Minimizing Power Consumption in Sensor Networks with Quality of Service Requirement

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Abstract

Minimizing energy and power consumption in wireless sensor networks is critical in extending the lifetime of the network. In this paper we consider efficient power/rate allocation strategies with certain quality of service constraints. The transmission rate achieved and the power used are related by a power-rate function for a given channel state. Specifically, two problems are formulated, one seeking to minimize the average power consumption subject to an average rate constraint, while the other seeking to maximize the average data rate subject to an average power constraint. We consider two scenarios of power management of a wireless node/device. In the first case the node always stays on thereby consuming power in circuitry as well as in transmission/reception. In the second case the node turns its transceivers off from time to time, and by doing so while avoiding circuitry power during sleep periods, consumes power in switching from the off state to the on state. For both problems stationary and deterministic policies are considered. We first study the optimum power/rate allocation when the nodes are always active and provide algorithms that produce optimal solutions to these two problems. We then consider a two-state channel model and study optimal joint power allocation and sleep scheduling for both problems.

1 Introduction

Energy and power efficiency is an essential factor in the design and operation of wireless sensor networks, since many sensor devices are battery powered and thus energy/power constrained. On the other hand, it is also desirable to be able to satisfy certain performance guarantee when transmitting data over a wireless sensor network, e.g., delay, throughput, loss requirements. How to meet such requirements while limited by energy/power is the central focus of this paper.

Specifically, we consider the problems of optimally assigning power (rate) to sensor nodes so as to minimize (maximize) the average power (rate) subject to an average rate (power) constraint These two problems are considered together as they share very similar structures and lead to similar solutions. The channel quality is assumed to be time varying, modeled via a power-rate function for any given channel state. Each point on the power-rate curve represents some combination of coding and modulation schemed used for data transmission.

While there are many different power-save and power management schemes given a particular sensor device platform, we will mainly consider two scenarios. In the first scenario, the user/device is assumed to be always active (with transceivers turned on), and thereby consuming energy in circuitry and data transmission. In this case an optimal policy for the problems outlined above needs to decide on the appropriate transmission power to be used in any given channel state. Within this setting we will develop for both problems outlined above an algorithm that allocates the rate/power optimally for concave power-rate functions.

In the second scenario, the user/device is assumed to alternate between an active/on state and an inactive/off state in which the transceivers are turned off (the duty cycling of the sensing element is left unspecified, and its energy consumption is not considered in this paper). In this case the device is assumed not to consume circuit power while it is asleep, but requires power in switching from the off state to the on state. In this case a policy needs to determine not only the transmission power, but also an appropriate sleep schedule (i.e., when to go to sleep and for how long). For this scenario we will study the optimal joint power allocation and sleep scheduling for both problems under the assumption of a two-state channel system and geometrically distributed sleep durations.

In this paper we will use the terms user, node, and device interchangeably.

Efficient power allocation has been the subject of many recent studies in wireless networks. In [1] the problem of joint routing, link scheduling and power control is studied. The average power is minimized in order for the nodes to satisfy some rate constraints. However, channel variation is not considered and the nodes are assumed to be always active (i.e. no sleep scheduling). [2] studies the problem of power control for the uplink in a single-cell and it is shown that the policy that allocates the power to the user with the best channel maximizes the capacity. [3] studied the stability of power allocation policies in a satellite network scenario. The users are always active (no sleep schedule) and the goal is to schedule transmissions in order to stabilize the queues.

Operating wireless sensor networks in low duty cycles has also be addressed in a number of studies. Examples include efficient medium access schemes, e.g., S-MAC [4], sleep scheduling to achieve coverage [5, 6], connectivity [7, 8], and general system design that may involve a paging channel [9]. While relevant, these methods are typically developed independent of power control, which is what we attempt to achieve in this paper.

The rest of the paper is organized as follows. In the next section we explain the system model we use in this paper and formulate the problem. In Section 3 we study the optimal policy where the nodes are always active and are not put to sleep. In Section 4 we study joint power allocation and sleep scheduling for a two state system. In Section 5 we discuss some possible extensions of the results presented here and conclude the paper.

2 System Description and Problem Formulation

Consider a channel that can be in any state from a finite set of states $S = \{1, 2, \dots, S\}$. Time is slotted and the channel state changes from one slot to the next according to a Markov process, given by the transition probabilities $q_{ij} = Pr[s_{t+1} = s_j | s_t = s_i], i, j \in S$.

