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Intelligent Contextual Information Collection in Internet of Things

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Abstract As we are moving towards the Internet of Things (IoT), a significant growth of stationary and mobile sensing & computing IoT devices continuously generate enormous amounts of contextual information, e.g., environmental data. Contextual information collection, reasoning, and inference plays critical role in IoT. In this paper, we consider the contextual information collection & harvesting problem in which stationary sensing and computing devices (sources), which are incapable to communicate with each other either due to their long distance, or for energy efficiency, or spatially dispersed network, rely on mobile IoT devices (collectors) to 'drain' their acquired contextual information. (e.g., generating from IoT applications: smart cities, smart metering, and smart agriculture). At the contact instances with the collectors, sources have to decide whether to deliver the contextual information obtained so far or postpone their delivery for later hitting epochs in an effort to sense fresher (or more critical) contextual information. We rest on the principles of Optimal Stopping Theory and propose an intelligent context collection scheme in IoT environments. We show through simulations with synthetic and real mobility data the effectiveness of our scheme compared to other approaches.

Keywords Contextual information collection · Internet of Things · time-optimized stochastic information delivery · optimal stopping theory.

1 Introduction

An aspect in context-aware mobile computing is the collection of contextual information (context) from certain sources in an Internet of Things (IoT) environment. We study the collection of context from stationary sources through

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mobile nodes, hereinafter referred to as 'collectors'. Collectors communicate in an ad-hoc manner with sources, which are sparsely distributed in an IoT environment, e.g., in a smart city. Collectors try to collect up-to-date pieces of context/measurements captured by sources and, then, deliver them to a Context-Aware Application (CAA) for further processing. The CAA exploits the collected context from different collectors in order to provide enhanced IoT services such as environmental monitoring, security surveillance, and smart city applications [27], [19], [20], [21].

We focus on an IoT environment consisting of two generic types of things: (a) IoT stationary devices (**sources**) equipped with sensors that generate (e.g., environmental) context (e.g., luminance, humidity, temperature), and (b) mobile IoT devices (**collectors**) that collect context from diverse sources and deliver it to IoT-enabled CAAs. Collectors accumulate context and gather as many pieces of context as possible from sources when being in contact of each other. The major characteristic of the considered IoT environment is that sources are not able to communicate directly, due to either their long distance compared to their transmission range or for saving energy due to their sensing tasks. In this case, context collection is achieved by the collectors that drain context from sources as they move around the IoT environment.

Contextual sensor data exhibits high complexity (e.g., due to the huge volumes and interdependency relationships between sources), dynamism (e.g., updates performed in real-time), accuracy, precision and timeliness [22], [23]. An IoT system should not concern itself with the individual pieces of contextual sensor data: rather, context should be intelligently *collected* and *interpreted* into a higher, domain relevant concept [29], [24], [28], [25], [26], [30], [31]. Many research efforts have studied IoT-enabled CAAs emphasizing in autonomous mobile collectors [32] for supporting distributed intelligence in IoT environments. Representative CAAs in this area apart from the 'standard' IoT services are: 'self-assembling' (reconfigurable robots) [33], 'localization' and 'coverage' (improvement of position accuracy; location of land mines) [34]. In this paper we propose an approach to intelligently harvest context in an IoT environment that supports IoT-enabled CAAs.

2 Related Work

The impact of mobility in contextual information harvesting & collection has been considered in the existing literature; the interested reader could refer to [10] for a detailed survey and the references therein.

Data mules [12] correspond to mobile devices whose motion can be controlled in light of collecting data from spatially dispersed WSN nodes. The concept of the data mules is that they travel across the sensing field and communicate with *every* sensing node (source) when it is in the proximity. Obviously, the benefit through this approach is that, by eliminating the need for multi-hop delivery / forwarding of contextual data, energy consumption at the nodes is reduced. Nonetheless, the major drawback is an increased data delivery latency, which is mainly governed by the motion of data mules. The authors in [11] provide a scheme to optimize the motion (path way) of data mules. Mobile collectors (sinks) in [13], [14] are adopted for contextual data harvesting. In these cases, ordinary sensor nodes are static and densely deployed in the sensing area. One or multiple mobile collectors move throughout the WSN to gather contextual data coming from all nodes. A different approach targeted for data collection in urban scenarios has been considered in [15], where citizens act as mobile collectors by collecting environmental data (such as pollutants concentration and weather conditions). Similar approaches have also been used in the context of opportunistic networks. Specifically, the message ferrying scheme [16] provides message relaying in sparse and mobile ad hoc networks. Message ferries move around in the network area and collect data from sources. They carry the stored data and forward them toward the destinations thus, they can be considered as a moving communication infrastructure, which enables data transfer in sparse WSNs. Moreover, opportunistic sensor networks have emerged, which exploit existing devices and sensors, such as cameras in mobile phones [2], [3], [4], [5]. Several of these networks are relevant to contextual information harvesting, because they can easily implement opportunistic dissemination protocols [6], [7], [9], [37]. Furthermore, MobEyes [1] is a middleware designed for vehicular sensor networks-based proactive urban monitoring. MobEyes exploits node mobility to opportunistically diffuse sensed data summaries among neighbor vehicles and to create index to query monitoring data. Mobile nodes periodically generate data summaries with extracted features and context information, whereas mobile agents move and opportunistically harvest summaries as needed from neighbor vehicles. Any regular node periodically advertises a new packet with generated summaries to its current neighbors to increase the opportunities for agents to harvest summaries. Finally, the mechanism in [43] introduces a context collection protocol for gathering data in a WSN through a registration framework. The collector node in [43] requires knowledge of the identity and data types of all sources in the network.

