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Maximizing Surveillance Quality of Boundary Curve in Solar-Powered Wireless Sensor Networks

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ABSTRACT Barrier coverage is an important issue aiming at finding a set of sensors from a given wireless sensor network for detecting the illegal crossing of a boundary. A large number of algorithms have been proposed for prolonging the network lifetime. However, most of them assumed that each sensor is battery powered and the Boolean Sensing Model (BSM) is applied. Sensors powered by battery have limited lifetime while the BSM is difficult to reflect the physical features of sensing. This paper proposes a barrier coverage mechanism, called MSQ, which considers the solar-powered sensors and allows the battery to be recharged for maintaining the perpetual lifetime of sensor networks. However, two challenges should be overcome. First, the schedule should take into account the state switching due to limited energy. Second, the cooperation between neighboring sensors should be considered since the Probabilistic Sensing Model (PSM) is applied. The evaluation of surveillance quality supported by the cooperative sensing should be further considered. Performance evaluations depict that the proposed mechanism improves the performance of existing studies in terms of surveillance quality and stability.

INDEX TERMS Rechargeable sensor, probabilistic sensing model (PSM), barrier coverage, wireless sensor networks.

I. INTRODUCTION

The coverage problem is one of the most important issues in wireless sensor networks. According to different applications, the coverage problems are classified into three categories [1]. The first one is target coverage, which aims to monitor a given set of points. The second one is area coverage, which aims to monitor a given area. The last one is barrier coverage. The barrier coverage aims to monitor a given boundary line or curve, detecting the invalid crossing of the intruder. Give a set of deployed sensors, the major issue of the barrier coverage is to determine a minimal subset of sensors which stay in active state and aim to construct a defense curve for monitoring the given boundary curve. The barrier coverage can be applied to many real applications, including the monitoring of country boundaries, boundaries of battlefields, forests and so on.

Most of the existing works [1]–[4] assumed that given boundary curve is a long and irregular belt. Since the boundary belt is often harsh or desolate, the considered wireless sensor networks are often assumed to be randomly and densely deployed. Each sensor is battery powered and has several functions including sensing, storing data, computing as well as wireless communication. The barrier coverage issue has been widely investigated in the past few years. These studies aim to effectively construct barriers for guaranteeing the coverage quality of the boundaries. Two influence factors that determine the performance of barrier coverage are the surveillance quality and energy management.

The surveillance quality highly depends on two factors: the sensing model and the schedule of sensors. The sensing model determines the sensing contribution of each sensor

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and the surveillance quality of the wireless sensor networks. In literature, a number of studies [2], [3], [9], [10] considered critical condition and aimed to minimize the set of working sensors which are responsible for establishing a monitoring barrier with k-coverage in a given belt region. However, most of them developed algorithms using Boolean Sensing Model (BSM), where the coverage range of each sensor is assumed to be a perfect disc. The Boolean Sensing Model is only a coarse approximation to the practical sensing capability of each sensor. On the contrary, the Probabilistic Sensing Model (PSM) reflects the practical sensing capability and assumes that detecting capability of a sensor is decreased with the distance between the sensor and the intruder [5]–[7]. Though PSM is more complicated than BSM, the physical sensing behaviors of most commercial sensors better match PSM, as compared with the BSM. This paper applies PSM as the sensing model to develop novel barrier coverage mechanism. This paper presents a novel barrier coverage mechanism which schedules sensors based on PSM, aiming at maximizing the surveillance quality for a given set of deployed sensors.

Another important parameter considered in the existing work is the energy management of sensors, which can determine the lifetime of the wireless sensor networks. In literature, the existing energy management schemes can be classified into two categories. One is Reducing Energy Consumption (REC) [1], [9], [10] and the other is Energy Harvesting (EH) [12]–[18]. The schemes fall in REC category aim to extend the network lifetime by using the minimum set of working sensors. They partition the sensors into different groups. The sensors in one group play the role of working sensors, all sensors in the other group stay in sleep mode. Sensors in different groups monitor the boundary in terms to achieve the purpose of energy conservation. Regardless of how energy can be managed efficiently, a battery-powered WSN will finally fail due to the limited energy resource. As a result, sensors or their batteries have to be replaced, which creates a costly procedure if the network is deployed in a harsh or adversarial environment.

Some other works belonging to the Energy Harvesting (EH) category consider the rechargeable battery. The rechargeable sensors could be recharged by an external energy source, such as solar of the studies [12], [13] and radio frequency (RF) of the studies [14], [15]. However, these developed schemes cannot be applied to solving the problem of barrier coverage. Moreover, one critical constraint of the solar technology is that it cannot be applied at night. To our knowledge, how to maintain the solar-powered networks running at night have not been mentioned in existing works.

Based on the abovementioned discussions, this paper aims to investigate the barrier coverage problem of solar-powered sensors by applying PSM. A barrier coverage mechanism, called Maximizing Surveillance Quality Algorithm or MSQ in short, is proposed for maximizing the surveillance quality of a given boundary curve. Two main challenges should be taken into consideration in the design of the proposed MSQ. The first one is the scheduling of sensing sensors for maximizing the surveillance quality, especially when considering the PSM. To overcome the challenge, this paper tries to identify "the bottleneck" which has the weakest surveillance quality. In other words, we should find out the location (where) and time (when) the surveillance quality is weakest. The proposed MSQ will prior allocate the new sensing sensors to improve the surveillance quality of the bottleneck. The other challenge is the energy recharge problem. The solar is the best option for unlimited network lifetime, but it can't be recharged at night. The proposed MSQ schedules each sensor to recharge periodically during the daytime, while ensuring the surveillance quality of sensor barriers, even though at night. In a sensing period of daytime, each sensor not only orderly recharges for the sensing work of that period, but also allocates the reserved electricity for the night.

The proposed MSQ helps all sensors switch orderly between recharging and activation states, and determines the sensing sensors that can cooperatively contribute their sensing capabilities for constructing a barrier with maximal surveillance quality. The key contributions of the proposed MSQ are itemized as follows:

(1) **Weakest-first policy for cooperative sensing.** The proposed MSQ algorithm considers the two dimensional (space and time) surveillance quality and prior allocates the sensor with maximal contribution to monitor the location with minimal surveillance quality. This policy significantly improves the surveillance quality of given defense barrier.
(2) **Making full use of all sensors.** Different with existing studies [1], [2] [9], [10], the proposed mechanism makes full use of all the sensors, rather than just picking out the best sensor to construct the defense barriers. As a result, the surveillance quality of the boundary can be significantly improved.
(3) **Considering the physical characteristics of the sensor.** Most of existing works used BSM to develop the barrier coverage algorithms [2]–[4]. Their estimations of coverage quality are not accurate, easily resulting in coverage holes in the actual applications. Unlike these works, this paper applies the probabilistic sensing model to evaluate the surveillance quality based on cooperative sensing.
(4) **Considering the solar-powered sensors sensing at night.** In study [13], the sensing time is assumed as a half day, because that the sensor can only be recharged in the daytime. However, sensor networks often have to work at night. This paper considers that sensors actually work whole day and divide one day into several cycles according to the battery capacity of sensors. The energy of sensors required for sensing at night will be reserved by scheduling sensors to be recharged in the daytime.

The rest of this paper is organized as follows. Section II presents the related work. Section III presents the network environment and problem statement. Section IV gives the detailed descriptions of MSQ algorithm. Section V presents the simulation results. Finally, a conclusion of the proposed algorithms and future work are drawn.

II. RELATED WORK

A large number of barrier coverage mechanisms have been proposed in the last decade. In general, these mechanisms are developed based on different assumptions on battery types and different sensing models. The following reviews these studies and presents the contributions of this paper against the existing works.

A. BARRIER COVERAGE BY APPLYING BSM (BOOLEAN SENSING MODEL)

A lot of studies developing the barrier coverage algorithms are based on the assumption of BSM. In this model, all sensors have identical constant sensing range. A sensor can detect the occurrence of an event if the event is occurred in the sensing range of the sensor. Liu et al. [2] proposed critical conditions for strong barrier coverage. This helps better understand the critical conditions for barrier coverage. In addition, they considered the boundary belt with irregular shape and proposed a distributed algorithm to partition the sensors into several working groups for energy conservation. Saipulla et al. [3] assumed that sensors are deployed along a line or multiple lines. Furthermore, an algorithm is proposed to construct more barriers based on the considered deployment. Silvestri et al. [4] proposed an autonomous deployment algorithm to cope with the k-barrier coverage problem using mobile sensors. The proposed algorithm coordinates sensor movements in order to construct k distinct complete barriers which guarantee the desired level of redundancy. The above mentioned literature is developed based on the assumption that the BSM is applied. Since the sensing probability can be dynamically changed with the distance between the sensor and the intruder, the performance estimations might not be accurate in real applications.

