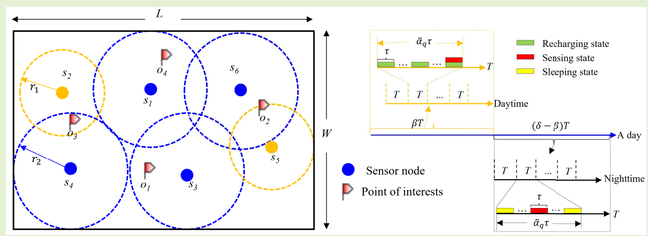
TCSAR: Target Coverage Mechanism for Sensors With Adjustable Sensing Range in WRSNs

Qiaoyun Zhang, Chih-Yung Chang, *Member, IEEE*, Zaixiu Dong, and Diptendu Sinha Roy

***Abstract*—In wireless rechargeable sensor networks (*WRSNs*), target coverage is an important issue. However, most studies assumed that the sensors were powered by battery with fixed sensing radiuses. Furthermore, most existing studies applied the Boolean Sensing Model (*BSM*) which cannot reflect the physical features of sensing. As a result, the detection accuracy was decreased in a real application. This paper proposes a target coverage mechanism, called *TCSAR*, which aims to maximize the surveillance quality of the point of interests (*POIs*) under the constraint of perpetual network lifetime. The proposed *TCSAR* applies the Probabilistic Sensing Model (*PSM*) and assumes that the sensing radius of each sensor is adjustable. The proposed mechanism consists of two phases. In the scheduling phase, the *TCSAR* initially evaluates the surveillance contribution of each sensor and then schedules the sensor with the maximal contribution to the bottleneck *POIs*. In the space time transformation phase, the surveillance quality for the *POIs* can be further improved by adjusting the sensing radius of some sensors from space dimension to time dimension. The experimental results show that the proposed mechanism outperforms the existing mechanisms in terms of the worst surveillance quality and the quality of monitoring.**



***Index Terms*—Target coverage, probabilistic sensing model, scheduling, wireless rechargeable sensor networks.**

I. Introduction

WIRELESS Sensor Networks (*WSNs*) can be applied in many applications, including intruder detection, traffic control, surveillance and environmental monitoring. A *WSN* consists of a large number of sensors which are responsible for sensing and are embedded with a battery. According to the network application requirement and feasibility, sensors can be deployed either randomly or deterministically [1]. In *WSNs*, coverage is one of the most important topics. In literature, the coverage issues can be further divided into three categories. First, the area coverage mainly concerns the surveillance quality of the entire monitoring area. Second, the barrier coverage aims to establish a defense barrier to detect the intruder crossing the boundary. The last one is the target coverage which aims to monitor some predefined targets and report if any suspicious event occurs near these targets. In the target coverage scenario, each interesting point must be covered by at least one sensor. There are many applications of *POIs* monitoring, including the monitoring of the key culture relics, military surveillance, and indoor guarding.

In literature, most studies concerned two issues for a given *WSN*: the lifetime and surveillance quality. Many studies discussed how to prolong the lifetime of a *WSN* because those sensors are generally powered by batteries which have limited energy [2], [3]. They focus on developing efficient sensors' scheduling mechanisms for energy management of the *WSNs*. Typically, there are two major operation states of each sensor: sleep and active states. In the sleep state, a sensor is sleeping to save energy. On the contrary, each sensor collects the information of the covered *POIs* in the active state. Therefore, the developed scheduling algorithms aim to alternate the modes of each sensor for providing the best surveillance for the predefined *POIs*. Therefore, the sensors' scheduling mechanisms play an important role which determines the lifetime and surveillance quality of a given network. However, the battery is restricted in terms of lifetime and requires to be replaced.

To obtain the perpetual lifetime of *WSNs*, recent studies [4]–[9] considered the Wireless Rechargeable Sensor Networks (*WRSNs*) and presented battery charging technolo-

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gies. They can be further divided into two categories: wireless energy transfer (*WET*) and environmental energy harvesting. In the *WET* category, Studies [4]–[6] assumed that the sensor's battery energy can be recharged wirelessly from recharger without the hassle of connecting cables to support the perpetual lifetime of the sensor. However, the *WET* always took a long time to charge all sensors and the recharger would consume much energy to visit all sensors, especially for a large-scale *WRSNs*.

Another energy harvesting takes advantages from the ubiquitous environmental energy sources [7]–[9]. It can provide an interminable and reliable energy for *WRSNs.* A sensor can be recharged by several possible renewable energy sources. Among these resources, the solar energy is more popular than others since it does not pollute the environment. The solar energy will never be used up as long as the sun does not go out, and the scale of sunlight is extensive. The sensors can be recharged by solar energy without charger moving toward any sensor because of the extensive scale of sunlight. Consequently, the sensor network can achieve the purpose of perpetual lifetime of a given *WRSN.*

In addition to the life time of a *WRSN*, another important issue is the surveillance quality which highly relies on the sensor detection model. In literature, many studies [10], [11] depicted a sensor detection effect applying deterministic Boolean Sensing Model (*BSM*) which is one of the most popular models. In BSM, sensor's sensing radius is defined as a circle which is centered at the location of the sensor. The sensing probability is a constant for any point falling in the circle. However, the BSM cannot reflect the physical features of sensing and the sensing accuracy will be decreased in a real application.

Recently, much research work [12]–[14] investigated the probabilistic sensing model (*PSM*). In this model, the sensing probability is not a constant for a point falling in the sensing range. Instead, the sensing probability is decreased with the sensing distance. The *PSM* is more practical to reflect the complex sensing probability of a sensor as compared to *BSM*.

This paper proposes a Target Coverage Mechanism for Sensors with Adjustable sensing Range in *WRSNs*, called *TCSAR*. The proposed *TCSAR* assumes that all sensors are powered by solar energy and their sensing radiuses are adjustable. A *PSM* is adopted since it is more practical than BSM. To support the continuous operations of sensors, the developed *TCSAR* schedules each sensor always staying in working or charging states in a duty cycle aiming to maximize the surveillance quality of *POIs* and maintain the perpetual lifetime of the given *WRSNs.* The proposed *TCSAR* consists of two phases: Scheduling Phase and Space Time Transformation Phase. In the Scheduling Phase, all sensors will be scheduled according to their sensing probabilities to the *POIs*. Then the new surveillance quality for each *POI* is recalculated. In the Space Time Transformation Phase, the surveillance quality for the *POIs* can be further improved by adjusting the sensing radiuses of some sensors from space domain to time domain.

