On Optimal Information Capture by Energy-Constrained Mobile Sensors

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***Abstract*—A mobile sensor is used to cover a number of *points of interest* (PoIs), where dynamic events appear and disappear according to the given random processes. The sensor, which is of sensing range r, visits the PoIs in a cyclic schedule and gains information about any event that falls within its range. We consider the temporal dimension of the sensing as given by a *utility function*, which specifies how much information is gained about an event as a function of the cumulative sensing or observation time. The *quality of monitoring* (QoM), i.e., the fraction of information captured about all events, depends on the speed of the sensor and has been analyzed in an earlier paper for different utility functions. The prior work, however, does not consider the energy of motion, which is an important constraint for mobile sensor coverage. In this paper, we analyze the *expected Information captured Per unit of Energy consumption* (IPE) as a function of the event type (in terms of the utility function), the event dynamics, and the speed of the mobile sensor. Our analysis uses a realistic energy model of motion, and it allows the sensor speed to be optimized for information capture. The case of multiple sensors will also be discussed. Extensive simulation results verify and illustrate the analytical results.**

***Index Terms*—Energy consumption, mobile sensor coverage, quality of monitoring (QoM), sensor network.**

I. Introduction

Wireless sensor networks are useful in a wide range of applications, such as environment monitoring, tracking of wildlife, healthcare, defense against natural hazards or malicious attacks, and social networks [2]–[4]. In sensor network design, the *coverage problem* is concerned with the allocation of sensing resources to different parts of a deployment area for effective information capture about interesting events.

Traditional work in sensor coverage can be classified into two broad categories [5], [6]. In a dense network, the problem is to optimally task subsets of the sensors, or to schedule the duty cycles of the sensors, to achieve area coverage (i.e., each point of the surveillance region is within range of at least one sensor) or area k-coverage (i.e., each point of the region is within range of at least k sensors) while maximizing the network lifetime before energy is depleted. In a sparse network, in which the sensor density is insufficient to provide significant redundancy of coverage, the goal is to optimally place the sensors so that the area of coverage or k-coverage is maximized.

More recently, the importance of mobile coverage is recognized [7]–[10]. Support for programmed mobility is, for example, made feasible by advances in robotics, which drive down deployment costs [11]. Mobile coverage is already the norm in certain existing applications, e.g., reconnaissance airplanes flying over enemy territories to collect intelligence, where the installation of an expansive static sensor network is out of the question. In other situations, real-life sensors (chemical, radiation, and biological sensors, among others) may have limited range. If there are insufficient sensors to cover a large geographical area all the time, mobility can be used to effect total coverage over time while requiring a significantly smaller number of sensors. In this case, the cost savings of using fewer sensors have to be balanced against the costs of supporting the mobility, but the tradeoff is interesting, particularly when the sensor mobility can be piggybacked onto that of an existing mobile entity, e.g., a patrol car.

In [12], the need for mobility is motivated for data collection from a number of data-collection points in an underwater environment, where high-signal attenuations preclude the communication of data over significant distances. To overcome the problem, a mobile device can be used to move among the data-collection points, download the collected data, and carry the downloaded data to a data sink for analysis. Similar use of a mobile device for data collection in other "hard-to-access" environments (e.g., underground) is justified, given the extreme challenges of placing a connected set of wireless access points for long-haul movement of data.

The problem of capturing stochastic events that dynamically appear and disappear at given *points of interest* (PoIs) by mobile sensors has been studied in [12]. Each event at a PoI probabilistically arrives, stays for a random time drawn from a statistical distribution, and is followed by another event after a random event absent time drawn from another distribution. The goal is to design a mobile coverage schedule to maximize the number of events captured, where an event is captured if it falls within range of one or more sensors during its lifetime. In [1], the mobile coverage problem is augmented in two respects. First, the authors additionally consider a *temporal dimension* of the sensing, in which they recognize that a nontrivial sensing

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time is often needed to gain information about many real-world events. How the information gained about an event increases with additional sensing time is captured by an *event utility function* for the type of events. The optimization objective then becomes the maximization of the total information gained about all captured events, instead of simply the number of these events. Second, they consider the paradigms of periodic and proportional-share scheduling of the coverage time among different PoIs. The proportional-sharing objective, in particular, allows more important PoIs to be covered for a larger fraction of time.

The *quality of monitoring* (QoM) of a deployment quantifies the fraction of information in the deployment capture about all existing events before they run out of energy. An analysis of the QoM is given in [1] for a mobile sensor moving among the PoIs in either a *linear periodic* or *general periodic* schedule. Results show how the QoM is affected by the event dynamics, the type of events (i.e., the event utility function), the proportional share of coverage time received by a PoI, and the fairness granularity over which the proportional share is achieved. Optimal mobile coverage algorithms are then designed to achieve given proportional shares while maximizing the QoM of the total system.

The prior work in [1] and [12] does not consider the energy use of the mobile sensors. In real life, however, mobile sensors often run on limited batteries. When they deplete their energy budgets, they will need to be recharged or replaced, or they will simply stop contributing to the sensor network. Hence, there is the dual objective of ensuring the effective operation of a sensor (in terms of maximizing its ability to capture information) on the one hand and prolonging the lifetime of the sensor (in terms of managing its energy use for mobility) on the other hand [13], [14]. In this paper, we quantify such dual performance of a mobile sensor. Our contributions are given here.

1) First, we use a realistic energy model to account for the cost of movement. This allows one to quantify the tradeoff between increased QoM due to a finer grained sharing of the coverage time between PoIs achieved by a faster sensor and increased lifetime of the sensor due to a lower rate of energy use by a slower sensor. The tradeoff is formally captured by a metric of *expected information capture per unit of energy consumption* (IPE). An optimal sensor speed v that maximizes the IPE can be determined.
2) Second, we illustrate how the IPE varies by different deployment parameters and the event dynamics. For example, we show that the IPE is a decreasing function of the average distance between PoIs (which is denoted by γ). Our analytical results are supported by simulation experiments. The experimental evaluation also compares the performance of the mobile sensor relative to a stationary sensor, thereby quantifying the benefits of mobility for the sensing task.

II. Related Work

There has been substantial research on the coverage problem in sensor networks. Meguerdichian *et al.* [5] discussed different forms of the coverage problem, i.e., deterministic, statistical, and worst- and best-coverage. Using computational geometry and graph algorithms, they provide optimal polynomial-time solutions for the coverage problem. Huang and Tseng [15] formulated the k-coverage problem as a decision problem, i.e., how to decide if every point in a service area is covered by at least k sensors. They present polynomial-time algorithms that can be realized via distributed protocols. Practical systems that apply solutions to the coverage problem exist. Chebrolu *et al.* [16] investigated the use of sensors to monitor the structural health of bridges and report when or where maintenance operations are needed.

The aforementioned work [5], [15], [16] considers the use of stationary sensors. Stationary sensors have some limitations. For example, a large number of sensors may be needed to fully cover a service area. In addition, holes may exist after the death or failure of certain sensors or after changes in the deployment environment.

Mobility can be applied to ameliorate the operation of a sensor network. The coverage problem has been studied for hybrid mobile or stationary sensor networks [10]. Wang *et al.* showed that the quality of coverage can significantly be improved by introducing a small fraction of mobile sensors. Liu *et al.* [8] defined three measures of coverage for a mobile sensor network: 1) area coverage; 2) area coverage over a time interval; and 3) detection time. They show that sensor mobility can be used to compensate for the lack of sensors and improve the coverage effectiveness. Eriksson *et al.* [7] described an application of mobile sensing, namely detecting and reporting the surface conditions of roads. In [11], Singh *et al.* presented a Gaussian process model for the relationship between underlying physical phenomena. They presented an efficient path-planning algorithm to maximize the amount of information captured by a mobile sensor. Chen *et al.* [17] used approximation algorithms for a mobile sensor for stochastic event monitoring to enable the tradeoff between computation and efficiency.

Since sensors often run on limited energies, power consumption can be a major consideration in sensor network design, beyond other performance metrics, such as fairness, latency, and bandwidth utilization [18]. Because of the advantages and need for unattended operations, maximizing the energy lifetime of a sensor network is an important challenge. Many protocols have been designed at different network layers for power saving and prolonging the network lifetime [19]–[21]. Our goal in this paper is to investigate the tradeoff between performance and energy use of a mobile sensor. Different energy models [13], [22]–[24] have been proposed for mobility under different operating conditions. They all recognize energy depletion due to outside forces, such as friction. We adopt such an energy model in this paper.

