

Designing intelligent energy harvesting communication systems

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Abstract

From being a scientific curiosity only a few years ago, energy harvesting (EH) is well on its way to becoming a game-changing technology in the field of autonomous wireless networked systems. The promise of long-term, uninterrupted and self-sustainable operation in a diverse array of applications has captured the interest of academia and industry alike. Yet the road to the ultimate network of perpetual communicating devices is plagued with potholes: ambient energy is intermittent and scarce, energy storage capacity is limited, and devices are constrained in size and complexity. In dealing with these challenges, this article will cover recent developments in the design of *intelligent energy management policies* for EH wireless devices and discuss pressing research questions in this rapidly growing field.

INTRODUCTION

EH wireless Devices (EHDs) are increasingly being deployed in practice, replacing their traditional, battery-operated counterparts, when inaccessibility or the sheer number of nodes often render battery replacement difficult and cost-prohibitive. Potential applications span the whole gamut of autonomous networked systems: from machine-to-machine and sensor networks, to building automation and monitoring in smart grids. It is no surprise that the global EH market is expanding at an unprecedented rate: it is expected to reach 1894.87 million dollars by 2017 at an estimated annual growth rate of approximately 24%¹. A major factor that has contributed to this growth is the evolution of ultra-low power electronics,

¹Source: marketsandmarkets.com, Global Forecast and Analysis of EH Market (2012-2017), August 2012.

which can run on the minuscule amounts of energy supplied by typical solar, vibration or thermal energy harvesters, and a number of companies are already offering system solutions consisting exclusively of EHDs².

The ultimate promise of EH is a self-sustainable, maintenance-free network of perpetually communicating devices. With this promise comes a fundamental shift in design principles compared to traditional systems with battery operated nodes: whereas minimizing energy consumption is crucial to prolong network lifetime in the latter, in networks of EHDs the objective is the *intelligent* management of the harvested energy to ensure long-term, uninterrupted operation. The goal of this article is to provide an overview of recent developments in the design of energy management policies for EHDs. We focus on analytical models that capture the fundamental challenges related to the design of *any* EH system: the intermittent nature of harvested energy, the limited capacity and leakage of energy storage devices, and the constraints on device complexity. The article is concluded with a discussion on what the authors believe are the most important research challenges that lie ahead.

A MATHEMATICAL MODEL FOR EHDs

The block diagram of a typical EHD is shown in Fig. 1. The device consists of an EH module that converts ambient energy to electrical energy, which is stored in a storage element (SE), typically a rechargeable battery or a (super) capacitor. The SE powers the micro-processor (μ P) and the sensing and radio apparatus. The sensor block performs the sensing functionality, i.e., collection and digitization of temperature, pressure, or motion data, depending on the application. The radio block is the portal of the device to the world, transmitting or receiving measurement and control data.

The μ P makes decisions about switching on/off the sensing, transmitting or receiving circuits, and stores sensed or received data in the data buffer. Since sensing, transmission and reception consume energy, *the heart of an intelligent energy management system lies at the μ P*. For the purposes of analysis and design, it is useful to think of the EHD as consisting of an energy and a data buffer; as illustrated in Fig. 1, the μ P controls the energy supply from the SE to the sensing apparatus and to the RF transceiver, thus, in turn, controlling the data input to (via sensing and reception) and from (via transmission) the data buffer. In performing these tasks, the μ P also consumes energy. The energy and data arrival rates to the corresponding buffers are modeled by the processes $H(t)$ and $I(t)$, and the states of the energy and data buffers at time t are denoted by $S(t)$ and $D(t)$, respectively. Both buffers are of finite capacity;

²EnOcean Technology, White Paper on Energy Harvesting Wireless, July 2011.

