Variable-Power Scheduling for Perpetual Target Coverage in Energy Harvesting Wireless Sensor Networks

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***Abstract*—We study perpetual target coverage with an energy harvesting wireless sensor network (WSN) assuming that each sensor can modulate its sensing range by dynamically varying its operating power, e.g., radar sensors. In this variable-power scheduling scenario, we first consider the maximum network lifetime problem for battery-powered WSNs. The solution to this problem allows us to decide if a given energy harvesting WSN is capable of perpetual operation satisfying energy neutrality. Then, we formulate the energy efficient perpetual target coverage problem and prove its NP completeness. A polynomial algorithm is proposed, and its effectiveness is validated through extensive numerical simulations.**

I. Introduction

Target coverage requires a set of specified targets or a region of interest (ROI) to be within the sensing range of operative sensors. Target coverage is a fundamental performance requirement for various wireless sensor network (WSN) applications. Target coverage problem has been well investigated in traditional WSNs with battery-powered nodes [1]–[3]. Due to the limited battery capacity, battery-operated sensors can remain active (and be sensing) only for a limited amount of time, until they run out of energy. This motivates the redundant deployment of sensors to cover the area of interest, and to schedule the sensors carefully in order to prolong the coverage time after deployment.

For applications that are expected to operate over long time periods limited available energy in battery-operated sensor nodes becomes a severe limitation. An alternative to circumvent this energy limitation is to employ rechargeable batteries, which can be charged with energy harvested from the environment, e.g., harvesting solar, thermal, RF and kinetic energies. With the introduction of the *energy harvesting* technology, perpetual operation of WSNs becomes possible. However, in many scenarios, due to the limited nature of the underlying energy sources, the rate of harvested energy could be significantly less than the rate of energy depletion during operation [4]. More specifically, the typical power derived from EH, which ranges from hundreds of μWs to tens of mWs, is not always sufficient to power sensor nodes for data-intensive applications, e.g., image sensors [5]. Therefore, efficient energy management is necessary for EH WSNs to achieve self-sustainable, maintenance-free, perpetual energy-neutral operation [6].

In this paper we study perpetual target coverage with an energy harvestign WSN. In [7], Pryyma et al. consider probabilistic models of energy arrival and expenditure and propose active time scheduling protocols to maximize coverage. Prediction on the probability of an event occurring at a target's location is utilized in [7] to dynamically activate sensors, in order to maximize the long-term utility of the system. In another related work [8], a linear programming based activation schedule is proposed to maximize network lifetime while ensuring target coverage with limited energy supply. However, these and most other works on coverage are based on fixed-power operation of sensors, which assumes that, when it is on, a sensor can only function at a fixed power, and hence, has a fixed sensing range.

For various types of sensors, the sensing range is related to the power level they operate at. For example, the sensing range of a radar sensor is defined as the maximal distance at which the reflected power is equal to the minimum detectable energy. The radar equation is given by [9]:

$$R^4 = k \cdot P, \tag{1}$$

where R is the sensing range of a radar sensor, P is the power of the radar to radiate, and k is a constant, related to the antenna gain, the effective aperture area, the target cross section and the minimum detectable signal. Hence, the energy efficiency and coverage lifetime of a WSN can be improved by optimizing the coverage area of the sensors over time. We investigate energy efficient variable-power scheduling of rechargeable sensors while ensuring perpetual target coverage and energy neutrality. Our main contributions can be summarized as below:

1) Different from the classical literature on target coverage in WSNs, we consider the variable-power target coverage problem, in which each sensor can modulate its coverage area by dynamically varying its operating power.
2) In this variable-power transmission model, we first solve the maximum lifetime problem with battery-powered sensors. We then show that the solution to the battery-limited target coverage problem can be used to decide if an energy harvesting WSN is capable of perpetual coverage while satisfying energy neutrality.
3) We formulate the energy efficient perpetual target coverage problem and prove its NP-completeness. A greedy polynomial time approximation algorithm is proposed, and its effectiveness is validated by extensive numerical simulations.

