Distributed Sampling Rate Control for Rechargeable Sensor Nodes with Limited Battery Capacity

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***Abstract*—Energy harvesting is a promising technology for extending the lifetime of battery-powered sensor networks. Due to time variations of harvested energy, one of the main challenging issues is to maximize the uninterrupted sampling rates of all sensor nodes, which represents the network performance. Most of existing works do not consider the limited capacity of rechargeable battery. In this paper, we are concerned with how to adaptively decide the sampling rate for each rechargeable sensor node with a limited battery capacity to maximize the overall network performance. To solve this problem, we firstly propose an adaptive Energy Allocation sCHeme (EACH) for each sensor node to manage its energy use in an efficient way. Then we develop a Distributed Sampling Rate Control (DSRC) algorithm to obtain the optimal sampling rate. Furthermore, an Improved adaptive Energy Allocation sCHeme (IEACH) is proposed to reduce the impact due to imprecise estimation of harvested energy. Extensive simulations using real experimental data obtained from Baseline Measurement System (BMS) of Solar Radiation Research Laboratory are conducted to demonstrate the efficiency of the proposed algorithms.**

***Index Terms*—Rechargeable sensor networks, limited battery capacity, energy allocation, sampling rate control.**

I. Introduction

ENERGY constraint has been a challenging bottleneck for further advance of wireless sensor networks (WSNs), although great success has been achieved in last decade. As the energy constraint mainly comes from the fact that sensor nodes are typically powered by battery with limited volume, recently, energy harvesting technologies have been employed in WSNs to address the issue of energy constraint with the goal to obtain perpetual and unattended networks [1][2][3][4]. Rechargeable sensor nodes can harvest energy from sources such as solar and wind in the surroundings, and store the harvested energy in the battery for future use when it can not be used immediately. As the energy source is typically time-varying and unreliable, it is desirable for sensor nodes to manage the energy use wisely and schedule sampling rate adaptively to maximize the overall network performance.

In order to obtain a solution for fair and high throughput of sampling in renewable sensor networks, Fan *et al.* [5] sought to compute an optimal lexicographic rate assignment for each sensor node, and then proposed a distributed and asynchronous algorithm, which obtained the optimal sampling rate for each sensor node provided that the routing tree is predetermined. Their approaches only guarantee that no sensor node will run out of energy, however the sensor nodes will miss the recharging opportunity when the battery reaches the highest energy level. Since the lexicograghic rates are unique for the whole time cycle and do not change in different slots, employing the optimal lexicograghic rates to provide service may degrade the actual performance in real applications. Liu *et al.* [6] considered the effect of the battery capacity, and formulated an optimization problem with the goal to maximize the aggregate utility. In order to maintain the battery at a certain desired level while stochastically maintain a high network utility, they proposed a distributed solution, called QuickFix, to compute the optimal sampling rate and routing paths, and a local algorithm, named SnapIt, to adapt the sampling rate. The rationale of their approach is to let sensor node consume more energy when its battery level is high and less energy otherwise. However, the approach may not be effective, as the energy harvesting rate may be much higher than the energy consumption rate and the deficiency of the battery capacity would result in the loss of recharging opportunity.

Though aforementioned works indicate the impact of the limited battery capacity on the overall network performance, they do not include this into algorithm design, and simply assume the capacity of rechargeable battery is sufficiently large to support applications. However, this may be not the case in many scenarios. Table I gives a collection of energy storage options [7][8], where shows Supercap is the only choice, if we desire a perpetual lifetime of the rechargeable battery. Taking the energy harvesting process at Columbus and California for example, the total energy harvested from a $37mm \times 33mm$ solar cell at Columbus in two days under different weather conditions (sunny and partly cloudy) are $655.15mWh$ and $313.70mWh$, respectively, and at California, the total energy harvested from the same solar cell under the same weather conditions is 2-3 times as that at Columbus [5]. Given that the maximal energy level and the volume of

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TABLE I
A NUMBER OF RECHARGEABLE BATTERY OPTIONS [7][8]

Type	Lead Acid	NiCd	NiMH	Li-ion	Li-polymer	Supercap
Weight energy density	26 Wh/Kg	42 Wh/Kg	100 Wh/Kg	165 Wh/Kg	156 Wh/Kg	5.06 Wh/Kg
Volume energy density	67 Wh/L	102 Wh/L	282 Wh/L	389 Wh/L	296 Wh/L	5.73 Wh/L
Charging cycle	500-800	1500	1000	1200	500-1000	>100000

Supercap are $0.304Wh$ and $53cm^3$, respectively, we need at least *two Supercapes* at Columbus, and *four* at California, to store all the harvested solar energy. This example demonstrates the importance of taking the battery capacity into account.

When battery capacity is too limited to store all the harvested energy, there are two shortcomings of existing algorithms: i) some sensor nodes may run out of energy and stop working at slot t, which interrupts the continuous sensing, and ii) the battery level of some sensor nodes may reach the maximum and thus recharging opportunity may be missed. The first case corresponds to an aggressive energy allocation scheme, which means the sensor node has used too much energy in the past, and is currently short of energy. The second case indicates a conservative scheme, in which the sensor node does not deplete much energy, so that the sensor nodes can not store all the harvested energy due to the limited capacity of the battery. Obviously, both cases will greatly limit the potential to improve the network performance.

In this paper, our objective is to design a distributed adaptive data sampling algorithm to maximize the overall network performance (characterized by utility) by taking the capacity of the rechargeable battery into consideration. Specifically, our contributions are summarized as follows:

- We propose an adaptive Energy Allocation sCHeme (EACH) to allocate the energy for each sensor node, so that each sensor node can use the harvested energy wisely according to current available energy.
- We design a Distributed Sampling Rate Control (DSRC) based on EACH to find the optimal sampling rate for each sensor node and theoretically analyze the performance of DSRC.
- We proposed an Improved adaptive Energy Allocation sCHeme (IEACH) to reduce the impact from imprecise estimation of harvested energy.
- Extensive simulations based on real experiment data are conducted to demonstrate the advantages of the EACH and DSRC over existing algorithms in terms of energy allocation and sampling rate, as well as network utility. Also the performance of the IEACH is verified by the simulations.

The remainder of this paper is organized as follows. We firstly introduce the related work in Section II and describe the network model and problem formulation in Section III. Then, an energy allocation scheme for each sensor node to manage its energy use is proposed and a distributed sampling rate control algorithm to find the optimal sampling rate is designed in Section IV. In addition, an Improved adaptive Energy Allocation sCHeme (IEACH) is proposed to reduce the impact from imprecise estimation of harvested energy in Section IV. We evaluate the performance of the proposed algorithms in Section V. Finally, the conclusion is given in Section VI.