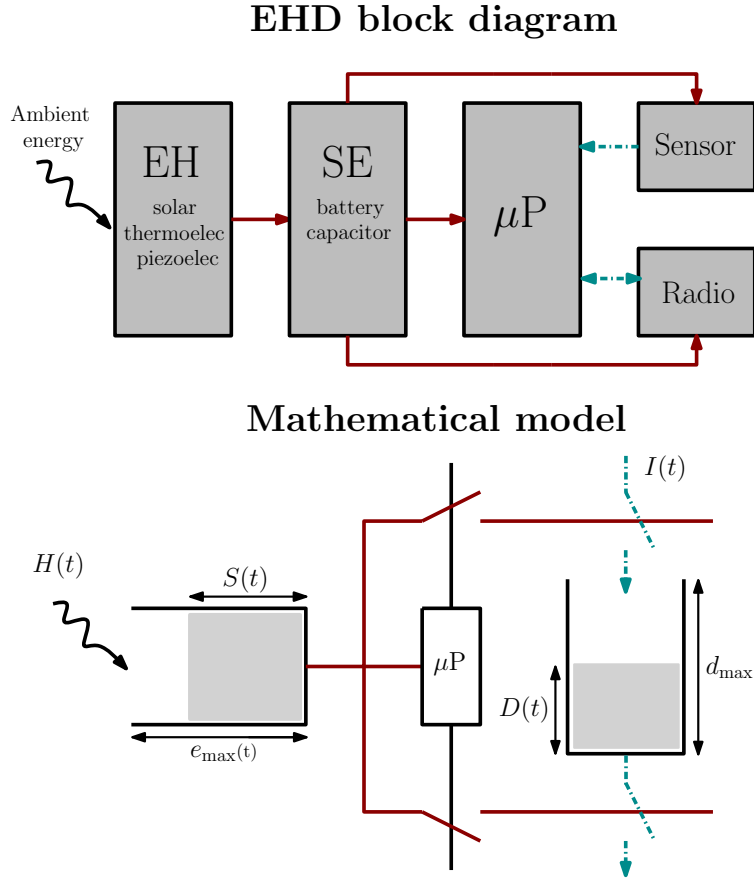


Figure 1. Block diagram of a typical EHD and its mathematical model. Solid and dash-dot lines indicate energy and data transfer, respectively. Energy is harvested at rate $H(t)$ and stored in the buffer of capacity $e_{\max}(t)$; input data (sensed or received) is generated at rate $I(t)$ and stored in the buffer of capacity d_{\max} . When sensing, transmitting or receiving, the EHD consumes energy; this is modeled by a set of switches, controlled by the μP , which, in the process, also consumes energy.

d_{\max} denotes the constant data buffer capacity, while $e_{\max}(t)$ denotes the SE capacity, which is generally time-varying, e.g., as in the case of electrochemical batteries, where the capacity is a decreasing function of the number of charge-discharge cycles.

This mathematical model is a powerful abstraction, which captures the fundamental characteristics of an EHD. An energy management policy for an EHD consists of the set of *rules* that govern the decisions of the μP to activate the switches of Fig. 1 at any given time t , with the goal of optimizing a utility function. The solution to this problem depends heavily on the characteristics of $H(t)$ and $I(t)$, the degree of knowledge of the μP about these processes, as well as the physical constraints. Accordingly, in the following sections, we present two fundamental approaches: in the *offline* optimization framework, it is assumed that the exact values of $H(t)$ and $I(t)$ are known in advance at the μP for the whole duration

of operation. In contrast, in the *online* optimization framework, it is assumed that the μP knows the past realizations of $H(t)$ and $I(t)$, but has only statistical knowledge of their future evolution.

OPERATION IN PREDICTABLE ENVIRONMENTS: OFFLINE OPTIMIZATION

The offline optimization framework is well suited to applications in which $H(t)$ and $I(t)$ are known in advance or can be accurately predicted. For example, if the EH module is a solar panel, depending on the location, season, time of the day and device characteristics, $H(t)$ can be accurately modeled, as shown, e.g., by the measurement campaigns in [1]. A sensor periodically taking measurements of fixed resolution is an example where $I(t)$ is known in advance.

We consider an EHD which transmits data to a receiver, and focus only on the energy consumed for data transmission. Let the *rate-power function*, $r(P)$, denote the information rate (in bits/s/Hz) achievable at a transmission power P by the particular transmission scheme used. We assume that $r(P)$ is a non-negative, monotonically increasing and strictly concave function. Most practical coding schemes, as well as Shannon's capacity function

$$r(P) = \frac{1}{2} \log(1 + P) \quad (1)$$

satisfy these properties.

In the case of a battery-operated device, there is an initial amount of energy H in the SE, and no energy is harvested. Given a deadline T , it can be proven using Jensen's inequality that transmitting at a constant power maximizes the total transmitted data by the deadline. In contrast, for an EHD, the EH profile typically varies over time; hence, a scheme that transmits at a constant power *and* consumes all the arriving energy by the deadline may not be feasible. This calls for the optimization of the transmission power based on the particular EH profile.

