

Optimal Sleep-Wake Policies for an Energy Harvesting Sensor Node

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Abstract—We study a sensor node with an energy harvesting source. In any slot, the sensor node is in one of two modes: Wake or Sleep. The generated energy is stored in a buffer. The sensor node senses a random field and generates a packet when it is awake. These packets are stored in a queue and transmitted in the wake mode using the energy available in the energy buffer. We obtain energy management policies which minimize a linear combination of the mean queue length and the mean data loss rate. Then, we obtain two easily implementable suboptimal policies and compare their performance to that of the optimal policy. Next, we extend the Throughput Optimal policy developed in our previous work to sensors with two modes. Via this policy, we can increase the throughput and stabilize the data queue by allowing the node to sleep in some slots and to drop some generated packets. This policy requires minimal statistical knowledge of the system. We also modify this policy to decrease the switching costs.

Keywords: Energy harvesting sensor nodes, Sleep-Wake Policies, Throughput Optimal Policies.

I. INTRODUCTION

Sensor networks consist of a large number of small, inexpensive sensor nodes. These nodes have small batteries with limited power and also have limited computational power and storage space. When the battery of a node is exhausted, it is not replaced and the node dies. When sufficient number of nodes die, the network may not be able to perform its designated task. Various studies have been conducted to increase the life time of the battery of a node by reducing the energy intensive tasks, e.g., reducing the number of bits to transmit ([9], [2]), making a node go into power saving modes (sleep/listen) periodically ([15]), using energy efficient routing ([17], [12]) and MAC ([18]). A general survey on sensor networks is [1] which provides more references on these issues.

The life time of the battery itself can be increased by energy harvesting techniques ([5], [8]). Common energy harvesting devices are solar cells, wind turbines and piezo-electric cells, which extract energy from the environment. Among these, solar energy harvesting seems to have emerged as a technology of choice ([8], [10]). Unlike for a battery operated sensor node, now there is potentially an *infinite* amount of energy available to the node. However, the source of energy and the energy harvesting device may be such that the energy cannot be generated at all times (e.g., a solar cell). Furthermore, the rate of generation of energy can be limited. Thus, one may need to modify the energy consumption profile of the sensor

node so that the node can perform satisfactorily for a long time, e.g., can operate in *energy neutral operation* ([5]).

In our previous work ([13], [14]), for data gathering applications, throughput optimal and mean delay optimal energy management policies were identified which made the system work in energy neutral operation. It was found that having energy storage allows larger stability region as well as lower mean delays. MACs for such sensor nodes have also been studied in [13]. In this paper, we extend this work to also include sleep mode which may be needed when energy neutral operation is not possible (necessary conditions for which were identified in [14]).

In the following, we survey the literature on sensor networks with energy harvesting nodes. Early papers on energy harvesting in sensor networks are [6] and [11]. A good recent contribution is [5]. It provides various deterministic theoretical models for energy generation and energy consumption profiles and provides conditions for energy neutral operation. In [4], the authors study optimal sleep-wake cycles such that event detection probability is maximized. In [7], finite state Markov models of solar energy harvesting are formulated, certain sleep-wake strategies are proposed and policy parameters optimized using Game Theory. A recent survey is [8] which also summarizes the results in [7].

In this paper, we consider a sensor node with an energy harvesting source that has two modes: Wake and Sleep. The sleep mode is a power saving mode in which the sensor only harvests energy and performs no other functions so that the energy consumption is negligible. We find an optimal policy that minimizes a linear combination of the mean queue length and the mean data loss rate. Next, we obtain a throughput optimal policy which is much easier to compute and does not require distributions of the system parameters. We find the optimal fraction of time the sensor should sleep and then specify a policy to schedule the sleep slots of the sensor. Interestingly, for stability of data queue, the throughput optimal policy may require dropping a fraction of packets after sensing and processing them. The results we obtain for a single node will be used in a sensor network later on. In contrast to finite state Markov models in [7], we have more general stationary stochastic models and our emphasis is on showing the existence of optimal policies and obtaining easily computable optimal and suboptimal policies.