B. BARRIER COVERAGE BY APPLYING PSM (PROBABILISTIC SENSING MODEL)

In the PSM, the detection probability of an event occurred in the sensing range is not a constant. Instead, the detection probability is decrease with the sensing distance. The PSM is more practical and can reflect the complex sensing effects of the real world, as compared with the BSM [7]. Si et al. [5] applied the exponential decay probabilistic sensing model for directional sensor networks. In addition, they proposed a fault-tolerant probabilistic sensing model for handling orientation error and rotation error. Furthermore, a hybrid probabilistic sensing model is formed by combining the exponential decay probability with the fault-tolerant probability. Li et al. [6] applied PSM to analyze the detection probability of a crossing path when the intruder has an invalid cross with the maximum moving speed. Akbarzadeh et al. [8] aimed to optimize the sensor placement problem and developed a novel probabilistic sensing model for sensors. The probabilistic sensing model considered more parameters including sensing range and sensing angle, which take into consideration sensing capacity probability and critical environmental factors such as terrain topography. Though the abovementioned existing work applied the PSM to analyze the performance of surveillance quality or develop barrier coverage mechanisms to achieve better performance, they did not consider the issue of energy management. To prolong the lifetime or even support the perpetual surveillance operations, some efforts are still required.

C. BARRIER COVERAGE AIMING AT PROLONGING NETWORK LIFETIME

In addition to achieve the surveillance quality, a number of existing studies aim at prolonging the network lifetime. These studies mainly assumed that sensors are powered by battery. Therefore, how to save energy when designing algorithms will be the main purpose. Mostafaei et al. [1] developed a learning automata scheme to cope with the barrier coverage problem. They presented a distributed algorithm which aims to maximize the number of barriers and minimize energy consumption. Chang et al. [9] proposed a decentralized scheme. The sensors will construct a defense barrier from left to right of the region based on their own contributions to the coverage. The proposed mechanism finds a maximal number of disjoint sets of sensors, such that each set is composed of minimum number of sensors but supports k-barrier coverage. Weng et al. [10] presented a graph model (CA-Net) which aims to simplify the problem of k-barrier coverage while reducing the complexity of computation. Based on the developed CA-Net, a decentralized approach, called TOBA, is presented to address the k-barrier coverage problem with the purposes of energy-balance and maximal lifetime. Kim et al. [11] considered the hybrid sensor network, which is organized by a number of energy-scarce ground sensors with homogenous initial battery level and energy-plentiful mobile sensors. The goal of this work is to maximize the lifetime of sensors which can support barrier coverage. Though studies fall in this category try to schedule the sensors for prolonging the network lifetime, the surveillance service cannot be continuously supported when the sensors in WSN exhaust their energies.

D. BARRIER COVERAGE AIMING AT UNLIMITED NETWORK LIFETIME

To support the perpetual surveillance operations for barrier coverage, some other studies considered that the rechargeable battery is mounted on the sensor, which can be recharged by an external energy source in order to prevent the energy exhaustion. Solar has been widely used in our lives, because solar panels have become cheaper to manufacture and are capable of providing high energy density. Gaudettez et al. [12] aimed to optimally control the sensing range of each sensor so as to maximize the quality of coverage, defined as the minimum number of targets that must be covered over a 24-hour period. Differing from it, Tang et al. [13] assumed that the sensor can only recharge in the passive state and work in active state. An efficient greedy hill-climbing algorithm is proposed for maximizing the monitoring quality of the entire sensor networks. Yang et al. [16] proposed a Linear Programming (LP) based method which scheduled the sensor nodes by considering the recharging issue for target coverage. However, the computational complexity of the proposed LP based solution is high. To cope with this problem, they additionally proposed a greedy algorithm which is a faster approach than the LP solution. Gaudette et al. [17] considered the wireless sensor network which consists of solar-powered sensor nodes. Their objective is to maximize the coverage quality of target coverage. They proposed method for determining proper sensing radii and routing paths such that the near-optimal performance can be achieved. Chen et al. [18] presented a reinforcement learning-based sleep scheduling as the basis of coverage algorithm (RLSSC) for the solar-powered wireless sensor network. The goal of this work is to maximize the area coverage. Although abovementioned studies have investigated the issues of solar recharging, the proposed algorithms cannot be applied to the barrier coverage. To the best of our knowledge, this is the first work to analyze surveillance quality of solar-powered sensor barriers using probabilistic sensing model and address problem of scheduling solar-powered sensors for maximizing surveillance quality.

III. ASSUMPTIONS AND PROBLEM STATEMENT

This section initially introduces the network model and assumptions of solar-powered sensor networks. Then, the important properties of the individual sensor and the problem formulations of our study are described.

A. NETWORK MODEL

This paper considered the boundary *Curve C* which is contained in a rectangle region R with size $L \times W$, where L and W are the length and width of R, respectively. Let $C = \{v_1, v_2, \ldots\ldots v_m\}$ denote the set of m representative points on curve C. Let (x_i^v, y_i^v) represent the coordinates of a given point v_i. In region R, there are n solar-powered sensors, denoted by $S = \{s_1, s_2, \ldots, s_n\}$, randomly and densely deployed. Each sensor has a unique ID. The sink is aware of the location of each sensor and the boundary curve C. Let $\left(x_j^s, y_j^s\right)$ represent geographical coordinates of a given sensor s_j. The sensing communication radiuses of each sensor are denoted by r_s and r_c, respectively, where $r_c \geq 2r_s$. All sensors are able to work synchronously and are operated at a predefined time. Through the exchanges of beacon messages with one-hop neighbors, each s_j can collect IDs and locations of its neighboring sensors. Fig. 1 gives a scenario of the considered network.

B. SENSING MODEL

In this paper, the PSM (probabilistic sensing model) [7] is applied. Fig. 2 depicts the main characteristics of the PSM.

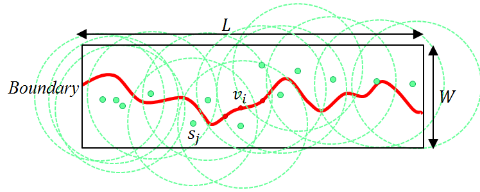


FIGURE 1. An example of the considered network.

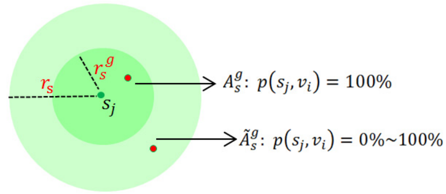


FIGURE 2. The applied probabilistic sensing model.

The sensing range of any sensor s_j consists of two regions: A_s^g and $\tilde{A}_s^g$. The radius of region A_s^g is r_s^g. When the event is occurred in region A_s^g, the detection probability of sensor s_j is 100%. However, in case that the event is occurred in region $\tilde{A}_s^g$, the detection probability of sensor s_j is decreased with the distance between sensor and the event location.

The following presents the detection of probability of sensor s_j. Let v_i denote the location of an occurred event. Let $p\left(s_j, v_i\right)$ denote the event detection probability of sensor s_j. Let $d\left(s_j, v_i\right)$ denote the distance of s_j and point v_i. Exp. (1) presents the event detection probability $p\left(s_j, v_i\right)$.

$$p\left(s_j, v_i\right) = \begin{cases} 1 & d\left(s_j, v_i\right) \leq r_s^g \\ e^{-\lambda\left(d\left(s_j, v_i\right) - r_s^g\right)^\gamma} & r_s^g < d\left(s_j, v_i\right) < r_s \\ 0 & d\left(s_j, v_i\right) \geq r_s \end{cases} \tag{1}$$

where λ and γ denote the path loss exponents of the sensing signal strength and could be adjusted with the physical properties of the sensor. The distance $d\left(s_j, v_i\right)$ in Exp. (1) can be calculated by

$$d\left(s_j, v_i\right) = \sqrt{\left(x_j^s - x_i^v\right)^2 + \left(y_j^s - y_i^v\right)^2}.$$

C. RECHARGING AND DISCHARGING MODEL

Assume that each solar-powered sensor is energy constraint and rechargeable. Each sensor has four possible states, including recharging-only, sensing-only, sensing & recharging and sleeping states. Each sensor consumes energy when it stays in sensing-only state or sensing & recharging state. A sensor staying in recharging-only state can be recharged from the solar energy resource when its power is not full. In the sensing & recharging state, each sensor can perform the operations of sensing and recharging simultaneously. Since each sensor can't be recharged at night, sensor staying in the sensing-only state can only perform sensing operation. In case that sensor staying in the sleeping state, it did not perform any operation, including recharging and sensing.

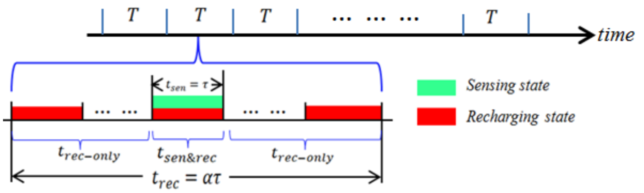


FIGURE 3. An example of a cycle under condition $\sigma = \alpha$.

