Delay-Sensitive Dynamic Resource Control for Energy Harvesting Wireless Systems with Finite Energy Storage

Fan Zhang and Vincent K. N. Lau

ABSTRACT

Energy harvesting technology has become a promising solution to enhance the energy efficiency and reduce carbon emissions in future wireless systems. In future wireless systems, most of the data throughput will come from *delay-sensitive* applications. To ensure a good experience for an end user, we target the optimization of the delay performance of an EH wireless system with finite energy storage. As such, it is necessary to adapt the resource allocation to the channel fading information, data queue length, and energy queue length information. The channel fading information provides the channel quality, the data queue length information provides the dynamic urgency of the transmitted data flows, and the energy queue length information provides the information on how much available energy is left in the energy buffer. Such a problem is quite challenging because it belongs to an infinite dimensional *stochastic optimization*. In this article, we review the existing works on the resource allocation problem in EH wireless systems. We also propose a low-complexity delay-sensitive resource control scheme and discuss valuable design insights.

INTRODUCTION

In recent years, energy harvesting (EH) technology has become a promising solution to the energy efficiency issue in future wireless systems because it not only prolongs the operation lifetime of battery-limited devices but also helps reduce greenhouse gas (such as carbon) emissions. Furthermore, EH technology is quite popular and is being intensively discussed for designing the future wireless systems, such as D2D communications, EH wireless sensor networks, and future cellular systems. Specifically, in EH wireless systems, the transmission nodes harvest energy from the ambient environment by means of EH devices, such as solar panels, wind turbines, and thermoelectric generators, and convert the harvested renewable energy into electricity [1]. However, since the renewable energy sources may appear to be random and bursty in nature, *energy storage* is needed to buffer the random and bursty supply of renewable energy. Due to the high cost of large-capacity energy storage, in practice, EH devices usually have finite energy storage. Moreover, it is important to dimension the energy storage capacity so as to achieve both stability and good performance of the EH network. On the other hand, delay-sensitive applications such as video streaming and online gaming will take up a significant portion of the capacity demand in future wireless systems. Current wireless systems, such as WiFi and third generation (3G), cannot ensure a good experience for an end user with delay-sensitive applications. Therefore, it is also very important to take into account the delay requirements in designing resource control schemes to support delay-sensitive applications in EH wireless systems.

In this article, we study dynamic resource control in an EH wireless system with finite energy storage, as shown in Fig. 1, to support real-time delay-sensitive applications. The transmitter is solely powered by a solar panel that harvests energy from the surrounding environment. In order to have good delay performance, the dynamic resource control should be adaptive to the channel state information (CSI), data queue state information (DQSI), and energy queue state information (EQSI). Specifically, the CSI reveals the transmission opportunities of the time-varying wireless fading channel between the transmitter and receiver, the DQSI reveals the dynamic urgency of data flows, and the EQSI reveals information on the quantity of available renewable energy in the energy buffer. A control policy adaptive to CSI, DQSI, and EQSI is very challenging because the dynamic resource control problem problem belongs to an infinite dimensional *stochastic optimization*. In addition, the coupling between the data queue and energy queue in an EH wireless system further complicates the problem. It is well known that the Markov decision process (MDP) is widely used to deal with such a stochastic optimization [2]. However, classical value iteration algorithms (VIAs) [3] for solving the MDP only give numerical solutions, which suffer from slow convegence issues and lack of design insights. In this

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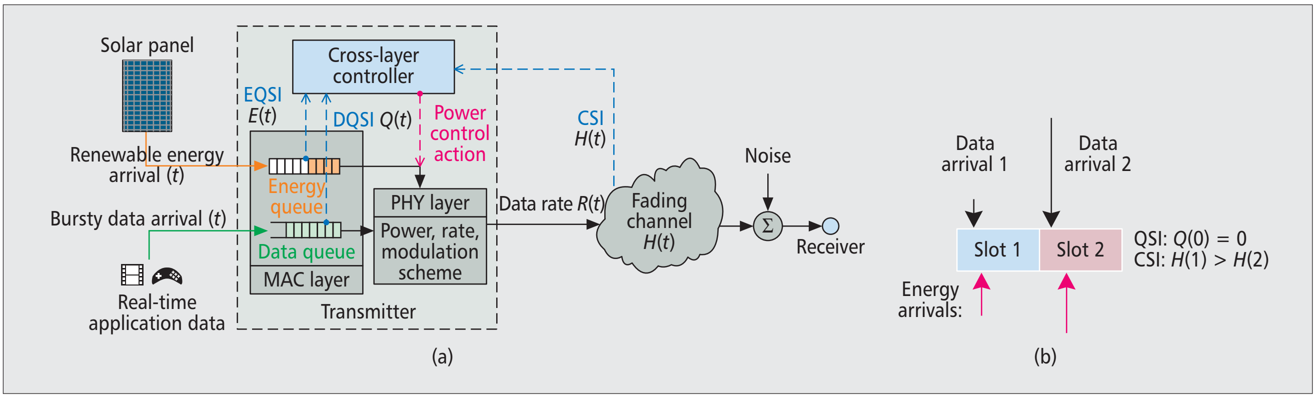


