STOCHASTIC ONLINE CONTROL FOR ENERGY-HARVESTING WIRELESS NETWORKS WITH BATTERY IMPERFECTIONS

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ABSTRACT

In energy harvesting (EH) network, the energy storage devices (i.e., batteries) are usually not perfect. In this paper, we consider a practical battery model with finite battery capacity, energy (dis-)charging loss, and energy dissipation. Taking into account such battery imperfections, we rely on the Lyapunov optimization technique to develop a stochastic online control scheme that aims to maximize the utility of data rates for EH multi-hop wireless networks. It is established that the proposed algorithm can provide a feasible and efficient data admission, power allocation, routing and scheduling solution, without requiring any statistical knowledge of the stochastic channel, data-traffic, and EH processes.

Index Terms— Stochastic optimization, energy harvesting, battery imperfections, wireless networks.

1. INTRODUCTION

Different from traditional communication systems, energy harvesting (EH) from environmental sources shifts the paradigm on resource allocation from reducing energy consumption to the most efficient utilization of opportunistic energy. Existing works [1–5] on EH communications mostly addressed offline optimizations, where the EH profiles were assumed to be known *a priori*. In practical scenarios, complete predictability of EH profiles is clearly an oversimplified assumption. Relying on past realizations of EH processes and certain statistics of their future evolutions, [2–4] developed some heuristic online algorithms, which, however, lack strong analytical performance guarantees. By modeling the EH and/or data processes as Markov processes, online optimizations were cast as Markov decision problems (MDP) and numerically solved with dynamic programming tools in [1, 5]. However, the well-known "curse-of-dimensionality" with such solutions precludes their application for all but the simplest practical networks.

Leveraging stochastic optimization tools, a few low-complexity online schemes were developed in [6–8]. These schemes assumed ideal energy storage devices (i.e., batteries) in use. Under this assumption, the energy-queue sizes at the batteries can play the role of "stochastic" Lagrange multipliers to develop a dual-subgradient based solver to the intended problems. However, the imperfections with practical batteries could disable this approach. In this paper, we consider a practical battery model accounting for finite battery capacity, energy (dis-)charging loss, and energy dissipation over time. By integrating and generalizing the Lyapunov optimization techniques in [8, 9], we re-establish a systematic framework to develop and analyze the stochastic online control schemes for EH wireless networks with such imperfect batteries. Specifically, we propose a data-backpressure based scheduling and degenerated energy-queue based power allocation scheme that can maximize the utility of data rates for EH multi-hop wireless networks, without requiring any statistical knowledge of the channel, data-traffic, and EH processes. Different from [8] where an EH admission mechanism is performed to ensure finite energy queues, we apply the sample path analysis in [10, 11] to derive the conditions that the proposed scheme is feasible for any given battery capacities without EH admission, which can help fully exploit the available harvested energy. In addition, we rigorously establish the performance guarantees of the proposed scheme in form of sub-optimality bounds in the presence of practical battery imperfections. Numerical results demonstrate that the proposed scheme significantly outperforms the existing alternatives.

The rest of the paper is organized as follows. The system models are described in Section II. The proposed dynamic resource management scheme is developed and analyzed in Section III. Numerical results are provided in Section IV, followed by conclusions.

2. SYSTEM MODELS

Consider a general EH multi-hop wireless network that operates in slotted time. For convenience, the slot duration is normalized to unity; thus, the terms "energy" and "power" can be sometimes used interchangeably. The network is represented by a graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N} = \{1, \dots, N\}$ denotes the nodes, and $\mathcal{L} = \{[n,m],\ \ n,m \in \mathcal{N}\}$ collects the directed links between nodes. For each node $n \in \mathcal{N}$, define two sets of neighbor nodes $\mathcal{N}_n^o := \{m :\ \forall [n,m] \in \mathcal{L}\}$, and $\mathcal{N}_n^i := \{m :\ \forall [m,n] \in \mathcal{L}\}$. Further define $d_{\max} := \max_n\{|\mathcal{N}_n^i|, |\mathcal{N}_n^o|\}$ as the maximum in- and out-degree for nodes in the network.

