Dynamic Power Control for Throughput Maximization in Hybrid Energy Harvesting Node

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Abstract. In this paper, we consider a wireless communication node with hybrid energy harvesting (EH) sources which results in great difficulty in obtaining the statistical knowledge of joint EH process. In addition, the wireless channel fluctuates randomly due to fading. Our goal is, under this condition, to develop a dynamic power control policy for the transmitter such that the time average throughput of the system is maximized over an infinite horizon, taking into account the circuit energy consumption and inefficiency of the rechargeable battery. Such a dynamic power control problem is formulated as a stochastic network optimization problem. The problem is solved by utilizing Lyapunov optimization and an efficient on-line algorithm with quite low complexity is obtained. Simulation results illustrate that the proposed algorithm has the same performance as the optimal one with giving statistical knowledge of the stochastic processes.

Keywords: Energy harvesting · Throughput maximization · Hybrid energy sources · Lyapunov optimization · Wireless communication

1 Introduction

In recent years, the energy harvesting (EH) technique has been advanced very rapidly, many communication devices are capable of harvesting energy from environments around us, such as solar, vibration, magnetic and thermoelectric energy sources, and so on. Due to several significant advantages over conventional grid-powered and non-rechargeable battery-powered wireless devices, such as reduction the usage of conventional energy and the accompanying carbon footprint, energy-sufficient operation with extent lifetime limited only by their hardware lifetime, and so on, the EH technology gains more and more applications in communications systems [1–3]. However, energy harvest brings new problem in the form of intermittency and randomness of

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available energy, which necessitates an efficiently utilization of the harvested energy in order to maximize the throughput of EH communication system.

Various power control and data scheduling schemes have been designed for EH communication systems with the aim of maximizing the throughput in the past few years [4–8]. These studies mainly divide into two categories based on EH model: deterministic model and statistics model. The Deterministic model refers to the availability of knowledge of events, such as energy arrival and channel fade level, prior to the start of data transmission; The statistics model refers to the availability of the statistics knowledge only causally over time, but not a priori. In [4], based on the deterministic model, optimal off-line broadcast scheduling polices for a single user EH communication system were presented to minimize the transmission completion time. Optimal offline and online power allocation algorithms for EH communication system in fading channels were proposed in [5] based on the above two models to minimize the outage probability. Similar as [5], the optimal power control time sequences were proposed in [6, 7] to maximize throughput by a deadline. Furthermore, EH relay was considered and both offline and online power allocation schemes were proposed to maximize the end-to-end throughput [8] based on the above two models.

In the aforementioned works [4–8] on EH communication systems, it is assumed that the EH transmitter was supplied solely by an energy harvester which collected energy from one specific type of renewable energy source. In practice, there is no actual model of the distributions of the stochastic energy arriving time and amount of arrived energy yet [9]. Especially, it is greatly difficult to know the statistical knowledge of the energy arrival generated jointly by multiple energy harvesters collecting energy from various renewable resources. Therefore, the results in the aforementioned literatures are not applicable to the EH communication systems supplied jointly by multiple EH energy sources with great difficulty in obtaining the statistical knowledge of the joint EH process.

In this paper, we address the above issues and focus on dynamic power allocation algorithm design for an EH communication node supplied jointly by multiple renewable energy sources under the condition of unknowing probability distributions of the joint EH process and channel state, such that the time average throughput of the wireless communication system is maximized. Such a problem can be formulated as a stochastic network optimization and solved by Lyapunov optimization developed in [10]. The early works [10, 11] used Lyapunov optimization technique show that the queuing naturally fits in the renewable supplier scheduling problem and present a simple dynamic algorithm that does not require prior statistical information. We apply the approach to EH transmitter with multiple energy harvesters in fading channel with additive Gaussian noise in this paper. At the same time, the efficiency of battery, the peak power of the transmitter and the special relationship between transmission rate and power is taken into account. The problem is now more complex and practical.

The contributions of this paper are summarized as follows: (1) we consider a wireless communication node powered together by multiple EH sources in fading channel without the statistical knowledge of the EH process and channel state, which has not been addressed before. (2) Under this case, we exploit an efficient online power control policy for the EH communication node, our proposed algorithm is universal and robust.