This paper is organized as follows. Section II describes

the model and provides the assumptions made for data and energy generation. Section III starts by considering an optimal policy that minimizes a cost which is a linear combination of the mean queue length and the mean data loss rate. Then, we obtain two easily implementable suboptimal policies and compare their performance to that of the optimal policy. In Section IV, we find a throughput optimal policy. Section V concludes the paper.

II. THE MODEL

In this section, we present our model for a single energy harvesting sensor node with two modes: Wake and Sleep.

We consider a sensor node which is sensing a random field and generating packets to be transmitted to a central node via a network of sensor nodes. The system is slotted. X_k bits are generated by the sensor in slot k which will be denoted by interval $[k, k + 1]$. Although the sensor may generate data as packets, we will allow arbitrary fragmentation of packets during transmission. Thus, packet boundaries are not important and we consider bit strings (or just fluid). The bits X_k are eligible for transmission after slot k . The queue length (in bits) at the beginning of slot k is q_k . The sensor can transmit $\min\{q_k, g(T_k)\}$ bits in the slot if it uses energy T_k for transmission where g is an appropriately defined function. We denote by E_k the energy available at the sensor at the beginning of slot k . In slot k , the sensor is able to replenish energy by Y_k which is available for use after slot k . The sensor uses energy Z_k for sensing and processing in slot k .

Initially, we will assume that the data buffer and energy buffer have infinite capacity. The sequence $\{(X_k, Y_k, Z_k)\}$ will be assumed to be (asymptotically) stationary, ergodic and sometimes even Markov. These assumptions are general enough to model relay sensor nodes also (which transmit data from other nodes as well as their own). In addition, Markov energy generation profiles (used in [7]) are also covered. We can even take $Z_k = h(X_k)$, a deterministic function of X_k . If, in a slot, the energy $E_k < Z_k$, then, in that slot, the node cannot even do its basic operations of sensing and processing. Thus, we introduce another state ‘sleep’ and if $E_k < Z_k$, then the node will enter the sleep mode. Now, X_k is the number of bits that would be generated and Z_k is the amount of energy that would be used for sensing and processing if the sensor was awake in slot k . In sleep mode, the sensor shuts down all its operations except the energy harvesting and thus consumes negligible amount of energy. The sleep mode can also be used at other times to optimize the overall performance. Also, from [14], for energy neutral operation, it is necessary (and sufficient) that

$$E[X_k] < g((E[Y_k] - E[Z_k])^+).$$

If this condition is not satisfied, then one needs to introduce the sleep mode for energy neutral operation. We consider such a scenario in this paper and develop optimal sleep-wake policies for a single node.

We define S_k to denote the mode of the sensor node in slot k : $S_k = 0$ implies that the node is awake in slot k ; $S_k = 1$

denotes the sleep mode.

The processes $\{q_k\}$ and $\{E_k\}$ satisfy

$$q_{k+1} = (q_k - I_{\{S_k=0\}}g(T_k))^+ + I_{\{S_k=0\}}X_k, \quad (1)$$

$$E_{k+1} = ((E_k - I_{\{S_k=0\}}T_k - I_{\{S_k=0\}}Z_k)) + Y_k \quad (2)$$

where $T_k \leq E_k - Z_k$. This assumes that the data buffer and the energy storage buffer are infinite. If in practice these buffers are large enough, this is a good approximation. If not, even then these results provide important insights and the policies obtained often provide good performance for the finite buffer case.

The function g will be assumed to be monotonically non-decreasing. An important such function is given by Shannon’s capacity formula

$$g(T_k) = \frac{1}{2} \log(1 + \beta T_k) \quad (3)$$

for Gaussian channels where β is a constant such that βT_k is the received SNR. This is a non-decreasing, concave function. At low SNR, (3) can be approximated by a linear function. Since sensor nodes are energy constrained, this is a practically important case. So, in the following, we limit our attention to linear and concave, nondecreasing functions g . We will also assume that $g(0) = 0$ which always holds in practice.

