Cool: On Coverage with Solar-Powered Sensors

ShaoJie Tang*, Xiang-Yang Li*, Xingfa Shen†, Jianhui Zhang†, Guojun Dai† and Sajal K. Das‡
*Department of Computer Science, Illinois Institute of Technology, Chicago, IL, 60616
†Institute of Computer Application Technology, Hangzhou Dianzi University, Hangzhou, China
‡The University of Texas at Arlington

***Abstract*— In this paper, we study the dynamic node activation schedule for the utility based coverage problem in solar-powered wireless sensor networks. We assume that the utility achieved by a WSN for coverage service is a submodular function over the set of sensors that will provide the service. We first present an integer programming formulation with submodular objective functions. We then present an efficient simple greedy hill-climbing algorithm such that the achieved average utility of the computed schedule is at least $1/2$ times that achieved by the optimal schedule. To the best of our knowledge, this is the first polynomial time algorithm that can ensure a good constant approximation of the achieved utility for multi-target coverage problem. We conduct extensive evaluations to study the performances of our proposed aggregation scheduling algorithm on real testbed. Our evaluation results corroborate our theoretical analysis.**

***Index Terms*—Wireless sensor networks, multi-target coverage, rechargeable battery, scheduling.**

I. Introduction

One of the key challenges in deploying wireless sensor networks is to increase the lifetime of sensor networks, since sensors are often powered by batteries only. There are only two different ways to increase the lifetime of sensor networks: (1) reducing the expenditure rate of energy, and (2) increasing the energy supply of batteries, by potentially harvesting the environmental energy. There are several options for controlling the power consumption of a sensor which directly affect its performance. If the sensors allow dynamic voltage scaling, its power consumption may be reduced by reducing its operating speed. Radio is a major energy consumer in embedded sensors, and reducing its transmission range may be helpful in reducing power required. This may of course not be always possible depending on network connectivity constraints. A third option is to switch the device between active and sleep modes. In this paper, we consider a system of sensor nodes that are highly energy-constrained and capable of harvesting environmental energy to support the activities of sensor nodes. The basic operation in such a wireless sensor system is to provide certain coverage service, and the systematic gathering of sensed data to be eventually transmitted to a base station for processing. We consider applications where sensors are deployed in a forest to monitor the environmental changes and we need to collect environment information (*e.g.* temperature, humidity and optical intensity) from all sensors to base station. The key challenge in such systems is dynamic node activation to maximize the system utility, such as the average coverage service. The benefits of using rechargeable batteries by harvesting environmental energy to prolong sensor network lifetime have been well recognized [1]–[11]. To this end, a lot of research have been directed towards node activity scheduling in the context of rechargeable sensor networks [1]–[11]. Although the potential benefit of using rechargeable sensors to prolong sensor network lifetime is significant, the theoretical difficulty of this problem is enormous. Several key components are tightly coupled in this problem.

The first challenge is to schedule the node activations (active, or idle) such that the performance of the system is maximized when sensor nodes are able to harvest the environmental energy. Previous studies assumed that the harvested energy and the energy expenditure follow some random distributions. In this work, we assume that the energy harvested can be more accurately estimated in a short time scale (such as 2 hours), and the energy expenditure when a node is active is often a fixed value, independent of the timeslots. Our extensive testbeds measurements show that the energy expenditure of a node only has a small fluctuation when a node is active (for either idle listening, packets receiving, and/or packets transmitting).

Utility of system: For a wireless sensor network, we will achieve different quality of service if different sets of sensors are set to be active at a timeslot. For different application scenarios, the same set of activated sensors will result in different utilities also. In this work, we assume a general utility model: given a set S of sensors that are activated at a timeslot t, the utility achieved by S is $U(S)$, where $U()$ is a submodular, non-decreasing, positive function. This assumption on utility function is general enough to capture the majority applications [6].

Energy harvesting estimation: Another key challenge in studying a WSN with rechargeable batteries is to estimate the energy to be harvested in the near future. Let μ_d and μ_r denote discharging and recharging speed for each sensor respectively. We assume that both μ_d and μ_r are predictable within short time duration. Although these two parameters may vary depending on different weather condition, our extensive experiments show that within a relatively small period, *e.g.*, 2 hours, they will not change significantly in sunny weather. Please refer to Section VI for details. In order to suit long-term monitoring case, *e.g.* one week, we can dynamically choose μ_d and μ_r according to different weather condition. Throughout this paper, we assume the working time $\mathcal{L}$ of the system is one day(daytime), *e.g.* $\mathcal{L} = 12$ hours. Then we try to design a dynamic activation scheme for sensors to maximize the utility in $\mathcal{L}$.

The main contributions of this paper are as follows.

1) *Near optimal node activation scheduling:* We study the

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node activation scheduling for solar-powered sensor network where each sensor has identical discharging and recharging speed. We propose a linear programming based solution for arbitrary submodular objective functions. Then we design a simple and effective greedy hill-climbing activation schedule scheme, for which we theoretically proved that the utility is at least $1/2$ of the optimal schedule. To the best of our knowledge, this is the first polynomial time algorithm that can ensure a good constant approximation for the achieved utility for multi-target coverage problem.

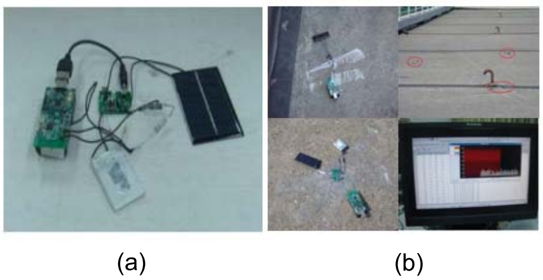


Fig. 1. (a) TelosB nodes with solar charging cells; (b) Our TestBed.