Figure 1. a) System model of a point-to-point EH wireless system with finite energy storage; b) an example of the bursty data arrivals and energy arrivals for two consecutive slots.

article, we provide an asymptotically optimal low-complexity delay-aware resource control scheme and obtain valuable design insights on the dynamic resource for EH wireless systems.

Prior Works on Resource Control for EH Wireless Systems

In this section, we review some of the prior works on resource control for EH wireless systems. The differentiations among them are summarized below.

Infinite/Finite Energy Storage Capacity

Due to the random and bursty nature of renewable energy sources, energy storage is used to buffer the renewable energy so that wireless devices can have a sustained energy supply for delivering data to remote receivers. For example, in a one-day span, sunlight is weak during sunrise and sunset, intense at noon, and gone in the night. Therefore, it is desirable to harvest sufficient solar energy in the daytime and save it in storage to maintain a functional wireless system without sunlight at night. Some prior works assume that the energy storage in wireless devices has infinite capacity [4]. However, this is not practical due to the high cost of high-capacity renewable energy storage, and *energy storage with finite capacity* is a key cost component in the EH wireless systems. As such, it is necessary to appropriately choose the renewable energy buffer size and analyze the impact on how the finite energy storage affects system performance. There are some works that consider EH systems with finite energy storage [5–7], but the derived schemes are not good for delay-sensitive applications. Later in the article, we give the minimum energy buffer size to not only ensure the stability but also achieve good delay performance of an EH system by taking into account the random and bursty nature of renewable energy sources.

Non-Casual/Casual Control

There are a lot of existing works on EH wireless systems in which it is presumed that the EH devices have non-causal knowledge of the time-varying wireless channel, bursty data arrival, and renewable energy arrival profiles [4–6]. That is, the wireless device knows the future realizations of the channel conditions, data arrivals, and renewable energy arrivals. Such an assumption enables mathematical tractability of the associated resource allocation problem. However, this assumption is not realizable in practice due to the difficulty in predicting the random channel conditions and renewable energy source activities. In the article, we consider causal power control, which means that the control action depends on the instantaneous CSI, DQSI, and EQSI. In addition, [8, 9] consider causal transmission mode control based on the observed system state for EH wireless systems with infinite energy storage. They consider the minimizations of average power consumption and packet error rate, and assume that the information flow is delay-insensitive, which does not guarantee any delay performance.

Control Objectives

For delay-sensitive applications, we need to target minimization of the end-to-end average delay performance of EH wireless systems. Specifically, we define delay as the average time between a data packet entering the data queue buffer at the transmitter to the time when the packet is received at the receiver. Different control objectives are considered in prior works on EH wireless systems. For example, some focus on maximization of the transmission data rate for a given deadline [5], while some consider minimization of the packet error rate or transmission complication time for a given data rate [6–9]. However, these formulations do not translate into delay minimization for delay-sensitive applications. We illustrate this using the toy example in Fig. 1b: we focus on two consecutive slots, where the CSI quality of the first slot is better than the second slot (i.e., $H(1) > H(2)$). The data arrival of the first slot is much smaller than the second slot, and there are some energy arrivals for both slots. Using the algorithms proposed in [5, 6], since $H(1) > H(2)$, more harvested energy is used to deliver data in slot 1 than slot 2. However, since data arrival 1 < data arrival 2, the average queue length (i.e., delay performance) will be larger. From the above