In the above model, for sake of simplicity, we have ignored certain practical details. For example, there will be leakage in the battery. This can be easily included in our model with minimal changes. Also, we have assumed that if $E_k < Z_k$, then the node goes to sleep. At time k , the node may not know Z_k . However in a practical scenario, Z_k may actually be a constant. Otherwise, we may assume that in the beginning of slot k , Z_k may not be known and if $E_k > 0$, the node may start in active mode. But, if it is not able to complete the operation of sensing and processing (because $E_k < Z_k$), E_k may then become zero and node enters sleep mode. This change in model will require only minimal changes in our analysis.

III. AN OPTIMAL POLICY

We determine S_k and T_k (when $S_k = 0$) as a function of $q_k, E_k, X_{k-1}, Y_{k-1}$ and Z_{k-1} such that the discounted cost

$$E \left[\sum_{k=0}^{\infty} \alpha^k (q_k + c I_{\{S_k=1\}} X_k) \right]$$

is minimized where $0 < \alpha < 1$ and $0 < c < \infty$ are suitable constants. This cost takes into account two important performance measures: mean queue length and mean data loss rate. The minimizing policy is called α -discount optimal. When $\alpha = 1$, we minimize

$$\lim_{n \rightarrow \infty} \sup \frac{1}{n} E \left[\sum_{k=0}^{n-1} (q_k + c I_{\{S_k=1\}} X_k) \right].$$

This optimizing policy is called average cost optimal. The average cost of a policy that sets $P(S_k = 1) = 1$ for all $k \geq 0$ is $cE[X]$ which is finite for a finite $E[X]$. Hence, the optimal

policy, if it exists, will have a finite cost and hence, a finite average queue length. If, for a given $(q_k, e_k, x_{k-1}, y_{k-1}, z_{k-1})$, the optimal action S_k and T_k (when $S_k = 0$) is uniquely specified independent of k , the optimal policy is called a stationary policy.

If $\{X_k\}$, $\{Y_k\}$ and $\{Z_k\}$ are Markov chains, then these optimization problems are Markov Decision Problems. For simplicity, in the following we consider these problems when $\{X_k\}$ and $\{Z_k\}$ are *i.i.d.* and $\{Y_k\}$ are modulated by finite state Markov chains. Then, following the arguments in [14], we obtain the existence of optimal policies (actually the proof now is much simpler because the average cost of the optimal policy is already known to be finite in the present case). The proof of the following theorem is omitted due to lack of space.

Theorem: If g is continuous and the energy buffer is finite, i.e., $E_k \leq \bar{e} < \infty$, then there exist α -discount optimal and average cost optimal policies. Also, the optimal α -discount policy tends to the optimal average cost policy as $\alpha \nearrow 1$ and

$$\lim_{\alpha \rightarrow 1} (1 - \alpha) \inf_{(q,e,y)} v_\alpha(q, e, y) = v$$

where $v_\alpha(q, e, y)$ is the optimal α -discount cost for the initial state (q, e, y) and v is the optimal average cost that does not depend on the initial state.

The optimal policy can be obtained via value iteration. However, it is computationally demanding. Next, we obtain two easily implementable suboptimal policies and compare their performance to that of the optimal policy.

A. Randomized Sleep Policy

In this policy, in every slot k with $E_k \geq Z_k$, the sensor chooses to remain awake with probability $(1 - p)$ independent of the other random variables, and in every slot that it remains awake it uses

$$T_k = \min \left\{ \frac{E[Y]}{1 - p} - E[Z] - \epsilon, E_k - Z_k \right\} \quad (4)$$

where ϵ is a small positive constant. The p can be selected to have small average cost.