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The rest of the paper is organized as follows. We present the system model and problem formulation in Section II. We consider the decision problem of whether perpetual coverage is possible for a given energy harvesting WSN in Section III. Energy efficient perpetual target coverage problem is studied in Section IV. Numerical simulations are presented in Section V. Finally, we conclude the paper in Section VI.

II. System Model and Problem Formulation

A. Network Model

Consider a WSN deployed in a region of interest (ROI) to monitor a set of targets $\{T_1, ..., T_M\}$. The sensors, $\{S_1, ..., S_N\}$, have rechargeable batteries, and can harvest ambient energy. E_i denotes the average energy harvesting rate of sensor S_i.

We consider radar sensors in this paper but the results can be easily extended to other types of sensors for which the coverage area depends on the operational power. The power that sensor S_i operates at time t is denoted by $p_i(t)$, $p_i(t) \in [0, P_i]$, where P_i is the maximum power of S_i. Define p_{ij} as the minimal power required for sensor S_i to cover target T_j:

$$p_{ij} \triangleq k_i \cdot D_{ij}^4, \tag{2}$$

where D_{ij} is the Euclidean distance between S_i and T_j, and k_i is a constant, which may be different for each sensor. We assume that $p_{ij} \neq p_{ik}$ for $j \neq k$. Note that $p_{ij} > p_{ik}$ implies that T_k is closer to S_i than T_j. Hence, when operated at power p_{ij}, sensor S_i covers target T_k as well as T_j. Without loss of generality, we assume $p_{ij} \leq P_i$, $\forall i, j$. Let $\mathcal{P}_i \triangleq \{p_{i0}, p_{i1}, \ldots, p_{iM}\}$ denote the *power level set* for S_i, where we set $p_{i0} = 0$, $\forall i$, corresponding to the sleep mode.

B. Problem Statement

Our goal is to provide continuous coverage of all the targets perpetually in the most energy efficient manner. These concepts will be formalized below. Let $(p_1(t), ..., p_N(t))$ denote the network state vector at time t, where $p_i(t)$ represents the operating power of S_i at t.

Definition 1: The network state $(p_1(t), ..., p_N(t))$ is a *sensor cover* if, for each target T_j, there exists at least one sensor S_i for which $p_i(t) \geq p_{ij}$.

We can formulate the **energy efficient perpetual target coverage (PTC) problem** as follows:

$$\min \int_{t=0}^{1} \sum_{i=1}^{N} p_i(t) dt \tag{3}$$

$$\text{s.t.} \int_{t=0}^{1} p_i(t) dt \leq E_i, \forall i \in [1:N], \tag{4}$$

$$\sum_{i=1}^{N} \mathbf{1}_{\{p: p \geq p_{ij}\}} \big(p_i(t)\big) \geq 1, \forall j \in [1:M], t \in [0,1]. \tag{5}$$

where the *indicator function* $\mathbf{1}_A(x) = 1$ if $x \in A$, and 0 otherwise. The objective function in (3) is the total energy consumption of the network in unit time. The constraint in (4) ensures energy neutrality, i.e., the energy consumption rate of each sensor must be less than its energy harvesting rate. The constraint in (5) guarantees that every target is continuously covered. Note that the result we aim to obtain by solving this optimization problem will give us the power scheduling over unit time, i.e., $t \in [0, 1]$. This schedule can be repeated over time to sustain perpetual operation. Note also that this is a continuous optimization problem, and hence, cannot be solved efficiently in its current form. Below, we show that it can be simplified into a discrete problem.

Lemma 1: In problem (3), the transmit power of S_i at any time t can be restricted to the set $\mathcal{P}_i$ without loss of optimality.