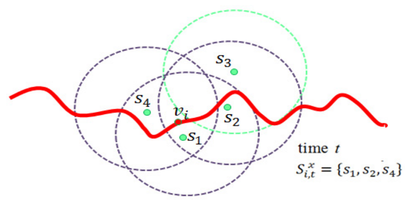


FIGURE 4. An example of the sensor set $S_{i,t}^x$.

For simplicity of the model, we assume that the energy of a sensor can be depleted to zero in sensing-only state and does not change in the sleeping state.

There are three physical parameters which impact the energy of solar powered sensor node, including battery capacity, discharging speed and recharging speed, which are denoted by E, u_{sen} and u_{rec}, respectively. Let t_{rec} denote the recharging time period, and t_{sen} denote the discharging time period. They could be formulated by

$$t_{rec} = \frac{E}{u_{rec}} \text{ and } t_{sen} = \frac{E}{u_{sen}}.$$

Let α denote the ratio of discharging and recharging speeds. The ratio α could be calculated by

$$\alpha = \left\lceil \frac{u_{sen}}{u_{rec}} \right\rceil = \left\lceil \frac{t_{rec}}{t_{sen}} \right\rceil,$$

and it is assumed to be an integer which satisfies the condition $\alpha \geq 1$. Let T denote a cycle which is divided into σ equal-sized time slots. Let $\tau = t_{sen}$ denote the length of each time-slot. Let $t_{sen-only}$, $t_{sen\&rec}$ and $t_{rec-only}$ denote the time periods that a sensor performs sensing operation only, recharging and sensing operations simultaneously, and recharging operation only, respectively. Fig. 3 depicts an example of a cycle when the number σ of time slots in a cycle is equal to the ratio of discharging and recharging speeds α. In the example of Fig. 3, the recharging time period t_{rec} includes time periods $t_{rec-only}$ and $t_{sen\&rec}$. Similarly, we have

$$t_{sen} = t_{sen\&rec}.$$

Since each sensor has the same schedule in each cycle, the developed algorithm only needs to cope with the scheduling of one cycle for each sensor. In each cycle, we assume that each sensor will be recharged for α time slots and perform sensing operation for one time slot. But, it is unnecessary that the sensing operation must be arranged at the last time slot in a cycle T. The sensing operation can be arranged in any time slot in a cycle T. This is because that sensor can be recharged in some time slots of the previous cycle. The recharged energy can support the energy consumption of sensing operation in any time slot of the current cycle.

Let t_h denote the h-th slot in a cycle T. The following further defines three Boolean symbols $M_{j,h}^{sen}$,$M_{j,h}^{rec}$ and $M_{j,h}^{slp}$, which are used to present the operation of sensor s_j at time slot t_h. That is,

$$M_{j,h}^{sen} = \begin{cases} 1, & \text{if } s_j \text{ performs sensing operation in } t_h \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$M_{j,h}^{rec} = \begin{cases} 1, & \text{if } s_j \text{ performs recharging operation in } t_h \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

$$M_{j,h}^{slp} = \begin{cases} 1, & \text{if } s_j \text{ sleeps in } t_h \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

For example, if sensor s_j stays in sensing & recharging state at certain time slot, we have $M_{j,h}^{sen} = 1$,$M_{j,h}^{rec} = 1$ and $M_{j,h}^{slp} = 0$.

D. PROBLEM STATEMENT

This paper essentially studies how to schedule the solar-powered sensors aiming at maximizing boundary surveillance quality. Let x denote a possible schedule and Φ denote the set of all possible schedule schemes. At any given time t, some sensors will be activated under schedule x. Based on schedule x, let $S_{i,t}^x$ denote the set of sensors that are scheduled in sensing state at time t and can cover the point $v_i \in C$. As shown in Fig. 4, there are four sensors, including s_1, s_2, s_3 and s_4. The schedule x arranges the four sensors to be activated at time t. Since only sensor s_1, s_2 and s_4 can monitor point v_i, we have $S_{i,t}^x = \{s_1, s_2, s_4\}$.

The probability that sensor s_j cannot detect the event is $1 - p\left(s_j, v_i\right)$. It implies that the probability of all sensors $s_j \in S_{i,t}^x$ cooperative sensing but still unable to detect the event is

$$\prod\nolimits_{s_j \in S_{i,t}^x} \left(1 - p\left(s_j, v_i\right)\right).$$

Let $P_{i,t}^x$ denote the detection probability of any sensor $s_j \in S_{i,t}^x$. The value of $P_{i,t}^x$ can be evaluated as shown in Exp. (5).

$$P_{i,t}^x = 1 - \prod\nolimits_{s_j \in S_{i,t}^x} \left(1 - p\left(s_j, v_i\right)\right) \quad (5)$$

Definition: The boundary surveillance quality based on schedule x.

Given a schedule x, the boundary surveillance quality, denoted by U^x, is the weakest sensing quality of any point on boundary curve C over all time instants t. That is,

$$U^x = \min_{x \in \Phi, v_i \in C} P_{i,t}^x, \forall t \quad (6)$$

The proposed *MSQ* mechanism aims to obtain the maximum surveillance quality, while implementing the perpetual lifetime of WSNs. The following presents the objective function and the constraints of the solar-powered sensor networks.

Object function:

$$x^{opt} = \arg \underset{x\in\Phi}{Max}\left(U^x = \min_{x\in\Phi, v_i\in C} P^x_{i,t}, \forall t\right) \tag{7}$$

where x^{opt} denote the best schedule which can maximize boundary surveillance quality over all time instants, for a given set of sensors S and the defense curve C. Some constraints given below should be further satisfied. Let $e_{recharge}$ and $e_{discharge}$ denote recharged and discharged capacities of each cycle, respectively, as shown in Exps. (8) and (9).

$$e_{recharge} = \sum_{h=1}^{\left\lceil \frac{T}{\tau} \right\rceil} M^{rec}_{j,h} \times u_{rec} \times \tau \tag{8}$$

$$e_{discharge} = \sum_{h=1}^{\left\lceil \frac{T}{\tau} \right\rceil} M^{sen}_{j,h} \times u_{sen} \times \tau \tag{9}$$

One day can be divided into two intervals: daytime and nighttime, and are denoted by L^{day} and L^{night}, respectively. During each cycle, each sensor needs to recharge its energy for not only daytime but also nighttime. Let β^{day} and β^{night} denote the number of cycles in L^{day} and L^{night}, respectively. That is,

$$\beta^{day} = \left\lceil \frac{L^{day}}{T} \right\rceil \text{ and } \beta^{night} = \left\lceil \frac{L^{night}}{T} \right\rceil.$$

Exp. (10) gives the constraint which ensures the recharging and discharging balance constraint which asks the total amount of recharging and discharging to be equal in one day. This constraint guarantees the perpetual lifetime of each sensor.

1) PERPETUAL LIFETIME CONSTRAINT

$$\sum_{l=1}^{\beta^{day}} e_{recharge} = \sum_{l=1}^{\beta^{day}+\beta^{night}} e_{discharge} \tag{10}$$

The following state constraint guarantees that each sensor can stay in one of the four possible states, including sensing & recharging, sensing-only, recharging-only and sleeping state, at any given time.

2) STATE CONSTRAINT

$$\left(M^{sen}_{j,h} + M^{slp}_{j,h}\right) \le 1 \text{ and } \left(M^{rec}_{j,h} + M^{slp}_{j,h}\right) \le 1,\ \forall j,\ \forall h \tag{11}$$

In each cycle, each sensor should be activated exactly for one time slot. The following working constraint reflects this requirement.

3) WORKING CONSTRAINT

$$\left(\sum_{h}^{h+T} M^{sen}_{j,h}\right) = 1, \forall h, \exists v_i \text{ and } p\left(s_j, v_i\right) > 0 \tag{12}$$

In view of the difference between daytime and nighttime, we must constrain the states of each sensor in the daytime and nighttime. In each cycle of daytime, a sensor can stay in sensing & recharging state for one time slot and stay in recharge-only state for the remaining time slots. On the other hand, in each cycle of nighttime, a sensor only can stay in sensing-only state for one time slot and stay in sleeping state in the remaining time slots. The following constraint reflects this requirement.

4) DAY AND NIGHT CONSTRAINT

$$\sum_{h=1}^{\left\lceil \frac{T}{\tau} \right\rceil} \left(M^{sen}_{j,h}+M^{rec}_{j,h}\right) = T+1,\ \forall s_j \in S_C,\ \forall T \in L^{day} \tag{13}$$

$$\sum_{h=1}^{\left\lceil \frac{T}{\tau} \right\rceil} \left(M^{sen}_{j,h}+M^{slp}_{j,h}\right) = T,\ \forall s_j \in S_C,\ \forall T \in L^{night} \tag{14}$$

where S_C denotes the set of sensors which have contributions to curve C. The following section presents the proposed scheduling algorithm which aims to achieve our object function given in (7), while satisfying constraints (10), (11), (12), (13) and (14).