2.1. Network Traffic and EH Model

The network delivers packets for data flows indexed by their destination nodes c. Per time slot t, a data admission is implemented by the network to decide the number $R_n^c(t)$ of packets for flow c that can be newly admitted at node n. We assume that

$$0 \le R_n^c(t) \le R_{\max}, \quad \forall n, c, \forall t. \tag{1}$$

Each node is capable of harvesting energy from the environmental sources to power its transmissions. The amount of harvested energy is clearly random over time. Let $\boldsymbol{e}(t) := [e_1(t), \dots, e_N(t)]$ be called the *energy state* at t, where $e_n(t)$ is the energy that node n harvests at slot t. We assume that $\boldsymbol{e}(t)$ takes values in some finite set and there exists $e_{\max}$ such that

$$0 \le e_n(t) \le e_{\max}, \quad \forall n, \forall t.$$

2.2. Transmission Model

Per slot t, let $\boldsymbol{S}(t)$ denote the time-varying, random *channel state*, which in general can be an N-by-N matrix, and the (n,m)

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component denotes the channel condition between nodes n and m. We assume that $\boldsymbol{S}(t)$ takes values in some finite set for all time. Given $\boldsymbol{S}(t)$, the network allocates a power vector $\boldsymbol{P}(t) := [P_{[n,m]}(t),\ \forall [n,m] \in \mathcal{L}]$ for data transmissions over links, where $P_{[n,m]}(t)$ denotes the power allocated to node n for link $[n,m]$ at time t. We assume that each node has a peak power constraint:

$$0 \leq \sum_{m \in \mathcal{N}_n^o} P_{[n,m]}(t) \leq P_{\max}, \quad \forall n, t. \tag{2}$$

Given $\boldsymbol{S}(t)$ and $\boldsymbol{P}(t)$, the transmission rate over the link $[n,m]$ is dictated by a rate-power function

$$\mu_{[n,m]}(t) = \mu_{[n,m]}(\boldsymbol{S}(t), \boldsymbol{P}(t)). \tag{3}$$

We also assume that each link has a peak rate constraint such that

$$\mu_{[n,m]}(t) \leq \mu_{\max}, \quad \forall [n,m] \in \mathcal{L}$$

for all time under any channel state $\boldsymbol{S}(t)$. Now let $\mu_{[n,m]}^c(t)$ denote the rate allocated to the data flow c over link $[n,m]$ at time t. It is clear that we have:

$$\sum_c \mu_{[n,m]}^c(t) \leq \mu_{[n,m]}(t), \quad \forall [n,m]. \tag{4}$$

Let $\boldsymbol{Q}(t) := [Q_n^c(t), \forall n, c \in \mathcal{N}]$ denote the data queue backlog vector at time t, where $Q_n^c(t)$ is the backlog data for flow c at node n. For the given data admission and rate allocation, we have

$$\begin{aligned} Q_n^c(t+1) \leq & \left[Q_n^c(t) - \sum_{m \in \mathcal{N}_n^o} \mu_{[n,m]}^c(t) \right]^+ \\ & + \sum_{m \in \mathcal{N}_n^i} \mu_{[m,n]}^c(t) + R_n^c(t), \quad \forall n, c \end{aligned} \tag{5}$$

with $Q_n^c(0) = 0, \forall n, c$, $Q_c^c(t) = 0, \forall t$, and $[x]^+ := \max\{x, 0\}$.

2.3. Imperfect Battery Model

Every node has a storage device, i.e., battery, to save the harvested energy. Consider a practical battery with: i) a finite capacity, ii) (dis-)charging loss, and iii) energy degeneration. Let $E_{\max} \in (0, \infty)$ denote the battery capacity, $\xi \in (0,1]$ the (dis-)charging efficiency (e.g., $\xi = 0.9$ means that only 90% of the charged or discharged energy is useful), and $\eta \in (0,1]$ the storage efficiency (e.g., $\eta = 0.9$ means that 10% of the stored energy will be "leaked" over a slot).

