Energy Harvesting Receivers: Finite Battery Capacity

Hajar Mahdavi-Doost
hmahdavi@winlab.rutgers.edu

Roy D. Yates
ryates@winlab.rutgers.edu

***Abstract*—When receivers rely on energy harvesting, energy outages will constrain reliable communication. To model the harvesting receiver, we decompose the processing tasks in two parts: first is sampling or Analog-to-Digital-Conversion (ADC) stage which includes all RF front-end processing, and second is decoding. We propose a model in which, for a given code rate, channel capacity, and battery size, the receiver can choose the sampling rate to balance the sampling and decoding energy costs. We then characterize the maximum reliable communication rate over the choice of sampling rate and code rate and we verify that the sampling rate should be maximized. In addition, we consider the fixed-timing transmission system and show that under some conditions the same rates can also be achieved.**

I. Introduction

Energy harvesting offers the promise of unbounded lifetime extension to battery powered devices; however, the randomness of the energy source has introduced new challenges. Although energy-harvesting can occur at both the transmitter and the receiver, recent research has been directed chiefly at harvesting transmitters in point to point channels [1]–[3] or in simple networks [4]–[9]. However, communication over short distances can achieve high rates with relatively small transmit power. In this case, the energy consumption associated with the complex detection and decoding operations of the receiver becomes the dominant system constraint. Yet, with some exceptions [10], there has been little work on the problem of energy harvesting at the receiver.

In this paper, we consider a transmitter that sends out codewords from a rate R codebook through a memoryless channel to a harvesting receiver. Even in this simple setting, there is no consensus model for receiver energy consumption. Known results are technology dependent; for example, practical energy consumption models of the receiver front-end have appeared in [11], [12]. In the context of LDPC, the decoding energy depends on the required number of iterations, which has been a subject of conjecture [13], [14]. Based on message passing, lower bounds on the decoding energy have been derived in [15] and, under an alternate model, in [16].

These prior contributions point to the need for an abstract system model that separates the analysis of rechargeable receivers from technology-specific implementation details. Thus we introduce a simple model that decomposes the processing tasks in two stages: (1) sampling and (2) decoding. We model the sampler such that each symbol sample has a fixed energy requirement. Thus the energy consumption of the sampler is proportional to the sampling rate, i.e., the fraction of symbol periods in which signal samples are collected. Since the complexity of decoding decreases with the sampling rate, we observe an energy trade-off: we can increase the sampling rate to reduce the decoding energy or collect fewer samples at the expense of additional decoding energy.

The common wisdom has been that the energy consumption of the sampler is relatively inconsequential compared to that of the decoder. While this may be true, the primary conclusion of this work is that the energy consumption of the sampler, even if it is small, cannot be ignored in an energy harvesting receiver. When the receiver chooses to sample a packet, the signal samples must be collected during the transmission time of that packet. Thus, the combination of stored battery energy and energy harvested during a slot must be sufficient to ensure the correct sampling rate. By contrast, once the samples have been collected, the decoding can occur offline at a processing rate (and thus energy consumption) matched to the energy harvesting process. This observation leads us to characterize how the battery capacity of the harvesting receiver must grow with the code block length to guarantee reliable communication rates.

II. System Model

We assume a block coding strategy such that a message $\mathbf{v} \in \{1, \ldots, 2^{nR}\}$ is communicated by the transmission of a codeword consisting of n uses of a channel. We will often call a transmitted codeword a packet and refer to the transmission period of a codeword as a slot. Slots are indexed by $i = 1, 2, \ldots$ such that the codeword transmitted in slot i is given by the vector $\mathbf{x}_i$. Here, after that the receiver samples the received packet, it will spend some time decoding it and also collecting energy for sampling the next packet. The transmitter sends out the next codeword $\mathbf{x}_{i+1}$ following an idle period of duration τ_i. This delay can be chosen such that the receiver is ready to sample and decode the next packet. We call this a *variable-timing* transmission strategy, in contrast to the traditional *fixed-timing* transmission in which $\tau_i = 0$ so that the end of one slot coincides with the start of the next.

In any event, the receiver front-end processes a symbol or waveform input to produce $\mathbf{y} = \begin{bmatrix} y_1 & \cdots & y_n \end{bmatrix}$. We refer to this operation as sampling even though it may also incorporate demodulation, filtering and quantization. In addition, we refer to the random mapping from $\mathbf{x}$ to $\mathbf{y}$ as a physical channel even though elements of the sampling process in the receiver front-end contribute to this mapping.