Our scheme is an approach to the problem of context harvesting in an IoT environment dealing with stationary sources and mobile collector nodes. Our scheme can be adopted by the above-mentioned opportunistic systems in order to enhance the quality/confidence of the collected context, thus, improving the provided CAA. Specifically, our scheme can enhance the context discovery process in [36] and the time-optimized data delivery mechanism in [38]. In context discovery [36], mobile collectors collaboratively explore, locate, and track sources that generate context. All collectors cooperatively pursue the acquisition of context of high quality by locating sources in an IoT environment. In our scheme, a source can improve the quality of the discovered context through the time-optimized decision framework. Collectors can then explore areas in a collaborative way as proposed in [36] and, in turn, provide the collected information for the exploration area to corresponding CAAs. Moreover, our scheme can enhance the contextual data harvesting mechanism introduced in [38]. The policy in [38] handles contextual data delivery in stationary wireless sensors networks assuming full connectivity among all IoT / sensor nodes. The scheme proposed in this paper can enhance the study focus of [38] since (a) it makes use of collectors' mobility assuming no connectivity among sources and (b) sources locally decide when to transmit context of high quality/confidence. Moreover, the context collection mechanisms in [39] and [40] provide a time-optimized decision framework for the collectors based on OST. Our scheme could supplementary support both mechanisms in [39] and [40] through the optimal context transmission decision framework for the sources.

3 Rationale of Our Approach

An IoT source in e.g., a smart city, can deliver the hitherto captured context immediately to an IoT collector while being in its transmission range with certain quality/confidence. However, the source could refrain from delivering context instantly to the visitor (collector) in order to capture more contextual information in light of increasing its confidence (or decrease the uncertainty) regarding a specific event. Nevertheless, it is uncertain when 'better' context will be available in terms of *quality*. This motivated us to introduce a **time-optimized, intelligent context collection** scheme for a source and treated it as an Optimal Stopping Theory (OST) problem [35]. According to the OST, the source has to intelligently decide *when to stop postponing context delivery* and, then, relay context to a visitor collector in order to maximize the average quality/confidence of the hitherto context. In this paper, we propose an intelligent context collector scheme for sources in an IoT environment based on time-based stochastic decision making optimization. The major technical contributions of the paper are:

- An analytical stochastic dynamic optimization context collection scheme for the IoT things: sources and collectors;
- An optimal stopping time-based decision making rule for intelligent contextual information delivery and collection in IoT environments;
- Analytical stochastic models for two alternative context collection schemes
- Performance and comparative assessment of the proposed scheme with other alternative collection schemes in IoT environments over simulated and real mobility data.

The outline of the paper is as follows. In Section 4 we define the context collection problem. Section 5 introduces the the time-optimized contextual information collection scheme along with the stochastic analytical model based on the Optimal Stopping Theory. We introduce two alternative context collection schemes in Section 6, while in Section 7 we provide an experimental evaluation and comparative assessment on our scheme. Finally, Section 8 concludes the paper with future research directions.

4 The Context Collection Problem

4.1 Problem Definition

We consider stationary **IoT sources** scattered in an area $\mathcal{A}$. The sources do not communicate directly, due to their long distance compared to their transmission range or for energy efficiency, but instead they rely on a number (M) of **IoT collectors** to drain their acquired / captured contextual information. A collector "hits" a stationary source whenever their distance is smaller than transmission range $r > 0$. We assume that the collectors move inside the covered area. The random mobility pattern is characterized by contacts which take place not regularly, but with a distribution probability. For instance, Poisson arrivals of an mobile nodes have been investigated in [17], while random direction mobile node mobility has been considered in [18]. In general, a node should perform discovery continuously, so that it can increase the chance of detecting contacts. However, when some knowledge on the mobility pattern of nodes can be exploited, the node can restrict discovery to the instants where the probability of an mobile node being in proximity is high. We assume that the movement of the collectors refer to the random direction waypoint model (RD) [41] or the random waypoint model (RW) [42]. For the moving models considered, the hitting points of a collector with a given source are approximated by Poisson process with parameter λ' [44]. Hence, the *inter-contact* time of a stationary source with an arbitrary collector is exponential with parameter $\lambda = M\lambda'$. The assumption of the collectors' mobility model, although it simplifies our analysis, but, nonetheless, we can generalize the proposed solution by considering intervals between successive contact epochs that are independent and identically distributed with an arbitrary distribution function. In this case the hitting process is a renewal process. Moreover, in the performance assessment Section 7, we evaluate the behavior of the proposed scheme adopting the Manhattan mobility model [47], to simulate urban mobility of the collectors in a city and also with real urban mobility traces from the Cabs Spotting Traces [48]. As it is substantiated by the performance assessment, the proposed scheme is robust in terms of the intelligent decision making for context delivery.

A source monitors its IoT environment and in the case of the presence of an *event*, e.g., measurements exceeding a predefined threshold, it starts to store the contextual data or a representative function of them, for example the maximum value or an aggregation function. The duration of the event, Y, is modeled as a random variable with cumulative distribution function $F_Y(y)$ which is known a-priori to the source. The source itself may detect the end of the event through the obtained measurements, e.g., consecutive measurements below a predefined threshold. At the contact points, the source should intelligently decide if it will transmit the contextual information obtained/captured so far to the collector, or it will postpone the delivery for later in order to collect more information, thus, increasing its *confidence* for the ongoing event. We assume that the sources transmit only once for energy efficiency, and that each contact is instantaneous (although the collector stays in the vicinity of the source for a small period of time). If the event has expired and the source has not transmitted yet, it will do so in the first contact epoch observed after Y.