We can model the battery using an energy queue. Let $E_n(t)$ denote the energy queue size, which indicates the amount of the energy left in the battery of node n at time t; and let $\boldsymbol{E}(t) := [E_n(t), \forall n \in \mathcal{N}]$. As the data transmissions are powered by the harvested energy stored in the batteries, the power allocation vector $\boldsymbol{P}(t)$ must satisfy the following "energy availability" constraint:

$$\sum_{m \in \mathcal{N}_n^o} P_{[n,m]}(t) \leq \xi \eta E_n(t), \quad \forall n \tag{6}$$

where the product $\xi\eta$ captures the discharging loss and energy degeneration.

For the given energy queue size, power allocation and energy state at time t, we have:

$$E_n(t+1) = \eta E_n(t) - \frac{\sum_{m \in \mathcal{N}_n^o} P_{[n,m]}(t)}{\xi} + \xi e_n(t), \tag{7}$$

$$0 \leq E_n(t) \leq E_{\max} \tag{8}$$

with $E_n(0) = 0, \forall n$.

2.4. Network Utility Maximization

Define the time-average rate for data flow c that is admitted into node n, as

$$\bar{r}_n^c = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{R_n^c(t)\}$$

where the expectation are taken over all sources of randomness. Each flow c is associated with a utility function $U_n^c(\bar{r}_n^c)$, which is assumed to be strictly increasing, differentiable, and concave. Let g_n^c denote the maximum first derivative of $U_n^c(r)$, and define $g_{\max} = \max_{n,c} g_n^c$, which is assumed to be finite.

Note that the energy state $\boldsymbol{e}(t)$ and the channel state $\boldsymbol{S}(t)$ are random processes. The EH wireless network is thus a stochastic system. The goal is to design an online resource management scheme that chooses the data admission amounts $\boldsymbol{R}(t) := [R_n^c(t), \forall n, \forall c]$, the power allocations $\boldsymbol{P}(t) = [P_{[n,m]}(t), \forall [n,m]]$, as well as the routing and scheduling decisions $\boldsymbol{\mu}(t) := [\mu_{[n,m]}^c(t), \forall [n,m], \forall c]$ per slot t, so as to maximize the aggregate utility of time-average data rates subject to (s. t.) network operation constraints. Upon defining $\mathcal{X} := \{\boldsymbol{R}(t), \boldsymbol{P}(t), \boldsymbol{\mu}(t), \forall t\}$, we wish to solve

$$\begin{aligned} U^{opt} := & \max_{\mathcal{X}} \sum_{n,c} U_n^c(\bar{r}_n^c) \\ & \text{s. t.} \quad (1), (2), (3), (4), (5), (6), (7), (8), \ \forall t. \end{aligned} \tag{9}$$

3. DYNAMIC RESOURCE MANAGEMENT SCHEME

The problem (9) is challenging as the optimization variables are coupled over time due to the queue dynamics and energy availability constraints in (5)–(7). We next resort to the Lyapunov optimization techniques in [8, 9] to develop a low-complexity online control algorithm, which can be proven to yield a feasible and near-optimal solution for (9) under conditions, without requiring any statistical knowledge of stochastic EH and channel processes.

3.1. Properties of Rate-Power Function

To start, we assume that the rate-power function in (3) satisfies the following two properties for any given channel state $\boldsymbol{S}$:

Property 1 *For two power allocation vectors $\boldsymbol{P}$ and $\boldsymbol{P}'$, where $\boldsymbol{P}'$ is obtained by changing any single component $P_{[n,m]}$ to zero, we have:*

i) $\mu_{[n',m']}(\boldsymbol{S}, \boldsymbol{P}) \leq \mu_{[n',m']}(\boldsymbol{S}, \boldsymbol{P}')$, $\forall [n', m'] \neq [n,m]$*;*

ii) $0 \leq \mu_{[n,m]}(\boldsymbol{S}, \boldsymbol{P}) - \mu_{[n,m]}(\boldsymbol{S}, \boldsymbol{P}') \leq \delta_1 P_{[n,m]}$*, for a finite constant* $\delta_1 \in [0, \infty)$.