B. Energy Threshold Policy

In this policy, the sensor uses T_k given in (4) with $\epsilon = 0$ in every slot in which $S_k = 0$ where S_k is chosen as follows:

$$\begin{aligned} S_k &= 1 \text{ if } E_k \leq E_{T_1}, \\ S_k &= 0 \text{ if } E_k \geq E_{T_2} \text{ and} \\ S_k &= S_{k-1} \text{ if } E_{T_1} < E_k < E_{T_2} \end{aligned}$$

where E_{T_1} and E_{T_2} are two energy levels such that $E_{T_1} \leq E_{T_2}$. We fix E_{T_1} and E_{T_2} so that the long term fraction of sleep states is a given p . For a given p , the switching rate of this policy is considerably less than that of the randomized sleep policy for large enough $E_{T_2} - E_{T_1}$, since then the average sleep and wake intervals of this policy are large, resulting in low cost in switching between the two modes.

C. Simulation Results

We compare Average Cost Optimal, Optimal Randomized Sleep and Optimal Energy Threshold policies for $c = 5$ and 10 via simulations. We fix $E_{T_1} = 10$ units and $E_{T_2} = 60$ units. The Optimal Randomized Sleep and Energy Threshold policies are obtained by finding the optimal p by exhaustive search, that minimizes the average cost. $\{X_k\}$ and $\{Y_k\}$ are discrete valued *i.i.d.* random variables. $E[Y] = 2$ and we take $Z_k = 1$ unit. For numerical computation of the optimal policy, we consider a finite data buffer of size 80 bits with quantisation size of 0.125 bits and a finite energy buffer of size 40 units with a quantisation size of 1 unit. From simulations, we found that average queue lengths and average throughputs, and hence optimal average costs, of Optimal Randomized Sleep and Optimal Energy Threshold policies are almost the same for different values of $E[X]$. Hence, in the following, we restrict our attention to only one of the suboptimal policies: the Optimal Randomized Sleep Policy.

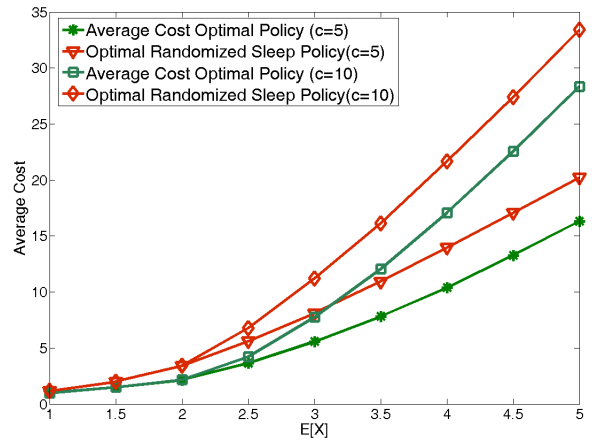


Fig. 1. Comparison of Average Cost Optimal Policy and Optimal Randomized Sleep (/Energy Threshold) Policy

In Fig. 1, we compare the average costs of the Average Cost Optimal and Optimal Randomized Sleep policies. We see that the average costs of the two policies are reasonably close to each other. In Fig. 2, we compare the average queue lengths and average throughputs of the two policies and see that for a given c , the average throughputs are close for the two policies although the average queue lengths are distinctly higher for the Optimal Randomized Sleep policy. Also, we find that for the larger c , the optimal policies have larger throughput although they have higher average queue lengths.

In Fig. 3, we compare the switching rates of the Optimal Randomized Sleep and Optimal Energy Threshold policies. We see that the switching rates are substantially less for the latter.

Fig. 4 depicts the T_k for the Average Cost Optimal Policy found for $c = 5$ and $E[X] = 4$. We see that the optimal policy uses $T_k = 6$, i.e., a constant amount of energy, for a large number of states and uses larger T_k only when q_k is not too large and energy level is high. We also found that for