2) *Testbed evaluations:* We conducted extensive simulations and also testbed verifications of our algorithm and protocols. Figure 1 (a) is the solar powered sensor used in our evaluation, and Figure 1 (b) illustrates the testbed deployed on top of the building. We deploy 100 TelosB nodes with solar charging cells.

TABLE I
NOTATIONS USED IN PAPER

Symbol	Meaning
$\mathbf{O}_i$	Target
T_d	Discharge time of the sensor node
T_r	Recharge time of the sensor node
T	Charging period of the system which is defined as $T_r + T_d$
$\mathcal{L}$	Working time of the system which is a multiple of T
ρ	Ratio between T_r and T_d
$U()$	The overall utility function
$U_i()$	The utility gathered by covering target $\mathbf{O}_i$

II. PROBLEM FORMULATION

A. Network Model

Assume that there are n sensors $V = \{v_1, v_2, \cdots, v_n\}$ distributed in a two-dimensional region. For simplicity of notations, we also assume that the sensor node v_i is at position v_i. We assume that the operation power of every sensor is fixed. Thus, the region $R(v_i)$ that a sensor node v_i can cover (monitor) is fixed. For simplicity, we assume that the *monitored region* $R(v_i)$ is known by certain measurement. Note that different sensors can be located at different points in the overall physical space of interest, and the coverage patterns of different nodes can be different.

B. Recharging and Discharging Model

We consider a discharge-recharge model similar as the one used in [1]. Specially, we assume each sensor is energy-constraint and rechargeable. And the time is divided into equal-sized slots (*e.g.*, each time-slot is of 15 minutes) and all sensors have synchronized clocks. Assume that the time-slots start from time 0. Sensors could be turned on and off at different time slots. Each sensor could be in one of three states at each time instant: *active*, *passive* and *ready*.In the *active* state, the sensor is powered on and begin sensing, communicating or computing and hence consumes its energy gradually. Once the energy of a sensor node is used up, it will enter the *passive* state and be recharged without any other operations. When its battery is fully charged, the sensor enters the *ready* state. Sensors in *ready* state do not participate in sensing and other operations until it is activated. Even though the sensors under ready state do not actively sense the target, they still need to wake up periodically in order to keep track of the system state. However, the energy discharge rate speed in the ready state is much slower than in the active state. Thus, we assume that the energy level of a sensor in the ready state does not change.

Remember that μ_d and μ_r denote discharging and recharging speed respectively. In this work, we study the case where all the sensors are *homogeneous*, that is both μ_d and μ_r are same for each sensor at the same time. For completeness of this work, we also briefly discuss the random charging model at last. For different weather conditions, although we may have different discharging/recharing pattern, our extensive experiments show that within a relatively small period, *e.g.*, 2 hours in day time under sunny weather, those two parameters will not change significantly. When the weather condition changes significantly, *e.g.*, during one week, we may choose different charging pattern accordingly. Throughout this paper, we assume the working time $\mathcal{L}$ of the system is half day, *e.g.* $\mathcal{L} = 12$ hours (since the sensor can only be recharged at daytime). Then the objective is to design a dynamic activation scheme for sensors in order to maximize the utility in $\mathcal{L}$. The battery capacity of each sensor is denoted as B and the energy can be depleted to zero. Then we define the *recharge time* as the time spent on the passive state, and *discharge time* as the time spent on the active state. In particular, the recharge time and discharge time can be formulated as $T_r = B/\mu_d$ and $T_d = B/\mu_r$. Based on the definition listed above, we further define the charging period T for the system as $T = T_r + T_d$. Let $\rho = T_r/T_d$ denote the ratio between recharge and discharge time. For simplicity of exposition, if $\rho \geq 1$ (or $\rho < 1$), we assume ρ (or $1/\rho$) is an integer without affecting the generality of our results. When $\rho > 1$(or $\rho \leq 1$), if we scale one time-slot to T_d(or T_r), each period will contain $1 + \rho$ (or $1 + 1/\rho$) time-slots, *e.g.*, $T = \rho + 1$ (or $T = 1 + 1/\rho$). Please see Figure. 2 for illustration. As verified by our experiments, ρ almost remains at the same level within 2 hours under sunny weather. Assume that the time-slot size is 15 minutes and $\rho = 3$. Then $T = (3 + 1) \times 15 = 60$ minutes,

$\mathcal{L} = 12 \times 60 = 720$ minutes. Throughout this paper, we will use T and $\rho + 1$ (or $1/\rho + 1$) interchangeably to denote the time-slots contained in one period. And we assume the overall working time of the system is a multiple of T, *e.g.* $\mathcal{L} = \alpha T$ for some integer $\alpha \geq 1$. Clearly, each sensor can only be activated one time-slot in one period when $\rho \geq 1$. Then depending on different values of ρ, we have two cases to study: $\rho > 1$ and $\rho \leq 1$.

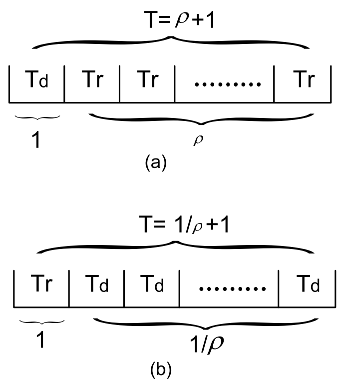


Fig. 2. (a) Illustration of one period when $\rho > 1$; (b)$\rho \leq 1$.

