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Energy-aware Selective Communications in Sensor Networks

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1. Introduction

During the last years, Wireless Sensor Networks (WSN) have attracted the attention of researchers from electronics, signal processing, communications, and networking communities due to their potential for providing new capabilities. Among the many design challenges that have been identified, the ability of sensors to behave in an autonomous and self-organized manner using limited energy and computation resources has emerged as a fundamental factor to take into account when WSN are deployed. In fact, the limitation of resources at the network nodes is often a critical factor that conditions the design of applications for sensor networks. Among the multiple limitations to consider, energy consumption emerges as a primary concern. This is because in many practical scenarios, sensor node batteries cannot be (easily) refilled, thus nodes have a finite lifetime. Since every task carried out by the WSN has an impact in terms of energy consumption, an enormous variety of solutions, both software and hardware, have been proposed in the literature to optimize energy management; see, e.g., (Shih et al., 2001; Akyildiz et al., 2002).

Communication processes are typically among the most energy-expensive of such tasks. Many works have focused on the minimization of the energy cost taking into account the physical behavior of the WSN; see, e.g., (Shih et al., 2001; Marques et al., 2008; Wang et al., 2008). However, energy savings can also be obtained by taking a higher level approach and considering the different nature of the information that nodes have to transmit. This way, in order to enlarge the network lifetime and optimize the overall network performance, sensor nodes should weigh up: (a) the potential benefits of transmitting information and (b) the cost of the subsequent communication process. A first step to address such optimum design is to properly quantify or estimate both costs and benefits. This is possible in many practical cases because the energy consumed during the different communications tasks (cost) is typically well-characterized and because applications where messages are graded according to an importance indicator (benefit) are frequent in WSN. The message importance can be, for instance, a priority value established by the routing protocol, or an information value specified by the application supported by the sensor network. Relevant examples in the context of Sensor Networks can be found in the fields of: security (attack reports (Wood & Stankovic, 2002)), medical care (critical alerts (Shnayder et al., 2005)), or data fusion (DAIDA algorithm in (Qiu et al., 2005)), to name a few.

In such scenarios, energy in WSN can be saved by making intelligent importance-driven decisions about message transmission, in an autonomous and self-organized manner, adapting

forwarding decisions to the traffic importance. This way, a *selective forwarding scheme* allows nodes to keep the capacity for managing their own resources at the same time that optimizes communication expenses by *only transmitting the most relevant messages*.

That is precisely the objective pursued in this work: to develop optimum selective message forwarding schemes for energy-limited sensor networks where sensors (re-) transmit messages of different importance (priority). In order to decide whether to transmit or discard a message, sensors will take into account factors such as the energy consumed during the different tasks that a sensor has to carry out (transmission, reception, etc.), the available battery, the importance of the received message, the statistical model of such importances, or their neighbors' behavior.

Related ideas have recently been explored in literature. The IDEALS algorithm (Merrett et al., 2005), built under the concept of message and power priorities, tries to extend network lifetime for important messages, discarding all messages except those of high importance when battery resources are scarce. The PGR (Prioritized Geographical Routing) algorithm (Mujumdar, 2004) selects the appropriated routing technique depending on the priority of the message (low, medium or high). Moreover, a fuzzy logic approach to deal with message transfer priority arbitration that considers fifteen different priority levels has been presented in (Rivera et al., 2007). Rather than using a heuristic approach, the aim here is to obtain analytical results that building on a mathematical formulation, provide basic guidelines to design such energy-efficient schemes. This will be done by following a probabilistic and statistical approach that will open the door to a long-term optimization of the network. The optimal forwarding schemes will be obtained then as the optimal solution of the formulated problem.¹

The initial step will be to carefully select the model for the WSN. On the one hand the model has to be rich enough so that different real scenarios can be fit into, on the other hand it has to be simple enough so that the mathematical formulation is tractable and closed-form solutions can be derived. This way, basic principles to guide the design of energy-efficient importance-driven schemes can be identified. Once the mathematical model is set, we will derive optimum schemes for three different scenarios.

First we will consider the case when the forwarding schemes are designed so that sensors maximize the importance of their own transmitted messages. Second, we enrich the model by also considering the behavior of neighboring nodes. Third, we develop a forwarding scheme for nodes optimizing the importance of the messages that successfully arrive to the sink. Clearly, from an overall network efficiency perspective the first scenario will perform worse than its counterparts, but it will require less signaling overhead. On the contrary, the last scheme will optimize the overall network performance, but it will require full coordination among the nodes of the WSN. Differences among the proposed schemes will be quantified both from a theoretical and numerical perspective. Together with those optimal schemes, suboptimal schemes that operate under less demanding conditions than those for the optimal ones are also developed.²

¹Noticeably, the statistical model presented in this chapter exhibits similarities to other problems in Operations Research and Stochastic Dynamic Programming (see, e.g., (Sennott, 1999)), and the equations describing the energy evolution at the sensor node and the importance sum can be restated as a particular type of Markov decision process. Nonetheless, our treatment of the problem and the theoretical derivations are self-contained.