III. Problem Statement

We consider n PoIs situated in a deployment region. The PoIs are connected by a circuit of length D. Stochastic events appear at each PoI. Each event stays for a random event *staying time*, which is drawn from some statistical distribution, and then, it disappears. Following the disappearance, a next event appears after another random event *absence time*, which is also drawn from some distribution. In this paper, we assume that the event staying and absence times at PoI i follow the exponential distribution with means $(1/\lambda_i)$ and $(1/\mu_i)$, respectively. For simplicity, we further assume that $\lambda_i = \lambda$ and $\mu_i = \mu$, for $i = 1, \ldots, n$.

A mobile sensor of sensing range r completes identical rounds of the circuit until its energy is depleted. In each round, the sensor passes through each PoI once and only once. We assume that, if there is an event present at a PoI, the sensor will gain information about the event while the event is within the sensing range. We further assume that different events are *identifiable*, i.e., when a sensor senses an event at a PoI, leaves, and later returns to the same PoI to sense the same event, it will recognize that it is the same event. Hence, the sensor will accumulate information about the event over a possibly non-contiguous interval of sensing. How the information increases with the sensing time is captured by a *utility function* for the type of events.

The utility function is monotonically increasing from zero to one, with zero meaning that no information is captured and one meaning that full information is captured about the event. In this paper, we consider three important forms of the utility function (see [1] for further forms of the function that have been proposed).

1) Step function: $U_I(t) = 1$, for $t > 0$. In this case, full information about an event is obtained as soon as the sensor detects the event. This function is useful, for example, if we are interested in counting the number of occurrences of an event whose presence can quickly and unequivocally be detected.
2) Exponential function: $U_A(t) = 1 - e^{-At}$. This function models the law of diminishing returns that characterizes a wide range of real-world phenomena. According to the function, information is learned at a high rate during the initial observation. As more information is learned, however, the marginal gain in information decreases with additional sensing time. When the sensing time is long enough, full information is obtained. The detection of radioactive sources can be modeled by this utility function [25], for example.
3) Delayed step function: $U_d(t) = U_I(t - d)$. There exists a delay in capturing events, i.e., no information is captured until the cumulative sensing time of the event exceeds a threshold value d, after which, full information is instantaneously captured. This utility function models the effects of a learning curve in the sensing, i.e., a critical mass of basic knowledge needs to be accumulated before the sensing task becomes effective. For example, if we were to certify the safety or suitability of a geographical area for a certain activity, the certification might require that a required number of safety tests be all passed.

We summarize the notations used in this paper in Table I.

TABLE I
NOTATION DEFINITIONS

Symbol	Definition
D	length of the circuit;
$\frac{1}{\lambda}$	mean of distribution of event staying times
$\frac{1}{\mu}$	mean of distribution of event absence times
$U(\cdot)$	utility function
r	sensing range of the mobile sensor
v	velocity of the mobile sensor
k_1	energy consumption coefficient for sensing
k_2	energy consumption coefficient for mobility
n	number of PoIs
α	constant parameter accounting for environmental factors in the energy models
A	constant parameter accounting for a class of Exponential functions
d	threshold value in the Delayed Step function

We assume that the mobile sensor runs on limited battery and is therefore energy constrained. We are interested in optimizing the sensor's movement for the highest QoM. Because of how it moves, the sensor will periodically visit a PoI, e.g., i, for q_i time every T time, where T is the time taken by the sensor to complete a round of the circuit. Assume that the energy budget is such that the sensor can complete N rounds of the circuit. Let $Q_i^{(k)}$ denote the total expected information gained by the sensor at PoI i in the kth round for $k = 1, 2, \ldots, N$. The total information the sensor gains at i during its lifetime is given by $Q_i = \sum_{k=1}^{N} Q_i^{(k)}$. For all the n PoIs, the total amount of information the sensor gains during its lifetime is given by $Q = \sum_{i=1}^{n} Q_i$.

In general, the sensor controls q_i and T by controlling its speed during the mobile coverage. We know that the expected fraction of information captured about each event is a function of q_i, T, and the type of events. If the sensor moves at a fixed speed, e.g., v, $q_i = 2r/v$, for $i = 1, \ldots, n$, and $T = D/v$, where D is the length of the circuit. For concave utility functions (e.g., step and exponential utilities), it has been shown that the fraction of information increases as v increases when the energy cost of the mobile coverage is ignored [1]. However, if the energy constraint of the sensor is important, increasing v will generally increase the rate at which energy is consumed to support the movement so that the sensor can only complete fewer rounds of the circuit. In this paper, we are therefore interested in quantifying the expected Information captured Per unit of Energy consumption (IPE) as a function of the sensor speed v i.e., IPE $= Q/E_*$, hereby E_* is the total energy the sensor has.

IV. Expected Information Captured per Unit Energy

A. Energy Models

To analyze the IPE of a mobile sensor, we need a realistic energy model for the sensor's motion. Energy consumption during travel can be complex [13], [14]. Existing energy models of motion [22]–[24] have generally considered the energy depleted due to friction, gravity, and other environmental factors. For a robot traveling on scope inclined at an angle of φ, according to [24], the energy cost of distance l is $mg(\kappa\cos(\varphi) + \sin(\psi)) \cdot l$. Here, a ψ is the gradient of the terrain face, κ is the friction coefficient between the mobile robot and the surface, and mg is the weight of the robot. It is pointed out [24] that this formula was experimentally confirmed within 10% for wheeled vehicles on slopes of less than 20%. Thus, when the mobile sensor travels with a velocity of v, the energy loss is k_2vt, where $k_2 = mg(\kappa\cos(\varphi) + \sin(\psi))$. When the device travels in a fluid, such as water, the viscous force is $f = k_2 v$ [26]. Therefore, when the device travels at a speed of v during the time interval $[0, t]$, the energy cost is equal to k_2v^2t. In other situations, the expression for the consumed energy may be different. In this paper, we use the expression $k_2v^\alpha t$ for the energy consumption, for the sensor traveling at speed v during time interval $[0, t]$, where α is a constant parameter accounting for environmental factors.

In addition to mobility, energy is needed for the sensing task. We assume that the sensing function continuously operating over time interval $[0, t]$ will consume $k_1 \times t$ amount of energy, where k_1 is a proportionality constant. For simplicity, we additionally assume that the sensing function is turned on all the time. Hence, considering both the mobility and sensing aspects, our sensor completing rounds of the circuit at speed v for t time will expend a total of $k_1t + k_2v^\alpha t$ energy during the deployment. We note that the assumption that the sensing function is turned on all the time is not restrictive. If the sensing module is turned off when the mobile sensor is not covering any PoI, then, for one round of travel spanning the time interval $[0, D/v]$, the total energy consumed is

$$k_1\frac{2nr}{v} + k_2v^\alpha\frac{D}{v} = k_1't + k_2v^\alpha t$$

where $k_1' = k_1(2nr/D)$, and $t = D/v$. Therefore, the assumption will not affect the optimization of the mobile sensor and, hence, we have our main results.

B. IPE Analysis

We now analyze the IPE of a sensor covering n PoIs in a closed circuit moving at a fixed speed v. The analysis will allow us to optimize v to achieve the highest IPE.

The strategy of computing the IPE is given as follows: Let E_* be the energy constraint or the maximum energy available. The time needed for one round is D/v. By the aforementioned energy model, the energy used per round is $(k_1 + k_2v^\alpha) \times D/v$. Hence, the sensor can complete $N = vE_*/D(k_1 + k_2v^\alpha)$ times of the circuit. Thus, the total information captured *per unit energy* is given by

$$\text{IPE} = \frac{v}{D(k_1 + k_2v^\alpha)} \times \text{QoM} \times (\text{Total number of events per round}). \quad (1)$$

Now, the number of events in each round is given by

$$(\text{Number of PoIs}) \times \left(\frac{1}{\lambda} + \frac{1}{\mu}\right)^{-1} \times \frac{D}{v}. \quad (2)$$

Thus, the overall IPE is given by

$$\text{IPE} = \left(\frac{n}{k_1 + k_2v^\alpha}\right)\left(\frac{\lambda\mu}{\lambda + \mu}\right)\text{QoM}. \quad (3)$$

In particular, for a stationary sensor, energy is consumed for the sensing of information only and not for mobility. Hence, its energy consumption is less than that of a mobile sensor. However, the gain of event information also becomes less. Quantitatively, from (3), in the case of only one stationary sensor, QoM $= 1$, $n = 1$, and $k_2v^\alpha = 0$. Then, the stationary sensor's IPE, which is denoted by IPE$_s$, is given by

$$\text{IPE}_s = \frac{\lambda\mu}{k_1(\lambda + \mu)}. \quad (4)$$

The succeeding paragraphs consider various forms of the QoM and study its competition with the energy use and, hence, its effect on the overall IPE. The formulas for the QoM are taken from [1].