Proof: Suppose $p_i(t)$, $t \in [0, 1]$, $i = 1, \ldots, N$, is the solution of (3), and $p_i(t) \notin \mathcal{P}_i$ for some i. Then $p_i(t) \in (p_{ij_i}, p'_{ij_i})$ for some $j_i \in \{0, \ldots, M\}$, where p'_{ij_i} is the smallest value from $\mathcal{P}_i$ that is larger than p_{ij_i}. Note that the network state $(p_{1j_1}, \ldots, p_{Nj_N})$ is also a sensor cover, while it has a lower energy consumption. This completes the proof. ■

Hence, as trasmit power level for sensor S_i at any time t we only need to consider values from the power level set $\mathcal{P}_i$ of S_i, which implies that there is only a finite number of sensor covers. Given the sensors and targets, suppose there are L sensor covers, which are denoted by $C_l = (p_1^l, ..., p_N^l)$, for $l = 1, 2, ..., L$. We can conclude that the network state at any time instant should be one of these sensor covers. Hence, we can rewrite the optimization problem as scheduling between sensor covers.

Let $\bar{P}_l$ denote the total power of sensor cover C_l, i.e.,

$$\bar{P}_l \triangleq \sum_{i=1}^{N} p_i^l.$$

Assume that the sensor covers are given, then the PTC problem can be reformulated as follows:

$$\min \sum_{l=1}^{L} f_l \cdot \bar{P}_l \tag{6a}$$

$$s.t. \begin{cases} \sum_{l=1}^{L} f_l \cdot \bar{P}_l \leq E_i, \forall i \in [1:N], & \text{(6b)} \\ \sum_{l=1}^{L} f_l \geq 1, & \text{(6c)} \\ f_l \geq 0, \forall l \in [1:L], & \text{(6d)} \end{cases}$$

where f_l denotes the frequency of operating in network state C_l.

For practical applications, we can divide the network lifetime into successive time slots. Let the length of each time slot be T. Then, each sensor cover will operate for a period of $f_l \cdot T$, $l = 1, ..., L$, within each time slot. Then, the length of the time frame, T, and the order of sensor covers can be determined according to the capacity of the sensor batteries. Here, we assume that the capacities of the sensor batteries are sufficient to sustain energy neutral operation.

Despite the dimension reduction in the optimization problem, thanks to Lemma 1, the next theorem states that the PTC problem is still hard to solve.

Theorem 1: PTC problem in (6) is NP complete.

Proof: To show that PTC $\in$ NP, consider we are given a certificate, i.e., $\{C_l\}_{l=1}^L$ and $\{f_l\}_{l=1}^L$, and P. Then, we can verify in polynomial time whether

- $\sum_{l=1}^L \bar{P}_l \cdot f_l \leq P$,
- $\sum_{l=1}^L p_i^l \cdot f_l \leq E_i$, $\forall i \in [1:N]$,
- Every target is covered in each network state C_l,
- $\sum_{l=1}^L f_l \geq 1$.

On the other hand, to prove that PTC is NP-hard, we first show that the conventional target coverage problem, in which sensors are either activated at a fixed power or turned off, is a special case of PTC. Suppose that the operating power of S_i is a constant p_i. We set $p_{ij} = p_i$ if S_i covers target T_j, otherwise $p_{ij} = \infty$. The PTC problem under this setting is equivalent to the constant-power target coverage problem.

We then prove that the simplest setting of the constant-power target coverage problem is NP-hard. Assume that the operating power of all sensors is set to 1, i.e., $p_i = 1$, when sensor S_i is active, and $p_i = 0$ if S_i is in sleep mode. Assume that the energy harvesting rate of all the sensors is equal to 1. Hence, the PTC problem can be solved by finding the *sensor cover* $(p_1^1, p_2^1, \ldots, p_N^1)$ with the minimal sum power, and operating in this network state perpetually. Then we can reformulate this problem as follows.

$$\min \sum_{i=1}^{N} p_i^1$$

$$s.t. \begin{cases} \sum\limits_{i=1}^{N} p_i^1 \cdot a_{ij} \geq 1,\ \forall j \in [1:M], \\ p_i^1 \in \{0,1\}, \forall i \in [1:N], \end{cases}$$

where $a_{ij} = 1$ indicates S_i covers T_j when $p_i = 1$, and $a_{ij} = 0$ otherwise. This is the well-known set cover problem, which is one of Karp's 21 NP-complete problems [10].