2 System Model and Problem Formulation

We consider a point-to-point wireless communication node where the transmitter (node) is equipped with multiple energy harvesters harvesting energy from various renewable energy sources as shown in Fig. 1, the wireless channel fluctuates randomly due to fading. The system has two queues, data queue and energy queue. The energy harvested jointly by multiple energy harvesters buffers in the rechargeable battery (energy queue) before it used to support the operation of wireless transmissions. We assume that the capacity of the energy storage buffer is infinite, so the harvested energy will not overflow. In practice the buffer is large enough (compared to energy consumed in a slot), this is a good approximation. Furthermore, it is assumed that the transmitter has an infinite backlog of data, so that there is always data to be sent.

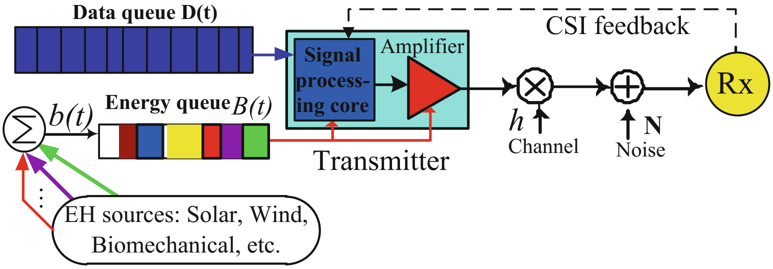

Fig. 1. The EH transmitter model with multiple energy-harvesters in fading channel

The system is slotted in time $t \in \{0, 1, 2, \cdots\}$ with fixed size Δt, where Δt is the time frame length. Without loss of generality, we assume the interval Δt is 1 s. The channel state fluctuates randomly due to fading and remains constant in the duration of each slot but may change at slot boundaries. Suppose that the channel state information (CSI) at the beginning of every timeslot is known at the transmitter via channel monitoring and feedback link [6]. The channel state in slot t (representing, for example, attenuation value and/or noise levels) is denoted by $h(t)$, and assume that it is independent and identically distributed (i.i.d.) over slots in a finite set H, i.e. $h(t) \in H$ for all t, but its probability distribution is not given. We further assume that the values of $h(t)$ is deterministically bounded by finite constants, $h_{\min} \leq h(t) \leq h_{\max}$.

The transmission rate μ_{ab} over the wireless link (a, b) depends on the channel state h_{ab} and transmission power $P_{tra}(t)$ with relationship, $\mu_{ab}(t) - g(P_{tra}(t), h_{ab}(t))$, where the rate-power function $g(\cdot)$ determines the number of bits in data queue that can be transferred over the wireless link (a, b). The function $g(\cdot)$ is assumed to be monotonically non-decreasing, such an important function is given by Shannon's capacity formula [6]:

$$\mu(t) = g(P_{tra}(t)) = \frac{1}{2}\log_2(1 + h(t)P_{tra}(t)) \quad \forall t \tag{1}$$

where $\mu(t)$ represents the transmission rate on timeslot t. The function $g(\cdot)$ is a non-decreasing concave function. At low values of $P_{tra}(t)$, $g(\cdot)$ becomes a linear function.

In practice, the power consumption of the transmitter during the timeslot t denoted by $P(t)$ consists of two parts:

$$P(t) = P_{\text{con}} + P_{\text{tra}}(t) \tag{2}$$

where P_{con} is a constant power required for signal processing at the transmitter in each timeslot, while $P_{\text{tra}}(t)$ represents the transmission power on timeslot t, which is our decision variable depended on the channel state and available energy in the battery. Further, the transmission power $P_{\text{tra}}(t)$ is limited by a continuous power constraint, i.e., $0 \leq P_{\text{tra}}(t) \leq P_{\text{peak}}$, where P_{peak} is the maximum transmission power of the transmitter.

Multiple energy harvesters harvest energy from various renewable resources simultaneously, and the sum of energy during timeslot t harvested jointly by multiple energy harvesters is denoted as $b(t)$ (that is, the input of the energy queue). The $\{b(t)\}$ is a general random process which the statistical knowledge is unknown and has deterministic boundary $0 \leq b(t) \leq b_{\max}$ for any t. In particular, we take into account energy efficiency in storing energy in the energy buffer, a portion of energy leakage from the energy buffer, during slot t only energy $\beta \cdot b(t)$ is stored in the buffer where $0 < \beta < 1$ and that in every timeslot e units of energy gets leaked from the buffer, here e is a constant. These seem to be realistic assumptions [12]. Then energy queue $B(t)$ updates as follows:

$$B(t+1) = \max[B(t) - P(t) - e, 0] + \beta \cdot b(t) \tag{3}$$

Apart from the fixed peak power constraint, the energy consumption of the transmitter during current timeslot t must conform to the energy stored constraint: $P(t) \cdot \Delta t \leq B(t)$, $\forall t$. Note that Δt is 1 s and does not influence the results. For convenience, we do not write the Δt in the following.