The main contributions of the proposed *TCSAR* are listed as follows:

1) ***Achieving the perpetual lifetime of the WRSNs.*** The proposed *TCSAR* schedules all sensors staying in working or recharging states in a duty cycle to achieve the perpetual lifetime of *WRSN*. This algorithm can further ensure that the recharged energy of each sensor satisfies the consumed energy in each cycle.
2) ***Achieving high surveillance quality for POIs.*** The proposed *TCSAR* selects the best unscheduled sensor which has the maximum sensing probability and schedules the sensor to monitor the bottleneck *POI* that has the minimum surveillance quality, aiming to maximize the surveillance quality of the entire *WRSN*.
3) ***Using the space time transformation by adjustable sensing radius.*** The proposed *TCSAR* adjusts sensing radiuses of some sensors and uses a space time transformation to further improve the surveillance quality of the bottleneck *POI*.

The rest of this paper is organized as follows. Section II reviews the related work. Section III presents the network environment, sensing model, recharging and discharging model and problem formulation. Section IV gives detailed descriptions of the proposed *TCSAR* algorithm. Section V investigates the performance evaluation. Finally, section VI gives the conclusion.

II. Related Work

In literature, many studies have been proposed for target coverage. They can be divided into two categories: energy conservation and energy harvesting.

In energy conservation, some related studies assumed that each sensor was powered by battery which had limited energy and is difficult to be replaced. To save energy and improve the surveillance quality of a given *WSN*, much research work developed efficient scheduling algorithms for sensors. Studies [2] and [3] divided sensors into set covers which can collectively monitor all *POIs*. In addition, they proposed an activation schedule to calculate for each cover such that the lifetime of the *WSN* was maximized. Critically, these studies didn't consider recharging opportunities and limited battery energy.

To obtain the perpetual lifetime of *WSN*, some other studies [4]–[9] proposed energy harvesting to obtain the perpetual lifetime of the *WSNs*. In *WET*, study [4] considered that sensors could be recharged energy from mobile crowd energy resources. However, the mobile rechargers might be allocated unfair so that some sensors could not be recharged in time. Study [5] proposed the rechargers which were intentionally deployed in surroundings of sensors to prolong lifetime of sensors. To avoid energy holes, study [6] proposed an efficient recharging energy algorithm which used clustering and evolutionary approaches to avoid energy holes. However, the *WET* always took a long time to charge all sensors and the recharger would consume much energy to visit each sensor, especially for a large-scale *WRSN*. Critically, it could not ensure that each *POI* can be monitored by sensors at any time.

Many researchers have concentrated on the solar energy of environmental energy harvesting to power *WSNs*. Study [7] designed harvesting systems of solar energy to maintain long and perpetual operations. Study [8] and [9] considered the energy recharging issue which adopted the energy source of solar, aiming at finding the largest power point for a *WSN*. Study [10] proposed an adaptive energy management strategy which aimed to optimize energy management of a given *WSN*. These studies could optimize production and consumption of sensors according to the solar-energy. Study [11] put forward an innovative solution to solve the limited battery energy problem by utilizing the solar energy harvesting. However, they did not consider the cooperative sensing for different *POIs*.

In the above-mentioned research works, the sensing model mainly adopted the *BSM*, a rough approximation of the practical sensing model. While the *PSM* seems to be a more practical sensing model [12]. Study [13] studied sensing coverage for *PSM* which has the greater range of sensing compared to *BSM*. Based on *PSM*, it proposed an optimization algorithm to achieve high coverage and prolong the network lifetime. Study [14] proposed probabilistic sensor coverage which aimed to find the least sensors to improve the barrier coverage for *WSNs*. Though the above researchers used the *PSM* to obtain a better performance, most of them didn't consider the scheduling of sensors.

III. Network Environment and Problem Formulation

This section introduces the network environment, sensing model, recharging and discharging models. Finally, the problem formulation is given.

A. Network Environment

Assume that there are m *POIs* $O = \{o_1, o_2, \ldots, o_m\}$ deployed in a two-dimensional region $\mathcal{R}$ with $L \times W$, where L and W are the length and width of $\mathcal{R}$, respectively. There is a set of n solar-powered sensors $S = \{s_1, s_2, \ldots, s_n\}$, randomly deployed in $\mathcal{R}$. The sensing radiuses of all sensors are adjustable, containing q levels, denoted by $\mathcal{R} = \{r_1, r_2, \ldots, r_q\}$, where r_1 is the minimum radius. Fig. 1 gives an example of the considered *WRSN*. As shown in Fig. 1, each flag represents one *POI* which is the target required to be monitored. Each node and its corresponding circle represent the sensor and its corresponding sensing range. The sensors s_2 and s_4 adopt sensing radiuses r_1 and r_2 aiming to *POI* o_3, respectively.

B. Sensing Model

This paper uses the *PSM* as the sensing model. In the *PSM*, the sensing range is considered to be changed with time. The physical properties of sensors can be affected by some factors, such as strength of transmitting signal, hardware of sensors, and behavior of the environment (such as building, foliage). As a result, the sensing range of a sensor is an irregular circle. According to the working principle of *PSM*, the sensing probability of the sensor to the *POI* is decreased with the

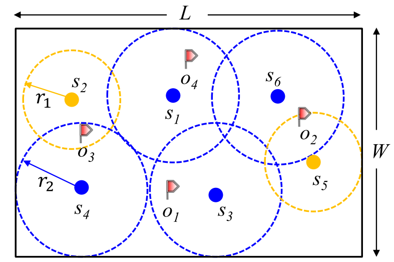
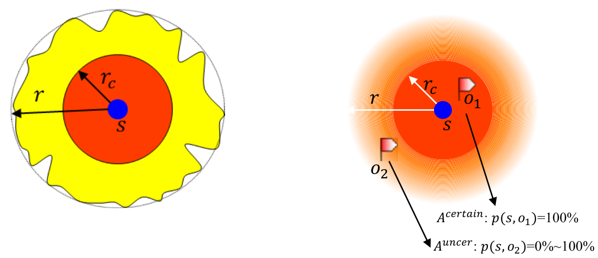


Fig. 1. A scenario of the considered *WRSN*.



(a). The applied *PSM*. (b). The example of *PSM*.

Fig. 2. An example of the *PSM*.

distance between them. As shown in Fig. 2(a), the sensing range of the sensor can contain two areas, which are the certain area, as marked with red color, and the uncertain area, as marked with yellow color. Let $A^{certain}$ and A^{uncer} denote the certain and uncertain areas, respectively. The radiuses of $A^{certain}$ and A^{uncer} are denoted by r_c and r, respectively. Any *POI* fallen in $A^{certain}$ can be certainly detected by sensor s. On the other hand, a *POI* fallen in A^{uncer} might not be detected by the sensor s.

Fig. 2(b) further illustrate the *PSM*. Sensor s monitors the *POIs* o_1 and o_2. In $A^{certain}$, as marked with the red color, the *POI* o_1 can be certainly monitored by sensor s. On the other hand, the *POI* o_2 falling in A^{uncer}, as marked with gradient red color, can be monitored by sensor s with a probability, according to the distance between the *POI* o_2 and sensor s. When the *POI* o_1 appears in $A^{certain}$, the sensing probability of sensor s is 100%. In contrast, if *POI* o_2 appears in the area A^{uncer}, the sensing probability of the sensor s is inversely proportional to the distance between the *POI* o_2 and sensor s.