Heavy data traffic scenario

Let us first consider the case where the data buffer is backlogged, i.e., there is always data available for transmission, and focus only on the effect of EH profile on the optimal transmission power. A useful visualization tool is to consider the *cumulative harvested energy curve*, denoted by $\bar{H}(t)$, which is the total amount of harvested energy until time t , i.e., the integral of $H(t)$ over time. The goal is to design a *transmission policy* $P(t)$, which specifies the transmission power over the interval $[0, T]$, such that the total amount of transmitted data by the deadline is maximized.

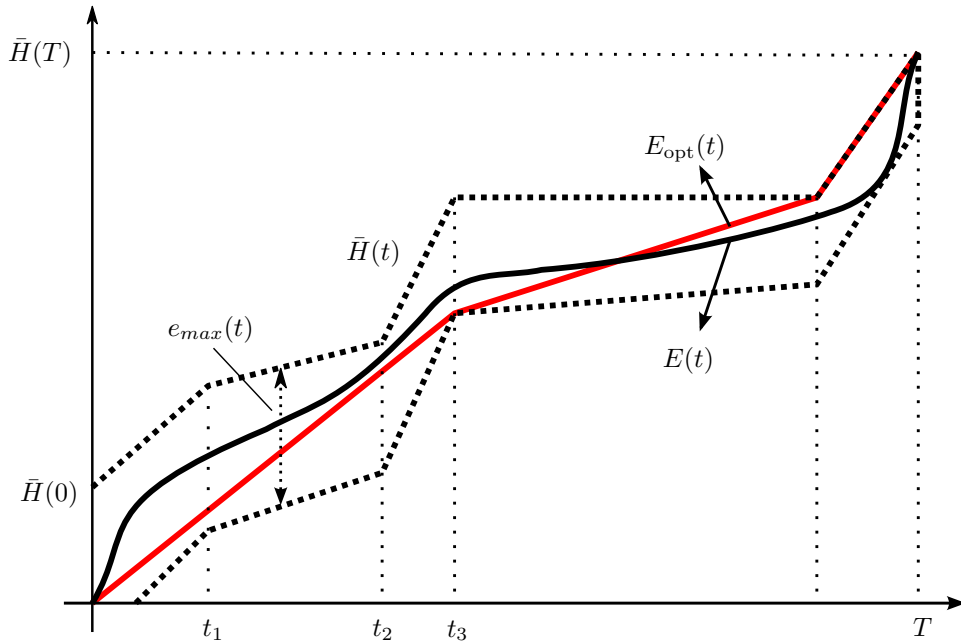


Figure 2. The cumulative harvested energy curve, $\bar{H}(t)$, a feasible transmitted energy curve, $E(t)$, and the optimal transmitted energy curve, $E_{opt}(t)$, for an EHD with decreasing energy storage capacity.

Similarly, we can also define a cumulative *transmitted energy curve*, $E(t)$, as the integral of $P(t)$ over time. Note that specifying a transmission policy is equivalent to specifying $E(t)$, which is a non-decreasing, continuous function. A natural constraint follows from *energy causality*, which dictates that energy cannot be used before it is harvested. This is equivalent to having transmitted energy curve lie under the harvested energy curve at all times. Moreover, the optimal transmission policy should not waste any energy; hence, there should be no SE overflows [2], that is, the difference between the harvested energy curve and the transmitted energy curve should never be larger than the SE capacity. Finally, all the harvested energy should be used by the deadline, that is, the transmitted energy curve should meet the harvested energy curve at time T .

In Fig. 2, $\bar{H}(t)$ and $\bar{H}(t) - e_{max}(t)$ are plotted as two dotted curves. Schematically, the aforementioned constraints imply that the optimal $E(t)$ should start from the origin, lie between the two dotted curves, and terminate at point $(T, \bar{H}(T))$. The black curve illustrates one such feasible curve. However, as shown in [3], due to the concavity of $r(P)$, the optimal transmission policy should follow *the shortest path* between the start and end points. The optimal transmitted energy curve, $E_{opt}(t)$, is shown in Fig. 2. In the case of discrete (packetized) energy arrivals, the optimal transmitted energy curve can be obtained

through a simple recursive algorithm [4].