1) Step Utility Function

Theorem 1: For the step utility function, the IPE is given by

$$\frac{n}{k_1 + k_2v^\alpha}\left(\frac{\lambda\mu}{\lambda + \mu}\right)\left[\frac{2r}{D} + \frac{v}{\lambda D}\left(1 - e^{-\lambda\left(\frac{D-2r}{v}\right)}\right)\right] \quad (5)$$

where n is the number of PoIs, and k_1 and k_2 are the dissipation coefficients previously defined for the energy model.

Proof: The proof directly follows from the formula of the QoM derived in [1, Th. 2, eq. (3)]. The corresponding formula is explicitly computed here for exponentially distributed event staying times

$$\text{QoM}_{\text{step}} = \frac{q}{p} + \frac{1}{p}\int_0^{p-q} \Pr(X \geq t)\,dt \quad (6)$$

where $q = 2r/v$ and $p = D/v$ are the time during which the sensor is present at a PoI and the time taken to complete one round of the circuit, respectively. The random variable X is the event staying time, which is exponentially distributed with parameter λ so that $\Pr(X \geq t) = e^{-\lambda t}$. The key point of the formula is that an event can be captured if it occurs while the sensor is present at the PoI, or if the sensor is absent, the event stays long enough for the sensor to come back. ■

We make four observations about the preceding result.

1) Note that the QoM$_{\text{step}}$ previously derived is an *increasing bounded* function of v such that

$$\lim_{v\to 0^+}\text{QoM}_{\text{step}} = \frac{2r}{D}, \qquad \lim_{v\to+\infty}\text{QoM}_{\text{step}} = 1.$$

On the other hand, the energy used per unit time is an *increasing unbounded* function of v. Hence, ultimately, the IPE will go to zero as $v \longrightarrow \infty$. In particular, we have

$$\lim_{v\to 0^+}\text{IPE} = \frac{n}{k_1}\left(\frac{\lambda\mu}{\lambda + \mu}\right)\frac{2r}{D}, \qquad \lim_{v\to+\infty}\text{IPE} = 0. \quad (7)$$

2) Let $Q(v) = $ QoM and $E(v) = (k_1 + k_2v^\alpha)$. Then, we have

$$\text{IPE}'(0) \propto \frac{E(0)Q'(0) - Q(0)E'(0)}{E^2(0)}. \quad (8)$$

If IPE$'(0)$ is *positive*, the IPE function *initially increases* and then ultimately *decreases* to zero. Thus, it will attain its *maximum* value at some *intermediate* v_*. We can analyze $\text{IPE}'(0)$ for different ranges of α as follows:

$$\lim_{v\to 0^+} \text{IPE}'(0) = \begin{cases} \frac{n\mu}{Dk_1(\lambda+\mu)}, & \text{for } \alpha > 1 \\ \frac{\mu(k_1-2r\lambda k_2)}{k_1^2 D(\lambda+\mu)}, & \text{for } \alpha = 1 \\ -\infty, & \text{for } \alpha < 1. \end{cases} \quad (9)$$

For $\alpha > 1$, it is clear that $\text{IPE}'(0) > 0$. The optimal value v_* can be found by various numerical root-finding algorithms, such as Newton's method. For $\alpha \leq 1$, $\text{IPE}'(0)$ can be negative. However, the experimental results in Section V systematically explore the impact of α by plotting the IPE against v for a range of α values. The results show that the initial decrease in the IPE is not significant in practice, and the same numerical optimization method will work for $\alpha \leq 1$ as well.

3) As mentioned before, k_2 is a parameter of the deployment environment. When k_2 increases, more energy is needed to support a certain speed of motion, which reduces the IPE. In the limiting cases

$$\lim_{k_2\to\infty} \text{IPE} = 0 \quad (10)$$

$$\lim_{v\to\infty, k_2\to 0^+} \text{IPE} = \frac{n}{k_1}\left(\frac{\lambda\mu}{\lambda+\mu}\right). \quad (11)$$

Hence, under conditions of higher motion resistance, we should use a lower speed of the sensor for optimal performance. When the resistance is low, the sensor can run at a high speed for higher information gain.

4) Denoting by $\gamma = D/n$ the average distance between PoIs along the circuit, we note that the IPE is a decreasing function of γ, which can directly be seen from Theorem 1.

2) Exponential Utility Function

Theorem 2: When the exponential utility function is used, the IPE is given by

$$\text{IPE} = \frac{n}{k_1 + k_2 v^\alpha}\frac{\lambda\mu}{\lambda+\mu}\text{QoM}_{\text{exp}}. \quad (12)$$

Here, QoM_{exp} is from [1, eq. (6)], i.e.,

$$\begin{aligned} \text{QoM}_{\text{exp}} = &\frac{Aq}{(A+\lambda)p} - \frac{1-e^{-\lambda q}}{\lambda p} \\ &+ \frac{\lambda\left(1-e^{(A+\lambda)q}\right)}{(A+\lambda)^2 p} + \frac{(e^{\lambda q}-1)^2}{\lambda p e^{\lambda q}(e^{\lambda p}-1)} \\ &- \frac{\lambda\left(e^{(A+\lambda)q}-1\right)^2 e^{-(A+\lambda)q}}{(A+\lambda)^2 p(e^{Aq+\lambda p}-1)} + \frac{2\left(e^{\lambda(p-q)}-1\right)}{p} \\ &\times\left[\frac{e^{\lambda q}-1}{\lambda(e^{\lambda p}-1)} - \frac{e^{(A+\lambda)q}-1}{(A+\lambda)(e^{Aq+\lambda p}-1)}\right] \\ &+ \frac{(e^{Aq}-1)e^{\lambda q}\left(e^{\lambda(p-q)}-1\right)^2}{\lambda p(e^{\lambda p}-1)(e^{Aq+\lambda p}-1)} \end{aligned} \quad (13)$$

where $q = 2r/v$, and $p = D/v$.

The proof is omitted as it is easily obtained using the appropriate QoM_{exp} function.

We make two observations for the preceding result.

1) Increasing the velocity of the mobile sensor is beneficial for the QoM_{exp}. In particular, we obtain

$$\lim_{v\to 0^+} \text{QoM}_{\text{exp}} = \frac{2r}{D}\frac{A}{A+\lambda}, \qquad \lim_{v\to\infty} \text{QoM}_{\text{exp}} = \frac{2rA}{2rA+\lambda D}$$

whereas, on the other hand, it is not the case for the IPE metric

$$\lim_{v\to 0^+} \text{IPE} = \frac{n}{k_1}\left(\frac{\lambda\mu}{\lambda+\mu}\right)\frac{2r}{D}\frac{A}{A+\lambda}, \qquad \lim_{v\to+\infty} \text{IPE} = 0.$$

2) From (7) and (14), we can see that the IPE of step utility is, in general, larger than that of exponential utility. Furthermore

$$\lim_{A\to\infty, v\to 0^+} \text{IPE} = \frac{n}{k_1}\left(\frac{\lambda\mu}{\lambda+\mu}\right)\frac{2r}{D}$$

which is the same as the case of the step utility function. From this perspective, we can see that step utility is a special case of exponential utility.

Although the formula of IPE for the exponential utility function is more complex than that of the step utility function, the optimal value v_* can be found similarly via numerical approaches. The behavior is also illustrated in the simulation results presented in Section V-B.

3) Delayed Step Utility Function

When the delayed step utility function is used, the corresponding QoM is complicated; specifically, it is a piecewise continuous function, as given by [1, Th. 4]. As previously discussed, to find out where the function peaks, two limiting cases are particularly interesting: 1) when the velocity of the mobile sensor is very small and approaches zero and 2) when the velocity is very large and approaches infinity. Hence, we compute the IPE under these two cases: 1) $2r/v \geq d$ and 2) $d = k(2r/v)$, $k = 1, 2, \ldots$. The results are given by the following theorem:

Theorem 3: For the delayed step utility function, when $2r/v \geq d$, the IPE is given by

$$\begin{aligned} \text{IPE} = &\frac{n}{k_1 + k_2 v^\alpha}\frac{\lambda\mu}{\lambda+\mu}e^{-\lambda d} \\ &\times\left[\frac{2r}{D} + \frac{(1-\lambda d)v}{\lambda D}\left(1-e^{-\lambda(D-2r)/v}\right)\right] \end{aligned} \quad (14)$$

and for $d = k(2r/v)$, $k = 1, 2, \ldots$, the IPE is given by

$$\text{IPE} = \frac{n}{k_1 + k_2 v^\alpha}\frac{\lambda\mu}{\lambda+\mu}e^{-\frac{\lambda d D}{2r}}\left[\frac{2r}{D} + \frac{v}{\lambda D}\left(e^{\lambda(D-2r)/v}-1\right)\right]. \quad (15)$$

The results can directly be obtained using (3) and [1, eqs. (8) and (9)].

