Energy Efficient Transmission Strategies for Body Sensor Networks with Energy Harvesting

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***Abstract*—This paper addresses the problem of developing energy efficient transmission strategies for Body Sensor Networks (BSNs) with energy harvesting. It is assumed that multiple transmission modes that allow a tradeoff between the energy consumption and packet error probability are available to the sensor nodes. Taking into account the energy harvesting capabilities of the nodes, decision policies are developed to determine the transmission mode to use at a given instant of time in order to maximize the quality of coverage. The problem is formulated as a Markov Decision Process (MDP) and the performance of the transmission policy thus derived is compared with that of energy balancing as well as aggressive policies. An upper bound on the performance of arbitrary policies, and lower bounds specific to energy balancing and aggressive policies are derived.**

I. Introduction

Many applications and services are expected to significantly benefit from the monitoring and data collection services that will be provided by BSNs. These include medical applications such as diagnostic techniques, health and stress monitoring, management of chronic diseases, and patient rehabilitation, as well as non medical applications such as biometrics, activity monitoring and learning, and sports and fitness tracking [1].

A major hurdle for the wide adoption of BSN technology is the energy supply [2]. Current battery technology does not provide a high enough energy density to develop BSN nodes with sufficiently long life and acceptable cost and form factor. Moreover, the relatively slow rate of progress in battery technology (compared to computing and communication technologies) does not promise battery driven BSN nodes in the near future [3]. Furthermore, replacing batteries is simply not an option in some cases, such as implanted BSN nodes. The most promising approach to deal with the energy supply problem for BSNs is energy harvesting or energy scavenging [1]. In this approach, nodes have an energy harvesting device that collects energy from ambient sources such as vibration and motion, light, and heat. However, to improve the performance of energy harvesting BSNs to a level that can be widely adopted, progress needs to be made both in energy harvesting techniques and communication protocols. Harvesting aware communication techniques that take into account and exploit the energy harvesting characteristics are particularly needed to optimize the operation of BSNs.

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This paper considers the problem of scheduling transmissions in BSNs with energy harvesting. The nodes are assumed to have the ability to choose from a set of available transmission modes, with each scheme consuming a different amount of energy. However, each scheme has a packet error probability that is a decreasing function of the energy used on transmission. The paper then develops solutions to answer the following question: *which transmission mode should be used for a given data packet so that the probability that the node does not have any energy to report future events when they occur is minimized while maximizing the likelihood of data reports being correctly transmitted?* While this paper is structured around BSNs, our framework can be applied to any wireless network based on energy harvesting devices.

This paper presents adaptive transmission policies that aim to maximize the likelihood of sensor nodes detecting and correctly reporting events of interest. The policies developed exploit the nodes' knowledge of its current energy level and the state of the processes governing the generation of data and battery recharge to select the appropriate transmission mode for a given state of the system. The transmission scheduling problem is then formulated as a MDP and the performance of the solution thus obtained is compared with two other strategies: energy balancing and aggressive. An upper bound on the performance of any arbitrary policy is obtained along with lower bounds for the energy balancing and aggressive policies. Simulations are used to compare the performance of the three policies.

The rest of the paper is organized as follows. Section II presents an overview of the related work and Section III describes the system model. Upper bounds on the performance of arbitrary transmission policies are developed in Section IV while Sections V and VI present bounds specific to the energy balancing and aggressive policies. A MDP formulation of the problem is presented in Section VII, simulation results are presented in Section VIII and Section IX concludes the paper.

II. Related Work

The use of energy harvesting has been proposed in the general framework of wireless sensor networks (WSNs) as well as for BSNs. However, existing results concerning the communication techniques for energy harvesting networks are limited. Furthermore, existing literature generally addresses the problem in the context of large scale WSNs. The problem of duty-cycling in general sensor networks with energy harvesting is considered in [5], [6]. In [7] it is shown that using cooperative automatic repeat request (ARQ) protocols, sensor nodes can match their energy consumption to their energy harvesting rate, thereby improving the throughput. The authors of [8] address the problem of sensor activation with battery recharging assuming temporally correlated events.

Existing work on energy aware communications for BSNs focus on battery operated sensors and do not consider energy harvesting [9], [10], [11]. The design requirements for BSNs are considerably different from those of large scale sensor networks. This is due to the specific characteristics of BSNs, such as traffic patterns, QoS requirements, and energy harvesting methods. To the best of our knowledge, there is no prior work on transmission policies for energy harvesting BSNs.

III. System Model

The network is considered to consist of a single, special device (e.g. cell phone or personal digital assistant) carried by the patient that acts as the base station or gateway, and a number of sensor nodes that are deployed on the patient's body. A star topology is assumed where each node directly communicates with the gateway. The gateway collects the data from all nodes and conveys it to the medical center or doctor. Since the gateways are not as energy critical as the sensor nodes (they have higher capacity batteries that are also easily replaced or recharged), our focus is only on the sensors.

We consider a discrete time model with time slotted in intervals of unit length. A slot is long enough to transmit one data packet and at most one data packet is generated in a slot. Each sensor node has a rechargeable battery and an associated energy harvesting device. The energy generation process of the node is modeled by a correlated, two-state process. In its on state (i.e. when ambient conditions are conducive to energy harvesting), the node generates energy at a constant rate of c units per time slot. In the off state, no energy is generated. If the node harvested energy in the current slot, it harvests energy in the next slot with probability q_{on}, with $0.5 < q_{on} < 1$, and no energy is harvested with probability $1 - q_{on}$. On the other hand, if no energy was harvested in the current slot, energy is harvested (not harvested) in the next slot with probability $1 - q_{off}$ (q_{off}), $0.5 < q_{off} < 1$. q_{on} and q_{off} are assumed to be greater than 0.5 to capture the positive time correlations in the physical processes behind energy harvesting [3], [4]. The two-state energy harvesting model captures the ambient characteristics governing the operation of vibration, motion and light based based energy harvesting devices [1], [3], [4]. Our models may be easily extended to harvesting models with additional states. To keep the analysis tractable, we assume that the battery capacity of each node is infinite. This assumption is relaxed in Section VII.

The process governing the generation of events (i.e. data packets) that the sensor nodes report to the sink are also governed by a correlated, two-state process. If an event is generated in the current slot, another event is generated (respectively, not generated) in the next slot with probability p_{on} (respectively, $1 - p_{on}$), $0.5 < p_{on} < 1$. Similarly, if no event is generated in the current slot, an event is generated (respectively, not generated) in the next slot with probability $1 - p_{off}$ (respectively, p_{off}), $0.5 < p_{off} < 1$. This two state model captures the transient physiological phenomena associated with many medical conditions of interest to health care professionals [12], [13]. Also, the assumption of atmost one event per slot is justified because of the small data packet size and sampling rates of physiological sensors. The probability that there are i continuous time slots with events is $P[N = i] = (p_{on})^{i-1}(1 - p_{on})$ and the average length of a period of continuous events is

$$E[N] = \sum_{i=1}^{\infty} i(p_{on})^{i-1}(1 - p_{on}) = \frac{1}{1 - p_{on}} \quad (1)$$

and the steady-state probability of event occurrence is

$$\pi_{on} = \frac{1 - p_{off}}{2 - p_{on} - p_{off}}. \quad (2)$$

Similarly, the average length of a period without events is $\frac{1}{1-p_{off}}$ and $\pi_{off} = 1 - \pi_{on}$. Along the same lines, the average length of a period with energy harvesting and the steady-state probability of such events are $\frac{1}{1-q_{on}}$ and $\mu_{on} = \frac{1-q_{off}}{2-q_{on}-q_{off}}$, respectively. Finally, the expected length of periods without recharging and its steady-state probability are $\frac{1}{1-q_{off}}$ and $\mu_{off} = 1 - \mu_{on}$, respectively.

In each slot, a node consumes δ_0 units of energy to run its circuits. Additional energy is expended if a node transmits data. Each node is assumed to be able to communicate using K transmission modes: "transmission mode i" consumes δ_i units of energy on the modulation, coding and transmission and achieves an expected packet error rate of $1 - \rho_i$. Each ρ_i includes the effects of channel impairments like fading, and collisions. We have $\delta_i > \delta_j$ and $\rho_i > \rho_j$ for $1 \le i < j \le K$, allowing a tradeoff between the energy consumed and reliability. For many medical applications it is more important to deliver the most recent data without delay rather than queue them behind retransmission attempts. In these scenarios, delayed data loses much of its value in the presence of more recent data. Since data is generated in continuous bursts in our model, no retransmissions are attempted for packets with error. Also, a node is considered available for operation if its available energy is greater than $\delta_0 + \delta_K$. If a node's energy level falls below this threshold, it moves to the *dead* state where it is incapable of detecting and reporting events and stays there until it harvests enough energy. A node does not spend any energy in the dead state.

The communication strategy of a sensor node is governed by a policy Π that decides on the transmission mode to be used for reporting an event. The action taken by the node in time slot t is denoted by a_t with $a_t \in \{0, 1, 2, \cdots, K\}$ denoting no transmission, and transmissions with mode 1, 2 and so on, respectively. The decision may be based on the current battery level of the node and the states of the recharge as well as the event generation process, with the basic objective of maximizing the *quality of coverage*, defined as follows. Let $\mathcal{E}_o(T)$ denote the number of events that occurred in the sensing region of the sensor over a period of T slots in the interval $[0, T]$. Let $\mathcal{E}_d(T)$ denote the total number of events that are detected and correctly reported by the node over the same period under policy Π. The time average of the fraction of events detected and correctly reported represents the quality of coverage and is given by

$$U(\Pi) = \lim_{T\to\infty} \frac{\mathcal{E}_d(T)}{\mathcal{E}_o(T)}. \tag{3}$$

The models developed in this paper can be extended to cover scenarios with packet priorities and QoS requirements by appropriately changing the objective function.