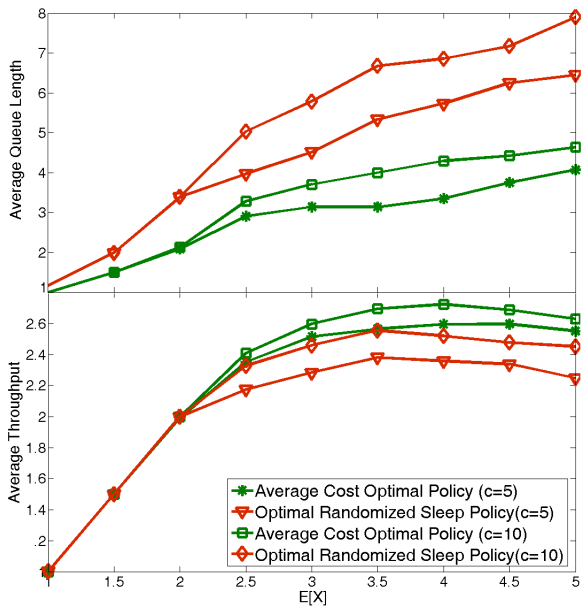


Fig. 2. Comparison of the Average Queue Length (Top) and Average Throughput (bottom) of Average Cost Optimal Policy and and Optimal Randomized Sleep (Energy Threshold) Policy

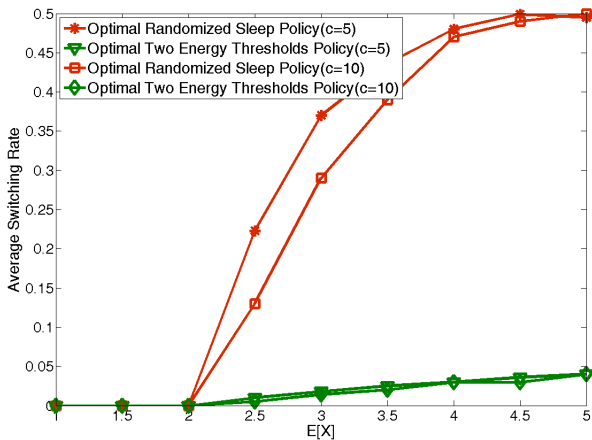


Fig. 3. Comparison of the Switching rates of Optimal Randomized Sleep Policy and Optimal Energy Threshold Policy

sufficiently large q_k , $S_k = 0$ for E_k greater than a threshold and the threshold increases with q_k . Similarly, for sufficiently large E_k , $S_k = 0$ for q_k greater than a threshold and the threshold decreases with E_k .

IV. THROUGHPUT OPTIMAL POLICY

One disadvantage of the Average Cost Optimal policy in Section III is that it is computed numerically and we get minimal insight regarding the structure of the optimal policy. The suboptimal policies obtained in the last section, although useful, do pay a performance penalty. If throughput is the dominant criterion, we can, as in [14], obtain an explicit, easily computable policy which maximizes the throughput.

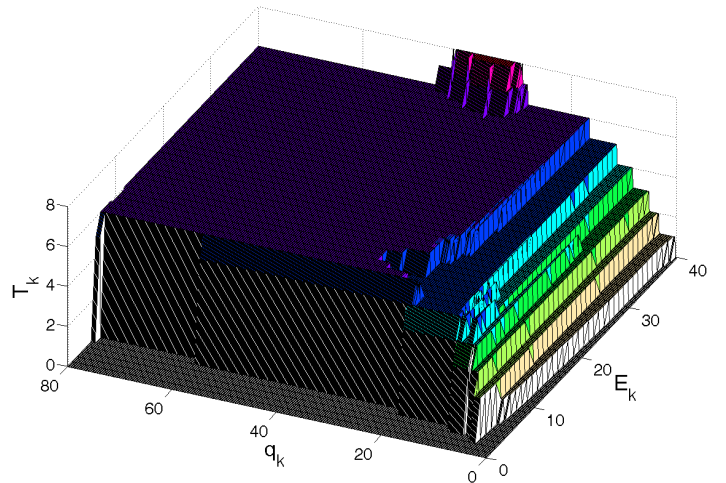


Fig. 4. T_k as a function of (q_k, E_k) in the the Average Cost Optimal Policy found for $c = 5$ and $E[X] = 4$