C. Utility Functions

Sensor networks are often deployed to monitor a given set of m targets $\mathcal{O} = \{\mathbf{O}_1, \mathbf{O}_2, \cdots, \mathbf{O}_m\}$ in a region or monitor the whole region Ω. In this paper, we use $V(\mathbf{O}_i)$ to denote the subset of sensors in V that can monitor the target $\mathbf{O}_i$, *i.e.*, $\mathbf{O}_i$ is inside the monitoring region $R(v_j)$ for each $v_j \in V(\mathbf{O}_i)$. Depending on the applications, different subset of sensors being activated will provide different service qualities for the system. We assume that the performance of the wireless sensor system is characterized by a continuous, non-decreasing, submodular function. More specifically, when WSN is used to monitor the set $\mathcal{O}$ of targets, $U_i(S)$ represents the utility gathered from the target $\mathbf{O}_i$ if the set S of sensors are activated. For example, for each sensor v_j that can monitor $\mathbf{O}_i$, let p_j be the probability that the sensor v_j will detect a certain event happened at target $\mathbf{O}_i$. Then the utility $U_i(S) = 1 - \prod_{v_j \in S}(1 - p_j)$ denotes the probability that the event happened at the target $\mathbf{O}_i$ will be detected by these S sensors. We always assume that, for every target $\mathbf{O}_i$, $U_i()$ is non-decreasing submodular function. Specially, it satisfies the follow conditions:

$$\begin{cases} U_i(\emptyset) = 0, \\ U_i(S_1) \leq U_i(S_2), \text{ if } S_1 \subseteq S_2, \text{ and} \\ U_i(S_1 \cup A) - U_i(S_1) \geq U_i(S_2 \cup A) - U_i(S_2), S_1 \subseteq S_2 \end{cases}$$

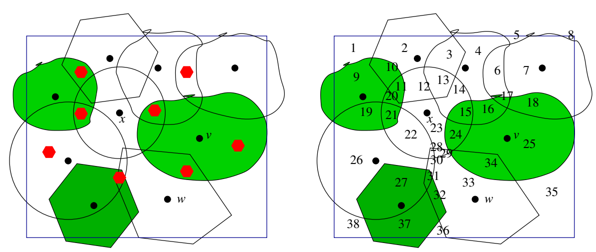
Note that if more sensors are activated, we may gain more utility. However, if the number of active sensors is already huge, due to the diminishing returns property of the submodular utility function, the incremental utility may be tiny by adding new active sensors at the same time-slot. Thus, we may want to let each sensor active evenly as intuition.

The overall utility achieved by the wireless sensor network is $f(U_1(), U_2(), \cdots, U_m())$. Here we assume that the function $f()$ is symmetric, *e.g.*, $f(U_1(), U_2(), \cdots, U_m(x)) = \sum_{i=1}^{m} U_i()$. In the rest of paper, when WSN is used to monitor a set of static targets, we always consider the overall utility function as

$$\sum_{i=1}^{m} U_i(). \tag{1}$$

Observe that here function $U_i()$ may be different for different targets.

When the sensors are used to monitor a given region Ω, we cannot simply use the number of activated sensors in the system to characterize the utility of the system. One possible way is to use the total area of regions that can be monitored by all activated sensors. In certain cases, we may have different monitoring preferences over different places in Ω. To capture this, we assume that the region Ω is divided into polynomial number of subregions defined by all monitored regions $R(v_i)$, for $v_i \in V$. For example, when regions $R(v_i)$, $v_i \in V$, are all convex, all such monitored regions $R(v_i)$ ($v_i \in V$) will subdivide the region Ω into at most n^2 subregions, where n is the number of sensors in the system. See Figure 3 for illustration of subregions. For simplicity, let



(a) monitoring targets (b) monitoring region Ω

Fig. 3. (a) Here the red hexagons are targets to be monitored by a WSN. (b) WSN is used to monitor a region Ω. The region Ω (denoted by a large rectangle area) is subdivided into a number of subregions (38 for this example).

$\mathcal{A} = \{A_1, A_2, \cdots, A_b\}$ be the set of b subregions produced, where b is bounded by a polynomial of n. Then, given a set of activated sensors $S(t)$ at time slot t, we know the subset of regions to be covered by this set of activated sensors S. The utility achieved by S is then characterized by a utility function

$$U(S) = \sum_{i=1}^{b} I_i(S) \cdot w_i \cdot |A_i|, \tag{2}$$

where $I_i(S) = 1$ if the subregion A_i is contained inside the monitored region of some sensors in S, and $I_i(S) = 0$ otherwise. Here $w_i > 0$ captures the preferences over different subregions, and $|A_i|$ is the area of the subregion A_i. Note that the coverage areas of different sensors will typically be different. This implies that at any time, utilities in different parts of the area of interest can differ significantly from one another. Recall that we divided the time into time-slots and at the beginning of every time-slot t, we will make decision on which sensors to be activated during time-slot t. Let variable $x(v_i, t) \in \{0, 1\}$ indicate whether the sensor node v_i is activated or not at time-slot t, *e.g.*, we set $x(v_i, t) = 1$ when node v_i is under active state at time slot t; otherwise, $x(v_i, t) = 0$.

D. Problem Statement

In this paper, we essentially will study how to dynamically activate the sensor nodes to maximize the utility achieved by the WSN. Assume that the sensor network is expected to work for $\mathcal{L}$ time-slots, where $\mathcal{L}$ is a multiple of T. Recall that we assumed that the energy recharging is periodic with a period $T = \rho + 1$ time-slots when $\rho \geq 1$. For example, we can estimate the energy harvesting pattern for a duration of 2 hours.

Most of previous works study the coverage problem under identical coverage model where all sensors can and will cover the same target. However, a WSN is not deployed to monitor only one target typically; it is often used to monitor a set of targets $\mathcal{O}$ distributed in a region Ω. Moreover, not all sensors can monitor any single target $\mathbf{O}_i \in \mathcal{O}$. In this case, the utility of the WSN at a time-slot t is $\sum_{i=1}^{m} U_i(S_X(\mathbf{O}_i, t))$, where $S_X(\mathbf{O}_i, t)$ is the set of activated sensors that can monitor the target $\mathbf{O}_i$ at times-lot t under a dynamic sensor activation policy X. Thus, the average utility of the WSN in its working time $\mathcal{L}$ is

$$U_X = \sum_{t=0}^{\mathcal{L}-1} \sum_{i=1}^{m} U_i(S_X(\mathbf{O}_i, t)).$$

Here we want to find a dynamic sensor activation policy X that will maximize the overall utility U_X. Note that the identical coverage model is a special case of the model studied in this paper.

