Energy-Efficient Probabilistic Area Coverage in Wireless Sensor Networks

Qianqian Yang, Shibo He, Junkun Li, Jiming Chen and Youxian Sun

***Abstract*—As the binary sensing model is a coarse approximation to the reality, the probabilistic sensing model has been proposed as a more realistic model to characterize the sensing region. A point is covered by sensor networks under the probabilistic sensing model if the joint sensing probability from multiple sensors is larger than a predefined threshold ε. Existing work focused on *probabilistic point coverage* since it is computationally infeasible to verify the coverage of a full continuous area (i.e., *probabilistic area coverage*). In this paper, we tackle such a challenging problem. We first study the sensing probabilities of two points with a distance of d and obtain the fundamental mathematical relationship between them: if the sensing probability of one point is larger than a certain value, the other is covered, i.e., the sensing probability is larger than ε. Based on such finding, we transform *probabilistic area coverage* into *probabilistic point coverage*, which greatly reduces the problem dimension. Then, we design ε-full area coverage optimization (FCO) to select a subset of sensors to provide *probabilistic area coverage* dynamically so that the network lifetime can be prolonged as much as possible. We also derive theoretically the approximation ratio obtained by FCO to that by the optimal one. Finally, through extensive simulations we demonstrate that FCO outperforms the state-of-the-art solutions significantly.**

***Keywords*-Probabilistic sensing model, Probabilistic Point Coverage, Probabilistic Area Coverage, Approximation Ratio**

I. Introduction

Coverage has been a fundamental issue for many applications in wireless sensor networks (WSNs) such as intrusion detection and environment monitoring [2]–[6], [9], [20], [33]. Due to the declining manufacturing cost, sensors are typically randomly deployed with high density in the region of interest (ROI). In addition, each sensor is energy constrained as it is typically powered by small-volume battery. A very important problem under such setting is the duty cycle scheduling which guarantees both energy efficiency and network coverage (i.e., energy-efficient coverage).

Most of previous works on energy-efficient coverage adopted the binary sensing model, by which the sensing region is a deterministic disc and a point is said to be covered by the sensor if and only if it falls into the disc. Binary sensing model enables basic understanding about the sensing region, and is highly desirable for theoretical derivation [21], [22]. However, such model only provides a coarse approximation to sensing region in reality since the sensing region described by binary sensing model is the inscribed circle of the actual one. Hence, the binary sensing model is too conservative, and once adopted, will limit the potential to enhance the energy-efficient coverage.

Recent research shows that the sensing model of a sensor is practically probabilistic instead of deterministic [7], [8], [10], [13]. The probabilistic sensing model thus was introduced, by which a sensor is able to sense a target at a distance d away with a probability $\lambda(d)$, where $\lambda(d)$ is a decreasing function $0 \leq \lambda(d) \leq 1$. Various $\lambda(d)$ functions have been proposed such as the cubic attenuation function [7] and exponential attenuation function [11] in different application scenarios.

Under the probabilistic sensing model, the coverage of a point is quantified by the joint sensing probability of the point being covered by sensors in the network. A point is said to be covered if the joint sensing probability is larger than a predefined threshold ε. Most of existing work focused on *probabilistic point coverage*, where only a set of points with finite cardinality should be covered [19], while few referred to the area coverage problem. Xing [12] considered to partition the ROI into grids and guaranteed that the coverage of vertices of each grid to approximate area coverage. This approach as an approximation solution reduces the computational complexity but it can not actually ensure the coverage of whole area. When a more precise coverage is imposed, the number of grids increases significantly, which requires remarkably higher computational cost. Probabilistic coverage protocol (PCP) is proposed in [14] to tackle with this problem. It activates a subset of deployed sensors to construct approximate triangular lattices in ROI which guarantees that any point in each lattice is covered. However, it can not guarantee area coverage since the deployment of sensors is random and sensors may not always be found in the desired position to form a triangular lattice. Though probabilistic sensing model has been introduced for a while, to the best of our knowledge, there is no work that can guarantee ε-full area coverage, i.e., every point in the ROI is covered with a probability larger than ε.

In this paper, we aim to tackle ε-full area coverage while maximizing the network lifetime. The main challenge is that the number of points in the ROI is infinite. To tackle this issue, we investigate the relationship of coverage probabilities between any two points with a distance of d and reveal that if the coverage probability of one is εe^{kd}, the coverage probability of the other is no less than ε (detailed information of e^{kd} can be found in Section IV). By doing so, we ensure the probabilistic area coverage of ROI only by guaranteeing the probabilistic coverage of some specific points. Based on the theoretical analysis, we transform the probabilistic area

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coverage into probabilistic point coverage and further propose an efficient solution to solve the problem.

Our mainly contribution can be summarized as follows:

1) To the best of our knowledge, we take the first attempt to study the mathematical relationship between the probabilistic coverage of two points in ROI. Such finding of mathematical relationship implies that if one of these two points is covered with a probability greater than a certain value εe^{kd}, the other one is covered with a probability no less than ε.
2) We formulate the *Minimum Weight ε-full area Cover Problem* and propose an efficient solution called *ε-full area coverage optimization* (FCO) to this problem. Theoretical analysis validates that FCO can fully provide ε-full area coverage to the monitored area and efficiently prolong the network lifetime. In addition, we theoretically investigate the performance of FCO and derive its approximation ratio of the aggregate weight obtained by FCO to that by the optimal one.
3) Based on *homo-APoint* [12], we propose an efficient method, named *hetero-APoint*, to determine the point set that can guarantee the coverage of full area as long as the coverage probabilities of points in the set is larger than a certain value. Extensive simulations are conducted to validate the effectiveness of our proposed algorithms in terms of both coverage maintenance and the network lifetime.
4) Based on *homo-APoint* [12], we propose an efficient method, named *hetero-APoint*, to determine the point set that can guarantee the coverage of full area as long as the coverage probabilities of points in the set is larger than a certain value. Extensive simulations are conducted to validate the effectiveness of our proposed algorithms in terms of both coverage maintenance and the network lifetime.
5) Under another typical probabilistic sensing model, i.e., cubic probabilistic sensing model, We also obtain the mathematical relationship of the coverage of two adjacent points and the theoretical and simulation results both show that this framework is still valid.

The rest of the paper is organized as follows. We discuss the existing work on coverage in Section II. We present preliminaries and problem formulation in Section III, followed by the problem transformation and the design of algorithm FCO in Section IV. We give the theoretical results about the algorithm FCO in Section V and discuss how to improve the results in Section VI. We perform extensive simulations to evaluate performance of algorithm FCO in Section VII. Finally, we conclude the paper in Section VIII.