Similar to the step and exponential utility functions, the limits of the IPE for the delayed step utility, as v approaches zero and infinity, can be obtained as follows:

$$\lim_{v\to 0^+} \text{IPE} = \frac{n}{k_1}\frac{\lambda\mu}{\lambda+\mu}\frac{2r}{D}e^{-\lambda d}, \qquad \lim_{v\to\infty} \text{IPE} = 0.$$

Intuitively, step utility is a special case of the delayed step utility, which can be verified by the following corollary.

Corollary 1: When the parameter d approaches zero, the IPE of the delayed step utility is equal to that of the step utility function.

Proof: When $v \to 0$, $2r/v \geq d$, the IPE is given by

$$\begin{aligned}\text{IPE} &= \lim_{d\to 0^+} \frac{n}{k_1+k_2v^\alpha}\frac{\lambda\mu}{\lambda+\mu}e^{-\lambda d} \\ &\quad\times\left[\frac{2r}{D}+\frac{(1-\lambda d)v}{\lambda D}\left(1-e^{-\lambda(D-2r)/v}\right)\right] \\ &= \frac{n}{k_1+k_2v^\alpha}\frac{\lambda\mu}{\lambda+\mu}\left[\frac{2r}{D}+\frac{v}{\lambda D}\left(1-e^{\frac{-\lambda(D-2r)}{v}}\right)\right]\end{aligned}$$

which is the IPE of the step utility function. ■

C. Randomly Distributed PoIs

So far, we have made the assumption that the positions of the PoIs are known to be uniformly spaced. This might not be practical as their actual locations may be irregular or even unknown. This motivates us to consider random placement of the PoIs. In this section, we assume that the PoIs are uniformly distributed along the circuit of length D. In this case, the distance of two PoIs may be less than $2r$. Here, we assume that the sensor covering more than one PoI can capture events from the different PoIs at the same time.

To have a rough idea of how random placement affects the IPE, we consider the simple case of a stationary sensor. Here, the number of PoIs covered by the sensor is a random variable. It is given by the binomial distribution, and its expected number $E(N)$ can be computed as

$$E(N)=\sum_{i=1}^{n} i\frac{n!}{i!(n-i)!}\left(\frac{2r}{D}\right)^i\left(\frac{D-2r}{D}\right)^{n-i}=\frac{n2r}{D}.$$

Hence, analogous to (3), the expected value of the total IPE is given by

$$E(\text{IPE})=\frac{n2r}{Dk_1}\left(\frac{\lambda\mu}{\lambda+\mu}\right)(\text{QoM}). \tag{16}$$

Note that, for a stationary sensor, $v=0$ in the energy model. Thus, we see that the overall effect of random placement is to change the number of PoIs n to the new value $n2r/D$. For concrete examples, for the step utility function, the QoM is equal to as much information about any event that will always be captured, whereas for the exponential utility function U_A and exponential staying time distribution with parameter λ, QoM is equal to

$$\int_0^\infty U_A(t)\Pr(X=t)\,dt=\int_0^\infty(1-e^{-At})\lambda e^{-\lambda t}\,dt=\frac{\lambda}{\lambda+A}.$$

D. Multiple Mobile Sensors

In this section, we discuss event capture by multiple mobile sensors. We note that the general coordination problem between multiple sensors is complex and is beyond the scope of the present paper. Here, we discuss a simplified form of the problem only, in which multiple mobile sensors, running at the same velocity, visit the PoIs in sequence for the capture of events characterized by the step utility function.

Assume that there are m mobile sensors visiting n PoIs along a circuit of length D. We assume $2mr<D$ as it is trivial when $2mr\geq D$. The distance (clockwise) between sensor i and sensor $i+1$ is denoted by l_i, $i<m$, and the distance between sensor m and sensor 1 is denoted by l_m. Let $a_i = l_i-2r$, $s_i=a_i/v$, $q=2r/v$, and $p=D/v$. Obviously, $D=\sum_{i=1}^m l_i=\sum_{i=1}^m a_i+2mr$. All the sensors travel along the circuit counterclockwise at the same velocity v. We have the following theorem:

Theorem 4: The IPE of the multiple sensors is given by

$$\text{IPE}=\frac{n}{k_1+k_2v^\alpha}\left(\frac{\lambda\mu}{\lambda+\mu}\right)\frac{\text{QoM}}{m} \tag{17}$$

where QoM is given by

$$\text{QoM}=\sum_{i=1}^{m}\left(\frac{q}{p}+\frac{1}{p\lambda}\left(1-e^{-\lambda\frac{a_i}{v}}\right)\right).$$

Proof: We first derive the QoM for the multiple sensors. An event occurring at PoI j will be captured if 1) it is instantaneously captured by one of the sensors i, $i=1,2,\ldots,m$, or 2) it occurs during s_i but stays long enough to be captured by sensor $i+1$. Based on this observation, the QoM is given by

$$\begin{aligned}\text{QoM}&=\frac{1}{p}\sum_{i=1}^{m}\left(\int_0^q dt+\int_0^{s_{i-1}}\Pr(X\geq s_{i-1}-t)\,dt\right)\\ &=\sum_{i=1}^{m}\left(\frac{q}{p}+\frac{1}{p\lambda}\left(1-e^{-\lambda\frac{a_i}{v}}\right)\right).\end{aligned}$$

Then, the IPE can be derived similarly to the case of a single sensor. ■

From Theorem 4, the IPE is a function of v and a_i, $i=1,2,\ldots,m$. The following corollary about how to choose $a_i, i=1,2,\ldots,m$, can directly be obtained from Theorem 4:

Corollary 2: For a fixed v, the maximum value of IPE can be obtained if and only if $a_1=a_2=\cdots=a_m$. The IPE is therefore

$$\text{IPE}=\frac{n}{k_1+k_2v^\alpha}\left(\frac{\lambda\mu}{\lambda+\mu}\right)\left(\frac{2r}{D}+\frac{v}{D\lambda}\left[1-e^{-\lambda\left(\frac{D/m-2r}{v}\right)}\right]\right). \tag{18}$$

Proof: From Theorem 4, the QoM is given by

$$\begin{aligned}\text{QoM}&=\sum_{i=1}^{m}\left(\frac{q}{p}+\frac{1}{p\lambda}\left(1-e^{-\lambda\frac{a_i}{v}}\right)\right)\\ &=\frac{mq}{p}+\frac{m}{p\lambda}-\frac{1}{p\lambda}\sum_{i=1}^{m}e^{-\lambda\frac{a_i}{v}}\\ &\leq\frac{mq}{p}+\frac{m}{p\lambda}-\frac{m}{p\lambda}e^{\lambda\frac{D/m-2r}{v}}.\end{aligned} \tag{19}$$

The inequality (19) holds due to the mean-value inequality. The QoM is maximum if and only if $a_1 = a_2 = \cdots = a_m$. From the formula of the IPE, our conclusion follows. ■

Remark: 1) Corollary 2 indicates in fact that the best option of scheduling the sensors is to let them run along the circuit, so that the distances between neighbor sensors are all the same. 2) Comparing (18) with (5), we know that the IPE of a single sensor is higher than that of multiple sensors. This is because, although multiple sensors will capture more information, they will consume even relatively more energy. 3) The formula of IPE for multiple sensors is very similar to that of the single sensor, and therefore, the observations for step utility that we made in Section IV-B for the single-sensor case apply to the multiple-sensor scenario as well.

V. Simulation Results

In this section, we present MATLAB simulation results to illustrate the analysis in the previous section. Modeling the sensor with its internal energy consumption for computing, sensing, and communication as in [27], we set k_1 in the motion energy model to be 2.5585 J/h. For the energy budget, which is denoted by E_{energy}, we assume two batteries each of capacity 1350 mAh so that $E_{\text{energy}} = 29\,160$ J.

In the simulations, the PoIs are uniformly located on a circuit, so that the distance between any two neighbors is the same. A mobile sensor is used to periodically visit the PoIs along the circuit. Events arrive and disappear at each PoI. The event staying and absence times follow the exponential distribution with means $1/\lambda$ and $1/\mu$, respectively. When the mobile sensor arrives at a PoIs (i.e., the distance between the sensor and the PoI is less than r), it can monitor events occurring at the PoI for information. We derive the IPE as the total amount of information captured during the sensor's lifetime (i.e., before it runs out of energy) divided by E_{energy}. The reported results are averages over 500 independent runs. The large numbers of runs give standard deviations that are extremely small. We therefore do not report the standard deviations.

As in Section IV, we use the step, exponential, and delayed step utility functions for the evaluations. Unless otherwise stated, the parameters in Section IV are set as follows: $D = 2000$ m, $r = 1$ m, $\lambda = \mu = 1$/h, $n = 15$, $k_2 = 15$ J/h, and $\alpha = 2$. As previously stated, the PoIs are uniformly placed on the circuit. Unless otherwise stated, the starting point of the mobile sensor on the circuit is uniformly chosen at random.