IV. An Upper Bound on the Performance

This section presents an upper bound on the performance of any possible operating policy (using a technique in [8]). Let T_1 be the number of slots in which a node was alive (i.e. not in the dead state) over the period $[0,T]$ consisting of T slots under the optimal policy Π_{OPT}. Let $P_S(t)$ denote the success probability of the node at time slot t under policy Π_{OPT}. $P_S(t)$ signifies the probability that an event occurs in time slot t and is successfully reported given that the node was not in the dead state in slot t. We define $P_S(t) = 0$ if the node is in the dead state in time t. The steady-state success probability is denoted by $\bar{P}_S$ and is

$$\bar{P}_S = \lim_{T\to\infty} \sum_{t=1}^{T} \frac{P_S(t)}{T_1}. \tag{4}$$

Since $\bar{P}_S$ is the steady-state probability of detecting and successfully reporting an event we also have

$$\bar{P}_S = \lim_{T\to\infty} \frac{\mathcal{E}_d(T)}{T}. \tag{5}$$

Let ρ_t denote the probability that a transmission attempt in slot t is successful and E_t (E_t^c) denote the event that a data packet to be reported is (not) generated in slot t. We denote by γ_i, $0 \le i \le K$, the fraction of slots with data events in which the policy takes action a_i. The probability of successfully detecting and reporting an event at time $t+1$ is given by

$$\begin{aligned}
P_S(t) &= P[E_t, \rho_t \mid a_t] = \frac{P[E_t, \rho_t, a_t]}{P[a_t]} \\
&= \frac{1}{P[a_t]} \left[P[E_t, \rho_t, a_t|E_{t-1}]P[E_{t-1}] \right.\\
&\quad \left. + P[E_t, \rho_t, a_t|E^c_{t-1}]P[E^c_{t-1}]\right] \\
&= \frac{1}{P[a_t]} \left[P[E_t, \rho_t|a_t, E_{t-1}]P[a_t|E_{t-1}]P[E_{t-1}] \right.\\
&\quad \left. + P[E_t, \rho_t|a_t, E^c_{t-1}]P[a_t|E^c_{t-1}]P[E^c_{t-1}]\right] \\
&= \frac{\sum_{i=1}^{K}\gamma_i\rho_i}{P[a_t]} \left[p_{on}P[a_t, E_{t-1}] + (1-p_{off})P[a_t, E^c_{t-1}]\right] \\
&\le p_{on} \left[\sum_{i=1}^{K} \gamma_i\rho_i\right] \left[P[E_{t-1}|a_t] + (1 - P[E_{t-1}|a_t])\right) \\
&= p_{on} \sum_{i=1}^{K} \gamma_i\rho_i.
\end{aligned} \tag{6}$$

where the inequality results from the fact that $1 - p_{off} \le p_{on}$ for $0.5 < p_{on}, p_{off} < 1.0$. Thus we have

$$\bar{P}_S \le p_{on} \sum_{i=1}^{K} \gamma_i\rho_i. \tag{7}$$

Let $Q_S(t)$ denote the probability that an event occurs in time slot t and a transmission is attempted for it (irrespective of the outcome of the transmission) given that the node is alive and let $\bar{Q}_S$ denote the steady-state probability of such events. Following along the lines of the derivation of $P_S(t)$, we have

$$\begin{aligned}
Q_S(t) = P[E_t \mid a_t] &= p_{on}P[E_{t-1}|a_t] + (1-p_{off})P[E^c_{t-1}|a_t] \\
&\le p_{on}P[E_{t-1}|a_t] + p_{on}(1 - P[E_{t-1}|a_t]) = p_{on}
\end{aligned}$$

and thus $\bar{Q}_S \le p_{on}$. Also, $\bar{P}_S \le \bar{Q}_S$ since $\bar{P}_S$ is the steady state probability of events being *successfully* reported while $\bar{Q}_S$ corresponds to all events for which transmissions are attempted. We denote the available energy at the node at the beginning of slot t by L_t and assume that the initial charge in the node was L_0. The expected charge level of the node at slot T is then given by

$$E[L_T] = L_0 + T_1 \left[\mu_{on}c - \delta_0 - \bar{Q}_S \sum_{i=1}^{K} \gamma_i\delta_i\right] + (T - T_1)\mu_{on}c \tag{8}$$

Rearranging the terms and using the facts that $E[L_T] \ge 0$ and $\bar{P}_S \le \bar{Q}_S$ we have

$$\lim_{T\to\infty} \frac{T_1}{T} \le \frac{\mu_{on}c}{\delta_0 + \bar{Q}_S(\sum_{i=1}^{K} \gamma_i\delta_i)} \le \frac{\mu_{on}c}{\delta_0 + \bar{P}_S(\sum_{i=1}^{K} \gamma_i\delta_i)} \tag{9}$$

Now, as $T \to \infty$, the number of event occurrences in the interval $[0,T]$ satisfies

$$\lim_{T\to\infty} \frac{\mathcal{E}_o(T)}{T} = \pi_{on} = \frac{1 - p_{off}}{2 - p_{on} - p_{off}}. \tag{10}$$

Combining Eqns. (5), (9) and (10) we have

$$\begin{aligned}
U(\Pi_{OPT}) &= \lim_{T\to\infty} \frac{\mathcal{E}_d(T)}{\mathcal{E}_o(T)} = \frac{\bar{P}_S}{\pi_{on}} \lim_{T\to\infty} \frac{T_1}{T} && (11)\\
&\le \left[\frac{1}{\pi_{on}}\right] \frac{\bar{P}_S\mu_{on}c}{\delta_0 + \bar{P}_S(\sum_{i=1}^{K} \gamma_i\delta_i)}. && (12)
\end{aligned}$$

Differentiating $U(\Pi_{OPT})$ with respect to $\bar{P}_S$ we have

$$\frac{dU(\Pi_{OPT})}{d\bar{P}_S} = \frac{\mu_{on}c}{\pi_{on}} \left[\frac{\delta_0}{(\delta_0 + \bar{P}_S(\sum_{i=1}^{K} \gamma_i\delta_i))^2}\right] > 0. \tag{13}$$

Thus $U(\Pi_{OPT})$ is a non-decreasing function of $\bar{P}_S$. From Eqns. (7) and (12) we then have

$$\begin{aligned}
U(\Pi_{OPT}) &\le \left[\frac{1}{\pi_{on}}\right] \frac{p_{on}(\sum_{i=1}^{K} \gamma_i\rho_i)\mu_{on}c}{\delta_0 + p_{on}(\sum_{i=1}^{K} \gamma_i\rho_i)(\sum_{i=1}^{K} \gamma_i\delta_i)} \\
&\le \left[\frac{1}{\pi_{on}}\right] \frac{p_{on}\rho_1\mu_{on}c}{\delta_0 + p_{on}\rho_K\delta_K}. && (14)
\end{aligned}$$

A. Fast Recharge Scenario

The bound provided in Eqn. (14) can be fairly loose if the recharge rate of the node is fast compared to its discharge rate. This fast recharge scenario is characterized by the condition $\mu_{on}c > \delta_0 + \bar{Q}_S(\sum_{i=1}^{K} \gamma_i\delta_i)$. This subsection evaluates a tighter bound for these scenarios.

Result 1: In the fast recharge scenarios where $\mu_{on}c > \delta_0 + \bar{Q}_S(\sum_{i=1}^{K} \gamma_i\delta_i)$, the performance of any policy is bounded by

$$U(\Pi_{OPT}) \le \frac{\left[(1 - p_{off})\mu_{on}c + (p_{on} + p_{off} - 1)\pi_{on}\delta_0\right]\rho_1}{\pi_{on}[\delta_0 + (1 - p_{off})\rho_K\delta_K]}. \tag{15}$$

Proof: The optimal policy should schedule its transmissions such that it should have enough energy to be alive in all slots in which events to be reported are generated. Consider the fraction of slots T_1 in which the node is alive. Then under the optimal policy

$$T_1 \bar{P}_S = T\pi_{on} p_{on} \sum_{i=1}^{K} \gamma_i \rho_i + (T_1 - T\pi_{on})(1 - p_{off}) \sum_{i=1}^{K} \gamma_i \rho_i \tag{16}$$

because only $T\pi_{on}$ of the slots can have an event with probability p_{on} while the remaining $T_1 - T\pi_{on}$ slots generate events with probability $1 - p_{off}$. Now, the fast recharge condition along with $T \geq T_1$ implies

$$\begin{aligned} T\mu_{on} c \ &\geq\ T_1\delta_0 + T_1 \bar{Q}_S \textstyle\sum_{i=1}^{K} \gamma_i \delta_i \ \geq\ T_1\delta_0 + T_1 \bar{P}_S \textstyle\sum_{i=1}^{K} \gamma_i \delta_i \\ &=\ T_1\delta_0 + [T_1(1 - p_{off}) + T\pi_{on}(p_{on} + p_{off} - 1)] \\ &\qquad \textstyle\sum_{i=1}^{K} \gamma_i \rho_i \sum_{j=1}^{K} \gamma_j \delta_j. \end{aligned} \tag{17}$$

Rearranging the terms on the equation above gives

$$\frac{T_1}{T} \leq \frac{\mu_{on} c - \pi_{on}(p_{on} + p_{off} - 1)(\sum_{i=1}^{K} \gamma_i \rho_i)(\sum_{i=1}^{K} \gamma_i \delta_i)}{\delta_0 + (1 - p_{off})(\sum_{i=1}^{K} \gamma_i \rho_i)(\sum_{i=1}^{K} \gamma_i \delta_i)}. \tag{18}$$