II. Related Work

Energy-efficient sensing with coverage maintenance has been attracting significant attention in WSNs [2]–[6], [9], [20]. Comprehensive surveys have been done in this area [23], [25]. One common approach is to divide the network operation duration into successive time slots and dynamically schedule sensors between the active and sleep mode in each slot. Extensive scheduling protocols have been proposed under different network settings, i.e., uniform or random sensor deployment, centralized or decentralized implementation. In [29], the Randomized Independent Scheduling (RIS) protocol designed by Kumar *et al.* divides operation time into cycles at the beginning of which each sensor decides to be active or inactive with a probability p or $1-p$. The decentralized protocol can increase the network lifetime by the ratio $\frac{1}{p}$. A centralized algorithm together with a distributed one was proposed in [17], where Berman *et al.* formulated the lifetime maximization problem as a packing problem. This formulation is to derive a small set of activated sensors and meanwhile balancing energy consumption among deployed sensors, which is provably efficient and frequently employed to address the energy-efficient coverage problem in the literature [13], [19], [30].

Most studies on coverage problem assumed a perfect disc model [18], [21], [26]–[28]. Cardei *et al.* [18] proposed two heuristics, LP-MSC and Greedy-MSC heuristics, to solve the maximum set covers (MSC) problem, where all the monitored targets are within the disc sensing range of at least one sensor in each set cover. For the area coverage problem, [21] utilized the intersection point concept to transfer the coverage of whole area into the coverage of the intersection points of the sensing discs of sensors and presented a distributed algorithm which guarantees $\mathcal{O}(\log n)$ approximate ratio.

However, compared to the disc sensing model, the probabilistic sensing model as a more accurate model to the practical sensing process, which is a continuously decreasing function of the distance between the target and the sensor, has drawn more and more attention. Moreover, as pointed out in [7], the collaborations of multiple operative sensors can remarkably improve the coverage performance. The point coverage problem based on probabilistic sensing model has been well invested. The minimum weight sensor coverage problem is transformed into a binary integer programming problem and is solved by the greedy method in [32], based on which intelligent algorithms with better performance are proposed by Chen *et al.* in [19].

Nevertheless, few existing works studied the area coverage problem based on the probabilistic sensing model. The work most relevant to ours is [14], where the proposed PCP algorithm is to activate a sensor set that forms a virtual triangular lattice over the whole area. However, due to the random deployment, PCP can not fully ensure the area coverage as sensor nodes may not always be found in the desired positions. In this paper, we explore and then utilize the mathematical relations between the coverage of two points in the ROI to transform the area coverage problem into the point coverage one. Our approach can energy-efficiently guarantee the area coverage which can be validated by both the theoretical analysis and simulation results.

III. Preliminary and Problem Formulation

A. Network Model

Consider a large region of interest (ROI) R where N sensors are deployed to cover the ROI. We assume that R is a two dimensional rectangle of size $S = l_1 \times l_2$ for simplicity and sensors are randomly deployed in R. We will use S_i to denote sensor S_i as well as its position when there is no ambiguity.

In this paper, we adopt the probabilistic model which is more realistic compared with the binary model. This model considers the uncertainty in sensing process and utilizes all information including what the binary model ignores. Let $\lambda(S_i, p)$ denote the probability of point p covered by sensor S_i. We use the exponential attenuation probabilistic model introduced in [15] for our problem formulation. The coverage probability decays with the sensing distance denoted by $d(S_i, p)$ as shown in the following equation:

$$\lambda(S_i, p) = \begin{cases} 1, & \text{if} \quad d(S_i, p) \leq r_s, \\ e^{-ka}, & \text{if} \quad d(S_i, p) > r_s, \end{cases} \tag{1}$$

where $a = d(S_i, p) - r_s$ and k is a decay factor reflecting the speed of the signal attenuation with regard to the distance. As the signal that a sensor receives is strong enough when event occurs within the distance of r_s, the sensor can definitely detect the event occurrence and the probability is set to be 1. On the contrary, when the event occurs far from the sensor, it can not distinguish the noise and the received signal. In such a case, the probability approaches 0. k and r_s vary with factors such as the type of sensors and environment, and can be obtained through experiments.

The coverage performance can be improved using data fusion as shown in [7]. There are three classes of data fusion protocols commonly used: data level fusion, feature level fusion and decision level fusion. We adopt the decision level fusion which requires the lowest communication cost compared to other two approaches since in decision level fusion each sensor makes local decision and global decision is achieved by fusing local decisions. The WSN detects the occurrence of event if at least one sensor node does. Therefore, this fusion rule can be illustrated by:

$$\gamma(\mathcal{S}, p) = \bigvee_{S_i \in \mathcal{S}} \gamma(S_i, p), \tag{2}$$

where $\gamma(\mathcal{S}, p)$ denotes the result of the network detecting the event occurring at the point p and $\gamma(S_i, p)$ denotes the result of individual sensor S_i and $\mathcal{S}$ is the fusion set of sensors which S_i belongs to.

B. Problem Statement

Based on the probabilistic model and the aforementioned fusion rule, the coverage of an arbitrary point p which denotes the probability of the detection of event occurring in p by operative sensors can be described as follows:

$$\lambda_p = 1 - \prod_{S_i \epsilon C} \left(1 - \lambda(S_i, p)\right), \tag{3}$$

where C is the set of operative sensors and $\lambda(S_i, p)$ is the probability of event occurring in p that is detected by sensor S_i, while λ_p is the joint sensing probability of point p by sensor set C. With the above equation, we define *ε-full coverage*.

Definition 1: (*ε-full area coverage*) Sensor set C provides *ε-full area coverage* to ROI R if coverage of any point in R is no less than ε, i.e., $\forall p \in A, \lambda_p \geq \varepsilon$.

The value of ε is decided by the requirements of practical applications and satisfies $0 \leq \varepsilon \leq 1$. Larger ε means higher coverage requirement, which may appeal for more working sensors. When $\varepsilon = 1$, this coverage model reduces to *area coverage* defined under the boolean sensing model. Due to the random deployment, the number of deployed sensors is usually much larger than the optimal [16], [20]. Therefore, to save energy and prolong network lifetime, sensors should operate alternatively between active mode and sleep mode. The operation duration of the WSN is divided into time slots and in each time slot we try to activate a small set of sensors to reduce the energy consumption [16], [17]. We formulate the problem to energy-efficiently provide *ε-full area coverage* below:

Minimum Weight ε-full area Coverage Problem: Given a ROI R, a set of N sensors, the weight coefficient ω_i associated with each sensor S_i, $i = 1, 2, ..., N$, *Minimum Weight ε-full area Coverage Problem* is to find a subset of sensors with the minimum aggregate weight to provide *ε-full area coverage* to ROI R.

The weight coefficient is a parameter which is negatively correlated to the residual energy of sensor, i.e., a sensor with more residual energy has lower weight coefficient. Activating a set with minimum aggregate weight during each time slot can efficiently reduce energy and balance the energy consumption among deployed sensors to improve the network lifetime.