IV. THE PROPOSED SCHEDULING SCHEME

Many previous studies aimed at finding a minimal number of sensors to support the predefined monitoring quality, such as k-coverage. Most of them assumed that each sensor is battery powered and the energy of each sensor is limited. To prolong the network lifetime, sensors can be partitioned into several disjoint sets. When sensors in one set perform the monitoring task, all sensors in the other sets can stay in sleep mode to conserve their energy. Sensors in different sets can perform the monitoring task in turn such that the network lifetime can be prolonged. However, since the sensors considered in this paper are solar-powered, the energy of each sensor can be recharged. This also implies that the lifetime of each sensor could be unlimited. Therefore, it becomes our focus to schedule the sensors working in an efficient way such that the cooperative sensing can support maximal monitoring quality under the constraint that the recharge schedule of each sensor should be taken into consideration to guarantee that the perpetual lifetime of each sensor. However, the monitoring quality of the whole boundary is defined by the quality of the weakest point lying on the boundary curve. Therefore, the developed mechanism aims to schedule sensors for maximizing the monitoring quality of the space time point which has the minimal monitoring quality. The proposed mechanism, called Maximizing Surveillance Quality (*MSQ*) mechanism, partitions the boundary curve into several segments, calculates the surveillance quality of each segment and then allocates sensors to improve the segment with the weakest quality. The following presents the details of the proposed *MSQ* mechanism.

The proposed *MSQ* mechanism consists of three phases: *space-time partitioning phase*, *computation phase* and *sensor scheduling phase*. In the *space-time partitioning phase*, sink node partitions the boundary curve into a number of segments and then partitions the time into several equal-length slots. In the *computation phase*, sink node calculates the cycle length which is determined by considering the ratio of daytime and the nighttime, and the ratio of recharging

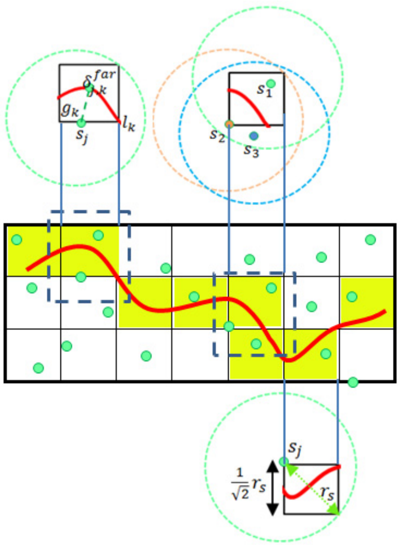


FIGURE 5. Partition boundary curve into curve segments based grids.

and discharging speed. Then the sink node calculates the contribution of each sensor to each segment. Finally, in the *scheduling phase*, the sink node schedules sensors based on their contributions to the segments, aiming to maximize the surveillance quality of the given boundary curve but guaranteeing the permanent network lifetime.

A. SPACE-TIME PARTITIONING PHASE

In this phase, sink node will perform two tasks: the space partitioning task and the time partitioning task. The following presents the details of the two tasks.

1) TASK I: SPACE PARTITIONING

In the space partitioning task, sink node will partition the boundary curve into several segments for reducing the calculation complexity. The sink node initially partitions the rectangle region R into a set of equal-sized grids. As a result, these grids partition the boundary curve C into a number of curve segments, as shown in Fig. 5.

Herein, we notice that the monitoring qualities of all points on a segment are considered to be identical. It is obvious that a grid with larger size can produce a larger segment and hence can better reduce the computational complexity. However, a large grid also leads to a problem that the calculation of monitoring quality of a segment is not accurate. The size of each grid should be small enough to satisfy the constraint that the sensing range of any sensor falling in a grid can fully cover that grid. To achieve this, the size of each grid must be smaller than and equal to $\frac{1}{\sqrt{2}}r_s$, as shown in Fig. 5.

With satisfaction of this condition, any sensor falling in one grid also indicates that the grid is fully covered by that sensor. Fig. 5. gives an example when the size of the grid edge is $\frac{1}{\sqrt{2}}r_s$. Since sensors s_1 and s_2 fall in the grid, they can fully cover the grid. Sensor s_3 does not fall in the grid, but it can also fully cover the curve segment. If the size of the grid edge is much smaller than $\frac{1}{\sqrt{2}}r_s$, more sensors can cover the curve segment, even if they do not fall in the grid. The impact of the grid size on performance will be further investigated in the simulation. Based on the partitioning, the monitoring quality of each segment will be measured, instead of measuring the monitoring quality of each point.

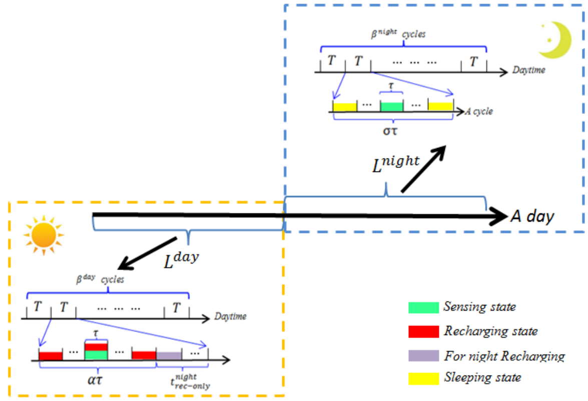


FIGURE 6. A cycle of daytime and nighttime.

2) TASK II: TIME PARTITIONING

In this task, the sink node will determine the slot length. Assume the solar cell capacity of a sensor is E. Herein, we notice that the sensor battery can only be recharged in the daytime. To support the energy for sensing in the nighttime, the battery should reserve some certain level of energy in the nighttime. Let E^{day} and E^{night} denote the battery capacities assigned to daytime and nighttime, respectively. Recall that t_{rec} and t_{sen} denote the required recharging time and the maximal sensing time, respectively. Their values can be calculated by

$$t_{rec} = \frac{E^{day}}{u_{rec}} \text{ and } t_{sen} = \frac{E^{day}}{u_{sen}}.$$

Recall that τ denotes the length of time slot. According to the recharging and discharging model, the length of t_{sen} is a slot length τ and the length of t_{rec} is $\alpha\tau$. Let L denote the length of a whole day. Recall that L^{day} and L^{night} denote the length of daytime and nighttime, respectively. Obviously, we have $L = L^{day} + L^{night}$, and they can be partitioned into a number of equal-length slots, as shown in Fig. 6.

B. COMPUTATION PHASE

This phase consists of two tasks: *cycle length calculation* and *sensing probability calculation.* Since the schedule of each sensor is cycle-based, the first task aims to calculate the length of a cycle. Then the second task calculates the detection probability of each sensor.

1) Task I: CYCLE LENGTH CALCULATION

The proposed *MSQ* algorithm is a cycle-based scheme. A cycle is composed of several time slots. Because the sensor cannot be recharged at night, each sensor not only needs to recharge its battery for their electricity energy consumption in the daytime, but also needs to recharge the reserved electricity energy consumption for the nighttime. Therefore, the work assigned to the sensor in the daytime is totally different to that in the nighttime. For each sensor, we notice that its schedules are identical for all cycles in the daytime while its schedules are also identical for all cycles in the nighttime. The proposed *MSQ* only needs to tackle the problem that how to schedule all sensors operating in a cycle of daytime and a cycle of nighttime.

Each sensor has three possible states in each cycle of daytime, namely sensing & recharging, recharging-only for daytime and recharging-only for nighttime. Let notation $t_{rec-only}^{night}$ denote the required recharging time aiming to be reserved for the night operations. A cycle of daytime consists of three parts, including $t_{sen\&rec}$, $t_{rec-only}$ and $t_{rec-only}^{night}$. Recall that T denotes the length of a cycle. We have

$$T = t_{sen\&rec} + t_{rec-only} + t_{rec-only}^{night} = \alpha\tau + t_{rec-only}^{night}. \quad (15)$$

Let notationt_{sleep} denote sleeping time which has $\sigma - 1$ slots in a cycle of the nighttime. Since a cycle in the nighttime consists of two parts: $t_{sen-only}$ and t_{sleep}, we have

$$T = t_{sen-only} + t_{sleep}= \sigma\tau. \quad (16)$$

Exp. (16) can be used to present a cycle of the nighttime. The lengths of cycles in daytime and nighttime are identical, as shown in Fig. 6. Herein, notations $t_{rec-only}^{night}$ and σ are two unknown variables needed to be calculated. According to the principle of electricity balance, we have

$$E^{night} = u_{rec}\beta^{day} t_{rec-only}^{night} = u_{sen}\beta^{night}\tau. \quad (17)$$

Recall that β^{day} and β^{night} denote the numbers of cycles in the daytime and nighttime, respective. Based on Exp. (17), the value of $t_{rec-only}^{night}$ can be derived.

$$t_{rec-only}^{night}= \alpha \left\lceil \frac{L^{night}}{L^{\text{day}}} \right\rceil \tau$$

According to Exps. (15) and (16), we have

$$\sigma = \alpha \left\lceil \frac{L^{night}}{L^{\text{day}}} \right\rceil .$$

As a result, the sink node finishes the calculations for the length of a cycle which is σ time slots in this task.