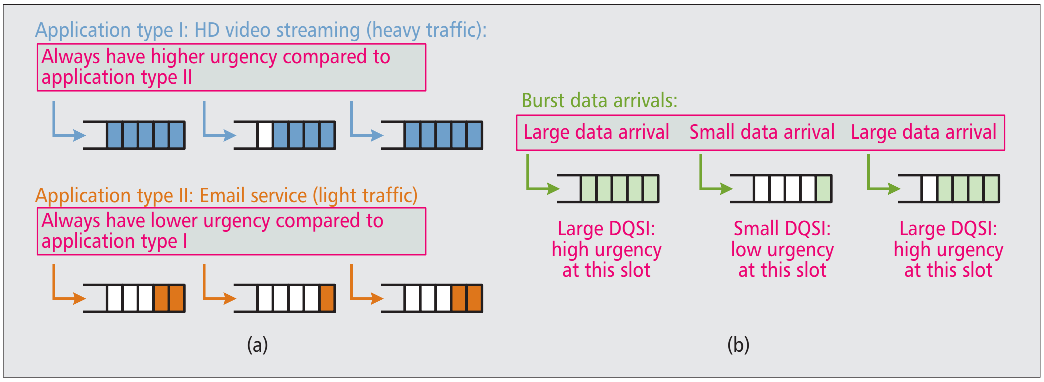


Figure 2. Illustrations of static urgency (priority) and dynamic urgency (priority).

Due to the random and bursty nature of renewable energy sources, energy storage is used to buffer the renewable energy so that wireless devices can have a sustained energy supply for delivering data to remote receivers. For example, in a one-day span, sunlight is weak during sunrise and sunset, intense at noon, and gone in the night.

example, it can be seen that throughput maximization for a given deadline in [5, 6] does not lead to smaller average delay performance because they have ignored the bursty (random) arrivals. Some existing works consider minimization of the average delay using the MDP approach for EH systems with finite energy storage [10]. However, the MDP problem therein is solved using numerical VIA, which gives no intuitional design insights. We propose a systematic low-complexity resource control scheme and give valuable control insights on how to dynamically control the renewable resource in EH wireless systems.

Delay-Sensitive Dynamic Resource Control

Motivation for Considering Delay-Sensitive Control

Since delay-sensitive applications will dominate the data stream in future wireless systems, it is necessary to design a dynamic resource control scheme that aims to provide good end-to-end delay performance. Control schemes aimed at physical layer objectives (e.g., throughput, packet error rate) cannot achieve good delay performance. Also, it is not optimal to just transmit all the data whenever there is sufficient energy. This is because one has to balance the current reward and future potential reward. We consider the following two examples with CSI = {Good, Bad}:

- **Good CSI and large DQSI**: If the current channel state is good and the data queue is long, it is wise to spend the power to empty the data queue.
- **Bad CSI and large DQSI:** If the channel state is bad but the data queue is long, it is not optimal to use all the energy to empty the entire data queue because you may not have power left for future time slots (where you may have a better CSI realization).

From this example, we can see that it is desirable to dynamically control the resource according to the instantaneous CSI, DQSI, and EQSI, where the CSI reflects the channel quality, the DQSI reflects the dynamic urgency of the data flow, and the EQSI reflects the energy availability conditions in the energy storage. We therefore propose a dynamic resource control scheme that can strike a balance among these factors.

Why Does DQSI Capture Data Flow Urgency?

Note that the urgency of a data flow dynamically changes (depending on the instantaneous queue length). Note that the average delay of a flow is given by average data queue length/average data arrival rate (according to Little's law). Hence, if the DQSI is large, it means that the average delay is likely to be large if you do not act on this. This is like going to a supermarket. If the shop manager sees a long queue at a particular counter, that counter needs to be served more urgently, he needs to act on it. In our case, if we see a large DQSI, it means the dynamic urgency or dynamic priority of the flow is higher, and even if we only have average CSI, we might still want to spend more power to transmit more data. On the other hand, if the DQSI is small (dynamic urgency is low), we probably do not want to transmit or transmit less. As such, it is not surprising that the DQSI indicates the *dynamic urgency* of a data flow. On the other hand, the urgency of a flow also depends on the application type, but that is static urgency or static priority. This is very different from the dynamic urgency of a flow as indicated by the instantaneous DQSI mentioned above. Figure 2 illustrates the static urgency (priority) w.r.t. application type and the dynamic urgency (priority) w.r.t. DQSI for a given application type.