We model the energy consumption of the ADC and other RF processing elements in the front-end as requiring γ energy units per sample. The constant γ is both technology and application dependent. That is, in designing a receiver front-end, the sampling and quantization of the ADC is designed to support the channel bandwidth and SNR needed for communication at intended rates. The receiver front-end design choices are then embodied in the channel from $\mathbf{x}$ to $\mathbf{y}$. We refer to this as the original physical channel and we assume it is memoryless and has single letter capacity C. As C depends on the performance of the receiver front-end, which is coupled to the sampling energy γ, it is useful to think of γ as fixed for a physical channel of capacity C. Without loss of generality we assume $\gamma = 1$. That is, energy is measured in the unit of the required energy to take one sample.

A. *Energy Trade-off at the Receiver*

Here, we examine energy trade-off ignoring the constraints imposed by the harvesting process or receiver battery size. The receiver must sample the signal and reliably decode. Due to the randomness of the energy arrivals, the receiving process may be interrupted. This can result in only a subset of transmitted symbols being sampled. On the other hand, a receiver may choose to sample only a subset of symbols in order to save energy for future operations. When the code has block length n and the sampler recovers samples of s out of n symbols, we say the sampling rate is $\lambda = s/n$. We model this selective sampling as an erasure channel concatenated to the original physical channel; symbols that are not sampled are erased. According to [17], if the original physical channel is memoryless with capacity C and the erasures are independent of the inputs and outputs of that channel and the proportion of erasures converges in probability to α (the erasures may have memory), then the capacity of such a channel is $C(1-\alpha)$ where α is the erasure probability and C is the capacity of the original channel. Thus sampling at rate λ corresponds to erasures at rate $\alpha = 1 - \lambda$. Fixing a sufficiently long blocklength n will ensure that a codeword that is sampled at rate λ will be decoded correctly with high probability if $R < \lambda C$.

In models of decoding in [15], the decoding energy $\mathcal{E}_D$ is an increasing function of the code rate R that diverges as R approaches capacity. While this model is hardware dependent inasmuch as it assumes LDPC decoding, it motivates the following abstraction of receiver energy consumption:

- Independent of the channel inputs and outputs, the receiver collects s out of n symbol samples such that s/n converges to λ in probability for large n.
- Each symbol sample requires unit energy.
- The decoding energy is $n\mathcal{E}_D(R/C\lambda)$ where $\mathcal{E}_D$ is a convex increasing function of normalized code rate $R/C\lambda$.

Under this model with fixed R and C, the decoding energy is a non-increasing convex function of the sampling rate as depicted in Fig. 1. Moreover, the energy consumed by the receiver to reliably decode one packet will be

$$n\mathcal{E} = s + n\mathcal{E}_D\left(\frac{R}{C\lambda}\right) = n\left[\lambda + \mathcal{E}_D\left(\frac{R}{C\lambda}\right)\right]. \qquad (1)$$

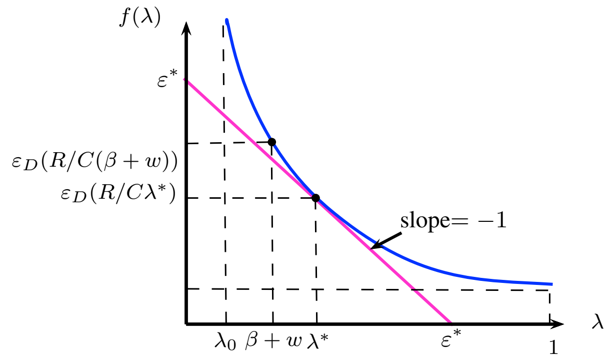

Fig. 1. Normalized decoding energy $f(\lambda) = \mathcal{E}_D(R/C\lambda)$ for a fixed R and C as function of the sampling rate λ. The total energy per symbol of the receiver is minimized at $\lambda = \lambda^*$.

We conclude for a given n, R, and C that there is an optimal sampling rate $\lambda^* = s^*/n$ such that

$$\mathcal{E}^*(R) = \lambda^*(R) + \mathcal{E}_D\left(\frac{R}{C\lambda^*(R)}\right). \qquad (2)$$

is the minimum energy *per symbol period* required to decode a single rate R codeword. We may sometimes drop the variable R. Furthermore, we emphasize that although energy is expended only on symbols that are sampled, $\mathcal{E}^*$ amortizes the energy cost of sampling over all symbols, sampled or not.