Since PTC problem belongs to the class NP and the simplest setting of it is NP-hard, we conclude that the PTC problem is NP-complete. ■

III. Verification of Perpetual Target Coverage

The assumption underlying the PTC problem in (6) is that the harvested energy is sufficient to provide perpetual target coverage. More specifically, there is at least one schedule $(f_1, f_2, ..., f_L)$, which satisfies (6b), (6c) and (6d). In this section, we study how to verify that an energy harvesting WSN is capable of providing perpetual coverage. This will be achieved by solving the equivalent maximum network lifetime problem with battery-powered sensors. There are plenty of existing works solving this problem for sensors that operate at a fixed power. We propose a greedy algorithm to maximize network lifetime under the variable-power scenario.

A. Maximum Network Lifetime Formulation

Assuming that all the sensor covers $C_1, ..., C_L$ are given, the following linear program can be used to decide whether perpetual coverage is possible, or not.

$$\max \sum_{l=1}^{L} f_l \tag{7a}$$

$$s.t. \begin{cases} \sum\limits_{l=1}^{L} p_i^l \cdot f_l \leq E_i, \forall i \in [1:N], & (7b) \\ f_l \geq 0, \forall l \in [1:L], & (7c) \end{cases}$$

where f_l can be regarded as the duration of operating at network state C_l. The constraint in (7b) guarantees that the total energy consumption of S_i is less than the energy harvested during one unit of time. Thus, this problem is equivalent to the maximal lifetime problem in a battery-powered WSN, where the battery capacity is equal to the energy harvesting rate.

Lemma 2: Given a WSN consisting of N sensors, where sensor S_i has an energy harvesting rate of E_i, $\forall i \in [1:N]$, if the solution of (7) is greater than or equal to 1, then the network is capable of perpetual coverage.

Particularly, if the maximal value of $\sum\limits_{l=1}^{L} f_l$ is equal to 1, the corresponding values of f_l, $l \in [1:L]$, are also the optimal solution for the energy minimization problem in (6). Similar to the PTC problem, this problem is also NP-complete [1].

B. Network Lifetime Approximation

To obtain an approximation to the maximum network lifetime, we consider successive time slots, and at each time slot, a *minimum weight sensor cover* (MWSC) is activated, which has been shown to prolong the network lifetime for a battery-powered sensor network [2].

Given the energy harvesting rate E_i for sensor S_i, the initial energy of S_i is assumed to be the amount of harvested energy in unit time, i.e., E_i. The weight coefficient w_{ij} is defined as follows:

$$w_{ij} \triangleq \begin{cases} 0.1^{E_{ri}/P_{ij}}, \text{if} \quad p_{ij} \cdot T/E_{ri} \leq 1, \\ W_M, \text{if} \quad p_{ij} \cdot T/E_{ri} > 1, \end{cases} \tag{8}$$

where E_{ri} is the residual energy of S_i, T is the length of the time slot, and W_M is a sufficiently large constant that can be regarded as infinity. The *minimum weight sensor cover problem* can be formulated as follows.

$$\min \quad \sum_{j=1}^{M} \sum_{i=1}^{N} w_{ij} \cdot x_{ij} \tag{9a}$$

$$s.t. \begin{cases} \sum\limits_{j=1}^{M} \sum\limits_{i=1}^{N} d_{ijk} \cdot x_{ij} \geq 1, k \in [1:M], & (9b) \\ \sum\limits_{j=1}^{M} x_{ij} \leq 1,\ \text{for } i \in [1:N], & (9c) \\ x_{ij} \in \{0,1\}, & (9d) \end{cases}$$

where $x_{ij} = 1$ means p_{ij} is assigned to S_i, i.e., $p_i = p_{ij}$, and, if $x_{ij} = 0$, $p_i \neq p_{ij}$; $d_{ijk} = 1$ if sensor S_i covers T_k when $p_i = p_{ij}$, otherwise, $d_{ijk} = 0$. The constraint in (9b) ensures that all the targets are covered by at least one active sensor, and