As shown in [14], if

$$E[X] < g((E[Y] - E[Z])^+), \quad (5)$$

then the optimal policy is: $S_k \equiv 0$ and $T_k = \min\{(E_k - Z_k)^+, E[Y] - E[Z] - \epsilon\}$ where ϵ is an arbitrarily small positive constant. Now, we obtain the throughput optimal policy when (5) is not satisfied. From Lemma 1 in [14], we obtain that for $\{S_k, T_k\}$ to be an asymptotically stationary ergodic policy that is jointly stationary with $\{(q_k, E_k, X_k, Y_k, Z_k)\}$ and for which q_k has a proper distribution under stationarity, it is necessary that

$$\begin{aligned} E_\pi [X_k I_{\{S_k=0\}}] &< E_\pi [g(T_k) I_{\{S_k=0\}}] \\ &\leq (1-p)g(E_\pi [T_k | S_k = 0]) \end{aligned} \quad (6)$$

where π is the stationary distribution and $p = P_\pi[S_k = 1]$, the probability of sleeping.

We can make this policy more flexible if we allow that after accepting (sensing) bits, these can be dropped from the data buffer with probability γ independent of other random variables. Then, in the necessary condition in (6) on the left side, we replace $E_\pi [X_k I_{\{S_k=0\}}]$ by $(1-\gamma)E_\pi [X_k I_{\{S_k=0\}}]$. If g is strictly concave, then the second inequality in (6) is also a strict inequality unless $[T_k | S_k = 0] = E[T_k | S_k = 0]$. If $\{X_k\}$ is *i.i.d.*, then S_k can be taken independent of X_k and then

$$E_\pi [X_k I_{\{S_k=0\}}] = E_\pi [X_k](1-p). \quad (7)$$

This also holds if instead of $\{X_k\}$, $\{S_k\}$ is *i.i.d.* and independent of $\{X_k\}$.

From [14], for $P_\pi[q < \infty] = 1$, we need

$$E_\pi [T_k I_{\{S_k=0\}}] < E_\pi [Y] - E_\pi [Z_k I_{\{S_k=0\}}]$$

which is equivalent to

$$E_\pi [T_k | S_k = 0] < \frac{E_\pi [Y]}{1-p} - E_\pi [Z_k | S_k = 0].$$

Since g is non decreasing, (6) implies that a necessary condition for the above result is

$$(1 - \gamma)E_\pi [X_k I_{\{S_k=0\}}] <$$

$$(1 - p)g \left(\frac{E_\pi[Y]}{1 - p} - E_\pi [Z_k | S_k = 0] \right) \quad (8)$$

and if (7) holds, we need

$$(1 - \gamma)E_\pi [X_k] < g \left(\frac{E_\pi[Y]}{1 - p} - E_\pi [Z_k | S_k = 0] \right). \quad (9)$$

Next, we provide a policy that satisfies (9).

We define $\{S_k\}$ *i.i.d.*, independent of $\{(X_k, Y_k, Z_k)\}$ and with $P(S_k = 1) = p$. Also, let

$$T_k = \min \left\{ E_k - Z_k, \frac{E_\pi[Y]}{1 - p} - E_\pi [Z_k] - \epsilon \right\} \text{ when } S_k = 0 \\ = 0, \text{ otherwise} \quad (10)$$

where $\epsilon > 0$ is arbitrarily small. Then, from (2), it is easy to show that $E_k \nearrow \infty$ a.s. and hence

$$T_k(\omega) = \left(\frac{E_\pi[Y]}{1 - p} - E_\pi [Z_k] - \epsilon \right) I_{\{S_k=0\}}$$

for all k large enough, for almost all ω . For the same reason, although in the beginning we may not be able to implement $S_k = 0$ (because E_k may be less than Z_k), later on this will rarely happen. Thus, we obtain $\{(T_k, S_k, X_k, Y_k, Z_k, E_k)\}$ asymptotically stationary and ergodic and if (9) is satisfied, we also obtain $\{(q_k, T_k, S_k, X_k, Y_k, Z_k, E_k)\}$ jointly asymptotically stationary with $P_\pi[q < \infty] = 1$.