II. RELATED WORK

Recently, there are many works on utilizing the solar energy to power the wireless sensors for environmental monitoring or other sampling applications. As the harvested energy is time-varying and unstable, the rechargeable sensor networks need efficient energy management and resource allocation schemes. Existing works on this issue can be mainly categorized into three folds according to their goals:

1) *Guaranteeing Fairness while Maximizing Throughput*. In order to obtain fair and steadily high data extraction from all sensor nodes, Fan *et al.* sought to compute an optimal lexicographic rate assignment for each sensor node [5]. In addition, they extended the distributed algorithm to jointly compute a routing structure and a high lexicograghic near-optimal rate assignment [9]. Sharma *et al.* employed the stochastic queuing theory to model data, energy generation and storage processes, and proposed stable throughput-optimal and mean delay-optimal energy management policies [10]. Joseph *et al.* proposed joint power control, routing and scheduling policies to ensure a fair utilization of network resources [11]. However, the quality of the service is restricted by the limited battery capacity, since the battery capacity may be too limited to store all the harvested energy. Thus, their approaches limit the potential to improve the network performance, as well as total network throughput.

2) *Maximizing Network Utility*. Gatzianas *et al.* considered the optimal control of renewable wireless networks, and proposed a policy, called Downlink Rechargeable Adaptive Backpressure Policy (DRABP), through which the network can achieve asymptotic optimality in case of sufficiently large battery capacity [12]. They also extended the DRABP to single-hop and multihop networks. In addition, they analytically and numerically evaluated the performance of the algorithms that guarantee fair energy allocation in systems with predictable and stochastic energy inputs [13]. Zhang *et al.* addressed the maximal utility rate allocation problem by designing a utility-based sensing rate allocation algorithm [14]. Liu *et al.* developed QuickFix algorithm to compute the optimal sampling rate and route, and SnapIt algorithm to adapt the sampling rate with the goal of maintaining the battery at a certain desired level [6]. However, when the battery capacity is deficient to reserve all the rechargeable energy, the sensor node will run out of energy or miss recharging opportunity. Thus, the network performance might be degraded.

3) *Maximizing Total Throughput*. Noh *et al.* showed how to use solar energy to maximize the amount of throughput by adaptively controlling the reliability [15]. In addition, they designed simple solar energy allocation (SSEA) and accurate solar energy allocation (ASEA) algorithms to optimally utilize the periodically harvested solar energy, while minimizing the variability of energy allocation [16]. Chen *et al.* investigated the problem of maximizing the throughput over a finite-

horizon time period and proposed a three-step approach to solve the problem [17]. Mao *et al.* proposed a joint data queue and battery buffer control algorithm to maximize the long-term average sensing rate of a single communication link in rechargeable sensor networks [18]. Zhao *et al.* exploited mobility for the joint design of energy replenishment and data gathering, and proposed an algorithm to achieve the system-wide optimum [19]. However, these approaches only focus on maximizing the amount of data or throughput, which may result in unfairness. For example, the sensor node near the sink node has the highest sampling rate than other sensor nodes.

Most of aforementioned works disregard the impact of battery capacity of renewable sensor nodes. They assume that the battery capacity is sufficiently large to store the harvested energy. Therefore, their approaches would miss some recharging opportunities in practice and may degrade the network performance when the battery capacity is too limited to store all the harvested energy. Different from existing works, our goal is to maximize the overall network performance while maintaining the fairness of the sensor networks by taking the limited battery capacity into account.

III. Network Model and Problem Statement

We consider a static wireless rechargeable sensor network, with N sensor nodes (including the sink nodes) and some unidirectional logistic links between sensor nodes. All sensor nodes are equipped with similar solar cells and rechargeable batteries with limited capacity. Hence, the harvested solar energy can be reserved for future use. The sink nodes are supposed to have sufficient energy, thus their energy consumptions are not considered in this paper. Each sensor node transmits sensory information to the sink nodes through multiple hops along a single path. Let $N_r(i)$ denote the set of sensor nodes in the path of sensor node i, $i = 1, 2, \cdots, N$, to sink nodes (excluding sensor node i), and $N_s(i)$ denote the set of sensor nodes that use sensor node i as intermediate relay node (excluding sensor node i).

The time cycle of energy harvesting is one day, which can be divided into T slots. Specifically in this paper, we set $T = 24$. Denote by $B_{i,t}$ the remaining energy of sensor node i at slot t. Let $\rho_{i,t}$ and $A_{i,t}$ denote the total amount of harvested energy and energy allocation for sensor node i at slot t, respectively. It is shown in [16][20] that the sensor nodes can estimate $\rho_{i,t}$ with high accuracy. Their results will be introduced in this paper to estimate $\rho_{i,t}$.

Denote the maximum battery level of sensor node i by B_i^{max}. Obviously, $B_{i,t+1} = [B_{i,t} + \rho_{i,t} - A_{i,t}]_0^{B_i^{max}}$, where $[\cdot]_0^{B_i^{max}} = \max(0, (\min(\cdot, B_i^{max}))$. For easy presentation of the paper, let $o_{i,t}$ be

$$o_{i,t} = B_{i,t} + \rho_{i,t} - A_{i,t} - B_i^{max}, \tag{1}$$

from which we know that the harvested energy can not completely be stored in the battery if $o_{i,t} > 0$.

The average energy consumption by sensor node i for sensing one unit of data is denoted by e_i^s, and we use e_i^t and e_i^r to denote the average energy cost for sensor node i to transmit and receive one unit data, respectively [21][22]. As the sensing and communication dominate the energy consumption, we only focus on measuring the energy depletion due to sensing, transmitting and receiving packets. Let $r_{i,t}$ represent the data sampling rate of sensor node i at slot t. The sensory information should be transmitted to sink nodes in slot t so that it can be retrieved timely. Therefore, the total amount of energy consumption $w_{i,t}$ for each sensor node i can be given by

$$w_{i,t} = (e_i^s + e_i^t) r_{i,t} + (e_i^r + e_i^t) \sum_{j \in N_s(i)} r_{j,t}, \tag{2}$$

which should be less than the allocated energy $A_{i,t}$, as,

$$A_{i,t} \geq w_{i,t}. \tag{3}$$

In addition, $A_{i,t}$ should be not larger than the total amount of current available energy, i.e.,

$$A_{i,t} \leq B_{i,t} + \rho_{i,t}. \tag{4}$$

Moreover, the sum of allocated energy should not exceed the total amount of harvested energy, so that the system can ensure a sustainable network,

$$\sum_{t=1}^{T} A_{i,t} \leq \sum_{t=1}^{T} \rho_{i,t}. \tag{5}$$

At each slot t, each sensor node has to decide the sampling rate $r_{i,t}$ and transmit the sensory information to sink nodes. Let $U(r_{i,t})$ be a utility function of sampling rate $r_{i,t}$, where utility can be a specific performance as required by applications. For example, $U(r_{i,t}) = \log(r_{i,t})$ can be used to guarantee the fairness of sampling rate [23]. $U(r_{i,t})$ is assumed to be an increasing, strictly concave, and twice differentiable function. Our objective is to maximize the network utility by choosing optimal sampling rate $r_{i,t}$ at each slot for all sensor nodes according to $B_{i,t}$ and $\rho_{i,t}$, i.e,

$$objective \quad \max_{r_{i,t}} \quad \sum_i \sum_t U(r_{i,t}) \tag{6}$$

$$s.t. \quad A_{i,t} \geq w_{i,t}, \qquad \forall i, t \tag{7}$$

$$A_{i,t} \leq B_{i,t} + \rho_{i,t}, \qquad \forall i, t \tag{8}$$

$$\sum_{t=1}^{T} A_{i,t} \leq \sum_{t=1}^{T} \rho_{i,t}, \qquad \forall i, t \tag{9}$$

where Eqs. (7) and (8) are used to guarantee the allocated energy of each sensor node at each time slot must be bigger than its energy consumption, but smaller than the available energy. Eq. (9) ensures that the sum of energy allocation does not exceed the total amount of energy it has harvested.