(9c) guarantees that each sensor is only assigned one power level. Activating a cover set with minimum aggregate weight during each time slot can efficiently reduce and balance the energy consumption among deployed sensors to improve the network lifetime.

For the special case that the weight coefficients for all the sensors are identical, the problem reduces to the set cover problem, which, as stated above, is NP-hard. A greedy algorithm is presented in Algorithm 1 to solve the *minimum weight sensor cover (MWSC) problem*. A_{ij} denotes the ratio between w_{ij} and the number of uncovered targets when S_i transmits at power level p_{ij}. At each iteration, p_{ij} with the best A_{ij} is assigned, which means that a sensor which covers the most number of uncovered targets with the smallest weight is activated with a particular power level.

Algorithm 1 Greedy MWSC Algorithm

1) Let $r = 1$, $x_{ij} = 0$, $d^r_{ijk} = d_{ijk}$, $p_i = 0$.
2) Calculate $A_{ij} \triangleq w_{ij} / \sum_{k=1}^{M} d^r_{ijk}$.
3) If for all i, j, $A_{yz} \le A_{ij}$, $y \in \{1, ..., N\}$, $z \in \{1, ..., M\}$, set $x_{yz} = 1$, $p_y = p_{yz}$ and $x_{yj} = 0$, $\forall j \ne z$.
4) If $\sum_{j=1}^{M} \sum_{i=1}^{N} d_{ijk} x_{ij} \ge 1$, $\forall k \in \{1, ..., M\}$, or $w_{yz} = W_M$, then terminate, and return $\mathcal{P} = \{p_1, p_2, ..., p_N\}$.
5) Update d^{r+1}_{ijk}: if $d^r_{yzk} = 1$ then $d^{r+1}_{ijk} = 0$, for all $i = 1, ..., N$, $j = 1, ..., M$; otherwise, $d^{r+1}_{ijk} = d^r_{ijk}$.
6) $r = r + 1$, return to Step 2.

The initial energy of each sensor is equal to the amount of energy harvested in one unit time, i.e., $E_{ri} = E_i$. In each time slot, we update the residual energy E_{ri} for each sensor, and conduct Algorithm 1 to obtain the network state vector $\mathcal{P}$. If the network with states implied by $\mathcal{P}$ does not provide *target coverage* then the lifetime of this network is considered to be terminated. If the network lifetime is larger than one unit of time, then the network is capable of perpetual coverage.

IV. Energy Efficient Perpetual Target Coverage

Recall the PTC problem formulated in (6). When the energy harvesting rate is sufficient for perpetual coverage, i.e., the perpetual coverage is possible, the objective is to find the perpetual coverage schedule which minimizes the total energy consumption.

Based on the problem statement in Section II-B, the optimal solution to the PTC problem can be partitioned into two subproblems. The first one is to find all the *sensor covers*, while the second one is to solve the linear program described in (6) based on these sensor covers. However, there are $(M+1)^N$ possible network states, $(p_1, p_2, ..., p_N)$, as each element of the state vector has $M+1$ possible values. To obtain all the *sensor covers*, we need to check every possible network state, which is computationally prohibitive, especially in large networks. To reduce the computational complexity, we propose a polynomial time algorithm to approximate the optimal solution of the PTC problem.