Let us consider the stochastic process X_n, $n \geq 0$, which represents the decision epochs, i.e., when the IoT source should intelligently deliver the so far captured contextual information to its IoT collector. We set $X_0 = 0$ and for $n \geq 1$ we define

$$X_n = \begin{cases} x & \text{if time } x \ (x < Y = y) \text{ has elapsed and the } n^{\text{th}} \\ & \text{contact takes place there.} \\ & \\ x_{\{y\}} & \text{if time } x \ (x > Y = y) \text{ has elapsed and the } n^{\text{th}} \\ & \text{contact takes place there, whereas the previous} \\ & n-1 \text{ contacts occurred before } y. \end{cases}$$

The $\{X_n\}$ is a Markov process with the states $x_{\{y\}}$ being absorbing, whereas the states x are transient. In the state space of the process, we define a function $g(\cdot)$ that reflects the cost of transmitting/delivering context at the n^{th} contact time. In this paper, we define a linear delivery cost with respect to the time elapsed from the beginning of the event and the (random) duration of the event, i.e.,
if $X_n = x$

$$g(x; y) = a(y - x) + bx, \tag{1}$$

whereas if $X_n = x_{\{y\}}$

$$g(x_{\{y\}}; y) = bx. \tag{2}$$

The first term in (1) accounts for the *uncertainty* (*confidence*) about the event, which decreases (increases) as more contextual data are sensed and processed until the event is over. The second term in (1) penalizes the delay of transmission. The parameters $a > 0$ and $b > 0$ regulate (through their ratio $c = a/b$), the relative importance of decreasing uncertainty versus reducing delivery delay. For analysis sake, we assume that $a > b$ since, in the opposite case, the cost is a non decreasing function and there is no need for the IoT source to postpone transmission.

Remark 1 The cost function could be any convex function of the time elapsed x from the beginning of the event and the (random) duration y of the event, given the fact that it reflects/interprets the trade-off of postponing a possible delivery to the IoT collector in light of increasing the confidence of the detected event by accumulating/processing more pieces of contextual information.

Before proceeding with a formal definition of our problem, we briefly provide a preliminary on the Optimal Stopping Theory; the reader could also refer to [46] for more information.

4.2 Optimal Stopping Theory

The theory of optimal stopping [46] is concerned with the problem of choosing a time instance to take a certain action, in order to minimize an expected loss or cost. A stopping rule problem is associated with:

- a sequence of random variables $X_1, X_2, \ldots$, whose joint distribution is assumed to be known and
- a sequence of cost/loss functions $(g_n(x_1, \ldots, x_n))_{1 \leq n}$ which depend only on the observed values of the corresponding random variables $X_1 = x_1, \ldots, X_n = x_n$.

The **optimal stopping rule problem** is defined as follows: We are observing the sequence of the random variables $X_1, \ldots, X_n$, and at each time instance n, we can choose to either stop observing or continue. If we stop observing at time instance n, we obtain loss/cost $g_n(x_1, \ldots, x_n)$. Otherwise, we continue to observe the X_{n+1}. We desire to choose a stopping rule or stopping time to minimize our expected loss.

Definition 1 An optimal stopping rule problem is to find the *optimal stopping time* n^*, which minimizes the expected cost, i.e.,

$$E[g_{n^*}] = \inf_{n \geq 1} E[g_n(X_1, \ldots, X_n)].$$

The available information up to n is a sequence $\mathcal{F}_n$ of values of the random variables $X_1, \ldots, X_n$ (a.k.a. filtration).

Definition 2 The 1-stage look-ahead (1-sla) stopping rule refers to the stopping criterion

$$n^* = \inf\{n \geq 1 : g_n \leq E[g_{n+1}|\mathcal{F}_n]\} \tag{3}$$

In other words, n^* calls for stopping at the first time instance n for which the loss g_n for stopping at n is (at most) as small as the expected loss of continuing to the next time instance $n+1$ and then stopping.

Definition 3 Let A_n denote the event $\{g_n \leq E[g_{n+1}|\mathcal{F}_n]\}$. The stopping rule problem is monotone if $A_0 \subset A_1 \subset A_2 \subset \ldots$ almost surely (a.s.)

A monotone stopping rule problem can be described as follows: The set A_n is the set on which the 1-sla rule calls for stopping at time instance n. The condition $A_n \subset A_{n+1}$ means that if the 1-sla rule calls for stopping at time n, then it will also call for stopping at time $n+1$ no matter what X_{n+1} happens to be. Similarly, $A_n \subset A_{n+1} \subset A_{n+2} \subset \ldots$ means that if the 1-sla rule calls for stopping at time n, then it will call for stopping at all future times no matter what the future observations turn out to be.

Theorem 1 *The 1-sla rule is optimal for monotone stopping rule problems.*

Proof See [46] □

In the remainder, we propose a 1-sla stopping rule corresponding to a time-optimized mechanisms over the decision epochs of the IoT sources.

4.3 Problem Formulation

Given the cost function $g(x)$ in (1) and (2) and the fact that the duration of the event y is random, we formulate the problem of the contextual information collection in IoT environments as follows:

Problem 1 Given an event duration $Y = y$ and the sequence of decision epochs $X_1, X_2, \ldots$, find the optimal stopping time x^* which minimizes $E_Y[g(x^*)] = \inf_{x \leq Y=y} E_Y[g(x)]$.

The idea is to find a stopping criterion/rule over the decision epochs X_n, $n \leq 1$, such that given the current value x of X_n corresponding to the current delivery cost $g(x; y)$ of context observed at the IoT source, the latter immediately decides whether to deliver context to the visiting IoT collector or to postpone context delivery. We require an immediate decision making over the decision epochs, thus, avoiding any redundant context delivery. As it will be shown in the remainder, our mechanism at each decision epoch n proceeds with a time-optimized decision in $O(1)$ time.

5 Intelligent Context Collection

In the following, we find the optimal policy of context delivery for the Problem 1. We first describe the transition probabilities for the Markov chain $\{X_n\}$. Specifically, we report on the transition probabilities:

– Transiting from the state $X_n = x$ to $X_{n+1} = x + s$ given that s is the time elapsed from the n^{th} hitting time–decision epoch (where a collector met the source) to the current hitting time–current decision epoch, at which the event is yet *active*, i.e., $0 \leq s, x + s \leq y$. Note that s (inter-contact time) is drawn from an exponential with parameter λ. That is,

$$P\{X_{n+1} = x + s \,|\, X_n = x\} = \lambda e^{-\lambda s} \frac{\bar{F}_Y(x+s)}{\bar{F}_Y(x)}, 0 \leq s, \quad x + s < y, \tag{4}$$

where $\bar{F}_Y(x) = 1 - F_Y(x)$.