Using Eqn. (16), the quality of coverage of the optimal policy is given by

$$\begin{aligned} U(\Pi_{OPT}) &= \lim_{T\to\infty} \frac{T_1}{T} \frac{\bar{P}_S}{\pi_{on}} \\ &= \lim_{T\to\infty} \frac{T\pi_{on} p_{on} \sum_{i=1}^{K} \gamma_i \rho_i + (T_1 - T\pi_{on})(1 - p_{off}) \sum_{i=1}^{K} \gamma_i \rho_i}{T\pi_{on}} \\ &= (p_{on} + p_{off} - 1) \sum_{i=1}^{K} \gamma_i \rho_i + \frac{(1 - p_{off})(\sum_{i=1}^{K} \gamma_i \rho_i)}{\pi_{on}} \lim_{T\to\infty} \frac{T_1}{T}. \end{aligned}$$

Substituting Eqn. (18) in the equation above then gives

$$U(\Pi_{OPT}) < \frac{[(1 - p_{off})\mu_{on} c + (p_{on} + p_{off} - 1)\pi_{on}\delta_0]\, \rho_1}{\pi_{on}\, [\delta_0 + (1 - p_{off})\rho_K \delta_K]} \tag{19}$$

which completes the proof. ∎

V. Energy Balancing Policies

The energy harvested by the node is used for two purposes: running the sensing and other onboard electronics and for communication. To utilize the available energy efficiently, one strategy is to use an energy balancing (or energy neutral) policy, Π_{EB}, that assigns the fraction of slots γ_i such that the total energy spent equals the energy generated, while maximizing the likelihood of detecting and reporting events without errors. This section develops and evaluates the performance of energy balancing policies.

To develop an energy-balancing policy, we first consider the behavior of the process governing the events to be reported. This process strictly alternates between periods with events (*on state*) and periods without events (*off state*). The instances when the event process enters the off state can be considered renewal instants of the event process state. The expected length of a renewal period is given by

$$E[T_R] = \frac{1}{1 - p_{on}} + \frac{1}{1 - p_{off}} = \frac{2 - p_{on} - p_{off}}{(1 - p_{on})(1 - p_{off})}. \tag{20}$$

The expected energy generated in a renewal period is then

$$E[C] = \mu_{on} c E[T_R] = \mu_{on} c \frac{2 - p_{on} - p_{off}}{(1 - p_{on})(1 - p_{off})}. \tag{21}$$

Now, the node may not have enough energy to be alive in all the slots in a renewal period and may thus be in the dead state in those slots. Then, the maximum possible energy that may be spent on running the on-board electronics of the node during a renewal period of $E[T_R]$ slots is $\delta_0 E[T_R]$. The expected amount of energy available for communications is thus at least

$$E[A] \geq \mu_{on} c E[T_R] - \delta_0 E[T_R] = (\mu_{on} c - \delta_0) \frac{2 - p_{on} - p_{off}}{(1 - p_{on})(1 - p_{off})}. \tag{22}$$

The expected number of events to be reported in a renewal period is $E[N]$ as given in Eqn. (1) and the expected number of events correctly reported in a renewal period is $E[N] \sum_{i=1}^{K} \gamma_i \rho_i$. The number of events detected and correctly reported in the period $[0, T]$ is then

$$\mathcal{E}_d(T) = \frac{\sum_{i=1}^{K} \gamma_i \rho_i}{1 - p_{on}}\ \frac{T}{E[T_R]}. \tag{23}$$

Also, since the steady state probability of event generation is π_{on}, the number of events generated in the period $[0, T]$ is $\mathcal{E}_o(T) = \pi_{on} T$. The performance of the policy is then

$$U(\Pi_{EB}) \ = \ \frac{\sum_{i=1}^{K} \gamma_i \rho_i}{\pi_{on}(1 - p_{on})}\ \frac{1}{E[T_R]} \ = \ \sum_{i=1}^{K} \gamma_i \rho_i. \tag{24}$$

To obtain a bound on the performance, arrange the ratios $\frac{\rho_i}{\delta_i}$ in decreasing order. Let ϕ be a function that maps the transmission modes to their respective position in the ordered list, i.e., ϕ_j denotes the transmission mode that is in the j-th position in the ordered list. Also, we define i^* as to denote the mode with the best ratio of $\frac{\rho}{\delta}$, i.e.

$$i^* \ = \ \phi_1 \ = \ \arg \max_{1\leq i\leq K} \left\{ \frac{\rho_i}{\delta_i} \right\}. \tag{25}$$

Consider the set $\mathcal{S} = \{s_0, s_1, s_2, \cdots, s_\kappa\}$ such that $s_0 = i^*$ and

$$s_i = \arg \max_{1\leq j< s_{i-1}} \left\{ \frac{\rho_j - \rho_{s_{i-1}}}{\delta_j - \delta_{s_{i-1}}} \right\}. \tag{26}$$

The number of elements in $\mathcal{S}$ (or κ) depends on the ρ_i's and δ_i's of the various modes. Define

$$\nu \ = \ \arg \min_{s_i\in\mathcal{S}} \left\{ \delta_{s_i} : \frac{\delta_{s_i}}{1 - p_{on}} \leq E[A] \right\} \tag{27}$$

$$\theta \ = \ \arg \max_{s_i\in\mathcal{S}} \left\{ \delta_{s_i} : \frac{\delta_{s_i}}{1 - p_{on}} > E[A] \right\}. \tag{28}$$

We then have the following bound on the performance of any energy balancing policy:

Result 2: The performance of an energy balancing policy is bounded by

$$U(\Pi_{EB}) \geq \begin{cases} \frac{(\mu_{on} c - \delta_0)(\rho_\theta - \rho_\nu) - \pi_{on}(\delta_\nu \rho_\theta - \delta_\theta \rho_\nu)}{\pi_{on}(\delta_\theta - \delta_\nu)} & \delta_{\phi_1} < \frac{E[A]}{E[N]} < \delta_1 \\ \frac{\mu_{on} c - \delta_0}{\delta_{\phi_1} \pi_{on}} \rho_{\phi_1} & \frac{E[A]}{E[N]} \leq \delta_{\phi_1} \\ \rho_1 & \frac{E[A]}{E[N]} \geq \delta_1 \end{cases} \tag{29}$$

where the relation for the last case holds with a strict equality, i.e., $U(\Pi_{EB}) = \rho_1$.

Proof: From Eqn. (24) the performance of any energy balancing policy is equal to $\sum_{i=1}^{K} \gamma_i \rho_i$. Thus the objective of the policy should be to choose the γ_i so as to maximize the expression in Eqn. (24) subject to the constraints on available energy. A linear programming formulation (LP1) for obtaining the γ_i that maximize the quality of coverage can be written as

LP1: maximize $\sum_{i=1}^{K} \gamma_i \rho_i$
subject to $\sum_{i=1}^{K} \gamma_i \le 1$ and $\frac{1}{1-p_{on}} \sum_{i=1}^{K} \gamma_i \delta_i \le E[A]$

We now consider the three cases and prove the result by determining the optimal γ_i in each case.

Case I: $(\delta_{\phi_i} E[N] < E[A] < \delta_1 E[N])$ The expected number of events to be reported in a renewal period is $\frac{1}{1-p_{on}}$. Thus in this case the energy available for communications is such that all transmissions may be made using mode ϕ_i but not enough to make all transmissions using mode 1. From Lemmas 1-4 in the Appendix, we know that the optimal policy has $\sum_i \gamma_i = 1$, $\gamma_0 = 0$ and $\gamma_i = 0$ for $i > \nu$. Let Π_{EB}^{x} denote an energy balancing policy that assigns $\{x_0, x_1, \cdots, x_K\}$ fraction of the slots to the various transmission modes, with $\sum_i x_i = 1$. Then consider the policy Π_{EB}^{γ} that only uses modes ν and θ. Since $\sum_i \gamma_i = 1$ for the optimal policy, we consider $\gamma_\nu + \gamma_\theta = 1$. Also, from the energy balancing property

$$\frac{E[A]}{E[N]} = \gamma_\nu \delta_\nu + \gamma_\theta \delta_\theta = (1-\gamma_\theta)\delta_\nu + \gamma_\theta \delta_\theta = \gamma_\theta(\delta_\theta - \delta_\nu) + \delta_\nu. \quad (30)$$

Solving the equation above for γ_ν and γ_θ gives

$$\gamma_\theta = \frac{E[A] - \delta_\nu E[N]}{E[N](\delta_\theta - \delta_\nu)} \qquad \gamma_\nu = \frac{\delta_\theta E[N] - E[A]}{E[N](\delta_\theta - \delta_\nu)} \quad (31)$$

To prove that Π_{EB}^{γ} is the optimum energy balancing policy, consider an arbitrary energy balancing policy Π_{EB}^{α} that also satisfies Lemmas 1, 2, 3 and 4, i.e., $\sum_i \alpha_i = 1$, $\alpha_0 = 0$ and $\alpha_i = 0$ for $i > \nu$. However, policy α may use modes i other than ν and θ such that $i < \nu$. Due to the energy balancing nature of policy Π_{EB}^{α}, we have

$$\sum_{i=1}^{\nu} \alpha_i \delta_i = \frac{E[A]}{E[N]}. \quad (32)$$

Substituting the expression above in Eqn. (30), we have

$$\gamma_\theta(\delta_\theta - \delta_\nu) = \sum_{i=1}^{\nu} \alpha_i \delta_i - \delta_\nu \quad \Rightarrow \quad \gamma_\theta = \frac{\sum_{i=1}^{\nu} \alpha_i \delta_i - \delta_\nu}{\delta_\theta - \delta_\nu}.$$