The intuitive idea to solve this problem is to activate the sensor cover with the minimum sum power for as long as possible. The *minimal sum power sensor cover (MSPSC) problem* is formulated as follows.

$$\min \quad \sum_{j=1}^{M} \sum_{i=1}^{N} p_{ij} \cdot x_{ij}$$

$$s.t. \begin{cases} \sum_{j=1}^{M} \sum_{i=1}^{N} d_{ijk} \cdot x_{ij} \ge 1, \quad \forall k \in [1:M] \\ \sum_{j=1}^{M} x_{ij} \le 1 \ge 1, \quad \forall i \in [1:N] \\ x_{ij} \in \{0,1\}, \quad \forall i \in [1:N], j \in [1:M]. \end{cases} \tag{10}$$

Similarly to the analysis in Section III-B, it is easily concluded that the MSPSC problem is also NP-complete. Algorithm 2 presents a low-complexity greedy power scheduling algorithm for energy efficient perpetual target coverage (EETC). At each iteration, Algorithm 2 selects a sensor cover with the smallest sum power until one of the sensors runs out of energy.

Algorithm 2 Greedy EETC Algorithm

1) Let $f = 1$, $E^f_i = E_i$, $\bar{\mathcal{S}} = \mathcal{S}$ where $\mathcal{S} = \{S_1, ..., S_N\}$.
2) Let $r = 1$, $x_{ij} = 0$, $d^r_{ijk} = d_{ijk}$, $p_i = 0$, $\mathcal{C} = \emptyset$.
3) For every sensor $S_i \in \bar{\mathcal{S}}$, and $j \in \{1, ..., M\}$, calculate $A_{ij} = p_{ij} / \sum_{k=1}^{M} d^r_{ijk}$.
4) If $A_{yz} \le A_{ij}$ for all i, j, $y \in \{1, ..., N\}$, $z \in \{1, ..., M\}$, set $x_{yz} = 1$, $p_y = p_{yz}$ and $x_{yj} = 0$, $\forall j \ne z$. Set $\mathcal{C} = \mathcal{C} \cup S_y$.
5) If $\sum_{j=1}^{M} \sum_{i=1}^{N} d_{ijk} x_{ij} \ge 1$, $\forall k \in \{1, ..., M\}$, then go to Step 8.
6) Update d^{r+1}_{ijk}: if $d^r_{yzk} = 1$ then $d^{r+1}_{ijk} = 0$ for all $i = 1, 2, ..., N$, $j = 1, 2, ..., M$; otherwise, $d^{r+1}_{ijk} = d^r_{ijk}$.
7) $r = r + 1$, return to Step 3.
8) Let $\mathcal{SP}_f = (p_1, p_2, ..., p_N)$. For every sensor $S_i \in \mathcal{C}$, compute $t_{fi} = E^f_i / p_i$. Let $t_f = \min_i \{t_{fi}\}$. If $\sum_{i=1}^{f} t_i \ge 1$ then $t_f = 1 - \sum_{i=1}^{f-1} t_i$, go to Step 10; otherwise, $E^{f+1}_i = E^f_i - p_i \cdot t_f$, $f = f + 1$.
9) For every sensor $S_i \in \bar{\mathcal{S}}$, if $E^{f+1}_i = 0$, $\bar{\mathcal{S}} = \bar{\mathcal{S}} - S_i$. If $\bar{\mathcal{S}} = \emptyset$, then go to Step 10; otherwise, go to Step 2.
10) Terminate and return $(\mathcal{SP}_1, \mathcal{SP}_2, ..., \mathcal{SP}_f)$ and $(t_1, t_2, ..., t_f)$.