– Transiting from the state $X_n = x$ to $X_{n+1} = (x + s)_{\{y\}}$ given that s is the time elapsed from the n^{th} hitting time–decision epoch (where a collector met the source) to the current hitting time–current decision epoch, at which the event is *expired*, i.e., $x < y < x + s$. That is,

$$P\{X_{n+1} = (x + s)_{\{y\}} \,|\, X_n = x\} = \lambda e^{-\lambda s} \frac{f_Y(y)}{\bar{F}_Y(x)}, x < y < x + s. \tag{5}$$

– Transiting from the state $X_n = x_{\{y\}}$ to $X_{n+1} = x_{\{y\}}$ given that the event is *expired* in both decision epochs n and $n + 1$, i.e., $y \leq x$. That is,

$$P\{X_{n+1} = x_{\{y\}} \,|\, X_n = x_{\{y\}}\} = 1, y \leq x. \tag{6}$$

The major objective to decide whether the IoT source delivers context at decision epoch n or not is to estimate the expected cost if the IoT source delivers context at $X_n = x$ and at $X_n = x_{\{y\}}$. In the former case the expected cost is given by:

$$C(x) = E_Y[g(x)] = \int_x^\infty a(y-x)dF_Y(y|x) + bx. \tag{7}$$

Note that $F_Y(y|x)$ denotes the conditional probability distribution function given by

$$F_Y(y|x) = P\{Y \leq y \,|\, Y > x\} = \frac{F_Y(y) - F_Y(x)}{1 - F_Y(x)} = \frac{F_Y(y) - F_Y(x)}{\bar{F}_Y(x)}, x \leq y. \tag{8}$$

Hence, clearly in (7),

$$dF_Y(y|x) = \frac{f_Y(y)}{\bar{F}_Y(x)}dy.$$

If the IoT source delivers context at $X_n = x_{\{y\}}$ then the expected cost is simply:

$$C(x_{\{y\}}) = bx. \tag{9}$$

The idea here is for the source to deliver context at the current decision epoch n iff it is guaranteed that the expected cost of postponing a context delivery at n and delivering context at some later decision epoch $n' > n$ is greater than the current cost at n. Through this (stochastic) reasoning, the source should rely on an 1-sla optimal policy stating that a postpone decision at decision epoch n is beneficial with respect to minimizing the expected cost. Specifically, if $g(x_n)$ represents the cost under a policy given that the source has a contact with a collector at x_n, using the 1-sla from (3), a delivery decision would be made once $E_Y[g(X_{n+1})|\mathcal{F}_n]$ should satisfy $g(x_n) \leq E_Y[g(X_{n+1})|\mathcal{F}_n] = C(X_{n+1})$, with filtration (information up to n) $\mathcal{F}_n \subset \{x_1, \ldots, x_n\}$ and $X_{n+1} = x_n + s$, and s being drawn from an exponential with parameter λ.

Theorem 2 *Given the decision epoch $X_n = x$ and the event duration Y with probability distribution function $F_Y(y)$, the IoT source delivers context to the IoT collector if for the current hitting time x the following criterion holds true*

$$\int_x^\infty e^{-\lambda(y-x)} \frac{f_Y(y)}{\bar{F}_Y(x)}dy \geq \frac{c-1}{c}, \tag{10}$$

with $c = \frac{a}{b}$.

Proof Let us estimate the expected cost $E_Y[g(X_{n+1})|\mathcal{F}_n]$ if at decision epoch $X_n = x$ the source decides to postpone the context delivery and observes $X_{n+1} = X_n + s = x + s$, i.e.,

$$E_Y[g(X_{n+1})|\mathcal{F}_n] = \int_0^\infty C(x+s)P\{X_{n+1} = x+s \,|\, X_n = x\}ds + \int_0^\infty \int_x^{x+s} C((x+s)_{\{y\}})P\{X_{n+1} = (x+s)_{\{y\}} \,|\, X_n = x\}dyds,$$

Based on the 1-sla optimal stopping rule, it is optimal for the source to deliver context at current time x if $C(x)$ is less or equal to $C(X_{n+1}) = E_Y[g(X_{n+1})|\mathcal{F}_n]$. Given the (7) and (9), we obtain:

$$
\begin{aligned}
E_Y[g(X_{n+1})|\mathcal{F}_n] &= \int_0^\infty \int_{x+s}^\infty (a(y-(x+s)) + b(x+s)) \frac{f_Y(y)}{\bar{F}_Y(x+s)} \lambda e^{-\lambda s} \frac{\bar{F}_Y(x+s)}{\bar{F}_Y(x)} dyds \\
&+ \int_0^\infty \int_x^{x+s} b(x+s)\lambda e^{-\lambda s} \frac{f_Y(y)}{\bar{F}_Y(x)} dyds \\
&= \int_0^\infty \int_x^\infty (a(y-(x+s)) + b(x+s))\lambda e^{-\lambda s} \frac{f_Y(y)}{\bar{F}_Y(x)} dyds \\
&- \int_0^\infty \int_x^{x+s} (a(y-(x+s)) + b(x+s))\lambda e^{-\lambda s} \frac{f_Y(y)}{\bar{F}_Y(x)} dyds \\
&+ \int_0^\infty \int_x^{x+s} b(x+s)\lambda e^{-\lambda s} \frac{f_Y(y)}{\bar{F}_Y(x)} dyds \\
&= \int_0^\infty \int_x^\infty (a(y-x) + bx)\lambda e^{-\lambda s} \frac{f_Y(y)}{\bar{F}_Y(x)} dyds \\
&+ \int_0^\infty \int_x^\infty (b-a)s\lambda e^{-\lambda s} \frac{f_Y(y)}{\bar{F}_Y(x)} dyds \\
&- \int_0^\infty \int_x^{x+s} a(y-(x+s))\lambda e^{-\lambda s} \frac{f_Y(y)}{\bar{F}_Y(x)} dyds \\
&= C(x) + \frac{b-a}{\lambda} + \int_0^\infty \int_x^{x+s} a(x+s-y)\lambda e^{-\lambda s} \frac{f_Y(y)}{\bar{F}_Y(x)} dyds
\end{aligned}
$$

