorem 7: For a small reward $r \in [0, c_i)$:

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

Proof: Let ν_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. In this case, with a probability p_i, user i will not meet any Wi-Fi, and he will not report to the service provider, so $\nu_i = -\sigma_i < 0$. With a probability $1 - p_i$, user i will report by Wi-Fi, so $\nu_i = r - \sigma_i - w_i$. User i chooses to participate if and only if his expected payoff $E[\nu_i] = p_i(-\sigma_i) + \big(1 - p_i\big)(r - \sigma_i - w_i) \geq 0$, i.e., $r \geq \frac{\sigma_i^{\text{new}}}{1-p_i}$. It should be noted that user i would not report through the cellular network anywhere, because it will result in an even smaller payoff under this small reward $r \in [0, c_i)$.

The proof of the reporting decision is the same as that of Theorem 2 discussed in Appendix B. □

Theorem 8: For a large reward $r \in [c_i, \infty)$:

- *Participation Decision*: User i chooses to participate if and only if $r \geq \sigma_i^{\text{new}} + p_i c_i$.
- *Reporting Decision*: If user i chooses to participate, then he 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 the cellular network in time slot T.

Proof: Let ν_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. In this case, with a probability p_i, user i will not meet any Wi-Fi, but he will report by cellular at deadline T to obtain the reward, so $\nu_i = r - \sigma_i - c_i$. With a probability $1 - p_i$, user i will report by Wi-Fi, so $\nu_i = r - \sigma_i - w_i$. User i chooses to participate if and only if his expected payoff $E[\nu_i] = p_i(r - \sigma_i - c_i) + \big(1 - p_i\big)(r - \sigma_i - w_i) \geq 0$, i.e., $r \geq \sigma_i^{\text{new}} + p_i c_i$.

The proof of the reporting decision is the same as that of Theorem 3 discussed in Appendix C. □

It should be noted that with this generalization, we can replace the parameter σ_i with the new parameter σ_i^{new} such that the analysis of the paper goes through. However, for the ease of exposition, we assume that $w_i = 0, \forall i \in \mathcal{I}$ in the paper.

22. Note that it is trivial to consider $w_i > c_i$, as a user will always prefer the cellular network, which is cheaper and ubiquitous, to the Wi-Fi network.

APPENDIX F
PROOF OF THEOREM 5

Conditioning on the different possible realizations of the random variables σ, c, and p, we obtain

$$\rho(r) = \sum_{\sigma\in\mathcal{S}}\sum_{c\in\mathcal{C}}\int_{p^{\min}}^{p^{\max}} \mathbb{P}\{r \mid \sigma, c, p\} f(p) f(\sigma) f(c) dp = \sum_{\sigma\in\mathcal{S}}\sum_{c\in\mathcal{C}} \rho(r|\sigma,c) f(\sigma) f(c), \quad (39)$$

where $\rho(r|\sigma,c) \triangleq \int_{p^{\min}}^{p^{\max}} \mathbb{P}\{r \mid \sigma, c, p\} f(p) dp$. Next, we consider the derivations under different cases.

$c < \sigma$ in (16): The analysis is based on case 1 in Fig. 13. First, we define the threshold $\gamma^{(2)} = \sigma + pc$ in case 1 in Fig. 13, which is a random variable. We have

$$\begin{aligned}\rho(r|\sigma,c) &= \mathbb{P}\{\gamma^{(2)} \le r|\sigma,c\} \\ &= \int_{p^{\min}}^{p^{\max}} \mathbb{P}\{\gamma^{(2)} \le r \mid \sigma, c, p\} f(p) dp \\ &= \int_{p^{\min}}^{p^{\max}} \mathbf{1}_{\{p\le\frac{r-\sigma}{c}\}} f(p) dp \\ &= \begin{cases} 0, & \text{if } r \in [0, \sigma + p^{\min} c), \\ \int_{p^{\min}}^{\frac{r-\sigma}{c}} f(p)dp, & \text{if } r \in [\sigma + p^{\min} c, \sigma + p^{\max} c), \\ \int_{p^{\min}}^{p^{\max}} f(p)dp = 1, & \text{if } r \in [\sigma + p^{\max} c, \infty), \end{cases}\end{aligned} \quad (40)$$

where $\mathbf{1}_{\{.\}}$ is the indicator function.