The utility of policy Π_{EB}^{γ} can then be written as

$$U(\Pi_{EB}^{\gamma}) = \gamma_\nu \rho_\nu + \gamma_\theta \rho_\theta = \frac{\sum_{i=1}^{\nu} \alpha_i \delta_i - \delta_\nu}{\delta_\theta - \delta_\nu}(\rho_\theta - \rho_\nu) + \rho_\nu. \quad (33)$$

The utility of policy Π_{EB}^{α} is $\sum_{i=1}^{K} \alpha_i \rho_i$. The utilities of policies Π_{EB}^{γ} an Π_{EB}^{α} are then related by

$$U(\Pi_{EB}^{\gamma}) - U(\Pi_{EB}^{\alpha}) = \frac{\sum_{i=1}^{\nu} \alpha_i \delta_i - \delta_\nu}{\delta_\theta - \delta_\nu}(\rho_\theta - \rho_\nu) + \rho_\nu - \sum_{i=1}^{\nu} \alpha_i \rho_i$$
$$= \left(\sum_{i=1}^{\nu} \alpha_i \delta_i - \sum_{i=1}^{\nu} \alpha_i \delta_\nu\right) \frac{\rho_\theta - \rho_\nu}{\delta_\theta - \delta_\nu} + \sum_{i=1}^{\nu} \alpha_i \rho_\nu - \sum_{i=1}^{\nu} \alpha_i \rho_i \quad (34)$$
$$= \sum_{i=1}^{\nu-1} \alpha_i (\delta_i - \delta_\nu) \frac{\rho_\theta - \rho_\nu}{\delta_\theta - \delta_\nu} - \sum_{i=1}^{\nu-1} \alpha_i (\rho_i - \rho_\nu) > 0 \quad (35)$$

where in Eqn. (34) we have used the fact that $\sum_{i=1}^{K} \alpha_i = 1$. The inequality above results because we have, for all $i < \nu$

$$\frac{\rho_\theta - \rho_\nu}{\delta_\theta - \delta_\nu} > \frac{\rho_i - \rho_\nu}{\delta_i - \delta_\nu} > \frac{\alpha_i(\rho_i - \rho_\nu)}{\alpha_i(\delta_i - \delta_\nu)}. \quad (36)$$

For arbitrary positive constants A, B, C, D, E and F, if $\frac{A}{B} > \frac{C}{D}$ and $\frac{A}{B} > \frac{E}{F}$, we have $\frac{A}{B} > \frac{C+E}{D+F}$. Thus,

$$\frac{\rho_\theta - \rho_\nu}{\delta_\theta - \delta_\nu} > \frac{\sum_{i=1}^{\nu-1} \alpha_i(\rho_i - \rho_\nu)}{\sum_{i=1}^{\nu-1} \alpha_i(\delta_i - \delta_\nu)} \quad (37)$$

and the result in Eqn. (35) follows. Thus the optimal energy balancing policy only uses modes ν and θ. Using Eqn. (31) and the expressions for $E[A]$ and $E[N]$, the utility of the optimum energy balancing policy is bounded by

$$U(\Pi_{EB}) = \gamma_\nu \rho_\nu + \gamma_\theta \rho_\theta$$
$$\ge \left[\frac{\pi_{on}\delta_\theta - \mu_{on}c + \delta_0}{\pi_{on}(\delta_\theta - \delta_\nu)}\right]\rho_\nu + \left[\frac{\mu_{on}c - \delta_0 - \pi_{on}\delta_\nu}{\pi_{on}(\delta_\theta - \delta_\nu)}\right]\rho_\theta$$
$$= \frac{(\mu_{on}c - \delta_0)(\rho_\theta - \rho_\nu) - \pi_{on}(\delta_\nu \rho_\theta - \delta_\theta \rho_\nu)}{\pi_{on}(\delta_\theta - \delta_\nu)}$$

which proves the result. Note that the values for γ_ν and γ_θ in Eqn. (31) are achievable because due to the energy balancing nature of the policy, the node always has energy to transmit, with probability one. To justify this result, consider each sensor node as a queue where the arrivals correspond to the energy harvested and the departures correspond to the energy spent. Thus the node represents a G/G/1 queue (i.e. a single server queue with arbitrary arrival and service distributions) where the arrival rate equals the departure rate (due to the energy balancing property). The results of [14], page 422, then imply that the queue remains non-empty with probability one and the expected queue length becomes unbounded. This in turn implies that we always have enough energy to transmit data with probability one.

Case II: $(E[A] \le \delta_{\phi_1} E[N])$ In this case the available energy is not enough to report all events with the transmission mode with the highest ratio of $\frac{\rho}{\delta}$. If all packets are transmitted using mode ϕ_1, $\frac{E[A]}{\delta_{\phi_1}}$ transmissions can be made resulting in an objective function of $\frac{E[A]}{\delta_{\phi_1}(1-p_{on})}\rho_{\phi_1}$. We prove the result for this case using contradiction. Assume that there exists a policy that assigns k_{ϕ_i} of the $\frac{1}{1-p_{on}}$ slots with data events to transmission mode i, $1 \le i \le K$, with at least one mode $j > 1$ with $k_{\phi_j} > 0$, such that its objective function is greater than that of the policy that uses mode ϕ_1 for all transmissions. The objective functions of the two policies then satisfies

$$\frac{k_{\phi_1}}{1-p_{on}}\rho_{\phi_1} + \frac{k_{\phi_2}}{1-p_{on}}\rho_{\phi_2} + \cdots + \frac{k_{\phi_K}}{1-p_{on}}\rho_{\phi_K} > \frac{E[A]}{\delta_{\phi_1}(1-p_{on})}\rho_{\phi_1}. \quad (38)$$

Now, $\frac{\rho_{\phi_2}}{\delta_{\phi_2}} > \frac{\rho_{\phi_i}}{\delta_{\phi_i}}$ for all $2 < i \le K$. Thus we have

$$\frac{k_{\phi_i}\delta_{\phi_i}}{\delta_{\phi_2}}\rho_{\phi_2} > k_{\phi_i}\rho_{\phi_i} \qquad 2 < i \le K. \quad (39)$$

Using the relation above in Eqn. (38) we have

$$k_{\phi_1}\rho_{\phi_1} + \sum_{i=2}^{K} \frac{k_{\phi_i}\delta_{\phi_i}}{\delta_{\phi_2}}\rho_{\phi_2} > \frac{E[A]}{\delta_{\phi_1}}\rho_{\phi_1}. \quad (40)$$

Now, in an energy balancing policy $E[A] = \sum_{i=1}^{K} k_{\phi_i}\delta_{\phi_i}$ and this in turn implies that $k_{\phi_1} = \frac{E[A]-\sum_{i=2}^{K} k_{\phi_i}\delta_{\phi_i}}{\delta_{\phi_1}}$. Substituting this in Eqn. (40) we have

$$\left[\frac{E[A]-\sum_{i=2}^{K}k_{\phi_i}\delta_{\phi_i}}{\delta_{\phi_1}}\right]\rho_{\phi_1}+\sum_{i=2}^{K}\frac{k_{\phi_i}\delta_{\phi_i}}{\delta_{\phi_2}}\rho_{\phi_2} > \frac{E[A]}{\delta_{\phi_1}}\rho_{\phi_1}$$

$$\Rightarrow \sum_{i=2}^{K}\frac{k_{\phi_i}\delta_{\phi_i}}{\delta_{\phi_2}}\rho_{\phi_2} > \sum_{i=2}^{K}\frac{k_{\phi_i}\delta_{\phi_i}}{\delta_{\phi_1}}\rho_{\phi_1} \quad \Rightarrow \quad \frac{\rho_{\phi_2}}{\delta_{\phi_2}} > \frac{\rho_{\phi_1}}{\delta_{\phi_1}}. \quad (41)$$

This is a contradiction of the initial assumption of $\frac{\rho_{\phi_1}}{\delta_{\phi_1}} > \frac{\rho_{\phi_2}}{\delta_{\phi_2}}$ and the proof is thus complete. Thus the policy should assign transmission mode ϕ_1 to all slots with data, as long as $L \geq \delta_0 + \delta_{\phi_1}$. Thus in this case we have $\gamma_{\phi_i} = 0$ for $i > 1$ and

$$\gamma_{\phi_1} = \frac{E[A]}{\delta_{\phi_1}}\frac{1}{E[N]} \geq \frac{\mu_{on}c-\delta_0}{\delta_{\phi_1}\pi_{on}}. \quad (42)$$

The quality of coverage for this case is then given by

$$U(\Pi_{EB}) = \gamma_{\phi_1}\rho_{\phi_1} \geq \frac{\mu_{on}c-\delta_0}{\delta_{\phi_1}\pi_{on}}\rho_{\phi_1}. \quad (43)$$

Case III: $(\delta_1 E[N] \leq E[A])$ Transmissions using transmission mode 1 are more likely to be successful and in this case the node has enough available energy to make all transmissions using this transmission mode. The solution to LP1 is thus trivial: $\gamma_1 = 1$ and $\gamma_j = 0$ for $2 \leq j \leq K$. The quality of coverage for this case is thus

$$U(\Pi_{EB}) = \gamma_1\rho_1 = \rho_1. \quad (44)$$

This completes the proof. ■

VI. Aggressive Transmission Policies

A transmission policy that uses transmission mode 1 for all transmissions as long as the available energy $L \geq \delta_0 + \delta_1$ is termed an aggressive policy Π_A. This section evaluates the performance of aggressive policies. It is shown that the performance of aggressive policies cannot exceed that of energy balancing policies, i.e., $U(\Pi_A) \leq U(\Pi_{EB})$. The results of this section are primarily aimed at characterizing the conditions under which an energy balancing policy reduces to an aggressive policy.