Changing the integral limits as $\int_0^\infty \int_x^{x+s} (\cdot) dyds = \int_x^\infty \int_{y-x}^\infty (\cdot) dyds$ we reach at the expression

$$
E_Y[g(X_{n+1})|\mathcal{F}_n] = C(x) + (b-a)\frac{1}{\lambda} + \int_x^\infty \frac{a}{\lambda} e^{-\lambda(y-x)} \frac{f_Y(y)}{\bar{F}_Y(x)} dy
$$

Therefore, it is optimal to deliver context at (hitting) time x, if the following criterion holds true

$$
\int_x^\infty e^{-\lambda(y-x)} \frac{f_Y(y)}{\bar{F}_Y(x)} dy \geq \frac{c-1}{c},
$$

using $c = a/b$. □

5.1 Event Duration Distribution

In order for the source to decide at hitting time x whether to deliver context or not, we have to calculate the integral at the left part of (10) and compare its value with the fraction $\frac{c-1}{c}$. We consider some special cases for the distribution function $F_Y(y)$ of the event duration.

5.1.1 Deterministic Duration

The simplest is the *deterministic case*, where $f_Y(y) = \delta(y - D)$, with fixed and known duration $D > 0$. In this case, the criterion (10) takes the form

$$e^{-\lambda(D-x)} \geq \frac{c-1}{c}. \tag{11}$$

Solving for the value of x that satisfies with equality the criterion in (11), we find that the source decides to deliver context if the current time x is greater or equal to x^*:

$$x^* = \max\left\{0, D - \frac{1}{\lambda}\log\left(\frac{c}{c-1}\right)\right\}. \tag{12}$$

The criterion (12) in the optimal stopping rule for the IoT source, when the duration of the event is known.

5.1.2 Uniformly Distributed Duration

Consider now the case that Y is uniformly distributed in the interval $[0, D]$ for some fixed $D > 0$. In this case $f_Y(y) = 1/D$ and $\bar{F}_Y(x) = (D - x)/D$. Therefore, the optimal stopping rule is to deliver context if the current time x is greater or equal to x^*:

$$x^* = \max\left\{0, D - \frac{c}{\lambda(c-1)}\right\}. \tag{13}$$

Remark 2 The criteria in (12) and (13) are constants, thus, the IoT source with a simple comparison, i.e., in $O(1)$ time, if for the current hitting time x it holds true that $x \geq x^*$, it minimizes the expected delivery cost.

6 Alternative Context Collection Schemes

The proposed context collection scheme will be contrasted to two alternative context collection schemes: (i) probabilistic context collection scheme and (ii) deterministic context collection scheme.

6.1 Probabilistic Context Collection

In this scheme, the IoT source delivers its context (at a hitting epoch) with probability $p \in [0, 1]$. If the event has expired then it will deliver context at the first contact observed after Y. In this case, by conditioning on the duration of the event $Y = y$ and the number of contacts in the interval $[0, y]$, we have for the average delivery cost:

$$U_{\text{rand}} = \int_0^\infty \sum_{k=0}^{\infty} E[V(y,k)|y,k] \frac{e^{-\lambda y}(\lambda y)^k}{k!} f_Y(y)dy \tag{14}$$

where

$$\begin{aligned} E[V(y,k)|y,k] = \int_0^y \int_0^{x_k} \cdots \int_0^{x_2} \Big[& p(c(y-x_1)+x_1) + \\ & p(1-p)(c(y-x_2)+x_2) + \ldots \\ & +p(1-p)^{k-1}(c(y-x_k)+x_k) + \\ (1-p)^k \int_{y-x_k}^{\infty} (x_k+s) & \frac{\lambda e^{-\lambda s}}{e^{-\lambda(y-x_k)}} \Big] \frac{k!}{y^k} dx_1 dx_2 \cdots dx_k \end{aligned}$$

In (14) we base on the fact that the contact epochs are uniformly distributed in $[0, y]$ given the number of contact points in this interval. Therefore, the probability distribution function of the order statistics of the random variables $x_1, \ldots, x_k$ is simply $k!/y^k$. It turns out that:

$$\begin{aligned} E[V(y,k)|y,k] = cy(1-(1-p)^k) + \frac{1}{k+1} p(1-c)y \sum_{i=1}^{k} i(1-p)^{i-1} \\ (1-p)^k (y+1/\lambda). \end{aligned} \tag{15}$$

Note that, in case of $p = 0$, that is the source always postpones transmission until time exceeds the event duration y, the cost is simply $y + 1/\lambda$ due to the exponential character of the inter-hitting process.

