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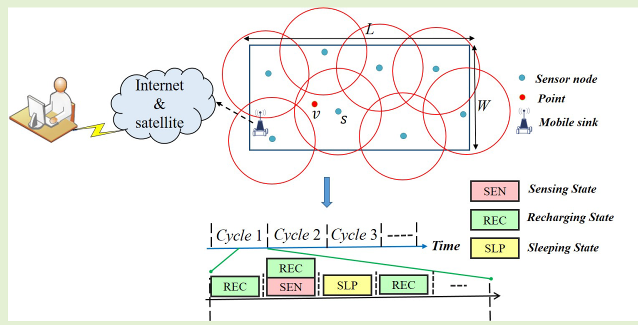
MSQAC: Maximizing the Surveillance Quality of Area Coverage in Wireless Sensor Networks

Bhargavi Dande, Chih-Yung Chang, *Member, IEEE*, Wen-Hwa Liao, *Member, IEEE*, and Diptendu Sinha Roy

***Abstract*—In wireless sensor networks (WSNs), area coverage is an important issue that aims to schedule a minimal number of sensors to cover the given monitoring area without any hole. Many of the existing strategies investigated that sensors are battery powered and considered Boolean Sensing Model (BSM). However, BSM affects the actual sensing quality since it did not consider the physical characteristics of the sensor. This study proposed an area coverage algorithm called *MSQAC*, which considers the rechargeable sensors and utilizes solar-powered energy. The proposed mechanism aims to maximize the surveillance quality for a given monitoring area by applying the Probabilistic Sensing Model (PSM). Two issues have been investigated while designing the *MSQAC* algorithm. The first one is the energy discharging rate of each sensor is larger than the energy recharging rate. Thus, how to better utilize the recharged energy by scheduling the right sensor in the right working time is a big challenge. The second challenge is the contribution of each sensor with or without cooperation is different by considering the PSM. If the neighboring sensors are scheduled at work in the same time slot, they can be treated as the combination set of neighboring sensors. It is another big challenge to find the best combination set of sensors for each space point at each time slot such that the minimal monitoring quality can be maximized. Through extensive simulations, it is shown that *MSQAC* yields the best performance in terms of monitoring quality (*QoM*), coverage ratio and fairness index.**



***Index Terms*—Area coverage, probabilistic sensing model, solar-powered sensors, wireless sensor network.**

I. INTRODUCTION

WIRELESS sensor network (WSN) is very important since it has number of applications such as health care [1], [2], smart home [3], [4] as well as monitoring and tracking [5]–[7]. Based on the application requirements, the network coverage can be categorized into barrier coverage, target coverage and area coverage. The barrier coverage [8] aims to surveil the boundary curve and detect the invalid crossing of intruders. The target coverage usually aims to monitor a set of specific objects, such as some important exhibition in museums and warehouses, which stores food and weapons [9]. Different from them, the area coverage aims to schedule a minimal number of sensors to cover the monitoring region without any hole. There were many algorithms proposed in the literature [10]–[12] that aimed to solve the area coverage issue. These studies considered the static sensors, which were densely deployed in the monitoring region. Most of them scheduled the sensors aiming to maximize the coverage and prolong the network lifetime. However, they did not consider the perpetual lifetime. Besides, most of them considered the Boolean Sensing Model (BSM), which considered the sensing area of each sensor as a perfect disk. However, the BSM was not practical because that it cannot reflect the physical characteristics of the actual sensing quality. Some other studies considered the Probabilistic Sensing Model (PSM), which evaluated the sensing ability based on the detection probability of each sensor. In the PSM, the detection probability of a certain point, which is monitored by a group of sensors is larger than that which is monitored by only one sensor. That is to say, a good schedule in PSM should consider the cooperation of sensors.

In addition to the sensing model, another important parameter that highly impacts the monitoring quality (QoM) is

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the lifetime of each sensor. Sensors are battery-constrained devices since they have limited energy. If a sensor runs out of the battery, it will die without performing any other operation in the network. Therefore, efficiently scheduling the sensors has become one of the major bottleneck issues to enhance the lifetime of a given WSN. To overcome the limited lifetime constraint, studies [13]–[18] considered battery recharging technologies, aiming to achieve the perpetual network lifetime. In literature, the battery recharging technologies [13]–[18] were further divided into two types: energy transferring [13]–[15] and environmental energy harvesting technologies [16]–[18]. The energy transferring technologies transferred the power from the transmitter device to the receiver device wirelessly. In general, the transmitter devices were mobile chargers which were periodically visited all the sensor nodes and recharged them, aiming to achieve a perpetual lifetime. However, the traveling path of the mobile chargers was very long, leading to the sensors buffer overflow or the mobile charger energy depletion.

The environmental energy harvesting technologies [16]–[18] were the potential way to solve the limited lifetime issue. Therefore, this paper utilizes environmental energy harvesting technology. Among the environmental resources, solar power is one of the best energy resources since the scale of sunlight is boundless [19]. Although solar power is a natural resource, its utilization leads to different difficulties. Since the battery capacity is limited and the energy discharging rate is usually larger than the energy recharging rate, the recharged energy of each sensor cannot support continuous working. Therefore, how to better utilize the recharged energy that scheduling the right sensor in the right working time is a key issue. Second, in the PSM, the contributions of each sensor with or without cooperation are quite different. The neighboring sensors scheduled to work at the same time slot can be treated as the combination set of neighboring sensors. According to the PSM, the monitoring quality of a fixed combination set of sensors can be determined. However, there are many combination sets of sensors for a given space point in the region at any time slot. It is another issue to find the best combination set of sensors for each space point at each time slot such that the minimal monitoring quality can be maximized.

According to the above-mentioned discussion, this study investigates the area coverage issue aiming to maximize the monitoring quality by adopting the PSM and utilizing the environmental energy harvesting technology. This paper proposes an algorithm called *Maximizing the Surveillance Quality of Area Coverage* or *MSQAC*, which mainly consists of three phases. In the *Space-Time Partitioning Phase*, the monitoring region is partitioned into several equal-sized grids and the timeline is divided into equal-length time slots. In the *Computation Phase*, the length of one cycle is calculated based on the recharging and discharging rates of one sensor. Then the detection probability of each sensor to each grid is calculated because the contribution of each sensor plays an important role in scheduling the sensors. In the *Scheduling Phase*, the *MSQAC* algorithm considers the cooperative working between the sensors and they are scheduled to maximize the surveillance quality aiming to achieve the perpetual life of the given network.

Most of the related works aimed to maximize the total area coverage quality. However, this policy might lead to the imbalanced monitoring quality of each point at any given time. This occurs because a point with minimal quality remains with the lowest monitoring quality while the other points with the higher quality obtain the monitoring quality improvements. Therefore, the proposed *MSQAC* finds the space-time point with the weakest monitoring quality and then schedules the sensor, which has the maximum detection probability to help improve the minimal monitoring quality of any point in the given area. Two main issues have been investigated while designing the *MSQAC* algorithm. The first one is scheduling the sensors by considering the cooperative working to maximize the minimal quality. To investigate this issue, the proposed *MSQAC* finds the space-time point with the weakest monitoring quality named "*bottleneck space-time point*" and then schedules the sensor, which has the maximum detection probability to maximize the monitoring quality of that bottleneck point. The second issue is to maintain the perpetual lifetime constraint of WSNs. That is to say, sensors are endlessly recharged to satisfy the constraint that the recharged energy can support energy consumption in each cycle. The proposed *MSQAC* calculates the cycle length based on the recharging and discharging rates of a sensor. Therefore, the energy management in the proposed *MSQAC* ensures that the sensor energy can always support the energy consumption for sensor working. The following gives the key contributions of this paper.

1) ***Developing the contribution-based strategy for cooperative sensing.*** Since the proposed *MSQAC* algorithm considered the PSM, the contribution of each sensor with or without cooperation is different. If the neighboring sensors are scheduled at work at the same time slot, they are treated as the combination set of these neighboring sensors. To find the best combination set of sensors for each space point at each time slot, the proposed algorithm calculates the cooperative detection probability of each sensor. Then the sensor with the largest contribution is scheduled to monitor it, aiming to improve the minimal quality of the given area.
2) ***Improving the minimal QoM based on the space-time transformed strategy.*** Different from the existing studies [17] and [18], the proposed algorithm adopts the space-time transformed strategy to maximize the minimal *QoM*. That is to say, the surveillance contribution of one space-time point is transformed to the other point. This strategy helps to improve the monitoring quality of bottleneck points in the given area.
3) ***The physical characteristics of the actual sensing quality are considered.*** Most of the existing works [16] and [18] adopted BSM to evaluate their sensing model. Since the sensing ability of BSM is perfect disk-shaped, it results in lower surveillance quality. The proposed *MSQAC* adopts the PSM, which can accurately measure the coverage impact from the physical characteristics of

sensors and explore the cooperative sensing opportunities among neighboring sensors.

4) ***Guaranteeing the perpetual network lifetime.*** Unlike [17] and [18], the proposed *MSQAC* calculates the cycle length based on the recharging and discharging rates of the sensor. Besides, the proposed scheme can guarantee that the recharged energy of each sensor is greater than the energy required for the sensor working in each cycle. Thus, the perpetual network lifetime can be achieved.

The remaining parts of this paper are organized as follows. Section II reviews the related works while section III presents the network environment and problem statement of this study. Section IV details the process of the proposed algorithm. Section V further evaluates the performance results of the proposed algorithm and section VI gives the conclusion of this paper.