²To facilitate exposition, most of the chapter will be devoted to the first (and simplest) scenario. Nevertheless it should be noted that the specific results presented only for that scenario can be easily extended to the other two scenarios. Under the same philosophy, no mathematical proofs have been included in the chapter. Readers who are interested can always check our original work in (Arroyo-Valles et al., 2009;

It will be shown that in most cases, the optimal forwarding scheme is fairly simple. More specifically, it will turn out that the optimal decision is made comparing the importance of the received message with a threshold whose optimum value varies along time. We will show that our schemes improve the global performance in terms of quantity and quality of the messages that really arrive at the destination node. Finally, it will be also shown that the gain of the selective forwarding schemes (compared to a non-selective ones) will critically depend on factors such as the relationship among the energy consumed during each of the tasks that nodes have to implement, the frequency of idle times, or the statistical distribution of the importances, to name a few.

The theoretical results will be complemented with numerical simulations that not only will corroborate the theoretical claims but also will help us to quantify the gains of implementing the selective scheme for a broader range of practical scenarios.

It is worth stressing that besides the theoretical value of this work: (i) the developed schemes can eventually be incorporated into many existing routing protocols; and (ii) our approach can also be easily integrated with a variety of existing data collection approaches, including schemes that support in network data aggregation.

2. Sensor model

For the purpose of the analysis that follows, we consider a sensor network as a collection of nodes $\mathcal{N} = \{n | n = 0, \dots, N - 1\}$. For the time being, we will focus on the behavior of each node, which receives a sequence of requests to transmit messages (no matter how the network topology is). The node dynamics will be characterized by two variables

- e_k : available energy at a given node at time k . It reflects the “internal state” of the node; and
- x_k : importance of the message to be sent at time k . It reflects the “external input” to the node.

For mathematical reasons, we assume that if the node does not receive any request to transmit at time k , then $x_k = 0$, while true messages will have $x_k > 0$.

At time k , the sensor node must make a decision, d_k , about sending or not the current message, so that $d_k = 1$ if the message is sent, and $d_k = 0$ if the node decides to discard it.

Nodes consume energy at each time slot, by an amount that depends on the message reception and the taken actions. In the literature, up to three different energy expenses are typically considered:

- E_I : energy spent at a silent time, when there is no message reception, and the node may stay at “idle” mode;
- E_R : energy spent when receiving a message; and
- E_T : energy spent when transmitting a message.

The value of these parameters will depend on the system specifications and the specific application (among the factors that will determine the energy costs we find mobility, sensed magnitude, or behavior of the batteries, to name a few). For example, for static dense networks, E_T and E_R values may be very similar, while for mobile networks operating over fading channels, $E_T \gg E_R$ is expected.

2008).

Energy at time k can be expressed recursively as

$$e_{k+1} = e_k - d_k E_1(x_k) - (1 - d_k) E_0(x_k), \quad (1)$$

where $E_1(x_k)$ is the energy consumed when the node decides to transmit the message, and $E_0(x_k)$ is the energy consumed when the message is discarded. For positive values of importance, energy consumption is independent of the message importance, and we have

$$E_1(x_k) = E_T + E_R, \quad x_k > 0 \quad (2)$$

$$E_0(x_k) = E_R, \quad x_k > 0. \quad (3)$$

Recalling that $x_k = 0$ means that no messages are received, we also have

$$E_1(0) = E_0(0) = E_I. \quad (4)$$

When the sensor node is the source of the message, E_R comprises the energy expense of the message generation process (possibly by a sensing device). When the sensor node acts as a forwarder, E_R comprises the energy expense of receiving the message from other node. Thus, we assume that E_R is the same no matter if the node is the source of the message or it has been requested to forward a message from other node. Even though this assumption is not critical and could be bypassed by splitting E_R between receiving and sensing costs, we adopt it for two reasons: (i) it leads to a simpler mathematical formulation and (ii) nodes are prevented from acting selfishly (note that if the energy cost of sensing were smaller than the cost of receiving, nodes would promote their own messages instead of forwarding others' messages).

Remark 1 *It is important to mention that although this chapter focuses on the case where the energy consumption is given by (2)-(4), we will formulate and solve the general case in (1) by assuming that both consumption profiles, $E_1(x)$ and $E_0(x)$, may arbitrarily depend on x . As a first approach, the model could even be applied to situations where E_T and E_R are random or time-variant (e.g., in sensors operating over fast fading channels where transmissions are adapted based on the channel state information) by substituting E_T and E_R by their respective mathematical expectations. In any case, we assume that both energy functions are perfectly known.*

3. Optimal selective transmission

To derive an optimal transmission policy we will consider that node decisions do not depend on the state and the actions of neighboring nodes, but only on the available information at each node. Therefore, at each time, k , the node decision depends on the internal state and the external input

$$d_k = g(e_k, x_k), \quad (5)$$

with the constraint

$$g(e_k, x_k) = 0, \text{ if } e_k < E_1(x_k) \quad (6)$$

reflecting that, if the sensor node does not have enough energy to receive and transmit the message, it cannot decide $d_k = 1$.