6.2 Deterministic Context Collection

In the deterministic context collection scheme, the source delivers context at a predetermined contact epoch, let us say the m^{th} contact epoch, unless, of course, the time y is exceeded in which case it transmits immediately in the first contact epoch observed after y. By conditioning again on the duration of $Y = y$ we have:

$$U_{\text{fix}} = \int_0^\infty E[V(y)|y] f_Y(y)dy. \tag{16}$$

If N is the random variable denoting the number of contact points in the interval $[0, y]$ then, in this case,

$$\begin{aligned} E[V(y)|y] = {} & P\{N < m\}(y + 1/\lambda) \\ & + \sum_{j=m}^{\infty} P\{N = j\} E[c(y - x_m) + x_m \,|\, j] \end{aligned} \tag{17}$$

Given that j contacts have occured ($j \geq m$), the probability distribution function of the x_m order statistic is

$$f_{X_m}(x) = \frac{j!}{(m-1)!(j-m)!}\left(\frac{x}{y}\right)^{m-1}\left(1-\frac{x}{y}\right)^{j-m}\frac{1}{y}$$

and, therefore,

$$E[x_m|\,j] = y\frac{m}{j+1}.$$

Hence, by substituting in (17), we obtain:

$$\begin{aligned} E[V(y)|y] = \sum_{j=0}^{m-1} \frac{e^{-\lambda y}(\lambda y)^j}{j!}(y + 1/\lambda) + \\ cy\sum_{j=m}^{\infty}\frac{e^{-\lambda y}(\lambda y)^j}{j!} + (1-c)ym\sum_{j=m}^{\infty}\frac{e^{-\lambda y}(\lambda y)^j}{(j+1)!}. \end{aligned}$$

7 Performance & Comparison Assessment

7.1 Simulation Setup

In this section we measure the delivery cost of the proposed time-optimized context collection scheme for an IoT source and compare it with the two alternative context collection schemes in an IoT environment. For each model we measure the incurred expected cost C over certain number of experiments against the basic models parameters, i.e., parameter ratio $c = \frac{a}{b}$ for all model, probability p for the probabilistic context collection model, and contact epochs m for the deterministic context collection model. We experiments with diverse mobility traces, and specifically, with (i) Random Direction Mobility Model [50], hereinafter referred to as 'Direction trace' for comparing the theoretical models with the simulation models, (ii) Manhattan Mobility Model [47] using the BonnMotion [49] mobility simulator tool, hereinafter referred to as 'Manhattan' trace for simulating a city area, and (iii) Real Urban Mobility Traces based on the Cabs Spotting Traces project [48], hereinafter referred to as 'Cabs' trace. The network simulations for the Manhattan and Cabs traces are carried out using Network Simulator 2 (NS–2) [8]. The Manhattan and Cabs mobility traces have been converted to the NS–2 format, thus, having been integrated into the Tool Command Language (TCL) scripts. The parameters for the NS–2 wireless communication are: (i) Wireless channel type with MAC Layer Protocol 802.11, (ii) Transmission range: 100 m, (iii) Packet Rate: 4 packet/s, and (iv) Data Payload: 512 bytes/packet.

7.2 Experimental Evaluation

7.2.1 Random Direction Model Mobility Traces

We set the λ parameter of the inter-contact time of IoT sources and collector, i.e., $\lambda = M \cdot \lambda' = 20 \cdot 2.31 = 4.62$, assuming a set of $M = 20$ IoT collectors in an area of size $\mathcal{A}$. The value of λ' corresponds to the mean rate of the Poisson meeting times of two mobile devices that move in a square are using the Random Direction Mobility Model (RDMM) [44]. The parameters of the RDMM are: (a) an area $\mathcal{A}$ of size 4Km$\times$4Km, (b) speed uniformly distributed in [1.2, 3] m/s, (c) exponentially distributed amount of travel time with mean 1/4 h, and (d) communication range equal to 100 m. Note that the value of λ' is only indicative since in our problem only the IoT collectors are moving while the IoT sources are stationary. We will consider the deterministic case for the event duration, that is the event has constant duration equal to $D = 2$h. For this value of D, we expect an average of nine contacts during the event. The results are obtained using 10,000 independent runs.

In Figure 1 we plot the average delivery cost U_{OST}, U_{rand}, and U_{fix}, obtained under the three context collection schemes: time-optimized collection, probabilistic collection, and deterministic collection, respectively, for various values of the parameter ratio $c = \frac{a}{b}$. The cost for the time-optimized scheme, U_{OST}, is the cost for transmitting at the first contact epoch that satisfies the optimal stopping criterion in (12) with $y = D$. The cost for the probabilistic alternative collection scheme, U_{rand}, is obtained from (14) and (15) conditioning on the number of contacts in the interval $[0, y]$. For the results plotted on Figure 1, we have set the collection probability parameter $p = 0.5$. The cost for the deterministic alternative collection scheme, U_{fix}, is obtained using (17) since there is no randomness for the parameter y. For the results on Figure 1, we have set the parameter m equal to $\mathrm{round}(\lambda y) = 9$. As it is observed from Figure 1 the simulation results match the analytical ones. Furthermore, it is seen that the time-optimized collection scheme outperforms the other alternatives especially for larger values of the ratio c. For small values of c, all schemes exhibit similar performance and this is due to the fact that the cost tends to be independent of the contact time. For example, for $c = 1$ the cost is $c(y - x) + x = y = 2$ independent of x, whereas for smaller values of c the cost is $cy + (1 - c)x$ which is an increasing function of x. In this case, for the time-optimized scheme, the IoT source will transmit as soon as possible with a cost close to cy.

Table 1 shows the value of $x^\star$ and the minimum delivery cost obtained under the proposed time-optimized scheme. As it is observed, as the value of c increases, $x^\star$ tends to $y = 2$h in an effort to minimize the high cost term of the cost function $c \cdot (y - x)$.

In Figure 2, we compare the performance of the time-optimized scheme with that of the probabilistic collection scheme for various values of delivery probability p. The parameter c was set equal to 5. For small values of p, the probabilistic collection scheme will postpone context deliveries until the

c	$x^\star$	Cost
2	1.850	2.150
3	1.912	2.175
4	1.937	2.186
5	1.951	2.193
6	1.960	2.197
7	1.966	2.200
8	1.971	2.202
9	1.974	2.204
10	1.977	2.205

Table 1 Optimal stopping times and corresponding delivery costs for various values of c.