IV. Full Coverage Optimization

It is extremely difficult to solve the *Minimum Weight ε-full area Coverage Problem* directly as the area coverage can be regarded as a point coverage problem with infinite number of points. In this section, we first study mathematical relationship between the coverage of a point and its nearby points. By exploring and utilizing this relationship, we transform the full area coverage problem into the discrete point coverage problem and design *ε-full area coverage optimization algorithm* (FCO) to solve the *Minimum Weight ε-full area Coverage Problem.*

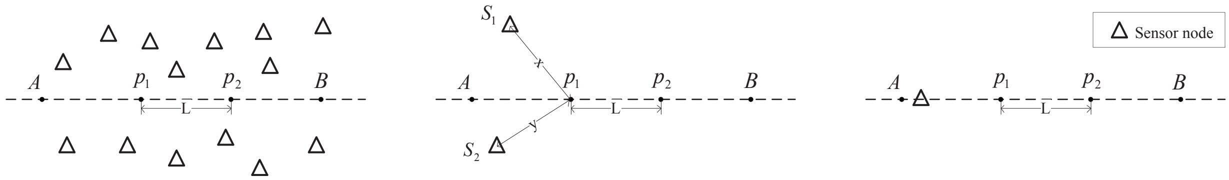
A. Problem Transformation

We start with deriving the mathematical relationship between the coverage of two adjacent points P_1 and P_2 as shown in Fig. 1. Denote the coverage probability of P_1 by ρ_1 and the coverage probability of P_2 by ρ_2. Lemma 1 characterizes, when the value of ρ_2 is τ, $0 < \tau < 1$, the number and the positions of active sensors that are needed to minimize ρ_2.

Lemma 1: Assume that there are n active sensors and ρ_1 is fixed at τ. Then, the coverage probability ρ_2 of P_2 is the minimum when these n active sensors are in the same position on line segment P_1A and $n = 1$ (see Fig. 1(c)).

Proof: We first consider the case where the number of active sensors is 2 (see Fig. 1(b)). These two sensors are denoted by S_1 and S_2, respectively. x is the Euclidean distance between S_1 and point P_1, while y is the Euclidean distance between S_2 and point P_1.

Note that the distance between sensor S_1 and P_2 gets the maximal value $L + x$ if S_1 locates at the line segment P_1A when x, as well as the distance between sensor S_2 and P_2, stays the same. Since the coverage decays with distance, it is



(a) n operating sensors. (b) Two operating sensors. (c) One operating sensors.

Fig. 1. An illustration of two adjacent points A and B.

apparent that the positions of sensors should be on P_1A to minimize ρ_2.

ρ_1 and ρ_2 can be calculated respectively by the equations

$$\rho_1 = 1 - (1 - e^{-ka_1})(1 - e^{-ka_2}), \tag{4}$$

and

$$\rho_2 = 1 - (1 - e^{-k(a_1+L)})(1 - e^{-k(a_2+L)}), \tag{5}$$

where $a_1 = x - r_s$, $a_2 = y - r_s$. Let $c_1 = e^{-ka_1}$, $c_2 = e^{-ka_2}$, $c_3 = e^{-kL}$, where $c_1, c_2, c_3 \in (0, 1)$. Then,

$$\rho_2 = 1 - (1 - c_3c_1)(1 - c_3c_2). \tag{6}$$

As assumed in Lemma. 1, ρ_1 equals to a constant τ, which means that

$$\tau = 1 - (1 - c_1)(1 - c_2). \tag{7}$$

Then, (6) can be re-written as

$$\rho_2 = 1 - (1 - c_3c_1)\left(1 - c_3\frac{c_1 - \tau}{c_1 - 1}\right).$$

Taking derivation with regard to c_1 for the above equation yields

$$\begin{aligned}\tfrac{\partial\rho_2}{\partial c_1} = \quad & c_3(1 - c_3\tfrac{c_1-\tau}{c_1-1}) \\ & +(\tfrac{c_3}{c_1-1} - c_3\tfrac{c_1-\tau}{(c_1-1)^2})(1 - c_3c_1).\end{aligned}$$

Since $\frac{\partial\rho_2}{\partial c_1} > 0$ for $c_1 < 1 - (1 - \tau)^{1/2}$ and $\frac{\partial\rho_2}{\partial c_1} < 0$ for $c_1 > 1 - (1 - \tau)^{1/2}$, we conclude that ρ_2 monotonically increases with c_1 when $c_1 < 1-(1-\tau)^{1/2}$ and monotonically decreases when $c_1 > 1-(1-\tau)^{1/2}$. Since $0 \le c_1 \le \tau$, ρ_2 gets the minimal value $c_3\tau$ when $c_1 = 0$ or $c_1 = \tau$, which implies a situation that one of these two sensors is far from the targeted points so that the detection performance can be neglected. This result for two sensors case can be easily extended into n sensors case, which completes the proof. ■

Henceforth, the mathematical relation between two adjacent points are given by following property.

Property 1: Let P_1 and P_2 be two adjacent points with distance L, if the value of ρ_1 is τ, $0 < \tau < 1$, then $\rho_2 \ge \tau e^{-kL}$.

Proof: It is concluded from Lemma 1 that the lowest coverage case for P_2 when ρ_1 of point p_1 is fixed at certain value τ, which specifies the active sensor topology minimizing ρ_2, is that one active sensor on the line P_1A as shown in Fig. 1(c). In this case,

$$\rho_2 = \tau e^{-kL}, \tag{8}$$

which implies in any case that $\rho_1 = \tau$, ρ_2 is no less than τe^{-kL}. ■

With Property 1, given the definition below, we can easily establish Theorem 1, which indicates that it suffices to provide the coverage to a piece of area by ensuring the coverage of a certain point in this area.

Definition 2: (ε*-coverage range*) The ε*-coverage range* of a point is the distance to this point within which any point is covered with a probability no less than ε if the coverage of p is no smaller than ε.

Theorem 1: Let p be an arbitrary point in ROI, if the coverage of p is εe^{kr}, then the ε-coverage range of p is r.

Note that the coverage of any point is upper bounded by 1 and it yields

$$r \le -\frac{1}{k}\ln\varepsilon,$$

which indicates the ε-coverage range is no larger than $-\frac{1}{k}\ln\varepsilon$.

Thus, we divide *Minimum Weight* ε*-full area Coverage Problem* into two subproblems: Firstly, find a set of anchor points (APoint) set PS in ROI such that any point in R is within the coverage range of at least one point in APoint; Secondly, find *Minimum Weight Cover* such that each point P_j in PS can be detected at a probability no less than ε_j, where $\varepsilon_j = \varepsilon e^{kr_j}$ and r_j is the ε-coverage range of p_j . Hence, the coverage of an arbitrary point p in A is guaranteed to be at least ε according to theorem 1.