Decisions at each node will be made with *infinite horizon*, i.e., by maximizing (on average) the importance sum of *all* transmitted messages

$$s_\infty = \sum_{k=0}^{\infty} d_k x_k. \quad (7)$$

Since nodes have limited energy resources, this sum only contains a finite number of nonzero values (eventually, for some k , $e_k < \min_k E_1(x_k)$, and $\forall k' \geq k$, we have $d_{k'} = 0$).

The following result provides an optimal selective transmitter.

Theorem 1 Let $\{x_k, k \geq 0\}$ be a statistically independent sequence of importance values, and e_k the energy process driven by (1). Consider the sequence of decision rules

$$d_k = u(x_k - \mu_k(e_k, x_k))u(e_k - E_1(x_k)), \quad (8)$$

where $u(x)$ stands for the Heaviside step function (with the convention $u(0) = 1$), and μ_k is defined recursively through the pair of equations

$$\mu_k(e, x) = \lambda_{k+1}(e - E_0(x)) - \lambda_{k+1}(e - E_1(x)) \quad (9)$$

$$\lambda_k(e) = (\mathbb{E}\{\lambda_{k+1}(e - E_0(x_k))\} + \mathbb{E}\{(x_k - \mu_k(e, x_k))^+ u(e - E_1(x_k))\}) u(e), \quad (10)$$

where $(z)^+ = zu(z)$, for any z .

The sequence $\{d_k\}$ is optimal in the sense of maximizing $\mathbb{E}\{s_\infty\}$ (with s_∞ given by (7)), among all sequences in the form $d_k = g(e_k, x_k)$ (with $g(e_k, x_k) = 0$ for $e_k < E_1(x_k)$).

The auxiliary function $\lambda_k(e)$ represents the expected increment of the total importance (expected reward) at time k , i.e.,

$$\lambda_k(e) = \sum_{i=k}^{\infty} \mathbb{E}\{d_i x_i | e_k = e\}. \quad (11)$$

The proof can be found in (Arroyo-Valles et al., 2009). Although Theorem 1 holds for any energy cost and importance value, it does not provide a clear intuition about the impact of $E_0(x)$ and $E_1(x)$ and the distribution of x_k on the design of the optimal transmission scheme. Moreover, the direct application of this theorem is difficult, because (9) and (10) state a time-reversed recursive relation: in order to make optimal decisions, the node should know the future importance distributions in advance. For these reasons, in the remainder of this chapter we will focus special attention on several particular cases that will lead us to tractable closed-form solutions.

3.1 Stationarity

If all variables x_1, \dots, x_k have the same distribution, then μ_k does not depend on k [c.f. (9) and (10)]. In this case, the following result can be shown (see (Arroyo-Valles et al., 2009)):

Theorem 2 Under the conditions of Th. 1, if the importance values $\{x_k, k \geq 0\}$ are identically distributed and $\inf_x \{E_i(x)\} > 0$, for $i = 0, 1$, the sequence of decision rules given by

$$d_k = u(x_k - \mu(e_k, x_k))u(e - E_1(x_k)), \quad (12)$$

where

$$\mu(e, x) = \lambda(e - E_0(x)) - \lambda(e - E_1(x)) \quad (13)$$

$$\lambda(e) = (\mathbb{E}\{\lambda(e - E_0(x))\} + \mathbb{E}\{(x - \mu(e, x))^+ u(e - E_1(x))\}) u(e), \quad (14)$$

is optimal in the sense of maximizing $\mathbb{E}\{s_\infty\}$ among all sequences of decision rules in the form $d_k = g(e_k, x_k)$ (with $g(e_k, x_k) = 0$ for $e_k < E_1(x_k)$).

It is important to stress that in most scenarios involving multiple sensors, the stationarity assumption, strictly speaking, is not true. For example, the distribution of messages arriving to a node depends on the transmission policy used by forwarding nodes. Since the optimal policy presented here is energy-dependent [c.f. either (9) or (13)] and the available energy clearly changes along time for all nodes, the importance distribution of the received messages will also change along time. However, it will be shown in the next sections that the simplification obtained in (13) is not only useful from a theoretical perspective, but also valid from a practical point of view for large networks. This (almost) stationary behavior can be justified based on different reasons. First, although the optimal forwarding policy varies along time, this variation turns out to be negligible during most of the time (i.e., it is almost-stationary). The underlying reason is that for medium-high values of available energy the optimal forwarding scheme is not very sensitive to energy changes. Only when nodes are close to run out of batteries, the decision threshold varies significantly as a function of the remaining energy. Second, even if the behavior of a single node is not stationary, the aggregate effect of the entire network may be stationary. In other words, the approximation given by (13) will be accurate during most of the time, and the discrepancy will only arise when the network is close to expire. Theoretical analysis and numerical results will corroborate this intuition.