The maximum throughput obtainable in this policy is

$$(1 - p) \min \left\{ E_\pi [X_k], g \left(\frac{E_\pi[Y]}{1 - p} - E_\pi [Z_k] - \epsilon \right) \right\}. \quad (11)$$

Thus, we find a p that maximizes this throughput. Since this is a maximization of a concave function, we can efficiently find the optimum p^* ([3]). It is possible that

$$E_\pi [X_k] > g \left(\frac{E_\pi[Y]}{1 - p^*} - E_\pi [Z_k] \right).$$

Then, the queue will be unstable. To make it stable, define γ as

$$(1 - \gamma)E_\pi [X_k] = g \left(\frac{E_\pi[Y]}{1 - p^*} - E_\pi [Z_k] \right) - \delta$$

for a positive δ .

The overall throughput optimal energy management and sleep policy is:

In slot k , sleep with probability p^* ,
otherwise, sleep if $E_k < Z_k$.

If awake, use

$$T_k = \min \left\{ E_k - Z_k, \frac{E_\pi[Y]}{1 - p} - E_\pi [Z_k] - \epsilon \right\}$$

and admit X_k to the queue with probability $1 - \gamma$ and drop otherwise.

If δ is picked small, we can have more throughput but we

will also have larger queue lengths.

If g is linear, we can get the parameters of the throughput optimal policy in closed form. If $g(x) = Kx$, then γ needed is zero and

$$p^* = \left(1 - \frac{KE_\pi[Y]}{E_\pi[X] + KE_\pi[Z] + K\epsilon} \right)^+.$$

The optimal throughput is $(1 - p^*)E_\pi[X]$. Also,

$$(1 - p^*)E_\pi[X] = K(E_\pi[Y] - (1 - p^*)(E_\pi[Z] + \epsilon)) \\ > K(E_\pi[Y] - (E_\pi[Z] + \epsilon))$$

when $p^* > 0$. From (5), $K(E_\pi[Y] - E_\pi[Z] - \epsilon)$ is the optimal throughput for a sensor that does not have sleep mode. Thus, when $E_\pi[X] > K(E_\pi[Y] - E_\pi[Z] - \epsilon)$, there is an increase in the optimal throughput by having a sleep mode. In the rest of the section, we will drop the subscript π from the notation.

Now, we provide an example to show the increase in throughput by allowing the sleep mode and the gain due to a non-zero γ . Consider three sensors: S_{NS} that does not have a sleep mode but can drop data, S_{ND} that has a sleep mode but does not drop sensed data, and S that has a sleep mode and can drop sensed data. So, S_{ND} does not accept bits that it cannot serve and thus avoids spending energy on sensing and processing such bits that might otherwise have to be dropped. Suppose $Z_k = h(X_k)$ for some function h . For simplicity, we consider a linear h : $h(x) = 0.1x + 0.1$. Fix $E[Y] = 1$ unit. It has been shown in [14] that the supremum of the achievable throughputs of sensor S_{NS} is $g((E[Y] - E[Z])^+)$. The optimal throughput for sensor S_{ND} is found by finding the optimal p that maximizes throughput after setting $\gamma = 0$ as an additional constraint; this value of p is given by

$$p^* = \left(1 - \frac{E[Y]}{g^{-1}(E[X]) + E[Z] + \epsilon} \right)^+.$$

The supremum of the achievable throughputs of sensors S_{ND} and S can be found by letting $\epsilon \nearrow 0$ and $\delta \nearrow 0$. Let $\tau_i^*(E[X])$ denote the supremum of the achievable throughputs of sensors $i = S_{NS}, S_{ND}$ and S .

