Delay-Constrained Distortion Minimization for Energy Harvesting Transmission over a Fading Channel

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***Abstract*—Distortion minimization for an energy harvesting sensor node communicating over a fading channel is studied. Slotted transmission is considered such that, new source samples and energy packets arrive at the beginning of each time slot (TS), and the fading channel state changes from one TS to the next. A delay constraint is imposed requiring each source sample to be reconstructed at the destination d TSs after its arrival. Assuming independent Gaussian samples with variances changing over TSs, total distortion is minimized under the offline optimization framework, i.e., energy arrivals, source variances and channel gains are assumed to be known non-causally. Optimal compression rates and transmission powers are found and some properties of the optimal strategy are discussed. A two-dimensional water-filling interpretation of the optimal solution is provided for a battery-run node with $d = 1$.**

I. Introduction

Wireless sensor networks observe physical phenomena and deliver the collected samples to a fusion center with the goal of reproducing the samples with sufficient accuracy. Typically, the physical environment and the channel, over which the sensors communicate, change in time, leading to time variation in the source and channel statistics. For time sensitive information, there are also delay constraints associated with the delivery of the source samples. Therefore management of the limited sensor energy is essential to ensure minimal reconstruction distortion at the fusion center.

Energy harvesting (EH) technology overcomes the energy limitations of the sensor devices by scavenging energy from the environment. However, the stochastic nature of the energy arrivals further complicate energy management, requiring the sensors to jointly consider energy harvesting, source and channel processes in order to satisfy the delay and distortion requirements.

In this paper, we consider an EH sensor node that collects samples of a Gaussian source and transmits them to a destination over a fading channel. We consider a time slotted system with N time slots (TSs) and assume that the source samples and energy packets arrive at the transmitter at the beginning of each TS. The channel gain and the source variance remain constant for the duration of each TS, but may vary from one TS to the next. The collected samples need to be delivered in at most d TSs. We assume that available energy is consumed only at the power amplifier, and hence, only used for transmission, though other types of processing energy can be considered as well [1]. The goal is to minimize the mean squared error distortion of all the samples at the destination subject to source and energy causality and delay constraints, by properly choosing the transmission power and compression rate allocation. We focus on *offline optimization* which assumes that all energy arrivals, channel gains and source variances are known a priori. We first obtain the solution for a battery-run sensor node assuming there is only a single energy arrival at the beginning of transmission, and then extend our results to a general EH sensor with multiple energy arrivals. We show that this problem can be cast into the convex optimization framework which allows us to identify the necessary and sufficient conditions for the optimal solution. For the special case of $d = 1$, we show that the optimal strategy has a *two-dimensional (2D) waterfilling* interpretation for a battery-run sensor and a *2D directional waterfilling* interpretation for a general EH system.

EH has received a lot of attention recently [1]-[5]. The current literature mostly focuses on throughput optimization ignoring the source coding aspects. Compression and transmission are jointly optimized in stochastic EH systems in [6] taking into consideration the energy used for source compression as well. Here we consider source coding jointly with transmission over the channel, but ignore the energy used for compression. Our main focus is on the allocation of compression rate and transmit energy while taking into consideration the causal arrival of the source samples and strict delay constraints. Our model intersects with and generalizes several recent results. For example, it reduces to the throughput optimization problem of [7] if we consider a single source arrival at $t = 0$ and relax the delay constraints on source reconstruction. When we consider a single energy packet arrival at $t = 0$ and take $d = 1$, our problem coincides with the one in [8] with the sensing costs ignored.

II. System Model

We consider an EH node communicating with a destination over a time slotted system with N TSs. We assume that the TS duration in terms of channel uses is large enough to invoke Shannon capacity arguments. The channel is modelled as additive white Gaussian noise with unit variance and transmission rate is given by the Shannon capacity $\frac{1}{2}\log(1+hp)$, where p is the transmission power, and h is the real valued channel gain. We assume that h remains constant within each TS, and its value for TS i is denoted by h_i.