III. Hardness of the problem

In the following theorem, we prove that the dynamic activation schedule problem is NP-Hard.

Theorem 3.1: The dynamic activation schedule problem is NP-Hard.

Proof: Here we only need to consider a simple case where there is only one target which can be covered by all sensors, the working time is one period, *e.g.*, $\mathcal{L} = T$. Assume $\rho \geq 1$, we next prove that even for this simplest case, it is already NP-Hard which implies the NP-Hardness for the original problem. In this case, since each sensor can only be activated one time-slot, the objective becomes finding a way to allocate all sensors to T time slots such that the utility is maximized. We will reduce it from the *Subset-Sum* Problem: Given a set of integers $I_1, \cdots, I_n$, determine whether there exists a subset of numbers from A such that the sum of those numbers $\sum_{I_i \in A^c} I_i = \sum_{I_i \in A} I_i/2$.

Then given an input as listed above, we construct a scheduling problem as follows: In the constructed scheduling problem, we have n sensors, and the period T is set to 2, *e.g.* $\rho = 1$. We further define the utility function as:

$$U(S) = \log(1 + \sum_{v_i \in S} I_i)$$

The utility function is clearly a non-decreasing submodular function. Thus based on the "diminishing returns" property of the submodular function, it can be easily proved that the utility gained by the optimum solution can achieve $2 \times \big(\log(1 + \sum_{i \in S} I_i)/2)\big)$ if and only if there exists a subset A^c of A such that $\sum_{I_i \in A^c} I_i = \sum_{I_i \in A} I_i/2$. This finishes the proof. ■

While the NP-hardness established in the previous theorem brought us negative news, the approximation hardness of the same problem should bring us good news. In the following sections, we propose a number scheduling schemes to tackle this problem.

IV. Scheduling Scheme

A. $\rho > 1$

We first study the case when the discharge time is shorter than recharge time. As mentioned before, we normalize one time-slot to T_d in this case. As observed in our experiment, this case is more likely to happen in realistic sensing environment.

1) Linear Programming Solution: We first formulate the node activation problem as an integer programming as follows. Let $x(v_i, t) \in \{0, 1\}$ denote whether sensor node v_i is activated at time slot t. And let a_{ij} be a indicator which is defined as follows:

$$a_{ij} = \begin{cases} 1 & \text{if sensor } v_i \text{ cover target } \mathbf{O}_j \\ 0 & \text{else.} \end{cases}$$

Since $\rho > 1$, each node can work for at most 1 time slot every T time slots in order to keep the residual energy in the node more than zero. In order to determine the optimal activating schedule for each node to maximize the overall network utility, we solve the $x(v_i, t)$ of each node v_i for from an integer programming problem as follows:

$$\begin{aligned} Max \quad & \sum_{t=1}^{\mathcal{L}} \sum_{j=1}^{m} U_j(S_X(\mathbf{O}_j, t)) \\ s.t \quad & 0 \leq U_j(S_X(\mathbf{O}_j, t)) \leq U_j(\cup_{i: x(v_i,t)=1, a_{ij}=1} v_i), \ \forall j, \forall t \\ & x(v_i, t) \in \{0, 1\}, \ \forall i, \forall t \\ & \sum_{t=t'}^{t+T} x(v_i, t') \in \{0, 1\}, \ \forall i, \forall 0 \leq t' \leq \mathcal{L} - T \end{aligned}$$

The first two conditions are straightforward. The third condition ensure the feasibility of the schedule. Specifically, during one period T, each sensor can be activated no more than one time-slot. By relaxing the conditions $x(v_i, t), \sum_{t=t'}^{t'+T} x(v_i, t) \in \{0, 1\}$ to $0 \leq x(v_i, t), \sum_{t=t'}^{t'+T} x(v_i, t) \leq 1$, the above integer programming becomes a linear programming problem. After solving the linear programming problem in polynomial time, we let each node v_i be active at time-slot t with probability $x(v_i, t)$. However, after the rounding procedure, all the constraints may not hold anymore. For example, some sensor may be active for more than two time slots within one charing period. To overcome this problem, we may use the iteration method proposed in [13]. Basically, the rounding procedure will not stop until a feasible solution is found. We can show that the *expected* utility is good here. Note that when n, m and T are large, the time spent by the rounding procedure will be too long to be practical. Thus, instead of keeping iterating the rounding procedure, we may carefully deactivate some sensors to achieve feasibility. The details are omitted here to save space.

2) Greedy Hill-Climbing Activation Scheme: In this section, we propose a simple and effective Greedy Hill-climbing Node Activation Scheme. We theoretically prove that this scheme can achieve $1/2$-approximation even for the general case. Later, our extensive evaluation results show that it can perform even better than the theoretical bound.

To describe our solution in a easier way, we first study a simple case where the working time of the system contains only one period, *e.g.*, $\mathcal{L} = T = \rho + 1$. Since each sensor can only be activated one time-slot during $\mathcal{L}$ in this case, our problem becomes how to allocate n sensors to $\rho+1$ time-slots in order to maximize the overall utility. Recall that the utility function at each time-slot is defined as:

$$\sum_{i=1}^{m} U_i(S_X(\mathbf{O}_i, t))$$

where $S_X(\mathbf{O}_i, t)$ is the set of activated sensors that can monitor the target $\mathbf{O}_i$ at times-lot t under a dynamic sensor activation policy X. Based on the assumption that the utility function $U_i(S)$ for each target $\mathbf{O}_i$ is non-decreasing submodular, it is easy to prove that the overall utility function $\sum_{i=1}^{m} U_i(S_X(\mathbf{O}_i, t))$ for each time-slot t is also non-decreasing submodular.