B. Solutions for Minimum Weight ε-full Cover Problem

We formulate the *Minimum Weight* ε*-full area Coverage Problem* as the following $0-1$ integer programming problem:

$$\begin{aligned} & Minimize \quad \sum_{i=1}^{N}\omega_i x_i \\ & subject\ to\ \forall p \in \mathrm{R}, \bigvee_{j=1}^{M}(D_{jp} < r_j) = 1, \\ & \qquad \forall P_j \in PS, 1 - \prod_{i=1}^{N}(1 - \lambda_{ij}x_i) > \varepsilon_j, \\ & \qquad x_i \in \{0, 1\}, \end{aligned} \tag{9}$$

where the values 1 and 0 of x_i denote the active and sleep mode of sensor S_i, D_{jp} is the distance between APoint P_j and point p, λ_{ij} is the probability of sensor S_i sensing P_j, PS is the set of selected APoints, M is the number of selected APoints. The first constraint maintains that any point in R is included in the coverage range of at least one APoint. The second constraint ensures that every APoint P_j with coverage range in PS is covered at a probability no less than ε_i, where $\varepsilon_i = \varepsilon e^{kr_i}$. Therefore, these two constraints guarantee the monitored area R is ε-full area covered. Based on this coverage maintenance, we minimize the weight sum of active sensors as described by the objective function.

This problem has already been proved to be NP hard in previous work [18]. We develop *ε-full area coverage optimization* (FCO) to solve this *Minimum Weight ε-full area Coverage Problem*.

Firstly, we elaborate on how to determine the APoint set PS. For simplicity, we partition ROI into congruent grids of size $l \times l$ and select all vertices of each grid as APoints as shown in Fig. 2. It suffices to meet the first constraint that the coverage range of each APoint is set as $\sqrt{2}l/2$, which implies that any point in ROI is within the coverage range of at least one APoint. Hence, according to Theorem 1, the coverage requirement of every APoint is ε', where

$$\varepsilon' = \varepsilon e^{k\sqrt{2}l/2}. \tag{10}$$

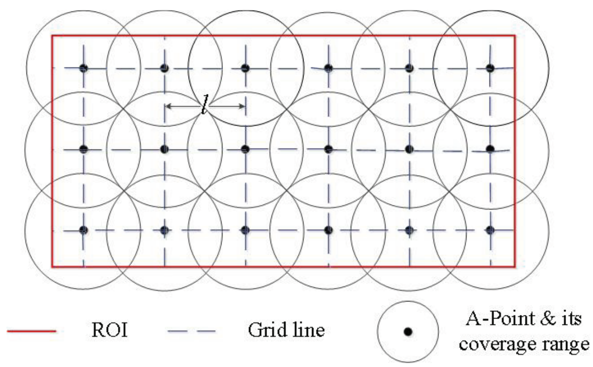


Fig. 2. An illustration of APoints

Thus, FCO can be solved by the minimum weight ε'-point coverage problem with M APoints which can be formulated as an integer programming problem described below:

$$\mathit{Minimize} \sum_{i=1}^{N} w_i x_i \tag{11}$$

$$\mathit{subject\ to}\ \forall\, P_j \in PS,\ \sum_{i=1}^{N} a_{ij} x_i \geq \xi_1,$$

where $\xi_1 = -\ln(1-\varepsilon')$ and

$$a_{ij} = \begin{cases} \xi_1, & if\ \lambda_{ij} \geq \varepsilon'; \\ -\ln(1-\lambda_{ij}), & if\ \lambda_{ij} < \varepsilon'. \end{cases}$$

Then, we show how to determine the sensor set C . There are a collection of algorithms presented in the literature that we can employ to deal with this point coverage problem, e.g., greedy method [15] and intelligent algorithms [19]. Although intelligent algorithms are proved to be much more efficient [19], it incurs huge computational cost. We thus adopt the simple Greedy algorithm [15] to estimate the performance of our method.

Algorithm 1 Greedy Algorithm for MWFCP

1) Let $r = 1$, $a_{ij}^r = a_{ij}$, $x_i = 0$, $C = \emptyset$, $\bar{\mathcal{S}} = \mathcal{S}$, where $\mathcal{S}$ is the set of the available sensors.
2) For every sensor $S_i \in \bar{\mathcal{S}}$, compute $A_i^r = \frac{\sum_j^M a_{ij}^r}{w_i}$. Select S_k that $A_k^r \geq A_i^r$ for any $S_i \in \bar{\mathcal{S}}$. Include S_k in C, exclude S_k from $\bar{\mathcal{S}}$ and $x_k = 1$.
3) If $\sum_{i=1}^{N} a_{ij} x_i \geq \xi_1$, for $\forall\, P_j \in PS$ or $w_i > B$, then end and return C.
4) Obtain a_{ij}^{r+1}: if $x_i = 1$ or $\sum_{i=1}^{N} a_{ij} x_i \geq \xi_1$, $a_{ij}^{r+1} = 0$; if $a_{ij}^r > \xi_1 - \sum_{i=1}^{N} a_{ij} x_i$, $a_{ij}^{r+1} = \xi_1 - \sum_{i=1}^{N} a_{ij} x_i$; else, $a_{ij}^{r+1} = a_{ij}^r$.
5) $r = r + 1$. Back to step 2.

Algorithm 2 FCO

1) Select the APoint Set PS that meets the first constraint in (11). Compute a_{ij} for each pair of S_i and P_j in PS.
2) Initialize the weight w_i for each S_i according to its residual energy e_i, $w_i = e^{-\frac{e_i}{E}}$, where E is a constant.
3) At the beginning of each time slot, obtain sensor set C by Algorithm 1. If $1 - \prod_{i=1}^{N}(1 - \lambda_{ij} x_i) > \varepsilon_j$ for $\forall P_j \in PS$, provided by C, then activate every sensor in C throughout this time slot; else, the network is terminated.
4) Update w_i: if $e_i > E_l$, $w_i = e^{-\frac{e_i}{E}}$, where E_l is the amount of energy a sensor need to operate throughout one time slot; else, $w_i = 10000$. Back to step 3.

C. Solutions under other probabilistic sensing models

The cubic attenuation probabilistic model which is commonly adopted for coverage analysis is given by:

$$\lambda(S_i, p) = \begin{cases} 1 & \text{if} \quad d(S_i, p) \leq r_s, \\ \frac{\alpha}{d^\beta} & \text{if} \quad d(S_i, p) > r_s, \end{cases} \tag{12}$$

where $\lambda(S_i, p)$ is the probability that sensor S_1 detects an event occurring at point p, α and β are constant, $\alpha > 0$ and $\beta > 1$, and d is the distance between the S_i and p, i.e., $d = d(S_i, p)$. To solve the area coverage problem, we explore the mathematical relation of detection probabilities between two points and have the following property:

Property 2: Let P_1 and P_2 be two points with distance L, if the value of ρ_1 is τ, $0 < \tau < 1$, then $\rho_2 \geq \frac{\alpha}{(d_1+L)^\beta}$, where $\frac{\alpha}{d_1^\beta} = \tau$.