To solve (6), we should optimize the data sampling rates $\boldsymbol{r}$, which are coupled with the total amount of energy allocation, i.e., $\boldsymbol{A} = \{A_{i,t}, i = 1, 2, \cdots, N, t = 1, 2, \cdots, T\}$. Hence, in the following section, we first develop an efficient energy allocation scheme for each sensor node, based on which we then design an optimal sampling rate control algorithm.

IV. Algorithm Design

In this section, an adaptive Energy Allocation sCHeme (EACH) for each sensor node is proposed to manage its energy allocation and then a Distributed Sampling Rate Control (DSRC) algorithm is designed to solve the Network Utility

Maximization problem. Moreover, an Improved adaptive Energy Allocation sCHeme (IEACH) is proposed to reduce the impact from imprecise estimation of harvested energy.

A. Adaptive Energy Allocation Scheme

Before presenting the DSRC algorithm, we first focus on the energy management for each sensor node, i.e., to allocate a specific amount of energy $A_{i,t}$ that will be consumed by sensor node i at slot t. As the amount of harvested energy for each rechargeable sensor node varies over time, a wise energy allocation scheme is significant for the overall performance of network utility.

For an energy allocation scheme, there are two shortcomings that we have to overcome: i) a sensor node runs out of energy and stops working at slot t, and ii) the battery level of a sensor node i reaches the maximum and thus i will miss some recharging opportunity. The first case corresponds to an aggressive energy allocation scheme, which means the sensor node has spent too much energy in the past, and is currently short of energy. The second case indicates a conservative scheme, in which the sensor node did not deplete much energy in the past so that the harvested energy can not be stored due to the limited capacity of battery at current slot.

We introduce an adaptive Energy Allocation sCHeme (EACH), which can avoid the aforementioned two shortcomings and obtain an efficient energy allocation scheme. Specifically, let

$$\pi_{i,t} = \frac{1}{T}\sum_{t=1}^{T}\rho_{i,t}. \tag{10}$$

If the capacity of rechargeable battery is large enough to store all the harvested energy at any slot t, the optimal energy allocation scheme can be $\pi_{i,t}$ for sensor node i at slot t, since the solution of the Network Utility Maximization problem depends on the energy allocation [6]. However, considering the limited capacity of the rechargeable battery, some harvested energy may not be stored. For example, let $T = 10$, $B_1^{max} = 10$, $\rho_{1,1} = \rho_{1,2} = \rho_{1,3} = 7$, $\rho_{1,4} = \rho_{1,5} = \cdots = \rho_{1,10} = 1$. So $\pi_{1,t} = \frac{1}{10}\sum_{t=1}^{10}\rho_{1,t} = 2.8$. At slot 3, $\sum_{t=1}^{3}(\rho_{1,t} - \pi_{1,t}) = 12.6 > 10$. Hence, at slot 3, 2.6 unit energy can not be stored in the battery. The example also indicates that more energy should be spent in the slots with a large $\rho_{i,t}$. Generally, the energy allocation scheme $A_{i,t}$ for each sensor node i at slot t can be

$$A_{i,t} = (1-\Delta_i)\pi_{i,t} + \Delta_i\rho_{i,t}, \tag{11}$$

where Δ_i, $0 \le \Delta_i \le 1$, is a weight to regulate the allocation scheme.

Different from a constant energy allocation in all slots in existing algorithm, EACH strives to allocate the energy adaptively dependent on the current amount of available energy. The Algorithm 1 gives how to obtain desirable Δ_i, where K, $K > 0$, is a sufficiently small constant. We have the following theorem on the performance of Algorithm 1.

Theorem 1: Algorithm 1 obtains a unique constant $\boldsymbol{\Delta} = \{\Delta_i \in [0,1], i \in N\}$ during each time cycle, no matter whether the rechargeable battery capacity for each sensor node i is sufficient or not.

Algorithm 1 Calculate Desirable Δ_i

repeat
  for $t = 1, 2, \cdots, T$
    $A_{i,t} = [(1-\Delta_i)\pi_{i,t} + \Delta_i\rho_{i,t}]_0^{B_{i,t}+\rho_{i,t}}$
    $o_{i,t} = B_{i,t} + \rho_{i,t} - A_{i,t} - B_i^{max}$
    $B_{i,t+1} = min(B_{i,t} + \rho_{i,t} - A_{i,t}, B_i^{max})$
  end
    $\Delta_i = [\Delta_i + K * max\{\frac{o_{i,t}}{\rho_{i,t}}, t = 1, 2, \cdots, T\}]_0^1$
until satisfying either of the following conditions:
1 $max\{o_{i,t}, t = 1, 2, \cdots, T\} = 0$
2 $max\{o_{i,t}, t = 1, 2, \cdots, T\} < 0$ while $\Delta_i = 0$
return $\Delta_i = \Delta_i$

Proof: With EACH each sensor node functions independently, and therefore, it is sufficient to prove the convergence of Algorithm 1 for one sensor node. If the capacity of the rechargeable battery of sensor node i is sufficient, $max\{\frac{o_{i,t}}{\rho_{i,t}}, t = 1, ...T\}$ will be negative for all the slots, which will result in $\Delta_i = 0$. If the capacity of rechargeable battery is deficient, the surplus variable will be positive, which will increase Δ_i, $\Delta_i \le 1$.

The desirable battery capacity $B_{i,t}^{des}$ for sensor node i at slot t is given by

$$\begin{aligned} B_{i,t}^{des} &= B_{i,t} + \rho_{i,t} - A_{i,t} \\ &= B_{i,t} + \rho_{i,t} - ((1-\Delta_i)\pi_{i,t} + \Delta_i\rho_{i,t}) \\ &= B_{i,t} + (1-\Delta_i)(\rho_{i,t} - \pi_{i,t}), \end{aligned} \tag{12}$$

where $\rho_{i,t}$ and $\pi_{i,t}$ are constants. The relationship between $o_{i,t}$ and $B_{i,t}^{des}$ is given by

$$o_{i,t} = B_{i,t}^{des} - B_i^{max}. \tag{13}$$

Hence, for sensor node i at slot t, there is a unique Δ_i such that $o_{i,t} = 0$, where $\rho_{i,t}$ must be larger than $\pi_{i,t}$.