II. Related Work

This section reviews the literature on area coverage issues in WSNs and compares the proposed *MSQAC* algorithm against the existing works. This literature is partitioned into three categories: area coverage issues [10]–[12], energy transferring technologies [13]–[15] and environmental energy harvesting technologies [16]–[18].

A. Area Coverage Issues

Study [10] assumed that static sensors could not cover all the space points in the given area, leading to the coverage holes. Thus, the mobile sensor nodes were deployed to visit the coverage holes. A mixed-integer linear programming formulation was proposed to determine the path taken by mobile sensor nodes aiming to maximize the area coverage. Another study [11] assumed that static sensor nodes could assist the mobile nodes in the task using a bidding protocol. This study proposed a distributed path planning and coordination technique for mobile sensor nodes. Chakraborty *et al.* [12] proposed an area coverage approach by considering the Euclidean distance between the sensors and the transmission range aiming to maximize the network reliability. Although the studies [10]–[12] prolonged the network lifetime by maximizing the coverage, all of them assumed that mobile sensor nodes could cover the coverage holes. However, the mobile sensor nodes always changed their position based on the requirement, which might lead to imbalanced monitoring quality in the network. Besides, they considered the BSM and cooperation between the sensors is not considered. In addition, their battery capacity is limited without considering the recharging of sensors. Therefore the network lifetime is limited, which is not perpetual.

B. Energy Transferring Technologies

In this category, the energy sources were mobile chargers, which were periodically visited all the sensor nodes and recharged them. Fu et. al [13] proposed a charging algorithm that aimed to consider the location for a charger to stop and decrease its cost of charging time. However, the mobile charger stopped at the sensor location before recharging it, which leads to a longer path length. Study [14] aimed to improve the usage of energy and coverage. This study proposed a collaborative algorithm, which allowed the mobile chargers to transfer energy between themselves. Another study [15] improved the charging utility by introducing the charging-oriented sensor placement. They jointly considered the optimized sensor positions and charger allocations, where a mobile charger visited the sensors to transfer the energy. This study utilized the area partition and charging energy discretization methods to formulate the utility maximization problem. All the above-mentioned algorithms highlight the improvement of energy unbalanced issues in wireless transferring technologies. For a huge static sensor network, studies [13]–[15] will result in higher hardware costs and visiting each sensor is not so practical because of the obstacle and the environmental problems. Additionally, the energy sources need a lot of time and consume vast energy for visiting each sensor individually.

C. Environmental Energy Harvesting Technologies

In the large-scale sensor network, visiting each sensor individually becomes impractical. Therefore, studies [16]–[18] perpetuated the network lifetime by adopting environmental energy harvesting technology. These studies allow each sensor to be rechargeable by an environmental energy source to avert energy depletion. In general, the scheduling mechanism of rechargeable WSNs scheduled the sensors to switch between active and sleep states to perpetuate the lifetime of WSNs by satisfying the desired area coverage requirement. Study [16] proposed an energy harvesting algorithm, called MSQ. This study applies the PSM and improves the sensing quality of the boundary line or curve. This mechanism firstly identified the bottleneck location and time of the sensor barriers, which have the lowest sensing quality. Then it scheduled the sensor to increase the quality of the bottleneck. The MSQ mechanism also monitored the barriers even at night by reserving some energy for the night. Although the aforementioned scheduling schemes investigated the environmental energy harvesting issue and developed for barrier coverage, they cannot be applied to area coverage.

Study [17] investigated the full area coverage issue by using the PSM in sensor networks. They investigated the mathematical relation between the two adjacent points in the given area. According to this assumption, the desired area coverage is transformed into a point coverage. Thereby, they designed the area coverage algorithm by dynamically selecting a group of sensors. Another study [18] adopted the reinforcement learning concept to schedule the sensors for area coverage (RLSSC) in rechargeable WSNs. This study adopted a two-stage sleep scheduling algorithm, which combines the precedence operator and Q learning. According to reinforcement learning, the RLSSC switches the sensors between active and sleep states to achieve full area coverage.

Studies [17] and [18] achieved the desired coverage by perpetuating the lifetime, but they did not ensure that the bottleneck point with the weakest monitoring quality will be maximized. Furthermore, cooperative sensing among the

TABLE I
COMPARISONS OF THE MSQAC WITH EXISTING WORKS

Related work	Rechargeable battery	Perpetual lifetime	Sensing and recharging simultaneously	Probabilistic sensing model	Maximizing the minimal surveillance quality of point
[13]	○	×	×	×	×
[14]	○	×	×	×	×
[15]	○	×	○	×	×
[16]	○	○	○	○	×
[17]	○	×	×	○	×
[18]	○	○	○	×	×
The proposed *MSQAC*	○	○	○	○	○

neighboring sensors was not considered. This paper proposed an algorithm called *Maximizing the Surveillance Quality of Area Coverage in Rechargeable* WSNs, named the *MSQAC* algorithm. The *MSQAC* considers the PSM and assumes that each sensor is solar-powered. Two issues have been investigated while designing the *MSQAC* algorithm. The first issue is to maximize the minimal quality of point by considering the cooperative working of all the sensors. To cope with this issue, the proposed *MSQAC* algorithm firstly considers the "*bottleneck space-time point*" and schedules the sensor, which has the maximum detection probability. The second issue is energy management for achieving the perpetual lifetime constraint. That is to say, sensors are endlessly recharged to satisfy the constraint that the recharged energy can support energy consumption in each cycle. Consequently, a point that has the weakest monitoring quality in the total area will be improved aiming to perpetuate the lifetime. Table I summarizes the comparisons between the *MSQAC* and the literature.

III. PRELIMINARY AND SYSTEM MODEL

The considered network model for the rechargeable WSNs and the problem statement of this paper are discussed in this section.

A. Network Environment

The considered monitoring region is denoted by R where the length and width are L and W, respectively. This paper assumes the set of n static sensors $S = \{s_1, s_2, \ldots, s_n\}$, distributed randomly over the given region R. The sensing and communication radiuses are denoted by r_s and r_c, respectively, where $r_c \geq 2r_s$. This study assumes that a mobile sink travels inside the network R for data collection. It also assumes that the mobile sink knows its location and the locations of all sensors in the network. A round is the time period required for the mobile sink starting from its original location, collecting data from all the sensors and returning to its original location. It is assumed that each sensor in each round generates that one data packet. This paper develops a scheduling algorithm that schedules sensors to work, recharge and sleep such that the maximum quality can be achieved while the network lifetime can be perpetual.

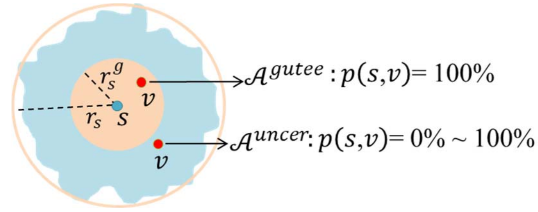

Fig. 1. The logical view of the PSM.

B. Sensing Model

The proposed *MSQAC* applies PSM to evaluate the detection probability of each sensor. Fig. 1. illustrates the logical view of the PSM. The sensing range of sensor s comprises of two zones: guaranteed zone $\mathcal{A}^{gutee}$ and uncertain zone $\mathcal{A}^{uncer}$, which are shown in light orange and light blue colors, respectively. Let r_s^g denote the radius of the region $\mathcal{A}^{gutee}$. If the red point v falls in $\mathcal{A}^{gutee}$, the detection probability of sensor s to the point v is 100%.

Let r_s denote the radius of the region $\mathcal{A}^{uncer}$. In case that the red point v falls in $\mathcal{A}^{uncer}$, the detection probability of sensor s to this red point v is reduced based on the distance between them, ranging from 100% to 0%.

Let $p(s, v)$ represent the detection probability of sensor s to the point v. Let $d(s, v)$ be the distance of sensor s and point v. The detection probability $p(s, v)$ of sensor s to the point v is shown in Exp. (1). The parameters λ and γ are the path-loss exponents.

$$p(s,v) = \begin{cases} 1, & if\ d(s,v) \leq r_s^g \\ e^{-\lambda(d(s,v)-r_s^g)^\gamma}, & if\ r_s^g < d(s,v) < r_s \\ 0, & if\ d(s,v) \geq r_s \end{cases} \quad (1)$$

In Exp. (1), the distance $d(s, v)$ can be obtained by applying the below expression, where the (x_v, y_v) are the coordinates of point v.

$$d(s,v) = \sqrt{(x - x_v)^2 + (y - y_v)^2}.$$

C. Recharging and Discharging Model

There are three possible states for each sensor in the daytime: recharging-only, sensing & recharging, and sleeping state. Meanwhile, there are two possible states for each sensor in the nighttime: sensing-only and sleeping state. Sensors staying in the sensing & recharging state will participate in the sensing and recharging operations at the same time. Once a sensor almost exhausts its energy, it will switch to the recharging-only or sensing & recharging states for energy recharge. When a sensor staying in a sensing-only state or sensing & recharging state, it will consume energy. The sensors will not perform any operations in the sleeping state, including recharging and sensing until it changes state.