Proof: To prove this property, we need to confirm that Lemma 1 is valid under model (12). Suppose that there are two sensors. Similarly define two sensors S_1 and S_2, two target points P_1 and P_2 as shown in Fig. 1(b), x and y are the distance from S_1 to P_1 and S_2 to P_1, respectively and assume that $y > x$. The detection probabilities of P_1 is denoted by ρ_1 and ρ_2.

ρ_1 and ρ_2 can be represented by following equations:

$$\rho_1 = 1 - (1 - \frac{\alpha}{x^\beta})(1 - \frac{\alpha}{y^\beta}), \tag{13}$$

and

$$\rho_2 = 1 - (1 - \frac{\alpha}{(x+L)^\beta})(1 - \frac{\alpha}{(y+L)^\beta}). \tag{14}$$

Assume that ρ_1 has a fixed value τ, i.e., $\rho_1 = \tau$. Therefore,

$$(\frac{\alpha}{\tau})^{\frac{1}{\beta}} \leq x \leq y.$$

Taking derivation of ρ_2 with respect to x yields

$$\begin{aligned} \tfrac{\partial \rho_2}{\partial x} = &-\alpha\beta(x+L)^{-\beta-1}[1 - \tfrac{\alpha}{(y+L)^\beta}] \\ &-\alpha\beta(y+L)^{-\beta-1}[1 - \tfrac{\alpha}{(x+L)^\beta}]\tfrac{\partial y}{\partial x} \end{aligned} \tag{15}$$

With (13) and $\rho_1 = \tau$, we can derive that

$$\frac{\partial y}{\partial x} = -\frac{y^{\beta+1} - \alpha y}{x^{\beta+1} - \alpha x}. \tag{16}$$

Define a function $g(t)$ as

$$g(t) = \frac{(y+t)^{\beta+1} - \alpha(y+t)}{(x+t)^{\beta+1} - \alpha(x+t)}. \tag{17}$$

Take derivation of $g(t)$ with regard to t, it yields

$$\begin{aligned} g'(t) = &\tfrac{(\beta+1)(y+t)^\beta(x+t)^{\beta+1} - \alpha(\beta+1)(x+t)(y+t)^\beta}{((x+t)^{\beta+1} - \alpha(x+t))^2} \\ &+\tfrac{\alpha(x+t) - \alpha(x+t)^{\beta+1}}{((x+t)^{\beta+1} - \alpha(x+t))^2} - \tfrac{\alpha(y+t) - \alpha(y+t)^{\beta+1}}{((x+t)^{\beta+1} - \alpha(x+t))^2} \\ &-\tfrac{(\beta+1)(x+t)^\beta(y+t)^{\beta+1} - \alpha(\beta+1)(y+t)(x+t)^\beta}{((x+t)^{\beta+1} - \alpha(x+t))^2} \end{aligned} \tag{18}$$

According to Lagrange mean value theorem, we have

$$\alpha(y+t)^{\beta+1} - \alpha(x+t)^{\beta+1} = \alpha(\beta+1)(\gamma+t)^\beta(y-x),$$

where $x \leq \gamma \leq y$. Thus, we have

$$\alpha(y+t)^{\beta+1} - \alpha(x+t)^{\beta+1} < \alpha(\beta+1)(y+t)^\beta(y-x).$$

Due to $(x+t)^\beta > \alpha$, $\beta > 1$ and $y > 1$, we can get that $g'(t) \leq 0$, which means

$$\frac{(y+L)^{\beta+1} - \alpha(y+L)}{(x+L)^{\beta+1} - \alpha(x+L)} < \frac{y^{\beta+1} - \alpha y}{x^{\beta+1} - \alpha x}.$$

With this results, we can obtain from (15) and (16) that $\frac{\partial \rho_2}{\partial x} > 0$, i.e., ρ_2 increases with x when $(\frac{\alpha}{\tau})^{\frac{1}{\beta}} < x \leq y$, which implies that when one sensor can fully maintain the detection requirement of P_1, i.e., $x = \frac{\alpha}{\tau}$ and the other can be neglected, i.e., $y \to \infty$. This yields the same results as shown in Sec. IV-A under sensing model (1). Thus, Lemma 1 is still valid under sensing model (12), which leads to Property 2. Henceforth, the proof is completed. ∎

We now establish Theorem 2 with Property 2, which transform the area coverage problem to the point coverage problem.

Theorem 2: Let p be an arbitrary point in ROI, if the coverage of p is $\rho_2 \geq \frac{\alpha}{(d_\varepsilon + r)^\beta}$, where $\frac{\alpha}{d_\varepsilon^\beta} = \varepsilon$, then the ε-coverage range of p is r.

The ε-coverage range has the same definition as in Sec. IV-A. Then, the *Minimum Weight ε-full area Coverage Problem* under model (12) can be solved following the same process presented by Sec. IV-B.

V. Theoretical Analysis

In this section, we theoretically analyze the performance of the proposed algorithm FCO.

Theorem 3: The performance ratio of Algorithm 1 is $H(\lceil M_{asum} \rceil)$, where $M_{asum} = \max_i(\sum_{j=1}^{M} a_{ij})$ and $H(\lceil M_{asum} \rceil) = \sum_{j=1}^{\lceil M_{asum} \rceil} \frac{1}{j}$.

Proof: We show nonnegative numbers $y_1, y_2, \ldots, y_M$ that each y_j is the weight paid by the Algorithm 1 for covering the point j. Then, it yields

$$\sum_{j=1}^{M} y_j = \sum_{i \in I^*} w_i$$

where I^* is the set cover derived by the greedy method. At the beginning of each iteration r, we derive the value of a_{ij}^r as follows: if node S_i has been selected or point P_j was covered in previous iterations, $a_{ij}^r = 0$; else, if the value of a_{ij} is larger than k_j where $k_j = \xi_1 - \sum_{i=1}^{N} a_{ij}x_i$, then $a_{ij}^r = k_j$; otherwise a_{ij}^r equals to a_{ij}. Without loss of generality, assume that after r iteration, node S_r is selected. It yields:

$$\frac{A_r^r}{w_r} \geq \frac{A_i^r}{w_i}, \qquad \forall i = 1, 2, ..., N,$$

where $A_r^r = \sum_{j=1}^{M} a_{rj}^r$ and $A_i^r = \sum_{j=1}^{M} a_{ij}^r$. Suppose that y_j^r is the weight value paid by node S_r for contributing to cover APoint j

$$y_j^r = \frac{a_{rj}^r w_r}{\sum_{j=1}^{M} a_{rj}^r},$$

If there are t iterations altogether, then

$$\sum_{i \in I^*} w_i = \sum_{r=1}^{t} w_r.$$

We have

$$\sum_{j=1}^{M} y_j = \sum_{j=1}^{M}\sum_{r=1}^{t} y_j^r = \sum_{r=1}^{t}\sum_{j=1}^{M} y_j^r = \sum_{r=1}^{t}\sum(\frac{a_{rj}^r w_r}{A_r^r}).$$