3.2 Constant energy profiles

Under the constant profile model given by (2)-(4), the optimal threshold can be written as

$$\mu_k(e, x) = \mu_k(e) I_{x>0}, \quad (15)$$

where $I_{x>0}$ is an indicator function (equal to unity if the condition holds and zero otherwise), and using (9) we have

$$\mu_k(e) = \lambda_{k+1}(e - E_R) - \lambda_{k+1}(e - E_T - E_R). \quad (16)$$

Also, (10) becomes

$$\begin{aligned} \lambda_k(e) &= P_I \lambda_{k+1}(e - E_I) + (1 - P_I) \lambda_{k+1}(e - E_R) - P_I \mu_k(e, 0) u(-\mu_k(e, 0)) u(e - E_I) \\ &\quad + (1 - P_I) \mathbb{E}\{(x_k - \mu_k(e, x_k))^+ | x_k > 0\} \cdot u(e - E_T - E_R) \\ &= P_I \lambda_{k+1}(e - E_I) + (1 - P_I) \lambda_{k+1}(e - E_R) \\ &\quad + (1 - P_I) \mathbb{E}\{(x_k - \mu_k(e, x_k))^+ | x_k > 0\} \cdot u(e - E_T - E_R) \end{aligned} \quad (17)$$

where $P_I = \Pr\{x = 0\}$. Defining

$$H_k(\mu) = \mathbb{E}\{(x_k - \mu)^+ | x_k > 0\}, \quad (18)$$

we can write

$$\begin{aligned} \lambda_k(e) &= P_I \lambda_{k+1}(e - E_I) + (1 - P_I) \lambda_{k+1}(e - E_R) \\ &\quad + (1 - P_I) H(\mu_k(e)) u(e - E_T - E_R). \end{aligned} \quad (19)$$

Thus, the optimal transmission policy for a sensor with a constant energy profile is described by (16) and (19). In order to analyze the influence of idle times and the relation between transmission and reception energy expenses separately, in the following examples we consider

the case of $P_I = 0$ and/or $E_I = 0$. Note that if any of these conditions holds, the expected importance sum in (19) can be rewritten as

$$\lambda_k(e) = \lambda_{k+1}(e - E_R) + H(\mu_k(e))u(e - E_T - E_R). \quad (20)$$

3.3 Examples

As we have already mentioned, there is no general explicit solution to the pair of equations (9) and (10), not even for the stationary case in (16) and (19). For this reason, in this section we focus on systems satisfying the operating conditions that gave rise to (20) (constant energy profiles, stationarity and zero idle energy) and solve the recursive relations for several importance distributions³. This simplification will lead to tractable expressions, providing insight into the behavior of the optimal forwarding scheme.

- **Uniform Distribution:** Let $U(0,2)$ denote the uniform distribution between 0 and 2 whose probability density function (PDF) is

$$p(x) = \frac{1}{2}(u(x) - u(x - 2)). \quad (21)$$

Substituting (21) into (18), we have

$$H(\mu) = E\{(x - \mu)^+\} = \frac{1}{4}(2 - \mu)^2, \quad (22)$$

and therefore, the expected reward is given by

$$\lambda(e) = \lambda(e - E_R) + \frac{1}{4}(2 - \mu(e))^2 u(e - E_T - E_R). \quad (23)$$

Figure 1(a) plots the threshold for *extremely small* values of available energy, e . $E_1(x) = 1$ and different values of the ratio E_T/E_R are considered. Note that, for values of e lower than 1, in spite of the threshold value is 0, there is no actual transmission because $u(e - E_T - E_R) = 0$. For $1 < e < E_1 + E_R$ there is only one opportunity to send the message, so the threshold is also 0, which means that the message will be transmitted whatever its importance value is. For larger energy values, the threshold increases, meaning that the transmission can be made more selective. Note, also, that $\mu(e)$ evolves in a staircase manner, because any energy amount in excess of a multiple of E_R is useless.

Figure 1(b) represents the expected reward ($\lambda(e)$). Note that the case $E_T = 0$ is equivalent to a non-selective transmitter (because, according to (16), the optimal threshold is 0 in that case, which means that no messages are discarded). Despite that, for e close to 2, there is not energy for a second transmission, the selective transmitter provides a significant expected income with respect to the non-selective one.

Figure 2(a) shows the optimal threshold for $E_T = 4$, $E_R = 1$ and *high* values of available energy. Note the sawtooth shape of the forwarding threshold: as the available energy is reduced to a value close to a multiple of the energy required to transmit, the forwarding threshold decreases, because if there is not any transmissions, the total number of possible messages to be sent is reduced by a unity.

Figure 2(b) represents the expected reward of the selective transmitter (continuous line) and the non-selective one (dotted line), which transmits all messages regardless of their importance value, until energy is used up.

³In the following, free parameters will be set so that all importance distributions have a mean value equal to one.