Let τ represent the length of a mini slot. Let recharging and discharging rates are defined by the recharged energy and consumed energy of each sensor in each mini slot, respectively. Let E^{max}, u^{sen} and u^{rec} denote the maximum battery capacity, sensing discharging rate and recharging rate, respectively. The factors u^{sen} and u^{rec} highly impact the remaining energy of

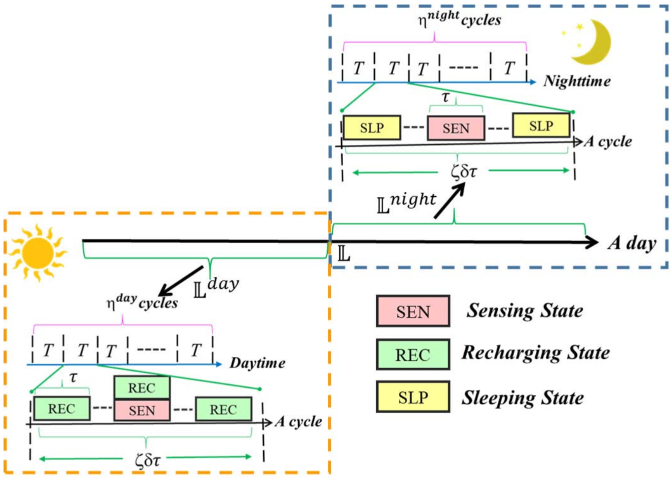

Fig. 2. An example of daytime and nighttime cycle.

each sensor. Let E^{min} denote the reserved energy for solar-panel activation and fixed energy value for transmission. That is, E^{min} is the energy threshold below which the sensor cannot work and should switch to recharging-only or sleeping states. The energy required for data transmission to the mobile sink is considered a fixed value. This is because there are many papers in the literature, which discussed the issue of data collection. Let t^{rec} denote the recharging time period which is the maximal time length required to fully recharge one sensor. Similarly, let t^{sen} denote the discharging time period which is the maximal time length that the sensor performs sensing task until its remaining energy is equal to E^{min}. The value of t^{rec} and t^{sen} can be calculated by applying Exp. (2).

$$t^{rec} = \frac{E^{max} - E^{min}}{u^{rec}} \text{ and } t^{sen} = \frac{E^{max} - E^{min}}{u^{sen}} \tag{2}$$

Let δ denote the ratio of sensing discharging rate u^{sen} to the recharging rate u^{rec}. The value of δ is shown in Exp. (3).

$$\delta = \left\lceil \frac{u^{sen}}{u^{rec}} \right\rceil = \left\lceil \frac{t^{rec}}{t^{sen}} \right\rceil \tag{3}$$

The value of δ is assumed to be an integer under the condition of $\delta \geq 1$. The time axis is divided into many cycles where each cycle is represented by T. Each cycle T is divided into σ mini slots and $\sigma = \delta + 1$. Fig. 2 presents the daytime and nighttime cycles. Let $\mathbb{L}$ denote the length of the whole day. As shown in Fig. 2, one day is partitioned into two intervals: daytime $\mathbb{L}^{day}$ and nighttime $\mathbb{L}^{night}$. That is to say, $\mathbb{L} = \mathbb{L}^{day} + \mathbb{L}^{night}$. Since the considered sensors are solar-powered, they cannot be recharged at nighttime. Therefore, the recharged energy in the daytime should be able to support the energy consumption of daytime and nighttime cycles. Let ζ denote the ratio of daytime to a whole day. We have,

$$\zeta = \left\lceil \frac{\mathbb{L}}{\mathbb{L}^{day}} \right\rceil$$

In the daytime, a sensor needs to be recharged for time-period $\delta\tau$ to support the working of one mini slot τ. That is,

$$T = \zeta t^{rec} = \zeta \delta \tau$$

For instance, $\mathbb{L}^{day} = \mathbb{L}^{night}$, then $\zeta = 2$. That is to say, each sensor needs to be recharged for $2\delta\tau$ in one cycle of daytime, one $\delta\tau$ is for sensing work in the daytime and the other $\delta\tau$ is reserved for supporting the nighttime working.

Let t_k represents the k-th mini slot. Let Boolean variables $\lambda_{i,k}^{sen}$, $\lambda_{i,k}^{rec}$ and $\lambda_{i,k}^{slp}$ represent the sensing, recharging and sleeping states of the sensor s_i at mini slot t_k. That is,

$$\lambda_{i,k}^{sen} = \begin{cases} 1, & if\ s_i\ performs\ sensing\ operation\ in\ t_k \\ 0, & otherwise \end{cases} \tag{4}$$

$$\lambda_{i,k}^{rec} = \begin{cases} 1, & if\ s_i\ performs\ recharging\ operation\ in\ t_k \\ 0, & otherwise \end{cases} \tag{5}$$

$$\lambda_{i,k}^{slp} = \begin{cases} 1, & if\ s_i\ sleeps\, in\ t_k \\ 0, & otherwise \end{cases} \tag{6}$$

For instance, if a sensor s_i is in the sensing & recharging state at a certain mini slot t_k. That is, $\lambda_{i,k}^{sen} = 1$, $\lambda_{i,k}^{rec} = 1$ and $\lambda_{j,k}^{slp} = 0$.

The following details the energy consumption model. Let E_s denote the energy cost for executing one sensing operation (generating k bits). Let n_i^{sen} denote the number of packets generated by each s_i in one cycle. The n_i^{sen} can be obtained by applying Exp. (7).

$$n_i^{sen} = \sum\nolimits_{t_k \in T} \lambda_{i,k}^{sen} \tag{7}$$

Let E_i denote the consumed energy of the sensor s_i, which is evaluated as shown in Exp. (8).

$$E_i = n_i^{sen} \times E_s \tag{8}$$

D. Problem Statement

The proposed *MSQAC* schedules the sensors by considering the cooperative working, aiming to maximize the minimal monitoring quality of any point in the given area. To cope with this problem, the proposed *MSQAC* algorithm firstly identifies the *bottleneck space-time point* and allocates the best sensor by calculating the cooperative detection probability of each sensor in each run. The other problem is energy management for achieving the perpetual lifetime constraint. That is to say, sensors are continuously recharged to satisfy the constraint that the recharged energy can support the energy consumption in each cycle. Consequently, a point that has the weakest monitoring quality in the total area will be improved.

Let x denote a feasible schedule. The set of feasible schedules are denoted by Φ. The following will discuss the calculation of monitoring quality under some schedule x at a given time t. Firstly, the monitoring quality of any given point υ will be discussed. Let a Boolean variable $\rho_{i,\upsilon}$ represent whether or not the sensor s_i can cover point υ. That is,

$$\rho_{i,\upsilon} = \begin{cases} 1, & if\ s_i\ can\ cover\ point\ \upsilon \\ 0, & otherwise \end{cases} \tag{9}$$

Let $S_{\upsilon,k}^{x}$ represent the set of sensors scheduled at t_k to monitor the point υ. We have

$$S_{\upsilon,k}^{x} = \left\{ s_i | \rho_{i,\upsilon} \times \lambda_{i,k}^{sen} = 1 \right\} \tag{10}$$

Recall that $p(s_i, \upsilon)$ denote the detection probability of sensor s_i to the point υ. Consider a space-time point (υ, k) where $\upsilon \in R$ and $k \in T$. The probability of all sensors $s_i \in S^x_{\upsilon,k}$, which cooperatively monitor the space-time point (υ, k) but is unable to detect an occurred event is

$$\prod\nolimits_{s_i \in S^x_{\upsilon,k}} (1 - p(s_i, \upsilon)).$$

Let $q_{\upsilon,k}$ denote the detection probability of point υ at mini slot t_k. The value of $q_{\upsilon,k}$ can be obtained from Exp. (11).

$$q_{\upsilon,k} = 1 - \prod\nolimits_{s_i \in S^x_{\upsilon,k}} (1 - p(s_i, \upsilon)) \tag{11}$$

Let q_υ denote the detection probability of point υ. This paper treats q_υ as the lowest monitoring quality (*QoM)* of point υ in all the mini slots, as shown in Exp. (12).

$$q_\upsilon = min_{t_k \in T} q_{\upsilon,k} \tag{12}$$

Definition: The *QoM* of the monitoring region is based on schedule x.

Based on the schedule x, let q^x_R denote the lowest *QoM* of any point in region R overall time instants t. The value of q^x_R can be evaluated by applying Exp. (13).

$$q^x_R = \min_{x \in \Phi, \upsilon \in R} q_\upsilon, \forall t \tag{13}$$

However, the number of points in R is infinite. This paper applies the grid-based approach to cope with this problem. The detail of this approach is presented in section IV. The proposed *MSQAC* maximizes the minimal *QoM* of the points in the given area under the constraint of the perpetual lifetime.

Objective function:

$$Max(q^x_R = \min_{x \in \Phi, \upsilon \in R} q_\upsilon, \forall t) \tag{14}$$

Exp. (14) should be achieved while satisfying the following constraints. The first constraint, which is shown in Exp. (15) ensures that each solar-powered sensor should stay either in the sensing state or recharging state or sleeping state at any given time.

1) State Constraint:

$$\left(\lambda^{sen}_{i,k} + \lambda^{rec}_{i,k}\right) \geq 1 \& \left(\lambda^{sen}_{i,k} + \lambda^{slp}_{i,k}\right) = 1 \& \left(\lambda^{rec}_{i,k} + \lambda^{slp}_{i,k}\right) = 1, \forall i, \forall k \tag{15}$$

As shown in Exp. (16), another constraint is the working constraint, ensuring that each sensor should participate in the sensing operation at least for one mini slot. This can guarantee that each sensor can contribute its coverage for achieving maximal surveillance quality.