The key idea of the greedy hill-climbing scheme is: We schedule the sensor *one by one* following a simple greedy rule described below: at each step, we schedule a sensor to some time-slot in order to maximize the *incremental utility* together with previous scheduled sensors. We keep repeating this procedure until all sensors are scheduled. Clearly, we need exactly n steps to finish the scheduling. Please refer to Algorithm 1 for details.

For example, if $\rho = 5$ and $n = 9$. Then we find a scheduling for each sensor one by one following the greedy rule, allocating a senor to some time-slot which can maximize the incremental utility. As illustrated in Figure. 4, at the first step, we allocated v_4 to time-slot t_1 since it can give us the largest utility. Then we delete v_4 from the candidate set, and we next find that allocating v_6 to t_3 has the maximum incremental utility by assuming v_4 is already activated at t_1. Following this greedy rule, we can finish the scheduling after 9 steps. The resulted activation schedule is: sensor v_4 is activated at time-slot t_1; v_2 and v_7 at t_2;v_6 at t_4; v_1 and v_5 at t_4; v_3 at t_5; v_8 and v_9 at t_6.

Next we first prove that the greedy activation scheme has $1/2$-approximation when $\mathcal{L} = T$. We further prove that by repeatedly using the same scheduling in each period, we can

Algorithm 1 Greedy Hill-Climbing Activation Scheme

Input: The sensor nodes set $V = \{v_1, v_2, \ldots, v_n\}$, the time slots set $\mathrm{T} = \{t_1, t_2, \ldots, t_T\}$, the targets set $\mathcal{O} = \{\mathbf{O}_1, \mathbf{O}_2, \ldots, \mathbf{O}_m\}$, the utility function $U()$.

