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Energy Loss through Standby and Leakage in Energy Harvesting Wireless Sensors

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***Abstract*—We present a performance model for an energy harvesting wireless sensor node in which data gathering and harvesting are slow random processes as compared to fast wireless communications. We assume that the system will use stored energy when collecting data in standby, and that energy will leak from capacitors and batteries. In the presence of these imperfections we derive the system's packet transmission capacity when its packet storage buffer and its energy storage unit have a finite capacity that may lead to both data packet overflows, and the loss of incoming energy in addition to standby losses. We also consider an infinite capacity model which operates in the presence of transmission errors due to channel noise and interference.**

***Index Terms*—Wireless Sensors; Energy Harvesting; Data Collection; Energy Packets; Standby Energy Loss; Energy Leakage; Transmission Errors**

I. Introduction and Problem Setting

Many stand-alone autonomous systems, such as digital sensors in the Internet of Things, require unattended long term operation to operate remotely without the mains or a change of batteries, and are also motivated by the need to save energy from standard sources [1].

Thus energy harvesting from solar, thermal, vibrations, or ambient electromagnetic radiation including light, are of particular interest [2], [3], [4], [5]. Some recent systems have also been designed to harvest energy from vibrations, when the vibrations themselves are being sensed [6], as in roadside sensing equipment that counts passing vehicles, and transmits this information using the energy harvested from the vibrations caused by the vehicles. Then, when energy is harvested the manner in which it is exploited and scheduled for transmission needs to take into account both the harvesting process and the communication needs [7]. Another motivation comes from the estimate that ICT's electrical energy consumption just for system operation has now exceeded 5% of electrical energy production worldwide [8], [9], [10], and techniques have been devised for data packet routing in backbone networks so as to minimise the total energy consumed per packet that is conveyed [11].

The random workload from computer and communication systems, together with the discretised random energy flow from energy harvesting, had also been studied [12], [13] based on G-networks [14], [15], and similar systems had actually been implemented [16]. However the approach we follow here is based on a random walk approach initiated in [17], [18], and focus on the processes that collect energy and data, assuming that when there is enough energy and data, the wireless transmission is instantaneous. Our main generalisation from the previous work is that we consider the effect of *energy loss* due to *standby operation* of the sensor, as well as the loss due to leakage from batteries and capacitors.

The wireless sensor node we consider collects data packets (DPs) at random, at a rate λ from sensing activities. It also harvests energy at random, at rate Λ energy packets (EPs) per second, where one EP is the amount of electrical energy, e.g. in microjoules, that is needed to transmit one DP. Λ and λ are assumed to be small (i.e. very slow) compared to the speed of transmitting a packet via wireless, so that the transmission time is supposed to be negligible. The node stores energy in a capacitor or battery. Its energy is depleted either for packet transmission, or it is depleted by standby operation and battery leakage [19] at a rate μ EP/sec.

II. Mathematical Model

As in some of our recent work [17], [18], the state of the system is represented by $K(t)$, the number of DPs stored at the node, and $M(t)$ the number of EPs that are stored at at time $t \geq 0$. Since the transmission time at the node is very short, whenever energy is available and there are DPs waiting, the DPs will be instantaneously transmitted till the energy is depleted.

Thus from a state $K(t) > 0, M(t) > 0$ the system instantaneously moves to either state $(0, M(t) - K(t))$ if $M(t) \geq K(t)$, or to $(K(t) - M(t), 0)$ if $K(t) \geq M(t)$. Writing $p(n, m, t) = Prob[K(t) = n, M(t) = m]$, we therefore only consider $p(n, m, t)$ for pairs of integers $(n, m) \in S = \{ (0,0), (n,0), (0,m) : n > 0, m > 0 \}$. In some sense, this is similar to a synchronising "join" primitive between flows of parallel processes [20], when the join operation is instantaneous.

Recently, we studied an N node model, with a simpler representation of the DP and EP backlog, and we showed that a feed-forward two-hop case has a product form solution in steady-state [21]. Here we will study nodes subject to ongoing energy loss through standby power consumption and leakage from batteries and capacitors, *and* with transmissions corrupted by noise and mutual interference.

A. Markov Chain Representation

In the sequel we will assume that the DP arrivals and EP harvesting are independent Poisson processes, and that the process of standby and leakage loss is exponentially distributed. These assumptions are made in order to allow us to develop the tractable mathematical models we describe below.