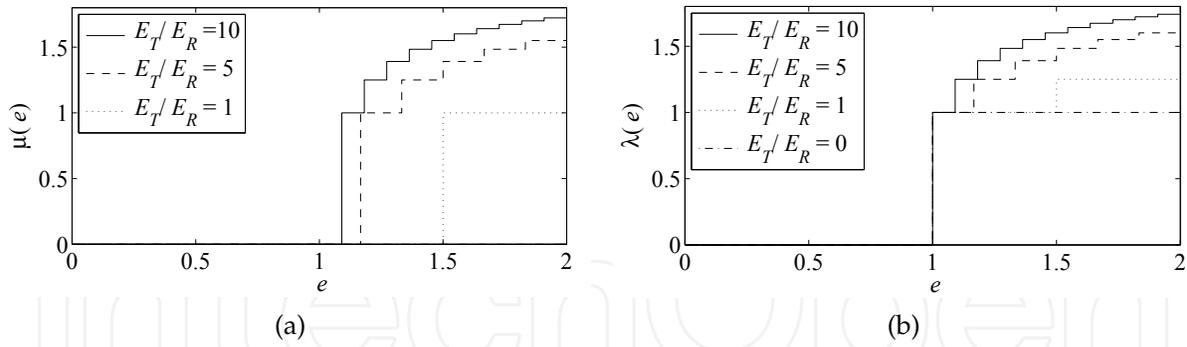


Fig. 1. Variation of the decision threshold (a) and the expected importance sum (b) with respect to the available energy, e . A uniform importance distribution $U(0,2)$ with $E_1(x) = E_R + E_T = 1$ is assumed. Different plots correspond to different values of E_T/E_R .

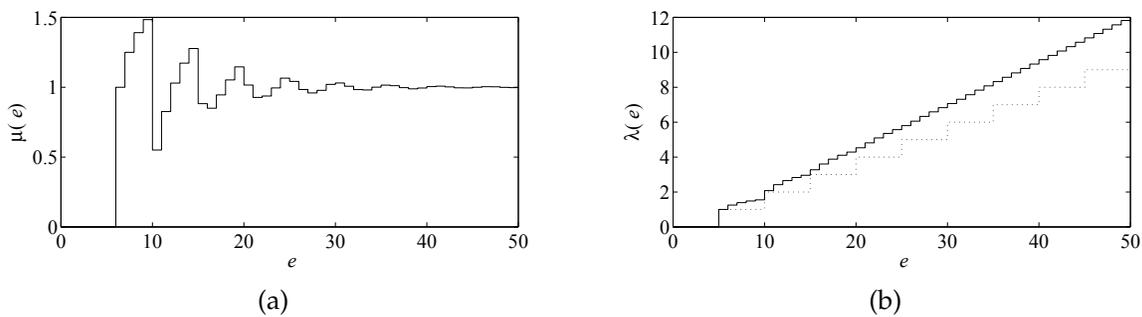


Fig. 2. The decision threshold (a) and the expected importance sum (b) (continuous line) as a function of the available energy. A uniform importance distribution $U(0,2)$ with $E_T = 4$ and $E_R = 1$ is assumed. The stepwise function (dotted line) reflects the behavior of a non-selective transmitter, which transmits any message whatever its importance value is.

- **Exponential:** For an exponential distribution of free parameter a , we have

$$p(x) = \frac{1}{a} \exp\left(-\frac{x}{a}\right) u(x), \tag{24}$$

and

$$H(\mu) = a \exp\left(-\frac{\mu}{a}\right), \tag{25}$$

so that

$$\lambda(e) = \lambda(e - E_R) + a \exp\left(-\frac{\mu(e)}{a}\right) u(e - E_T - E_R). \tag{26}$$

The variation of μ for an exponential distribution with $a = 1$, $E_T = 4$ and $E_R = 1$ is illustrated in Figure 3. The more restrictive threshold, compared to that one shown in Figure 2(a) for the uniform distribution, gives rise to a higher increase in the expected reward with regard to the non-selective forwarder.

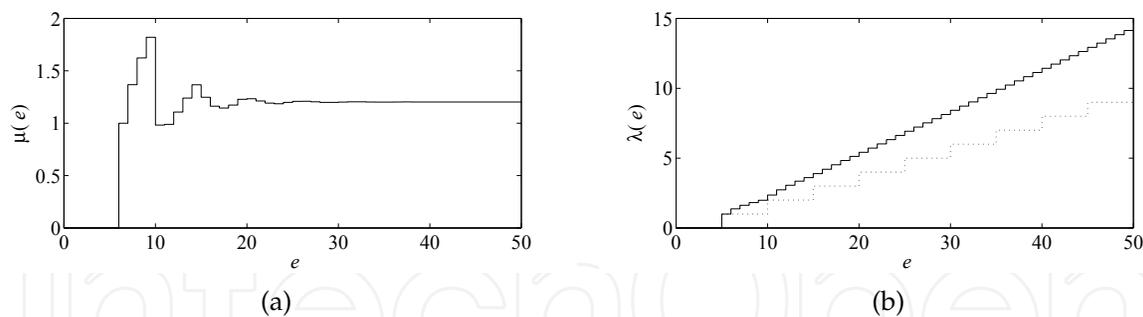


Fig. 3. Variation of the decision threshold (a) and the expected importance sum (b) (continuous line) with respect to the available energy. An exponential importance distribution with $a = 1$, $E_T = 4$ and $E_R = 1$ is assumed. The dotted line represents the expected importance sum of the non-selective transmitter.