$c \ge \sigma$ and $1 - \frac{\sigma}{c} < p^{\min}$ in (17): The proof is similar to that in (40).

$c \ge \sigma$ and $1 - \frac{\sigma}{c} \ge p^{\max}$ in (18): The analysis is based on case 3 in Fig. 13. Let $W \in \{0, 1\}$ be a random variable that describes whether a user can meet Wi-Fi by deadline T. So it is a Bernoulli random variable, with a probability mass function given by $\mathbb{P}\{W = 1 \mid p\} = 1 - p$ and $\mathbb{P}\{W = 0 \mid p\} = p$. Let $\gamma^{(1)} = \frac{\sigma}{1-p}$ be the threshold in case 3 in Fig. 13. For $r < c$, we obtain

$$\begin{aligned}&\rho(r|\sigma,c) \\ =& \mathbb{P}\{(\gamma^{(1)} \le r) \cap (W = 1) \mid \sigma, c\} \\ =& \int_{p^{\min}}^{p^{\max}} \mathbb{P}\{(\gamma^{(1)} \le r) \cap (W = 1) \mid \sigma, c, p\} f(p) dp \\ =& \int_{p^{\min}}^{p^{\max}} \mathbb{P}\{\frac{\sigma}{1-p} \le r\} \mathbb{P}\{W = 1 \mid p\} f(p) dp \\ =& \int_{p^{\min}}^{p^{\max}} \mathbf{1}_{\{p\le 1-\frac{\sigma}{r}\}} (1-p) f(p) dp \\ =& \begin{cases} 0, & \text{if } r \in [0, \frac{\sigma}{1-p^{\min}}), \\ \int_{p^{\min}}^{1-\frac{\sigma}{r}} (1-p) f(p)dp, & \text{if } r \in [\frac{\sigma}{1-p^{\min}}, \frac{\sigma}{1-p^{\max}}), \\ \int_{p^{\min}}^{p^{\max}} (1-p) f(p)dp, & \text{if } r \in [\frac{\sigma}{1-p^{\max}}, c). \end{cases}\end{aligned} \quad (41)$$

Moreover, we have $\rho(r|\sigma,c) = 1$ for $r \ge c$ from case 3 in Fig. 13.

$c \ge \sigma$ and $p^{\min} \le 1 - \frac{\sigma}{c} < p^{\max}$ in (19):

$$\begin{aligned}\rho(r|\sigma,c) &= \int_{p^{\min}}^{p^{\max}} \mathbb{P}\{r \mid \sigma, c, p\} f(p) dp \\ &= \overbrace{\int_{p^{\min}}^{1-\frac{\sigma}{c}} \mathbb{P}\{r \mid \sigma, c, p\} f(p) dp}^{\rho^b(r|\sigma,c)\triangleq} + \overbrace{\int_{1-\frac{\sigma}{c}}^{p^{\max}} \mathbb{P}\{r \mid \sigma, c, p\} f(p) dp}^{\rho^a(r|\sigma,c)\triangleq},\end{aligned} \quad (42)$$

where we analyze $\rho^a(r|\sigma,c)$ and $\rho^b(r|\sigma,c)$ separately.