General data traffic scenario

We now consider the more general scenario in which data, as well as energy, arrive at the corresponding buffers over time. The goal may be to minimize the transmission time [4], or to maximize the energy remaining in the SE [5], while transmitting all the arriving data. Let $\bar{I}(t)$ and $\bar{O}(t)$ denote the total number of bits that have arrived and that have been transmitted by time t , respectively. By *data causality*, $\bar{O}(t)$ should lie under $\bar{I}(t)$ at all times. Accordingly, the optimal transmission policy derived for a backlogged system may not be feasible if there is not enough data in the data buffer. Additionally, if no data can be dropped, $\bar{O}(t)$ must always lie above $\bar{I}(t) - d_{max}$. A transmission strategy has both a transmitted energy curve and a corresponding transmitted data curve. The optimal transmission strategy must jointly account for the constraints in both the data and energy domains. For discrete energy and data arrivals, i.e., $\bar{H}(t)$ and $\bar{I}(t)$ are increasing step functions, the optimal transmission policy can be obtained through a recursive algorithm that checks the conditions on transmitted data and energy curves jointly [4].

Data transmission over time-varying channels: Directional waterfilling

So far in our treatment, we have considered a constant EHD-receiver channel. We now turn our attention to a time-varying channel with a backlogged transmitter, for which the rate-power function varies over time according to (1), with P replaced by $\phi(t)P(t)$, where $\phi(t)$ denotes the squared magnitude of the channel gain. Moreover, we assume that the changes in $\phi(t)$ and $\bar{H}(t)$ occur only at certain time instants $0 = t_0 < t_1 < t_2 < \dots < t_N = T$. We denote the channel state in epoch $[t_{i-1}, t_i)$, $i = 1, \dots, N$, as ϕ_i . Assuming that, in addition to harvested energy amounts, channel states are also known in advance, the problem is that of determining $P(t)$ such that the total amount of transmitted data by time T is maximized.

We first consider a battery-operated device with total energy $2H$. The problem reduces to the well studied problem of power allocation over parallel Gaussian channels. Let us consider a simple scenario consisting of only two epochs of equal length, with $\phi_1 > \phi_2$. The optimal power allocation is given by the celebrated *waterfilling algorithm*, and is illustrated in Fig. 3(a), where the shaded areas represent the energy allocated to each epoch, and the height of the shaded region, P_i , is the constant transmission power for that epoch. We can see that more power is allocated to the better channel state.

For a general EH profile, direct application of the waterfilling algorithm may not be feasible. For example, assume that H units of energy are harvested at times 0 and $T/2$, respectively. The waterfilling

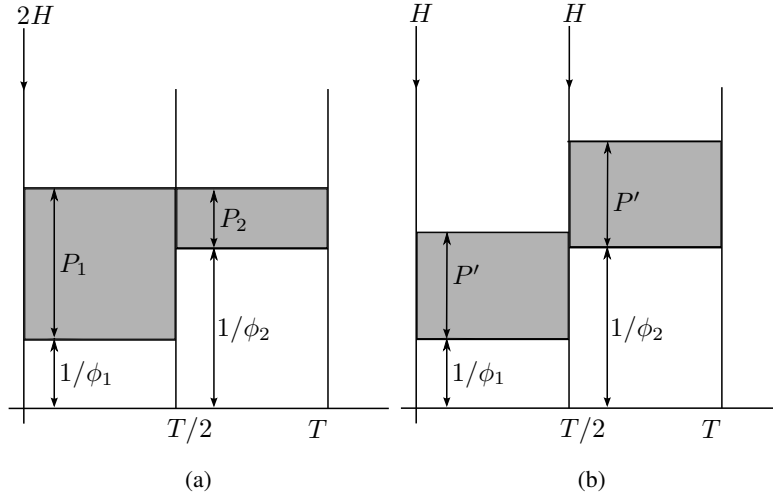


Figure 3. Power allocation over time-varying channel with $\phi_1 > \phi_2$. (a) $2H$ units harvested at time 0, (b) H units harvested at times 0 and $T/2$.

algorithm allocates more than half of the total energy to the first epoch. However, due to the energy causality constraint, we can allocate at most H units of energy to the first epoch, and hence, the waterfilling solution in Fig. 3(a) is no longer feasible. The optimal allocation under energy causality, illustrated in Fig. 3(b), is called *directional waterfilling* [6]. The algorithm owes its name to the fact that harvested energy can only be allocated to the epochs following its arrival.