We recognize that this is a speculative model of a receiver; the most questionable assumption is that the decoding energy grows *linearly* for fixed code rate R and channel capacity C. We do note that this model is consistent with the conjecture that the decoding complexity of LDPC grows as $O((n/\delta)\ln(1/\delta))$ where $\delta = 1 - R/C\lambda$ [13], [14].

In addition, we observe that this model does impose restrictions that preclude certain performance enhancements. For example, in a slowly varying channel, the receiver could exploit channel state information (CSI) to collect its symbol samples when the channel is unusually good. Similarly, the transmitter and receiver could coordinate transmission and reception so that a power-constrained transmitter could use more power for those symbols that the receiver will sample. A coordinated sleep protocol is the limiting case of this approach.

B. *Energy Harvesting Models*

The energy provided by the environment can be described by a discrete time exogenous stochastic process W_t of energy arrivals in each symbol period. The harvesting process often has considerable memory. For a solar collector, the full range of harvesting rates may be revealed over several days.

Here we assume that energy $\bar{w}$ arrives deterministically in every symbol period. We believe this is an appropriate model when code words are transmitted in milliseconds and the coherence time of the energy harvesting process is on the order of minutes or hours. On the other hand, when codewords are much longer than the harvesting coherence time, it also can be shown that system performance chiefly depends on the average harvesting rate $\bar{w} = \mathrm{E}[W_t]$.

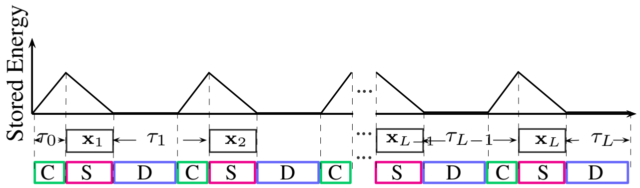

Fig. 2. Variable-timing optimum policy: Transmitted packets are labeled $\mathbf{x}_1, \mathbf{x}_2, \ldots$ while intervals marked "C," "S," and "D" mark when the receiver is (C)harging the battery, (S)ampling a packet, and (D)ecoding that packet. The corresponding graph depicts the receiver's stored energy.

C. Performance Metrics

Assume that the transmitter sends packets/codewords $1, \ldots, N(t)$ by time t while packet i is encoded at rate R_i. We define the reliable communication rate as the number of information bits that are decoded per symbol period. It is denoted by ρ and defined as

$$\rho(t) = \frac{1}{t}\sum_{i=1}^{N(t)} R_i I_i, \tag{3}$$

where the indicator $I_i = 1$ if the receiver reliably decodes packet i. We assume that all packets are sent at a fixed rate R and we seek to find the maximum reliable communication rate, over any possible policy.

III. Variable Timing

Now we derive the maximum reliable communication rate when the transmitter follows a variable-timing protocol. In particular if the battery size is large enough we have the freedom to design a policy that samples packets at the optimal rate $\lambda^*(R)$. However, sampling a packet is an online process that must be completed during the transmission slot of that packet. Thus sampling rate may be constrained by the receiver energy that is available in that slot. We assume that $\bar{w} < \mathcal{E}^*$; otherwise, all packets will be decoded. We note that the arrival energy in an n-symbol packet is $n\bar{w}$, which scales with n. We will see that the battery size must also scale with n. Thus, we describe an energy harvesting system by a *battery growth rate* β such that we employ a battery of size $B = \beta n$ when the block length is n. Here we assume that the code rate R is fixed and derive the maximum reliable communication rate. Optimization over R is deferred to Section IV.