2) TASK II: SENSING PROBABILITY CALCULATION

In this task, the detection probability of each sensor to each segment will be calculated. As shown in Fig. 5, those grids which are passed through by the boundary curve are marked with yellow ink. Let g_k denote the k^{th} yellow grid counting from left boundary, and l_k denote the curve segment in grid g_k. The boundary curve C can be represented as a set of m consecutive curve segments $C = \{l_1, l_2, \ldots, l_m\}$. Let $p(s_j, l_k)$ denote the probability of sensor s_j detecting an event occurred at segment l_k. Let $\delta_{j,k}^{far}$ denote farthest point on curve segment l_k from sensor s_j. That is,

$$\delta_{j,k}^{far} = arg \max_{v\in l_k} d\left(v, s_j\right).$$

For simplicity, the sink node selects $\delta_{j,k}^{far}$ as the representative point of l_k and the probability $p(s_j, l_k)$ will be calculated based on this point, as shown in Fig. 5. A probability sensing model presented in Exp. (1) will be applied to calculate the probability $p\left(s_j, \delta_{j,k}^{far}\right)$ for approximating the value of $p\left(s_j, l_k\right)$. That is,

$$p\left(s_j, l_k\right) = p\left(s_j, \delta_{j,k}^{far}\right). \quad (18)$$

So far, the sensing probability of each sensor to each segment can been obtained. If the sensing probability of a sensor s_j to a segment l_k is larger than zero, sensor s_j has surveillance contribution to the segment l_k. Let S_k denote the set of sensors which have contribution to curve segment l_k. That is,

$$S_k = \left\{s_j | p\left(s_j, l_k\right) > 0\right\}.$$

As a result, the sink maintains S_k for each segment l_k for the use of later phase.

When we finished calculation of the length of a cycle T and the probabilities $p\left(s_j, l_k\right)$ for each segment, the next step is to perform the scheduling phase. The following summarizes the presented operations of Space-Time Partitioning Phase and the Computation Phase.

Fig.7. presents the designed operations for space-time partitioning and computation phase. The space-time partitioning phase mainly consists of two tasks: space partitioning and time partitioning. In space partitioning task, the boundary curve is partitioned into a number of curve segments as shown in the steps 1 to 8. In time partitioning task, the main objective is to obtain the length of time slot which is the smallest time unit in step 9. Step 10 further calculates the ration α between recharging time period and discharging speed. The computation stage also consists of two tasks: cycle length calculation and sensing probability calculation. Steps 11 and 12 mainly calculate the length T of a cycle. Steps 13 to 16 calculate the sensing probability of each sensor to each segment. The sink will finally construct the set S_k which includes all sensors that can cover segment l_k, and update $p\left(s_j, l_k\right)$ of each sensor in S_k.

C. SCHEDULING PHASE

The phase aims to schedule each sensor for maximizing the surveillance quality of the given boundary curves. The key idea is to prior allocate the unscheduled sensor to improve the surveillance quality of the bottleneck segment. However, the sensor recharging and discharging constraints should be satisfied, as shown in Exps. (10), (11), (12), (13) and (14). That is, each sensor can only work for one time-slot in a cycle, and will be recharged in the rest time slots.

In the conceptual level, the scheduling is cycle-based. That is, for each sensor, the schedules of different cycles are

Procedure: ***Space-Time Partitioning Phase and Computation Phase***

Inputs:
1. A boundary curve C lies on rectangle R
2. A set of sensors $S = \{s_1, s_2, \ldots, s_n\}$ deployed randomly in rectangle area R
3. The physical location (x_j^s, y_j^s) of each sensor s_j where $s_j \in S$
4. The physical location (x_i^v, y_i^v) of each point v_i on curve C.
5. The length of each grid is less than $\frac{1}{\sqrt{2}} r_s$

6.The solar power features: $E, E^{night}, E^{day}, u_{rec}, u_{sen}, L^{night}, L^{day}$

Outpts: $p(s_j, l_k), T$

```
/* Space Partitioning */
Partition R into c1 × c2 grids;
k = 1;
For(p = 1; p ≤ c1; p++) {
   For(q = 1; q ≤ c2; q++){
      If ( grid g(p,q) intersects with curve C ) {
         g(p,q) → g_k;
         set the curve segment in the grid g_k to be l_k;
         k++;  }}}
/* Time Partitioning */
         τ = t_sen = E^day / u_sen;
         α = u_rec / u_sen;
/* Cycle length calculation*/
         σ = α ⌈L^night / L^day⌉;
         T = στ;
/* Sensing Probability Calculation*/
For(j=1; j ≤ n; j++){
  For(k=1;k≤ m; k++){
      p(s_j, l_k) = p(s_j, δ_{j,k}^far) ;
      If (p(s_j, l_k) > 0) {
         S_k = S_k ∪ {s_j};
         update p(s_j, l_k);   }}}
```

FIGURE 7. **Procedure of Space-Time Partitioning Phase and Computation Phase.**

identical. The curve segments of the given boundary curve C and the time cycle can be treated as a two-dimensional space-time point. Each space-time point will be assigned with a surveillance quality value based on the scheduled sensors. This phase mainly consists of two tasks. The first one aims to identify the bottleneck point of the two-dimension space-time points. Then, the second one aims to schedule the best sensor to be stayed in working state for improving the surveillance quality of the bottleneck point. The following presents the designs of the two tasks.

1) TASK I: IDENTIFICATION OF THE "BOTTLENECK POINT"

Let $T = \{t_1, \ldots, t_h, \ldots, t_\sigma\}$. Consider a particular curve segment, say l_k. Let $a_{k,h}$ denote time-space point associated with curve segment l_k at time-slot h.Given a certain time point t, let S^{un_sch} denote the sets of sensors that have been unscheduled. Let $S_{k,*}^{un\_sch}$ denote sensor set which can cover curve segment l_k but has not yet been scheduled to any time-slot. Let $S_{*,h}^{sch}$ denote the set of sensors which have been scheduled to time slot h. Let $S_{k,h}^{sch}$ denote the set of sensors which have been scheduled for monitoring segment l_k at time-slot h. That is,

$$S_{k,*}^{un-sch} = \left\{ s_j | s_j \in S_k \cap S^{un-sch} \right\} \tag{19}$$

$$S_{k,h}^{sch} = \left\{ s_j | s_j \in S_k \cap S_{*,h}^{sch} \right\} \tag{20}$$

Initially, all sensors are not scheduled. That is,

$$S_{k,*}^{un\_sch} = S_k.$$

It is obvious that

$$S_{k,h}^{sch} = \emptyset$$

holds in the initial time. Let $u_{k,h}$ denote the surveillance quality of space-time point $a_{k,h}$. The value of $u_{k,h}$ is determined by the cooperative detection probability. As shown in Exp. (21), the value of $u_{k,h}$ is measured by the probability contributed from any sensor $s_j \in S_{k,h}^{sch}$ which can detect the event occurred at $a_{k,h}$.

$$u_{k,h} = 1 - \prod\nolimits_{s_j \in S_{k,h}^{sch}} \left(1 - p\left(s_j, l_k\right)\right) \tag{21}$$

Let $a_{\hat{k},\hat{h}}^{weakest}$ denote the bottleneck point of boundary curve C. The $a_{\hat{k},\hat{h}}^{weakest}$ can be obtained by applying Exp. (22).

$$a_{\hat{k},\hat{h}}^{\text{weakest}} = arg \min_{1 \le k \le m, 1 \le h \le \sigma} u_{k,h} \tag{22}$$

It is noted that the number of bottleneck points might be more than one. This condition can be occurred in several starting time slots. Let $A^{weakest}$ denote the set of all bottleneck points. The Task II will select one sensor with largest contribution from $A^{weakest}$ to enhance the surveillance qualities of the bottleneck point.

2) TASK II: SCHEDULING THE SENSOR FOR "THE BOTTLENECK"

This task is performed round by round until the surveillance quality of boundary curve C cannot be further improved. In each round, the major work aims to select one sensor with the largest contribution for improving the monitoring quality of the bottleneck point in set $A^{weakest}$. The selected sensor should satisfy the following three criteria.

(i) The sensing range of that sensor should cover the bottleneck points.
(ii) The sensor should be unscheduled.
(iii) The contribution of this sensor to the bottleneck point should be maximal.