In the long run, the time average energy consumption of the transmitter must be less than or equal to the time average energy harvested, namely the system must satisfy the following constraint: $\bar{P} \leq \beta \bar{b} - e$, where

$$\bar{P} = \lim_{t \to \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} E\{P(\tau)\}$$

$$\bar{b} = \lim_{t \to \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} E\{b(\tau)\}$$

Our goal is maximize the time average throughput over an infinite horizon based on the above system model, under energy causality constraint, power constraint and the data transmission constraint. The throughput maximization problem can be formulated as follows:

$$\max : \lim_{t \to \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} E\{\mu(\tau)\} \tag{4}$$

$$\text{s.t.}: \ \bar{P} \leq \beta\bar{b} - e \tag{5}$$

$$P(t) \leq B(t)\,\forall t \tag{6}$$

$$0 \leq P_{\text{tra}}(t) \leq P_{\text{peak}}\,\forall t \tag{7}$$

Next, we establish a virtual queue $Q(t)$ as energy budget queue. Indeed, defining $Q(0) = 0$, we propagate the energy budget queue $Q(t)$ value according to the following equality:

$$Q(t+1) = \max[Q(t) - \beta \cdot b(t), 0] + P(t) + e \tag{8}$$

This virtual queue $Q(t)$ can ensure the inequality constraint (5) holds when it is mean rate stable, which follows the virtual queue stable theorem in [10]. Thus the constraint (5) can be transferred into that the virtual queue Q(t) is mean rate stable.

Specifically, a discrete time queue $Q(t)$ is mean rate stable if

$$\lim\sup_{t\to\infty}\frac{1}{t}E\{Q(t)\} = 0$$

according to the definition in [10].

The problem can be formulated as a stochastic network optimization, the harvested energy and the channel state during every slot are random variables, and transmission power $P_{\text{tra}}(t)$ is our decision variable. We must decide for each timeslot whether or not to allocate power and how much power on the current time or wait for a more energy-efficient future channel state, taking into account currently available energy stored in the battery, such that the time average throughput is maximized over an infinite horizon.

3 Solution of the Optimization Problem

In this section, we utilize Lyapunov optimization to solve the above optimization problem and present a dynamic power control policy. First we define Lyapunov function: $L(t) \triangleq \frac{1}{2}Q(t)^2$, the conditional Lyapunov drift in one timeslot is given by the following definition:

$$\Delta(L(t)) \triangleq E\{L(t+1) - L(t)\,|\,Q(t)\} \tag{9}$$

Our dynamic algorithm is designed to observe the current queues backlog $Q(t)$, $B(t)$, the current channel state $h(t)$ and the incoming energy $b(t)$, then to make a decision $P_{\text{tra}}(t)$ to minimize a bound on the following expression every slot t:

$$\min : \Delta(L(t)) - V \cdot E\{\mu(t)|Q(t)\} \tag{10}$$

(10) is called drift-plus-penalty expression [10], and V is a positive parameter that is used to tune the tradeoff between performance and queue backlog. The objective is to minimize the weighted sum of drift and penalty, which can be proven bounded in the following:

$$\begin{aligned}&\Delta(L(t)) - VE\{\mu(t)|Q(t)\}\\&\leq C - VE\{\mu(t)|Q(t)\} + Q(t)E\{P(t) + e - \beta b(t)|Q(t)\}\end{aligned} \tag{11}$$

where

$$C = \frac{(P_{\text{peak}} + e)^2 + \beta^2 \cdot b_{\max}^2}{2} \tag{12}$$

The proof uses the Lyapunov optimization technique, and is given in [10].