Let (x_i, y_i) and (x_k, y_k) denote the coordinates of s_i and o_k, respectively. Let $d(s_i, o_k)$ denote the Euclidean distance of the *POI* o_k and sensor s_i. We have

$$d(s_i, o_k) = \left((x_i - x_k)^2 + (y_i - y_k)^2\right)^{1/2} \tag{1}$$

The following formally presents the sensing probability of a *POI* o_k by sensor s_i. Let $p(s_i, o_k)$ denote the sensing utility of *POI* o_k by sensor s_i. Exp. (2) presents the sensing utility $p(s_i, o_k)$ of sensor s_i to *POI* o_k.

$$p(s_i, o_k) = \begin{cases} 1, & if\ d(s_i, o_k) \le r_c \\ e^{-\lambda(d(s_i,o_k)-r_c)^{\gamma}}, & if\ r_c < d(s_i, o_k) < r \\ 0, & if\ r \ge d(s_i, o_k) \end{cases} \tag{2}$$

Where the λ and γ denote the path-loss exponents of signal. They can be adjusted based on physical character of the sensor.

C. Recharging and Discharging Models

The sensors which are powered by solar energy mainly have four states: recharging only, recharging & sensing, sensing and sleeping states. In the daytime, the sensors can stay in recharging only, recharging & sensing state or sensing state. In case that sensor has exhausted its energy, it should stay in the recharging only state. However, when the recharged energy of the sensor can support sensing operation for a period, the sensor will stay in recharging & sensing state, where sensors perform both sensing and recharging operations at the same time. In this state, sensors can be recharged from solar energy and monitor the covered *POIs* in the region $\mathcal{R}$. In the nighttime, since there is no solar energy, the sensors can stay in either sleeping state or sensing state. In the sleeping state, the sensors will not execute any operation.

Assume that the battery of each sensor has no energy leakage or loss, and the battery capacity is limited. Let E present the battery capacity of the sensor. In recharging state, the energy recharging rate of each sensor is denoted by ρ^{chg}. The time required for a fully exhausted sensor to be fully recharged is denoted by T^{chg} which can be calculated by Exp. (3).

$$T^{chg} = \frac{E}{\rho^{chg}} \tag{3}$$

In the sensing state, the energy discharging rate of each sensor which adopts sensing radius r_j is denoted by ρ_j^{dischg}. According to study [15], the discharging rate ρ_j^{dischg} can be calculated by Exp. (4).

$$\rho_j^{dischg} = \sigma r_j^2 \tag{4}$$

where σ is a constant. It can be de calculated by Exp. (5).

$$\sigma = E/2\left(\sum_{j=1}^{q} r_j^2\right) \tag{5}$$

Let T_j^{sen} denote the maximal period for a sensor adopting sensing radius r_j in sensing state. The T_j^{sen} can be obtained by the Exp. (6).

$$T_j^{sen} = \frac{E}{\rho_j^{dischg}} = \frac{E}{\sigma r_j^2} \tag{6}$$

Let α_j represent discharging and recharging rate when the sensor adopts sensing radius r_j. We have

$$\alpha_j = \left\lceil \frac{\rho_j^{dischg}}{\rho_j^{chg}} \right\rceil = \left\lceil \frac{T^{chg}}{T_j^{sen}} \right\rceil$$

Recall that the sensing radius of the sensor can be adjusted and r_q is maximum sensing radius. Let τ represent a time slot which is the length of maximal sensing time when the sensing radius of the sensor uses r_q. The τ can be obtained by Exp. (7).

$$\tau = T_q^{sen} = \frac{E}{\rho_q^{dischg}} = \frac{E}{\sigma r_q^2} \tag{7}$$

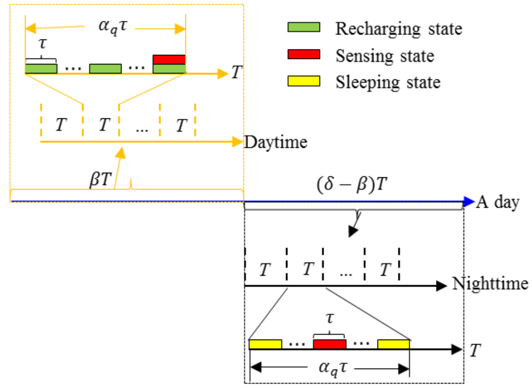


Fig. 3. A cycle of a day.

Let T denote a recharging cycle of the sensor. In addition, the sensor stays in either recharging-only states or sensing & recharging. The T can be obtained by Exp. (8).

$$T = \alpha_q \tau \tag{8}$$

For example, assume that we have $T^{chg} = 4\tau$, $T_q^{sen} = \tau$ and hence $\alpha_q = 4/1 = 4$. This indicates that the sensor is continuously recharged its energy for four time slots and the recharged energy can only support for executing sensing operation for only single time slot. This also indicates that the sensor should be recharged every four time slots. Hence, the recharged cycle $T = \alpha_q \tau = 4$ time slots.

Assume that there are δ recharging cycles for a whole day. Moreover, there are β cycles and $(\delta - \beta)$ cycles in the daytime and nighttime, respectively. Assume that sensors must reserve enough energy to monitor the *POIs* since they cannot recharge battery at night time. Fig. 3 depicts the relations of time slot τ, recharging cycle T, daytime as well as nighttime. As shown in Fig. 3, a day is divided into daytime and nighttime. The recharging state, sensing state and sleeping state are marked with green color, red color and yellow color, respectively. The sensor stays in either recharging-only or sensing & recharging states in the daytime, while it stays in either sleeping or sensing state at night because of no solar energy.

D. Problem Formulation

The paper proposes an activation schedule mechanism to maximize the surveillance quality of the *POI* and perpetual network lifetime. This section initially presents the objective function. And then, it proposes several satisfied constraints when obtaining the maximal surveillance quality of the objective function.

Let S_k represent the set of sensors which cover the *POI* o_k. That is,

$$S_k = \{s_i | d(s_i, o_k) < r\}, \quad s_i \in S \tag{9}$$

Consider a sensor $s_i \in S_k$. Let $\lambda_{i,k,x}$ be a Boolean variable which represents whether the s_i can detect the POI o_k at time slot t_x. That is,

$$\lambda_{i,k,x} = \begin{cases} 1, & \text{if } s_i \text{ detects } o_k \text{ at } t_x \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

The undetected probability of sensor s_i to target o_k at time slot t_x is

$$1 - \lambda_{i,k,x}\, p\,(s_i, o_k) \tag{11}$$

Definition (Surveillance Quality): In this paper, the collaborative coverage probability of a sensor set to any *POI* is defined as the surveillance quality of that *POI*. Let $Q_{k,x}$ denote the surveillance quality of *POI* o_i for any sensor $s_i \in S_k$ at time slot t_x. The $Q_{k,x}$ can be obtained by Exp. (12).

$$Q_{k,x} = 1 - \prod_{s_i \in S_k} \left(1 - \lambda_{i,k,x}\, p\,(s_i, o_k)\right) \tag{12}$$

Let Q_k denote the surveillance quality of *POI* o_k. The Q_k is the minimum surveillance quality of *POI* o_k in any time slot.

$$Q_k = \min_{t_x \in T} Q_{k,x} \tag{13}$$

The following gives the objective function of the *WRSNs*.