The physical phenomena sampled by the sensor in each TS is modeled by a given source distribution. We assume that the statistical properties of the underlying physical phenomena change over time. To model this change, we assume that the samples arriving at TS i come from a zero-mean, variance σ_i^2 Gaussian distribution. The samples are independent from each other within and across TSs. Source samples arriving in a TS need to be delivered in at most d TSs. In each TS the number of source samples collected is equal to the number of channel uses, though it is easy to extend the results to the case in which there is bandwidth expansion/compression. Note that this model can be considered as multiterminal source-channel communication under orthogonal multiple access such that each encoder observes a subset of the sources. Using [9] we can argue optimality of source-channel separation in this setting.

We assume that the sensor node harvests energy in packets of finite amount at the beginning each TS. The energy packet harvested at TS i has energy E_i (normalized by TS duration), and the battery has non-zero energy E_1 at time $t=0$. There are no losses associated with storing and retrieving energy to and from the battery, and we focus only on the consumption due to the transmit energy.

From the previous results on EH communication systems [1], and considering that source statistics do not change within a TS, constant power transmission within each TS is optimal. A *transmission policy* refers to a power allocation function p_i for $i=1,...,N$. A feasible transmission policy should satisfy the energy causality constraint:

$$\sum_{j=1}^{i} p_j \leq \sum_{j=1}^{i} E_j, \quad i=1,..,N. \tag{1}$$

Due to the continuous nature of the samples, lossy reconstruction at the destination is unavoidable. The goal is to minimize the sum distortion of the samples at the destination where mean squared error distortion measure is used. Let D_i be the average distortion of the samples collected at TS i. Then the objective function is to minimize $D \triangleq \sum_{i=1}^{N} D_i$. We define $R_{i,j}$ as the total rate allocated to source i in TS j. We need

$$\sum_{i=j-d+1}^{j} R_{i,j} \leq \frac{1}{2}\log\left(1+h_j p_j\right), \quad j=1,...,N, \tag{2}$$

$$\frac{1}{2}\log\left(\frac{\sigma_i^2}{D_i}\right) \leq \sum_{j=i}^{i+d-1} R_{i,j}, \quad i=1,...,N, \tag{3}$$

with $R_{i,j}=0$ for $j>i+d$ or $j<i$, where (2) follows from the limit on the maximum rate that can be transmitted over each TS, while (3) follows from the rate-distortion theorem. It can be shown using Fourier-Motzkin elimination [10] that the above inequalities (2) and (3) are equivalent to the following causality and delay constraints, respectively. Details are omitted due to space considerations.

$$\sum_{j=i}^{N} \frac{1}{2}\log\left(\frac{\sigma_j^2}{D_j}\right) \leq \sum_{j=i}^{N} \frac{1}{2}\log\left(1+h_j p_j\right), \quad i=1,...,N, \tag{4}$$

$$\sum_{j=k}^{i} \frac{1}{2}\log\left(\frac{\sigma_j^2}{D_j}\right) \leq \sum_{j=k}^{i+d-1} \frac{1}{2}\log\left(1+h_j p_j\right), \tag{5}$$

$$i=k,...,N-d, \quad k=1,...,N-d.$$

The causality constraints in (4) suggest that the samples can only be transmitted after they have arrived. The delay constraints in (5) stipulate that the samples collected in TS i need to be transmitted to the destination within the following d TSs.

The goal of the transmitter is to allocate its transmission power p_i within each TS and choose distortion levels D_i for each source $i=1,...,N$ such that the energy causality and delay constraints are satisfied, while the sum distortion D at the destination is minimized. We are interested in *offline optimization*, that is, we assume that the transmitter knows all the energy amounts, sample variances, and the channel gains in advance.

III. Distortion Minimization for a Battery-Run System

For ease of exposure, and to get insights on the optimal solution, we first assume that there is a single energy packet arrival at time $t=0$, modelling a battery-run system with no EH capability.