As with energy balancing policies, the performance of an aggressive policy can also be evaluated in terms of the renewal process governing the event generation process. As before, the expected length of a renewal period $E[T_R]$ and expected energy available for communications during a renewal period $E[A]$ are given by Eqns. (20) and (22), respectively. Since $\gamma_i = 0$ for $2 \leq i \leq K$ in an aggressive policy, the expected number of events correctly reported in a renewal period is $E[N]\gamma_1\rho_1$. The exact value of γ_1 depends on the system parameters and $E[A]$. The number of events detected and correctly reported in the period $[0,T]$ is then

$$\mathcal{E}_d(T) = \frac{\gamma_1\rho_1}{1-p_{on}}\frac{T}{E[T_R]}. \quad (45)$$

Since the expected number of events generated in the period $[0,T]$ is $\mathcal{E}_o(T) = \pi_{on}T$, the performance of the aggressive policy is given by

$$U(\Pi_A) = \lim_{T\to\infty}\frac{\mathcal{E}_d(T)}{\mathcal{E}_o(T)} = \frac{\gamma_1\rho_1}{\pi_{on}(1-p_{on})}\frac{1}{E[T_R]} = \gamma_1\rho_1. \quad (46)$$

A. Upper Bound on the Performance

We have the following upper bound on the performance of an aggressive policy:

Result 3: The performance of an aggressive transmission policy is bounded by

$$U_L(\Pi_A) \leq \begin{cases} \frac{\mu_{on}}{\delta_0+\delta_1}\left[\frac{c}{\pi_{on}} - \frac{\delta_0(1-p_{on})}{1-p_{off}}\right]\rho_1 & \frac{\delta_1}{1-p_{on}} > E[A] \\ \rho_1 & \text{otherwise} \end{cases} \quad (47)$$

where the relation for the last case holds with a strict equality.

Proof: **Case I:** $\left(E[A] < \frac{\delta_1}{1-p_{on}}\right)$. With μ_{on} representing the steady state probability of a node's battery being recharged in a slot, the expected energy generated by the node in a renewal period is given by $\mu_{on}cE[T_R]$. Now, the expected duration of the off period of the event generation process in the renewal period is $\frac{1}{1-p_{off}}$ and the expected charge generated in this period is thus $\frac{\mu_{on}c}{1-p_{off}}$. An energy of δ_0 is expended by the circuits in each slot during this period if the node is not in the dead state. Thus the energy available to the node at the beginning of the on period of the event process in the renewal period is maximized if the $\frac{\mu_{on}}{1-p_{off}}$ slots with recharge occur at the very end of the off period (since this minimizes the number of slots in the off period in which the node may have enough energy to be in the alive state). The energy expended on the circuits in the off period is then at least $\frac{\mu_{on}\delta_0}{1-p_{off}}$ and the energy available during the on period, $E[D]$, satisfies

$$\begin{aligned} E[D] &\leq \mu_{on}cE[T_R] - \frac{\mu_{on}\delta_0}{1-p_{off}} \\ &= \frac{\mu_{on}c(2-p_{on}-p_{off})}{(1-p_{on})(1-p_{off})} - \frac{\mu_{on}\delta_0}{1-p_{off}}. \end{aligned} \quad (48)$$

The expected number of slots in the on period where the node has sufficient energy to transmit a packet, M, is then bounded by

$$M \leq \frac{\mu_{on}}{\delta_0+\delta_1}\left[\frac{c(2-p_{on}-p_{off})-\delta_0(1-p_{on})}{(1-p_{on})(1-p_{off})}\right]. \quad (49)$$

The fraction of these M slots in which data is reported correctly is $\rho_1 M$ and the performance of the policy is then

$$U(\Pi_A) = \frac{\rho_1 M}{E[N]} \leq \frac{\mu_{on}}{\delta_0+\delta_1}\left[\frac{c}{\pi_{on}} - \frac{\delta_0(1-p_{on})}{1-p_{off}}\right]\rho_1. \quad (50)$$

Case II: $\left(E[A] \geq \frac{\delta_1}{1-p_{on}}\right)$. Since there is enough energy to transmit all packets using transmission mode 1, the aggressive policy in this case results in $\gamma_1 = 1$. Thus

$$U(\Pi_A) = \gamma_1\rho_1 = \rho_1 = U(\Pi_{EB}). \quad (51)$$

This completes the proof. ■

Now, Case I in Claim 3 corresponding to $E[A] < \frac{\delta_1}{1-p_{on}}$ subsumes Cases I and II in Claim 2 while Case II in Claim 3 is equivalent to Case III of Claim 2. The results of Claim 3 and

2 then lead to the following result comparing the performance of the two policies:

Corollary 1: The performance of the aggressive and energy balancing policies is related by

$$\frac{U(\Pi_{EB})}{U(\Pi_A)} \geq \begin{cases} \frac{(\mu_{on}c-\delta_0)(\rho_\theta-\rho_\nu)-\pi_{on}(\delta_\nu\rho_\theta-\delta_\theta\rho_\nu)}{c(1-p_{off})-\delta_0\pi_{on}(1-p_{on})} & \delta_{\phi_1} < \frac{E[A]}{E[N]} < \delta_1 \\ \quad \times \frac{(\delta_0+\delta_1)(1-p_{of})}{\rho_1\mu_{on}(\delta_\theta-\delta_\nu)} & \\ \frac{\rho_{\phi_1}(\mu_{on}c-\delta_0)(\delta_0+\delta_1)(1-p_{off})}{\rho_1\delta_{\phi_1}\mu_{on}[c(1-p_{off})-\delta_0\pi_{on}(1-p_{on})]} & \delta_{\phi_1} \geq \frac{E[A]}{E[N]} \\ 1 & \delta_1 \leq \frac{E[A]}{E[N]} \end{cases} \tag{52}$$

where the relation for the last case holds with a strict equality.

B. Lower Bound on the Performance

We have the following lower bound on the performance of an aggressive policy:

Result 4: The performance of an aggressive transmission policy is bounded by

$$U_L(\Pi_A) \geq \begin{cases} \frac{\mu_{on}c-\delta_0}{\delta_1\pi_{on}}\rho_1 & \frac{\delta_1}{1-p_{on}} > E[A] \\ \rho_1 & \text{otherwise} \end{cases} \tag{53}$$

where the relation for the last case holds with a strict equality.

Proof: **Case I:** $\left(E[A] < \frac{\delta_1}{1-p_{on}}\right)$. The energy available for communications in this case is not sufficient to transmit in all slots with events using transmission mode 1. Since the policy always schedules transmissions with transmission mode 1, we have

$$\gamma_1 = \frac{1}{E[N]}\frac{E[A]}{\delta_1} \;\geq\; \frac{\mu_{on}c-\delta_0}{\delta_1\pi_{on}}. \tag{54}$$

Then

$$U(\Pi_A) \;=\; \gamma_1\rho_1 \;\geq\; \frac{\mu_{on}c-\delta_0}{\delta_1\pi_{on}}\rho_1. \tag{55}$$

Case II: $\left(E[A] \geq \frac{\delta_1}{1-p_{on}}\right)$. Since there is enough energy to transmit all packets using transmission mode 1, the aggressive policy in this case results in $\gamma_1 = 1$. Thus

$$U(\Pi_A) = \gamma_1\rho_1 = \rho_1 = U(\Pi_{EB}). \tag{56}$$

This completes the proof. ■

The sub-optimality of using transmission mode 1 in all slots in cases I and II of Claim 2 implies that the performance of the aggressive policy cannot exceed that of the energy balancing policy. Finally we note that the performance of a policy that uses a single arbitrary mode can also be modeled using the derivations in this section.

VII. Markov Decision Process Formulation

The solution to the problem of assigning the transmission mode for each slot so that the quality of coverage is maximized can be also obtained by formulating it as a Markov Decision Process. Denote the system state at time t by $X_t = (L_t, E_t, Y_t)$ where $L_t \in \{0, 1, 2, \cdots\}$ represents the energy available in the node at time t. $E_t \in \{0, 1\}$ equals one if an event to be reported occurred at time t and zero otherwise. $Y_t \in \{0, 1\}$ equals one if the node is being charged at time t and zero otherwise. As before, the action at time t is denoted by $a_t \in \{0, 1, 2, \cdots, K\}$.