The finite SE capacity should also be taken into account when applying the directional waterfilling algorithm. This can be seen by swapping the channel states of the two epochs, i.e., $\phi_2 > \phi_1$. As shown in Fig. 4(a), the directional and classical waterfilling algorithms achieve the same solution since the energy harvested at time $t = 0$ can be allocated to the second epoch. However, the energy carried to the second epoch from the first epoch together with the harvested energy at time $t = T$ should be stored in the SE. We can allocate at most e_{\max} energy units to the second epoch. For example, if $e_{\max} = H$, no additional power can be allocated to the second epoch, and the optimal solution allocates H energy units to each epoch, as shown in Fig. 4(b).

The optimal directional waterfilling algorithm needs to satisfy both the energy causality and the SE capacity constraints, and it can be obtained through a recursive algorithm which starts from the last energy packet and goes backwards [5].

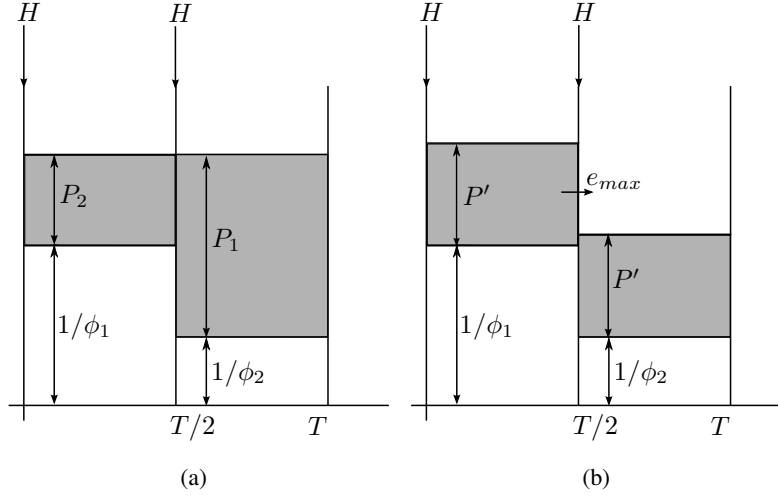


Figure 4. Power allocation over time-varying channel with $\phi_1 < \phi_2$ and H units harvested at time 0 and T . (a) No SE capacity constraint, (b) SE capacity $e_{\max} = H$.

Processing energy cost: Directional glue-pouring

In a long-distance communication link radio transmission dominates the energy consumption at the EHD; hence, the framework presented so far results in optimal energy management policies. However, in short-range communications, other sources of energy consumption, such as converters, mixers, filters, become more significant and need to be included in the analysis. When the *processing energy cost* is negligible, the transmitter remains active until the deadline, since low power transmission is more efficient in terms of bits per unit energy. However, when the processing energy cost is comparable to the transmission energy, increasing the transmission duration results in a tradeoff between the total amount of transmitted data and the energy spent by the processing circuitry. The optimal transmission scheme is bursty, separated by “sleep” periods, during which the transmitter remains silent. The optimal power allocation can be found as the solution of a convex optimization problem, and interpreted as a *backward directional glue-pouring algorithm* [5], in which a minimum power level is set for each epoch depending on the channel state and the processing cost, and energy is “poured” into an epoch at this power level with increasing duration. The power allocated to an epoch increases beyond this level only after the whole epoch is covered.

OPERATION IN UNPREDICTABLE ENVIRONMENTS: ONLINE OPTIMIZATION

In the previous section, non-causal knowledge of the energy and data arrival processes allowed solving for the optimal policy through a one-shot optimization problem. However, in many practical scenarios,

these processes are not known in advance. In this case, the μ P must make intelligent decisions in an online fashion based on possibly available statistical information on $H(t)$ and $I(t)$, and (possibly incomplete) knowledge of the *system state*, which includes current values of $S(t)$ and $D(t)$ and past values of $H(t)$ and $I(t)$. An approach that has been adopted is to come up with heuristic online algorithms and compare their performance with the offline benchmark [5], [6]. Alternatively, determining the optimal policy can be formally stated as a *stochastic control* problem, with the objective to determine the optimal decision rules such that the *expected outcome* of the decisions is maximized.