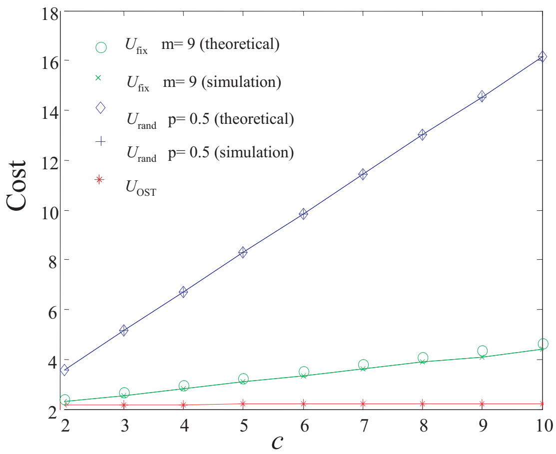

Fig. 1 Context delivery cost vs. ratio c for the time-optimized collection scheme, the probabilistic collection scheme, and the deterministic collection scheme; $p = 0.5$, $m = 9$.

duration y has been exceeded, in which case the delivery cost is close to $y + 1/\lambda = 2.21$. For larger values of p, the delivery cost increases reaching a limit which is equal to $c(y - 1/\lambda) + 1/\lambda = 5(2 - 1/4.62) + 1/4.62 = 9.1$. This is due to the fact that for $p = 1$, the probabilistic collection scheme will transmit in the first contact time which is on average equal to $1/\lambda$.

Finally, in Figure 3, we compare the performance of the time-optimized collection scheme with that of the deterministic collection scheme for various values of contact epochs m. The parameter c was set equal to 5. As it is observed, the performance deteriorates for small values of m since in this case the deterministic collection scheme delivers context earlier than necessary. As a consequence, the context delivery cost is large. For values of m greater than 9, the deterministic collection scheme delivers context at epochs that are usually larger than y and, thus, the cost obtained is close to $y + 1/\lambda = 2.21$.

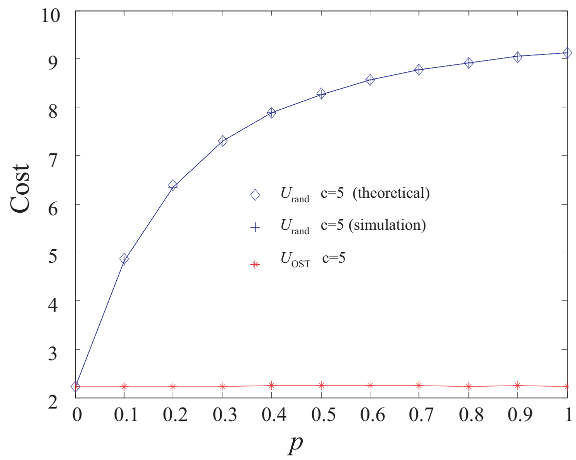

Fig. 2 Context delivery cost comparison of the time-optimized collection scheme and the probabilistic collection scheme against delivery probability p.

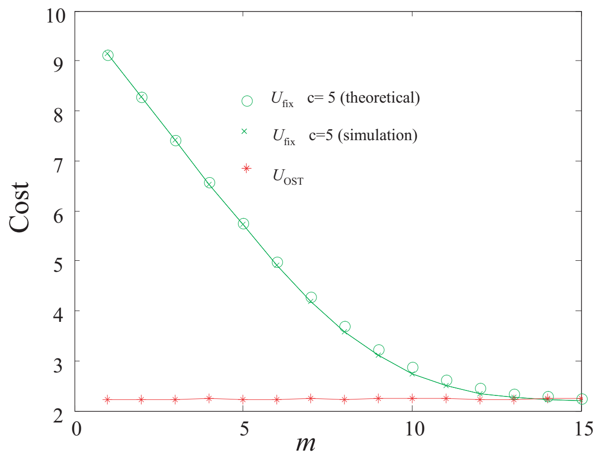

Fig. 3 Context delivery cost comparison of the time-optimized collection scheme and the deterministic collection scheme against parameter m.

7.2.2 Manhattan Model Mobility Traces

In this section, we evaluate the performance of the three context collection models assuming movement of mobile collectors under the Manhattan Mobility Model (MMM) [47]. In MMM, we simulate an urban area, where the road topology is a grid consisting of horizontal and vertical roads on a terrain $\mathcal{A}$ of area 5Km $\times$ 5Km. The distance between two road intersections is set to 200 m. Whenever a vehicle (which corresponds to a mobile collector) reached an intersection, the probability of moving on the same street is 0.5, and probability of turning left/right is 0.25/0.25, respectively. We assume that 200 mobile collectors travel at speeds between 5 m/s and 20 m/s, with pause times in $\{0, 20, 40, 60, 80, 100\}$ seconds. The acceleration is uniformly distributed between 0.1m/s^2 and 1 m/s^2, and the simulation time of 7200 seconds. The results are obtained using 1,000 independent runs.

Figure 4 shows the expected cost for all the models for different c ratios with $m \in \{5, 9\}$ for the deterministic model and $p = 0.5$ for the probabilistic model. We observe that our model outperforms the two alternatives, even in the case of movements governed by MMM. This is due to the fact that, apart from the randomness of a collector's movement, each source intelligently decides when to transmit its context taking into consideration the ratio c. Hence, for each specific ratio, our model attempts to optimize the expected delivery cost.

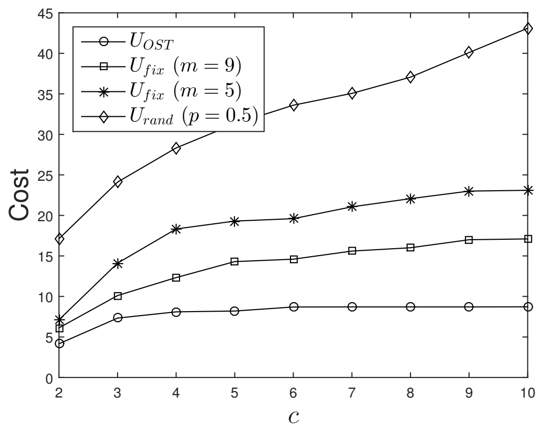

Fig. 4 Context delivery cost vs. ratio c for the time-optimized collection scheme, the probabilistic collection scheme with $p = 0.5$, and the deterministic collection scheme with $m \in \{5, 9\}$, over Manhattan mobility traces.