Consider a single user that always has data to transmit (i.e., an infinite source). In each time slot the user can be in one of two modes: active/on or asleep/off. If the user is active, it transmits data with a chosen transmission power. We assume that the user knows the channel state if it is active, and decides on the transmission power based on this knowledge. The transmission rate it achieves is given by a power-rate function $\mu = f_s(p)$ associated with state s. This $f_s()$ is assumed to be a one-to-one, continuous, increasing, differentiable, and concave function of p. Thus $f_s^{-1}(\mu)$ is well-defined and is a one-to-one, continuous, increasing, differentiable, and convex function of the transmission rate μ . There is a maximum transmission power P_m that the user cannot exceed regardless of the channel state it is in.

Definition 1 We say that a state s_i is better than another state s_j (in notation $s_i \succ s_j$), if we have $f_{s_i}(p) \ge f_{s_j}(p)$ for all $0 \le p \le P_m$.

We assume that there is an ordering between the states and without loss of generality we assume $s_1 \succ s_2 \succ \cdots \succ s_s$.

Problem P-1 (Optimal rate allocation): Determine the transmission rates $\mu(t)$ at time t so as to minimize the average power consumption subject to an average rate constraint $\bar{\mu}$:

minimize
$$\limsup_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} f^{-1}(\mu)$$

s.t.
$$\liminf_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mu(t) \ge \bar{\mu}$$

and $0 \le \mu(t) \le f_{s_t}(P_m), \quad \forall t$ (1)

Problem P-2 (Optimal power allocation): Determine the transmission power p(t) at time t so as to maximize the average data rate subject to an average power constraint \bar{p} :

maximize
$$\liminf_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} f_{s_t}(p(t))$$

s.t.
$$\limsup_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} p(t) \le \bar{p}$$

and $0 \le p_t \le P_m, \quad \forall t$ (2)

As we will see the structure of these two problems are very similar and they lead to similar solutions. We will limit our attention to the set of stationary and deterministic policies for the above optimization problems. Specifically, a policy π is said to be stationary if the decision on the transmission rate (or power) only depends on the current channel state. A policy is called deterministic if at each decision

epoch only one action is taken with probability one. The set of all stationary and deterministic policies is denoted by Π^{SD} .

Only transmission power is explicitly considered in the above formulation. Note that when a node is always active, the circuit power can be easily incorporated into this formulation. For example problem **P-1** would remain the same when we include the circuit power as it is a constant. In problem **P-2**, the constraint can be changed to the average transmission power less a constant circuit power.

On the other hand, when a user alternates between the active and sleep modes, then the circuit power is no longer a constant but a function of the sleep schedule. Furthermore, we need to consider the switching power consumed between the off and on modes. This will be discussed in more detail in Section 4. In the next section we present algorithms for solving problems **P-1** and **P-2** presented above.

3 Optimal Power and Rate Allocation Policies

As mentioned before, for this section we will assume that the user is active at all times, and thus ignore the circuit and switching power. Let q_s be the steady-state probability of the channel being in state s. A policy in Π^{SD} assigns a transmission rate or power for each state $s \in S$, which we denote by p_s and μ_s , respectively. In this case the above optimizations reduce to the following.

Problem P-1: This problem can be written as

minimize
$$\sum_{s} q_{s} \cdot f_{s}^{-1}(\mu_{s})$$
(3)
s.t.
$$\sum_{s} q_{s} \cdot \mu_{s} \ge \bar{\mu}$$

and
$$0 \le \mu_{s} \le f_{s}(P_{m}), \quad \forall s .$$

Problem P-2: This problem can be written as

maximize
$$\sum_{s} q_{s} \cdot f_{s}(p_{s})$$
s.t.
$$\sum_{s} p_{s} \cdot q_{s} \leq \bar{p}$$
and
$$0 \leq p_{s} \leq P_{m}, \quad \forall t .$$
(4)

Below we study these problems through their dual problems.