If both the data buffer and the energy storage capacity are finite, the system can be modeled as a finite Markov chain with states (n, m) and $0 \leq n \leq B$, $0 \leq m \leq E$. Since process $[K(t), M(t), t \geq 0]$ is an irreducible and aperiodic Markov chain, the stationary probabilities $p(n, m) = \lim_{t\to\infty} Pr[K(t) = n, M(t) = m]$ satisfy:

$$\begin{aligned}
p(0,0)[\lambda + \Lambda] &= \Lambda p(1,0) + \lambda p(0,1) + \mu p(0,1), \\
p(n,0)[\lambda + \Lambda] &= \Lambda p(n+1,0) + \lambda p(n-1,0), \\
&\quad 0 < n < B.\ p(B,0)\Lambda = p(B-1,0)\lambda, \\
p(0,E)[\lambda + \mu] &= p(0,E-1)\Lambda, \\
p(0,m)[\lambda + \Lambda + \mu] &= \Lambda p(0,m-1) \\
&\quad + \lambda p(0,m+1) + \mu p(0,m+1),\ 0 < m < E,
\end{aligned}$$

with a solution of the form:

$$\begin{aligned}
p(n,0) &= \alpha^n C_d,\ \alpha = \frac{\lambda}{\Lambda}, \\
p(0,m) &= \theta^m C_e,\ \theta = \frac{\Lambda}{\lambda + \mu},
\end{aligned}$$

where C_d, C_e are constants, so that:

$$\begin{aligned}
p(0,0) &= \frac{1 - \alpha - \theta + \alpha\theta}{\alpha^{B+1}(\theta - 1) + \theta^{E+1}(\alpha - 1) + 1 - \alpha\theta}, \\
p(n,0) &= \alpha^n \frac{1 - \alpha - \theta + \alpha\theta}{\alpha^{B+1}(\theta - 1) + \theta^{E+1}(\alpha - 1) + 1 - \alpha\theta}, \\
&\qquad 0 \leq n \leq B, \\
p(0,m) &= \theta^m \frac{1 - \alpha - \theta + \alpha\theta}{\alpha^{B+1}(\theta - 1) + \theta^{E+1}(\alpha - 1) + 1 - \alpha\theta}, \\
&\qquad 0 \leq m \leq E.
\end{aligned}$$

When the energy storage capacity is finite, or the DP buffer is finite, we will have energy loss or DP loss. These loss rates L_e, L_d in EPs and DPs per second, respectively, are:

$$\begin{aligned}
L_e &= \Lambda\theta^E \frac{1 - \alpha - \theta + \alpha\theta}{\alpha^{B+1}(\theta - 1) + \theta^{E+1}(\alpha - 1) + 1 - \alpha\theta}. \\
L_d &= \lambda\alpha^B \frac{1 - \alpha - \theta + \alpha\theta}{\alpha^{B+1}(\theta - 1) + \theta^{E+1}(\alpha - 1) + 1 - \alpha\theta}.
\end{aligned}$$

B. Optimum Energy Efficiency of Transmissions

The sensor we consider receives Λ EPs/sec (in power units, e.g. milliwatts) from energy harvesting, and only effectively transmits $\lambda - L_d$ DP/sec. Thus its energy consumption per effectively transmitted packet is:

$$\sigma = \frac{\Lambda}{\lambda - L_d}. \tag{1}$$

Thus it is of interest to see what the best operating point may be for this system, in terms of the energy it is consuming. We therefore take the derivative of various terms in the expression with respect to Λ and see that:

$$\sigma' = \frac{\lambda - L_d + \Lambda.L'_d}{(\lambda - L_d)^2}, \tag{2}$$

so that the extremum for σ is reached for the value of Λ which gives:

$$L'_d = -\frac{\lambda - L_d}{\Lambda}. \tag{3}$$

In addition, we have

$$\sigma'' = \frac{\Lambda.L''_d(\lambda - L_d) - 2(\lambda - L_d + \Lambda.L'_d)L'_d}{(\lambda - L_d)^3},$$

so that at the value of Λ which satisfies (3) we have:

$$\sigma'' = 0,$$

so that (3) is a point of inflection of the efficiency function σ.

Figure(1) shows σ versus Λ for the case of $\lambda = 10$, $B = 100$ and $E = 100$, with several values of μ. We see that that to keep the energy efficiency high, i.e. to have σ as low as possible, the power

Λ that is supplied from harvesting should remain *below* the nominal need to satisfy all the flow λ of DPs that are being harvested.