Output: The set of (v_i, t_k) pairs indicating sensor v_i will be activated at time-slot t_k.

```
l = n;
while l > 0 do
    for each sensor v_i ∈ V do
        for each time-slot t_j ∈ T do
            Choose and assign the pair (v_max, t_max) which
            can maximize the incremental utility by activating
            v_max at time-slot t_max;
            V := V\v_max;
        end for
    end for
    l := l − 1;
end while
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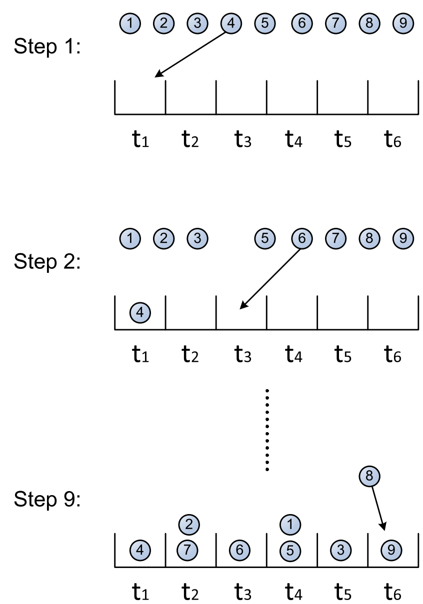


Fig. 4. In this example, $\rho = 5$ and $n = 10$. In each step, we allocate a sensor to some time-slot which can maximize the incremental utility.

still achieve $1/2$-approximation when $\mathcal{L} = \alpha T$ for any integer $\alpha \geq 1$.

Lemma 4.1: The greedy hill-climbing activation scheduling scheme can achieve $1/2$-approximation when $\mathcal{L} = T$.

Proof: We prove it through induction. Let P denote the original problem with n sensors and $\rho + 1$ available time slots. We define P' as a new problem with $n - 1$ sensors by assuming the first sensor has already been scheduled by Algorithm 1, *i.e.* sensor v_1 is scheduled to be active at time slot i by Algorithm 1. In other words, we will not consider v_i anymore in problem P'. Instead, we redefine the utility function at time slot i by activating subset of sensors A as

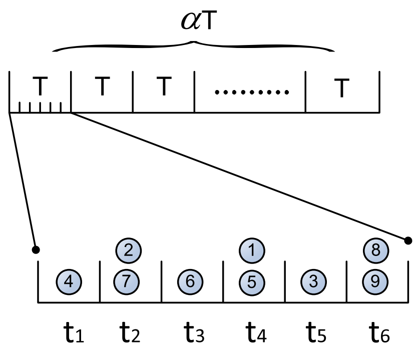


Fig. 5. This figure illustrates the structure of our schedule when $\mathcal{L} = \alpha T$. Basically, we repeatedly use the previous schedule in each single period.

$U'(i, A) = U(i, A \cup \{v_1\}) - U(i, \{v_1\})$ where $U(i, S) = U(S)$ is the original utility function for any subset S. The utility function for all other time slots except i is not changed. Actually, we can consider our hill climbing algorithm as scheduling sensor v_1 at time slot i first. Then we run it on problem P' recursively. We use U^{P}_{ALG} to denote the utility gained by the hill climbing algorithm on problem P, and U^{P}_{OPT} to denote the utility gained by the optimal solution. For simplicity of analysis, let $z = U(\{v_1\})$. Clearly, we have $U^{P}_{ALG} = U^{P'}_{ALG} + z$ based on the definition of problem P'. We next try to show that $U^{P}_{ALG} \leq U^{P'}_{ALG} + 2z$. Let $Q_1, \cdots Q_{\rho+1}$ be the optimal scheduling for problem P, where Q_j represents the active sensors at time slot j under optimal scheduling. we next have two cases to study:

Case 1: We first study the case when $v_1 \in Q_i$. Since we assume that v_1 is also scheduled at time slot i by Algorithm 1, it indicates that the scheduling of v_1 by Algorithm 1 is optimal. Thus, $U^{P}_{OPT} = U^{P'}_{OPT} + z$ based on the definition of P and P'.

Case 2: When $v_1 \notin Q_i$, we can modify the optimal schedule by rescheduling v_1 at time slot i. All other sensors still have the same scheduling. Obviously, this is a possible scheduling for P'. Based on the submodularity of utility function and the greedy manner of our algorithm, we can guarantee that the loss resulted from removing v_1 is at most z. Thus, we have $U^{P}_{OPT} \leq U^{P'}_{OPT} + 2z$.

Finally, we get $U^{P}_{OPT} \leq U^{P'}_{OPT} + 2z$. The proof can be finished by induction on P' since the utility function defined in P' is also submodular based on Lemma 4.2. Thus,

$$U^{P}_{OPT} < U^{P'}_{OPT} + 2z < 2U^{P'}_{ALG} + 2z = 2U^{P}_{ALG}.$$

This finishes the proof. ■

Lemma 4.2: The utility function defined in problem P' is still submodular.

Proof: The detailed proof can be found in Appendix. ■

To this end, we have proved that the greedy scheme can guarantee a constant approximation when $\mathcal{L} = T$. However, when $\mathcal{L} = \alpha T$ for arbitrary integer $\alpha \geq 1$, can we still get a constant approximation by repeatedly implementing the previous schedule in each period T? Our answer is positive. In particular, we will prove that by applying the same schedule in each period, we can still get a $1/2$-approximation.

Theorem 4.3: The greedy hill-climbing activation scheduling scheme can achieve $1/2$-approximation when $\mathcal{L} = \alpha T$ for any integer $\alpha \geq 1$.

Proof: We first show that by repeatedly using the previous schedule in each period, it is still a feasible schedule, that is, each sensor is activated at most once among any consecutive T time-slots. Clearly, by following our greedy scheme, each sensor is activated *exactly* once among each period which implies its feasibility.

Next, we prove that it also achieves $1/2$-approximation. Assume that $\mathcal{L} = \alpha T$ for some integer $\alpha > 1$. Let $U^{<T>}_{OPT}$ and $U^{<\alpha T>}_{OPT}$ denote the utility of the optimal solution when $\mathcal{L} = T$ and $\mathcal{L} = \alpha T$ respectively; $U^{<T>}_{ALG}$ and $U^{<\alpha T>}_{ALG}$ denote the utility gained from our greedy scheme when $\mathcal{L} = T$ and $\mathcal{L} = \alpha T$ respectively. Then we have $U^{<\alpha T>}_{OPT} \leq \alpha U^{<T>}_{OPT}$. Since we repeatedly using the greedy scheme in each period, then together with Lemma 4.1, we get

$$U^{<\alpha T>}_{ALG} = \alpha \cdot U^{<T>}_{ALG} \geq \alpha \cdot \frac{1}{2} U^{<T>}_{OPT}$$

$$\text{Thus, } U^{<\alpha T>}_{ALG} \geq \alpha \cdot \frac{1}{2} U^{<T>}_{OPT} \geq \frac{1}{2} U^{<\alpha T>}_{OPT}$$

This finishes the proof. ■

Obviously the time-complexity of the hill-climbing method is $O(n/\rho)$ for a network of n nodes and $\rho < 1$.

B. $\rho \leq 1$

In this section, we will study the activation problem when $\rho \leq 1$. Clearly, by modifying some conditions, we can still use the integer programming scheme to derive a activation schedule. The details are ignored due to space limit.