2) Working Constraint:

$$\sum\nolimits_{k=1}^{\left\lceil \frac{T}{\tau} \right\rceil} \left(\lambda^{sen}_{i,k} \geq 1\right) \forall s_i \in S \tag{16}$$

Let E_r denote the energy supplement of a sensor in the recharging-only state. The perpetual lifetime constraint, which is shown in Exp. (17) ensures that the recharged energy of each sensor can support its consumption required for working in each cycle.

TABLE II
SUMMARY OF COMMON NOTATIONS

Symbol	Description
$p(s, \upsilon)$	The detection probability of sensor s to point υ
E^{max}	Maximum battery capacity
E^{min}	Reserved energy for solar panel activation
$S^x_{\upsilon,k}$	Set of sensors scheduling at t_k and cover point υ
$q_{\upsilon,k}$	Detection probability of point υ at t_k
$g_{(x,y)}$	Grid with coordinates (x, y)
E^{night}_i	Reserved energy of sensor s_i for nighttime
$q_{(x,y),j}$	The QoM value of the element $\mathcal{M}^{QoM}[(x, y), j]$
$\wp^{weak}_{(x,y),j}$	The bottleneck point with coordinates $(g^{weak}_{(x,y)}, t^{weak}_j)$
ST^{weak}	The set of all bottleneck points
G_z	The set of grids covered by the sensor s_z
$B^{best}_{(x,y),j}$	The maximum benefit to the bottleneck point
$s^{best}_{(x,y),j}$	A sensor with the highest probability to monitor grid $g_{(x,y)}$ at t_j
$c_{i,(x,y)}$	Surveillance contribution of sensor s_i to grid $g_{(x,y)}$
S^{sch}	Set of scheduled sensors
S^{un_sch}	Set of unscheduled sensors

3) Perpetual Lifetime Constraint:

$$\sum\nolimits_{t_k \in T} \lambda^{rec}_{i,k} \times E_r \geq \sum\nolimits_{t_k \in T} (\lambda^{sen}_{i,k} \times E_s) \forall s_i \in S \tag{17}$$

Since the sensors are solar-powered and each sensor needs to reserve the required energy for supporting the sensing operation executed in the nighttime. Let η^{day} and η^{night} denote the numbers of cycles in the daytime and nighttime, respectively. Recall that the notation E_i denote the consumed energy of the sensor s_i in each cycle. Let E^{night}_i represent the reserved energy, which supports sensor s_i in the nighttime. Therefore, E^{night}_i should be greater than the consumption of s_i in the nighttime as shown in Exp. (18).

4) Reserved Energy Constraint:

$$\eta^{night} \times E_i \leq E^{night}_i \tag{18}$$

Table II summarizes the common notations used in this paper. Section IV presents the details of the proposed *MSQAC* algorithm, which efficiently schedules the sensors to achieve the objective function (14) while satisfying the constraints given in (15), (16), (17) and (18).

IV. The Algorithm Description

This paper proposed an algorithm called *Maximizing the Surveillance Quality of Area Coverage* (*MSQAC*), which aims to maximize the minimal *QoM* of the points in the given area. The proposed *MSQAC* aims to efficiently schedule the working slots of each sensor such that cooperative monitoring helps the proposed mechanism to maximize the minimal *QoM*. The term surveillance quality means how well the sensors can improve the minimal quality of each point in the given monitoring area. That is to say, the surveillance quality of each point depends

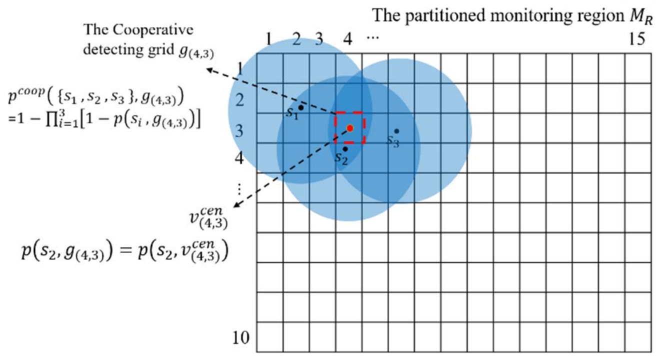

Fig. 3. A scenario where three sensors are cooperatively monitoring the grid $g_{(4,3)}$.

on the scheduling of sensors and their cooperative detection probability.

The proposed *MSQAC* is mainly partitioned into three phases, including the *Space-Time Partitioning Phase*, *Computation Phase* and *Scheduling Phase*. The first phase initially partitions the monitoring region R into several equal-sized grids and the time axis into equal mini-slots. The *Computation Phase* further calculates the cycle length and detection probability of each sensor to each grid. The *Scheduling Phase* firstly finds the bottleneck point and schedule the best sensor for monitoring it, aiming to maximize the minimal *QoM* of a given area while maintaining the perpetual lifetime constraint.

A. Space-Time Partitioning Phase

This phase aims to find the bottleneck points of all possible points and maximize the detection probability of bottleneck points in each cycle. However, the possible points in the monitoring area are infinite. To reduce computation complexity, the grid-based approach is adopted in this study. The region R is partitioned to m equal-sized grids. The detection probability of one sensor to all the points in one grid is considered to be identical. A grid with coordinates (x, y) is represented by $g_{(x,y)}$. Initially, the top grid which is on the left column is named (1,1). The value of x will be added by one if the grid is shifted to the right position from $g_{(x,y)}$. A similar rule will be applied in the y-coordinate. As depicted in Fig. 3, the region R is portioned into 15×10 grids. The sensors s_1, s_2 and s_3 are the three active sensors which are cooperatively detecting the grid $g_{(4,3)}$.

B. Computation Phase

One of the major works in this phase is to calculate one cycle length according to the recharging and discharging rates of one sensor. Then the detection probability of each sensor to each grid is evaluated.

Task I. Cycle Length Calculation: Since the solar-powered sensors cannot recharge at night, each sensor should recharge its battery for daytime working and reserve energy for nighttime working. In the proposed *MSQAC* algorithm, the scheduling of each sensor is cycle-based. That is, each sensor has an identical schedule in all the cycles. Thereby, the proposed *MSQAC* further scrutinizes the issue of scheduling all the sensors in one cycle of daytime and nighttime. Initially, each sensor deployed in the monitoring region will report its ID and location to the base station. Then the base station will apply the proposed algorithm to calculate the schedule of one cycle. The schedule of this cycle will be applied to every cycle. That is to say, every sensor has similar working, sleep and recharging behaviours. In one cycle, if all the time slots are scheduled for every space-time point, then the scheduling result is broadcasted to all sensors. Then all the sensors work in every cycle by following the schedule of the base station. If a node fails right after starting a cycle, the proposed algorithm schedules the other sensor nodes based on their detection probability instead of the failed nodes.

Recall, η^{day} and η^{night} represent the number of cycles in daytime $\mathbb{L}^{day}$ and nighttime $\mathbb{L}^{night}$. We have,

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

Recall E_i^{night} denote the reserved energy, which supports the working of the sensor s_i in the nighttime. The sensor s_i cannot use all the energy E^{max} in the daytime because it should reserve E_i^{night} for nighttime working. However, the reserved energy constraint given in Exp. (18) should be satisfied. Besides, the required energy for solar panel activation E^{min} should also be reserved. Thereby, the energy utilized by the sensor s_i in the daytime can be evaluated by applying Exp. (19).

$$\eta^{day}(E^{max} - E^{min}) - E_i^{night} \tag{19}$$

Let $\varphi_i^{daytime\_sen}$ represent the number of mini slots that the sensor s_i performs the sensing operation in the daytime. The value of $\varphi_i^{daytime\_sen}$ will be obtained by applying Exp. (20).

$$\varphi_i^{daytime\_sen} = \left\lfloor \frac{\eta^{day}\left(E^{max} - E^{min}\right) - E_i^{night}}{E_s} \right\rfloor \tag{20}$$

Recall that E_r denote the recharged energy of a sensor. The energy of a sensor that can be used in each mini slot is $\left(E_r - E^{min}\right)$. Let $\varphi_i^{daytime\_rec}$ is the number of mini slots that the sensor s_i recharges its battery in the daytime. That is,

$$\varphi_i^{daytime\_rec} = \left\lceil \frac{\eta^{day}\left(E^{max} - E^{min}\right) - E_i^{night}}{\left(E_r - E^{min}\right)} \right\rceil \tag{21}$$

Let $\gamma_i^{daytime}$ denote the ratio of recharging and discharging rate of the sensor s_i. The value of $\gamma_i^{daytime}$ is shown in Exp. (22).

$$\gamma_i^{daytime} = \left\lceil \frac{\varphi_i^{daytime\_rec}}{\varphi_i^{daytime\_sen}} \right\rceil \tag{22}$$

Therefore, the value of T can be calculated as shown in Exp. (23).

$$T = \gamma_i^{daytime} + 1 \tag{23}$$

Let $\gamma_i^{nighttime\_sen}$ denote the number of mini slots where the sensor s_i performs sensing operation in the nighttime.

The $\gamma_i^{nighttime\_sen}$ is evaluated according to Exp. (24).

$$\gamma_i^{nighttime\_sen} = \left\lfloor \frac{E_i^{night}}{E_s} \right\rfloor \tag{24}$$

To ensure the reserved energy that supports sensing operations in the nighttime, each sensor executes the sensing operation in one of the mini slots while satisfying the constraint given in Exp. (16) and remains in the sleeping state for the rest of the mini slots.