Slotted EH Wireless System Model

In this article, we consider a point-to-point EH wireless system with finite energy storage, as shown in Fig. 1. The transmitter delivers data to the remote receiver over the time-varying wireless channel $H(t)$. The transmitter is solely powered by the renewable energy source. For example, the transmitter is equipped with a solar panel that converts harvested solar energy to electricity for operation. The data to be delivered can be video streaming packets or game interactive data, and the remote end user is sensitive to delay of the arrival data flow. Specifically, if there is severe delay, the end user will experience playback interruption of high-quality video or freezing of an online game. In the transmitter, there are two buffers: the date queue buffer and energy queue buffer. The data queue buffer $Q(t)$ is for buffering the bursty traffic data flows toward the end user. The data queue is a

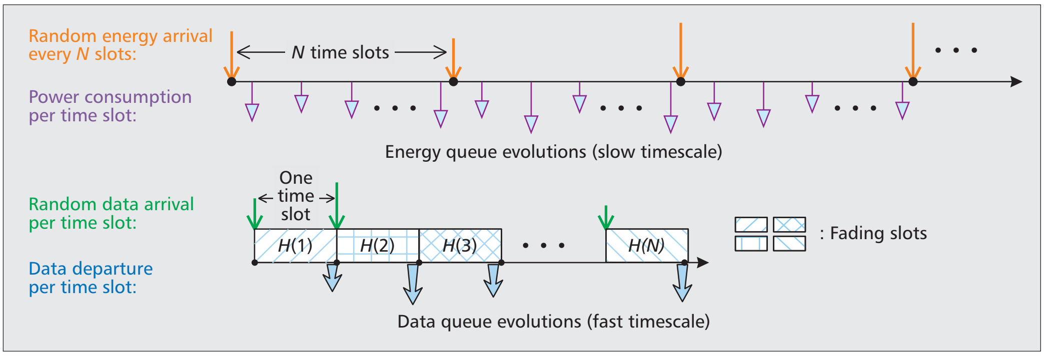


Figure 3. Illustration of evolutions for the data queue and energy queue in two timescales with slot duration. The energy queue evolves on a slow timescale, while the data queue evolves on a fast timescale.

For delay-sensitive applications, it is important to dynamically control the communication resource according to the CSI, DQSI, and EQSI. Therefore, the global system state is characterized by the CSI, DQSI, and EQSI in the EH wireless system.

controlled Markov chain with random data arrivals. The energy queue buffer $E(t)$ is for buffering the bursty renewable energy arrivals. The energy queue is also a controlled Markov chain with random energy arrivals. We consider that the data queue has infinite buffer size for simplicity. In practice, this may not be unreasonable because the cost of data storage is much cheaper than energy storage, and it is easy to equip wireless devices with large amounts of data storage. For example, a wireless sensor module (e.g., ConnectCore i.MX53 module) with a 1 GB external flash can store about 3×10^4 packets under a packet size of 1.5 kB in a Long Term Evolution (LTE) network for supporting video streaming. For a data network with a data rate of 10.8 Mb/s (slot duration = 10 ms), this buffer size is large enough for data storage. Therefore, it is very close to an infinite data queue. However, since high-capacity renewable energy storage is very expensive, it is presumed that renewable energy storage has finite capacity.

The EH wireless system works as a *slotted system* like most practical wireless systems. The realizations of the energy arrivals change every N consecutive time slots, and those of the data arrivals change once per time slot. Figure 3 illustrates the arrival processes of the energy and data arrivals, as well as the evolutions of the data and energy queues.

Dynamic Resource Control Problem Statement

For delay-sensitive applications, it is important to dynamically control the communication resource according to the CSI (captures the transmission opportunities), DQSI (captures the data urgency), and EQSI (captures the energy availability). Therefore, the global system state is characterized by the CSI, DQSI, and EQSI in the EH wireless system. The objective of the delay-sensitive control optimization is to find a power control policy[1] that minimizes the infinite horizon average delay as follows:

Delay-Sensitive Power Control Optimization:

minimize *average delay*
subject to *energy availability constraint*

The control policy should satisfy the *energy availability constraint*. This means that the energy consumption at each time slot cannot exceed the current available energy in the renewable energy storage.

Key Technical Challenges

The delay-sensitive power control problem in the EH wireless system is an infinite dimensional MDP. There are several challenges associated with the MDP problem.

Challenges due to queue-dependent control: Control policies adaptive to the data and energy queue evolutions are quite challenging because the underlying problem embraces *information theory* (to model the channel dynamics) and *queueing theory* (to model the queue dynamics).

Complex coupling between the data queue and energy queue: The data rate of the transmitter in the EH wireless network depends on the current available energy in the energy storage. As such, the dynamics of the data and energy queues are coupled together. This further makes the MDP problem a *coupled multi-dimensional* stochastic optimization problem.