Property 2 *For two power allocation vectors $\boldsymbol{P}$ and $\boldsymbol{P}'$, where $P'_{[n,m]} = P_{[n,m]} + \frac{\Delta P}{|\mathcal{N}_n^o|}$, $\forall m \in \mathcal{N}_n^o$, and $P'_{[n',m]} = P_{[n',m]}$, $\forall n' \neq n$, we have:*

i) $\mu_{[n,m]}(\boldsymbol{S}, \boldsymbol{P}) \leq \mu_{[n,m]}(\boldsymbol{S}, \boldsymbol{P}')$, $\forall m \in \mathcal{N}_n^o$*;*

ii) $0 \leq \sum_{n' \neq n} \sum_{m \in \mathcal{N}_{n'}^o} [\mu_{[n',m]}(\boldsymbol{S}, \boldsymbol{P}) - \mu_{[n',m]}(\boldsymbol{S}, \boldsymbol{P}')] \leq \delta_2 \Delta P$*, for a finite constant* $\delta_2 \in [0, \infty)$.

Properties 1 and 2 will be the keys for our feasibility and optimality gap analysis. They are actually satisfied by most rate-power functions. For example, consider the interference-free case. Let $h_{[n,m]}$ denote the channel coefficient from node n to node m, then the rate function is $\mu_{[n,m]} = \log\left(1 + \frac{|h_{[n,m]}|^2 P_{[n,m]}}{\sigma^2}\right)$. We readily have $\delta_1 = \max\{\frac{|h_{[n,m]}|^2}{\sigma^2}, \forall [n,m]\}$, $\delta_2 = 0$.

3.2. The Proposed Algorithm

We assume the following two conditions for the system parameters in development of the proposed algorithm:

$$\xi e_{\max} \leq (1-\eta)E_{\max} + \frac{P_{\max}}{\xi}; \tag{10}$$

$$E_{\max} \geq \frac{P_{\max}}{\xi} + \xi e_{\max}. \tag{11}$$

Condition (10) is a necessary condition to maintain the stability of the energy queues $E_n(t)$ for every sample path. If $\xi e_{\max} > (1-\eta)E^{\max} + \frac{P_{\max}}{\xi}$, i.e., the maximum energy arrival is deterministically greater than the largest energy departure possible, then there exists a sample path of energy queue $E_n(t)$ that grows unbounded. On the other hand, condition (11) dictates that the battery capacity is large enough to accommodate the largest possible charging/discharging range.

Our algorithm depends on two algorithmic parameters, namely a "queue perturbation" parameter Γ and a weight parameter V. The two parameters are in the Lyapunov technique. The derivation is from the feasibility requirement (see Proposition 1 in the sequel), which is one of our main contributions. Any pair (V, Γ) that satisfies the following conditions can be used:

$$0 < V < V^{\max}, \quad \Gamma^{\min} \leq \Gamma \leq \Gamma^{\max} \tag{12}$$

where

$$V^{\max} := \frac{E_{\max} - \xi e_{\max} - \frac{P_{\max}}{\xi}}{\xi(\delta_1+\delta_2)g_{\max}}; \tag{13}$$

$$\Gamma^{\min} := \frac{P_{\max}}{\xi\eta} + \frac{\xi}{\eta}\delta_1 g_{\max} V; \tag{14}$$

$$\Gamma^{\max} := \frac{E_{\max} - \xi e_{\max}}{\eta} - \frac{\xi}{\eta}\delta_2 g_{\max} V. \tag{15}$$

Note that the interval for V in (12) is well-defined under the condition (11), and the interval for Γ is valid when $V \leq V^{\max}$.

We now present the proposed algorithm:

Initialization: Select a pair of (V, Γ) satisfying (12), and a constant $\Theta = R_{\max} + d_{\max}\mu_{\max}$.

At every time slot t, observe states $\{\boldsymbol{e}(t), \boldsymbol{S}(t)\}$, and queues $\{\boldsymbol{Q}(t), \boldsymbol{E}(t)\}$, then determine $\boldsymbol{R}^*(t)$, $\boldsymbol{P}^*(t)$, and $\boldsymbol{\mu}^*(t)$ as follows.