A. Achievability

Variable-timing provides the flexibility to send the next packet when the receiver is ready. As depicted in Fig. 2, the transmitter sends packet $\mathbf{x}_i$ following an idle period of duration τ_{i-1} that enables the receiver to decode the previous packet and recharge the battery for sampling. Specifically, as shown in the figure, the receiver starts by collecting energy $n(\lambda - \bar{w})$ in time τ_0. Next, the transmitter sends packet $\mathbf{x}_1$ in slot 1 and the receiver samples this packet while also harvesting energy at rate $\bar{w}$. However, when $\lambda > \bar{w}$, sampling the packet drains the receiver battery such that the battery is empty at the end of the slot. What follows is a decoding period in which the receiver decodes the sampled packet. The receiver stores no energy in this interval because the decoder is run on a "pay as you go" basis; the decoder runs at a speed such that its energy consumption is matched to the energy harvesting rate $\bar{w}$. When decoding of packet $\mathbf{x}_1$ is completed, the receiver stores energy at rate $\bar{w}$ in preparation for sampling the next packet. This process of sampling and decoding packet i and recharging the battery for packet $i+1$ is repeated for each packet. The time needed for decoding and recharging the battery is given by

$$\tau_i = \frac{n\varepsilon_D(R/C\lambda) + n(\lambda - \bar{w})}{\bar{w}}, \qquad i = 1, \ldots, L, \tag{4}$$

since energy $n\mathcal{E}_D(R/C\lambda)$ is collected for decoding and energy $n(\lambda - \bar{w})$ is harvested to recharge the battery prior to sampling the next packet. When this stored energy is added to the energy $n\bar{w}$ that is harvested while sampling, the receiver will have sufficient energy to sample at rate λ. After transmitting L packets, each carrying nR information bits, the communication rate is

$$\rho(L) = \frac{nLR}{Ln + \sum_{i=0}^{L}\tau_i}. \tag{5}$$

From (4) and (5) that we obtain the communication rate

$$\rho = \lim_{L\to\infty}\rho(L) = \frac{\bar{w}R}{\varepsilon_D(R/C\lambda) + \lambda}. \tag{6}$$

Thus, to maximize the communication rate, we need to minimize the total required energy. According to Fig. 1 , we can see that if there is no bound on the battery size, this minimum will happen at the sampling rate λ^*. However, for a limited battery, we must consider three possibilities,

- $\lambda^* \leq \bar{w}$: There is no need to store energy for sampling before the block starts. Since enough energy arrives in each symbol period, the packet can be sampled while no energy is stored in the battery. To minimize the total energy requirement, we set the sampling rate to λ^*.
- $\bar{w} < \lambda^* < \beta + \bar{w}$: The energy collected in one block is not enough to sample at rate λ^*. However, the battery has enough capacity to store such energy. It implies that some time should be spent before sampling to collect required energy for sampling at rate λ^*.
- $\beta + \bar{w} < \lambda^*$: Not only is the energy collected in one slot insufficient for sampling at rate λ^*, the battery is also not big enough to enable sampling at this rate. By fully charging the battery prior to sampling, the largest possible sampling rate is $\beta + \bar{w}$. As shown in Fig. 1, the convexity of the decoding energy function dictates that the minimum total energy happens at the maximum sampling rate. Therefore, to maximize the communication rate, we should set the sampling rate at $\beta + \bar{w}$.

Thus the sampling rate at which the energy requirement is minimum is

$$\tilde{\lambda}(R) = \min\{\lambda^*(R), \beta + \bar{w}\}, \tag{7}$$

and then the total minimum energy would be

$$\tilde{\mathcal{E}}(R) = \mathcal{E}_D(R/C\tilde{\lambda}) + \tilde{\lambda}(R). \tag{8}$$

This implies the following claim.

Theorem 1. *A variable-timing transmission system with packets encoded at rate R can achieve the communication rate*

$$\rho = \frac{wR}{\tilde{\mathcal{E}}(R)}. \tag{9}$$

B. Outer Bound

Assume that from L transmitted blocks of data encoded at rate R, K blocks are decoded. We assume that between packets i and $i+1$, there is an idle time τ_i in which energy is harvested but no message is received.

Energy conservation dictates that the total consumed energy cannot exceed the total arrival energy plus what is stored in a fully charged battery. According to (8), the minimum energy required to decode a packet is $\tilde{\mathcal{E}}(R)$, implying

$$Kn\tilde{\mathcal{E}}(R) \leq \bar{w}\,(Ln+\tau) + \beta n. \tag{10}$$

where $\tau = \sum_{i=1}^{L} \tau_i$ is the total idle time. It follows from (10) that

$$\rho(L) = \frac{KnR}{Ln+\tau} \leq \frac{wR}{\tilde{\mathcal{E}}(R)} + \frac{\beta nR}{(Ln+\tau)\tilde{\mathcal{E}}(R)}. \tag{11}$$

This implies

$$\rho = \lim_{L\to\infty} \rho(L) \leq \frac{wR}{\tilde{\mathcal{E}}(R)}. \tag{12}$$

Thus, when packets are sent at rate R, the achievable rate in (9) is optimum. This is not surprising as (12) is based simply on energy conservation at the receiver and the key feature of the achievable scheme is that no energy is wasted at the receiver.