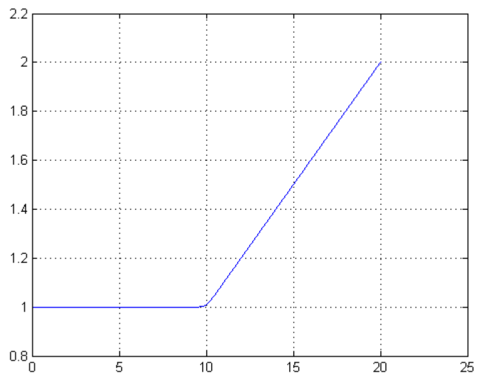

Fig. 1. The average energy consumed per data packet σ as a function of the harvested power Λ, for $\lambda = 10$, $B = 100$ and $E = 100$ for $\mu = 0.1$

III. Unlimited Data and Energy Buffers with Transmission Errors and Energy Loss

Now assume that **transmission errors** can occur due to (a) wireless interference, and in particular the interference caused by $N-1$ *other* wireless sensors that are in proximity of a given sensor, and (b) noise. Obviously Λ energy packets/sec expressed in units of power (i.e. milliwatts, etc.), flow into the wireless node via harvesting. When a transmission error is detected, the same DP will be *retransmitted* until an error-free transmission occurs or until energy is depleted.

Thus if a DP is waiting in queue and an EP arrives, the DP is is transmitted and a transmission error may occur with probability π, so that the DP is not deleted from the queue. Similarly, if a DP arrives to the node when one or more EPs are waiting, then a transmission error may occur with probability p and the transmission will be repeated independently with probability p until success occurs or until all the EPs are depleted. With the standby (and leakage) energy depletion rate μ, DP arrival rate λ and EP arrival rate Λ, we have the state transitions:

- $(0,m) \rightarrow (0,m-1)$, $(n,0) \rightarrow (n+1,0)$ and $(0,m) \rightarrow (0,m+1)$, respectively, and also:
- At rate $\Lambda\pi$ the transition $(n,0) \rightarrow (n,0)$ occurs when $n \geq 1$: an EP arrives to an empty energy buffer and since upon arrival of an EP, if another DP transmission is requested immediately just after a DP transmission with probability π, then due to lack of an EP, the new DP transmission will not be successful and will replace the previous one.
- Similarly $\Lambda(1-\pi)$ is the rate for the transition $(n,0) \rightarrow (n-1,0)$ *when* $n \geq 1$.
- At rate λp the transition $(0,1) \rightarrow (1,0)$ occurs when a DP arrives to an empty data buffer and a single EP is present, and after the DP transmission a second one is needed but no EP is present.
- The transition $(0,m) \rightarrow (0,m-1)$ *when* $m > 0$ at rate $\lambda(1-p)$, when a DP arrives to an empty data buffer and is served by an EP already in queue so that the number of EPs is reduced by 1. Likewise, the arrival of a DP may result in a sequence of k successive retransmissions due to successive errors starting from a state $(0,m)$, $m > 0$, with probability $p^k(1-p)$ where $m \geq k \geq 0$, so that $(0,m) \rightarrow (0,m-k)$ *when* $m \geq k > 1$.
- Finally, when the arrival of a DP to the system in state $(0,m)$ is one transmission and followed by $m-1$ retransmission requests, the DP's transmission depletes all EPs are depleted giving rise to the transition $(0,m) \rightarrow (1,0)$ with rate λp^m. Obviously $\sum_{k=0}^{m-1} p^k(1-p) + p^m = 1$.

The equilibrium equations for the system in steady-state then become:

$$p(0,0)[\lambda+\Lambda] = \lambda\sum_{l=1}^{\infty} p^{l-1}(1-p)p(0,l) + \Lambda(1-\pi)p(1,0) + \mu p(0,1),$$
$$p(1,0)[\lambda+\Lambda(1-\pi)] = \lambda\sum_{l=0}^{\infty} p^{l}p(0,l) + \Lambda(1-\pi)p(2,0), \quad (4)$$
$$p(n,0)[\lambda+\Lambda(1-\pi)] = \lambda p(n-1,0) + \Lambda(1-\pi)p(n+1,0),\ n>1,$$
$$p(0,m)[\lambda+\Lambda+\mu] = \lambda\sum_{l=1}^{\infty} p^{l-1}(1-p)p(0,m+l) + \Lambda p(0,m-1) + \mu p(0,m+1),\ m>0.$$

IV. Analytical Results

We start with a preliminary result. In the model we use, each time a packet is transmitted, an EP is consumed of which a fraction c is radiated, and $(1-c)$ is dissipated in the node's electronics. The power radiated is then a fraction c of an EP, divided by the interarrival time that triggered the transmission, which is either λ^{-1} or Λ^{-1}, depending on whether the transmission was triggered by the arrival of a DP or the arrival of an EP.

Lemma 1 If $\lambda < \Lambda$, then it follows that $p > \pi$.