Task II. Detection Probability Calculation: The detection probability of each sensor to each covered grid is calculated in the following. Assume that grid $g_{(x,y)}$ is covered by the sensor s_i. The detection probability is determined by the size of the covered area of the grid $g_{(x,y)}$. If a grid $g_{(x,y)}$ is partially covered by s_i, the detection probability of sensor s_i to grid $g_{(x,y)}$ is 0. On the contrary, if a grid $g_{(x,y)}$ is fully covered by s_i, the detection probability is determined by the distance between s_i and the center point of the grid $g_{(x,y)}$.

Let $p\left(s_i, g_{(x,y)}\right)$ denote the detection probability of s_i to grid $g_{(x,y)}$. Let $v_{(x,y)}^{cen}$ represent the center point in the grid $g_{(x,y)}$, which is given below.

$$v_{(x,y)}^{cen} = arg \min_{v \in g(x,y)} d(v, s_i) \tag{25}$$

The point $v_{(x,y)}^{cen}$ is selected as the representative point of the grid $g_{(x,y)}$. According to Exp. (1), the value $p\left(s_i, v_{(x,y)}^{cen}\right)$ is calculated for approximating the value of $p\left(s_i, g_{(x,y)}\right)$. That is,

$$p\left(s_i, g_{(x,y)}\right) = p\left(s_i, v_{(x,y)}^{cen}\right) \tag{26}$$

Let ξ_i represent a Boolean variable denoting whether or not the sensor s_i is active. The value of ξ_i is calculated by applying Exp. (27).

$$\xi_i = \begin{cases} 1 & if\ s_i\ is\ active \\ 0 & otherwise \end{cases} \tag{27}$$

Let $\mathbb{C}_i$ denote the coverage range of sensor s_i. Let ∂_i represent a Boolean variable denoting whether or not the grid $g_{(x,y)}$ falls in $\mathbb{C}_i$. The value of ∂_i is shown in Exp. (28).

$$\partial_i = \begin{cases} 1 & if\ g_{(x,y)} \in \mathbb{C}_i \\ 0 & otherwise \end{cases} \tag{28}$$

Let $\Phi_{(x,y)} = \{s_1^{act}, s_2^{act}, \ldots, s_f^{act}\}$ represent the set of active sensors that fully covers the grid $g_{(x,y)}$. The sensor s_i will be included in $\Phi_{(x,y)}$ only if it satisfies the condition $\xi_i \times \partial_i = 1$. Let $p^{coop}\left(\Phi_{(x,y)}, g_{(x,y)}\right)$ represent the cooperative detection probability of all sensors in $\Phi_{(x,y)}$ to grid $g_{(x,y)}$, which is calculated by applying Exp. (29).

$$p^{coop}\left(\Phi_{(x,y)}, g_{(x,y)}\right) = 1 - \prod_{k=1}^{f} \left[1 - p\left(s_k^{act}, g_{(x,y)}\right)\right] \tag{29}$$

Let $c_{i,(x,y)}$ represent the sensing contribution of sensor s_i to grid $g_{(x,y)}$. The value of $c_{i,(x,y)}$ can be calculated as shown in Exp. (30).

$$c_{i,(x,y)} = \left(p^{coop}\left(\Phi_{(x,y)}, g_{(x,y)}\right)\right) - \left(p^{coop}\left(\Phi_{(x,y)} \backslash \{s_i\}, g_{(x,y)}\right)\right) \tag{30}$$

The next phase schedules the sensors based on their detection probabilities to the bottleneck points.

C. Scheduling Phase

This phase schedules a set of active sensors working in different time slots for monitoring the given area while the lifetime of each sensor can be perpetuated. The key concept is to schedule a sensor that has the maximum contribution. To achieve this, the scheduling phase consists of two tasks. The first one finds the bottleneck point based on the current schedule. The second task further schedules the most appropriate sensor to monitor the bottleneck point. However, all the constraints in Exps. (15), (16), (17) and (18) should be satisfied. The two tasks of this phase are repeatedly executed.

Task I. Finding the "Bottleneck Space-Time Point": First, the concept of space-time point will be presented. Recall that the monitoring region is divided into several equal-size grids, time line is partitioned into several cycles and each cycle consists of several mini slots. The proposed *MSQAC* aims to schedule some sensors for each grid at each mini slot, say grid $g_{(x,y)}$ and time slot t_j. The scheduled sensors will cooperatively work to provide the surveillance quality for grid $g_{(x,y)}$ and t_j. To ease the presentation, the following treat grid $g_{(x,y)}$ and t_j as one space-time point. That is, the proposed *MSQAC* should aim to schedule sensors to $g_{(x,y)}$ at time slot t_j. Two matrices including $\mathcal{M}_{m\times\eta}^{sch}$ and $\mathcal{M}_{m\times\eta}^{QoM}$ are adapted to maintain the current scheduling results and the corresponding *QoM* values. The space-time scheduling matrix is denoted by $\mathcal{M}_{m\times\eta}^{sch}$, where the size m represents the number of sensors and η represents the length of the cycle. The elements $\mathcal{M}^{sch}[(x,y), j]$ in $\mathcal{M}^{sch}$ represents the set of sensors scheduled to cover the grid $g_{(x,y)}$ at mini slot $t_j \in T$. The scheduling results of each bottleneck point of the grid $g_{(x,y)}$ at mini slot $t_j \in T$ is presented in the scheduling matrix.

According to the scheduling matrix $\mathcal{M}^{sch}$, each space-time point of the grid $g_{(x,y)}$ holds *QoM* value at mini slot $t_j \in T$. The *QoM* matrix is denoted by $\mathcal{M}_{m\times\eta}^{QoM}$ where the size m represents the number of sensors and η represents the length of the cycle. The elements $\mathcal{M}^{QoM}[(x,y), j]$ in $\mathcal{M}^{QoM}$ represents the *QoM* values of grid $g_{(x,y)}$ at mini slot $t_j \in T$. The *QoM* value of each space-time point of the grid $g_{(x,y)}$ at mini slot $t_j \in T$ is presented in the *QoM* matrix.

The *QoM* value of the element $\mathcal{M}^{QoM}[(x,y), j]$ is represented by $q_{(x,y),j}$ as shown in the following Exp. (31).

$$q_{(x,y),j} = 1 - \prod_{s_k \in \mathcal{M}^{sch}[(x,y),j]} \left(1 - p\left(s_k, g_{(x,y)}\right)\right) \tag{31}$$

Let $q_{(x,y),j}^{weak}$ denote the minimal value in $\mathcal{M}^{QoM}[(x,y),j]$, which can be calculated by applying Exp. (32).

$$q_{(x,y),j}^{weak} = \min_{q_{(x,y),j} \in \mathcal{M}^{QoM}[(x,y),j]} q_{(x,y),j} \tag{32}$$

Let $(g_{(x,y)}, t_j)$ represent the space-time point of M^{QoM} corresponding the grid $g_{(x,y)}$ at mini slot t_j. Let $\wp_{(x,y),j}^{weak}$ represent the weakest space-time point with the coordinates $(g_{(x,y)}^{weak}, t_j^{weak})$ corresponding to $q_{(x,y),j}^{weak}$ which is shown in Exp. (33).

$$\wp_{(x,y),j}^{weak} = (g_{(x,y)}^{weak}, t_j^{weak}), \quad \forall \wp_{(x,y),j}^{weak} \in ST^{weak} \tag{33}$$

Let ST^{weak} represent the set of weakest space-time points. That is,

$$ST^{weak} = \{\wp^{weak}_{(x,y),j} | \mathcal{M}^{QoM}[(x,y),j] = q^{weak}_{(x,y),j}\} \quad (34)$$

Finally, the ST^{weak} can be identified in this task.

Task II. Scheduling the Best Sensor for the "Bottleneck": The cooperative detection probability of bottleneck points $\wp^{weak}_{(x,y),j} \in ST^{weak}$ will be improved in this task. As shown in Exp. (35), the set of scheduled sensors is denoted by S^{sch}.

$$S^{sch} = \bigcup_{1 \le g_{(x,y)} \le m} \mathcal{M}^{sch}[(x,y),j] \; 1 \le j \le \left\lceil \frac{T}{\tau} \right\rceil \quad (35)$$

Similarly, the set of unscheduled sensors is denoted by S^{un_sch} as shown in Exp. (36).

$$S^{un\_sch} = S \backslash S^{sch} \quad (36)$$

Consider each unscheduled sensor $s_z \in S^{un\_sch}$. If sensor s_z is scheduled, the contribution to the $\mathcal{M}^{QoM}$ is evaluated in the following.