The input of each round is the bottleneck point set $A^{weakest}$ of previous round. The task II will be terminated if the surveillance qualities of all points in $A^{weakest}$ can not be further improved. In each round, the sink node will recalculate the improved surveillance quality of each bottleneck point when a new selected sensor participates in monitoring task. Let $u_{k,h}^{s_j}$ denote the updated surveillance quality of the space-time point $a_{k,h}$. The value of $u_{k,h}^{s_j}$ can be calculated by applying Exp. (23).

$$u_{k,h}^{s_j} = 1 - \prod\nolimits_{s \in S_{k,h}^{sch} \cup \{s_j\}} \left(1 - p\left(s, l_k\right)\right) \tag{23}$$

The surveillance qualities of all bottleneck space-time points $a_{\hat{k},\hat{h}}^{weakest}$ can be predicted when different sensors join to monitor these points. Let s^{best} denote the best sensor that has maximal contribution to improve the surveillance quality of bottleneck set $A^{weakest}$. We have,

$$s^{best} = arg \max_{s_j \epsilon S_k^{un-sch}, a_{\hat{k},\hat{h}} \in A^{weakest}} \left(u_{\hat{k},\hat{h}}^{s_j} - u_{\hat{k},\hat{h}} \right). \tag{24}$$

Let S_{temp}^{best} denote the set of best sensors s_j^{best} that satisfy Exp. (24). In case that there is only one sensor in set S_{temp}^{best}, the proposed MSQ will allocate the best sensor s_j^{best} to stay in sensing state for improving the surveillance quality of the bottleneck space-time point $a_{\hat{k},\hat{h}}^{weakest}$. It is possible that more than one sensor play the role of s_j^{best} because that many sensors might have identical contributions to the bottleneck point.

In this case, the proposed MSQ mechanism will further check the other advantages contributed by each of these sensors. That is, the MSQ will select the sensor that can cover the maximal number of curve segments other than l_k at time-slot h, as shown in Exp. (25).

$$s^{best} = arg \max_{s_j \in S_{temp}^{best}} \underset{1=<k<=m}{count} \left(s_j \in S_k \right) \tag{25}$$

where the $count(s_j)$ is a function which returns the number of segments covered by sensor s_j. The sensors which satisfy Exp. (25) will be retained in the candidate set S_{temp}^{best}. In case that there are still more than one sensor in set S_{temp}^{best}, Exp. (26) will be further applied to select the best sensor which has maximal total contributions of all segments at time-slot $\hat{h}$.

$$s^{best} = arg \max_{s_j \in S_{temp}^{best}} \sum_{k=1}^{m} \left(u_{k,\hat{h}}^{s_j} - u_{k,\hat{h}} \right) \tag{26}$$

If Exp. (26) does not uniquely determine the best sensor s^{best}, the one with the smallest sequence number in set S_{temp}^{best} is selected as s^{best}. As a result, the best sensor s^{best} can be identified.

Let $a_{\hat{k},\hat{h}}^{s^{best}}$ denote the space-time point for which the best sensor s^{best} is arranged. The improved bottleneck point $a_{\hat{k},\hat{h}}^{s^{best}}$ can be expressed by Exp. (27).

$$a_{\hat{k},\hat{h}}^{s^{best}} = arg \max_{a_{\hat{k},\hat{h}} \in A^{weakest}} u_{\hat{k},\hat{h}}^{best} \tag{27}$$

Based on Exp. (27), the weakest segment has been found and the sensor s^{best} has been arranged to stay in the sensing state for improving the surveillance quality of space-time point $a_{\hat{k},\hat{h}}^{s^{best}}$. Since sensor s^{best} has been scheduled, the sensor set S^{un_sch} will be updated by applying the following operation.

$$S^{un\_sch} = S^{un\_sch} \setminus \{s^{best}\}.$$

Exps. (19) and (20) further update the unscheduled sensor set $S_{k,*}^{un\_sch}$ and the scheduled sensor set $S_{k,\hat{h}}^{sch}$ of the bottleneck space-time point $a_{\hat{k},\hat{h}}^{s^{best}}$.

$$S_{k,*}^{un\_sch} = S_{k,*}^{un\_sch} \setminus \{s^{best}\}, \ if \ s^{best} \in S_k,$$

Procedure : Scheduling Phase

Inputs:
1. The sensing probability $p(s_j, l_k)$, $\forall s_j \in S_k, \forall l_k \in C$;
2. The time-slot set $T = \{t_1, \ldots, t_h, \ldots, t_\sigma\}$ in a cycle
3. A two-dimension space-time point $a_{k,h}$ associated with segment l_k at time-slot h;
4. The sensor set S_k which can cover curve segment l_k;

Outputs:
1. S^{un_sch} denote the sets of sensors that have been unscheduled
2. S_h^{sch} denote the set of sensors which have been scheduled to time slot h
3. $u_{k,h}$ denote the surveillance quality of the space-time point $a_{k,h}$

/* Identification of the bottleneck point */
$S_{k,*}^{un\_sch} = S_k$;
$S_{*,h}^{sch} = \emptyset$;
$S_{k,h}^{sch} = \emptyset$;
For (each space-time point $a_{k,h}$){
  Calculate $u_{k,h}$ according to Exp. (21) ;
  Calculate $a_{\hat{k},\hat{h}}^{weakest}$ according to Exp. (22) ;
  $A^{weakest} = A^{weakest} \cup \{a_{\hat{k},\hat{h}}^{weakest}\}$; }
Repeat {
/* Scheduling the sensor for the bottleneck point*/
  For (each sensor $s_j \in S_k^{un\_sch}$){
    Calculate $u_{k,h}^{s_j}$ according to Exp. (23);
    Calculate s^{best} according to Exp. (24);
    $S_{temp}^{best} = S_{temp}^{best} \cup \{s^{best}\}$; }
  If ($|S_{temp}^{best}| > 1$)
    For (each sensor $s_j \in S_{temp}^{best}$)
      If s_j does not satisfy Exp. (25)
        $S_{temp}^{best} = S_{temp}^{best} \setminus \{s_j\}$;
  If ($|S_{temp}^{best}| > 1$)
    For (each sensor $s_j \in S_{temp}^{best}$)
      If s_j does not satisfy Exp. (26)
        $S_{temp}^{best} = S_{temp}^{best} \setminus \{s_j\}$;
  Let s^{best} be the one with the smallest sequence number in set S_{temp}^{best};
  Calculates $a_{\hat{k},\hat{h}}^{s^{best}}$ according to Exp. (27);
  Calculates $u_{\hat{k},\hat{h}}^{s^{best}}$ according to Exp. (28);
  $S_{k,*}^{un\_sch} = S_{k,*}^{un\_sch} \setminus \{s^{best}\}$, if $s^{best} \in S_k$;
  $S_{k,\hat{h}}^{sch} = S_{k,\hat{h}}^{sch} \cup \{s^{best}\}$, if $s^{best} \in S_k$;
Until (Exp. (29) holds)

FIGURE 8. Procedure of the scheduling phase.

$$S_{k,\hat{h}}^{sch} = S_{k,\hat{h}}^{sch} \cup \left\{ s^{best} \right\}, \ if \ s^{best} \in S_k.$$

As shown in Exp. (28), the sink node should also update the surveillance qualities of all the segments which are covered by s^{best}.

$$u_{k,\hat{h}}^{s^{best}} = 1 - \prod_{s^{best} \in S_{k,\hat{h}}^{sch}} \left(1 - p\left(s^{best}, l_k \right) \right), if \ s^{best} \in S_k \tag{28}$$

Since the surveillance qualities of all the segments covered by sensor s^{best} have been updated. A new weakest space-time point set $A^{weakest}$ will be recalculated by applying Exp. (22). The next round will be started to find another best sensor to improve the surveillance qualities of points in set $A^{weakest}$. The task II will be terminated if the following condition (29)

TABLE 1. Simulation parameters.

Monitoring Area	$20m \times 200m$
Number of Sensors	$300-700$
Sensing Radius	$5m$–$20m$
Communication Radius	Twice of sensing radius
Deployment	Randomly
Grid Size	$2m$–$6m$
Recharging Rate	20 units /hour
Discharging Rate	80 units/hour

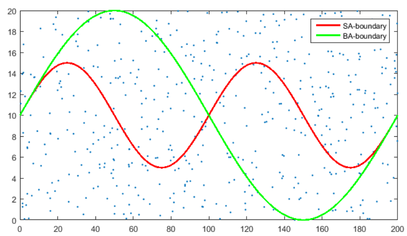


FIGURE 9. Small Amplitude(SA) and Big Amplitude(BA) boundaries.

holds.

$$u_{\widehat{k},\widehat{h}}^{s_j} = u_{\widehat{k},\widehat{h}}, \forall s_j \in S^{un\_sch}, \forall a_{\widehat{k},\widehat{h}}^{weakest} \in A^{weakest} \tag{29}$$

Fig. 8 summarizes the operations of scheduling phase. This phase mainly consists of two stages: identification of the bottleneck point and scheduling the sensor for the bottleneck point. Steps 1 to 3 initialize the sets including $S_k^{un\_sch}$, S_h^{sch} and $S_{k,h}^{sch}$. Steps 4 to 7 find out the set of bottleneck points which have minimal surveillance quality. Steps 9 to 12 choose the best sensors which have maximal contribution to improve the surveillance qualities of the bottleneck points. Steps 16 to 21 further identify the best sensor if the number of candidates of s^{best} is larger than one. Step 22 identifies the bottleneck space-time point which plays the role of bottleneck point. Step 23 further updates the surveillance quality after the best sensor joins the sensing work. Steps 24 and 25 update the schedule and unscheduled set of sensors, respectively. The process of scheduling one sensor for the weakest bottleneck point will be repeated executed until no sensors in unscheduled sensor set can improve the boundary surveillance quality, as shown in step 27.