Specifically, for $\rho^a(r|\sigma,c)$, from case 2 in Fig. 13, we have

$$\begin{aligned}\rho^a(r|\sigma,c) &= \int_{1-\frac{\sigma}{c}}^{p^{\max}} \mathbb{P}\{\gamma^{(2)} \le r \mid \sigma, c, p\} f(p) dp \\ &= \int_{1-\frac{\sigma}{c}}^{p^{\max}} \mathbf{1}_{\{p\le\frac{r-\sigma}{c}\}} f(p) dp \\ &= \begin{cases} 0, & \text{if } r \in [0, c), \\ \int_{1-\frac{\sigma}{c}}^{\frac{r-\sigma}{c}} f(p)dp, & \text{if } r \in [c, \sigma + p^{\max} c), \\ \int_{1-\frac{\sigma}{c}}^{p^{\max}} f(p)dp, & \text{if } r \in [\sigma + p^{\max} c, \infty). \end{cases}\end{aligned} \quad (43)$$

For $\rho^b(r|\sigma,c)$, if $r \le c$, from case 3 in Fig. 13, we obtain

$$\begin{aligned}\rho^b(r|\sigma,c) &= \int_{p^{\min}}^{1-\frac{\sigma}{c}} \mathbb{P}\{(\gamma^{(1)} \le r) \cap (W = 1) \mid \sigma, c, p\} f(p) dp \\ &= \int_{p^{\min}}^{1-\frac{\sigma}{c}} \mathbb{P}\{\frac{\sigma}{1-p} \le r\} \mathbb{P}\{W = 1 \mid p\} f(p) dp \\ &= \int_{p^{\min}}^{1-\frac{\sigma}{c}} \mathbf{1}_{\{p\le 1-\frac{\sigma}{r}\}} (1-p) f(p) dp \\ &= \begin{cases} 0, & \text{if } r \in [0, \frac{\sigma}{1-p^{\min}}), \\ \int_{p^{\min}}^{1-\frac{\sigma}{r}} (1-p) f(p)dp, & \text{if } r \in [\frac{\sigma}{1-p^{\min}}, c). \end{cases}\end{aligned} \quad (44)$$

On the other hand, for $\rho^b(r|\sigma,c)$, if $r \ge c$, we have

$$\rho^b(r|\sigma,c) = \int_{p^{\min}}^{1-\frac{\sigma}{c}} f(p) dp. \quad (45)$$

Overall, from (42), we have

$$\begin{aligned}&\rho(r|\sigma,c) = \rho^a(r|\sigma,c) + \rho^b(r|\sigma,c) \\ &= \begin{cases} 0, & \text{if } r \in [0, \frac{\sigma}{1-p^{\min}}), \\ \int_{p^{\min}}^{1-\frac{\sigma}{r}} (1-p) f(p)dp & \text{if } r \in [\frac{\sigma}{1-p^{\min}}, c), \\ \int_{p^{\min}}^{\frac{r-\sigma}{c}} f(p)dp, & \text{if } r \in [c, \sigma + p^{\max} c), \\ 1, & \text{if } r \in [\sigma + p^{\max} c, \infty), \end{cases}\end{aligned} \quad (46)$$

which completes the proof. ■

APPENDIX G
PROOF OF COROLLARY 1

From Theorem 5, we need to handle two forms of integrals when deriving the probability of reporting in closed-form under the truncated normal distribution with pdf $f(p)$ in (20): $\int_{p^{\min}}^{\frac{r-\sigma}{c}} f(p)dp$ and $\int_{p^{\min}}^{d} (1-p) f(p)dp$, where $d = 1 - \frac{\sigma}{r}$ or $d = p^{\max}$.

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First, we notice that

$$\int_{p^{\min}}^{\frac{r-\sigma}{c}} f(p)dp = F(\frac{r-\sigma}{c}) - F(p^{\min}) = F(\frac{r-\sigma}{c}), \quad (47)$$

as $F(p^{\min}) = 0$. For the second integral, we have

$$\int_{p^{\min}}^{d} (1-p)f(p)dp = \int_{p^{\min}}^{d} f(p)dp - \int_{p^{\min}}^{d} pf(p)dp \\ = F(d) - g(p^{\min}, d), \quad (48)$$

where the function $g(c,d)$ is defined in (25). Here, the integral $\int_{p^{\min}}^{d} pf(p)dp$ can be handled by integration by parts and expressed using the error function erf(x) and the cdf $\Phi(y)$ in the function $g(c,d)$ in (25). ■