- **Data admission**: Choose $R_n^{c*}(t)$, $\forall n, c$, to be the optimal solution of the following problem:

$$\begin{aligned} \max_{R_n^c(t)} \; & [VU_n^c(R_n^c(t)) - Q_n^c(t)R_n^c(t)] \\ \text{s. t. } \; & 0 \leq R_n^c(t) \leq R_{\max} \end{aligned} \tag{16}$$

- **Power allocation**: Define the link weight as $W_{[n,m]}(t) = \max_c W_{[n,m]}^c(t)$, where $W_{[n,m]}^c(t) = [Q_n^c(t) - Q_m^c(t) - \Theta]^+$. Choose $\boldsymbol{P}^*(t)$ to be the optimal solution of the following problem:

$$\begin{aligned} \max_{\boldsymbol{P}(t)} \; & \sum_n \Big[\sum_{m \in \mathcal{N}_n^o} [W_{[n,m]}(t)\mu_{[n,m]}(t)] \\ & + \frac{\eta}{\xi}(E_n(t) - \Gamma) \sum_{m \in \mathcal{N}_n^o} P_{[n,m]}(t) \Big] \\ \text{s. t. } \; & 0 \leq \sum_{m \in \mathcal{N}_n^o} P_{[n,m]}(t) \leq P_{\max}, \quad \forall n \end{aligned} \tag{17}$$

  Note that $\mu_{[n,m]}(t)$ is a function of $\boldsymbol{P}(t)$. Having obtained $\boldsymbol{P}^*(t)$, the rate allocated to link $[n,m]$ is $\mu_{[n,m]}^*(t) = \mu_{[n,m]}(\boldsymbol{S}(t), \boldsymbol{P}^*(t))$.

- **Routing and scheduling**: For each node n, choose any $\check{c} \in \arg\max_c W_{[n,m]}^c(t)$. If $W_{[n,m]}^{\check{c}}(t) > 0$, set

$$\mu_{[n,m]}^{\check{c}*}(t) = \mu_{[n,m]}^*(t), \text{ and } \mu_{[n,m]}^{c*}(t) = 0, \; \forall c \neq \check{c}.$$

  This is the well-known MaxWeight matching scheduling.

- **Queue updates**: Update $Q_n^c(t)$ and $E_n(t)$ via (5) and (7), respectively, based on $\boldsymbol{R}^*(t)$, $\boldsymbol{P}^*(t)$, and $\boldsymbol{\mu}^*(t)$.

Some comments are in order.

i) Different from the ESA algorithm in [8], there is no EH admission mechanism in the proposed algorithm; the available harvested energy could be then fully capitalized on for data transmission.

ii) The perturbed energy queue-size $E_n(t) - \Gamma$ is weighted by $\frac{\eta}{\xi}$ in the problem (17) to determine the optimal power allocation. These weights are used to account for the battery degeneration and discharging loss.

The proposed algorithm is an online scheme, which dynamically makes *instantaneous* greedy control decisions for the stochastic system under consideration, without a-priori knowledge of any statistics of the underlying random processes.

3.3. Feasibility Guarantee

Note that in the proposed algorithm, energy availability constraint (6) and the bounded energy queue constraint (8) are ignored. It is then not clear whether the algorithm is feasible for the problem (9). Yet, we can show that by using any pair (V, Γ) in (12) and $\Theta = R_{\max} + d_{\max}\mu_{\max}$, the proposed algorithm is a feasible one under the conditions (10)–(11). To this end, we first show that[1].