Here we are more interested in designing a greedy hill-climbing scheme while sustaining a constant approximation. Surprisingly, by slightly modifying the previous greedy scheme, we can still get a constant approximation. Notice that when $\rho \leq 1$, each sensor can be active for $1/\rho$ time-slots while only needing to be passive for 1 time-slot. The key idea of our scheme is, instead of studying how to allocate the active time-slot for each sensor as in previous case, we try to allocate the passive time-slot for each sensor in order to maximize the utility.

Similarly, we first study the case when $\mathcal{L} = T$. Initially, we assume all sensors are active all T time-slots. Then we allocate the passive time of each sensor in the following greedy manner: At each step, we allocate the passive time of some sensor to some time-slot in order to minimize the decremental utility. We can also extend the greedy scheme to the case when $\mathcal{L} = \alpha T$ by simply repeating the same schedule in each period. Then we have the following theorem whose proof is omitted to save space:

Theorem 4.4: The greedy hill-climbing activation scheduling scheme can achieve $1/2$-approximation when $\rho \leq 1$.

(a) SolarMote 1 (b) SolarMote 2 (c) SolarMote 3 (d) Testbed

Fig. 6. TelosB nodes with solar charging cells.

V. Discussion on Other Charging Models

In some cases, the discharging time is not a fixed value. Instead, it is a variable depending on some random events that happen with some probability distribution, such as Poisson arrival with a rate λ_a. For each event, assume the time duration follows the exponential distribution with the mean duration λ_d. Let T_d denote the discharging time when a sensor is working or sensing continuously. Thus, the mean discharging time $\overline{T_d}$ monitoring the event is $T_d/\lambda_a \cdot \lambda_d$. We will ignore the mechanism for waking up sensors when some event happens.

On the other hand, recharging time T_r may also be a random variable even for one day. We assume that this variable follows the normal distribution with mean $\overline{T_r}$.

We then define $\rho' = \overline{T_r}/\overline{T_d}$ as the ratio between the expected discharging and recharging speeds instead of ρ defined in Section II. Then we can use the new defined ratio ρ' in the linear programming based solution. However, it is non-trivial to extend the greedy scheme under this model. Thus, we leave it as possible future work.

VI. Evaluation

This section describes our experiments established on real solar-powered sensor network. We implement a series of experiments to validate the algorithms designed in previous sections. Our experiment contains two parts: *energy charging pattern measurement* and *algorithms testing*. In the first part, we conducted a number of experiments using TelosB nodes with solar cells in different scenarios. By these experiments, we obtain the charging patterns under different weather conditions. In the second part of our experiment, a number sensor nodes with solar-cell charger are composed to form a real sensor network, in which our algorithms are implemented and evaluated.

A. Charging Pattern Measurement

To obtain the charging pattern under different weather condition, we build a testbed which is on the top of a building as shown in Figure 6 (d). In order to sample the information from the real network, we locate a sink in a lab in the building and deploy several relay nodes. Each TelosB node is equipped with one or two solar cells as shown in Figure 6. Each sensor can harvest energy by solar cell and store energy. We conducted experiments to find different charging patterns under different weather conditions. The experiment is launched at 21:55:51 GMT+08:00, July 16, 2009. 2009, and ended at 19:54:59 GMT+08:00, July 17, 2009. The experimental results are shown in Figure 7, the charging pattern is presented as the voltage vs. light strength. We only reported the pattern of 2 nodes here due to space limit although we measured the patterns of much more sensors.

Based on the observed experimental results, we find that within one day, the light strength varies significantly. However, the charging voltage almost remains at the same level as long as it starts to harvest the energy. These results verify our claim that T_r is fixed within a relatively small working time, *e.g.* one day. Since all sensors used in our testbed are identical, they also have same and fixed discharging speed T_d. Typically, for the sensors used in our experiments, the recharge time is around 45 minutes and the discharge time is 15 minutes when weather is sunny. Thus, we will set $T_d = 15$ and $T_r = 45$ in our following algorithm evaluation. Note that we may choose different pattern each day for different weather condition.

B. Evaluation of the Greedy Hill-Climbing Algorithms

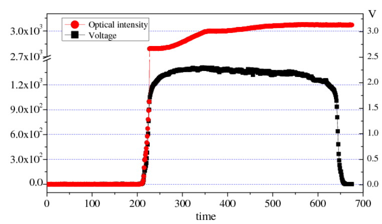
To evaluate our greedy algorithm, we deployed 100 sensors with solar charge cells and let the system run 30 days (daytime). In the following contents, we define the average utility as the average utility achieved per target per time-slot. We first study the case when there is only one target. Here the *average utility* is

$$\overline{U} = \frac{\sum_{t=1}^{\mathcal{L}} 1-(1-p)^{|S(t)|}}{\mathcal{L}}$$

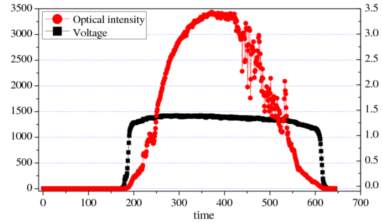
where $p = 0.4$, $S(t)$ is the set of activated sensors at time-slot t and $|S(t)|$ is the size of $S(t)$. The upper-bound on the optimum utility is computed using formula $\overline{U}^* = 1-(1-p)^{\overline{n}}$ where $\overline{n} = \lceil n/T \rceil$ and n is the total number of sensors.