V. SIMULATION

This section compares the performance of the proposed MSQ against the existing Top-down One-coverage Barrier Approach (TOBA) and Branch Mechanism (BRA). The BRA algorithm [9] can find a maximal number of distinct k-barriers each of which is composed of minimum number of sensors. Based on the developed CA-Net, a decentralized approach, called TOBA [10], is presented to address the k-barrier coverage problem with the purposes of energy-balance and maximal lifetime. The following firstly shows the simulation model and then discusses the simulation results.

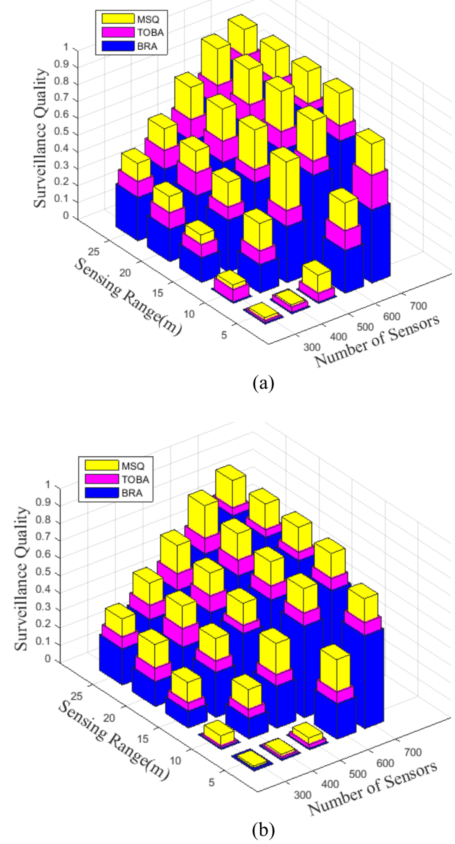


FIGURE 10. Performance comparison of MSQ, TOBA and BRA in terms of surveillance quality by deploying different number of sensors and considering different sensing radiuses. (a) SA-boundary. (b) BA-the boundary.

A. SIMULATION MODEL

The simulation parameters are given in Table 1. There are two different amplitude boundaries in 20m × 200m monitoring area as shown in Fig. 9. The first one is called small amplitude boundary, or called SA-boundary in short, while the second one is called big amplitude, or called BA-boundary in short. A number of sensors, ranging from 300 to 600, are randomly deployed in monitoring area. The communication radius is twice of the sensing radius which is ranging from 5m to 20m. The grid size is set ranging from 2m to 6m. The recharging and discharging rates of the solar battery are 20 units/hour and 80 units/hour, respectively. That is to say, the ratio of recharging over discharging time periods is 4, and the cycle length is 5 time slots.

B. SIMULATION RESULTS

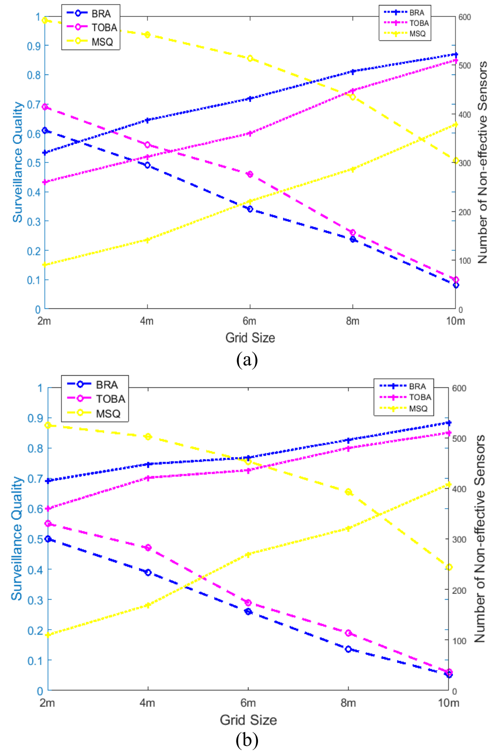
Fig. 10 compares the surveillance quality of the boundaries under the condition of different numbers of sensors and different sensing radiuses. As shown in Fig. 10, the surveillance qualities of the three compared algorithms significantly increase with number of sensors. This occurs because more sensors can participate in the monitoring task in each time slot, resulting in higher surveillance qualities. Fig. 20 also shows the impact of sensing radius on surveillance quality.

Since a larger sensing radius results in a larger coverage area, the surveillance quality is increased with the sensing radius. In comparison, the proposed MSQ outperforms the other two methods, in terms of surveillance quality. This occurs because that the proposed MSQ selects the sensors which are closer to the boundaries. Based on the probabilistic sensing model, the selected sensors have larger contributions to the surveillance quality. The existing TOBA and BRA aimed to select the minimal number of sensors for constructing the 1-barrier. This policy can save the total energy consumption for constructing a barrier. However, the selected sensors might not have largest contributions to the boundaries. As a result, the MSQ achieves the best performance, as compared with the other two existing algorithms.

The proposed barrier coverage mechanism is a centralized algorithm. Since the size of monitoring region and the location of each sensor is known, the algorithm can partition the monitoring region into a number of equal-sized grids. By labeling each grid with coordinates, our algorithm can easily calculate the grid in which each sensor falls. The grid size can impact the performance of our algorithm. In fact, the coverage contribution of each sensor depends on the total area size of the covered grids. Therefore, grids with small size can increase the coverage contribution of each sensor. However, the computing complexity for grids with small size is high. In this paper, the edge of each grid is set at $\frac{1}{\sqrt{2}}r_s$, where r_s, denotes sensing radius. This can guarantee that each sensor can full cover the grid it falls in. Fig. 11 aims to measure the impact of the grid size on the surveillance quality and the number of non-effective sensors.

Herein, we notice that the effective sensors represent the sensors which can fully cover the segment partitioned by the grids. Sensors which are not effective are called non-effective sensors. These sensors cannot participate in the monitoring task because that the grid scheme and segmentation scheme are applied in existing and this works, respectively. In general, the surveillance quality will be decreased with the number of non-effective sensors. As shown in Fig. 11, the growth of the grid size reduces the number of effective sensors and hence leads to lower surveillance quality. This trend can be generally found in the performance results of the three compared algorithms. This occurs because that fewer sensors can fully cover the grid when the grid size grows. Consequently, fewer sensors can play the role of effective sensors. In comparison, the proposed MSQ outperforms the existing TOBA and BRA in terms of surveillance quality. This occurs because that TOBA and BRA aimed to simplify the computation and hence they set up more constraint for the effective sensors, as compared with the proposed MSQ. This also implies that the number of candidate sensors for constructing *1*-barrier is reduced with the grid size.

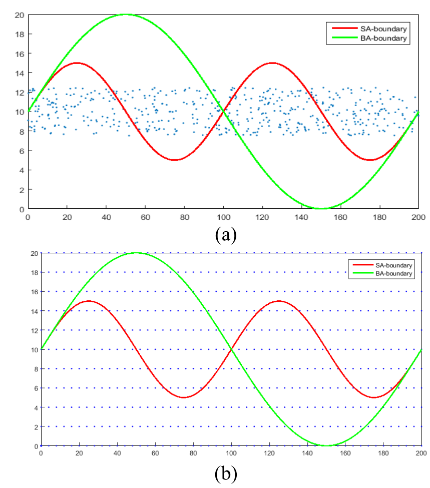
In addition to the random deployment as shown in Fig. 9, Figs. 12(a) and 12(b) show two more deployments, called centralized and uniform deployments, respectively, using 500 sensor nodes. The centralized deployment mainly deploys sensors around the center line, as shown in Fig. 12(a),



(a)

(b)

FIGURE 11. Performance comparison of MSQ, TOBA and BRA in terms of surveillance quality and the number of effective sensors by varying different grid sizes. (a) SA-boundary. (b) BA-boundary.



(a)

(b)

FIGURE 12. Two different boundaries (SA-Boundary and SB-Boundary) are monitored by centralized, uniform deployment sensors. (a) Centralized deployment sensors. (b) Uniform deployment sensors.

while the uniform deployment deployed sensors uniformly as shown in Fig. 12(b). Three algorithms, including the existing TOBA, BRA and the proposed MSQ, are compared in terms of surveillance quality.