Lemma 1 *The power allocation policy obeys: i)* $\sum_{m \in \mathcal{N}_n^o} P_{[n,m]}^*(t) = 0$*, if* $E_n(t) < \Gamma - \frac{\xi}{\eta}\delta_1 g_{\max} V$*; and ii)* $\sum_{m \in \mathcal{N}_n^o} P_{[n,m]}^*(t) = P_{\max}$*, if* $E_n(t) > \Gamma + \frac{\xi}{\eta}\delta_2 g_{\max} V$*,* $\forall n$*.*

Lemma 1 reveals partial characteristics of the proposed dynamic policy. Specifically, when the energy queue at node n is large enough, peak power can be afforded for its data transmissions; i.e., $\sum_{m \in \mathcal{N}_n^o} P_{[n,m]}^*(t) = P_{\max}$. On the other hand, when the energy queue at node n is small enough, no power should be allocated; i.e., $\sum_{m \in \mathcal{N}_n^o} P_{[n,m]}^*(t) = 0$.

Based on Lemma 1, we then establish the following result.

Proposition 1 *Under the conditions (10)–(11), the proposed algorithm guarantees: i)* $\sum_{m \in \mathcal{N}_n^o} P_{[n,m]}^*(t) = 0$*, if* $\xi\eta E_n(t) < P_{\max}$*, and ii)* $0 \leq E_n(t) \leq E_{\max}$*,* $\forall n$*,* $\forall t$*.*

Proposition 1 implies that the proposed algorithm with proper selection of (V, Γ) and Θ can always yield a feasible control policy for (9) under the conditions (10)–(11). Note that Proposition 1 is a *sample path* result; i.e., it holds for every time slots under *arbitrary*, even non-stationary, $\{\boldsymbol{e}(t), \boldsymbol{S}(t)\}$ processes.

[1]The proofs for the lemmas and propositions can be found in [12].

3.4. Optimality Gap

By assuming that the random process for $\{\boldsymbol{e}(t), \boldsymbol{S}(t)\}$ is independent and identically distributed (i.i.d.) over time slots, we establish the following optimality result.

Proposition 2 *Suppose that conditions (10)–(12) hold, and $\{\boldsymbol{e}(t), \boldsymbol{S}(t)\}$ is i.i.d. over slots. Let $\bar{r}_n^{c*}(T)$ be the time-average admitted rate vector achieved by the proposed algorithm up to time T, i.e., $\bar{r}_n^{c*}(T) = \frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{R_n^{c*}(t)\}$. Then*

$$\lim_{T\to\infty}\inf\sum_{n,c} U_n^c(\bar{r}_n^{c*}(T)) \geq U^{opt} - \frac{B}{V}$$

where the constant

$$B = N^2B_1 + N(B_2 + B_3), \tag{18}$$

with $B_1 = 2d_{\max}^2\mu_{\max}^2 + \frac{1}{2}R_{\max}^2 + 2d_{\max}\mu_{\max}R_{\max}$, $B_2 = \frac{1}{2}\max\{[\frac{P_{\max}}{\xi} + (1-\eta)\Gamma]^2, [-\xi e_{\max} + (1-\eta)\Gamma]^2\}$, $B_3 = \eta(1-\eta)\max\{(E_{\max}-\Gamma)^2, \Gamma^2\}$ and U^{opt} is the optimal value of (9) under any feasible control algorithm, even the one knowing future random realizations.

Proposition 2 asserts that the proposed algorithm asymptotically yields a time-average utility with an optimality gap smaller than $\frac{B}{V}$. The proposed scheme is in fact a modified version of the queue-length based stochastic optimization scheme, where the "perturbed" queue lengths play the role of "stochastic" Lagrange multipliers with a dual-subgradient solver to the problem of interest. The gap N^2B_1/V is inherited from the underlying stochastic subgradient method. On the other hand, the gap NB_2/V is due to the combined effect of energy-queue perturbation and battery imperfections, while the gap NB_3/V is incurred by the battery degeneration.

Based on Propositions 1 and 2, we arrive at the main result.

Theorem 1 *Suppose that conditions (10)–(12) hold and $\{\boldsymbol{e}(t), \boldsymbol{S}(t)\}$ is i.i.d. over slots. The proposed algorithm yields a feasible dynamic control scheme for* (9)*, which has an optimality gap $\frac{B}{V}$; i.e.,*

$$U^{opt} \geq \lim_{T\to\infty}\inf\sum_{n,c} U_n^c(\bar{r}_n^{c*}(T)) \geq U^{opt} - \frac{B}{V}.$$

where $\bar{r}_n^{c*}(T) = \frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{R_n^{c*}(t)\}$ and B is given by (18).