4. Asymptotic analysis

4.1 Large energy threshold

The above examples show that for large energy values e , the threshold converges to a constant value, and the expected reward tends to grow linearly. Both behaviors are closely related because, as (9) shows, the optimal threshold is the difference between two expected rewards. In this section, we discuss the asymptotic behavior of any selective transmitter in the stationary case. To do so, we first define the *income rate* of a selective transmitter.

Definition 1 The income rate of a selective transmitter with expected reward $\lambda(e)$ is defined as

$$r = \lim_{e \rightarrow \infty} \frac{\lambda(e)}{e}. \quad (27)$$

The following theorem (Arroyo-Valles et al., 2009) provides a way to compute the income rate of the optimal selective transmission policy.

Theorem 3 The only threshold function $\mu(e, x)$ which is a solution of (13) and (14) and is constant with e is given by

$$\mu(e, x) = \mu(x) = (E_1(x) - E_0(x))r, \quad (28)$$

where r is a solution of

$$\mathbb{E}\{E_0(x)\}r = \mathbb{E}\{(x - (E_1(x) - E_0(x))r)^+\}. \quad (29)$$

Moreover, if $E_1(x) \geq E_0(x)$, for all x , this solution is unique.

An important consequence of Theorem 3 is that, if $\lim_{e \rightarrow \infty} \mu(e, x)$ exists, it must be equal to (28). Even though we will not show any theoretical convergence result, we have found a systematic empirical convergence, and we guess that this could be a general result for any importance distribution, provided it is stationary.

For the constant profile case, the asymptotic threshold (28) becomes

$$\mu(x) = E_T r I_{x > 0}. \quad (30)$$

The recursive expression in (29) can be written as a function of $\mu^* = E_T r$ as

$$(P_I E_I + (1 - P_I) E_R) \mu^* = (1 - P_I) E_T H(\mu^*) \quad (31)$$

where $H(\mu^*)$ is given by (18). Defining

$$\rho = \frac{(1 - P_I) E_T}{P_I E_I + (1 - P_I) E_R} \quad (32)$$

we get

$$\mu^* = \rho H(\mu^*). \quad (33)$$

As a reference for comparison, we will consider the income rate of the non-selective transmitter (i.e., the node transmitting any message requested to be sent, provided that the battery is not depleted), which can be shown (Arroyo-Valles et al., 2009) to be equal to

$$r_0 = \frac{\mathbb{E}\{x\}}{\mathbb{E}\{E_1(x)\}}. \quad (34)$$

4.2 Gain of a selective forwarding scheme

In this section we analyze asymptotically the advantages of the optimal selective scheme with regard to the non-selective one. To do so, we define the *gain* of a selective transmitter as the ratio of its income rate, r , and that of the non-selective transmitter, r_0 ,

$$G = \frac{r}{r_0}. \quad (35)$$

For the optimal selective transmitter in the constant profile case, combining (29) and (34), we get

$$\begin{aligned} G &= \frac{\mu^* \mathbb{E}\{E_1(x)\}}{E_T \mathbb{E}\{x\}} = \frac{\mu^* (P_I E_I + (1 - P_I) (E_T + E_R))}{E_T \mathbb{E}\{x\}} \\ &= (1 - P_I) (1 + \rho^{-1}) \frac{\mu^*}{\mathbb{E}\{x\}} = \frac{1 + \rho}{\rho} \frac{\mu^*}{\mathbb{E}\{x|x > 0\}}. \end{aligned} \quad (36)$$

In the following, we compute the gain for several importance distributions.

4.3 Examples

Let us illustrate some examples taken from the constant profile case,

- **Uniform Distribution:** Substituting (22) into (33), we get

$$\mu^* = \frac{1}{4} \rho (2 - \mu^*)^2, \quad (37)$$

which can be solved for μ^* as

$$\mu^* = 2 \left(\frac{1 + \rho}{\rho} - \sqrt{\left(\frac{1 + \rho}{\rho} \right)^2 - 1} \right) \quad (38)$$

(the second root is higher than 2, which is not an admissible solution). Note that, for $\rho = 4$, we get $\mu^* = 1$, which agrees with the observation in Fig.2(a).