So,

$$\begin{aligned} \sum_{j=1}^{M} a_{ij}y_j &= \sum_{r=1}^{t}\sum(\frac{a_{ij}a_{rj}^r w_r}{A_r^r}) \\ &\leq \sum_{r=1}^{t}\sum \xi_1(a_{ij}^r - a_{ij}^{r+1})\frac{w_r}{A_r^r} \\ &= \sum_{r=1}^{t} \xi_1(A_i^r - A_i^{r+1})\frac{w_r}{A_r^r}. \end{aligned}$$

If s is the largest superscript such that $A_i^s > 0$ then

$$\begin{aligned} \sum_{j=1}^{M} a_{ij}y_j &\leq \sum_{r=1}^{s} \xi_1(A_i^r - A_i^{r+1})\frac{w_r}{A_r^r} \\ &\leq w_i\xi_1\sum_{r=1}^{s}(A_i^r - A_i^{r+1})\frac{1}{A_i^r}. \end{aligned}$$

Therefore, we get

$$\sum_{r=1}^{t}(A_i^r - A_i^{r+1})\frac{1}{A_i^r} \leq \sum_{r=1}^{t}(H(\lceil A_i^r \rceil) - H(\lceil A_i^{r+1} \rceil)) = H(\lceil A_i^1 \rceil) \quad (19)$$

and

$$A_i^1 = \sum_{j=1}^{M} a_{ij}.$$

Then, it implies

$$\sum_{j=1}^{M} a_{ij}y_j \leq \xi_1 H(\left\lceil \sum_{j=1}^{M} a_{ij} \right\rceil) w_i.$$

Note that the incidence vector $x = (x_j)$ of an arbitrary cover satisfies

$$\sum_{i=1}^{N} a_{ij}x_i \geq \xi_1.$$

We can get the following inequality

$$\begin{aligned} \xi_1 \sum_{i=1}^{N} H(\left\lceil \sum_{j=1}^{M} a_{ij} \right\rceil) w_i x_i &\geq \sum_{i=1}^{N}(\sum_{j=1}^{M} a_{ij}y_j)x_i \\ &= \sum_{j=1}^{M}(\sum_{i=1}^{N} a_{ij}x_i)y_j \geq \xi_1 \sum_{j=1}^{M} y_j \\ &= \xi_1 \sum_{i \in I^*} w_i, \end{aligned}$$

which means the ratio of the weight sum of an arbitrary cover including the optimal cover to that of I^* is no larger than $H(\lceil M_{asum} \rceil)$. ■

VI. Discussion

To transform the area coverage into point coverage, we impose a higher coverage requirement ε' other than ε on the selected points named APoints, as described in (10). The selected APoint is referred to as *homo-APoint*, in the sense that each point in APoint set is homogeneous with identical coverage range. The *homo-APoint* is easy to implement and can facilitate theoretical analysis, however, it may limit the potential to extend network lifetime. We in this section discuss how to improve the selection of APoint set.

To prolong the network lifetime, sensors with more residual energy are preferable to be activated for energy balance. Note that the points with more sensors nearby can gain high coverage probabilities by fewer active sensors. We proceed to design an APoint selection method, named *hetero-APoint* in the sense that the selected points are heterogeneous with different coverage ranges associated with different coverage thresholds. The *hetero-APoint* consists of two steps: 1) divide the ROI into several subareas a_k, $k = 1, 2, ..., K$, and define the *surrounding area* sa_k for each subarea a_k which includes a_k and its adjacent subareas; 2) apply the *homo-APoint* method to each subarea a_k to determine the coverage range r_k of each APoint by calculating the aggregate residual energy es_k of sensors in the *surrounding area* by $r_k = L \times es_k/E_u$, where L and E_u is a predefined constant.

An illustration of the *hetero-APoint* method can be given as follows. Suppose we have a rectangular ROI of size $20m \times 30m$ as shown in Fig. 3, which is divided into 4×6 subareas of identical size $5m \times 5m$. For each subarea a_k, $k = 1, 2, ..., 24$, the *surrounding area* sa_k is defined as the area including a_k and all the subareas adjacent to a_k. For instance, the *surrounding area* sa_8 of subarea a_8 consists of subareas a_1, a_2, a_3, a_7, a_8, a_9, a_{13}, a_{14} and a_{15}, while sa_1 of a_1 consists of a_1, a_2, a_7 and a_8. The *homo-APoint* method is applied to each subarea a_k,$k = 1, 2, ..., 24$ and the coverage range r_k of each APoint is determined according to the aggregate residual energy es_k of available sensors in the *surrounding area*, i.e., $r_k = L \times es_k/E_u$. For example, assume that every sensor in Fig. 3 has identical weight C_e, $L = 1m$ and $E_u = 9C_e$, then the value of es_8 is $9C_e$, which results $r_k = 5/3m$. The same process is employed to each subarea a_k, which yields APoint distribution of ROI as shown in Fig. 3. Larger es_k results in a larger coverage range r_k associated with higher coverage threshold. Guaranteeing the coverage of every APoint no less than its threshold can fully provide coverage to the whole area.

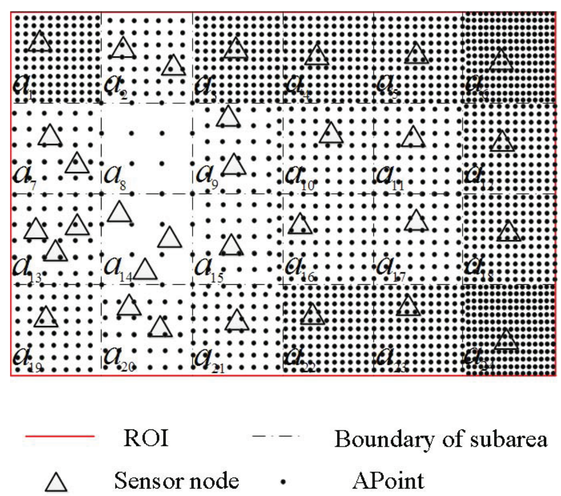


Fig. 3. An illustration of *hetero-APoint*.