Appendix H
Proof of Theorem 6

From Theorem 5, we notice that given $\sigma \in \mathcal{S}$ and $c \in \mathcal{C}$, we have

$$\rho(r|\sigma, c) = \begin{cases} 0, & \text{if } r < \sigma, \\ 1, & \text{if } r \geq \sigma + c, \end{cases} \quad (49)$$

which implies that

$$\rho(r|\sigma, c) = \begin{cases} 0, & \text{if } r < \sigma^{\min}, \\ 1, & \text{if } r \geq \sigma^{\max} + c^{\max}, \end{cases} \forall \sigma \in \mathcal{S}, c \in \mathcal{C}. \quad (50)$$

Thus, from (15), we have

$$\rho(r) = \begin{cases} 0, & \text{if } r < \sigma^{\min}, \\ 1, & \text{if } r \geq \sigma^{\max} + c^{\max}. \end{cases} \quad (51)$$

First, for $r \geq \sigma^{\max} + c^{\max}$, from (51), we have $\rho(r) = 1$ so

$$\mathbb{P}(n, r) = \begin{cases} 1, & \text{if } n = I, \\ 0, & \text{if } n = 0, 1, \ldots, I-1. \end{cases} \quad (52)$$

From (28), we have $\phi(r) = u(I) - rI$, which is a decreasing function in r. So we obtain

$$\arg\max_{r \geq \sigma^{\max} + c^{\max}} \phi(r) = \sigma^{\max} + c^{\max}. \quad (53)$$

Second, for $0 \leq r < \sigma^{\min}$, from (51), we have $\rho(r) = 0$ so

$$\mathbb{P}(n, r) = \begin{cases} 1, & \text{if } n = 0, \\ 0, & \text{if } n = 1, 2, \ldots, I. \end{cases} \quad (54)$$

From (28), we have $\phi(r) = 0$.

Overall, from (53) and the result that $\phi(r) = 0$ for $0 \leq r < \sigma^{\min}$, we have

$$\max_{r \geq 0} \phi(r) \\ = \max\{\max_{0 \leq r < \sigma^{\min}} \phi(r), \max_{\sigma^{\min} \leq r \leq \sigma^{\max} + c^{\max}} \phi(r), \max_{r > \sigma^{\max} + c^{\max}} \phi(r)\} \\ = \max\{0, \max_{\sigma^{\min} \leq r \leq \sigma^{\max} + c^{\max}} \phi(r)\}, \quad (55)$$

which completes the proof. ■

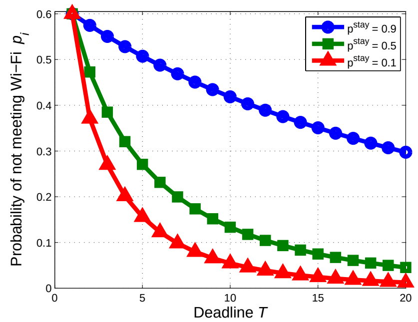

Fig. 14. The probability p_i of not meeting Wi-Fi versus the deadline T for different p^{stay}.

Appendix I
Additional Simulation Result

Impact of deadline on Wi-Fi availability: In Fig. 14, we plot the probability p_i of not meeting Wi-Fi in (35) against the deadline T for different values of p^{stay} under the Markovian mobility. First, since we assume that $p^{\text{wifi}} = 0.4$, then $p_i = 1 - p^{\text{wifi}} = 0.6$ when $T = 1$ in all the cases. For a user with a high mobility (with a small p^{stay}), we can see that he has a high chance to meet a Wi-Fi hotspot within $T = 20$ time slots. However, for a user with a low mobility (with a large p^{stay}), the chance of not meeting Wi-Fi decreases with T at a much slower rate than that of a user with a high mobility.