The next state of the system depends only on the current state and the action taken. Thus the system constitutes a Markov Decision Process. The node gains a reward of one with probability (w.p.) ρ_i if $E_t = 1$ and $a_t = i$, $1 \leq i \leq K$, and a reward of zero w.p. one if $E_t = 1$ and $a_t = 0$. The reward function is then

$$r(X_t, a_t) = \begin{cases} p_{on}\rho_i & \text{if } a_t = i, L_t \geq \delta_0+\delta_i \text{ and } E_{t-1} = 1 \\ (1-p_{off})\rho_i & \text{if } a_t = i, L_t \geq \delta_0+\delta_i \text{ and } E_{t-1} = 0 \\ 0 & \text{otherwise} \end{cases} \tag{57}$$

where $1 \leq i \leq K$. This reward function implies that the average total reward of the MDP is the quality of coverage. Let g_t and l_t be the energy gained and lost by the node in the interval $[t, t+1)$, respectively. Then

$$g_t = \begin{cases} c & \text{w.p. } Y_t q_{on} + (1-Y_t)(1-q_{off}) \\ 0 & \text{otherwise} \end{cases} \tag{58}$$

$$l_t = \begin{cases} \delta_0+\delta_i & \text{w.p. } [E_t p_{on} + (1-E_t)(1-p_{off})] I_i(a_t) \text{ if } L_t \geq \delta_0+\delta_i \\ \delta_0 & \text{w.p. } I_0(a_t) \text{ if } L_t \geq \delta_0+\delta_K \\ 0 & \text{otherwise} \end{cases} \tag{59}$$

where $1 \leq i \leq K$ and $I_A(a_t)$ represents the indicator function that equals one only when $a_t = A$ and zero otherwise. To complete the MDP formulation, the next state of the system $X_{t+1} = (L_{t+1}, E_{t+1}, Y_{t+1})$ is

$$L_{t+1} = L_t + g_t - l_t \tag{60}$$

$$E_{t+1} = \begin{cases} 1 & \text{w.p. } E_t p_{on} + (1-E_t)(1-p_{off}) \\ 0 & \text{otherwise} \end{cases} \tag{61}$$

$$Y_{t+1} = \begin{cases} 1 & \text{w.p. } Y_t q_{on} + (1-Y_t)(1-q_{off}) \\ 0 & \text{otherwise} \end{cases} . \tag{62}$$

The optimal solution can be computed by using the well known value iteration technique [15]. The battery capacity of the sensor node is assumed to be B. Since the induced Markov chain is unichain, from Theorem 8.5.2 of [15], there exists a deterministic, Markov, stationary optimal policy Π_{MD} which also leads to a steady-state transition probability matrix. Considering the average expected reward criteria, the optimality equations are given by [16]

$$h^*(X) = \max_{a\in\{0,1,\cdots,K\}} \left[r(X,a) + \lambda^* + \sum_{X'=(0,0,0)}^{(B,1,1)} p_{X,X'}(a) h^*(X') \right]$$
$$\forall X \in \{(0,0,0), \cdots, (B,1,1)\} \tag{63}$$

where $p_{X,X'}(a)$ represents the transition probability from state X to X' when action a is taken, λ^* is the optimal average reward and $h^*(i)$ are the optimal rewards when starting at state $i = (0,0,0), \cdots, (B,1,1)$. For the purpose of evaluation, the relative value iteration technique [16] may be used to solve Eqn. (63).

VIII. Simulation Results

In this section we use simulation results to compare the performance of the three strategies and also to evaluate the impact of various system parameters on the performance. The simulations were done using a custom built simulator written

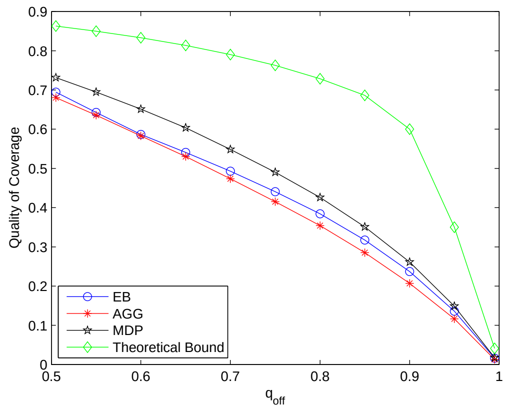


Fig. 1. Comparison of the quality of coverage. Parameters used: $q_{on} = 0.75$, $p_{off} = 0.9$, $\rho_1 = 0.9$, $p_{on} = 0.6$, $\rho_2 = 0.4$ $\left(\frac{\rho_1}{\delta_1} > \frac{\rho_2}{\delta_2}\right)$ and $\delta_0 = 1$.

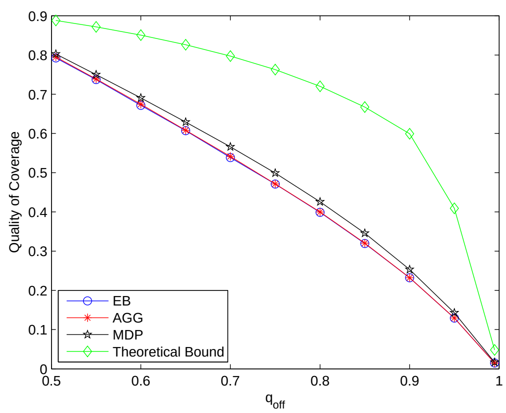


Fig. 2. Comparison of the quality of coverage. Parameters used: $q_{on} = 0.75$, $p_{off} = 0.9$, $\rho_1 = 0.9$, $p_{on} = 0.7$, $\rho_2 = 0.6$, $\left(\frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}\right)$ and $\delta_0 = 1$.

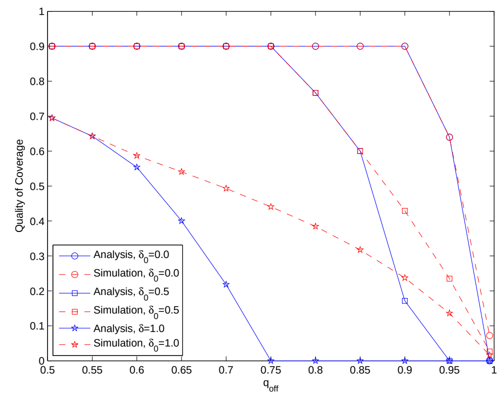


Fig. 3. Effect of δ_0 on the theoretical bound. Parameters used: $q_{on} = 0.75$, $p_{on} = 0.7$, $p_{off} = 0.9$, $c = 2$, $\rho_1 = 0.9$, $\rho_2 = 0.6$, $\delta_1 = 2$ and $\delta_2 = 1$.

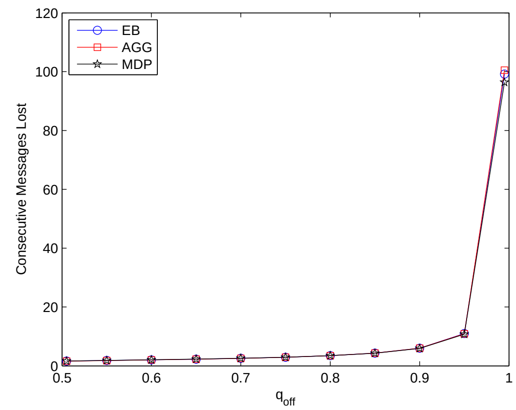


Fig. 4. Comparison of the average number of consecutive lost messages. Parameters used: $q_{on} = 0.75$, $p_{off} = 0.9$, $p_{on} = 0.6$, $\rho_1 = 0.9$, $\rho_2 = 0.4$ $\left(\frac{\rho_1}{\delta_1} > \frac{\rho_2}{\delta_2}\right)$ and $\delta_0 = 1$.

in C. All simulations were run for a duration of 5000000 time units and used $c = 2$, $\delta_1 = 2$ and $\delta_2 = 1$. The results consider a scenario with two modes so that the relationship between various parameters can be easily observed.

Figures 1 and 2 compare the performance of the three policies (labeled EB: energy balancing, AGG: aggressive and MDP: Markov Decision Process) in terms of the quality of coverage U as the recharge rate is varied by changing q_{off}. Two scenarios corresponding to $\frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}$ and $\frac{\rho_1}{\delta_1} > \frac{\rho_2}{\delta_2}$ are considered. In both cases, the policy obtained by the MDP outperforms the EB and AGG policies. In the case where $\frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}$ the performance of the EB and AGG policies are almost the same while the difference is larger in the other case. The tightness of the theoretical bound depends on a number of factors including the value of δ_0. Figure 3 compares the bound with the simulation results from the EB scenario for three different values of δ_0. We note that when the energy spent on the circuits is small compared to the energy spent on communications, the bound is fairly tight.

Figures 4, 5 6 and 7 compare the performance of the three strategies in terms of two other metrics: the average number of consecutive messages that are not successfully delivered by the node and the fraction of slots in which it is in the dead state. The number of consecutive messages that are not delivered by the node is important in certain medical applications. Note that a measure of the overall fraction of messages that are not delivered can be observed from Figures 1 and 2 where the quality of coverage is the complement of the fraction of messages that are lost. We observe that the performance of the three strategies is quite close though AGG has the worst performance. Also, while MDP performs better than EB when $\frac{\rho_1}{\delta_1} > \frac{\rho_2}{\delta_2}$, EB outperforms MDP in the other case. While the differences in the performances is more pronounced in the case of the fraction of dead slots, a similar relationship is observed in all the results. The smaller number of dead slots with EB when $\frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}$ is because now EB transmits in more slots using transmission mode 2. While this decreases the fraction of dead slots, it does not necessarily result in better quality of coverage, as can be seen from Figures 1 and 2.

Next, we explore the impact of various system parameters on the performance of the communication strategies. For purposes of illustration, we show the results for the MDP based policy and the other policies follow the same trend. Figure 8 explores the effect of the recharge process on the performance

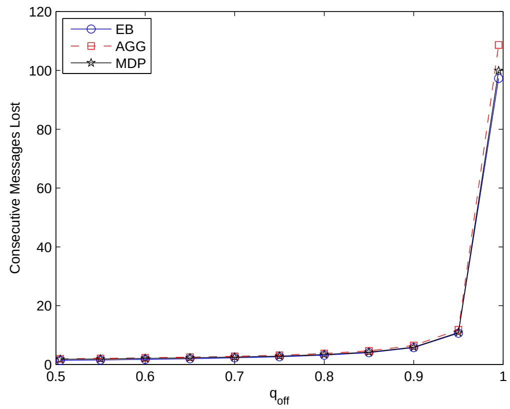


Fig. 5. Comparison of the average number of consecutive lost messages. Parameters used: $q_{on} = 0.75$, $p_{off} = 0.9$, $p_{on} = 0.7$, $\rho_1 = 0.9$, $\rho_2 = 0.6$ $\left(\frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}\right)$ and $\delta_0 = 1$.