Challenges due to the random and bursty nature of the renewable energy source: In the previous literature on EH wireless systems, the bursty energy arrivals are modeled as independent and identically distributed (i.i.d.) random processes for analytical tractability. In practice, most of the renewable energy arrivals are not i.i.d., and such a *non-i.i.d. nature* will have a huge impact on the dimensioning of the energy storage capacity.

Low-Complexity Delay-Aware Resource Control Scheme

In this section, we propose an asymptotically optimal low-complexity power control solution for solving the delay-sensitive MDP problem.

Dynamic Power Control Solution

The delay-sensitive power control problem in EH wireless systems is an infinite horizon average cost MDP. Using the divide-and-conquer principle, the infinite dimensional MDP is transformed into a per-stage optimization problem

[1] A power control policy is a mapping from the global system state to the power control action of the transmitter.

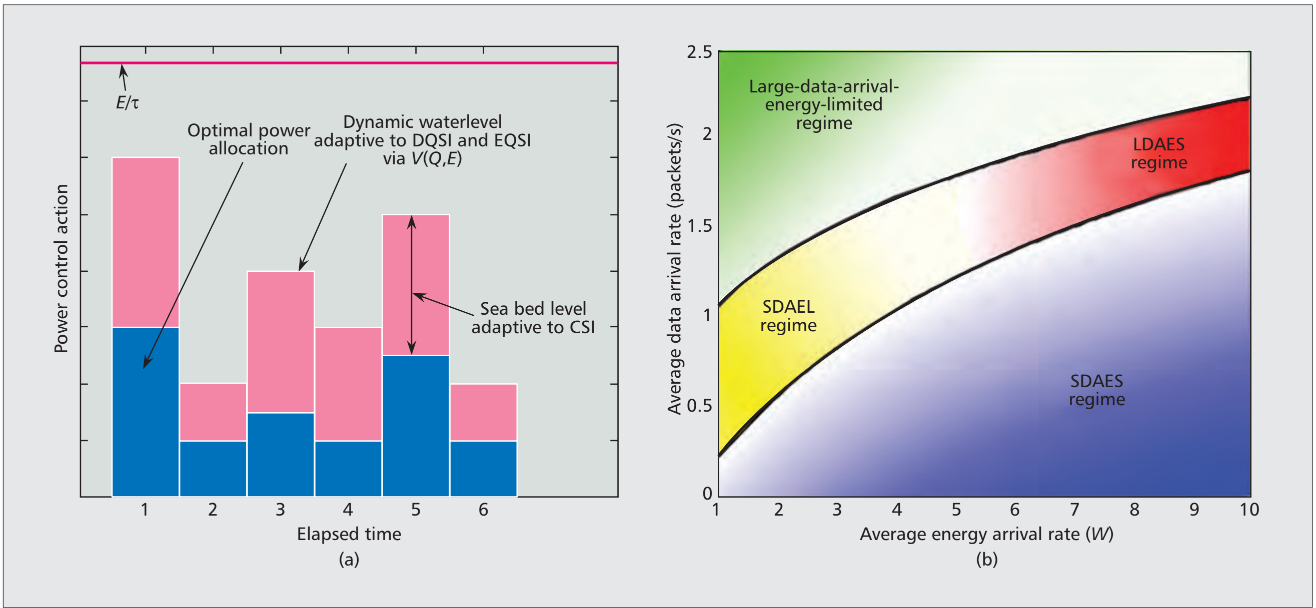


Figure 4. a) An example of the dynamic multi-level water-filling structure; b) asymptotic operating regimes. The two curves represent log-increasing functions w.r.t. the average energy arrival rate. The green area is less interesting because it corresponds to the heavy traffic regime for the data queue, and the delay will be large no matter what control policy is adopted (since the traffic loading of the system is at the instability margin).

given by the *Bellman equation* [3]. The optimal power control solution of the Bellman equation has the following structure:

$$\min\left\{\left(\underbrace{f(V(Q,E)}_{\text{dynamic water level}}-\frac{1}{H^2}\right)^{+}\frac{E}{\tau}\right\},$$

where $V(Q, E)$ is called the *priority function* that captures the dynamic priority of the data flow under different system state realizations w.r.t. DQSI and EQSI.

It can be observed that the optimal power control solution is very similar to the classical water-filling solution, but with a *dynamic multi-level water-filling* structure as shown in Fig. 4a. Furthermore, the optimal power control solution depends on the instantaneous CSI, DQSI, and EQSI via priority function $V(Q, E)$, which captures how the DQSI and EQSI affect the *overall priority* of the data flow. Furthermore, the optimal power control also depends on the current available energy E in the energy buffer.