V. Numerical Results

In this section, we assess the performance of the proposed algorithms for variable-power scheduling under energy harvesting constraints. As there is no previous work for comparison, we compare our results with the conventional sensor scheduling problem, in which the sensors are either turned off, or on at a fixed power value. The parameters for the simulation setup are given as follows. We consider 10 radar

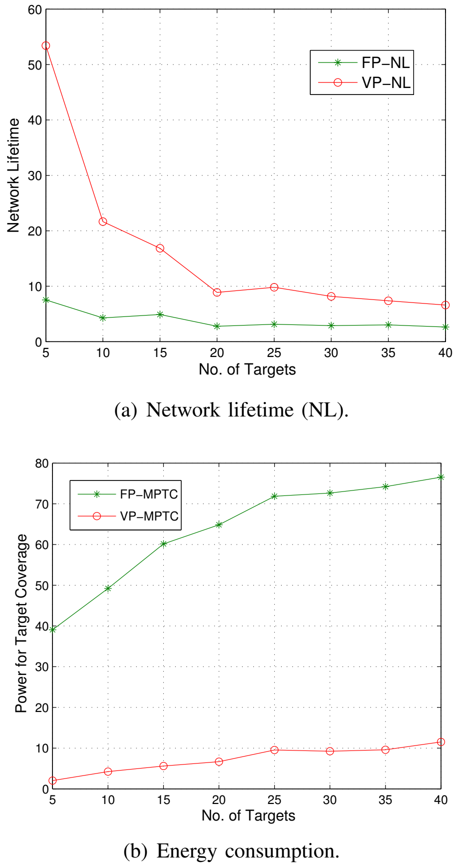

Fig. 1. Comparison of VP scheduling and FP scheduling.

sensors randomly distributed in a ROI of size $10\text{m} \times 10\text{m}$. The energy harvesting rates are randomly assigned between 40 and 60 to each sensor node. We have taken the value of k_i in (2) identical, and equal to $1/40$, $\forall i$.

We first compare the performance of variable-power (VP) scheduling investigated in this paper with fixed-power (FP) scheduling in terms of network lifetime and energy consumption. The operating power for the fixed-power scenario is assumed to be 15.625, and identical for all the sensors. At this power level, each sensor covers the targets within a distance of 5m from it. For the evaluation of the network lifetime, we consider the battery-powered WSN scenario, in which the initial battery energy for each sensor is equal to the amount of energy it harvests in unit time. The results shown in Fig. 1 indicate that compared to FP scheduling, VP scheduling can prolong the network lifetime remarkably with the same battery energy supply (Fig. 1(a)), and greatly reduce the total operating power of the network (Figure. 1(b)).

We also compare the results obtained by the proposed greedy approximation algorithm with the optimal ones in Table I and Table II. The optimal solutions are derived through an exhaustive search for all the possible sensor covers, and then by solving the corresponding linear program. These two tables present the average results of 5 simulations under each setup. The results verify that the proposed greedy algorithm performs very close to the optimal, although the gap typically increases with the number of targets.

TABLE I. NETWORK LIFETIME

No. of Target	VP-NL	VP-Optimal
4	83.6500	91.3638
6	46.5000	49.5927
8	41.5800	45.8943

TABLE II. ENERGY CONSUMPTION

No. of Target	VP-PTC	VP-Optimal
4	0.9250	0.9000
6	3.5500	3.1500
8	3.3750	3.3250

VI. CONCLUSION

We have considered perpetual target coverage with an energy harvesting WSN, consisting of variable-power sensors, e.g., radar sensors, deployed in a sensing environment. We have addressed the problem of minimizing the total energy consumption whilst ensuring that all the targets are monitored perpetually by at least one sensor node at any time instant. To evaluate the capability of the WSN to provide perpetual coverage, we have solved an equivalent maximum network lifetime problem with battery-powered sensors, in which the battery capacity of each sensor is equal to the amount of energy it harvests within unit time. Then, we have formulated the energy efficient perpetual coverage problem, and proved that it is NP-complete. A low-complexity greedy algorithm is proposed to approximate the optimal variable-power schedule. Our simulation results demonstrate that the capability of the sensors to modulate power levels significantly improves the performance of the WSN in terms of coverage lifetime and energy efficiency. The numerical results show that the proposed algorithms provide reasonably close approximations to the optimal solution, while reducing the complexity and running time significantly.

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