When there are two different weight variables $\Delta_{i,1}$ and $\Delta_{i,2}$ ($\Delta_{i,2} > \Delta_{i,1}$), such that $o_{i,t_1} = 0$ at slot t_1 and $o_{i,t_2} = 0$ at slot t_2, while satisfying $max\{o_{i,t}, t = 1, 2, \cdots, T\} = 0$ simultaneously accordingly. B_{i,t_1}^{des} and B_{i,t_2}^{des} are given by

$$B_{i,t_1}^{des}(\Delta_{i,2}) = B_{i,t_1} + (1-\Delta_{i,2})(\rho_{i,t_1} - \pi_{i,t_1}), \tag{14}$$
$$B_{i,t_2}^{des}(\Delta_{i,1}) = B_{i,t_2} + (1-\Delta_{i,1})(\rho_{i,t_2} - \pi_{i,t_2}). \tag{15}$$

We have

$$\begin{aligned} B_{i,t_1}^{des}&(\Delta_{i,2}) - B_{i,t_1}^{des}(\Delta_{i,1}) \\ &= (\Delta_{i,1} - \Delta_{i,2})(\rho_{i,t_1} - \pi_{i,t_1}), \end{aligned} \tag{16}$$
$$\begin{aligned} B_{i,t_2}^{des}&(\Delta_{i,1}) - B_{i,t_2}^{des}(\Delta_{i,2}) \\ &= (\Delta_{i,2} - \Delta_{i,1})(\rho_{i,t_2} - \pi_{i,t_2}). \end{aligned} \tag{17}$$

Since $\rho_{i,t_1} > \pi_{i,t_1}$, $\rho_{i,t_2} > \pi_{i,t_2}$ and $\Delta_{i,2} > \Delta_{i,1}$, Eq. (17) will be larger than zero, implying $B_{i,t_2}^{des}(\Delta_{i,1})$ is larger than $B_{i,t_2}^{des}(\Delta_{i,2}) = B_i^{max}$. Thus $o_{i,t_2} > 0$ for $\Delta_{i,1}$, which is contradictory to the fact that $max\{o_{i,t}, t = 1, 2, \cdots, T\} = 0$.

Thus, there is only one Δ_i for the sensor node i during each time cycle, such that $max\{o_{i,t}, t = 1, 2, \cdots, T\} = 0$. ■

According to the second set of the constraints and the desirable Δ_i calculated by EACH, we can conclude that the sum of energy consumption will not exceed the total amount of collected energy, as

$$\begin{aligned}\sum_t w_{i,t} &\le \sum_t A_{i,t}\\ &= \sum_t [(1-\Delta_i)\pi_{i,t} + \Delta_i \rho_{i,t}]\\ &= \sum_t [(1-\Delta_i)\frac{1}{T}\sum_{t=1}^{T}\rho_{i,t}] + \sum_t \Delta_i \rho_{i,t}\\ &= \sum_t \rho_{i,t}.\end{aligned}$$

Moreover, since the maximum of the surplus variable o_i must be zero or negative, the battery level for the next slot can be written as follows:

$$B_{i,t+1} = B_{i,t} + \rho_{i,t} - A_{i,t}, \quad \forall i,t. \tag{18}$$

B. Distributed Sampling Rate Control

With the energy allocation $A_{i,t}$, we proceed to give the DSRC algorithm to solve the Network Utility Maximization problem, which can be rewritten as

$$objective \quad \max_{r_{i,t}} \quad \sum_i \sum_t U(r_{i,t}) \tag{19}$$

$$s.t. \quad A_{i,t} \ge w_{i,t}, \qquad \forall i,t \tag{20}$$

The optimization variables are sampling rates $\boldsymbol{r}$. As the energy allocation $A_{i,t}$ may be different at different slots t, the sampling rate $r_{i,t}$ should be decided dynamically at each slot t for each sensor node i.

We aim at deriving a distributed algorithm to solve the problem (19) by employing the theory of dual decomposition [24][25][26]. Let $\mu_{i,t} \in R_+$ be the dual variable associated with the energy consumption constraint (i.e., Eq. (20)) for the sensor node i at slot t, and $R_+ = [0,\infty)$. The Lagrangian of the problem (19) is

$$\begin{aligned}L(\boldsymbol{\mu}) = \max_{r_{i,t}} \sum_i \sum_t \{U(r_{i,t}) + \mu_{i,t}[A_{i,t} - (e_i^s + e_i^t) r_{i,t}\\ +(e_i^r + e_i^t)\sum_{j\in N_s(i)} r_{j,t}]\}.\end{aligned} \tag{21}$$

The dual problem of (19) then is

$$\min_{\mu_{i,t}} L(\boldsymbol{\mu}). \tag{22}$$

The dual problem can be decomposed in each slot t, as follows:

$$\begin{aligned}L(\boldsymbol{\mu}_t) = \max_{r_{i,t}} \sum_i \{U(r_{i,t}) + \mu_{i,t}[A_{i,t} - (e_i^s + e_i^t) r_{i,t}\\ +(e_i^r + e_i^t)\sum_{j\in N_s(i)} r_{j,t}]\}.\end{aligned} \tag{23}$$

The sub-gradient method can be adopted to update Lagrangian multiplier $\boldsymbol{\mu}$ iteratively as follows:

$$\begin{aligned}\mu_{i,t}(m+1) = [\mu_{i,t}(m) - \alpha(A_{i,t} - (e_i^s + e_i^t) r_{i,t}\\ +(e_i^r + e_i^t)\sum_{j\in N_s(i)} r_{j,t}]^+,\end{aligned} \tag{24}$$

where m is the iteration number, α is a constant step size satisfying $\alpha > 0$, and $[\cdot]^+ = \max(0,\cdot)$.