Closed-Form Approximation of Priority Function

The optimal power control solution depends on the priority function $V(Q, E)$. In the following, we focus on obtaining an *analytical expression* of the priority function. Note that obtaining the priority function is equivalent to solving a system of nonlinear fixed point equations (i.e., the Bellman equation). Classical VIA can only give numerical solutions, and suffers from slow convergence issues and lack of design insights. To overcome this challenge, we shall adopt a continuous time perturbation (CTP) approach [11] so as to obtain closed-form solutions and low-complexity control schemes, and discuss valuable design insights.

Using the CTP approach, we obtain the closed-form approximate priority function under the following asymptotic regimes, illustrated in Fig. 4b.

Large-data-arrival-energy-sufficient (LDAES) regime: In this regime (red area in Fig. 4b), we have a large average data arrival rate and a large average energy arrival rate. This regime corresponds to the scenario where the wireless device has sufficient renewable energy supply for the energy queue to combat the heavy data traffic for the data queue.

Small-data-arrival-energy-limited (SDAEL) regime: In this regime (yellow area in Fig. 4b), we have a small average data arrival rate and a small average energy arrival rate. This regime corresponds to the scenario where we have insufficient energy supply for the energy queue, but the data traffic for the data queue is light.

Small-data-arrival-energy-sufficient (SDAES) regime: In this regime (blue area in Fig. 4b), we have a small average data arrival rate and a large average energy arrival rate. This regime corresponds to the scenario where we have a very sufficient renewable energy supply in the energy queue to keep the data queue stable and maintain a low data queue length.

The overall solution is asymptotically optimal when the slot duration is small. Please refer to [11] for the detailed derivations on this CTP approach. Furthermore, the small slot duration condition is easily satisfied in practical wireless systems. For example, in LTE, the physical layer is organized into radio frames (corresponding to the slots in our system), and the generic radio frame has a time duration of 10 ms.

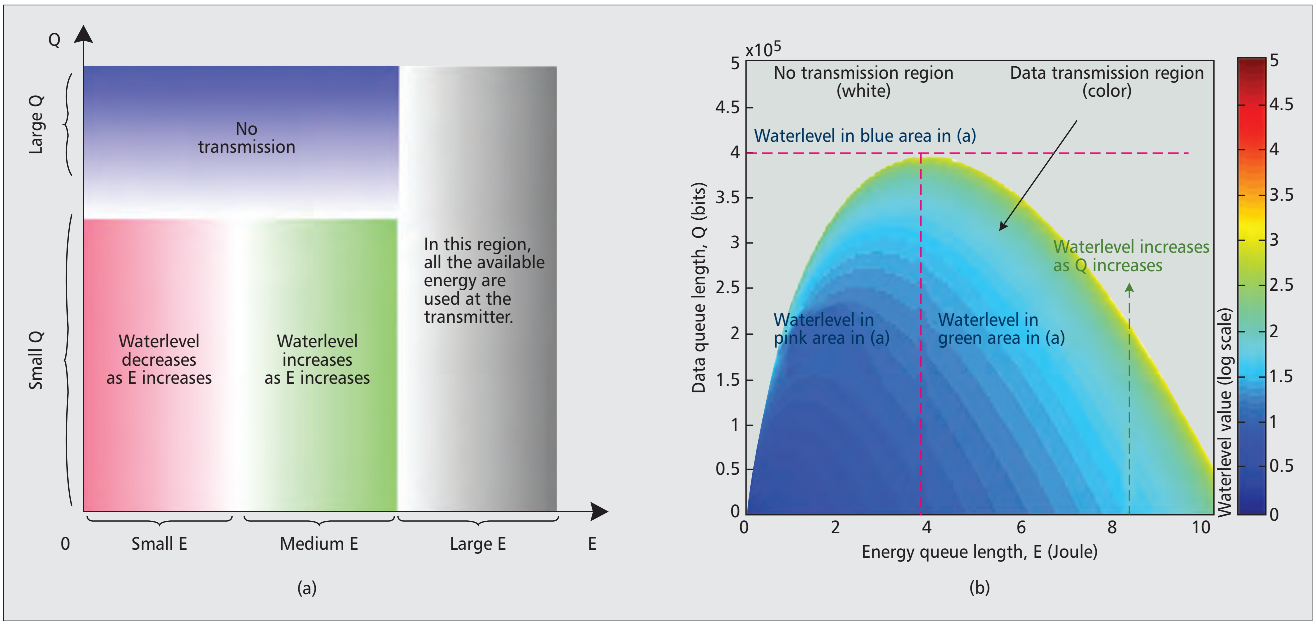


Figure 5. a) Decision region partitioning w.r.t. (Q, E); b) an example of the water level for LDAES and SDAEL regimes.