Objective function:

$$\max_{o_k \in O} Q_k \tag{14}$$

The objective of the proposed *TCSAR* is to maximize the surveillance quality of the *POI* which has the minimal surveillance quality while maintaining the perpetual lifetime of *WRSNs*.

Some constraints given below must be satisfied.

Let t_x represent the x-th time slot in cycle T. Let Boolean variables $\beta_{i,x}^{chg-only}$, $\beta_{i,x}^{chg}$, $\beta_{i,x}^{sen}$ and $\beta_{i,x}^{slp}$ represent whether the sensor s_i stays in the recharging only, recharging & sensing, sensing and sleeping states, respectively. That is,

$$\beta_{i,x}^{chg-only} = \begin{cases} 1, & s_i \text{ stays in recharging only state in } t_x \\ 0, & otherwise \end{cases} \tag{15}$$

$$\beta_{i,x}^{chg} = \begin{cases} 1, & s_i \text{ stays in recharging \& sensing state in } t_x \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

$$\beta_{i,x}^{sen} = \begin{cases} 1, & s_i \text{ stays in sensing state in } t_x \\ 0, & \text{otherwise} \end{cases} \tag{17}$$

$$\beta_{i,x}^{slp} = \begin{cases} 1, & s_i \text{ stays in sleeping state in } t_x \\ 0, & \text{otherwise.} \end{cases} \tag{18}$$

First, the *state constraint* ensures that the sensor can stay in one of recharging only, recharging & sensing, sensing, and sleeping states at any given time slot.

(1) *State Constraint:*

$$\beta_{i,x}^{chg-only} + \beta_{i,x}^{chg} + \beta_{i,x}^{sen} + \beta_{i,x}^{slp} = 1 \tag{19}$$

Second, the following *active constraint* makes sure that the number of sensing sensors must be less than or equal to the total sensors for each time slot in the monitoring region $\mathcal{R}$.

(2) *Active Constraint:*

$$\sum\nolimits_{s_i \in S} \beta_{i,x}^{sen} \le |S|\,, \quad \forall t_x \in T \tag{20}$$

Finally, the *energy constraint* makes sure that the energy recharged by each sensor should be larger than or equal to the energy consumed by that sensor which adopts a sensing radius r_j in any time slot of a cycle *T*.

(3) *Energy Constraint:*

$$\sum\nolimits_{t=1}^{\alpha_q} \rho^{chg} * t * \beta_{i,x}^{chg} \ge \sum\nolimits_{t=1}^{\alpha_q} \rho_j^{dischg} * t * \beta_{i,x}^{sen}, \quad \forall s_i \in S \tag{21}$$

IV. Target Coverage Mechanism Sensors With Adjustable Sensing Range

This paper aims to schedule the working time slots of the sensors to maximize the surveillance quality of the *POIs*. The proposed *TCSAR* consists of two phases: *Scheduling Phase and Space Time Transformation Phase*. In the *Scheduling Phase*, each sensor will be scheduled based on surveillance quality for *POIs*. Based on this scheduling, the new surveillance quality for each *POI* is calculated. In the *Space Time Transformation Phase*, the surveillance quality for the *POIs* can be further improved by adjusting the sensing radius of some sensors from space dimension to time dimension.

A. Scheduling Phase

In this phase, assume that all sensors use the maximum sensing radius. The base station will schedule working time slots of all sensors in one cycle T over the monitoring region $\mathcal{R}$.

This phase consists of four steps. First, the base station initializes the network environment. Then, the second step identifies the bottleneck point which has the lowest surveillance quality by calculating the surveillance quality of each *POI*. Thirdly, the base station selects the best unscheduled sensor that has the largest surveillance quality to the bottleneck point. Finally, the best unscheduled sensor is scheduled to the bottleneck point. The latter three steps will be repeatedly executed until all sensors have been scheduled. The following presents the detail of each step.

Step 1: Network Initialization

This step aims to initialize the network environment. In the considered monitoring region $\mathcal{R}$, there are m *POIs* and n solar-powered sensors. Let M_{m*n} be a two-dimensional monitoring capability of each *POI*. The element $M\,[o_k, s_i]$ denotes the monitoring capability of sensor s_i that adopts the maximal sensing radius r_q to monitor *POI* o_k. Its value can be calculated by Exp. (2).

Step 2: Identification of the "Bottleneck Point"

This step aims to identify the bottleneck point which has the lowest surveillance quality for the *POI* $o_k \in O$ at time slot $t_x \in T$ by calculating the surveillance quality of each *POI* at all time slots. Recall that a cycle T contains α_q time slots. Let $\mathbb{S}_{m*\alpha_q}$ be a two-dimensional matrix which denotes the set of scheduled sensors at each time slot for each *POI*. Each element $\mathbb{S}[k, x]$ denotes a set of sensors scheduled to monitor *POI* $o_k \in O$ at time slot $t_x \in T$.

According to the current scheduling matrix $\mathbb{S}_{m*\alpha_q}$, each *POI* has a surveillance quality in each time slot. Let $\mathbb{Q}_{m*\alpha_q}$ be a two-dimensional matrix which denotes the surveillance quality of *POI* at each time slot. Each element $\mathbb{Q}[k, x]$ denotes the quality of monitoring for the *POI* $o_k \in O$ at time slot $t_x \in T$. The $\mathbb{Q}[k, x]$ can be calculated by Exp. (22).

$$\mathbb{Q}[k, x] = 1 - \prod\nolimits_{s_i \in \mathbb{S}[k,x]} (1 - M[o_k, s_i]) \tag{22}$$

Let $\mathbb{Q}^{weak}_{\hat{k},\hat{x}}$ denote the lowest surveillance quality in $\mathbb{Q}$. It can be derived by Exp. (23).

$$\mathbb{Q}^{\text{weak}}_{\hat{k},\hat{x}} = \min_{\mathbb{Q}[k,x] \in \mathbb{Q}} \mathbb{Q}[k, x] \tag{23}$$

Let $(o^{weak}_{\hat{k}}, t^{weak}_{\hat{x}})$ denote the minimal surveillance quality point corresponding to $\mathbb{Q}^{weak}_{\hat{k},\hat{x}}$. Let $\mathbb{Q}^{weak}$ denote a set of all weakest points. The weakest points can be derived by Exp. (24).

$$\mathbb{Q}^{\text{weak}} = \left\{ \left(o^{\text{weak}}_{\hat{k}}, t^{\text{weak}}_{\hat{x}} \right) \mid \mathbb{Q}^{\text{weak}}_{\hat{k},\hat{x}} \in \mathbb{Q} \right\} \tag{24}$$

The next step aims to choose the best unscheduled sensor for the bottleneck point.