The problem (23) can be rewritten as

$$\begin{aligned}L(\boldsymbol{\mu}_t) = \max_{r_{i,t}} \sum_i \{U(r_{i,t}) + \mu_{i,t}A_{i,t} - \mu_{i,t} r_{i,t}(e_i^s + e_i^t)\\ -r_{i,t}\sum_{j\in N_r(i)} \mu_{j,t}(e_j^r + e_j^t)\}.\end{aligned} \tag{25}$$

For all $\boldsymbol{\mu}$, a unique maximizer, denoted by $r_{i,t}(\boldsymbol{\mu})$, exists since $U(r_{i,t})$ is strictly concave. When $\mu_{i,t}$, $i = 1,2,\cdots,N$, are scalars, by the Kuhn-Tucker theorem, $r_{i,t}(\boldsymbol{\mu})$ should be

$$\begin{aligned}r_{i,t}^* = \max_{r_{i,t}} \sum_i \{U(r_{i,t}) + \mu_{i,t}A_{i,t} - \mu_{i,t} r_{i,t}(e_i^s + e_i^t)\\ -r_{i,t}\sum_{j\in N_r(i)} \mu_{j,t}(e_j^r + e_j^t)\}\end{aligned} \tag{26}$$

$$= [U'^{-1}(\nu_{i,t}^i + \nu_{i,t}^j)]_0^{r_i^{max}}, \tag{27}$$

where

$$\nu_{i,t}^i = \mu_{i,t}(e_i^s + e_i^t), \tag{28}$$

$$\nu_{i,t}^j = \sum_{j\in N_r(i)} \mu_{j,t}(e_j^r + e_j^t). \tag{29}$$

Here, ${U_r}'^{-1}$ is the inverse of ${U_r}'$.

The detailed description of DSRC algorithm is shown in Algorithm 2. We have the following theorem on the performance of DSRC algorithm.

Algorithm 2 DSRC

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repeat
  for $i = 1,2,\cdots,N$.
  1 Each sensor node locally updates the Lagrange Multipliers $\mu_{i,t}$ using Eq. (24).
  2 Each sensor node sends its $\mu_{i,t}$ to the sensor node j, $j \in N_s(i)$, meanwhile collecting and forwarding the information $\mu_{j,t}$, $j \in N_r(i)$.
  3 Each sensor node calculates $\nu_{i,t}^i$ and $\nu_{i,t}^j$ using the Eq. (28) and (29).
  4 Sensor node i calculates its sampling rate using (27).
  end
  if $D_t == \{r_{i,t}, i = 1,2,\cdots,N\}$
    $D_t^* = D_t$.
  else
    $D_t = \{r_{i,t}, i = 1,2,\cdots,N\}$.
  end
until $D_t^* \ne \emptyset$
return$\{r_{i,t}^*, i = 1,2,\cdots,N\} = D_t^*$.

Theorem 2: For sufficiently small positive constant α and fixed energy allocation $\boldsymbol{A}$, the DSRC algorithm converges to optimum sampling rate $\boldsymbol{r}^*$.

Proof: Since the utility function $U(r_{i,t})$ is an increasing, strictly concave, and twice differentiable function, a unique sampling rate $r_{i,t}$ can be calculated by using the Eq. (27). Since the relationship between Lagrangian multiplier $\boldsymbol{\mu}$ and the sampling rates $\boldsymbol{r}$ is linear and utility function $U(r_{i,t})$ is strictly concave, there exists a step size α that guarantees $\mu_{i,t}$

to converge to the optimal dual solution $\boldsymbol{\mu}$, according to [27]. It is easy to find that $\triangledown L(\boldsymbol{\mu})$ satisfies Lipschitz continuous on $(0, r_i^{max}]$, since the curvatures of the utility functions are bounded away from zero [23]. Therefore, the DSRC algorithm with a constant step size α, $0 < \alpha < 2/\boldsymbol{L}$, converges to optimum sampling rate r^*, where

$$\| \triangledown L(\boldsymbol{\mu}_1) - \triangledown L(\boldsymbol{\mu}_2) \| = \boldsymbol{L} \| \boldsymbol{\mu}_1 - \boldsymbol{\mu}_2 \|, \quad \forall \boldsymbol{\mu}_1, \boldsymbol{\mu}_2 \in \{\boldsymbol{\mu}, | \ \boldsymbol{\mu} \geq 0\}. \tag{30}$$

■

C. Reduce the Impact of Imprecise Estimation of Harvested Energy

In this subsection, we discuss the case of imprecise estimation of harvested energy in the next few slots, and propose an algorithm to reduce its impact effectively.

In order to calculate the desirable Δ_i for sensor node i, the sensor nodes should estimate the amount of harvested energy for every slots in entire time cycle. Let $\rho_{i,t}^{est}$ denote the estimated harvested energy for sensor node i at slot t. Thus, the estimated battery level is given by

$$B_{i,t+1}^{est} = B_{i,t}^{est} + \rho_{i,t}^{est} - A_{i,t} \leq B_i^{max}, \quad \forall i, t, \tag{31}$$

where $A_{i,t}$ is calculated by Algorithm 1 using the estimated harvested energy. At the beginning slot, $A_{i,t}^{est} = A_{i,t}$.

Let $\rho_{i,t}^{real}$ denote the real harvested energy. The expected battery level $B_{i,t+1}^{exp}$ and the estimation error $\rho_{i,t}^{error}$ can be given by

$$B_{i,t+1}^{exp} = B_{i,t}^{exp} + \rho_{i,t}^{real} - A_{i,t}, \tag{32}$$

$$\rho_{i,t}^{error} = \rho_{i,t}^{real} - \rho_{i,t}^{est}. \tag{33}$$

Let $B_{i,t+1}^{error}$ denote the cumulative error for slot $t+1$ between the expected battery level and the estimated battery level, i.e.,

$$B_{i,t+1}^{error} = B_{i,t+1}^{exp} - B_{i,t}^{est} = \sum_{t=1}^{t+1} \rho_{i,t}^{error}. \tag{34}$$

If the expected battery level $B_{i,t+1}^{exp}$, which equals to the sum of the cumulative error $B_{i,t+1}^{error}$ and the estimated battery level $B_{i,t+1}^{est}$, is larger than the maximal battery capacity, the surplus variable will be positive. This indicates that the sensor node will miss recharging opportunity. Thus, it is necessary to adjust the energy allocation scheme to eliminate the impact of estimation error.

In order to yield an effective energy allocation scheme and improve the performance of EACH, we propose an Improved adaptive Energy Allocation sCHeme (IEACH), based on EACH. Specifically, at each slot t, let

$$\overline{\rho}_{i,t}^{error} = \frac{\rho_{i,t}^{error}}{T - t + 1}. \tag{35}$$

Then, for all $t' \in [t, T]$, the estimated energy allocation $A_{i,t'}^{est}$ and the expected battery level $B_{i,t'+1}^{exp}$ at slot t can be updated by

$$A_{i,t'}^{est} = A_{i,t'}^{est} + \overline{\rho}_{i,t}^{error}, \tag{36}$$

$$B_{i,t'+1}^{exp} = B_{i,t'}^{exp} + \rho_{i,t'} - A_{i,t'}^{est}, \tag{37}$$

where

$$B_{i,t}^{exp} = B_{i,t}^{real}, \tag{38}$$

$$\rho_{i,t'} = \begin{cases} \rho_{i,t}^{real}, & \text{if } t' = t \\ \rho_{i,t'}^{est}, & \text{else .} \end{cases} \tag{39}$$

By comparing with the expected battery level and the maximal energy level, the peak of battery level $B_{i,t}^{peak}$ is given by

$$B_{i,t}^{peak} = max\{max\{B_{i,t'}^{exp}, t' \in [t,T]\}, B_i^{max}\}. \tag{40}$$

If $B_{i,t}^{peak} > B_i^{max}$, let $t^* = t'$, otherwise, $t^* = t$. Here t^* indicates the slot where the expected battery level $B_{i,t'}^{exp}$ reaches to $B_{i,t}^{peak}$.