A. Step Utility Function

We first present results for step utility. Fig. 1 shows the effects of the energy model on the IPE. We vary k_2 in the motion energy model to be 10, 15, 20, and 25 J/h to correspond to different energy costs of the motion. Plots of the IPE against the speed of the sensor, for the different values of k_2, are shown in Fig. 1(a). In the figure, we also show, as the horizontal line, the IPE of a stationary sensor placed at one of the PoIs for comparison. (Notice that the IPE of the stationary sensor is different from the IPE of the mobile sensor at speed 0 since the stationary sensor is guaranteed to be located at a PoI.) From

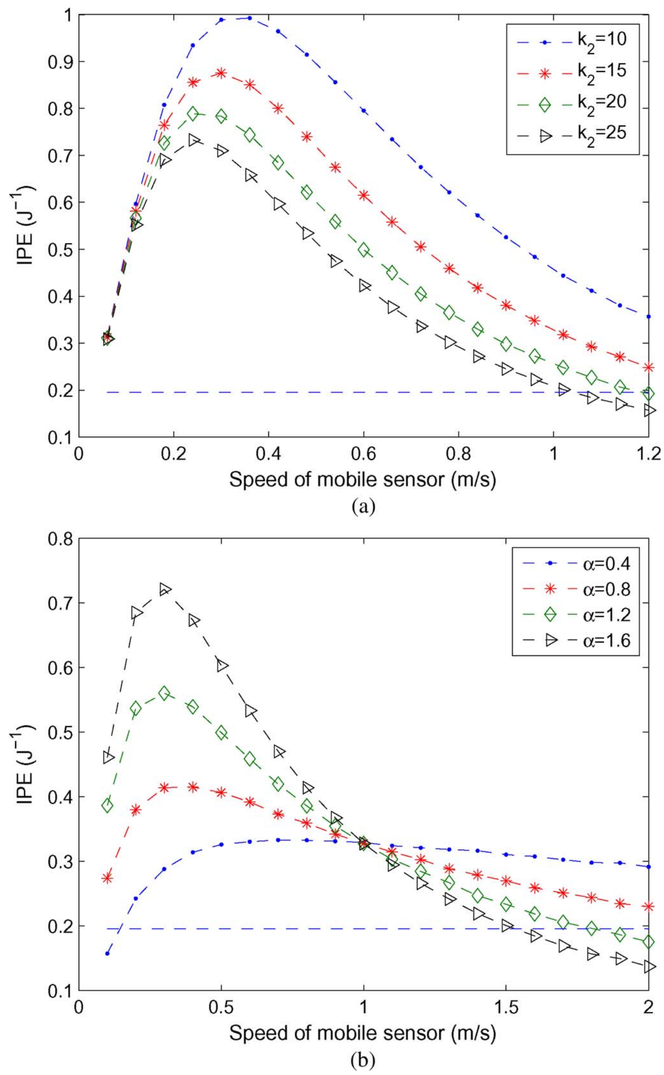

Fig. 1. Impact of the energy model on the IPE for events that have step utility function. (a) IPE as a function of v for different k_2's. (b) IPE as a function of v, for different α's.

the figure, we see that mobility is beneficial most of the time, as long as the sensor is not moving too fast, so that not too much energy is consumed for motion. This is because, for step utility, all the information about an event is learned as soon as the event is detected. Even though the event stays, there is no motivation for the sensor to remain at the same PoI and observe the same event longer. Instead, the sensor gains information by moving elsewhere to look for new events. Hence, modulo the energy cost of motion, the rate at which information is captured increases with the sensor speed. When the energy cost is also considered, as in the experiments, there is a competitive effect between the increased rate of information captured and the higher rate of energy consumption for a faster sensor. Hence, the optimal IPE occurs at an intermediate speed. The optimal speed is, in general, smaller when the energy cost of motion is higher, i.e., when k_2 is larger.

The effects of α on the IPE can be seen from Fig. 1(b), which plots the IPE against the sensor speed v for varying values of α. (In general, a higher α implies stronger environmental resistance against motion.) From the figure, note that, when

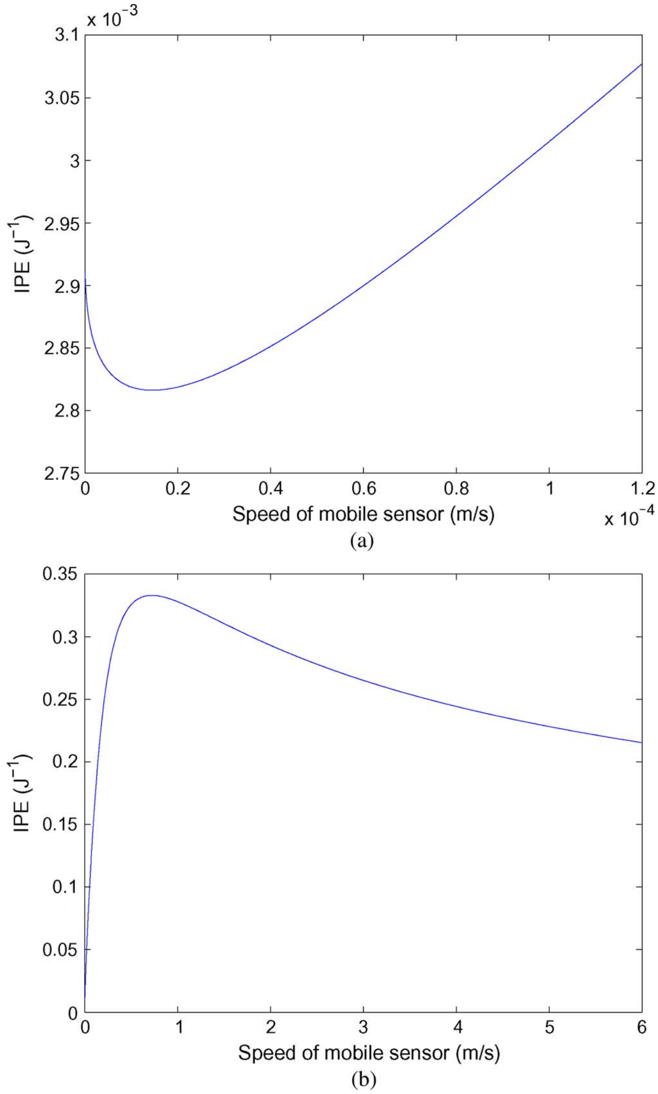

Fig. 2. Numerical results. Plot of IPE as a function of v for $\alpha = 0.4$. (a) IPE over a range of *low* sensor speed v. (b) IPE over a broader range of sensor speed v.