A framework for solving online problems: Markov decision processes

If $H(t)$ and $I(t)$ are modeled as Markov processes, the online problem can be cast under the powerful framework of Markov decision processes (MDPs). At each time, the μ P decides on an action given the system state; the action yields a reward and the system moves to a new state with a given probability, which depends on the current state and action. The optimal policy is a set of decision rules that maximizes the expected reward over a time-horizon. In the context of EHDs, the reward function may be the priority [7], importance [8] or amount [6], [9] of transmitted data, or the detection of an interesting event [10]. The fundamental tradeoff pertinent to EHDs is related to the energy cost of transmission or sensing. On the one hand, if a policy is too “generous”, i.e., it activates the radio or sensor too often, it risks emptying the SE, thus rendering the EHD potentially unable to transmit important data or detect an interesting event. On the other hand, if it is too frugal, i.e., it rarely transmits or senses, it “accrues” little reward; moreover, the SE may overflow, and newly harvested energy is wasted.

The policy that strikes the best tradeoff can be found numerically with standard dynamic programming tools such as the policy iteration algorithm (PIA), as, e.g., in [6], [7], and can then be programmed into the μ P. The problems with this approach are the implementation complexity, which grows with the size of the state space, as well as the lack of analytical insight. This motivates the search for simpler policies which seek to balance energy consumption and harvesting, with limited state information at their disposal, and whose performance can be evaluated and optimized analytically. The advantages of this approach are illustrated in the following representative scenario.

Low-complexity transmission policies for time-correlated EH

Consider a time-slotted system, such that, every time unit (slot), a new data packet of a given importance enters the data buffer of Fig. 1, and must either be immediately transmitted at a cost of one energy unit or dropped. The importance of the data packet at time i , $i \in \mathbb{Z}$, is denoted by $V(i)$, and we assume that

$\{V(i)\}$ are independent and identically distributed according to a given distribution function which is known at the μP . In addition, in each slot, some amount of energy is harvested and stored in the SE of capacity e_{\max} , according to a two-state Markov chain: in the GOOD state, one energy unit is harvested, whereas, in the BAD state, no energy is harvested. The transitions from GOOD to BAD, and vice versa, occur with given probabilities, such that the average durations of the GOOD and BAD periods are T_G and T_B , respectively, and the probability of harvesting an energy unit in a slot is $\beta = T_G/(T_G + T_B)$. The model is simple, yet it allows us to introduce time correlation in the energy source, the degree of which depends on the values of T_G and T_B .³

At each time i , the μP must decide whether to transmit the current packet to the receiver or to drop it, with the objective to maximize the average importance of transmitted data in the long-term. The decision depends on the system state, i.e., the importance of the arriving packet, $V(i)$, the energy available in the SE, $S(i)$, and the amount of energy harvested in time slot $[i - 1, i)$, $H(i) \in \{0, 1\}$. It can be shown that the optimal policy has a *threshold structure*, i.e., the packet is transmitted if $V(i)$ is greater than a given value v_{th} , which depends on *both* $S(i)$ and $H(i)$ [7], [8], and the optimal thresholds can be found numerically with the PIA. However, a simpler policy is the non-adaptive balanced policy (NABP) that employs only one threshold v_{th} such that the probability of transmission is always equal to the probability that an energy unit is harvested in a slot, β . Denote by $g(\beta)$ the average importance of data with value greater than v_{th} . It can be shown that, for large values of e_{\max} and T_B , the average long-term importance per time unit is

$$G = g(\beta) \left(\beta + (1 - \beta) \frac{\rho}{\rho + \beta} \right), \quad (2)$$

where $\rho = e_{\max}/T_B$ is the power-to-depletion, i.e., the maximum power that, on average, can be continuously supplied by a fully charged SE over a BAD period (in which no harvesting occurs).

Essentially, ρ reflects the ability of the SE to absorb the fluctuations in the ambient energy supply. If ρ is much greater than β , the SE can (with high probability) support a constant energy consumption rate β , without emptying in the BAD periods or overflowing in the GOOD periods, and, from (2), $G \approx g(\beta)$, which is the best achievable reward by any policy [8]. In contrast, if ρ is much smaller than β , adaptation to $H(t)$ is critical to achieve good performance. Intuitively, a “smarter” balanced policy should be generous in the GOOD state by transmitting with a high probability η_G , and conservative in the BAD state by transmitting with a lower probability $\eta_B < \eta_G$. The optimal probabilities η_G and η_B can be analytically derived to determine the optimal balanced policy (OBP) [8].