3.1 Optimal rate allocation

Consider problem **P-1** as formulated in (3) and define $g_s(\mu) = f_s^{-1}(\mu)$ to be the required power to transmit with rate μ in state s. The Lagrangian of the problem is as follows:

$$L(\mu,\lambda) = \sum_{s} q_s \cdot g_s(\mu_s) + \lambda(\bar{\mu} - \sum_{s} q_s \cdot \mu_s) .$$
 (5)

Let $\mathcal{D} = \{\mu : 0 \leq \mu_s \leq f_s(P_m), \forall s \in \mathcal{S}\}$, then the Lagrange dual function can be written as follows:

$$L(\lambda) = \inf_{\mu \in \mathcal{D}} \left\{ \sum_{s} q_s \cdot g_s(\mu_s) + \lambda(\bar{\mu} - \sum_{s} q_s \cdot \mu_s) \right\} \,. \tag{6}$$

The dual objective is to maximize the dual function over $\lambda \geq 0$. Since the value function and the constraints are all convex, there is no duality gap and the primal and dual optimal values are the same. Below we first look at the special case of linear power-rate functions and then study the more general case of concave power-rate functions.

3.1.1 Linear Power-Rate Functions

Suppose the power-rate functions are linear, i.e. $f_s(p) = a_s \cdot p$ for some values a_s . This is a reasonable assumption in the low SNR regime. Thus $g_s(\mu) = \frac{\mu}{a_s}$. In this case Equation (6) becomes

$$L(\lambda) = \inf_{\mu \in \mathcal{D}} \{ \sum_{s} \frac{1}{a_{s}} q_{s} \mu_{s} + \lambda (\bar{\mu} - \sum_{s} q_{s} \cdot \mu_{s}) \}$$
$$= \inf_{\mu \in \mathcal{D}} \{ \sum_{s} q_{s} \mu_{s} (\frac{1}{a_{s}} - \lambda) + \lambda \bar{\mu} \} .$$
(7)

The first term (linear in μ_s) states that as long as $\frac{1}{a_s} < \lambda$, the user should transmit at the maximum rate allowed by the maximum power and the power-rate function in state s. For all $s \in S$ such that $\frac{1}{a_s} > \lambda$ the rate should be zero. As we will show in Section 3.1.2, the dual variable λ should be chosen so as to achieve equality in the average rate constraint.

If follows that the optimal policy can be implemented as follows. Start from the best state (i.e. largest a_s). Allocate power until the maximum power is reached or the average rate criterion is satisfied. If the maximum power is reached and the average rate criterion is not satisfied, go to the next best state and repeat the same procedure.

3.1.2 Concave power-rate functions

In this part we consider general concave power-rate functions, i.e. f(p) is a concave function. In this case $g(\mu)$ will be convex. Rearranging (6) we have

$$L(\lambda) = \inf_{\mu \in \mathcal{D}} \{ \sum_{s} q_s (g_s(\mu_s) - \lambda \mu_s) \} + \lambda \bar{\mu} .$$
(8)

In order to minimize the first term with respect to μ we must have

$$g'_s(\mu_s) = \lambda, \quad \forall s \in \mathcal{S}.$$
 (9)

This means that for all the states for which $\mu_s > 0$ either $\mu_s = f_s(P_m)$ or the derivative of $g_s(.)$ with respect to μ_s has to be equal to λ (equal for all states with $\mu_s > 0$).

We now show that the value λ should be chosen to achieve equality in the average rate constraint, i.e. $\sum_{s \in \mathcal{S}} q_s \mu_s = \overline{\mu}$. Let λ^* be the value of λ that satisfies this constraint and let the corresponding transmission rates that satisfy (9) be μ_s^* . Given that λ^* is chosen to satisfy the average rate constraint we have that

$$L(\lambda^*) = \sum_s q_s \cdot g_s(\mu_s^*) \; .$$

Lemma 1 For any value $\lambda \geq 0$, we have $L(\lambda) \leq L(\lambda^*)$.

Proof - Let the corresponding rates for λ be denoted by μ , where these rates satisfy (9). Using (8) we have the following:

$$L(\lambda) - L(\lambda^{*}) = \sum_{s \in S} q_{s}(g_{s}(\mu_{s}) - g_{s}(\mu_{s}^{*})) - \lambda(\sum_{s \in S} q_{s}\mu_{s} - \sum_{s \in S} q_{s}\mu_{s}^{*})$$

$$= \sum_{s \in S} q_{s}(\lambda(\mu_{s}^{*} - \mu_{s}) - (g_{s}(\mu_{s}^{*}) - g_{s}(\mu_{s}))) .$$
(10)

Due to the convexity of $g_s(\cdot)$ and noting that $\lambda = g'_s(\mu_s)$, every term in the summation in the above expression is non-positive. Therefore we have $L(\lambda) \leq L(\lambda^*)$.