IV. Properties of the Optimum Rate

So far we studied the maximum communication rate for a fixed code rate R with variable-timing transmission. Now, we look at the maximization problem over both sampling rate and the code rate. Since we have observed that the sampling rate cannot exceed

$$\lambda_{\max} \triangleq \min\{\beta + \bar{w}, 1\}, \tag{13}$$

we wish to solve the following problem:

$$\hat{\rho} = \max_{R,\lambda} \quad \frac{wR}{\mathcal{E}(R)} \tag{14a}$$
$$\text{s.t.} \quad 0 < R < C\lambda \tag{14b}$$
$$\lambda \leq \lambda_{\max}. \tag{14c}$$

We assume that $\mathcal{E}_D(R/C\lambda)$ is zero only at $R = 0$. Also we assume that the function of $\mathcal{E}_D(z)$, where $z = R/C\lambda$, is differentiable.

According to the KKT optimality conditions, complementary slackness implies that the Lagrange multipliers corresponding to the strict inequalities should be zero. Defining μ as the Lagrange multiplier, the Lagrangian is

$$L(\lambda, R, \mu) = \frac{wR}{\mathcal{E}_D(R/C\lambda) + \lambda} - \mu(\lambda_{\max} - \lambda). \tag{15}$$

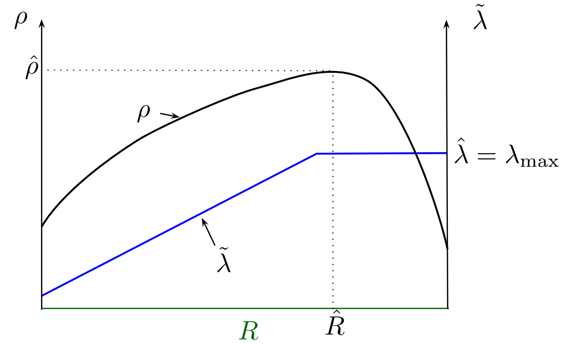

Fig. 3. The black and blue curve depict the reliable communication rate and the optimum sampling rate (for each code rate) versus code rate respectively. It can be seen that ρ is maximized when the sampling rate takes its maximum.

If $\mu = 0$, then, $\partial L/\partial \lambda = 0$ and $\partial L/\partial R = 0$, yielding

$$1 - \frac{R}{C\lambda^2}\mathcal{E}'_D(\frac{R}{C\lambda}) = 0 \tag{16a}$$
$$\mathcal{E}_D(\frac{R}{C\lambda}) + \lambda - \frac{R}{C\lambda}\mathcal{E}'_D(\frac{R}{C\lambda}) = 0. \tag{16b}$$

Eq. (16) gives $\mathcal{E}_D(R/C\lambda) = 0$, implying $\hat{R} = 0$, which conflicts with our modeling assumptions. So, $\mu \neq 0$ and, according to complementary slackness, the constraint (14c) should be active at the optimum point. So, $\hat{\lambda} = \lambda_{\max}$ at this point and

$$\frac{d}{dR}\left(\frac{wR}{\mathcal{E}_D(R/C\lambda_{\max}) + \lambda_{\max}}\right)|_{R=\hat{R}} = 0. \tag{17}$$

This implies

$$\mathcal{E}_D(\frac{\hat{R}}{C\lambda_{\max}}) = \mathcal{E}'_D(\frac{\hat{R}}{C\lambda_{\max}})\frac{\hat{R}}{C\lambda_{\max}} - \lambda_{\max}. \tag{18}$$

Then, for the optimum communication rate we will have

$$\hat{\rho} = \frac{\bar{w}C\lambda_{\max}}{\mathcal{E}'_D(\hat{R}/C\lambda_{\max})}.$$

This solution is depicted in Fig. 3 .