³A more general approach can be found in [8].

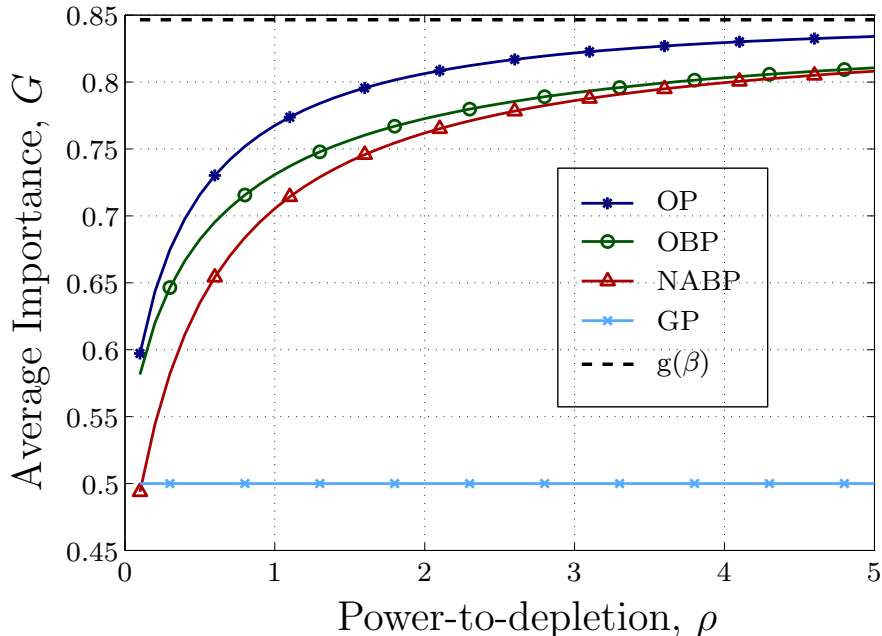


Figure 5. Average transmitted data importance G vs. power-to-depletion ρ ($\beta = 0.5$, $F_V(v) = 1 - e^{-v}$).

In Fig. 5, G is plotted vs. ρ for exponentially distributed importance values, under the following transmission policies: the optimal policy (OP), computed numerically with the PIA, the OBP, the NABP, and the greedy policy (GP), which always transmits when there is energy in the buffer. Fig 5 reveals that the performance loss of OBP with respect to OP is less than 5% for the selected parameters. NABP performs poorly for small ρ , but approaches the optimal performance for growing ρ , since adaptation becomes less crucial. Finally, the penalty paid by using GP increases with ρ , which illustrates the importance of maintaining a steady energy consumption rate, instead of constantly emptying the buffer by indiscriminate data transmission.

Transmission policies for bursty data

The previous scenario assumed the arrival of a new data packet in each slot and a strict delay constraint for its delivery (transmit or drop). However, in a number of applications, data may arrive randomly in bursts, and may be buffered in the data buffer before being transmitted. Minimizing the mean delay of the buffered data, or, equivalently, $\mathbb{E}[D(t)]$, is generally a complicated problem, owing to the combined randomness in $I(t)$ and $H(t)$. In [9], various heuristic delay-minimizing policies are proposed for both constant and time-varying channels. The main idea behind these policies is to adjust the transmission

power based on the amount of data $D(t)$ in the buffer at any given time t , in order to avoid wasting harvested energy when there is not enough data in the buffer. Similar concepts are also explored in [11], where a certain drift-based policy is shown to be asymptotically throughput-optimal as e_{\max} and d_{\max} become very large.

Sensing policies for time-correlated events

The previous two scenarios dealt with the energy management problem if data transmission is the only cause of energy expenditure. Instead, in [10] the MDP framework is employed to address the problem of optimal sensing. In particular, under a given energy cost of activating the sensor and taking a measurement, the objective is to find a policy that maximizes the long-term probability of detecting an event whose occurrence (0 or 1) follows a two-state Markov chain. Here, the tradeoff that arises is that the μP may save energy by switching off the sensing circuitry if it anticipates that the event will not occur, at the risk of not reporting it in case it does. It is shown that, under an infinite e_{\max} and perfect knowledge about the event occurrence in slot $[i - 1, i)$, the optimal action at time i is to always sense if the event occurred in $[i - 1, i)$ and there is adequate energy in the SE, and to sense with a certain probability which is a function of the statistics of $H(i)$ and $V(i)$, if the event did not occur. In the case where the μP does not have knowledge of the event occurrence when the sensor is switched off, [10] also derives properties of the optimal policy using the framework of partially-observable MDPs.