4. NUMERICAL TESTS

Consider a multi-hop network in Fig. 1, where the nodes 1–4 collect data and send data to the sink node 7 through relay nodes 5 and 6 [8]. In simulations, we assume imperfect batteries at nodes, with storage efficiency $\eta = 0.98$ and (dis-)charging efficiency $\xi = 0.95$. Table 1 lists the values for $d_{\max}$ (the maximum in- and out-degree for nodes in the network), $R_{\max}$ (the maximum packets that can be newly admitted), $P_{\max}$ (the peak power), $\mu_{\max}$ (the maximum rate over all the links) and $E_{\max}$ (the battery capacity). The utility function is selected as: $\sum_{n,c} U_n^c(\bar{r}_n^c) = \ln(1+\bar{r}_1^7) + \ln(1+\bar{r}_2^7) + \ln(1+\bar{r}_3^7) + \ln(1+\bar{r}_4^7)$. Suppose that all the links are independent with each other, implying $\delta_2 = 0$. The link state $S_{[n,m]}(t)$ can be either good or bad with equal probability. One unit of power can deliver two packets when the link state is good, while it can be only used to transmit one packet upon bad link state. We also assume that the harvested energy $e_n(t)$ is i.i.d. for each node; $e_n(t)$ is either $e_{\max}$ or 0 with equal probability. As a result, we have: $g_{\max} = 1$, $\delta_1 = 2$ and $\Theta = d_{\max}\mu_{\max} + R_{\max} = 7$.

Table 1. Parameters Configuration.

$d_{\max}$	$R_{\max}$	$P_{\max}$	$\mu_{\max}$	$E_{\max}$
2	3	2	2	160

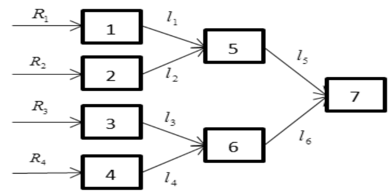

Fig. 1. Data collection network.

Fig. 2 compares the performance of the proposed algorithm with the ESA in [8] and a heuristic greedy algorithm for different $e_{\max}$. It is shown that the proposed algorithm evidently outperforms the ESA and the greedy algorithm for any given $e_{\max}$. The greedy algorithm in fact schedules the links in a time division multi-access (TDMA) manner; the resultant utility is low in general and its performance changes only slightly for different $e_{\max}$. The proposed algorithm achieves higher utility than the ESA due to two reasons. The first reason is that the ESA cannot make use of all available energy because of its EH admission mechanism, while the proposed algorithm harvests all available energy. On the other hand, the ESA also has a performance loss for small $e_{\max}$ case since it does not take into account the battery imperfections. For instance, when $e_{\max} = 2$, simulations show that the utilization of available energy for the ESA is 100%; yet, the utility with the proposed algorithm is still 17.2% larger than that with the ESA in this case.

5. CONCLUSIONS

Taking into account imperfect finite-capacity energy storage devices, a stochastic optimization was formulated to maximize the long-term utility subject to the energy availability constraints for general EH wireless networks. Capitalizing on Lyapunov optimization technique, an online control algorithm was proposed to provide a feasible and asymptotically near-optimal control solution.

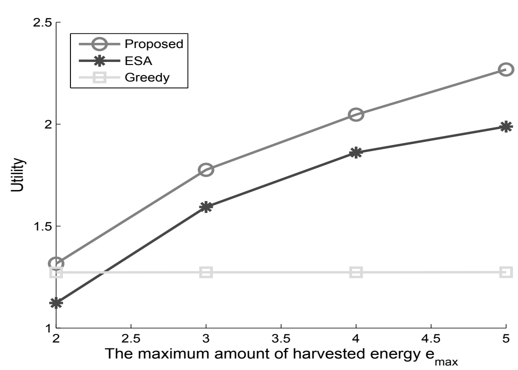

Fig. 2. Comparison of the proposed algorithm, the ESA and the greedy algorithm.

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