Defining new variables $r_i \triangleq \frac{1}{2}\log\left(\frac{\sigma_i^2}{D_i}\right)$, which represents the total source rate for the samples collected in TS i, and $c_i \triangleq \frac{1}{2}\log\left(1+h_i p_i\right)$, which is the channel capacity for TS i for power p_i, we can formulate a convex optimization problem as follows:

$$\min_{r_i,c_i} \quad \sum_{i=1}^{N} \sigma_i^2 e^{-2r_i} \tag{6a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} \frac{e^{2c_i}-1}{h_i} \leq E_1, \tag{6b}$$

$$\sum_{j=i}^{N} r_j \leq \sum_{j=i}^{N} c_j, \quad i=1,...,N, \tag{6c}$$

$$\sum_{j=k}^{i} r_j \leq \sum_{j=k}^{i+d-1} c_j, \tag{6d}$$

$$i=k,...,N-d, \quad k=1,..,N-d,$$

$$e^{-2r_i} \leq 1 \quad \text{and} \quad 0 \leq c_i, \quad i=1,...,N. \tag{6e}$$

where the constraint in (6b) ensures that the total consumed energy is less than the energy available in the battery at $t=0$. The constraints in (6c) and (6d) are the causality and delay constraints from (4) and (5), respectively.

Since the optimization problem in (6) is convex, efficient numerical methods to compute the optimal solution exist [12]. Next, we identify the properties of the optimal solution using the Karush-Kuhn-Tucker (KKT) optimality conditions. The Lagrangian of (6) with $\lambda \geq 0$, $\gamma_i \geq 0$, $\delta_{i,k} \geq 0$, $\beta_i \geq 0$ and $\mu_i \geq 0$ as Lagrange multipliers corresponding to (6b)-(6e) is the following:

$$\begin{aligned}\mathcal{L} &= \sum_{i=1}^{N} \sigma_i^2 e^{-2r_i} + \lambda \left(\sum_{i=1}^{N} \frac{e^{2c_i}-1}{h_i} - E_1 \right) \\ &+ \sum_{i=1}^{N} \gamma_i \left(\sum_{j=i}^{N} r_j - \sum_{j=i}^{N} c_j \right) \\ &+ \sum_{k=1}^{N-d} \sum_{i=k}^{N-d} \delta_{i,k} \left(\sum_{j=k}^{i} r_j - \sum_{j=k}^{i+d-1} c_j \right) \\ &+ \sum_{i=1}^{N} \beta_i \left(e^{-2r_i} - 1 \right) - \sum_{i=1}^{N} \mu_i c_i. \end{aligned} \tag{7}$$

Differentiating the Lagrangian with respect to r_i and c_i, we obtain

$$\frac{\partial \mathcal{L}}{\partial r_i} = \begin{cases} \sum_{j=1}^{i} \gamma_j + \sum_{k=1}^{i} \sum_{j=i}^{N-d} \delta_{j,k} - 2(\sigma_i^2 + \beta_i) e^{-2r_i} = 0, \\ \qquad i = 1, ..., N-d, \\ \sum_{j=1}^{i} \gamma_j - 2(\sigma_i^2 + \beta_i) e^{-2r_i} = 0, \\ \qquad i = N-d+1, ..., N, \end{cases} \tag{8}$$

$$\frac{\partial \mathcal{L}}{\partial c_i} = \lambda \frac{2e^{2c_i}}{h_i} - \sum_{j=1}^{i} \gamma_j - \sum_{k=1}^{i} \sum_{j=i-d+1}^{N-d} \delta_{j,k} - \mu_i = 0, \ \forall i, \tag{9}$$

where $\delta_{j,k} = 0$ for $j = 2-d, ..., 0$, $\forall k$.