Moreover, Figure 5 shows the expected cost for our model and the probabilistic model for different values of p with ratio $c = 5$ over MMM mobility traces. We observe that an increase in the probability p results in high expected cost for the probabilistic model. This is attributed to the fact that the probabilistic model delivers context with high probability at each contact epoch, thus, it does not take into account the cost minimization with respect to confidence on the measurements.

Figure 6 shows the expected cost for our model and the deterministic model for different values of m with ratio $c = 5$ over the Manhattan mobility traces. One can observe that as m increases, the determination model delays in delivering context in light of achieving lower expected cost. This is attributed to the fact that context is delivered at epochs larger than y, where of course the degree of confidence of the measurements is high. However, this implies a relatively high delay in context delivery. A low value of m indicates that the deterministic model delivers context earlier than necessary.

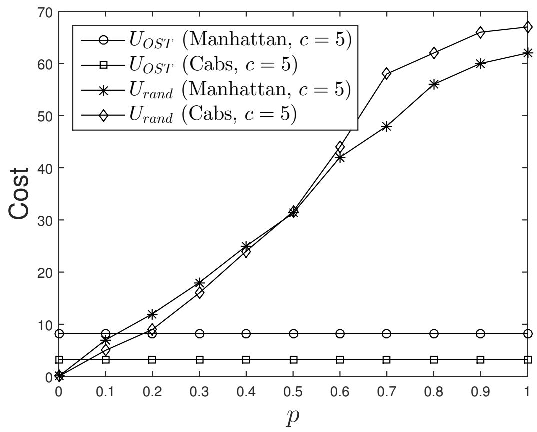

Fig. 5 Context delivery cost vs. collection probability p for the time-optimized collection scheme and the probabilistic collection scheme with $c = 5$ over the Cabs and Manhattan mobility traces.

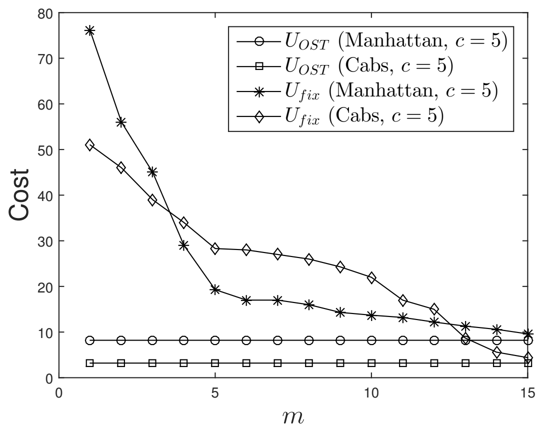

Fig. 6 Context delivery cost vs. deterministic delivery epochs m for the time-optimized collection scheme and the deterministic collection scheme with $c = 5$ over the Cabs and Manhattan mobility traces.

7.2.3 Real Urban Mobility Traces

In this section, we evaluate the performance of the three context collection models using real mobility traces. Specifically, the Cabs traces [48] refers to mobility traces of taxis moving in the San Francisco (SF) area. We selected mobility traces that contain GPS coordinates of 200 taxis (cabs), corresponding to mobile collector, collected for 14,400 seconds (4 hours) and the average time interval between two consecutive location readings is approximately 10 seconds. The average speed in the SF down town area is calculated to be approximately 11.11 m/s.

Figure 7 shows the expected cost for all the models for different c ratios with $m \in \{5, 9\}$ for the deterministic model and $p = 0.5$ for the probabilistic model over the Cabs mobility trace. In addition, Figures 5 and 6 show the performance of our model with the probabilistic and deterministic model, respectively, for the Cabs traces. Our model significantly outperforms the two alternatives in the case of real mobility traces. This indicates the applicability of our model for context harvesting utilizing optimally scheduled context delivery decisions.

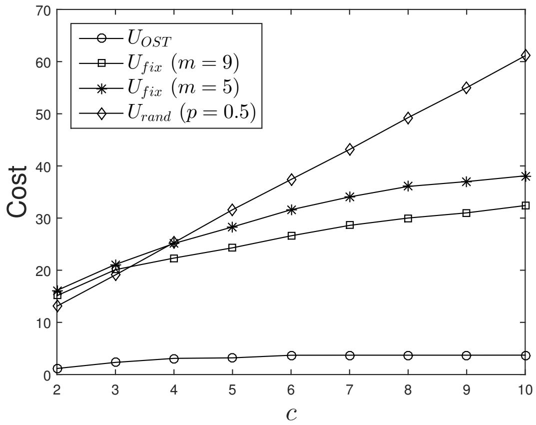

Fig. 7 Context delivery cost vs. ratio c for the time-optimized collection scheme, the probabilistic collection scheme with $p = 0.5$, and the deterministic collection scheme with $m \in \{5, 9\}$, over Cabs mobility traces.

8 Conclusions & Future Work

We considered the problem of optimally scheduled contextual information harvesting in an IoT environment. We dealt with stationary IoT sources that have only one delivery chance (due to energy constraints) and have to make an intelligent decision regarding at which contact point with an IoT collector they will deliver their context. The problem is formulated in the framework of the Optimal Stopping Theory and the efficiency of its solution is contrasted against to two different context collection schemes: a deterministic and a probabilist context collection scheme. Simulation results corroborated the analysis provided in the paper, and demonstrated the superiority of the proposed solution. Moreover, experimental evaluation with the Manhattan / City mobility model and real mobility traces in urban areas show the superiority of the proposed model over the two alternatives, thus, being applicable in urban-oriented IoT context-aware applications. Future extensions include the option of varying the transmission power of the IoT sources resulting in a non-homogeneous Poisson process for the contact points. Moreover, the solution could be generalized for the case that the contact process is modeled as a renewal process.

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