The average utility achieved by our algorithm is 0.983408764, while the optimum solution is upper bounded by 0.999380. Please see Figure. 8 (a) for illustration. We then study the multi-target case where the number of targets varies from 2 to 4, the achieved utilities have been demonstrated in Figure. 8(b)(c)(d). Obviously, the performance of our greedy scheme is sufficiently close to the optimal solution in most cases. Here the optimal solution is obtained by enumerating all possible scheduling.

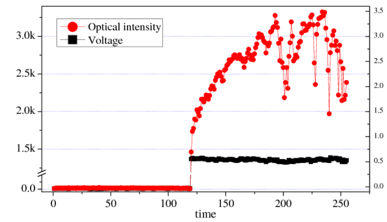
We then simulate a larger sensor system using the real data collected from 100 sensors we deployed. Please refer to Figure. 9 for illustration. This experiment result basically disclose the performance of the greedy scheme under various



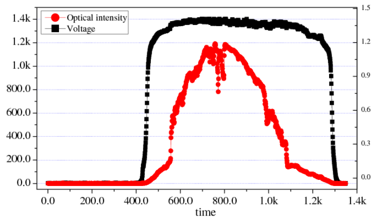
(a) Node 5 at 15^{th},



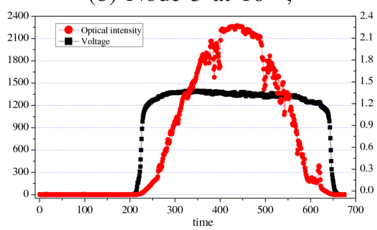
(b) Node 5 at 16^{th},



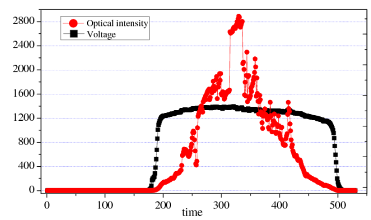
(c) Node 5 at 17^{th}



(d) Node 6 at 15^{th},



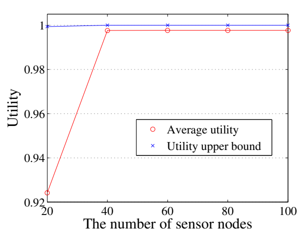
(e) Node 6 at 16^{th},



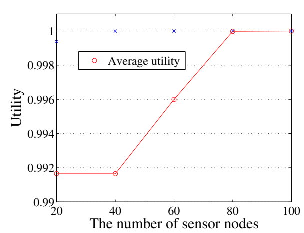
(f) Node 6 at 17^{th}

Fig. 7. Time vs. Light strength vs. Charging voltage.

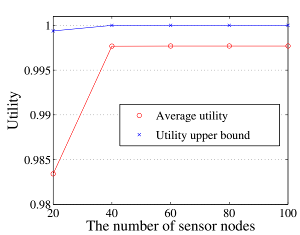
environments, *e.g.* number of sensors varies from 100 to 500 and the number of targets varies from 10 to 50. When the amount of deployed sensors is around $100-200$, the achieved average utility is at least 0.69. In contrast, when the number of sensors is increased to $300-500$, the average utility is no less than 0.78. Thus, in either case, the average utility is no less than 0.5 which corroborates our theoretical analysis (since the maximum average utility is no more than 1).



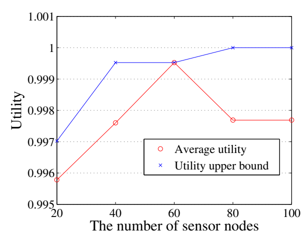
(a)



(c)



(b)



(d)

Fig. 8. The average utility achieved by our methods when the number of targets m is fixed. (a)m=1; (b)m=2; (c)m=3; (d)m=4

VII. Related Work

This section will review related work on rechargeable sensor networks. The literature on the topics of wireless sensor networks with rechargeable battery that harvest the environmental energy (such as solar [14], [15], wind [16], and thermal [17])

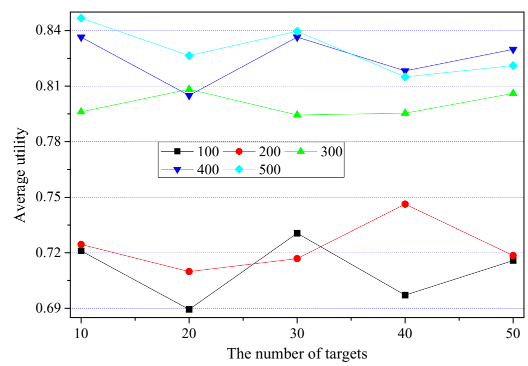


Fig. 9. The average utility achieved by our methods: number of sensors vs. number of targets.

has been greatly expanded in recent years. In [1], [6], [12], Jaggi *et al.* examined a scenario where the derived utility (*e.g.*, probability of event detection) depends only on the number of currently activated sensors. In [2], the sensors are allowed to be activated even when partially recharged and an asymptotically optimal policy is proposed. In [3], the authors considered the activation question for a single sensor where events have temporal correlations, and posed it in a stochastic decision framework. In [4], the authors modeled the rechargeable sensor system as a system of finite-buffer queues. In [7], each rechargeable sensor node can hold up to K quanta of energy. In [8], Kansal *et al.* studied the scheduling for single sensor with rechargeable energy. In [10], Pryyma *et al.* aim to provide uniformly distributed sensing throughout the entire life-time of the network. Compared with our system model, in all these results [1]–[3], [6], [12], either the energy discharge, or the energy harvesting, or both are assumed to be random events, following Poisson distributions or exponential distributions. In addition, only efficient suboptimal policies are proposed and numerically evaluated for multiple node networks [6]. They also assumed that the mean discharge rates and the mean charging rates are same for all sensor nodes. Further they assumed that the mean charging rate is smaller than the mean discharge rate. Efficient routing and admission control for sensor networks with rechargeable batteries has also been studied. In [18], Lin *et al.* studied the admission control and routing problem for wireless sensor networks with rechargeable battery. They considered a multihop network where the nodes have knowledge of the short-term future recharge process. In [11], Gatzianas *et al.* considered the problem of cross-layer resource allocation for single-hop, time-varying, wireless networks operating with rechargeable batteries.

VIII. Conclusion

There are a number of challenging problems left for future work. In this work we assumed that a node can be activated only if it is fully charged. We would like to study the case that allow partially recharged sensors to be activated. The second challenge is to design efficient method for heterogenous sensor network where different sensor may have different charging/recharging pattern even at the same time.

IX. ACKNOWLEDGEMENT

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Appendix

Proof For Lemma 4.2:

Proof: Since the utility function is unchanged for all other time slots except i according to the definition of P'. We only need to prove that the utility function at time slot i is also submodular. Recall that $U'(i, A) = U(i, A \cup \{v_1\}) - U(i, \{v_1\})$, let $X \subseteq Y$, we have,

$$\begin{aligned}
&\left[U'(i, S\cup X) - U'(i, X)\right] - \left[U'(i, S \cup Y) - U'(i, Y)\right] \\
&= [(U(i, S \cup \{v_1\} \cup X) - U(i, \{v_1\})) - (U(i, X \cup \{v_1\}) - U(i, \{v_1\}))] \\
&\quad - [(U(i, S \cup \{v_1\} \cup Y) - U(i, \{v_1\})) - (U(i, Y \cup \{v_1\}) - U(i, \{v_1\}))] \\
&= [U(i, S \cup \{v_1\} \cup X) - U(i, \cup\{v_1\} \cup X)] \\
&\quad - [U(i, S \cup \{v_1\} \cup Y) - U(i, \cup\{v_1\} \cup Y)] \\
&= [U(i, S \cup X') - U(i, X')] - [U(i, S \cup Y') - U(i, Y')] \\
&> 0
\end{aligned}$$

The last equality is because of the following: (1) we denote $X \cup \{v_1\}$ by X' and $Y \cup \{v_1\}$ by Y', (2) since $X \subseteq Y$, we have $X' \subseteq Y'$, (3) $U(i, X)$ is submodular.

It follows that for any $X \subseteq Y$, we have

$$U'(i, S \cup X) - U'(i, X) \geq U'(i, S \cup Y) - U'(i, Y).$$

This finishes the proof. ∎