V. Fixed Timing

The traditional method of transmission is fixed timing: the transmitter always sends the next packet without any delay. Since fixed timing is a special case of variable timing, the outer bound (12) holds for fixed-timing. However, this rate may not be achievable. There may be a mismatch between the integer number of time slots between sampled packets and the time required to charge the battery prior to sampling. Specifically, i slots may not be sufficient to charge the battery but charging for $i+1$ slots may exceed the battery capacity, resulting in energy being discarded. One possibility is to use this excess energy to decode the backlog of already-sampled blocks. But if the required decoding energy is small, the decoding backlog may be insufficient to absorb the excess energy.

For fixed timing, we make the following claim.

Theorem 2. *If $\mathcal{E}_D(R/C\tilde{\lambda}) + \tilde{\lambda} \geq \bar{w}\left\lceil\tilde{\lambda}/\bar{w}\right\rceil$, then the outer bound* (12) *is achievable under fixed timing.*

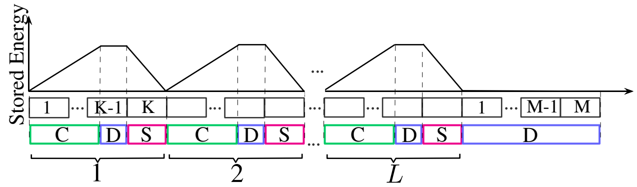

Fig. 4. Fixed timing policy: Intervals labeled "C," "S," and "D" mark when the receiver is (C)harging the battery, (S)ampling a packet, and (D)ecoding that packet.

The condition in Theorem 2 requires that the decoding task is sufficiently energy-hungry to guarantee that the backlog always grows during the sampling phase of the protocol.

Before presenting the proof, we first describe the scheme. As shown in Fig. 4, we employ a K slot *sampling frame* in which the first $K-1$ slots are used for energy harvesting (and the transmitted packets are ignored) followed by sampling the packet in slot K. We sample L packets using L such sampling frames. We again assume that $\tilde{\mathcal{E}}(R) \geq \bar{w}$; otherwise all the packets are decoded. In the following theorem, for a fixed code rate R and fixed-timing assumption, we will give an achievability scheme under a condition that guarantees that no energy loss happens.

Proof: Referring to Fig. 4, consider the following scheme:

1) Given an integer L, let $i = 1$, $K = \left\lceil \tilde{\lambda}/\bar{w} \right\rceil$ and
$$M = \left\lceil \left(L\mathcal{E}_D(R/C\tilde{\lambda}) - LK\bar{w} + L\tilde{\lambda} \right) / \bar{w} \right\rceil. \tag{19}$$
2) Collect energy $n(\tilde{\lambda} - \bar{w})$ in the first $K-1$ slots of sampling frame i; drop the corresponding $K-1$ packets.
3) After battery charging, there may be time left at the end of slot $K-1$. Use the residual energy harvested in this time interval for decoding the backlog, if it is not empty.
4) Sample packet K at rate $\tilde{\lambda}$ and save it in the decoding backlog.
5) $i \leftarrow i+1$. If $i \leq L$ go to step 2.
6) For the next M slots decode the backlog.

From (19), the packet rate can be obtained as
$$\rho(L) = \frac{nLR}{nLK + nM} = \frac{LR}{\left\lceil L\mathcal{E}_D(R/C\tilde{\lambda})/\bar{w} + L\tilde{\lambda}/\bar{w} \right\rceil}. \tag{20}$$
As L goes to infinity,
$$\rho = \lim_{L\to\infty} \rho(L) = \frac{\bar{w}R}{\mathcal{E}_D(R/C\tilde{\lambda}) + \tilde{\lambda}}. \tag{21}$$
■

When the decoding energy is so small that the above fixed timing policy results in discarded energy, neither finding an optimum policy nor tightening the previous outer bound appear to be straightforward tasks. However, we note that it can be shown that the outer bound rate (12) can be achieved by increasing the size of the battery in order to store the energy that would otherwise be discarded.

VI. Discussion

Based on a simple model for receiver energy consumption, we have shown in this work that reliable communication to an energy harvesting receiver can be constrained by the energy harvesting rate as well as the battery size. We have also found that a variable-timing transmission scheme in which the transmitter sends packet when the receiver is ready to sample and decode can achieve an outer bound based on receiver energy conservation.

These conclusions have been reached using the simplest model of deterministic energy arrivals in every symbol period. We expect that the results derived here will also hold under stochastyic energy arrivals if the codewords are long enough to experience the ergodic variation of the harvesting.

Acknowledgement

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