Using this lemma the following theorem directly follows.

Theorem 1 The value λ that maximizes Equation (8) is the value chosen to satisfy the average rate constraint, i.e. $\sum_{s \in S} q_s \mu_s = \overline{\mu}$.

The following algorithm finds the optimal rate allocation.

- Choose a (small) step-size δ .
- Set $\mu_s = 0$ for all $s \in \mathcal{S}$.
- (*) For all $s \in \mathcal{S}$: if $\mu_s \ge g_s(P_m) \delta$, then $\mathcal{S} \leftarrow \mathcal{S} \{s\}$
- Calculate $\frac{dg_s(\mu_s)}{d\mu_s}$ for all $s \in \mathcal{S}$.
- Choose s' such that $\frac{dg_{s'}(\mu_{s'})}{d\mu_{s'}} \leq \frac{dg_s(\mu_s)}{d\mu_s}$ for all $s \in \mathcal{S}$.
- $-\mu_{s'} \leftarrow \mu_{s'} + \delta.$
- If $\sum_{s} q_{s} \mu_{s} = \bar{\mu}$, then stop; else go to (*).

3.2 Optimal power allocation

We now consider problem **P-2**, which is very similar to problem **P-1** and yields similar results. In particular, the dual function of problem **P-2** can be written as follows:

$$L(\gamma) = \sup_{0 \le p_s \le P_m} \{ \sum_s q_s (f_s(p_s) - \gamma p_s) \} + \gamma \bar{p},$$

which has to be maximized over all values $\gamma \geq 0$. It can be seen that the values p_s have to be chosen in order to satisfy $f'(p_s) = \gamma$. Similar to the argument we had in Section 3.1.2, it can be shown that the value γ should be chosen to satisfy the average power constraint, i.e. we must have $\sum_{s \in S} q_s p_s = \bar{p}$. The following algorithm finds the optimal power allocation.

- Choose a (small) step-size δ .
- Set $p_s = 0$ for all $s \in \mathcal{S}$.
- (*) For all $s \in \mathcal{S}$: if $p_s \ge P_m \delta$, then $\mathcal{S} \leftarrow \mathcal{S} \{s\}$.
- Calculate $\frac{df_s(p_s)}{dp_s}$ for all $s \in \mathcal{S}$.
- Choose s' such that $\frac{df_{s'}(p_{s'})}{dp_{s'}} \ge \frac{df_s(p_s)}{dp_s}$ for all $s \in \mathcal{S}$.
- $p_{s'} \leftarrow p_{s'} + \delta$.
- If $\sum_{s} q_{s} p_{s} = \bar{p}$, then stop; else go to (*).



Figure 1: Two state channel model

4 Optimal Sleeping Scheduling

In the previous section we assumed that the user always stays on and therefore the decision is limited to selecting a transmission power p_s when it is in channel state s. In this section we study the case when the user can switch between on and off states, and seek the optimal power/rate control as well as sleep scheduling in such cases.

Formally, we will consider three types of powers consumed by the user, namely the transmission power (given by the rate-power function $g(\mu)$ as shown earlier), the circuit power denoted by p_c , and the switching power denoted by p_{sw} . Under our assumption, p_c is applied whenever the user is active/on even if it decides not to transmit, and the switching power p_{sw} is applied when the user transitions from the sleep/off state to the active/on state. We also assume that when the user is asleep its transceivers are turned off and therefore does not have channel state information.

Within this context, a stationary and deterministic policy specifies whether the user should transmit (and at what power level $p_s > 0$) in state s or go to sleep, and when the user should wake up while in the sleep state. In this section instead of looking for an optimal stationary and deterministic policy, we will tackle the simpler problem of optimizing the parameters of a more limited class of policies.