Let $b_{(x,y),j,z}$ denote the benefit of sensor s_z monitoring the grid $g_{(x,y)}$ at mini slot $t_j \in T$, which is shown in the Exp. (37).

$$b_{(x,y),j,z} = 1 - \prod_{s_k \in \mathcal{M}^{sch}[(x,y),j] \cup \{s_z\}} \left(1 - p\left(s_k, g_{(x,y)}\right)\right) - q_{(x,y),j} \quad (37)$$

Let $\zeta_{(x,y),j}$ represent a Boolean variable denoting whether or not a space-time point $(g_{(x,y)}, t_j)$ is in the ST^{weak}.

$$\zeta_{(x,y),j} = \begin{cases} 1 & if (g_{(x,y)}, t_j) \in ST^{weak} \\ 0 & otherwise \end{cases} \quad (38)$$

Let G_z represent the set of grids covered by the sensor s_z. Let $B^{weak}_{(x,y),j,z}$ represent the overall benefit of sensor s_z to the bottleneck points which belongs to the ST^{weak} is shown in Exp. (39).

$$B^{weak}_{(x,y),j,z} = \sum_{g_{(x,y)} \in G_z} b_{(x,y),j,z} \times \zeta_{(x,y),j} \quad (39)$$

Similar to Exp. (39), let $B^{non\_weak}_{(x,y),j,z}$ denote the overall benefit of sensor s_z to the non-bottleneck points which do not belongs to ST^{weak}. The value of $B^{non\_weak}_{(x,y),j,z}$ is shown in Exp. (40).

$$B^{non\_weak}_{(x,y),j,z} = \sum_{g_{(x,y)} \in G_z} b_{(x,y),j,z} \times \left(1 - \zeta_{(x,y),j}\right) \quad (40)$$

Let G denote the whole grids in the given monitoring area. The overall benefit of sensor s_z to QoM of $g_{(x,y)} \in G$ is shown in Exp. (41).

$$B_{(x,y),j,z} = \omega \left(B^{weak}_{(x,y),j,z}\right) + (1-\omega) B^{non\_weak}_{(x,y),j,z} \quad (41)$$

where ω denotes the weight controlling the importance of $B^{weak}_{(x,y),j,z}$ and $B^{non\_weak}_{(x,y),j,z}$.

Let $B^{best}_{(x,y),j}$ is the maximum benefit to the bottleneck point $(g^{weak}_{(x,y)}, t^{weak}_j)$ achieved by taking all possible $s_z \in S^{un\_sch}$ into account. That is,

$$B^{best}_{(x,y),j} = \max_{s_z \in S^{un\_sch}} B_{(x,y),j,z} \quad (42)$$

Let $s^{best}_{(x,y),j}$ represent the best sensor that achieves Exp. (42). We have,

$$s^{best}_{(x,y),j} = arg \max_{s_z \in S^{un\_sch}} B_{(x,y),j,z} \quad (43)$$

The $s^{best}_{(x,y),j}$ is the best sensor to maximize the specific bottleneck point $\wp^{weak}_{(x,y),j} \in ST^{weak}$. There may be more than one $\wp^{weak}_{(x,y),j}$ in ST^{weak}, the bottleneck point that acquires maximum benefit from $s^{best}_{(x,y),j}$ should be identified. The best sensor, denoted by s^{best}, which will be scheduled is shown in Exp. (44).

$$s^{best} = arg \max_{\wp^{weak}_{(x,y),j} \in ST^{weak}} B^{best}_{(x,y),j} \quad (44)$$

The maximum benefit acquired from all schedules to the bottleneck point in ST^{weak} is represented by $B^{best}_{(\hat{x},\hat{y}),\hat{j}}$.

$$B^{best}_{(\hat{x},\hat{y}),\hat{j}} = \max_{\wp^{weak}_{(x,y),j} \in ST^{weak}} B^{best}_{(x,y),j} \quad (45)$$

The best bottleneck point that acquires the maximum benefit from s^{best} is denoted by $\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}}$ which is shown in the Exp. (46).

$$\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}} = arg \max_{\wp^{weak}_{(x,y),j} \in ST^{weak}} B^{best}_{(x,y),j} \quad (46)$$

According to $\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}}$, the s^{best} is selected from S^{un_sch} to monitor the best bottleneck point.

$$\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}} = (g^{weak}_{(\hat{x},\hat{y})}, t^{weak}_{\hat{j}})$$

After finding the s^{best} and $\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}}$, the base station will schedule s^{best} to monitor the $\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}}$ which can improve the cooperative detection probability. Finally, s^{best} will be added in the scheduling matrix according to Exp. (47).

$$\mathcal{M}^{sch}\left[(\hat{x},\hat{y}),\hat{j}\right] = \mathcal{M}^{sch}\left[(\hat{x},\hat{y}),\hat{j}\right] \cup \{s^{best}\} \quad (47)$$

Thereby, the QoM matrix will update according to the Exp. (48).

$$\mathcal{M}^{QoM}\left[\left(\hat{x},\hat{y}\right),\hat{j}\right] = q_{(\hat{x},\hat{y}),\hat{j}} = 1 - \prod_{s_k \in \mathcal{M}^{sch}[(\hat{x},\hat{y}),\hat{j}]} \left(1 - p\left(s_k, g_{(\hat{x},\hat{y})}\right)\right) \quad (48)$$

Then, the s^{best} should be removed from S^{un_sch} as shown in Exp. (49).

$$S^{un\_sch} = S^{un\_sch} \backslash \{s^{best}\} \quad (49)$$

Finally, the sensor s^{best} should be added in S^{sch}.

$$S^{sch} = S^{sch} \cup \{s^{best}\} \quad (50)$$

The new $\wp^{weak}_{(x,y),j}$ will be repeatedly identified from ST^{weak}.

Fig. 4 depicts an example to illustrate the selection of s^{best} to monitor $\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}}$. We only consider the partial set of sensor $S = \{s_1, s_2, s_3, s_4\}$ that can cover the grids $g_{(1,1)}$, $g_{(2,1)}$ and $g_{(3,1)}$ in partitioned monitoring region. By applying the

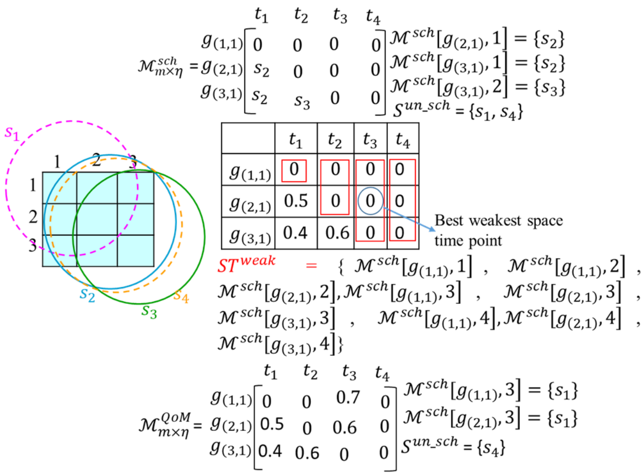

Fig. 4. The selection of s^{best} as s_1 to monitor the $\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}} = (g^{weak}_{(2,1)}, t^{weak}_3)$.

Exp. (42), the detection probability of each sensor to the grids $g_{(1,1)}$, $g_{(2,1)}$ and $g_{(3,1)}$ are calculated. As shown in Fig. 4, the sensors s_2 and s_3 are active and they are scheduled for monitoring the grids $g_{(2,1)}$ and $g_{(3,1)}$. The sensor s_2 monitor the grids $g_{(2,1)}$ and $g_{(3,1)}$ at t_1 and the sensor s_3 monitor grid $g_{(3,1)}$ at t_2. Since the sensor s_1 has very large contributions to the grids $g_{(1,1)}$ and $g_{(2,1)}$, it is scheduled to monitor the $\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}} = (g^{weak}_{(2,1)}, t^{weak}_3)$. The sensor s_4 has a very small coverage contribution to the grids $g_{(1,1)}$ and $g_{(2,1)}$ as compared with the sensor s_1. Therefore, the sensor s_1 is selected as s^{best} and it is scheduled to monitor $\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}}$. The values in $\mathcal{M}^{sch}[g_{(1,1)}, 3]$ and $\mathcal{M}^{sch}[g_{(2,1)}, 3]$ are updated accordingly.

Fig. 5 summarizes the process of the *MSQAC* algorithm. The computational complexity of the proposed algorithm is discussed in the following. The proposed *MSQAC* mainly consists of three phases. The *space-time partitioning phase* is summarized in steps 1 and 2 while the *computation phase* is summarized in steps 3 and 4. Finally, steps 5 and 6 summarize the *scheduling phase*. In the first phase, the partition of space and time takes constant time. Therefore, the complexity of steps 1 and 2 is O(1). The goal of the second phase is to calculate the cycle length and the detection probability of each sensor to each grid. In step 3, the calculation of cycle length takes constant time leading to the complexity of O(1). In step 4 the complexity of Exps. 26 and 29 are O($n * m$) and O(n), respectively. Therefore, the total complexity of the second phase is O($n * m$)+ O(n). In step 5, the complexities of Exps. (31) and (32) are O(m) and O($m * |T|$). In step 6, the complexities of Exps. (37), (46) and (48) are O($m * |T|$). In the worst case, the complexity of Exp. (42) is O(n). Therefore, the complexity of for loop in step 6 is O(n). Consequently, the complexity of the third phase is O(m)+ O($m * |T|$)+ O(n). In general, the number of sensors is much larger than the number of grids. Finally, the total complexity of all three phases of the proposed *MSQAC* is simplified as O($n * m$).

The *MSQAC* algorithm

Inputs:
1. Set of solar-powered sensors $S=\{s_1, s_2, \ldots, s_n\}$.
2. The solar power features: E^{max}, E^{min}, u^{sen}, u^{rec}, $\mathbb{L}^{day}$ and $\mathbb{L}^{night}$.

Outputs:
1. S^{sch} the set of scheduled sensors
2. $q_{(x,y),j}$ the *QoM* value of an element in $\mathcal{M}^{QoM}[(x, y), j]$.