In Fig. 5, we compare the supremum of achievable throughputs of the three sensors for a linear and a non-linear g . For $g(x) = \log(1 + x)$, we see that they are the same for $E[X] < 0.61$. From $E[X] \approx 0.61$, S_{NS} and S start to drop data and since S_{ND} cannot drop data, S_{ND} starts to sleep and uses more energy when awake. Since g is concave, this is inefficient when $E[Z_k]$ is small. Hence, $\tau_{S_{ND}}^*(E[X])$ is less. For $E[X] > 1.35$, $\tau_{S_{NS}}^*(E[X])$ is less than $\tau_S^*(E[X])$ since $E[Z_k]$ is large and staying awake results in spending more energy on sensing and processing leaving less energy for transmission of bits. For $E[X] \geq 9$, $\tau_{S_{NS}}^*(E[X]) = 0$. For $g(x) = 2x$, sensor S too does not drop any data (since γ needed is 0 for linear g) and so, $\tau_{S_{ND}}^*(E[X]) = \tau_S^*(E[X])$ for all $E[X]$. We see that for $E[X] > 1.5$, $\tau_{S_{NS}}^*(E[X]) < \tau_S^*(E[X])$ and for $E[X] \geq 9$, $\tau_{S_{NS}}^*(E[X]) = 0$.

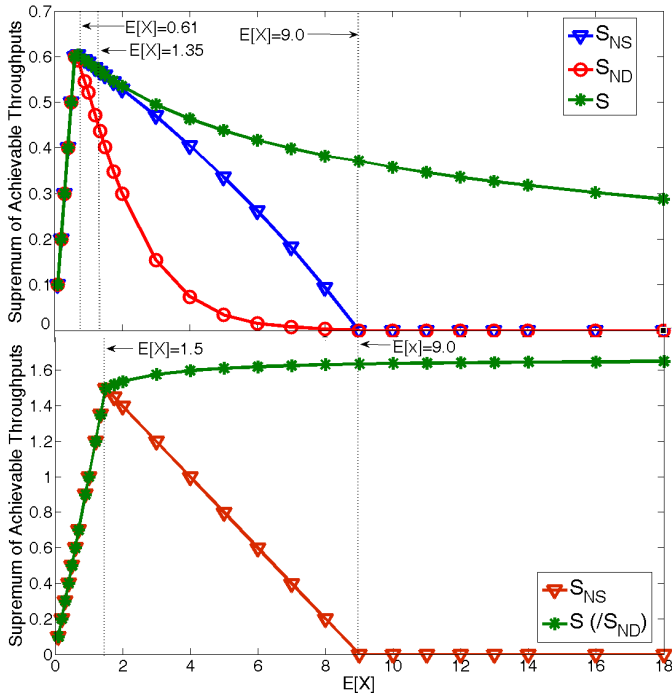


Fig. 5. Comparison of the maximum throughputs of S_{NS} , S_{ND} and S with $g(x) = \log(1+x)$ (Top) and $g(x) = 2x$ (Bottom)

A. Energy Threshold Policy as a Throughput Optimal Policy

The Throughput Optimal policy developed above corresponds to the Randomized Sleep Policy in Section III. It also has the drawback of high switching costs. Thus, it can be modified to obtain a policy corresponding to Energy Threshold policy in Section III. Now, the thresholds E_{T_1} and E_{T_2} should correspond to p^* obtained above. If $\{X_k\}$ and $\{Z_k\}$ are *i.i.d.*, this will again provide a Throughput Optimal Policy (along with γ) but with much lower switching costs.

V. CONCLUSIONS

We studied an energy harvesting sensor node with two modes: Wake and Sleep. We obtained energy management policies which minimize a linear combination of the mean queue length and the mean data loss rate. Then, we obtained two easily implementable suboptimal policies: Randomized Sleep Policy and Energy Threshold Policy, and via simulations their performance was found to be reasonably close to that of the Average Cost Optimal Policy. Next, we found a Throughput Optimal Policy that essentially uses a constant amount of energy for transmission in every slot it is awake. We also showed that using this policy, we can increase the throughput and stabilize the data queue by allowing the node to sleep in some slots and to drop some generated packets. Furthermore, this policy requires minimal statistical knowledge of the system parameters. We also modified this policy to decrease the switching costs.

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