3.1 The Dynamic Algorithm

Due to the left-hand-side of (11) tightly bounded by the right-hand side of (11), minimizing the right-hand-side of the drift-plus-penalty bound (11) every slot t leads to the following dynamic optimization algorithm:

Every slot t, observing $B(t)$, $Q(t)$, $h(t)$ and $b(t)$, then we choose $P_{\text{tra}}(t)$ according to the following optimization:

$$\begin{aligned}\min:\ &Q(t)[P(t) + e - \beta \cdot b(t)] - V \cdot \mu(t)\\&s.t: P(t) \leq B(t) \forall t\\&0 \leq P_{\text{tra}}(t) \leq P_{\text{peak}}\ \forall t\end{aligned} \tag{13}$$

Then we update the actual and virtual queue $B(t)$ and $Q(t)$ by (3) and (8), respectively.

Substituting the rate-power formula (1) and energy consumption (2) into (13), then differentiating with respect to the transmission power P_{tra}, we obtain the optimal transmission power which maximize (13) in timeslot t and denote it as $P_{\text{tra}}^*(t)$,

$$P_{\text{tra}}^*(t) = \frac{V}{2\ln 2 \cdot Q(t)} - \frac{1}{h(t)} \tag{14}$$

However, based on the power constraint (6) and (7), on slot t, the practical transmission power is given by:

$$P_{\text{tra}}(t) = \min\{B(t) - e - P_{\text{con}}, \min[P_{\text{peak}}, \max(P_{\text{tra}}^*(t), 0)]\} \tag{15}$$

The dynamic power control algorithm proposed is given in detail in Table 1.

Table 1. Dynamic power allocation algorithm.

Algorithm 1. Dynamic power allocation algorithm

Initialization:

1: $P_{\mathrm{con}},\ P_{\mathrm{peak}},\ \beta,\ \ e,\ V,\ T,\ Q(1)=0,\ B(1)$

Repeat:

2: for $t=1:1:T$

Observe $B(t),\ \ Q(t),\ h(t)$ and $b(t)$,

Solve $P^{*}_{\mathrm{tra}}(t)$ according to $P^{*}_{\mathrm{tra}}(t)=\frac{V}{2\ln 2\cdot Q(t)}-\frac{1}{h(t)}$

3: Choose the practical transmission power according to

$$P_{\mathrm{tra}}(t)=\min\{B(t)-e-P_{\mathrm{con}},\min[P_{\mathrm{peak}},\max(P^{*}_{\mathrm{tra}}(t),0)]\}$$

4: Update the queues $B(t)$ and $Q(t)$ by

$$B(t+1)=\max[B(t)-P(t)-e,0]+\beta\cdot b(t)$$
$$Q(t)=\max[Q(t)-\beta\cdot b(t),0]+P(t)+e$$

end

3.2 Analysis of Complexity of the Proposed Algorithm

The proposed on-line power control algorithm in this paper is simple to implement. As shown in Table 1, we just need to observe $B(t)$, $Q(t)$, $h(t)$ and $Q(t)$ every slot t and choose $P_{\mathrm{tra}}(t)$ such that Eq. (13) is minimized. Besides, our algorithm based on Lyapunov optimization does not need a priori statistical knowledge of the EH process and the channel state, so the dynamic power control proposed in this paper is a universal policy and apply to any general EH communication node.

The performance analysis of the algorithm in theory cannot be showed for lack of space.

4 Simulation Results

To evaluate the performance of the proposed real-time power control algorithm, first of all, note that we adopt the following distributions just for exposition purpose. The analysis in the previous section does not depend on the distributions. The related simulation settings is summarized in Table 2.

To better evaluate the performance of our proposed algorithm, in following we compare Lyapunov optimization (L.O) algorithm used in our work against the throughput optimization (T.O) algorithm developed in [12], which requires the priori statistical knowledge of the incoming energy. The comparison about the normalized throughput and the accumulated throughput using two different algorithms is shown in Figs. 2 and 3. In Fig. 2, we assume that the rechargeable battery has initial energy of 200 J, we can see that the throughput exploited Lyapunov optimization algorithm is better than of the algorithm using in [12]. The reason is that the throughput optimization algorithm in [12] is designed for no initial energy stored in the battery at beginning of system operation.

Table 2. Simulation settings.