Step 3: Best Sensor Selection

This step aims to choose the best sensor which has the maximum surveillance quality to cope with the problem of bottleneck point. Assume that S^{sch} denotes the set of scheduled sensors. The initial value of S^{sch} is

$$S^{sch} = \emptyset \tag{25}$$

Let S^{unsch} denote a set of sensors which have not been unscheduled. The initial value of S^{unsch} is

$$S^{unsch} = S \tag{26}$$

Let the best unscheduled sensor be denoted by s_{best}, where $s_{best} \in S^{unsch}$. The s_{best} should have the largest sensing ability for the weakest target $o^{weak}_{\hat{k}}$. It can be derived by Exp. (27).

$$s_{best} = arg \max_{o^{weak}_{\hat{k}} \in \mathbb{Q}^{\text{weak}}, s_i \in S^{unsch}} M\left[o^{weak}_{\hat{k}}, s_i\right] \tag{27}$$

In the next step, the sensor s_{best} will be scheduled to cope with the problem of bottleneck point $(o^{weak}_{\hat{k}}, t^{weak}_{\hat{x}})$.

Step 4: Best Sensor Scheduling

This step aims to schedule the sensor s_{best} derived from the front step, aiming to monitor the weakest point $(o^{weak}_{\hat{k}}, t^{weak}_{\hat{x}})$. Let γ_k denote whether the sensor s_{best} has monitoring contribution to target o_k. That is

$$\gamma_k = \begin{cases} 1, & M[o_k, s_{best}] \neq 0, o_k \in O \\ 0, & otherwise. \end{cases} \tag{28}$$

Since o_k can be monitored by s_{best} if $\gamma_k = 1$ holds, the s_{best} should be added to the element $\mathbb{S}[k, \hat{x}]$. Exp. (29) makes this change.

$$\mathbb{S}[k, \hat{x}] = \begin{cases} \mathbb{S}[k, \hat{x}] \cup \{s_{best}\}, & \gamma_k = 1 \\ \mathbb{S}[k, \hat{x}], & otherwise. \end{cases} \tag{29}$$

Then, the values in the $\hat{x}$-*th* column of matrix $\mathbb{Q}$ should be recalculated according to Exp. (30) if sensor s_{best} has contribution to target o_k.

$$\mathbb{Q}[k, \hat{x}] = \begin{cases} 1 - \prod_{s_i \in \mathbb{S}[k,\hat{x}]} (1 - M[o_k, s_i]), & \gamma_k = 1 \\ \mathbb{Q}[k, \hat{x}], & otherwise. \end{cases} \tag{30}$$

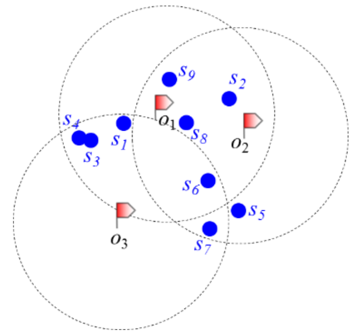


Fig. 4. An example of the considered network environment.

TABLE I
THE VALUE OF M_{3*9}

$M[o_k, s_i]$	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8	s_9
o_1	0.9	0.5	0.25	0.2	0	0	0	0.9	0.7
o_2	0	0.6	0	0	0.8	0.7	0.1	0.5	0.2
o_3	0.1	0	0.25	0.2	0.1	0.2	0.5	0.2	0

Finally, s_{best} should be removed from S^{unsch} by applying Exp. (31).

$$S^{unsch} = S^{unsch} \setminus \{s_{best}\} \tag{31}$$

At the same time, the sensor s_{best} should be added to scheduled sensors S^{sch} by Exp. (32).

$$S^{sch} = S^{sch} \cup \{s_{best}\} \tag{32}$$

The base station will repeatedly execute steps 2 to 4 until all the unscheduled sensors have been scheduled.

Herein, an example is given to illustrate the *Scheduling Phase*. There are three *POIs* $O = \{o_1, o_2, o_3\}$ which are monitored by nine sensors $S = \{s_1, s_2, \ldots, s_9\}$ as shown in Fig. 4. The circle represents the monitoring range of each *POI*. That is, any sensor falling in the circle indicates that the sensor can cover the corresponding *POI*.

Table I depicts the sensing probability of matrix M_{3*9} is calculated by applying step 1.

Assume that a cycle T is divided into three time slots. That is

$$\alpha_q = 3$$

In the first round, all values in S_{3*3} and $\mathbb{Q}_{3*3}$ are $\emptyset$ and 0, respectively. According to step 2, the bottleneck point is (o^{weak}_1, t^{weak}_1). By applying step 3, the best sensor can be derived by

$$s_{best} = arg \max_{s_i \in S^{unsch}} M[o_1, s_i] = s_1$$

By applying step 4, the matrices $\mathbb{S}$ and $\mathbb{Q}$ are shown in Tables II and III, respectively.

After the last round, the results of matrix $\mathbb{S}$ and $\mathbb{Q}$ are shown in Tables IV and V, respectively.

B. Space Time Transformation Phase

This phase aims to further improve the minimum surveillance quality of *POI*. Recall that, the sensing radius of all

TABLE II
THE VALUE OF $\mathbb{S}$

	t_1	t_2	t_3
o_1	s_1	$\emptyset$	$\emptyset$
o_2	$\emptyset$	$\emptyset$	$\emptyset$
o_3	s_1	$\emptyset$	$\emptyset$

TABLE III
THE VALUE OF $\mathbb{Q}$

	t_1	t_2	t_3
o_1	0.9	0	0
o_2	0	0	0
o_3	0.1	0	0

TABLE IV
THE VALUE OF $\mathbb{S}$

	t_1	t_2	t_3
o_1	s_1, s_2	s_3, s_9	s_4, s_8
o_2	s_2,s_7	s_5, s_6, s_9	s_8
o_3	s_1, s_7	s_3,s_5, s_6	s_4,s_8

TABLE V
THE VALUE OF $\mathbb{Q}$

	t_1	t_2	t_3
o_1	0.95	0.775	0.92
o_2	0.64	0.952	0.5
o_3	0.55	0.46	0.36

sensors can be adjusted. Based on the adjusting sensing radius model, the sensors can consume different energy when they apply different sensing radiuses. Hence, they can have different working duration in each cycle. It is obvious that each sensor can consume less energy by applying a smaller sensing radius, leading to longer working duration in each cycle. This phase aims to select some sensors and reduce their sensing range such that they have longer working duration. The increased working duration can be scheduled for monitoring the bottleneck *POI* such that the surveillance quality of the *POI* can be further improved.