Therefore, the gain is given by

$$G = 2 \frac{1+\rho}{\rho} \left(\frac{1+\rho}{\rho} - \sqrt{\left(\frac{1+\rho}{\rho}\right)^2 - 1} \right). \quad (39)$$

- **Exponential:** Using (25) we find that μ^* is the solution of

$$\mu^* = aW(\rho), \quad (40)$$

where $W(x) = y$ is the real-valued Lambert's W function which solves the equation $ye^y = x$ for $-1 \leq y \leq 0$ and $-1/e \leq x \leq 0$ (Corless et al., 1996). Thus,

$$G = (1 + \rho^{-1})W(\rho). \quad (41)$$

Figure 4 compares the gain of the uniform and the exponential distributions as a function of ρ . The graphic remarks that, under exponential distributions, the difference between the selective and the non-selective forwarding scheme is much more significant. The better performance of the exponential distribution compared to the uniform may be attributed to the tailed shape. We may think that, for a long-tailed distribution, the selective transmitter may be highly selective, saving energy for rare but *extremely important* messages. This intuition is corroborated by the Pareto distribution (see (Arroyo-Valles et al., 2009) for further details).

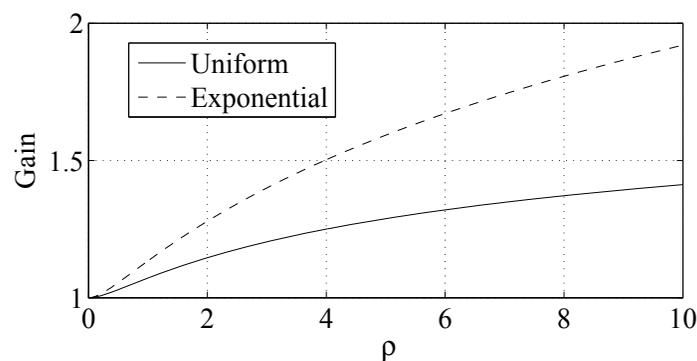


Fig. 4. Gain of the uniform and exponential distributions, as a function of ρ .

4.4 Influence of idle times

The above examples show that the gain of the optimal selective transmitter increases with ρ . By noting that ρ in (32) is a decreasing function of P_I and E_I , the influence of idle times becomes clear: as soon as the frequency of idle times or the idle energy expenses increases, the gain of the selective transmission scheme reduces.

5. Network Optimization

5.1 Optimal selective forwarding

Since each message must travel through several nodes before arriving to destination, the message transmission is completely successful if the message arrives to the sink node. In general, an intermediate node in the path has no way to know if the message arrives to the sink (unless

the sink returns a confirmation message), but it can possibly listen if the neighboring node in the path propagated the message it was requested to forward. If d_k denotes the decision at node i , and q_k denotes the decision at the neighboring node j , the transmission is said to be locally successful through j if $d_k = 1$ and $q_k = 1$.

In this case, we can re-define the cumulative sum of the importance values in (7) by omitting all messages that are not forwarded by the receiver node, as

$$s_\infty = \sum_{i=0}^{\infty} d_i q_i x_i, \quad (42)$$

and, as we did in Section 3, the goal at each node is to maximize its expected value of s_∞ . Note that (42) reduces to (7) by taking $q_i = 1$ for all i .

The following result provides the optimal selective forwarder.

Theorem 4 Let $\{x_k, k \geq 0\}$ be a statistically independent sequence of importance values, and e_k the energy process given by (1). Consider the sequence of decision rules

$$d_k = u(Q_k(e_k, x_k)x_k - \mu_k(e_k, x_k))u(e - E_1(x_k)), \quad (43)$$

where $u(x)$ stands for the Heaviside step function (with the convention $u(0) = 1$),

$$Q_k(x_k, e_k) = \mathbb{E}\{q_k | e_k, x_k\} = P\{q_k = 1 | e_k, x_k\} \quad (44)$$

and thresholds μ_k are defined recursively through the pair of equations

$$\mu_k(e, x) = \lambda_{k+1}(e - E_0(x)) - \lambda_{k+1}(e - E_1(x)) \quad (45)$$

$$\lambda_k(e) = (\mathbb{E}\{\lambda_{k+1}(e - E_0(x_k))\}) + \mathbb{E}\{(Q_k(e_k, x_k)x_k - \mu_k(e, x_k))^+ u(e - E_1(x_k))\} u(e). \quad (46)$$

Sequence $\{d_k\}$ is optimal in the sense of maximizing $\mathbb{E}\{s_\infty\}$ (with s_∞ given by (42)) among all sequences in the form $d_k = g(e_k, x_k)$ (with $g(e_k, x_k) = 0$ for $e_k < E_1(x_k)$).

The auxiliary function $\lambda_k(e)$ represents the increment of the total importance that can be expected at time k , i.e.,

$$\lambda_k(e) = \sum_{i=k}^{\infty} \mathbb{E}\{d_i q_i x_i | e_k = e\}. \quad (47)$$

The proof can be found in (Arroyo-Valles et al., 2009). It is interesting to re-write (43) as

$$d_k = u\left(Q_k(x_k, e_k) - \frac{\mu_k(e)}{x_k}\right) u(e_k - E_1(x_k)) \quad (48)$$

which expresses the node decision as a comparison of Q_k with a threshold inversely proportional to the importance value, x_k . This result is in agreement with our previous models in (Arroyo-Valles et al., 2006), (Arroyo-Valles, Alaiz-Rodriguez, Guerrero-Curieses & Cid-Sueiro, 2007).