Control Insights under Asymptotic Operating Regimes

Control insights under LDAES and SDAEL regimes: For both the LDAES and SDAEL regimes, the priority function has different closed-form properties in each of the four areas in Fig. 5a. Figure 5b illustrates an example of the water level vs. the DQSI and EQSI for small and medium E. Specifically:

- **Small and medium E, large Q (blue area of Fig. 5a):** We do not use any renewable energy to transmit data. The reason is that even though we can use the limited energy for data transmission, the data queue length will not decrease significantly, which contributes very little to the delay performance. Instead, if we do not use the energy at the current slot, we can save it and wait for the future good transmission opportunities.
- **Small E, small Q (pink area of Fig. 5a):** We use the available energy for transmission, and the water level is increasing w.r.t. Q, which is in accordance with the high urgency of the data flow. Furthermore, large E leads to a lower water level. This is reasonable because it is appropriate that for small E, we can save some energy in the current slot for better transmission opportunities in future slots.
- **Medium E, small Q (green area of Fig. 5a):** We use the available energy for transmission, and the water level is increasing w.r.t. Q. Furthermore, large E leads to a higher water level because we have sufficient available energy, and it is appropriate to use more power to decrease the data queue.
- **Large E (grey area of Fig. 5a):** The transmitter uses all the available energy to make room for future energy arrivals.

Solution and control insights under SDAES regime: For the SDAES regime, based on the priority function, the optimal power control solution is to use all the available energy in the energy buffer at each time slot. This is reasonable because in this regime, there is plenty of renewable energy, and it is sufficient to use all the available energy to support the data traffic and maintain the data queue stability.

Stability Conditions

In this part, we discuss the conditions that ensure the stability of EH wireless systems (i.e., the stability of the data queue).

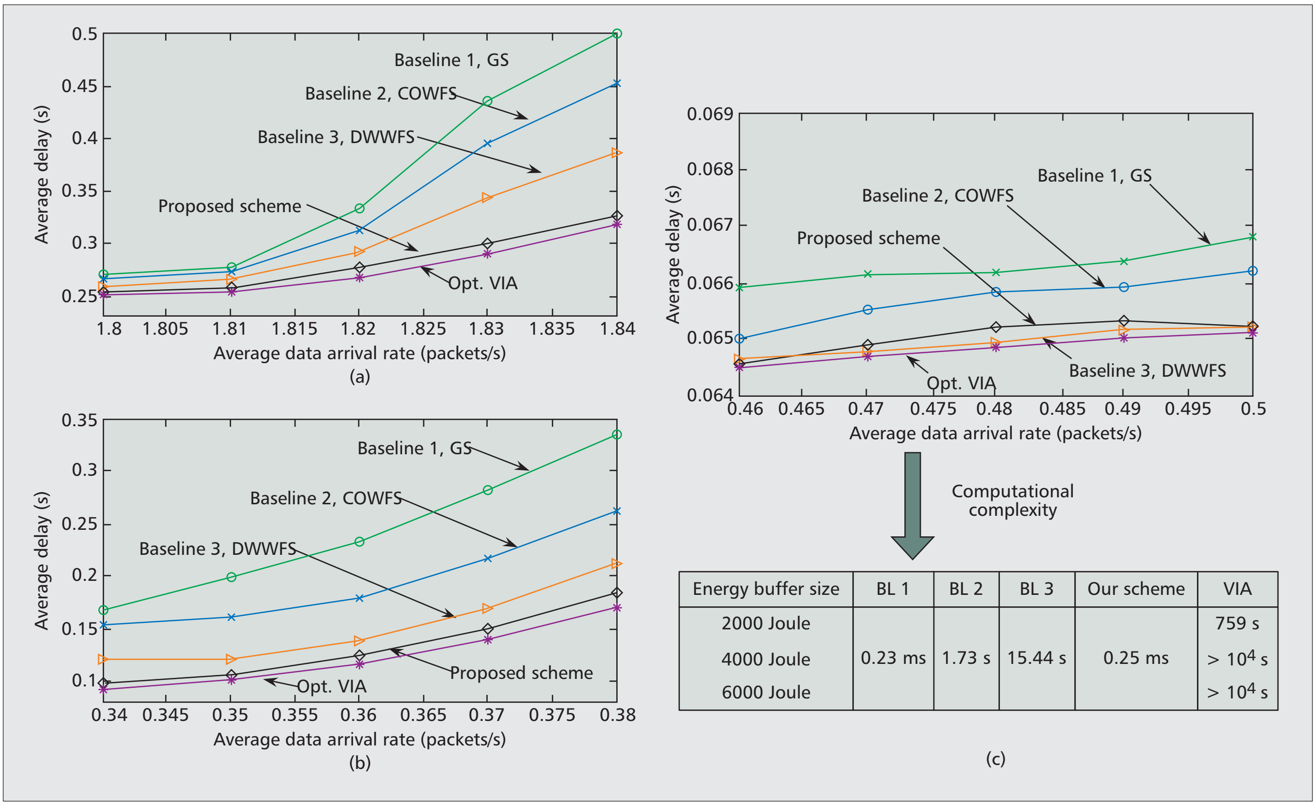
Condition on the energy harvesting capability: We require that the average energy arrival rate be at least at exponential order of the average data arrival. This means that for given average data arrival rate, if the EH rate is too small, even if we use all the available energy in the energy buffer at each time slot, the data queue cannot be stabilized.