This phase consists of three steps. First, the base station identifies the bottleneck point that has the minimum surveillance quality. Since this can be achieved by applying similar operations as shown in step 2 of *Schedule Phase*, we omit the detail of the first step herein. Second, the base station selects the best sensor which can reduce the sensing radius and increase the working time duration to further improve the surveillance quality of the bottleneck point. Thirdly, the base station actually changes the schedule. In what follows, the details of the last two steps are presented.

Let $\mathcal{F}_{s_i,r_h}$ denote a transformation function from space dimension to time dimension by reducing sensing radius r_h of sensor s_i. Assume that the sensor s_i reduces its sensing radius from r_h to r_l, where $r_l, r_h \in R$, $r_l < r_h$. We have

$$\mathcal{F}_{s_i,r_h} : \mathbb{S}[*, x]\{s_i, r_h\} \rightarrow \mathbb{S}[*, x]\{s_i, r_l\} + \mathbb{S}[*, \hat{x}]\{s_i, r_l\} \tag{33}$$

Where $\mathbb{S}[*, x]\{s_i, r_h\}$ denotes the set of sensors which have been originally scheduled at time slot t_x and sensor s_i is in $\mathbb{S}[*, x]$. Since sensor s_i applies a smaller sensing radius r_l, it can reserve more energy to execute monitoring task at bottleneck time slot $t_{\hat{x}}$. Hence, the sensor s_i can monitor at both new time slot $t_{\hat{x}}$ and the old time slot t_x. The function F_{s_i,r_h} denotes the transformation from $\mathbb{S}[*, x]\{s_i, r_h\}$ to $(\mathbb{S}[*, x]\{s_i, r_l\} + \mathbb{S}[*, \hat{x}]\{s_i, r_l\})$.

According to step 1, the weakest point is $(o_{\hat{k}}^{weak}, t_{\hat{x}}^{weak})$. Let s_{best} denote the best sensor which has the largest surveillance quality to improve the weakest *POI* $o_{\hat{k}}^{weak}$. To guarantee the application of transformation function can improve the overall surveillance quality, the s_{best} needs to satisfy the following two criteria.

Constraint (1): Generation of new benefit

Let $s_{i,x}^{adj}$ denote the sensor which intends to play the role of s_{best}. Since the sensor $s_{i,x}^{adj}$ should have coverage contribution to the bottleneck point, this constraint asks that the reduced sensing radius r_l can cover the bottleneck point $(o_{\hat{k}}^{weak}, t_{\hat{x}}^{weak})$. That is to say, the space contribution must satisfy the following Exp. (34).

$$M\left[o_{\hat{k}}^{weak}, s_{j,l}^{adj}\right] > 0 \tag{34}$$

Constraint (2): Maintenance of basic benefit

Let $O_{i,h}$ denotes the set of *POIs* covered by sensor s_i using radius r_h. The quality of monitoring of non-bottleneck for each $o_k \in O_{i,h}$ at time slot t_x when the radius is adjusted as r_l. It can be calculated by Exp. (35).

$$\mathbb{Q}[k, x] = 1 - \prod_{s_i \in (\mathbb{S}[\hat{k},x] \setminus \{s_{i,x}^{adj}\}) \cup \{s_{i,l}^{adj}\}} (1 - M[o_k, s_i]), o_k \in O_{i,h} \tag{35}$$

After reducing sensing radius of sensor $s_{j,l}^{adj}$, it should not play a role of new bottleneck space-time point. That is

$$\min_{o_k \in O_{i,h}} (\mathbb{Q}[k, x]) > \mathbb{Q}[\hat{k}, \hat{x}]) \tag{36}$$

Exp. (35) indicates that the surveillance quality of all *POIs* covered by sensor $s_{i,x}^{adj}$ in time-slot t_x should still be more than the quality of monitoring of bottleneck $\mathbb{Q}[\hat{k}, \hat{x}]$ after reducing sensing radius of the sensor $s_{i,x}^{adj}$.

There may be more than one sensor that can meet the above criteria. Let S^{adj} denote the adjustable sensors. Its initial value is $\emptyset$. It can be derived by Exp. (37).

$$S^{adj} = S^{adj} \cup \{s_{j,l}^{adj}\} \tag{37}$$

The sensor s_{best} must be further checked to promise that it achieves maximum surveillance quality to bottleneck $(o_{\hat{k}}^{weak}, t_{\hat{x}}^{weak})$. That is

$$s_{best} = arg \max_{s_{j,l}^{adj} \in S^{adj}} M\left[o_{\hat{k}}^{weak}, s_{j,l}^{adj}\right] \tag{38}$$

Up to now, the best adjustable sensor s_{best} can be determined. According to Exp. (22), the base station must recalculate the surveillance quality of $o_{\hat{k}}^{weak}$ at time slots t_x and $t_{\hat{x}}$. The bottleneck space-time points are also recalculated. The above criteria will be repeatedly executed until $S^{adj} = \emptyset$.

In the last step, all elements of the matrix $\mathbb{S}$ and $\mathbb{Q}$ should be updated according to Exps. (29) and (30), respectively.

TABLE VI
THE VALUE OF $\mathbb{S}$

	t_1	t_2	t_3
o_1	s_1, s_2	s_3, s_9	s_3, s_4, s_8
o_2	s_2, s_7	s_5, s_6, s_9	s_8
o_3	s_1, s_7	s_3, s_5, s_6	s_3, s_4, s_8

TABLE VII
THE VALUE OF $\mathbb{Q}$

	t_1	t_2	t_3
o_1	0.95	0.775	0.94
o_2	0.64	0.952	0.5
o_3	0.55	0.46	0.52

Herein, an example is given to illustrate the detailed process of the *Space Time Transformation Phase*. Based on the schedule result of the *Schedule Phase*, as shown in Table. V, the bottleneck point can be derived by applying step 1 of the *Space Time Transformation Phase*.