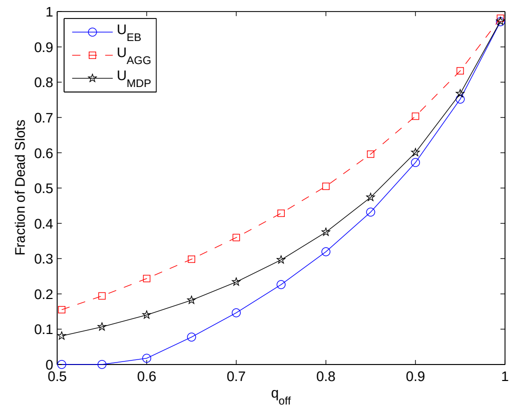


Fig. 7. Comparison of the fraction of dead slots. Parameters used: $q_{on} = 0.75$, $p_{off} = 0.9$, $p_{on} = 0.7$, $\rho_1 = 0.9$, $\rho_2 = 0.6$ $\left(\frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}\right)$ and $\delta_0 = 1$.

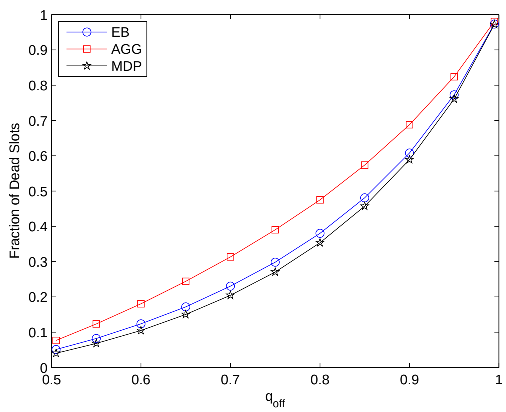
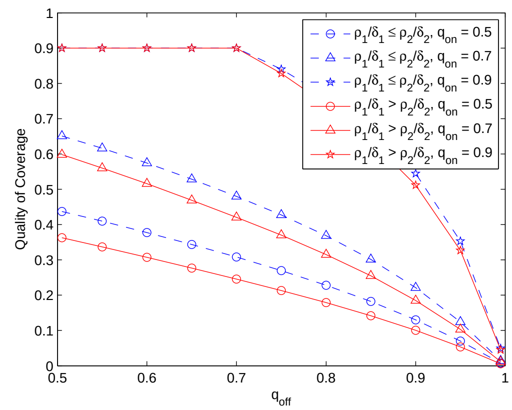


Fig. 6. Comparison of the fraction of dead slots. Parameters used: $q_{on} = 0.75$, $p_{off} = 0.9$, $p_{on} = 0.6$, $\rho_1 = 0.9$, $\rho_2 = 0.4$ $\left(\frac{\rho_1}{\delta_1} > \frac{\rho_2}{\delta_2}\right)$ and $\delta_0 = 1$.



$\{\rho_1 = 0.9, \rho_2 = 0.6\}$ and $\{\rho_1 = 0.9, \rho_2 = 0.4\}$

Fig. 8. Effect of q_{on} and q_{off} on the quality of coverage for the MDP based policy. Parameters used: $p_{on} = 0.7$, $p_{off} = 0.9$ and $\delta_0 = 1$.

for the two cases of $\frac{\rho_1}{\delta_1} \leq \frac{\rho_2}{\delta_2}$ and $\frac{\rho_1}{\delta_1} > \frac{\rho_2}{\delta_2}$ by varying the values of q_{on} and q_{off}. While the performance improves as q_{on} increases or q_{off} decreases, q_{on} has a greater impact on the performance. This is because a larger q_{on} increases the charge available and thus allows more transmissions using mode 1 (preferred in this case). Finally, Figure 9 evaluates the impact of p_{on} and p_{off} on the performance. For higher values of p_{on}, p_{off} has a smaller impact on the performance since the number of events generated here is much higher than the recharge events. As p_{on} decreases, an increase in p_{off} has a greater effect on the performance.

IX. Conclusions

To facilitate the development of communication technology to assist in the deployment of BSNs, this paper addressed the problem of developing transmission strategies for BSNs with energy harvesting. Three strategies for scheduling transmissions at different energy consumption levels are considered and bounds are obtained on the achievable performance. Simulation results show that a strategy based on a MDP formulation has better quality of coverage that both energy balancing and aggressive policies. In certain scenarios, the energy balancing policy may outperform the other two in terms of the number of dead slots and the average number of consecutive messages that are not reported correctly.

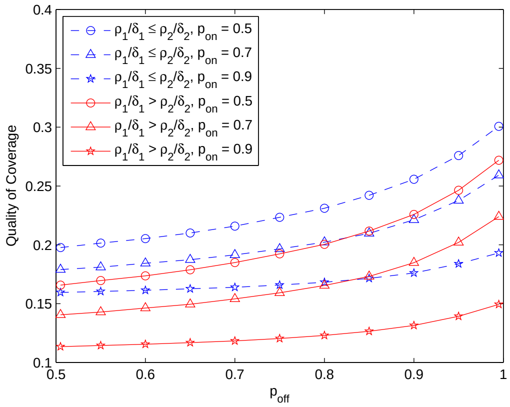
X. Appendix

For the case where $(\delta_{\phi_i} E[N] < E[A] < \delta_1 E[N])$, we have the following results:

Lemma 1: The optimal energy balancing policy only uses modes i with $i \leq i^*$, i.e. $\gamma_i = 0$ for all $i > i^*$.

Proof: To prove this, we start with an arbitrary energy balancing policy Π_{EB}^{α}, i.e. $\sum_i \alpha_i = 1$ and $\sum_i \alpha_i \delta_i = \frac{E[A]}{E[N]}$ (that assigns a fraction α_i of transmission slots to mode i) and show that another energy balancing policy Π_{EB}^{β} exists such that $U(\Pi_{EB}^{\beta}) > U(\Pi_{EB}^{\alpha})$, and $\beta_i = 0$ for all $i > i^*$. Consider a mode $m > i^*$. Given α, construct β' by

$$\beta_i = \begin{cases} \alpha_0 + \left(1 - \frac{\delta_m}{\delta_{i^*}}\right)\alpha_m & i = 0 \\ \alpha_{i^*} + \frac{\delta_m}{\delta_{i^*}}\alpha_m & i = i^* \\ 0 & i = m \\ \alpha_i & \text{otherwise} \end{cases} . \quad (64)$$



$\{\rho_1 = 0.9, \rho_2 = 0.6\}$ and $\{\rho_1 = 0.9, \rho_2 = 0.4\}$

Fig. 9. Effect of p_{on} and p_{off} on the quality of coverage for the MDP based policy. Parameters used: $q_{on} = 0.7$, $q_{off} = 0.9$ and $\delta_0 = 1$.

Note that $\sum_i \beta_i = 1$ and $\sum_i \beta_i \delta_i = \frac{E[A]}{E[N]}$ and thus β is an energy balancing policy. Let the difference in the utilities of α and β be $\Delta_\alpha^\beta = U(\Pi_{EB}^\beta) - U(\Pi_{EB}^\alpha)$. Then

$$\begin{aligned}\Delta_\alpha^\beta &= \left[\alpha_{i^*} + \frac{\delta_m}{\delta_{i^*}}\alpha_m\right]\rho_{i^*} - \alpha_{i^*}\rho_{i^*} - \alpha_m\rho_m \\ &= \alpha_m\delta_m\left[\frac{\rho_{i^*}}{\delta_{i^*}} - \frac{\rho_m}{\delta_m}\right] > 0.\end{aligned}$$

since $\frac{\rho_{i^*}}{\delta_{i^*}} > \frac{\rho_m}{\delta_m}$ for all i. Thus β does not use mode m, and has better utility than α. We can repeat this procedure for all $m > i^*$, and eliminate all such modes, meanwhile only improving the utility. ■

Lemma 2: The optimum energy balancing policy sends all packets, i.e. $\gamma_0 = 0$.

Proof: We prove the lemma by starting from an arbitrary energy balancing policy Π_{EB}^α with $\alpha_0 > 0$. We then show that an energy balancing policy Π_{EB}^β can be constructed such that $U(\Pi_{EB}^\beta) > U(\Pi_{EB}^\alpha)$ and $\beta_0 < \alpha_0$. Furthermore, we will show that by repeating this procedure, we will reach a policy such that $U(\Pi_{EB}^\beta) > U(\Pi_{EB}^\alpha)$ and $\beta_0 = 0$.

Consider a mode m with $\frac{\delta_m}{1-p_{on}} > E[A]$. We have two cases:

Case I: If

$$\alpha_m \geq \frac{\delta_{i^*}}{\delta_m - \delta_{i^*}}\alpha_0 \tag{65}$$

then construct the energy balancing policy Π_{EB}^β such that

$$\beta_i = \begin{cases} 0 & i = 0 \\ \alpha_m - \frac{\delta_{i^*}}{\delta_m - \delta_{i^*}}\alpha_0 & i = m \\ \alpha_{i^*} + \frac{\delta_m}{\delta_m - \delta_{i^*}}\alpha_0 & i = i^* \\ \alpha_i & \text{otherwise} \end{cases}. \tag{66}$$

Note that $\sum_i \beta_i = 1$ and $\sum_i \beta_i \delta_i = \frac{E[A]}{E[N]}$ and thus Π_{EB}^β is an energy balancing policy. Policy Π_{EB}^β has better utility since

$$\Delta_\alpha^\beta = \frac{\delta_m \delta_{i^*}}{\delta_m - \delta_{i^*}}\alpha_0\left[\frac{\rho_{i^*}}{\delta_{i^*}} - \frac{\rho_m}{\delta_m}\right] > 0. \tag{67}$$

Furthermore, we have $\beta_0 = 0$, which completes the proof.