Solving for (8) and complementary slackness conditions, and replacing r_i^* with $\frac{1}{2} \log \left(\frac{\sigma_i^2}{D_i^*} \right)$, we obtain

$$D_i^* = \begin{cases} \left(\frac{\sigma_i^2}{2(\sigma_i^2 + \beta_i)} \right) \left(\sum_{j=1}^{i} \gamma_j + \sum_{k=1}^{i} \sum_{j=i}^{N-d} \delta_{j,k} \right), \\ \qquad i = 1, ..., N-d, \\ \left(\frac{\sigma_i^2}{2(\sigma_i^2 + \beta_i)} \right) \sum_{j=1}^{i} \gamma_j, \quad i = N-d+1, ..., N. \end{cases} \tag{10}$$

The complementary slackness conditions require that, whenever $\beta_i > 0$, we have $D_i^* = \sigma_i^2$. Therefore, the optimal distortion D_i^* can be further simplified as

$$D_i^* = \begin{cases} \xi_i, & \text{if } \xi_i < \sigma_i^2, \\ \sigma_i^2, & \text{if } \xi_i \geq \sigma_i^2, \end{cases} \tag{11}$$

where ξ_i satisfies the following:

$$\xi_i = \begin{cases} \frac{1}{2} \sum_{j=1}^{i} \gamma_j + \frac{1}{2} \sum_{k=1}^{i} \sum_{j=i}^{N-d} \delta_{j,k}, \\ \qquad i = 1, ..., N-d, \\ \frac{1}{2} \sum_{j=1}^{i} \gamma_j, \qquad i = N-d+1, ..., N. \end{cases} \tag{12}$$

Note that ξ_i can be interpreted as the *reverse water level* similar to the classical solution of the optimal distortion levels for parallel Gaussian sources [11]. While the classical solution has a fixed reverse water level, i.e., ξ_i is independent of i, in our formulation, due to causality and delay constraints, the reverse water level depends on the source index i.

We next identify the structure of the optimal power allocation. Solving for (9) and the complementary slackness conditions, and replacing c_i^* with $\frac{1}{2} \log(1 + h_i p_i^*)$, we obtain the following

$$p_i^* = \left(\frac{\sum_{j=1}^{i} \gamma_j + \sum_{k=1}^{i} \sum_{j=i-d+1}^{N-d} \delta_{j,k}}{2\lambda} - \frac{1}{h_i} \right)^+, \quad \forall i, \tag{13}$$

where $\delta_{j,k} = 0$ for $j = 2-d, ..., 0$, $\forall k$. Defining $\nu_i = \frac{\sum_{j=1}^{i} \gamma_j + \sum_{k=1}^{i} \sum_{j=i-d+1}^{N-d} \delta_{j,k}}{2\lambda}$ we can interpret (13) as being similar to the classical waterfilling solution obtained for power allocation over parallel channels with *water level* being equal to ν_i. However, similar to (11) this differs from the classical fixed waterfilling in that ν_i depends on i due to causality and delay constraints.

In Section III-A, we provide some properties of the optimal distortion and power allocation without delay constraints. These properties not only provide us a better understanding of the optimal solution, but also are potentially useful in obtaining online algorithms, when the channel gains and source statistics may not be known in advance. Then in Section III-B, we consider the special case of $d = 1$ and provide a 2D waterfilling interpretation of the optimal solution.

A. *No delay constraint* ($d = N$)

In this section, we consider the case when there is no delay constraint, i.e., $d = N$. For $d = N$, constraint (6d) is no longer necessary and $\delta_{i,k} = 0$ $\forall i, k$.

Lemma 1: For $d = N$, the reverse water level ξ_i in (12) is non-decreasing, and whenever ξ_i increases from TS i to TS $i+1$, all samples collected until TS i must be transmitted until the end of TS i.