Hence, the estimated energy allocation $A_{i,t'}^{est}$ at slot $t', t' \in [t, T]$, can be updated by

$$A_{i,t'}^{est} = \begin{cases} A_{i,t'}^{est} + \frac{B_{i,t}^{peak} - B_i^{max}}{t^* - t + 1}, & \text{if } t' \in [t, t^*] \\ A_{i,t'}^{est} - \frac{B_{i,t}^{peak} - B_i^{max}}{T - t^*}, & \text{if } t' \in [t^* + 1, T]. \end{cases} \tag{41}$$

Now, the desirable real $A_{i,t}^{real}$ and the real battery level $B_{i,t+1}^{real}$ at slot t are

$$A_{i,t}^{real} = A_{i,t}^{est}, \tag{42}$$

$$B_{i,t+1}^{real} = B_{i,t}^{real} + \rho_{i,t}^{real} - A_{i,t}^{real}. \tag{43}$$

We sketch IEACH in the Algorithm 3. Based on EACH, IEACH strives to allocate the energy adaptively dependent on past estimation error, current real amount of harvested energy and the estimated amount of harvested energy in each time cycle.

Algorithm 3 IEACH

1) Initialization
   - Each sensor node updates the expected battery level $B_{i,t}^{exp}$ and the harvested energy $\rho_{i,t'}$ according to (38) and (39), respectively.
   - Each sensor node updates $\overline{\rho}_{i,t}^{error}$ according to (35).
2) Calculate peak of battery level $B_{i,t}^{peak}$ and t^*
   for $t' = t, t+1, \cdots, T$
   - Each sensor node updates the estimated energy allocation $A_{i,t'}^{est}$ and the expected battery level $B_{i,t'+1}^{exp}$ according to (36) and (37), respectively.
   - Each sensor node searches for the peak of battery level $B_{i,t}^{peak}$ according to (40), and obtains the value of t^*.

   end
3) Update desirable real $A_{i,t}^{real}$ at slot t
   for $t' = t, t+1, \cdots, T$
   - Each sensor node updates the estimated energy allocation $A_{i,t'}^{est}$ according to (41).

   end
   - Each sensor node sets the desirable real $A_{i,t}^{real}$ and the real battery level $B_{i,t+1}^{real}$ according to (42) and (43), respectively.

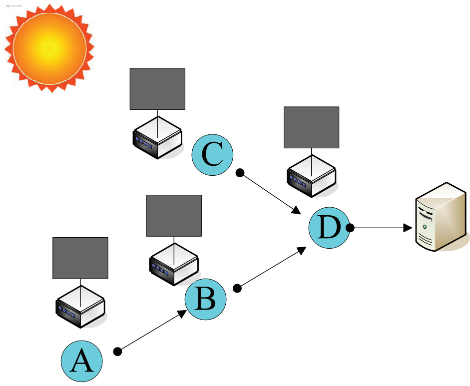


Fig. 1. Network topology for the simulations.

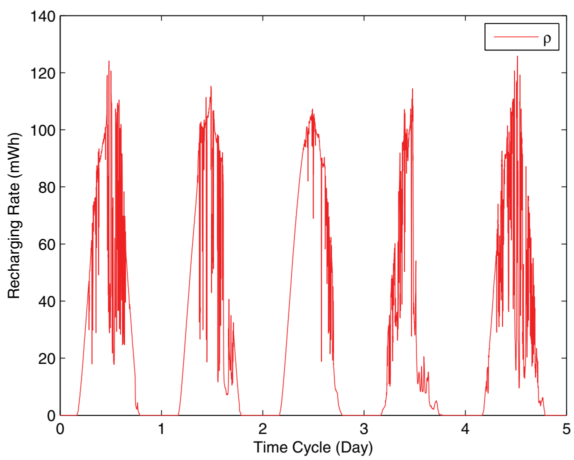


Fig. 2. Experimental data of solar panels obtained from BMS during duration from July 2nd to July 6th.

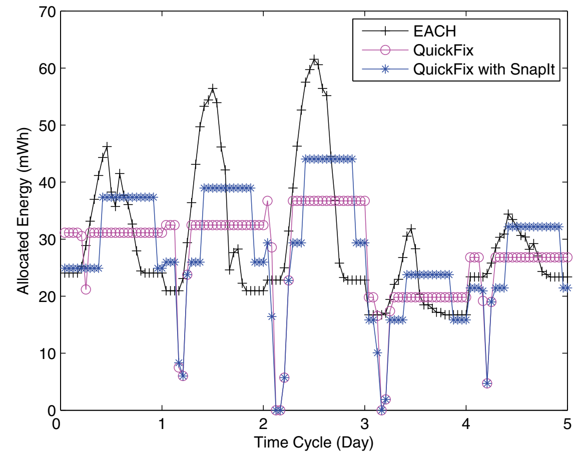


Fig. 3. Energy allocation $A_{D,t}$ calculated by EACH, QuickFix and QuickFix with SnapIt, respectively.

V. Performance Evaluation

In this section, simulation results are provided to demonstrate the performance of the proposed EACH and DSRC algorithms over the existing algorithms. In addition, the simulation results in V-D show that the IEACH can reduce the impact of imprecise estimation of harvested energy effectively comparing with EACH. We also discuss the desirable battery capacity. All the results are obtained by MATLAB.

A. Simulation Setting

Figure 1 shows the simple network topology and the corresponding link contention. All sensor nodes are static, having a $37 \times 33mm^2$ solar cell and a Supercap, whose nominal maximal energy level is $304mWh$. Moreover, all the sensor nodes have the same wireless module, such as TelosB from Crossbow [5], and the consumption power (i.e., energy consumption per second) in receiving, transmitting and sensing mode are $69mW$, $63mW$ (when the transmit power is $0dBm$, transmit data rate is $250kbps$), and $5.4mW$, respectively. The experimental data obtained from Baseline Measurement System (BMS) of Solar Radiation Research Laboratory (SRRL) is used to model the energy harvesting process [28]. Figure 2 shows the data obtained from BMS for a period from July 2nd to July 6th, 2011. The total amount of harvested energy for the five days are $746.9mWh$, $779.3mWh$, $880.9mWh$, $475.6mWh$ and $643.6mWh$, respectively. Let the initial energy of the rechargeable battery for all senor nodes be $150mWh$, and the utility function be $U(r_{i,t}) = log(r_{i,t})$ for each sensor node i at slot t.