VII. Simulation Results

In this section, we evaluate our proposed FCO by extensive simulations using Matlab. We verify the correctness of our algorithm and compare our FCO with other existing protocols, e.g., *Probabilistic Coverage Protocol* (PCP) [14] and *Greedy-MSC Heuristic* [18] in Sec. VII-A. In Sec. VII-B, we compare the performance of *hetero-APoint* scheme with that of the *homo-APoint* one.

The parameters for experiments are set as follows unless otherwise specified. Assume that the ROI R is a square with the size of 100m × 100m and the value of ε is 0.9. The parameters in probabilistic model are chosen the same as in the simulation of [14], i.e., $r_s = 5$ and $k = 0.05$. The initial energy of a sensor is assumed to be 1 unit and a sensor consumes 0.1 unit energy when it is active in a time slot.

TABLE I
PARAMETER DESCRIPTION

Parameter	Description
r_s	parameter of the probabilistic sensing model
k	parameter of the exponential sensing model
α	parameter of the cubic sensing model
β	parameter of the cubic sensing model
R_s	sensing range of the Greedy-MSC
l	side length of the grids
σ	the smallest circle with at least one node inside

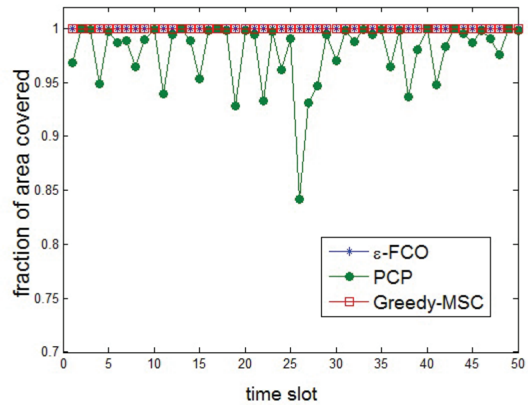
A. *Comparing FCO versus other probabilistic coverage protocol*

We compare the performance of our FCO with the *Probabilistic Coverage Protocol* (PCP) and the *Greedy-MSC Heuristic*. The idea of PCP is to activate a subset of deployed sensors to construct an approximate triangular lattice in R. PCP has been validated to be more efficient than other probabilistic area coverage protocol [14]. Meanwhile, *Greedy-MSC Heuristic* [18] is the best algorithm to maximize the lifetime of network for full area coverage under disc sensing model, to our best knowledge.

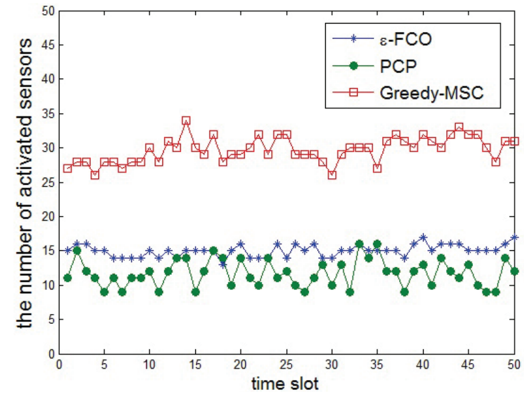
To conduct fair comparisons, we use the same probabilistic model (1) with the same parameters for FCO and PCP as aforementioned. Under this experimental setup, the maximum separation between any two active sensors on the triangular lattice is calculated to be 30.227m. The sensing range R_s of sensors for *Greedy-MSC Heuristic* is chosen as the value below which the coverage can be achieved with a probability of 0.9, i.e., $R_s = 17.1072$.

In the first experiment, we randomly deploy 400 sensor nodes in R. The POI set is selected as 101×101 points on the vertices of the grids of the side length $l = 1m$. The detection threshold calculated by (10) is 0.9659. The δ for PCP is calculated as $\delta = 2\sqrt{2} \times 100/(\sqrt{500}-1) \approx 14$. We plot the performance comparisons provided by these three protocols in terms of area coverage, the number of active sensors and average residual energy of active sensors respectively in Fig. 4(a), Fig. 4(b), Fig. 4(c). These simulation results can be summarized as follows: 1) FCO and *Greedy-MSC Heuristic* can guarantee ε*-full coverage* to ROI R while PCP cannot guarantee due to random sensor deployment; 2) compared to the *Greedy-MSC*, our algorithm can significantly reduce the energy consumption since fewer sensors are activated during each time slot as showed in Fig. 4(b) while providing ε*-full area coverage*; 3) it can be seen from Fig. 4(c) that the ε-FCO activates sensors with more residual energy to balance the energy consumption among all sensors, which has been proven more efficient to prolong the overall network lifetime in previous literature [16], [17].

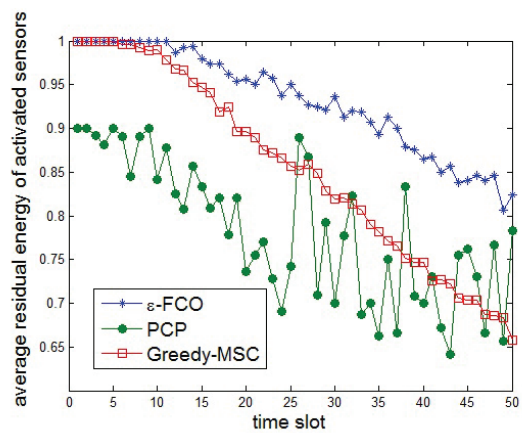
In the second experiment, we present the simulation results about the network lifetime performed by FCO and *Greedy-MSC Heuristic*. The simulation of PCP is not conducted as PCP can not provide ε*-full area coverage* to R. We define the network lifetime as the number of time slots that ε*-full area coverage* is guaranteed. The lifetimes shown in Fig. 5 are the averages of 10 simulation results under different initial sensor number, which indicates that FCO outperforms *Greedy-MSC Heuristic* significantly in terms of network lifetime.



(a) Fraction of the area covered with a probability higher than ε.



(b) The number of active sensors in each time slot.



(c) Average residual energy of sensors in active sensor cover.

Fig. 4. Comparisons of performance with existing algorithms.

In Fig. 6, we present the lifetime performance comparison under the cubic probabilistic sensing model. The parameters are set as $\alpha = 58$, and $\beta = 1.5$, $r_s = 15$. Thus, according to Theorem 2, the coverage threshold of APoint is 0.9910 as the selected APoint set stays the same to the first experiment. Fig. 6 shows that under the cubic probabilistic sensing model, the proposed FCO is still efficient and can remarkably prolong the network lifetime compared to *Greedy-MSC Heuristic*.