$$(o_3^{weak}, t_3^{weak}) = 0.36$$

Assume that the original sensing radius of each sensor is r_3 and $r_2 = r_3 * 1/2$. This implies that a sensor adopting radius r_2 can further extend its working time duration for two more time slots, as compared with the adoption of radius r_3. According to the constraint of *Generation of new benefit*, the set of adjustable sensors is $\{s_{3,3}^{adj}, s_{5,3}^{adj}, s_{6,3}^{adj}\}$. Take $s_{3,3}^{adj}$ as an example. After adjusting the sensing radius of $s_{3,3}^{adj}$ to r_2, it satisfies the first constraint of *Generation of new benefit.* And it has surveillance quality to improve the bottleneck point o_3^{weak} since it satisfies condition: $M\left[o_3^{weak}, s_{2,3}^{adj}\right] > 0$. The sensor $s_{3,3}^{adj}$ has been scheduled in time-slot t_2 for monitoring *POIs* o_1 and o_3. After adjusting sensor s_3 from radius r_3 to r_2, the monitoring qualities $\mathbb{Q}[1, 3]$ and $\mathbb{Q}[3, 3]$ have been changed to

$$\mathbb{Q}[1, 3] = 0.94 \text{ and } \mathbb{Q}[3, 3] = 0.52$$

which are still higher than the bottleneck quality 0.36. That is to say, sensor $s_{3,3}^{adj}$ satisfies the second constraint. Consequently, the sensor $s_{3,3}^{adj}$ can be added into the set S^{adj}. The sensors $s_{5,3}^{adj}$ and $s_{6,3}^{adj}$ can apply the similar calculations and are also added to the set S^{adj}. As a result, we have $S^{adj} = \{s_{3,3}^{adj}, s_{5,3}^{adj}, s_{6,3}^{adj}\}$. According to Exp. (38), sensor $s_{3,3}^{adj}$ is choose as the best sensor to improve surveillance quality of the bottleneck (o_3^{weak}, t_3^{weak}). Therefore, the values in the $\mathbb{S}$ and $\mathbb{Q}$ are updated according to the schedule of sensor $s_{3,3}^{adj}$. The results of S and $\mathbb{Q}$ are shown in Tables VI and VII, respectively.

V. PERFORMANCE EVALUATION

This section evaluates the performance improvement of the proposed *TCSAR* against the original scheduling and existing *MMQT* (Maximizing the Surveillance quality for Targets mechanism) [16]. The existing *MMQT* assumed that all sensors were powered by the solar energy and adopted *PSM* as its sensing model. It only scheduled the sensors without considering the adjustment of the sensing radius for improving the surveillance quality of the *POIs*. The following gives the simulation environment and simulation results.

TABLE VIII
SIMULATION PARAMETERS

Parameters	Values
Simulator	MATLAB
Node deployment	Random
Monitoring region	1000 m×1000 m
Number of sensors	500 – 2000
Number of *POIs*	20 - 100
Sensing Radius r_l	10 m
Sensing Radius r_h	20 m
Recharging rate	20Joule/hour
Discharging rate	40 Joule/hour

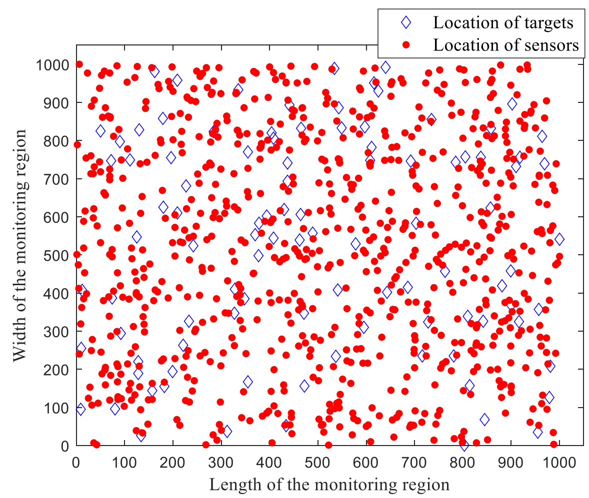


Fig. 5. 100 *POIs* and 800 sensors are randomly deployed in 1000m × 1000 m region.

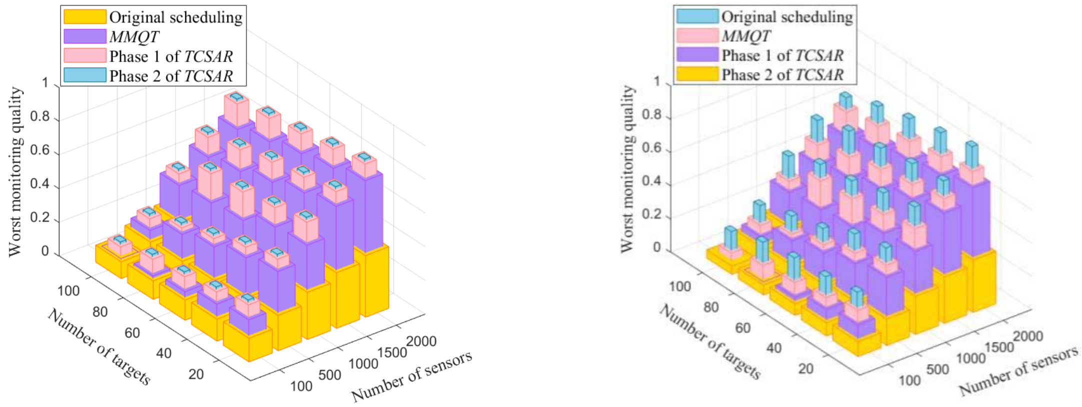
A. Simulation Environment

Table. VIII lists the simulation parameters [16]. The simulator uses MATLAB. We randomly deploy 500 to 2000 sensors in the 1000m×1000m monitoring region where 20 to 100 *POIs* are deployed. The sensing radiuses r_l and r_h are 10m and 20m, respectively. The recharging and discharging rates of the solar battery is 20 Joule/hour and 40 Joule/hour, respectively. In other words, the ration of recharging over discharging time is 2 if each cycle T contains 3 time slots.

Fig. 5 depicts a screenshot of the deployed *WRSN* in the experiment. There are 800 sensors marked with red ink and 100 *POIs* marked with the blue diamond. They are randomly deployed in a 1000m × 1000m monitoring region.

B. Simulation Results

Figs. 6(a) and 6(b) compare the performance of the four algorithms which are original scheduling, *MMQT*, phase 1 of



(a) (b)

Fig. 6. (a) Comparison of Original scheduling, *MMQT*, Phase 1 of *TCSAR*, Phase 2 of *TCSAR* by changing the number of *POIs* and sensors with sensing radius r_h. (b). Comparison of Original scheduling, *MMQT*, Phase 1 of *TCSAR*, Phase 2 of *TCSAR* by changing the number of *POIs* and sensors with sensing radius r_l.

the proposed *TCSAR* and phase 2 of the proposed *TCSAR*, in terms of the worst surveillance quality with sensing radius r_h and r_l, respectively. The number of *POIs* is changed from 20 to 100 and the number of sensors is changed from 500 to 2000. A common trend can be observed that the worst surveillance qualities of the four algorithms are increased with the number of sensors and are decreased with the number of *POIs*. The reason is that the increasing number of sensors can improve the worst surveillance quality. The proposed *TCSAR* outperforms the other compared algorithms in all cases. It is because that the proposed *TCSAR* always considers the surveillance quality of the bottleneck *POI* which has the lowest surveillance quality and further schedules the best unscheduled sensor which has the largest sensing probability for the bottleneck *POI*. Consequently, the surveillance quality of all *POIs* can be significantly improved. Further, it is observed that the improvement of the phase 2 of *TCSAR* in Fig. 6(b) outperforms the one in Fig. 6(a). The reason is that, the proposed *TCSAR* algorithms can adjust the sensor's sensing radius from r_h to r_l to further improve the surveillance quality of the bottleneck *POI* from space dimension to time dimension.