Specifically, we will only consider a two-state channel model where $S = \{s_1, s_2\}$ and $s_1 \succ s_2$. Consider a policy under which the user transmits with power p when in state s_1 and goes to sleep when in state s_2 . While asleep, the user will wake up with probability $0 \le r \le 1$ in each slot, i.e., the sleep duration is geometrically distributed with parameter r, also called the *sleep parameter*. Our goal is to find the transmission power/rate in state s_1 and the sleep parameter r so as to solve problem **P-1/P-2** by replacing the transmission power p with a combination of transmission, circuit and switching power as we show next. As we will see these two parameters are closely related such that finding one leads to the other.

4.1 Sleep Scheduling and Rate Allocation

In this part we consider the problem of minimizing the average power consumption subject to an average rate constraint using the policy outlined above. The channel variation follows a Markov process (Figure 1) with the following transition probability matrix:

$$\mathbb{P} = \begin{pmatrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{pmatrix}$$
When the user to

When the user transitions between on and off states, the system can be described in a three-state Markov chain shown in Figure 2. The three states are:



Figure 2: System states with the sleeping schedule

1. the user is on and the channel is in state s_1 (state s_1 -on). 2. the user is off and the channel is in state s_1 (state s_1 -off). 3. the user is off and the channel is in state s_2 (state s_2 -off).

The transition probability matrix is as follows:

$$\hat{\mathbb{P}} = \begin{pmatrix} q_{11} & 0 & q_{12} \\ rq_{11} & (1-r)q_{11} & q_{12} \\ rq_{21} & (1-r)q_{21} & q_{22} \end{pmatrix}$$

We note that power is consumed only in state s_1 -on, and in transitions from the two off states to state s_1 -on. Here we will adopt a simplification that when the user wakes up in state s_2 , it will go back to sleep without incurring energy expenditure in switching or sensing the channel state ¹.

To calculate the average power consumption, we only need to know the average amount of time spent in state s_1 -on. For this reason, we can combine the two off states, s_1 -off and s_2 -off into one state (off) as shown in Figure 2. The state transition probability matrix of the new two-state chain is given by:

$$\tilde{\mathbb{P}} = \begin{pmatrix} q_{11} & q_{12} \\ r(q_{11} + q_{21}) & 1 - r(q_{11} + q_{21}) \end{pmatrix}.$$
The steedy state probability of being i

The steady-state probability of being in state s_1 -on is therefore given by

$$q_1 = \frac{r(q_{11} + q_{21})}{q_{12} + r(q_{11} + q_{21})}.$$
(11)

In order to satisfy the average rate requirement we must have:

$$\mu_1 q_1 = \bar{\mu} \Rightarrow r = \frac{\bar{\mu} q_{12}}{(q_{11} + q_{21})(\mu_1 - \bar{\mu})} .$$
(12)

In order to minimize the average transmission power we need to minimize the following as a function of μ_1 .

$$P(\mu_1) = q_1(p_c + g(\mu_1)) + (1 - q_1)r(q_{11} + q_{21})p_{sw},$$
(13)

where the first term corresponds to circuit plus transmission power and the second term corresponds to the switching power. We can then find the optimum sleeping

¹Note that the switching power consumed in waking up in state s_2 and going back to sleep can be easily incorporated, by separating the single transition from s_2 -off to itself into two different transitions, one with probability $p_{22}(1-r)$, which does not incur p_{sw} , and the other with probability $p_{22}r$, which incurs p_{sw} . However, we will not consider this further in our paper.

schedule from (12). Using the fact that $q_1 = \frac{\bar{\mu}}{\mu_1}$ and taking the derivative of $P(\mu_1)$ with respect to μ_1 it can be seen that the optimal transmission rate μ_1^* has to satisfy the following:

$$\mu_1^* g'(\mu_1^*) - g(\mu_1^*) - q_{12} p_{sw} - p_c = 0.$$
(14)

The above equation can be either solved analytically (if an explicit expression for $g(\mu)$ is available or numerically (if an expression is not available for $g(\mu)$). Note that when $p_c \leq q_{12}p_{sw} - p_c$, then the power spent for switching is higher than the circuit power for any value μ_1 and therefore it is optimal not to put the node to sleep. The optimal sleeping factor r^* can be derived as follows.

$$r^* = \frac{\bar{\mu}q_{12}}{(q_{11} + q_{21})(\mu_1^* - \mu)} .$$
(15)

4.2 Sleep Scheduling and Power Allocation

In this part we adopt the same two-state channel model as in the previous subsection, and optimize the policy for maximizing the rate subject to an average power constraint. The constraint can be written as follows.