Fig. 13 compares the surveillance quality using random, centralized and uniform deployment policies. The number of sensors is ranging from 300 to 700. As shown in Fig. 13(a), the surveillance qualities of the proposed MSQ using three deployment policies applied to SA-Boundary and

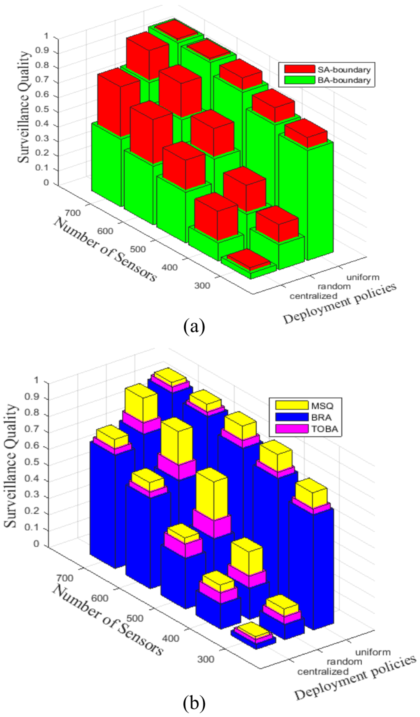


FIGURE 13. **Performance comparison of boundary surveillance quality by applying different deployment policies and varying the number of sensors. (a) Using *MSQ* to compare SA-boundary and SB-boundary. (b) Using SA-boundary to compare *MSQ*, *TOBA* and *BRA*.**

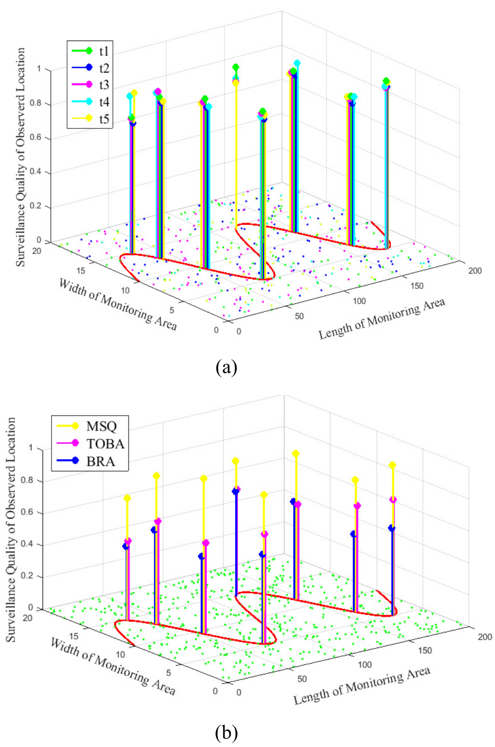


FIGURE 14. **Performance comparison of surveillance quality by randomly selecting points for SA-boundary. (a) Different time slots of *MSQ*. (b) Different algorithms.**

BA-Boundary are measured. The performance SA-Boundary is obviously better than that of BA-Boundary in all cases. This occurs because that the large amplitude of BA-Boundary

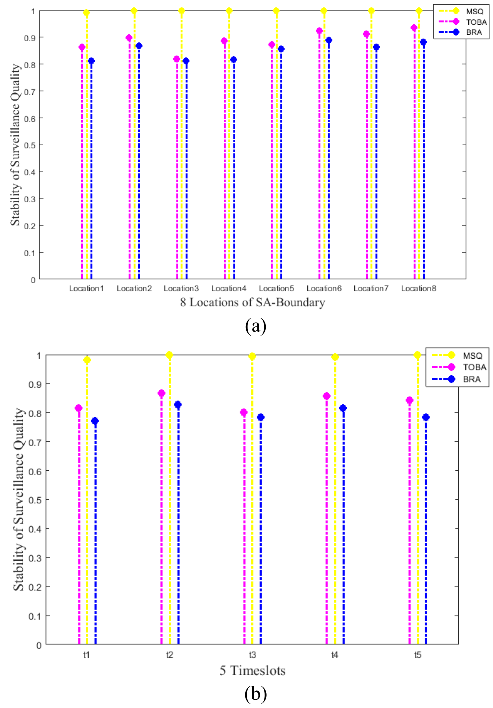


FIGURE 15. **Performance comparison of the surveillance quality stability at each time-space point on the SA-boundary. (a) Stability of each observed location (o_j, for $1 =< j <= 8$). (b) Stability of each observed timeslot (o_i, for $1 =< i <= 5$).**

leads to the segments to be widely distributed. As a result, the segments are difficult to be covered by the deployed sensors. Fig. 13(b) compares the surveillance qualities of MSQ, TOBA and BRA algorithms using different deployment policies. In general, three algorithms have similar trend that the uniform deployment policy obtains the best result while the centralized deployment policy results in the worst result. This occurs because that sensors deployed by applying uniform policy can uniformly monitor any location of the boundary since all sensors are uniformly distributed over the region. However, the uniform deployment is costly and not practical in real applications, as compared with the random deployment. The MSQ algorithm outperforms the other two existing algorithms in all cases, especially for random deployment scenario. This occurs because that the proposed MSQ adaptively considers the boundary location with the weakest surveillance quality and prior arranges sensors to improve its surveillance quality.

Fig. 14 investigates surveillance quality of randomly selected 8 points on the SA-boundary when 500 sensors are randomly deployed in a monitoring region. The sensing radius of each sensor is set at 20m. Fig. 14(a) shows the surveillance qualities of the selected 8 points by applying the proposed MSQ. The surveillance qualities of the selected monitoring points are similar. It implies that the proposed MSQ supports good stability of surveillance qualities. This occurs because that the MSQ concerns the bottleneck of the surveillance qualities in the two dimensional space-time points and select the sensor with the best contribution to the bottleneck point. The selection policy helps balance the surveillance qualities of different space-time points and hence supports good stability of surveillance qualities. Fig. 14(b) further compares the surveillance qualities of the proposed MSQ and existing TOBA, BRA and MSQ. The observed boundary locations and time slots are identical to those of Fig. 14(a). The major difference between Figs. 14(a) and (b) is that Fig. 14(b) only compares the weakest surveillance quality of one cycle (containing five time slots) for these observed locations. As shown in Fig. 14(b), the proposed MSQ has better balance of the surveillance quality of each time-space point on the SA-boundary.

Fig. 15 further compares the stability of surveillance quality of each time-space point on the SA-boundary. The observed time-space points are identical to those as shown in Fig. 14(a). The stability of surveillance quality can be measured by the difference degree of surveillance quality for a given n slots or a given m locations. Let $x_{i,j}$ denote the surveillance quality of j-th location at i-th time slot. The stability of the j-th location for n timeslots is defined by o_j, where

$$o_j = \frac{\left(\sum_{i=1}^{n} x_{i,j}\right)^2}{n \sum_{i=1}^{n} x_{i,j}^2}.$$

Similarly, the stability of the$i$-th slot on m locations is defined by o_i, where

$$o_i = \frac{\left(\sum_{j=1}^{m} x_{i,j}\right)^2}{n \sum_{j=1}^{m} x_{i,j}^2}.$$

The value of the stability approaching to 1 indicates that the surveillance qualities of n segments are similar. On the contrary, the value of the stability approaching to 0 indicates that the surveillance qualities of n segments are different.

Fig. 15 compares the stability of 8 locations of SA-boundary. The proposed MSQ outperforms the other two existing algorithms in terms of stability and almost achieves 1 for all observed locations. This occurs because that MSQ prior schedules sensor to improve the surveillance quality of the weakest time-space point. Fig. 15(b) further compares the stability of each timeslot of one particular observed cycle for the selected 8 locations. Similar to the result of Fig. 15(a), the proposed MSQ outperforms the other two existing algorithms in terms of the stability of each time slot for the SA-boundary.

VI. CONCLUSION

This paper proposes a barrier coverage algorithm, called *MSQ*, aiming at maximizing the surveillance quality of a given boundary curve by appropriately scheduling a set of solar-powered sensors. The proposed *MSQ* applies the probabilistic sensing model and additionally considers the issue that recharging additional energy in daytime for sensors working at night. To maintain the sensor networks with perpetual lifetime, each sensor should be carefully scheduled such that the cooperative surveillances among sensors can achieve maximal quality. To reduce the computational complexity, the monitoring region and boundary curve are partitioned into grids and segments, respectively. Then proposed scheduling algorithm identifies the segment with weakest surveillance quality and schedules the sensor which has maximal contribution to that segment. Experimental studies show that the proposed *MSQ* achieves better performance than existing TOBA and BRA in all cases in terms of surveillance quality.

The proposed mechanism has a wide range of applications. In the border monitoring, it can detect illegal immigrants crossing the border. In security monitoring of the communities or hospitals, it can monitor the people illegal entering dangerous regions. However, the proposed mechanism also has its limitations in real applications. One limitation is that the sensors should be homogenous. This constrains the application of our mechanism in monitoring a complex environment where different types of sensors are needed. Another limitation is the fixed sensing range of each sensor. This can result in no contribution to the monitoring task if the sensor is deployed far away the boundary curve. The future work would consider the issues of heterogeneous sensors and the sensors with adjustable sensing range.

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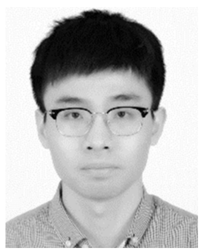

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