Step 1. /* *Space Partitioning* */
Partition the R into m equal-sized grids;

Step 2. /* *Time Partitioning* */
$t^{sen} = \frac{E^{max}-E^{min}}{u^{sen}}$ and $t^{rec} = \frac{E^{max}-E^{min}}{u^{rec}}$; $\delta = \left\lceil\frac{u^{sen}}{u^{rec}}\right\rceil = \left\lceil\frac{t^{rec}}{t^{sen}}\right\rceil$;

Step 3. /* *Cycle length Calculation* */
$\eta^{day} = \left\lceil\frac{\mathbb{L}^{day}}{T}\right\rceil$, $\eta^{night} = \left\lceil\frac{\mathbb{L}^{night}}{T}\right\rceil$;
$\gamma_i^{daytime} = \left\lceil\frac{\varphi_i^{daytime\_rec}}{\varphi_i^{daytime\_sen}}\right\rceil$; $T = \gamma_i^{daytime} + 1$;

Step 4. /* *Detection Probability Calculation* */
If (grid $g_{(x,y)}$ is fully covered by the sensor s_i)
Calculates $p(s_i, g_{(x,y)})$ according to Exp. (26);
else if (grid $g_{(x,y)}$ is covered by a set of sensors $\Phi_{(x,y)}$)
Calculates $p^{coop}(\Phi_{(x,y)}, g_{(x,y)})$ as shown in Exp. (29);

Repeat {

Step 5. /* *Finding the "Weakest Space Time Point"* */
For (each element in $\mathcal{M}^{QoM}[(x, y), j]$){
Calculate $q_{(x,y),j}$ as Exp. (31);
Calculate $q^{weak}_{(x,y),j}$ according to Exp. (32);
$ST^{weak} = \{\wp^{weak}_{(x,y),j} | \mathcal{M}^{QoM}[(x, y), j] = q^{weak}_{(x,y),j}\}$;
}

Step 6. /* *Scheduling the Best Sensor for the "Bottleneck"* */
Repeat {
For (each sensor $s_z \in S^{un\_sch}$){
Calculate $b_{(x,y),j,z}$ as shown in Exp. (37);
Calculate $B^{best}_{(x,y),j}$ according to Exp. (42);
If (s_z satisfies Exp. (42)) { $s^{best}_{(x,y),j} = s^{best}_{(x,y),j} \cup \{s_z\}$ }
If ($|s^{best}_{(x,y),j}| = 1$) { $s^{best} = s_z$}
Else If ($|s^{best}_{(x,y),j}| > 1$)
Randomly select one sensor in $s^{best}_{(x,y),j}$ as the s^{best};
Calculates $\wp^{weak}_{(\hat{x},\hat{y}),\hat{j}}$ according to Exp. (46);
Calculates $q_{(\hat{x},\hat{y}),\hat{j}}$ according to Exp. (48);
$S^{un\_sch} = S^{un\_sch} \setminus \{s^{best}\}$, *if* $s^{best} \in S_z$;
$S^{sch} = S^{sch} \cup \{s^{best}\}$, *if* $s^{best} \in S_z$; }
}
}

Until S^{sch} is unchanged;

Fig. 5. The process of the MSQAC algorithm.

V. Performance Evaluations

The proposed *MSQAC* is compared with the existing area coverage algorithms *FCO* and *RLSSC*. The *FCO* [17] investigated the desired area coverage under PSM aiming at achieving a perpetual lifetime. The *RLSSC* algorithm [18] proposed an area coverage algorithm where the sensors operated in duty cycle mode for solar-powered sensor networks.

A. Simulation Environment

In the experimental study, the MATLAB R2019b is used as the simulation tool. The size of the considered area is $400m \times 400m$. To evaluate the experiments of this study, 300 to 700 sensors are deployed randomly. The value of r_s is considered from $5m$ to $25m$ where the r_c is twice of it. The size of the grid is adjusted between $2m$ and $10m$. The values of E^{max} and E^{min} are set at 1210J and 10J while u^{rec} and u^{sen} are set at 20 and 60 Joules /hour, respectively. Table III presents the simulation settings [18] of this study.

TABLE III
SIMULATION SETTINGS

Parameters	Values
Simulation tool	MATLAB R2019b
Monitoring region	$400\ m \times 400\ m$
Deployed sensors	300 – 700
r_s	$5m - 25m$
r_c	$2r_s$
Deployment	Random
Grid size	$2m$-$10m$
E^{max}	1210 Joule
E^{min}	10 Joule
u^{rec}	20 Joules/hour
u^{sen}	60 Joules/hour

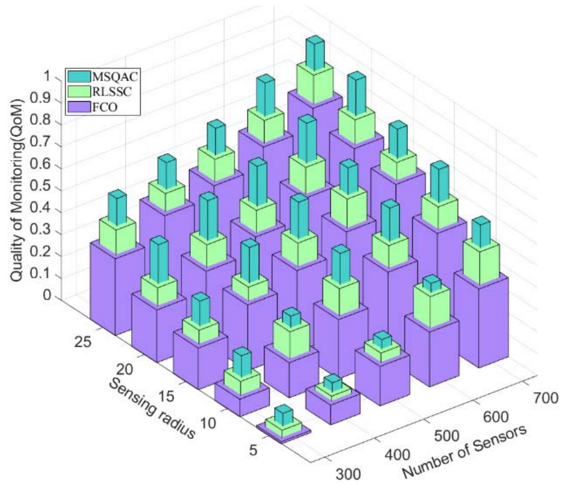

Fig. 6. Comparison of monitoring quality for MSQAC, RLSSC and FCO by varying the number of sensors and sensing radius.

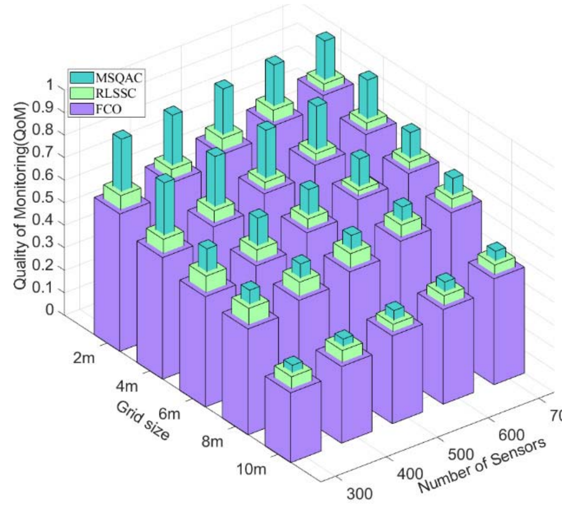

Fig. 7. Comparison of monitoring quality for MSQAC, RLSSC and FCO under the settings of different sensors and grid size.

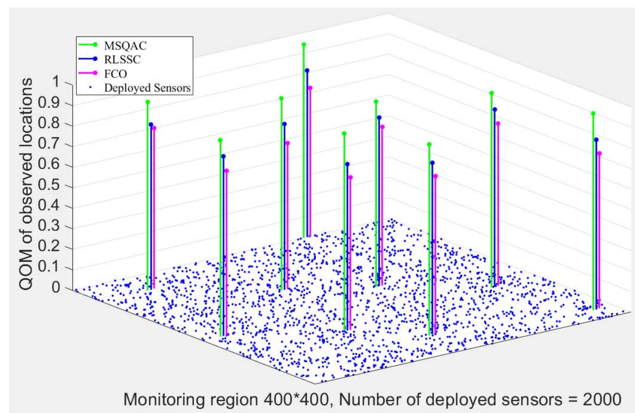

Fig. 8. Comparison of QoM for three algorithms by randomly selecting the locations.

B. Simulation Results

Fig. 6 presents the comparison of *MSQAC*, *RLSSC* and *FCO* in terms of monitoring quality (*QoM*). In this experiment, the number of sensors considered is 300 to 700 while the sensing radius of the sensors is set from $5m$ to $25m$. As depicted in Fig. 6, a common trend shows that *QoM* increases with the deployed sensors. A larger number of deployed sensors will increase the number of active sensors in each mini slot, which leads to higher monitoring quality. On the other hand, the *QoM* also increases with the sensing radius. Generally, a sensor with a larger sensing radius can cover a larger area, which increases the monitoring quality. The *MSQAC* firstly finds the bottleneck point and schedules an unscheduled sensor with the maximum contribution aiming to maximize the minimal *QoM*. Consequently, the *MSQAC* yields the best performance compared to the *RLSSC* and *FCO* algorithms.

Fig. 7 investigates the impact of grid size on monitoring quality. When conducting this experiment, the number of sensors deployed is 300 to 700 and the size of the grid is adjusted between $2m$ and $10m$.

The performance results of Fig.7 show that monitoring quality increases with the number of sensors and decreases with the grid size. This occurs because more sensors are required to cover a grid with a large size and hence leads to lower monitoring quality when the grid size grows. In comparison, the proposed *MSQAC* yields the best performance in terms of *QoM*, as compared to the *RLSSC* and *FCO*. This occurs because the proposed *MSQAC* calculates the probability of all sensors to the covered grid and schedules the sensor, which has the maximum detection probability aiming to improve the cooperative detection probability of each grid.

In Fig. 8, the experiment randomly selects nine locations from the monitoring region, aiming to have a closer observation on the performance of *MSQAC* in terms of the *QoM*. The size of the monitoring area considered in this experiment is $400m * 400m$ and the number of deployed sensors is 2000. The sensing range of solar-powered sensors is fixed at $20m$. Fig. 8 compares the monitoring qualities of the *MSQAC*, *RLSSC* and *FCO*. The *QoM* of the proposed *MSQAC* is almost similar in all the observed locations, which is approximating to 1. That is to say, there is no much difference in the *QoM* of the proposed *MSQAC* even though the observed locations are different. This occurs because the proposed *MSQAC* finds the bottleneck point and aims to maximize the minimal monitoring quality of that point rather than improving the total area coverage quality. This strategy increases the *QoM* of each bottleneck point, leading to a higher *QoM*.