Proof: Assume that the i-th sensor is operating in proximity to other wireless devices, and its designated receiver encounters an *interference plus noise* whose total power (at the receiver) is $I + B$, where B, I is the interference power from other wireless transmissions at the designated receiver of the i-th sensor, while B is the noise at the receiver. If the i-the sensor transmitter radiates an amount of power P to transmit a data packet, the resulting error probability at the designated receiver will be of the form [22]:

$$e = 1 - f(\frac{\kappa P}{I + B}), \quad (5)$$

where κ is the fraction of transmitter power that reaches the receiver, and $f(x) \geq 0$, $0 \leq f \leq 1$, is a function that represents the probability of *correct* reception of a packet which *strictly increases* with its argument x. We know that packet transmissions can occur either on arrival of:

- A DP, which occurs at rate λ so that c EPs energy are radiated in time radiates at rate $\frac{1}{\lambda}$, i.e. an amount $c\lambda$ in units of power each time it attempts to transmit a DP, resulting in an error probability
$$p = 1 - f(\frac{c\kappa\lambda}{I + B}), \quad (6)$$
- An EP, occurring at rate Λ so that c energy packets are radiated into the channel in time $\frac{1}{\Lambda}$, so that the amount of power radiated is $c\Lambda$ to attempt to transmit a DP, and
$$\pi = 1 - f(\frac{c\kappa\Lambda}{I + B}). \quad (7)$$

Thus since $\lambda < \Lambda$, it follows from (6) and (7) that $p > \pi$.

The next theorem generalises the main result in [17] to the case where energy is depleted both through *standby energy depletion* and by DP transmissions:

Theorem 1 If $(\Lambda - \mu)(1-p) < \lambda < \Lambda(1-\pi)$, and $p,\ \pi < 1$ then:
- $\lambda < \Lambda$ and by Lemma 1 we have $p > \pi$.
- Also, the stationary probability distribution corresponding to the equilibrium equations (4) exists and is given by:
$p(0,m) = p(0,0)Q^m,\ m \geq 0,$
$p(n,0) = p(1,0)q^{n-1},\ n \geq 1,$ where:
$q = \frac{\lambda}{\Lambda(1-\pi)}$, $Q = \frac{\lambda+\mu+\Lambda p - \sqrt{(\lambda+\mu+\Lambda p)^2 - 4\mu\Lambda p}}{2\mu p}$,
$p(0,0) = \frac{(1-q)(1-Q)(1-pQ)}{q(1-Q)+(1-q)(1-pQ)}$, $\frac{p(1,0)}{p(0,0)} = \frac{q}{(1-pQ)}$.

Proof Substituting the proposed solution in the balance equations, after some algebra we get:

$$Q^m[\lambda + \Lambda + \mu] = \lambda(1-p)Q^{m+1}\frac{1}{1-pQ} + \Lambda Q^{m-1} + \mu Q^{m+1},$$
$$0 = (Q-1)[Q^2(\mu p) + Q(-\Lambda p - \lambda - \mu) + \Lambda],$$

whose roots are $Q_{1,2} = \frac{\lambda+\mu+\Lambda p \pm \sqrt{(\lambda+\mu+\Lambda p)^2 - 4\mu\Lambda p}}{2\mu p}$. But $Q_1 > 1$, since:

$$\frac{\lambda+\mu+\Lambda p + \sqrt{(\lambda+\mu+\Lambda p)^2 - 4\mu\Lambda p}}{2\mu p} \geq \frac{\lambda+\mu+\Lambda p}{2\mu p} > \frac{1}{2}(\frac{1}{p} + \frac{\Lambda}{\mu}).$$

Since $p < 1$ and $\mu < \Lambda$, the root Q_1 should not be considered, and Q_2 is the only viable root. Since we must have $Q_2 < 1$, we have $(\Lambda - \mu)(1-p) < \lambda$.

Also we must have $q < 1$ and note that (4) has a solution of the form below for a constant $C > 0$:

$$p(n,0) = q^{n-1}C,\ where\ q = \frac{\lambda}{\Lambda(1-\pi)}, C = p(1,0).$$

Thus, $\lambda < \Lambda(1-\pi)$, which completes the proof. After further analysis, and with $q < 1$, $Q < 1$, we also obtain:

$$p(0,0) = \Big(\frac{\frac{2\mu\lambda}{(\Lambda(1-\pi)-\lambda)}}{[\mu - \lambda - \Lambda p + \sqrt{(\lambda+\Lambda p+\mu)^2 - 4\mu\Lambda p}]} + \frac{2\mu p}{2\mu p - (\lambda+\Lambda p+\mu) + \sqrt{(\lambda+\mu+\Lambda p)^2 - 4\mu\Lambda p}}\Big)^{-1}.$$

Remark 1 We know that we will operate with $p > \pi$; but if $p \approx \pi$ and $\mu << \Lambda$ then by Theorem 1, the values of λ and Λ also need to be very close to each other for the system to be stable.