The proposed algorithms are compared with QuickFix and QuickFix with SnapIt in [6]. QuickFix uses the average energy harvesting rate π (see Eq. 10) as the optimal energy allocation, and then distributively calculates the optimal sampling rate for each time cycle. SnapIt is designed to adapt the sampling rate with the goal of maintaining the battery at a desired level, with the $\delta = 0.2r_i$.

B. Performance Evaluation of EACH

Figure 3 shows the results of energy allocation $A_{D,t}$ for sensor node D computed by our EACH, QuickFix and QuickFix with SnapIt, respectively. It can be observed that values of $A_{D,t}$ by QuickFix or QuickFix with SnapIt are 0 at some slots during the five days, which means sensor node D runs out of energy at these slots. However, energy allocation using EACH does not have this problem. Moreover, the minimal values of $A_{D,t}$ for each time cycle by EACH are very stable, and those obtained by two other algorithms are changed with energy harvesting rate, which indicates the advantage of EACH.

The battery level states are shown in Fig. 4. If the sensor node employs QuickFix or QuickFix with SnapIt, the battery level of the sensor node reaches the highest energy level or the lowest energy level at some consecutive slots, which means that node D is missing recharging opportunity or running out of energy. Whereas, if the sensor node adopts EACH to compute the energy allocation, these can be avoided. In addition, at the end of each day, the battery level based on EACH is the highest battery level, indicating that EACH can reserve more energy for future use.

To show the efficiency of EACH in energy allocation, a new variable $O^+_{i,t} = \max(0, o_{i,t})$, called positive surplus, is introduced. Recalling the definition of $o_{i,t}$, positive surplus $O^+_{i,t}$ means the amount of harvested energy that can not be reserved in the rechargeable battery. The results of $O^+_{D,t}$

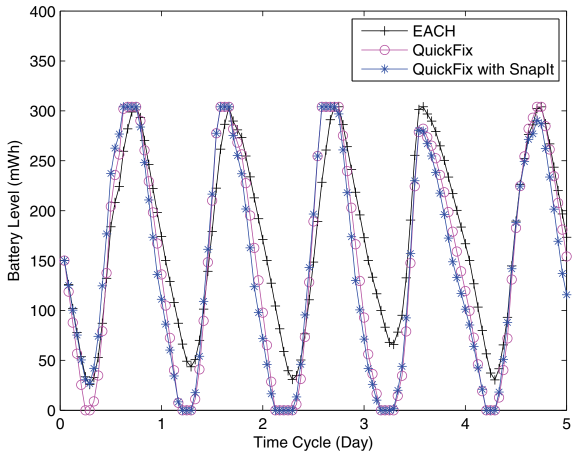


Fig. 4. Battery level of sensor node D under EACH, QuickFix and QuickFix with SnapIt, respectively.

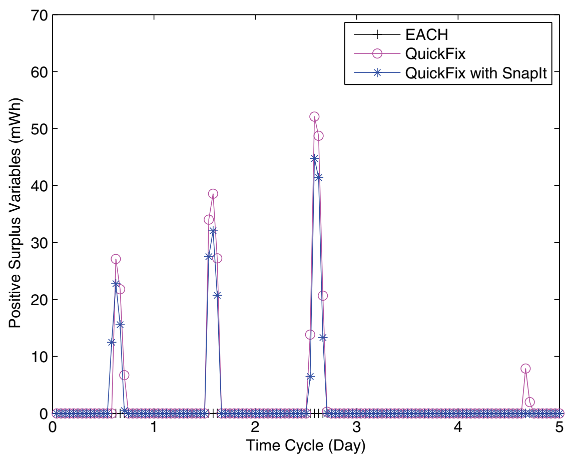


Fig. 5. Values of $O^+_{D,t}$ under EACH, QuickFix and QuickFix with SnapIt, respectively.

for different slots are shown in Fig. 5. It can be seen that sensor node D employing QuickFix or QuickFix with SnapIt algorithms can not store all the harvested energy at some slots during the five days. Hence, some harvested energy are wasted, which can be used to sample and thus increase the network utility in DSRC algorithm.

C. Performance Evaluation of DSRC

Figure 6 shows the total sampling rates of all sensor nodes under DSRC, QuickFix and QuickFix with SnapIt, respectively. It can be seen that trend of the total sampling rates is similar to those of energy allocation $A_{i,t}$. Sampling rates at some slots under QuickFix or QuickFix with SnapIt are zero, which means some sensor nodes do not work at these slots as they have run out of energy.

The total sampling rate of each day is shown in Fig. 7. DSRC achieves the highest total sampling rate of each day except the first day. This is because of the impact of the initial battery level (as sensor nodes can use the initial energy irrespective of the harvested energy). For a sensor network, larger amount of sampling rates means better network performance.

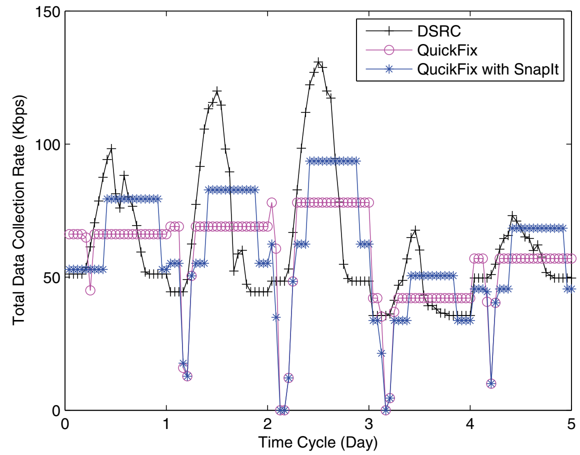


Fig. 6. Total sampling rates obtained by DSRC, QuickFix and QuickFix with SnapIt, respectively.

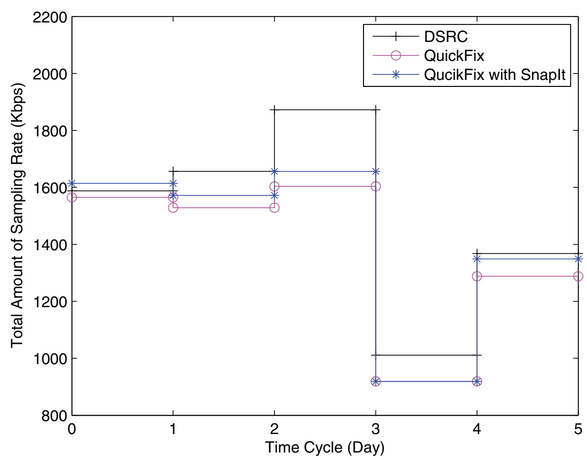


Fig. 7. The total sampling rate for each day obtained by DSRC, QuickFix and QuickFix with SnapIt, respectively.

DSRC has the largest total sampling rates among the three algorithms, which demonstrates the efficiency of DSRC.