Fig. 7 randomly selects one *POI* and observes the surveillance quality of the four compared algorithms of one cycle. It shows the performance of a cycle T which has 3 time slots, denoted by t_1, t_2 and t_3 in terms of surveillance quality. The proposed phase 1 of *TCSAR* outperforms the original scheduling and *MMQT* in all cases. The reason is that it schedules the best unscheduled sensor to the bottleneck point for improving its surveillance quality. Further, it observed that the phase 2 of *TCSAR* achieves the best surveillance quality. The reason is that it selects some sensors to increase their working duration by reducing their sensing radiuses, and then schedules the selected sensors to cope with the bottleneck problem.

Fig. 8 further compares the surveillance quality of 6 *POIs* which are randomly selected by applying the original scheduling, *MMQT*, Phase 1 of *TCSAR* and Phase 2 of *TCSAR*. In this experiment, there are 800 sensors randomly deployed in the

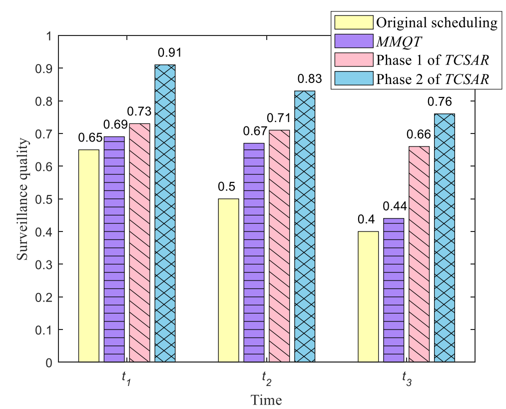


Fig. 7. Comparison of Original scheduling, *MMQT*, Phase 1 of *TCSAR*, Phase 2 of *TCSAR* by varying time slot.

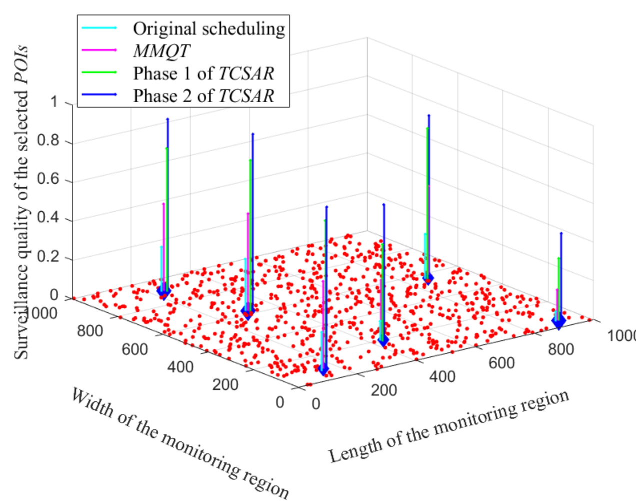


Fig. 8. Comparison of Original scheduling, *MMQT*, Phase 1 of *TCSAR* and Phase 2 of *TCSAR* in terms of surveillance quality of the selected *POIs*.

1000m ∗1000mmonitoring region. It can be seen that, the proposed *TCSAR* algorithm achieves better result as compared with the other algorithms in terms of the surveillance quality of the selected *POIs*. The reason is that the proposed

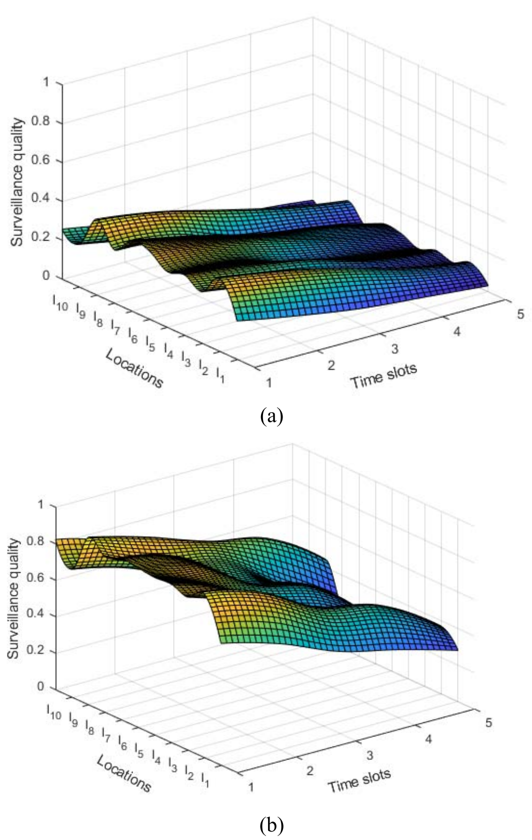


Fig. 9. (a). Surveillance quality of 10 selected locations for 5 time slots with original scheduled. (b). Surveillance quality of 10 selected locations for 5 time slots with applying *TCSAR*.

TCSAR algorithm considers the surveillance quality of the bottleneck *POI*.

Figs. 9(a) and 9(b) aim to investigate the impact of the number of time slots on the surveillance quality. Initially, the experiment randomly selects 10 locations and varies the number of time slots in interval [1, 5]. Figs. 9 (a) and (b) show the experimental results obtained by original scheduling and *TCSAR*, respectively. As shown in Fig. 9(a), it is clearly observed that the surveillance quality of the selected *POIs* decreases with the number of time slots. The reason is that the working time slots of all sensors should be distributed over all time slots and thus fewer working sensors can be allocated to each slot in average.

As shown in Fig. 9(b), the surveillance quality achieved by *TCSAR* outperforms original scheduled. This occurs because that the proposed *TCSAR* algorithm always considers the bottleneck *POI* which has the smallest surveillance quality. Then the *TCSAR* adopts adjustable sensing radiuses of sensors and proposes a space time transformation to further improve the surveillance quality of the bottleneck *POI*.

VI. Conclusion

This paper investigates the target coverage problem, and proposes *TCSAR*, which aims to maximize the surveillance quality of the bottleneck *POI* and achieves the perpetual network lifetime by scheduling the solar-powered sensors. The proposed *TCSAR* applies the *PSM* to evaluate the cooperative sensing probability of sensors, identifies the bottleneck *POI* and schedules the best unscheduled sensor to the bottleneck *POI*. Then the proposed *TCSAR* adjusts the sensing radiuses of the sensors which have the best surveillance quality for the bottleneck *POI* to further improve the surveillance quality from space dimension to time dimension. Experimental results show that the proposed *TCSAR* outperforms the existing mechanisms. The future work will further consider the other variable parameters of coverage problems, which include different types of sensors of heterogeneous *WSNs*, coverage requirement, and many more.

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