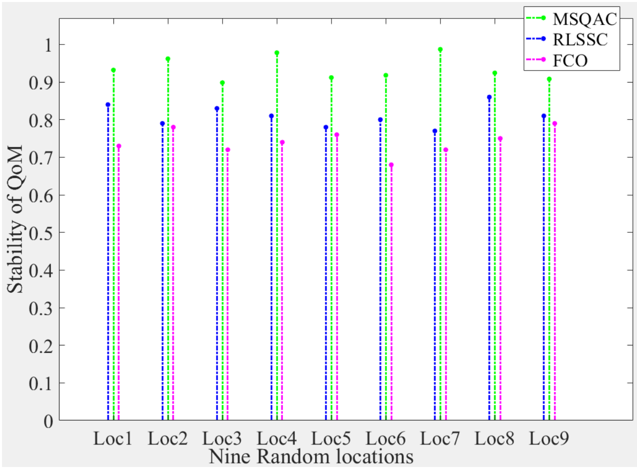

Fig. 9. Performance comparison of the stability of the QoM.

Fig. 9 further investigates the stability of the *QoM* of nine randomly selected locations in the monitoring region. The observed locations in Fig. 9 are similar to the nine locations observed in Fig. 8. The *QoM* stability is measured for υ locations. Let $q_{x,y}$ represent the *QoM* of the *y-th* location at the *x-th* mini slot. Let ς_x denote the *x-th* slot stability for υ locations, which is defined as shown in Exp. (51).

$$\varsigma_x = \frac{\left(\sum_{y=1}^{\upsilon} q_{x,y}\right)^2}{\upsilon \sum_{y=1}^{\upsilon} q_{x,y}^2} \tag{51}$$

As shown in Fig. 9, the value of stability is approximating to 1, which indicates that the *QoM* of the nine randomly selected space-time points in four mini slots have good *QoM* stability. The stability of nine observed locations for four mini slots is depicted in Fig. 9. A common trend, which can be seen in Fig. 9 is that the *MSQAC* yields the best performance in terms of *QoM* stability as compared with *RLSSC* and *FCO*. It is because the *MSQAC* takes into account the bottleneck points and schedule sensor which maximizes the cooperative detection probability of that point. Unlike *MSQAC,* the *RLSSC* and *FCO* improve the total area coverage quality rather than the minimal quality of the bottleneck point.

Fig. 10 depicts the comparison of *MSQAC*, *RLSSC* and *FCO* in terms of fairness index. The sensors deployed are 300 to 700 and the grid size is adjusted between 2*m* to10*m*. The *fairness index* $\varphi_{fairness}$ of *QoM* is defined in Exp. (52). Let n represent the number of sensor nodes and ϱ_i represent the monitoring quality of the sensor s_i. Fig. 10 illustrates a common trend where the fairness index increases with sensors. A large number of sensors will increase the number of active sensors in each mini slot, leading to a higher fairness index. Contrarily, the fairness indices of the three algorithms decrease with grid size. This occurs because more sensors are required to cover a large size grid. Therefore, the fixed number of sensors and the growth of the grid size decrease the fairness.

$$\varphi_{fairness} = \frac{\left(\sum_{i=1}^{n} \varrho_i\right)^2}{n \sum_{i=1}^{n} \varrho_i^2} \tag{52}$$

Fig. 11 compares the coverage ratio of three algorithms under the setting of number of sensors and sensing radius.

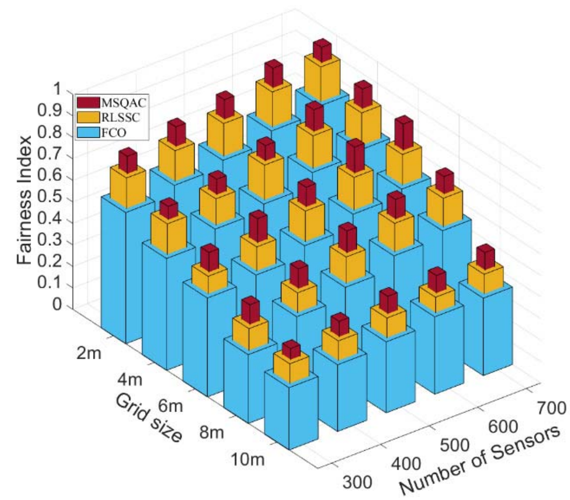

Fig. 10. Comparison of MSQAC, RLSSC and FCO in terms of fairness index.

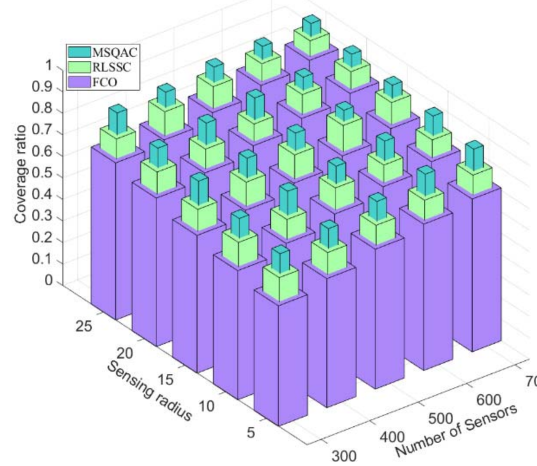

Fig. 11. Performance comparison of MSQAC, RLSSC and FCO in terms of coverage ratio under different sensors and sensing radius.

The number of sensors deployed is 300 to 700 and the sensing radius is adjusted between 5*m* and 25*m*. Fig. 11 depicts that, the coverage ratio grows with both the deployed sensors and radius. A large sensing radius can cover a larger area. Therefore, the monitoring quality of each point is increased, leading to a higher coverage ratio. Besides, when the deployed sensors are more, there are many sensors to work cooperatively in one mini slot, increasing the coverage ratio. Finally, the *MSQAC* outperforms *RLSSC* and *FCO* in terms of coverage ratio, as illustrated in Fig. 11. The proposed *MSQAC* firstly finds the bottleneck point and schedules an unscheduled sensor that has maximum contribution to the bottleneck point, aiming to maximize the minimal *QoM*. Consequently, the monitoring quality of the bottleneck point is significantly improved. Therefore, the proposed *MSQAC* significantly outperforms the *RLSSC* and *FCO* in terms of coverage ratio. Meanwhile, the coverage of the proposed *MSQAC* is relatively stable, as compared with the *RLSSC* and *FCO*.

Fig. 12 depicts the comparison of *MSQAC*, *RLSSC* and *FCO* in terms of *QoM* by applying centralized, random and

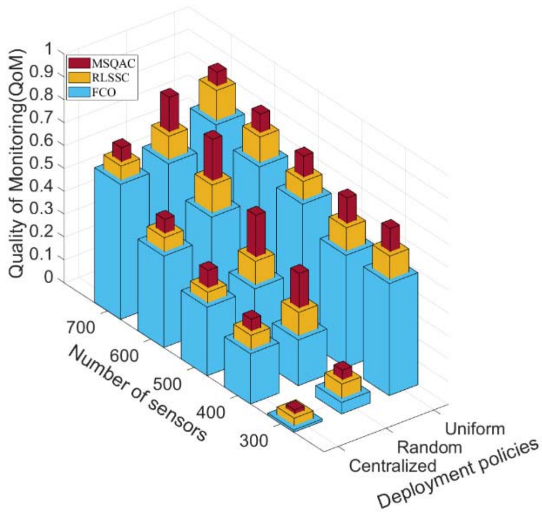

Fig. 12. Performance comparison of *QoM* in terms of number of sensors and deployment policies for *MSQAC*, *RLSSC* and *FCO*.

uniform deployment policies. The sensors deployed are 300 to 700. As illustrated in Fig. 12, the uniform deployment policy yields the best performance in all cases, as compared to the other two policies. This occurs because the uniform deployment of sensors can evenly monitor any point in the given monitoring area. However, compared with the random policy, the uniform policy is costly and is not practical in a real application. In comparison, the *MSQAC* outperforms the *RLSSC* and *FCO*, notably for random deployment policy. This occurs because the proposed *MSQAC* considers the bottleneck points and prior allocates a sensor to increase its cooperative detection probability.

VI. Conclusion

In this paper, an area coverage algorithm called *MSQAC* is proposed for rechargeable WSNs. The proposed *MSQAC* algorithm aims to maximize the minimal quality of any point in the given monitoring area. Two main issues have been investigated while designing the *MSQAC* algorithm. The first one is to maximize the minimal quality of point by considering the cooperative working of all the sensors. To investigate this issue, the *MSQAC* algorithm finds the "*bottleneck space-time point*" and schedules the sensor, which has the maximum detection probability. The second issue is to ensure that sensors are endlessly recharged to guarantee energy consumption in each cycle, aiming to achieve a perpetual lifetime. Experimental results present that the *MSQAC* yields the best performance compared to the *RLSSC* and *FCO* in all the cases. Future work is to develop the *MSQAC* by considering heterogeneous WSNs, which consist of different types of sensors. In addition, we will relax the constraints of this study while the sensing range of each sensor is adjustable.

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