Parameters	Value
Bandwidth	B
Timeslot length	1 s
Channel fading	Gaussian
Average SNR	100 dB
Avg. harvesting rate	120 mJ/slot
EH process	i.i.d. poisson process
Max transmission power	400 mW
Constant power P_{con}	15 mW
Efficiency factor β	0.9
Energy leakage e	5 mJ/slot

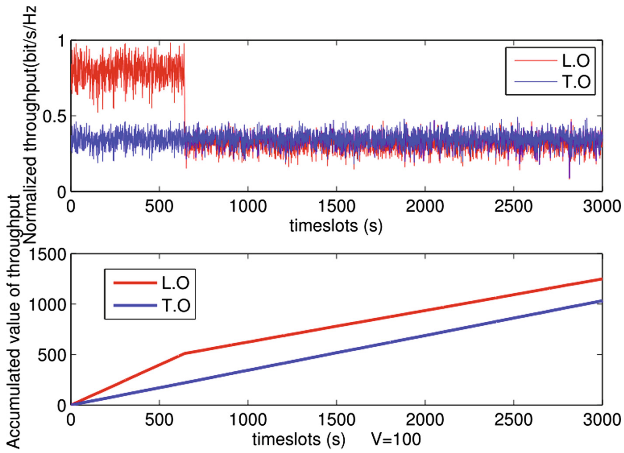

Fig. 2. Comparison between two different algorithms (Battery has initial energy of 200J)

Then we assume B(0) = 0, as shown in Fig. 3, the performance curve of two algorithm overlap. It means that our proposed algorithm has the same performance over the long time compared with the optimal throughput algorithm in [12], but our proposed algorithm has own advantage which does not require the priori statistical knowledge of the incoming energy, while the T.O algorithm developed in [12] requires the priori statistical knowledge of the incoming energy. Hence the algorithm proposed in this paper has universality.

In order to study the impact of parameter V on the performance, we have plotted Fig. 4 showing the relationship between the performance and the value of V. We can see that the performance reach saturation when V is larger than a certain value (V = 100 seen from Fig. 4).

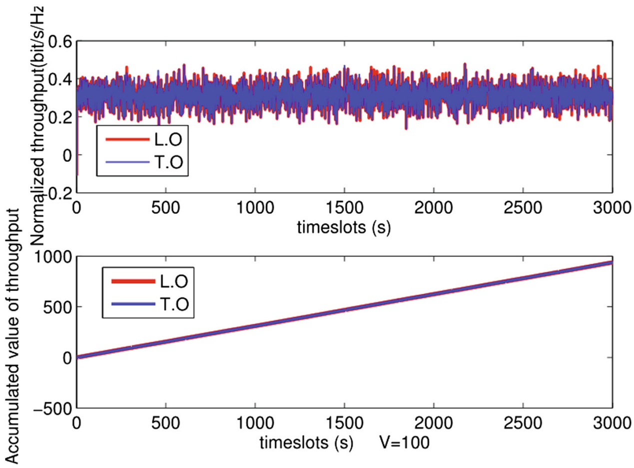

Fig. 3. Comparison between two different algorithms (Battery has no initial energy)

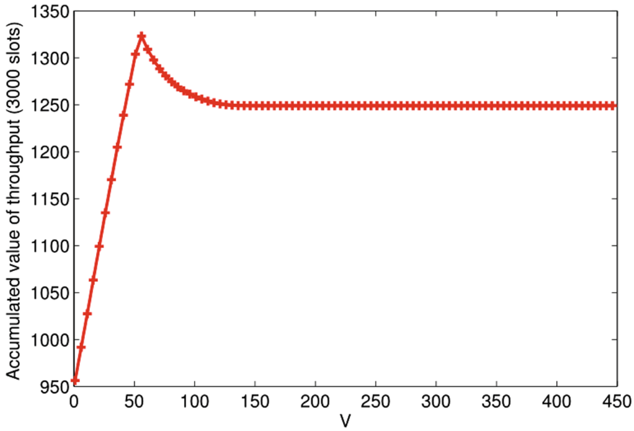

Fig. 4. Performance for different V value (Battery has initial energy of 200J)

5 Conclusion

The dynamic power control for a single-user wireless communication node with multiple renewable sources has been discussed. Under the condition that the EH process and channel state are time-varying with unknown statistics knowledge, we develop a universal power control policy which can be applied to any general EH communication node by utilizing Lyapunov optimization towards the goal of the time average throughput maximization. It was proved that the proposed algorithm is efficient and simple to implement due to its low complexity. Simulation results demonstrate that the proposed algorithm has the not worse performance with the optimal one which needs the statistical knowledge of the stochastic processes.

While we treat single-user communication case in this paper, it has only one data queue. The furture work will include the consideration of multiple-user communication case where multiple data queues are adopted for different customers with different deadlines, a new transmission scheduling will be developed between multiple users with the new power control scheme.

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