Remark 2 If $\mu << \Lambda$ then

$$Q \approx \frac{\Lambda}{\lambda + \mu + p\Lambda}. \quad (8)$$

Remark 3 The power used by a node for transmission, including that which is used in its internal electronics, is simply the power entering the node from harvesting, minus that which is lost through leakage:

$$X = [\Lambda - \mu\sum_{m=1}^{\infty} p(0,m)] = [\Lambda - \frac{\mu Q(1-q)(1-pQ)}{1 - Q(p+q-pq)}], \quad (9)$$

while the average energy used per transmitted packet is simply the power consumed by the system divided by the transmission rate of DPs, namely $\sigma = \Lambda/\lambda$.

Now consider that a particular sensor, say the i-th, is operating in proximity with a total number of

N identical sensors, each radiating on average cX power where X is defined in (9), so that we write (6) and (7) as:

$$p = 1 - f(\frac{c\kappa\lambda}{c\kappa(N-1)X + B}), \quad (10)$$

$$\pi = 1 - f(\frac{c\kappa\Lambda}{c\kappa(N-1)X + B}), \quad (11)$$

where κ is a factor representing the reduction of interference power reaching the receiver.

A. A numerical example

If A collection of N sensors is placed in relatively close proximity of each other, for instance when the temperature of several rooms in a building or house is being monitored, the power emitted by each sensor interferes with the DP transmissions of other sensors as mentioned previously. Assuming a standard BPSK modulated coding transmission scheme is used [22], when each DP consists of n independent binary symbols which are transmitted over the channel with noise and interference, but without a specific error correcting code, the receiver will decode each binary symbol separately and the DP is decoded successfully if all the bits are decoded correctly. The probability of correctly decoding each binary symbol is [22]:

$$1 - Q(\sqrt{\frac{\kappa P}{I + B}}). \quad (12)$$

where $Q(x) = \frac{1}{2}[1 - erf(\frac{x}{\sqrt{2}})]$, and the function f for this transmission scheme is:

$$f(x) = [1 - Q(\sqrt{x})]^n, \quad (13)$$

It follows from (13) that:

$$p = 1 - [1 - Q(\sqrt{\frac{c\kappa\lambda}{c\kappa(N-1)X + B}})]^n, \quad (14)$$

$$\pi = 1 - [1 - Q(\sqrt{\frac{c\kappa\Lambda}{c\kappa(N-1)X + B}})]^n. \quad (15)$$

We observe that $f(0) = 2^{-n} > 0$ for this specific transmission scheme, i.e. the receiver can reconstruct the symbols correctly with a very small positive probability even if no transmission occurred, but f(0) approaches zero with big n.

Although closed-form expressions for the transmission errors p and π are elusive, their values can be found numerically. As an example, if $\lambda = 12$, $\Lambda = 20$, $\mu = 10$, $c = \kappa = 0.5$, $N = 11$ and $B = 1$, with $n = 1$ we have $p = 0.4024$ and $\pi = 0.3748$.

V. Conclusions

This paper analyses the performance of wireless sensors that gather both data and energy, so that they may operate autonomously. A stochastic model of the harvested energy, and of the sensor's data gathering, is considered in terms of Poisson flows of data (DP) and energy (EP) packets. In addition, we include the effect of energy loss through standby operation, and battery or capacitor leakage, which is represented by an exponentially distributed decay rate. Based on this model, where an EP is the minimum amount of energy required to transmit a data packet, we consider two variants.

In the first model, transmission errors do not occur, but the data buffer is finite, as is the battery storage capacity A closed form solution for all the quantities of interest is obtained, including the loss rate of energy and data due to the fact that both the battery and data buffer have finite capacity. We also discuss the issue of energy efficiency to understand the appropriate operating point that would use the minimum amount of energy consumed per transmitted packet. The second model still includes energy losses, but assumes that the DP buffer, and energy storage capacity, are unlimited. This is a useful idealisations when the capacities are very large. However this latter model introduces the interesting question of stability. The model also incorporates transmission error probabilities due to noise and interference. This analysis also allows us to explicitly compute the error probabilities, when N wireless sensors operate in proximity to each other. Future work will address the network case, when the wireless devices are interconnected, and DPs can travel over multiple hops, and also study cases where sensible routing [23] may be based on the availability of energy at specific nodes.

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