Condition on the energy storage capacity: The capacity of the energy storage should be at least at a similar order of $N \times$ average energy arrival per time slot. The condition gives *a first order design guideline* on the dimensioning of the energy storage capacity. This condition ensures that the energy storage at the transmitter has sufficient stored energy to support data transmission for N slots when energy arrivals are small.

Performance Evaluation

We compare our proposed low-complexity power control solution with the following baselines:

- **Baseline 1, greedy strategy (GS) [10]:** Full power is always used.
- **Baseline 2, CSI-only water-filling strategy (COWFS) [10]:** Classical CSI-dependent water-filling power control is used by maximizing the ergodic channel capacity.
- **Baseline 3, DQSI-weighted water-filling strategy (DWWFS) [12]:** CSI- and DQSI-dependent water-filling power control is



Energy buffer size	BL 1	BL 2	BL 3	Our scheme	VIA
2000 Joule	0.23 ms	1.73 s	15.44 s	0.25 ms	759 s
4000 Joule					> 10^4 s
6000 Joule					> 10^4 s

Figure 6. a) Delay performance under the LDAES regime; b) delay performance under the SDAEL regime; c) delay performance under the SDAES regime. Comparison of the MATLAB computational time under the SDAES regime.

used by maximizing the queue weighted ergodic capacity.

In the performance evaluation, the base station (BS) is equipped with 5-cascaded 2 m × 2 m solar panels with energy harvesting performance 1~10 mW/cm^2. If the surrounding environment has sufficient sunlight, the EH performance is high. Otherwise, the EH performance is low [13]. The noise spectral density is –174 dBm/Hz, path loss is 160 dB, bandwidth is 20 MHz, and slot duration is 10 ms. The energy arrival rate at the BS changes every 5 min, and the renewable energy is stored in a 1.2 V 2000 mAh lithium-ion battery. Under this practical scenario, the BS can provide a data rate of 10.8 Mb/s for supporting delay-sensitive application of the mobile user.

Figure 6 illustrates the average delay vs. the average data arrival rate for the LDAES, SDAEL, and SDAES regimes. The proposed scheme achieves significant performance gain over all the baselines. The gain is contributed by the *DQSI- and EQSI -aware* dynamic water-filling structure. It can also be observed that the performance of the proposed low-complexity solution is very close to the optimal VIA [3]. Figure 6c also illustrates the comparison of the MATLAB computational time of the proposed solution, the baselines, and the brute-force VIA [3]. Note that the proposed scheme has similar complexity to baseline 1 due to the closed-form priority function. Therefore, our proposed scheme achieves significant performance gain with negligible computational cost.

Conclusion

Dynamic delay-sensitive power control for EH wireless systems with finite energy storage is challenging. This article surveys some of the existing works on resource control in EH wireless systems. To address the dynamic control challenge, we use a CTP approach to propose a low-complexity power control solution, which is adaptive to the CSI, DQSI, and EQSI. We also give valuable design insights on the dynamic control structures. Numerical results show that the proposed power control scheme has much better performance than the state-of-the-art baselines.

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