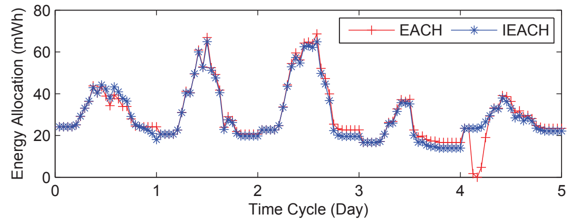
The network utility of each day is given in Table II. It can be seen that DSRC obtains the highest network utility in each day except the first day (due to the reason discussed in the previous paragraph) among the three algorithms (i.e., DSRC, QuickFix and QuickFix with SnapIt). Note that the utility obtained by QuickFix and QuickFix with SnapIt drops to negative infinity in the third and fourth days, because some sensor nodes during these days do not function and therefore the fairness is greatly impaired. Moreover, the overall network utility of the five days obtained by DSCR is larger than the other two algorithms. All these demonstrate that the performance of DSRC is better than those of the other two algorithms.

D. Performance Evaluation of IEACH

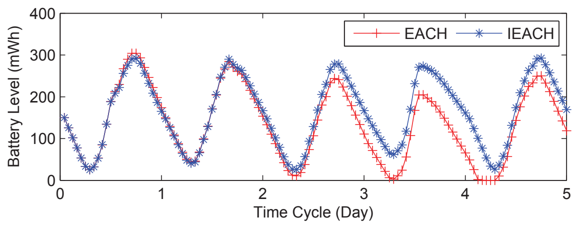
It is assumed that the maximal ratio of estimation error to estimated harvested energy is 20% and the ratio of total estimation error to the total estimated harvested energy for all five days are 1.14%, -2.12%, -4.87%, -7.74% and

TABLE II
NETWORK UTILITY FOR EACH DAY

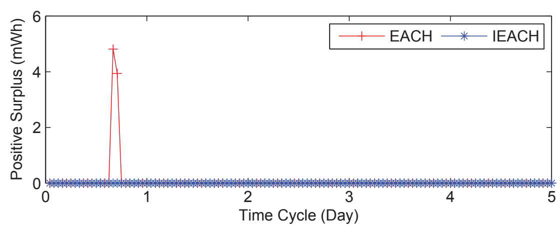
Approach	Total Network Utility				
	First Day	Second Day	Third Day	Fourth Day	Fifth Day
DSRC	266.71	266.09	277.23	223.79	254.18
QuickFix	267.73	259.50	-∞	-∞	245.25
QuickFix with SnapIt	269.01	260.64	-∞	-∞	247.94



(a) Energy allocation



(b) Battery level



(c) Positive surplus $O^{+}_{D,t}$

Fig. 8. Simulation results for the sensor node D employing EACH and IEACH, respectively.

-3.79%, respectively. Figure 8(a)-8(c) show the results of energy allocation, battery level and positive surplus for the sensor node employing EACH and IEACH, respectively. It can be seen that, if only employing EACH and the estimation of harvested energy is imprecise, the sensor node D misses recharging opportunity at some slots during the first day, since the battery level of the sensor node reaches the highest energy level and the amount of harvested energy is more than the amount of the energy allocation at some consecutive slots during the first day. Furthermore, the battery level of the sensor node reaches the lowest energy level at some consecutive slots, which means the sensor node runs out of energy and stops working, and the positive surplus $O^{+}_{D,t}$ shows the amount of harvested energy that can not be reserved in the rechargeable battery. But with IEACH, the sensor node can avoid these problems. In short, the simulation results show that the imprecise estimation of harvested energy may degrade the network performance and the IEACH can reduces the impact of estimation error effectively.

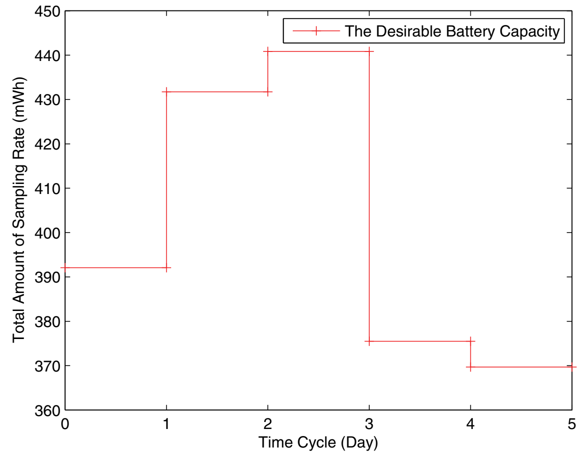


Fig. 9. The desirable battery capacity for sensor node D during the five days.

E. The Desirable Battery Capacity

The battery capacity represents the ability to store the energy, and is critical to the performance of rechargeable sensor network. The Eq. (12) with $\Delta_i = 0$ is used to calculate the desirable battery capacity, which is the minimum battery capacity to store all the harvested energy for each day. The result for each day is shown in the Fig. 9.

It can be seen that the desirable battery capacity for the same sensor node during the five days changes significantly, due to the sharp change of harvested energy. The desirable battery capacity is not only affected by the amount of harvested energy, but also by the rate of harvested energy. For example, the total harvested energy for the fourth day and fifth day are $475.6mWh$ and $643.6mWh$, but the desirable battery capacity during the fourth day is larger than that during the fifth day. This is because the rate of harvested energy during the fourth day is much larger than that during the fifth day. Since the desirable battery capacity for the same sensor node changes in the different days, it is extremely difficult to find a desirable battery capacity for each sensor node. Therefore, designing an efficient energy allocation is the only feasible way to obtain desirable network performance.

VI. CONCLUSION

In this paper, we have studied distributed sampling problem using a rechargeable battery with limited capacity to maximize the overall network utility. As the sampling rate is coupled with the energy allocation, we first proposed an adaptive Energy Allocation sCHeme (EACH) in which each sensor node can manage its energy use in an efficient way. Then we developed a Distributed Sampling Rate Control (DSRC) algorithm to obtain the optimal sampling rate, by employing theory of convex optimization and dual decomposition. In addition, we proposed an Improved adaptive Energy Allocation sCHeme (IEACH) based on EACH to eliminate the impact of estimation error. We performed extensive simulations to demonstrate the efficiency of our algorithms by comparing with existing algorithms. For our future work, we will focus on investigating the impacts of storage space and Quality of Service on network utility under general interference patterns in the rechargeable sensor networks.

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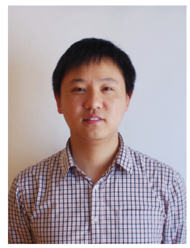

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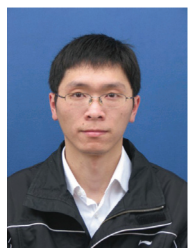

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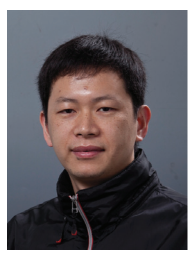

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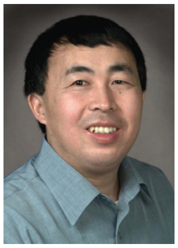

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