Proof: From (12) with $\delta_{j,k} = 0$, we have

$$\xi_{i+1} - \xi_i = \frac{\gamma_{i+1}}{2}, \qquad i = 1, ..., N. \tag{14}$$

Therefore, when $\xi_{i+1} - \xi_i > 0$, γ_{i+1} must be positive. From the complementary slackness conditions, we know that whenever $\gamma_{i+1} > 0$, the constraint in (6c) is satisfied with equality, i.e., $\sum_{j=i+1}^{N} r_j = \sum_{j=i+1}^{N} c_j$. This means that all samples collected until TS i must be transmitted until the end of TS i since the later TSs can only support the source rates r_j, $j \geq i+1$. Non-decreasing property of ξ_i follows from non-negativity of γ_i. ■

Lemma 2: For $d = N$, the water level ν_i is non-decreasing, and whenever ν_i increases from TS i to TS $i+1$, all samples collected until TS i must be transmitted by the end of TS i.

Proof: For $\delta_{j,k} = 0$, we can show $\nu_{i+1} - \nu_i = \frac{\gamma_{i+1}}{2\lambda}$. Therefore, when $\nu_{i+1} - \nu_i > 0$, γ_{i+1} must be positive. Using arguments similar to the proof of Lemma 1, the proof can be completed. ■

B. *Strict delay constraint* ($d = 1$)

In this section, we investigate the case in which the samples need to be transmitted within the following TS, i.e., $d = 1$. Note that this is equivalent to the problem investigated in [8] when sensing energy cost is zero. Here we provide a

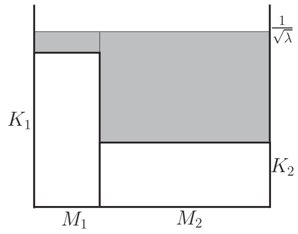

Figure 1. 2D water-filling algorithm.

2D waterfilling interpretation for the solution. Solving the optimization problem in (6) for $d = 1$ we find

$$p_i^* = \frac{\sigma_i}{\sqrt{h_i}} \left[\frac{1}{\sqrt{\lambda}} - \frac{1}{\sigma_i \sqrt{h_i}} \right]^+ . \tag{15}$$

Defining $M_i \triangleq \frac{\sigma_i}{\sqrt{h_i}}$ and $K_i \triangleq \frac{1}{\sigma_i \sqrt{h_i}}$, the optimal power in (15) can be written as

$$p_i^* = M_i \left[\frac{1}{\sqrt{\lambda}} - K_i \right]^+ . \tag{16}$$

Since $\frac{1}{2} \log \left(\frac{\sigma_i^2}{D_i} \right) \le \frac{1}{2} \log (1 + h_i p_i)$ is satisfied with equality for $d = 1$, the optimal distortion D_i^* is

$$D_i^* = \begin{cases} M_i \sqrt{\lambda}, & \text{if } M_i \sqrt{\lambda} < \sigma_i^2, \\ \sigma_i^2, & \text{if } M_i \sqrt{\lambda} \ge \sigma_i^2. \end{cases} \tag{17}$$

The above solution is illustrated in Fig. 1 for $N = 2$. For each TS, we have rectangles of width M_i and height K_i. The total energy is poured above the level K_i for each TS up to the water level $\frac{1}{\sqrt{\lambda}}$. The power allocated to TS i is given by the shaded area below the water level and above K_i. If $p_i^* > 0$, the distortion for source i is given by $M_i \sqrt{\lambda}$, i.e., the width M_i times the inverse water level, and if $p_i^* = 0$, the distortion for source i is $\sigma_i^2 = \frac{M_i}{K_i}$.

IV. Distortion Minimization with Energy Harvesting

In this section, we extend the formulation in Section III to include EH. The distortion minimization problem in (6) remains the same except that constraint (6b) is replaced by (1), which, in the convex reformulation of (6) can be replaced by

$$\sum_{j=1}^{i} \frac{e^{2c_i} - 1}{h_i} \le \sum_{j=1}^{i} E_j, \quad i = 1, ..., N. \tag{18}$$