THE WAY FORWARD: RESEARCH CHALLENGES

Under the prism of the approaches presented so far, we now discuss what we believe are the main challenges that lie ahead for the design of autonomous and reliable EH communication systems.

Learning-theoretic algorithms for EH systems

The assumption of non-causal information about the EH and data arrival profiles in the offline optimization framework is too optimistic in practice, unless the underlying processes are deterministic or highly predictable. This assumption is relaxed in the online optimization framework, in which the μP possesses only statistical information about the future evolution of these processes. Nonetheless, in many practical scenarios, statistical characteristics may change over time, or such information may not be available before deployment. In this case, neither the online nor the offline optimization framework will be applicable. An alternative solution is to employ *learning theoretic* algorithms to learn the characteristics of the EH and data arrival processes in real time, and to adapt the transmission policy accordingly. In [12], Q-learning,

a reinforcement learning technique, is considered for learning the optimal transmission strategy when the EH, data arrival and channel states are modeled as Markov processes with unknown state transition probabilities. It is shown that the online optimization performance can be achieved after a reasonable learning period. The exploration of other learning algorithms as well as of reduced complexity suboptimal techniques constitutes an interesting research direction.

Networks of EHDs and energy cooperation

As in conventional battery-operated systems, a network of EHDs is much harder to study than a single link. Some basic multi-user scenarios (such as broadcast [3], relay [13], multiple access and interference [14] channels) have been studied in the literature. In general, the complexity in characterizing the optimal policies increases significantly with the number of nodes in the network. Even in a simple two-hop scenario, the transmission schedule of the source node affects the data arrivals at the relay node, coupling the optimal transmission schemes across the network [13]. Moreover, optimal policies depend heavily on the available knowledge of the EH profiles across different devices. This information may be hard to obtain or even unattainable in practical systems, therefore solutions based only on local information should be sought, such as in [15], [16]. In [15], a routing algorithm is proposed which is shown to achieve an asymptotically optimal competitive ratio with respect to any offline scheme, as the number of nodes in the network grows large, while [16] derives an optimal random access policy based on a game-theoretic formulation of the multiple access problem.

A fascinating aspect of networks of EHDs arises when the devices can share/transfer energy, e.g., electromagnetic energy, among each other, as proposed in [17]. In particular, if the receiver can harvest electromagnetic energy, it is possible to wirelessly transmit data and energy simultaneously over the same carrier signal, which leads to many open research problems regarding resource allocation and interference management.

Accurate modeling of EH processes and SE imperfections

The proposed mathematical models render the performance analysis of EHDs tractable; however, they may not always be accurate in practice. It is thus desirable to enhance them based on real-world data, while, at the same time, maintaining their simplicity and analytical tractability. Towards this goal, measurement campaigns, such as the one in [1], are required, so that statistical models for the harvested energy are identified based on the application. Moreover, realistic storage and power consumption models, based as much as possible on actual EH modules, SEs and μ P circuits, should be developed, and employed

in the design of energy management algorithms. As a first step in this direction, in [18], a statistical framework is developed, which models the *state of health* of the SE and captures the impact of the SE degradation on the optimal energy management policy. It is shown that a “degradation aware” energy management policy significantly improves the SE lifetime, while guaranteeing a minimum required quality of service. A similar observation is made in [3] for the offline optimization problem considering energy leakage as well as degrading SE capacity.

CONCLUDING REMARKS

This article has provided an overview of the main mathematical tools and approaches in the design of EH communication systems. We have placed special emphasis on analytical models, whose study sheds light on the fundamental tradeoffs involved in the design of energy management policies for EHDs. At the moment, there appears to be a divide between communications and electronics engineers involved in EH research; the authors believe that many exciting research opportunities exist at the intersection of the two fields. We expect that the increasing deployment of EHDs in practice will bring about more cross-disciplinary research, and thus the development of smarter and more reliable EH wireless communication systems.

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