Case II: If

$$\alpha_m < \frac{\delta_{i^*}}{\delta_m - \delta_{i^*}}\alpha_0 \tag{68}$$

then construct the energy balancing policy Π_{EB}^β such that

$$\beta_i = \begin{cases} \alpha_0 - \frac{\delta_m}{\delta_{i^*}}\alpha_m & i = 0 \\ 0 & i = m \\ \alpha_{i^*} + \frac{\delta_m}{\delta_{i^*}}\alpha_m & i = i^* \\ \alpha_i & \text{otherwise} \end{cases}. \tag{69}$$

Again, $\sum_i \beta_i = 1$ and $\sum_i \beta_i \delta_i = \frac{E[A]}{E[N]}$ and thus Π_{EB}^β is an energy balancing policy. Also, the policy Π_{EB}^β has better utility since

$$\Delta_\alpha^\beta = \alpha_m\delta_m\left[\frac{\rho_{i^*}}{\delta_{i^*}} - \frac{\rho_m}{\delta_m}\right] > 0. \tag{70}$$

Furthermore, we have $\beta_0 < \alpha_0$. Thus we have eliminated transmissions using mode m, and reduced the number unsent packets. We now pick a new mode m and continue this until Eqn. (65) becomes true. Note that we cannot run out of modes before Eqn. (65) becomes true because if that happens, we are left with a combination of modes, all with $\frac{\delta_i}{1-p_{on}} < E[A]$, but there are still unsent packets. ■

Lemma 3: The optimal energy balancing policy only uses modes that belong to $\mathcal{S}$, i.e. $\gamma_i = 0$ if $i \notin \mathcal{S}$.

Proof: Consider an arbitrary energy balancing policy Π_{EB}^α, with $\alpha_i = 0$, for $i = 0$ and $i^* + 1 \geq i \geq K$ (as a consequence of Lemma 1 and 2. Now consider any mode m such that $m \notin \mathcal{S}$ and $s_{j-1} < m < s_j$, with s_{j-1} and s_j being the $(j-1)$-th and j-th elements of the set $\mathcal{S}$. Now construct another energy balancing policy Π_{EB}^β such that

$$\beta_i = \begin{cases} \alpha_{s_j} + \frac{\delta_m - \delta_{s_{j-1}}}{\delta_{s_j} - \delta_{s_{j-1}}}\alpha_m & i = s_j \\ 0 & i = m \\ \alpha_{s_{j-1}} + \frac{\delta_{s_j} - \delta_m}{\delta_{s_j} - \delta_{s_{j-1}}}\alpha_m & i = s_{j-1} \\ \alpha_i & \text{otherwise} \end{cases}. \tag{71}$$

Note that $\sum_i \beta_i = 1$ and $\sum_i \beta_i \delta_i = \frac{E[A]}{E[N]}$ and thus Π_{EB}^β is an energy balancing policy. Also, $\beta_0 = 0$ and we have divided the transmissions using mode m in policy Π_{EB}^α between modes s_{j-1} and s_j in policy Π_{EB}^β. The policy Π_{EB}^β has better utility since

$$\Delta_\alpha^\beta = \alpha_m(\delta_m - \delta_{s_{j-1}})\left[\frac{\rho_{s_j} - \rho_{s_{j-1}}}{\delta_{s_j} - \delta_{s_{j-1}}} - \frac{\rho_m - \rho_{s_{j-1}}}{\delta_m - \delta_{s_{j-1}}}\right] > 0$$

since $\frac{\rho_{s_j} - \rho_{s_{j-1}}}{\delta_{s_j} - \delta_{s_{j-1}}} > \frac{\rho_i - \rho_{s_{j-1}}}{\delta_i - \delta_{s_{j-1}}}$ for all $1 \leq i < s_{j-1}$. Thus we can eliminate transmissions using mode m and improve the utility. Repeating the process above, all modes that are not in $\mathcal{S}$ can be eliminated. ■

Lemma 4: The optimum energy balancing policy does not use any mode m with $m \in \mathcal{S}$ such that $m > \nu$ (recall that $\nu = \arg\min_{s_i \in \mathcal{S}}\left\{\delta_{s_i} : \frac{\delta_{s_i}}{1-p_{on}} \leq E[A]\right\}$).

Proof: From Lemmas 1 and 3, the optimal energy balancing policy does not use any transmission modes greater than i^* and modes that are not in $\mathcal{S}$. Then consider an arbitrary energy balancing policy Π_{EB}^α with $\alpha_{s_j} \neq 0$ and $s_j \in \mathcal{S}$ and $s_j < \nu$. Then pick a mode m such that $m > \nu$ and $\alpha_m > 0$. Note that such a mode m necessarily exists otherwise we would have $\sum_i \alpha_i \delta_i < \frac{E[A]}{E[N]}$. Then we have two cases:

Case I: If

$$\alpha_m \geq \frac{\delta_{s_{j+1}} - \delta_{s_j}}{\delta_m - \delta_{s_{j+1}}} \tag{72}$$

then construct another energy balancing policy Π_{EB}^{β} such that

$$\beta_i = \begin{cases} \alpha_{s_{j+1}} + \frac{\delta_{s_j}}{\delta_{s_{j+1}}}\alpha_{s_j} + \frac{\delta_{s_{j+1}}-\delta_{s_j}}{\delta_m-\delta_{s_{j+1}}}\frac{\delta_m}{\delta_{s_{j+1}}}\alpha_{s_j} & i = s_{j+1} \\ 0 & i = s_j \\ \alpha_m - \frac{\delta_{s_{j+1}}-\delta_{s_j}}{\delta_m-\delta_{s_{j+1}}}\alpha_{s_j} & i = m \\ \alpha_i & \text{otherwise} \end{cases}. \tag{73}$$

Note that $\sum_i \beta_i = 1$ and $\sum_i \beta_i \delta_i = \frac{E[A]}{E[N]}$ and thus Π_{EB}^{β} is an energy balancing policy. Now, policy Π_{EB}^{β} has better utility since

$$\Delta_\alpha^\beta = \alpha_{s_j}\left[\frac{\delta_m-\delta_{s_j}}{\delta_m-\delta_{s_{j+1}}}(\rho_{s_{j+1}}-\rho_{s_j}) - \frac{\delta_{s_{j+1}}-\delta_{s_j}}{\delta_m-\delta_{s_{j+1}}}(\rho_m-\rho_{s_j})\right] > 0.$$

since $\frac{\rho_{s_{j+1}}-\rho_{s_j}}{\delta_{s_{j+1}}-\delta_{s_j}} > \frac{\rho_i-\rho_{s_j}}{\delta_i-\delta_{s_j}}$ for all $1 \leq i < s_j$. Thus we can eliminate transmissions using mode s_j and improve the utility. We can thus start the mode s_0 and repeat the process sequentially for $s_1, s_2, \cdots$ and so on for all modes s_i in $\mathcal{S}$ that satisfy $s_i > \nu$ to arrive at the desired result.

Case II: If

$$\alpha_m < \frac{\delta_{s_{j+1}} - \delta_{s_j}}{\delta_m - \delta_{s_{j+1}}} \tag{74}$$

then construct another energy balancing policy Π_{EB}^{β} such that

$$\beta_i = \begin{cases} \alpha_{s_{j+1}} + \alpha_m + \frac{\delta_m-\delta_{s_{j+1}}}{\delta_{s_{j+1}}-\delta_{s_j}}\alpha_m & i = s_{j+1} \\ 0 & i = m \\ \alpha_{s_j} - \frac{\delta_m-\delta_{s_{j+1}}}{\delta_{s_{j+1}}-\delta_{s_j}}\alpha_m & i = s_j \\ \alpha_i & \text{otherwise} \end{cases}. \tag{75}$$

Note that $\sum_i \beta_i = 1$ and $\sum_i \beta_i \delta_i = \frac{E[A]}{E[N]}$ and thus Π_{EB}^{β} is an energy balancing policy. Now, policy Π_{EB}^{β} has better utility since

$$\Delta_\alpha^\beta = \alpha_m(\delta_m - \delta_{s_j})\left[\frac{\rho_{s_{j+1}} - \rho_{s_j}}{\delta_{s_{j+1}} - \delta_{s_j}} - \frac{\rho_m - \rho_{s_j}}{\delta_m - \delta_{s_j}}\right] > 0$$

since $\frac{\rho_{s_{j+1}}-\rho_{s_j}}{\delta_{s_{j+1}}-\delta_{s_j}} > \frac{\rho_i-\rho_{s_j}}{\delta_i-\delta_{s_j}}$ for all $1 \leq i < s_j$. Thus policy Π_{EB}^{β} has higher utility that policy Π_{EB}^{α} and we have $\beta_{s_j} < \alpha_{s_j}$. Now we can pick a new mode m and continue the process above till Eqn. (72) is satisfied. Note that we cannot run out of modes before Eqn. (72) becomes true because if that happens, we are left with a combination of modes, all with $\frac{\delta_i}{1-p_{on}} < E[A]$ such that all packets are transmitted and we are thus left with extra energy. Thus by continuing the process, we can eliminate transmissions using mode s_j and still improve the utility. We can thus start the mode s_0 and repeat the process sequentially for $s_1, s_2, \cdots$ and so on for all modes s_i in $\mathcal{S}$ that satisfy $s_i > \nu$ to arrive at the desired result. ■

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