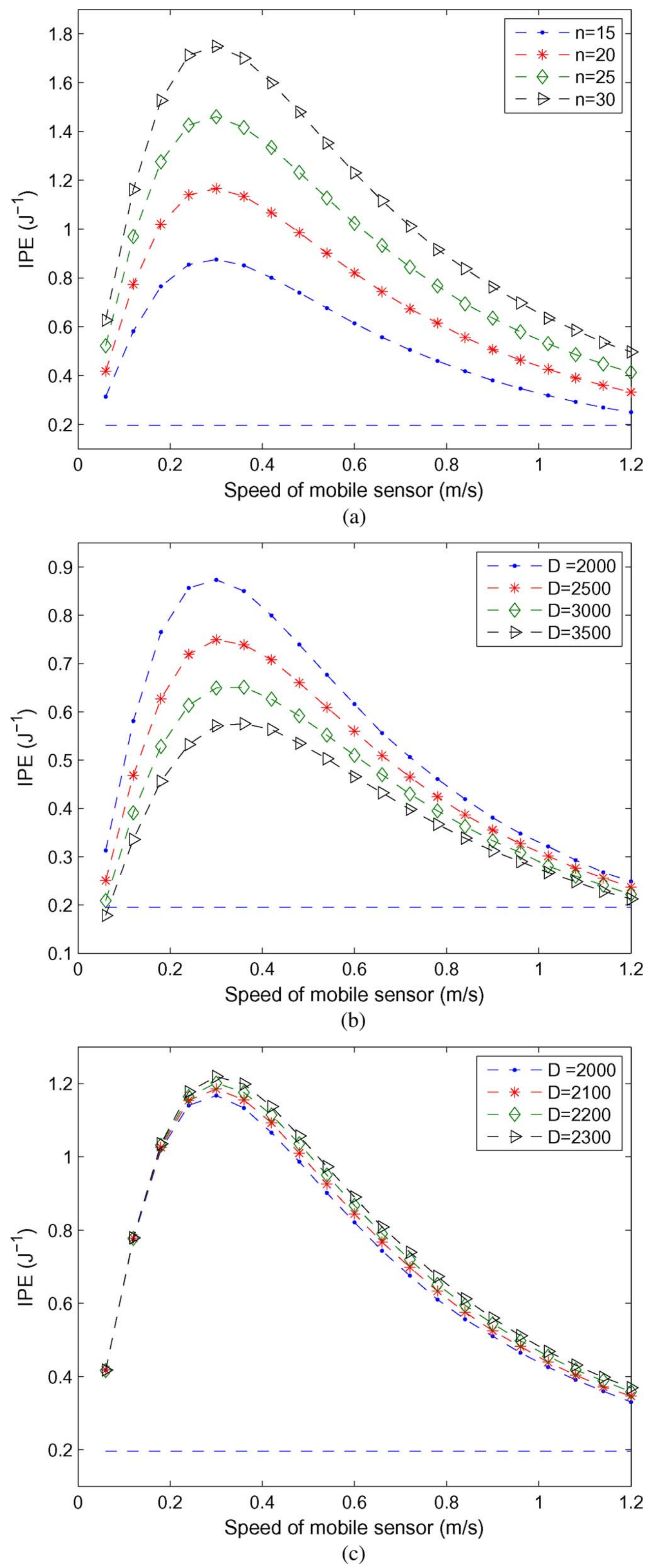

Fig. 3. Impact of PoI distribution on the IPE for the step utility function. (a) IPE as a function of v for different n's. (b) IPE as a function of v for different D's. (c) IPE as a function of v for different D's while fixing γ.

$v = 1$ m/s, the IPE is the same for the different α values. For $v > 1$ m/s, the IPE decreases as α increases, whereas, for $v < 1$ m/s, the IPE increases as α increases. All these results agree with Theorem 1. From (9), we know that the IPE initially *decreases* for $\alpha < 1$. However, a numerical plot of the IPE in Fig. 2(a) shows that the initial decrease is quite brief, and at a low sensor speed (< 0.2 m/s), the IPE again rises with v. The numerical plot in Fig. 2(b) shows that, over a broader range of v, the IPE mostly increases in the beginning and then decreases afterward. This general trend of the IPE is in agreement with the plots in Fig. 1(b) across the range of α values used, i.e., the IPE first increases and then decreases. Hence, the globally optimal IPE is reached at an intermediate v, and the numerical optimization of v discussed in Section IV-B can be applied, even when $\alpha \leq 1$.

We present IPE results for different distributions of the PoIs. Fig. 3(a) shows plots of the IPE against v for different values of n, whereas the other parameters are kept the same as before. Fig. 3(b) shows the IPE plots against v for different values of D, whereas n is now fixed to be 15. The figures show that the IPE increases either as n increases or as D decreases because of the increased density of information available for capture (per unit distance) on the circuit. Recalling $\gamma = D/n$, we show in,

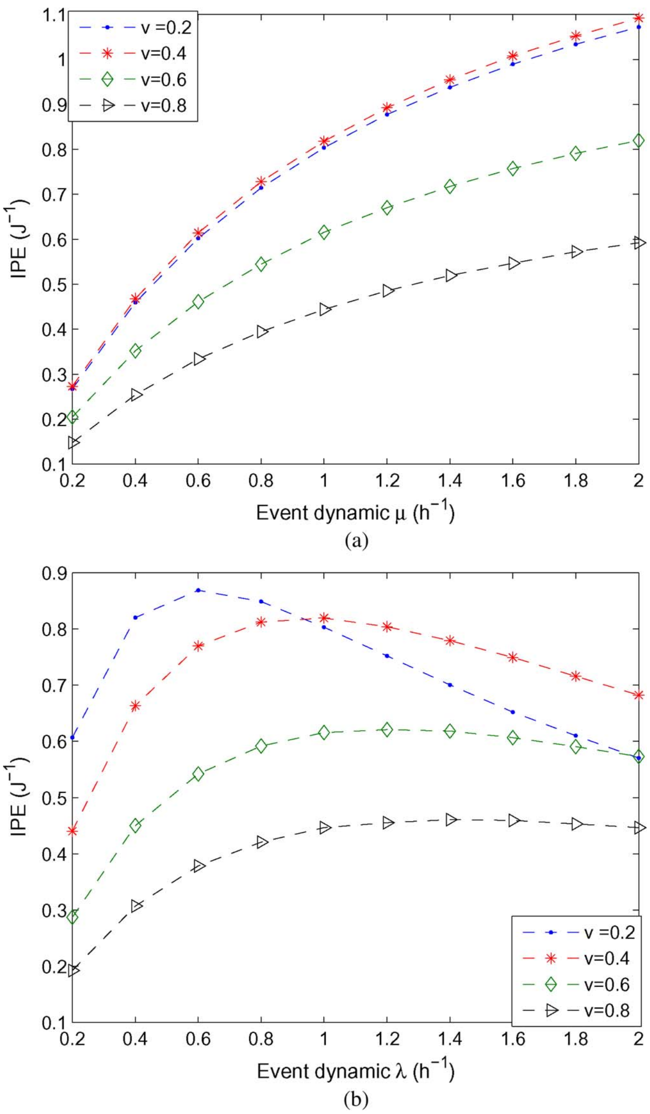

Fig. 4. Impact of event dynamics on the IPE for the step utility function. (a) IPE as a function of μ for different v's. (b) IPE as a function of λ for different v's.

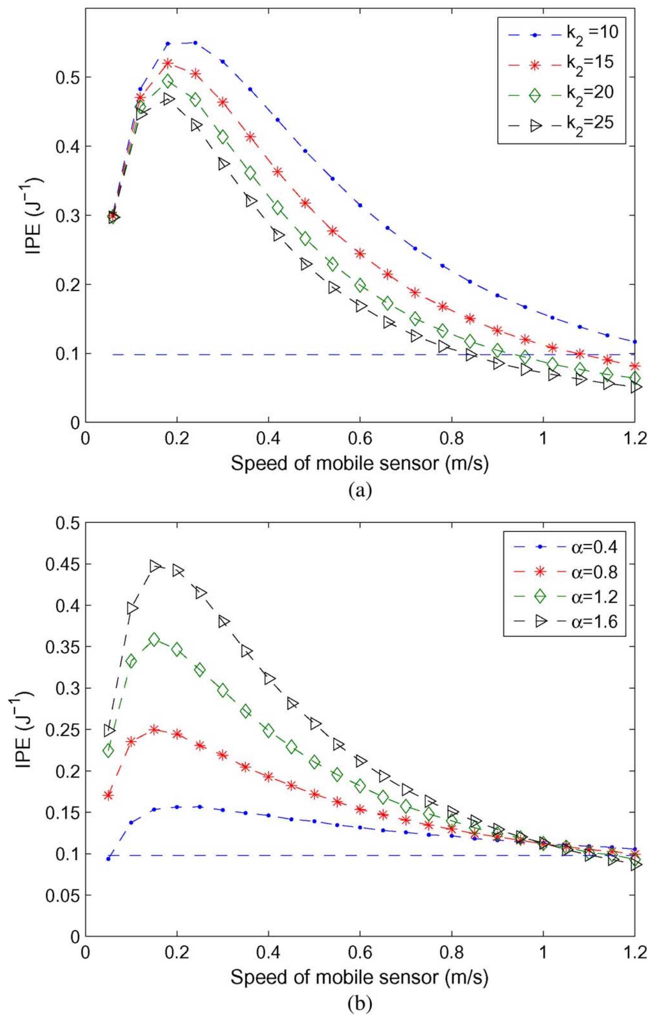

Fig. 5. Impact of energy model on the IPE for events that have exponential utility function. (a) IPE as a function of v for different k_2's. (b) IPE as a function of v for different α's.

Fig. 3(c), the IPE for different values of D but with the value of γ fixed. We can see that, in this case, the IPE is not affected much as the value of D is varied to be 2000, 2100, 2200, and 2300 m.

We now discuss the effects of the event dynamics μ and λ on the IPE. With the other parameters fixed, we vary v to be 0.2, 0.4, 0.6, and 0.8. For each v value, we show the IPE as a function of μ in Fig. 4(a). From Fig. 4(a), it can be seen that a larger μ will increase the IPE. This is because, when μ is large, more events arrive per unit time, which increases the opportunities for the sensor to capture more information. Similarly, we plot the IPE against λ under different values of v. From Fig. 4(b), notice that the IPE first increases and then decreases as a function of λ. In the case of step utility, the sensor captures full information about an event as soon as it detects the event. Hence, when λ is too small, meaning that events will last for a long time, on average, the number of events available per unit time decreases, although it is highly likely that each event will be captured (i.e., the QoM is high). When λ is too large, meaning that events will appear only briefly, many events at a PoI will disappear before the sensor returns to the PoI (i.e., the QoM is low) so that the IPE will be small. Hence, as λ increases, the IPE first increases and then decreases.