This leads to the Lagrangian with $\lambda_i \ge 0$, $\gamma_i \ge 0$, $\delta_{i,k} \ge 0$, $\beta_i \ge 0$ and $\mu_i \ge 0$ as the Lagrange multipliers:

$$\begin{aligned} \mathcal{L} = & \sum_{i=1}^{N} \sigma_i^2 e^{-2r_i} + \sum_{i=1}^{N} \lambda_i \left(\sum_{j=1}^{i} \frac{e^{2c_i} - 1}{h_i} - \sum_{j=1}^{i} E_j \right) \\ & + \sum_{i=1}^{N} \gamma_i \left(\sum_{j=i}^{N} r_j - \sum_{j=i}^{N} c_j \right) \\ & + \sum_{k=1}^{N-d} \sum_{i=k}^{N-d} \delta_{i,k} \left(\sum_{j=k}^{i} r_j - \sum_{j=k}^{i+d-1} c_j \right) \\ & + \sum_{i=1}^{N} \beta_i \left(e^{-2r_i} - 1 \right) - \sum_{i=1}^{N} \mu_i c_i. \end{aligned} \tag{19}$$

The derivative of the Lagrangian with respect to r_i is (8); hence the structure of the optimal distortion is the same as in Section III. The optimal channel rate c_i^* of TS i must satisfy

$$\frac{\partial \mathcal{L}}{\partial c_i} = \frac{2e^{2c_i}}{h_i} \sum_{j=i}^{N} \lambda_j - \sum_{j=1}^{i} \gamma_j - \sum_{k=1}^{i} \sum_{j=i-d+1}^{N-d} \delta_{j,k} - \mu_i = 0,$$

for $i = 1, ..., N$ where $\delta_{j,k} = 0$ for $j = 2 - d, ..., 0$, $\forall k$.

This leads to the optimal power levels p_i^* as

$$p_i^* = \left(\frac{\sum_{j=1}^{i} \gamma_j + \sum_{k=1}^{i} \sum_{j=i-d+1}^{N-d} \delta_{j,k}}{2 \sum_{j=i}^{N} \lambda_j} - \frac{1}{h_i} \right)^+ , \ \forall i. \tag{20}$$

Note that for $d = N$ Lemma 1 still holds, while Lemma 2 is updated as follows under EH. Defining $\pi_i = \frac{\sum_{j=1}^{i} \gamma_j + \sum_{k=1}^{i} \sum_{j=i-d+1}^{N-d} \delta_{j,k}}{2 \sum_{j=i}^{N} \lambda_j}$, we can interpret (20) similarly to the directional waterfilling solution of [7] with water level equal to π_i. In our problem, the water level π_i depends on the source index i due to the causality and delay constraints.

Lemma 3: For $d = N$, the water-level π_i is non-decreasing and whenever π_i increases from TS i to TS $i + 1$, either all collected samples until TS i are transmitted, or the battery is empty by the end of TS i, or both.

Proof: From (20), with $\delta_{j,k} = 0$, we can argue that when $\pi_{i+1} - \pi_i > 0$, either γ_{i+1} or λ_i, or both must be positive. For $\gamma_{i+1} > 0$ we use the arguments in the proof of Lemma 1 to argue that all samples collected until TS i must be transmitted until the end of TS i. In addition, when $\lambda_i > 0$, the constraint in (18) is satisfied with equality due to the complementary slackness conditions and the battery is empty at the end of TS i. Since $\gamma_{i+1} \ge 0$ and $\lambda_i > 0$, π_i is non-decreasing. ■

Extending Section III-B, we can interpret the EH solution for $d = 1$ as *directional 2D water-filling* such that the harvested energy E_i can only be allocated to TSs $j > i$. The optimal transmission power and distortion in terms of M_i and K_i can be obtained as

$$p_i^* = M_i \left[\frac{1}{\sqrt{\sum_{i=i}^{N} \lambda_i}} - K_i \right]^+ , \tag{21}$$

$$D_i^* = \begin{cases} M_i \sqrt{\sum_{i=i}^{N} \lambda_i}, & \text{if } M_i \sqrt{\sum_{i=i}^{N} \lambda_i} < \sigma_i^2, \\ \sigma_i^2, & \text{if } M_i \sqrt{\sum_{i=i}^{N} \lambda_i} \ge \sigma_i^2. \end{cases} \tag{22}$$