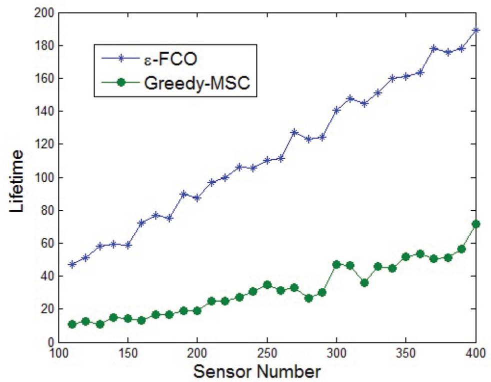


Fig. 5. The network lifetime comparison under exponential probabilistic sensing model.

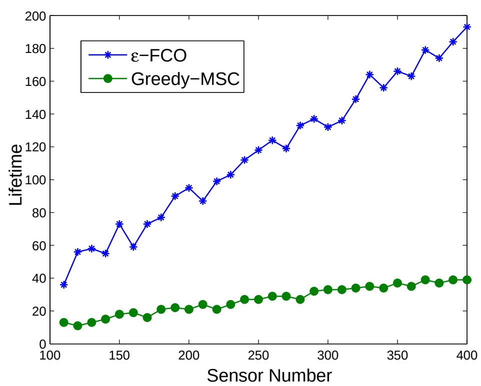


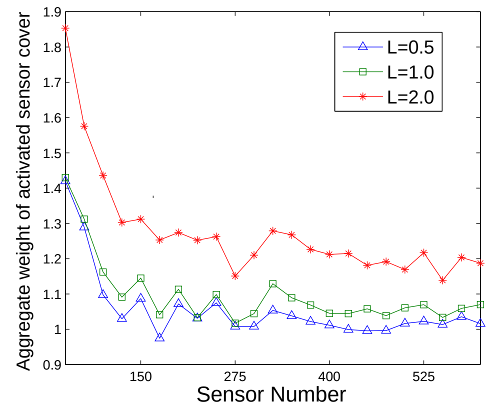
Fig. 6. The network lifetime comparison under cubic exponential probabilistic sensing model.

B. Comparing FCO with different APoint set

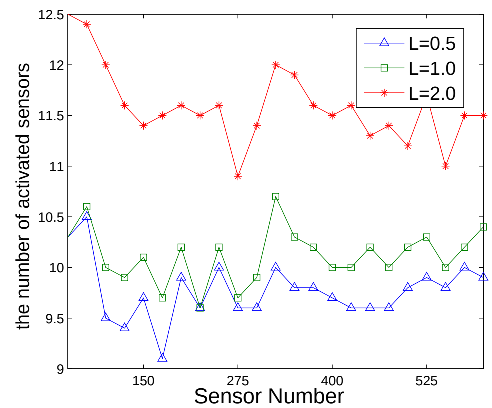
We perform simulations to show the algorithm performance under *homo-APoint* and *hetero-APoint*.

In the first set of simulations, we compare the performance of *homo-APoint* with different side length of each grid, i.e., $L = 0.5, 1.0, 2.0$. A shorter side length needs an Apoint set with larger cardinality. Under different sets of randomly deployed sensors with their cardinality varying from 25 to 650 in the ROI, we proceed to compare the performance in terms of aggregate sensor weight, the number of active sensors and algorithm runtime. The simulation results are plotted in Fig. 7. To conduct fair comparison, each value is the average of 10 experiment results under the same setup. Fig. 7(a) and Fig. 7(b) reveals that larger Apoint set leads to a smaller aggregate weight of activated sensors, but results in a larger computational cost as shown in 7(c). Fig. 7(c) shows that the difference of computational cost become more significant with the increasing of the sensor number as the time complexity is $\mathcal{O}(n^2)$. These results indicate a tradeoff between energy efficiency and computational cost as aforementioned in Sec. VI.

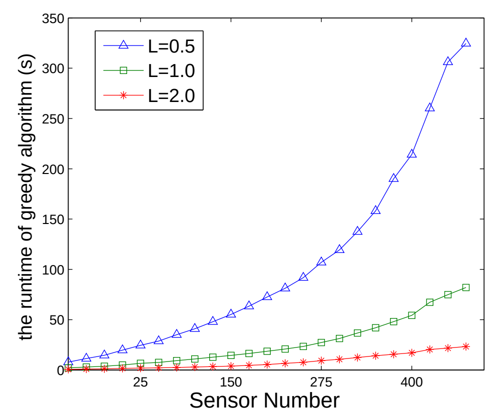
The Fig. 7(a) and Fig. 7(b) reveals that APoint selection has a significant impact on the performance of network lifetime. In the second set of simulations, we focus on the network lifetime performed by FCO using *homo-APoint* or *hetero-APoint* with different number of APoints. We present the results about the network lifetime in Fig. 8. The $x-$axis represents the number of APoints in PS. We can summarize that the network lifetime increases with the number of APoints and under the same amount of the APoints, which reveals computational cost is the same, *hetero-APoint* clearly outperforms *homo-APoint* in terms of the network lifetime.



(a) Aggregate weight of active sensor cover.



(b) The number of active sensors in each time slot.



(c) The runtime of the Greedy Algorithm.

Fig. 7. Performance comparisons of FCO with different APoint sets.

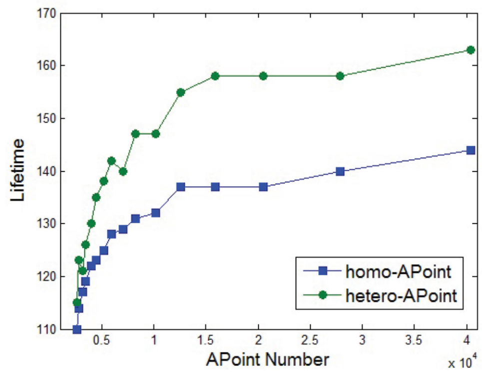


Fig. 8. The network lifetime under homo-APoint and hetero-APoint.

VIII. Conclusion

In this paper, we investigated full area coverage problem under the probabilistic sensing model in the sensor networks. We have studied the mathematical relationship between the coverage of two adjacent points and transformed the full area coverage problem into the point coverage problem. Based on these results, we proposed FCO algorithm to solve the *Minimum Weight ε-full area Coverage Problem*, and put forward two methods to select the APoint set. Our theoretical analysis and simulation results demonstrate that ε-FCO algorithm can fully ensure ε-full area coverage and outperforms other probabilistic coverage protocols in term of the number of active sensors, average residual energy and network lifetime. Moreover, the results are not limited to the exponential sensing model, and can be easily extended to other probabilistic sensing models.

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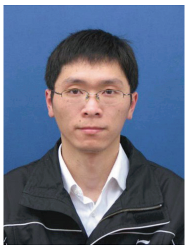

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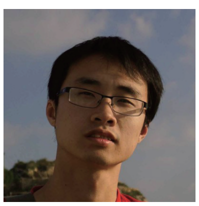

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