B. Exponential Utility Function

We next present corresponding simulation results for the exponential utility function. We set the parameter A in the exponential utility function to be 360. The sequence of experiments reported and their parameter settings are identical to the case of step utility in Section V-A From Figs. 5 and 6, we can see that the exponential utility results show similar trends as the step utility results. However, there are two differences. First, the IPE for exponential utility is smaller than that for step utility. This is because, for exponential utility, a longer sensing time is needed before full information can be captured. Moreover, some of the events may not stay long enough for them to be captured at their full information. Second, the optimal v to maximize the IPE is, in general, smaller than that for step utility, indicating a less-strong motivation for mobility in the case of exponential utility. This is because, for exponential utility, the

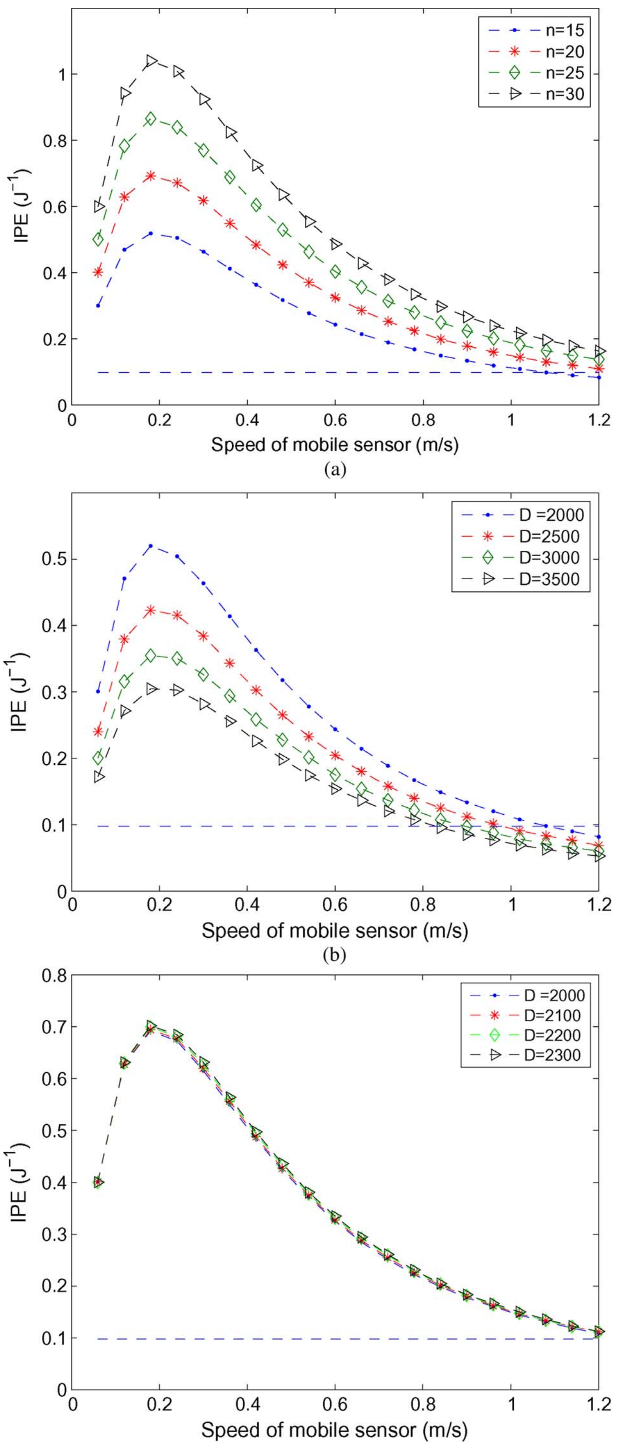

Fig. 6. Impact of PoI distribution on IPE for the exponential utility function. (a) IPE as a function of v for different n's. (b) IPE as a function of v for different D's. (c) IPE as a function of v for different D's while fixing γ.

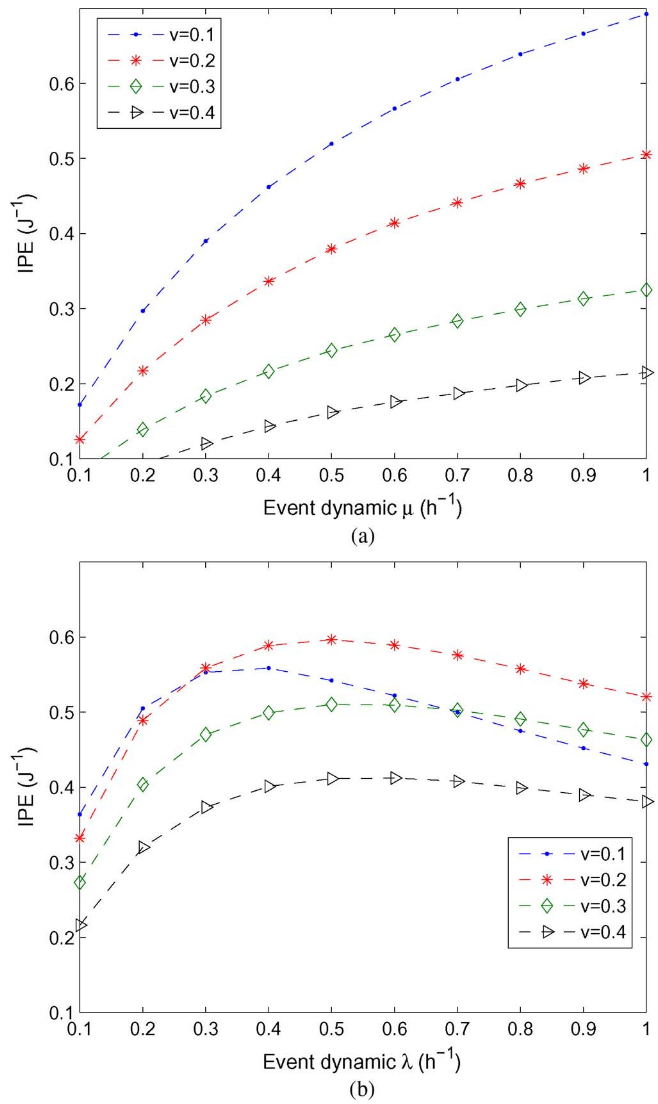

Fig. 7. Impact of event dynamics on the IPE for the exponential utility function. (a) IPE as a function of μ for different v's. (b) IPE as a function of λ, for different v's.

sensor that detects an event at a PoI may continue to gain some more useful information by staying at the PoI and observing the event longer. Hence, relative to step utility, there is a somewhat less strong case for the sensor to move elsewhere. However, it is still true that, for exponential utility, the rate of information captured increases as the sensor speed increases [1]. However, as before, the increased rate of information captured must be balanced against the increased rate of energy consumption for the optimal IPE, and the balance is shifted toward a lower speed for exponential utility relative to step utility.

The effects of the event dynamics λ and μ on the IPE are shown in Fig. 7 for exponential utility. The plots are similar to those for step utility (Fig. 4), and we shall omit our comments.

We now show that the IPE of exponential utility can approach that of step utility when A approaches infinity. We vary parameter A to be 500, 1500, 3000, 5500, and repeat the aforementioned experiments. The results are plotted in Fig. 8. It is clear that, when A is sufficiently large, the IPE of the exponential utility function behaves like that of the step utility function.

C. Delayed Step Utility Function

We now present corresponding simulation results for the delayed step utility function. We set the parameter d in the delayed step function to be 0.001 h. Similar to step and exponential utility functions, we consider the impacts of the energy model

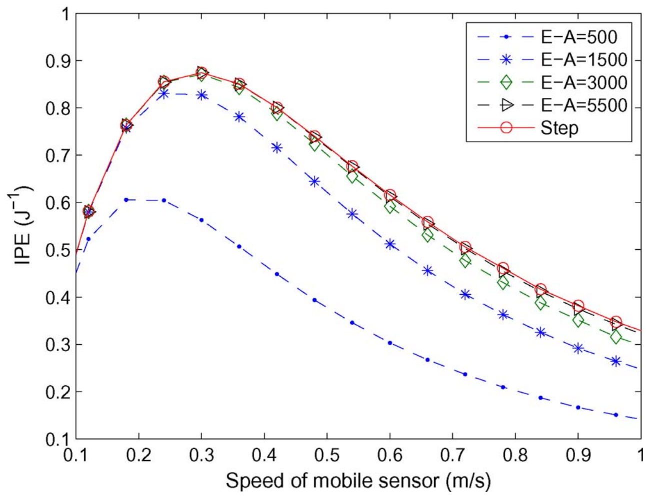

Fig. 8. Approximation of the exponential utility function to the step utility function when A becomes very large.