$$q_1(p_1 + p_c) + (1 - q_1)r(q_{11} + q_{21})p_{sw} = \bar{p} \Rightarrow q_1 = \frac{\bar{p}}{p_1 + p_c + q_{12}p_{sw}}.$$
 (16)

Using Equation (11) to calculate r as a function of q_1 and replacing in (16) we have:

$$q_1 = \frac{\bar{p}}{p_1 + p_c + q_{12} p_{sw}} \tag{17}$$

We need to maximize the average rate $q_1 f(p_1)$ subject to (17). Replacing q_1 with (17) and taking the derivative with respect to p_1 results in the following condition for the optimal transmission power p_1^* :

$$(p_1^* + p_c + q_{12}p_{sw})f'(p_1^*) - f(p_1^*) = 0.$$
(18)

Again the above equation can be either solved by analysis, if the function f(p) is in closed from, or numerically otherwise. After finding the optimal transmission power, the corresponding steady-state probability in state s_1 , can be calculated from Equation (17). Let q_1^* be this probability, then the optimal sleeping factor can be calculated as following.

$$r^* = \frac{q_1^* q_{12}}{(q_{11} + q_{21})(1 - q_1^*)}$$

5 Conclusion

In this paper we studied two resource allocation problems concerning the energy efficient operation of wireless devices used for data transmission. The first problem aims at minimizing the average power consumption subject to an average data rate constraint; the second problem aims at maximizing the average data rate subject to an average power constraint. We first considered the case where the user/device always stays on, and provided for both problems an algorithm that allocates the rate/power optimally for concave power-rate functions. We then considered the case where the user/device can turn off its transceivers to conserve energy, and studied the optimal joint power allocation and sleep scheduling for both problems under the assumption of a two-state channel system and geometrically distributed sleep durations.

The assumptions of continuity and differentiability of the power-rate functions may not hold in some practical systems. Extending our results to such scenarios is part of our future research. We would also like to include randomized policies in our study. Another important extension is to extend the results of Section 4 to more than two states. Moreover, we have only calculated the optimal sleeping factor for a given sleeping policy. Finding the optimal policy (i.e., in which states to transmit or go to sleep) is part of our future research.

References

- [1] R. L. Cruz and A. V. Santhanam, "Optimal routing link scheduling and power control in multi-hop wireless networks," *IEEE INFOCOM*, 2003.
- [2] R. Knopp and P. Humblet, "Information capacity and power control in single cell multiuser communications," Proc. IEEE Int. Computer Conf (ICC' 95), 1995.
- [3] M. J. Neely, E. Modiano, and C. E. Rohrs, "Power allocation and routing in multibeam satellites with time-varying channels," *IEEE/ACM Transactions on Networking, Vol. 11, No. 1*, pp. 138–152, 2003.
- [4] W. Ye, J. Heidemann, and D. Estrin, "Medium access control with coordinated adaptive sleeping for wireless sensor networks," *IEEE/ACM Transactions on Networking*, vol. 12, no. 3, pp. 493–506, June 2004.
- [5] D. Tian and N. D. Georganas, "A coverage-preserving node scheduling scheme for large wireless sensor networks," in *First ACM International Workshop on Wireless Sensor Networks and Applications (WSNA)*, 2002.
- [6] C. Hsin and M. Liu, "Network coverage using low-duty cycled censors: Rangom & coordinated sleep algorithms," in ACM/IEEE International Symposium on Information Processing in Sensor Networks (IPSN), 2004.
- [7] Y. Xu, J. Heidemann, and D. Estrin, "Geography-informed energy conservation for ad hoc routing," in ACM/IEEE International Conference on Mobile Computing and Networking (MOBICOM), 2001.
- [8] B. Chen, K. Jamieson, H. Balakrishnan, and R. Morris, "Span: An energyefficient coordination algorithm for topology maintenance in ad hoc wireless networks," in ACM/IEEE International Conference on Mobile Computing and Networking (MOBICOM), 2001.
- [9] C. Schurgers, V. Tsiatsis, S. Ganeriwal, and M. Srivastava, "Optimizing sensor networks in the energy-latency-density design space," *IEEE Transactions on Mobile Computing*, vol. 1, no. 1, 2002.