V. Illustration of the Results

In this section, we provide numerical results to illustrate the structure of the optimal rate and power allocation. Throughout this section, we consider $N = 10$ TSs. The channel gains are chosen as $\mathbf{h} = [0.4, 0.2, 0.2, 0.5, 0.4, 0.6, 0.9, 0.3, 0.4, 1]$ and the source variances are $\sigma^{\mathbf{2}} = [0.7, 0.6, 1, 0.5, 0.3, 0.6, 0.2, 0.3, 0.7, 0.5]$. We first set $d = 1$ and consider a battery-run system with initial energy $E_1 = 5$. The 2D waterfilling solution is shown in Fig. 2, resulting in the optimal distortion $D = 4.32$.

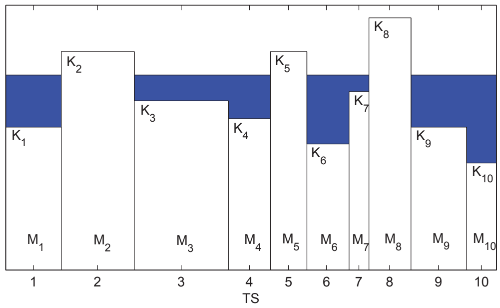

Figure 2. 2D waterfilling for battery-run system.

We next consider an EH system with energy packets of sizes $E_1 = 1, E_6 = 4, E_i = 0$ otherwise. The 2D directional waterfilling solution is given in Fig. 3. Note that the water level changes after TS 5 because of directional waterfilling. The resulting optimal distortion is $D = 4.37$, larger than the battery-run system with the same total energy as expected.

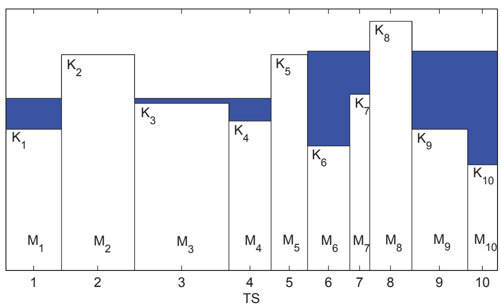

Figure 3. 2D waterfilling for EH system.

Finally, we investigate the variation of the optimal distortion D with respect to delay d. We consider a battery-run system with initial energy $E_1 = 5$. The distortion values for increasing d are given in Fig. 4 showing that the optimal distortion decreases monotonically for $d \leq 4$ and remains constant after $d = 4$.

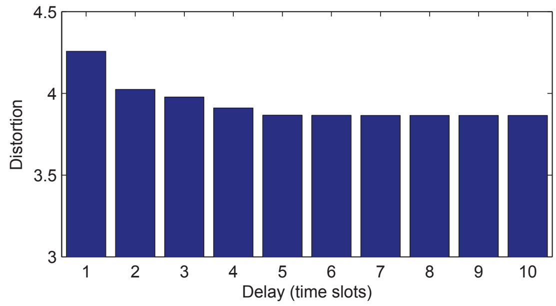

Figure 4. Total distortion D versus delay d for battery-run system

VI. Conclusions

In this paper, we have studied the delay limited transmission of a time varying Gaussian source over a fading channel. The transmitter has EH capability and both energy and source samples arrive in a time-slotted fashion. The delay constraints stipulate that the source samples are delivered in d TSs. We have provided a convex optimization formulation and identified optimal compression and transmission policies for minimizing the total mean squared distortion at the destination. The convex optimization framework has allowed the identification of some properties of the optimal distortion and power levels for $d = N$. For $d = 1$, we have suggested a 2D directional waterfilling interpretation for the optimal transmission scheme.

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