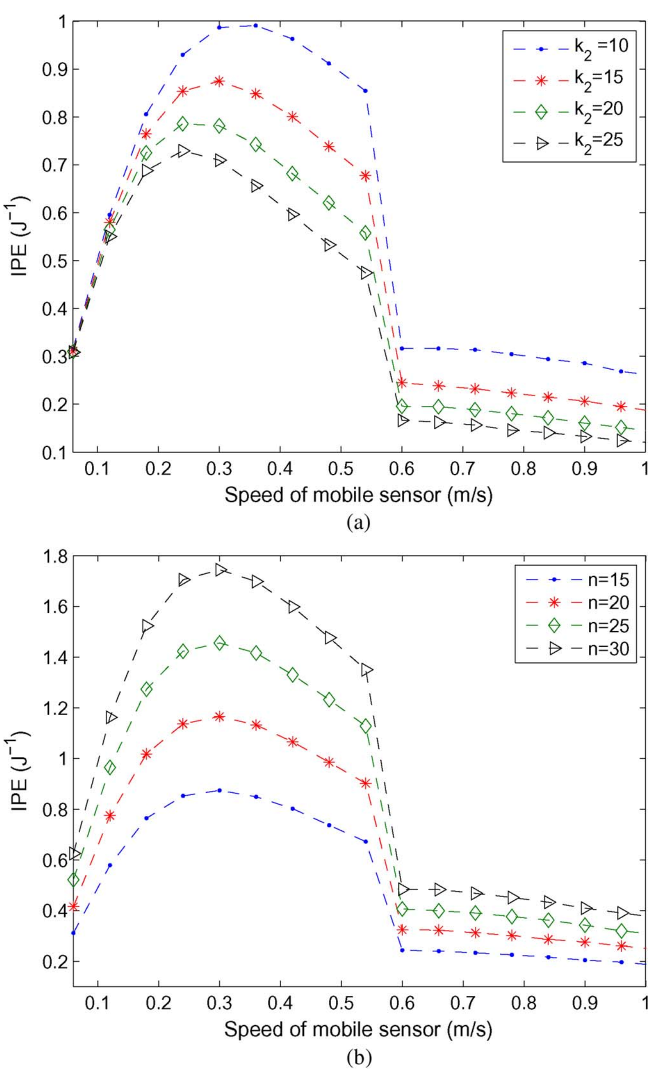

Fig. 9. Impacts of the energy model and PoI distribution on the IPE for events that have the delayed step utility function. (a) IPE as a function of v for different k_2's. (b) IPE as a function of v for different n's.

and the PoI distribution on the IPE for the events. The results for different parameters of k_2 and n are shown in Fig. 9. From Fig. 9, we can see that 1) the IPE of the delayed step utility

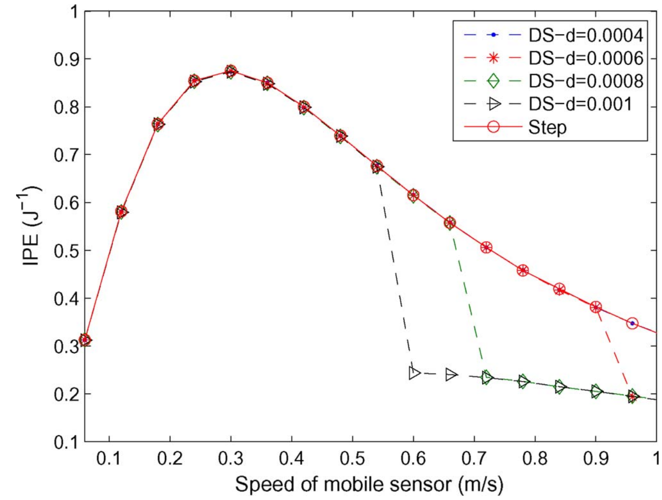

Fig. 10. IPE of delayed step utility approaches that of step utility as d becomes small.

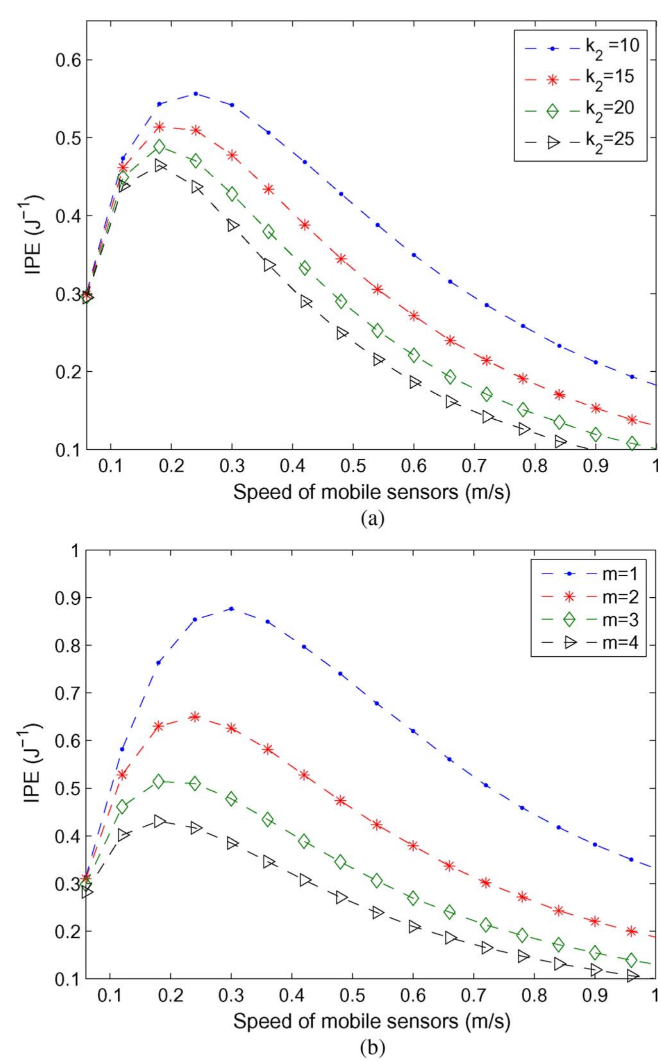

Fig. 11. IPE for events that have step utility for multiple sensors. m is the number of sensors. (a) IPE as a function of v for different k_2's; $m = 3$. (b) IPE as a function of v for different m's.

is a piecewise continuous function of v, and 2) $v = 2r/d = 2/(0.001 * 3600) = 0.556$ is one of the points of discontinuity. These results validate our analysis. The impacts of k_2 and n

are very similar to those cases of step and exponential utilities; hence, we omit their discussions.

We illustrate some relationships between the IPEs of step utility and delayed step utility. We vary the parameter d to be 0.0004, 0.0006, 0.0008, and 0.001 h, and the results are shown in Fig. 10. As expected, the IPE of delayed step utility approximates that of step utility as d becomes small.

D. Multiple-Sensor Scenario

In this section, we evaluate the IPE when multiple sensors are used. We first fix the number of sensors to be $m = 3$ and measure the IPE as a function of v under different values of k_2. The results are shown in Fig. 11(a). It can be seen that the IPE for multiple sensors is very similar to that for the single sensor, except that the former value is a bit smaller than the latter. To discover the impact of m on the IPE, we further perform simulations for different m. The results are shown in Fig. 11(b). As discussed in the analysis, although increasing the number of sensors can improve the QoM, in fact, it can have a negative impact on the IPE.

VI. Conclusion

We have analyzed the expected IPE for a mobile sensor repeatedly covering n PoIs in a circuit of length D. Our analysis has quantified the effects of the event dynamics (i.e., statistical distributions of the event staying and absence times); the types of events as captured by the step, exponential, or delayed step utility function; the sensor speed v; and the density of the PoIs given by $\gamma = D/n$. The analytical results have allowed us to optimize v for the highest IPE. In addition, we have compared the performance of mobile coverage against the use of a stationary sensor in two situations. First, the locations of the PoIs are known, and the stationary sensor is optimally placed to cover a PoI for maximum information capture. Second, the PoIs are uniformly distributed at random along the circuit, and a stationary sensor is likewise placed at a random location. We have analyzed conditions when the mobile coverage can perform better than the static coverage in terms of the IPE. We have also discussed the case of multiple sensors. Our analytical results have been illustrated and verified by the reported simulation experiments.

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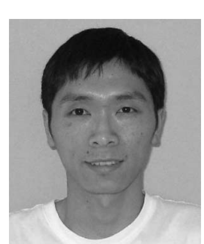

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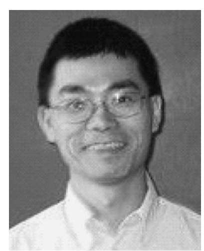

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