5.2 Global network optimization applying a selective transmission policy

In order to complete the theoretical study, the network optimization at a global level is analyzed. In general, and as we mentioned in Sec. 5.1, an intermediate node in the path has no way to know if the message arrives to the sink unless the sink sends a confirmation message. Let's denote a_k as the arrival of a message to the sink node and let's define A_k as $A_k(x_k, e_k) = \mathbb{E}\{a_k | e_k, x_k\} = P\{a_k = 1 | e_k, x_k\}$, similar to Q_k definition from Theorem 4. The optimal selective policy when optimizing the global performance can be obtained from Theorem 4 just replacing q_k and Q_k by a_k and A_k . The difference among both theorems will stay in the interpretation of variables a_k and q_k . While q_k indicates the action of a forwarding node, a_k refers to the success of the whole routing process.

6. Algorithmic design

In practice, to compute the optimal forwarding threshold in a sensor network, $Q_k(x_k, e_k)$, $A_k(x_k, e_k)$ and the importance distribution of messages, $p_k(x_k)$, are required. As they are unknown, they can be estimated on-the-fly with data available at time k .

6.1 Estimating Q_k and A_k

A simple estimate of the forwarding policy $Q_k = E\{q_k | x_k, e_k\}$ can be derived by assuming that (1) it does not depend on e_k (i.e., the subsequent forward/discard decision of the receiver node is independent of the energy state at the transmitting node), and (2) each node is able to listen to the retransmission of a message that has been previously sent (i.e. each node can observe q_k when $d_k = 1$). Following an approach previously proposed in (Arroyo-Valles et al., 2006) and (Arroyo-Valles, Marques & Cid-Sueiro, 2007), in (Arroyo-Valles et al., 2008) we propose to estimate Q_k by means of the parametric model

$$Q_k(x_k, w, b) = P\{q_k = 1 | x_k, w, b\} = \frac{1}{1 + \exp(-wx_k - b)} \quad (49)$$

Note that, for positive values of w , Q_k increases monotonically with x_k , as expected from the node behavior. We estimate parameters w and b via ML (maximum likelihood) using the observed sequence of neighbor decisions $\{q_k\}$ and importance values $\{x_k\}$, by means of stochastic gradient learning rules

$$\begin{aligned} w_{k+1} &= w_k + \eta(q_k - Q_k(x_k, w_k, b_k))x_k \\ b_{k+1} &= b_k + \eta(q_k - Q_k(x_k, w_k, b_k)) \end{aligned} \quad (50)$$

where η is the learning step.

Similarly, the estimation algorithm given by (49) and (50) can be adapted to estimate A_k in a straightforward manner, but it requires the sink node to acknowledge the reception of messages back through the routing path, so as to provide the nodes with a set of observations a_k for the estimation algorithm.

6.2 Estimating asymptotic thresholds

The optimal threshold depends on the distribution of message importances, which in practice may be unknown. Another alternative, apart from estimating it (see (Arroyo-Valles et al., 2009)), consists of estimating parameter r in (29) and replace the optimal threshold function by its asymptotic limit. Parameter r can be estimated in real time based on the available data $\{x_\ell, \ell = 0, \dots, k\}$ at time k .

However, first of all we should update (29) to incorporate to the formula the information obtained from neighboring nodes and thus, define a formula as general as possible. Comparing (8) and (43), we realize that x in the optimal transmitter is replaced by $xQ(x)$ in the optimal forwarder and so, (29) should be replaced by

$$\mathbb{E}\{E_0(x)\}r = \mathbb{E}\{(xQ(x) - (E_1(x) - E_0(x))r)^+\}. \quad (51)$$

Defining $\Delta(x) = E_1(x) - E_0(x)$, we can estimate the expected value on the right-hand side of (51) as

$$\mathbb{E}\{(xQ(x) - \Delta(x)r)^+\} \approx m_k \quad (52)$$

where

$$m_k = \frac{1}{k} \sum_{i=1}^k (x_i Q(x_i) - \Delta(x_i)r)^+ = \left(1 - \frac{1}{k}\right) m_{k-1} + \frac{1}{k} (x_k Q(x_k) - \Delta(x_k)r)^+ \quad (53)$$

According to (51), we can then estimate r at time k as $r_k = m_k / \epsilon_0$, where $\epsilon_0 = \mathbb{E}\{E_0(x)\}$. Using (53) we get

$$r_k = \left(1 - \frac{1}{k}\right) r_{k-1} + \frac{(x_k Q(x_k) - \Delta(x_k)r)^+}{k\epsilon_0} \quad (54)$$

Unfortunately, the above estimate is not feasible, because the left-hand side depends on r . But we can replace it by r_{k-1} , so that

$$r_k = \left(1 - \frac{1}{k}\right) r_{k-1} + \frac{(x_k Q(x_k) - \Delta(x_k)r_{k-1})^+}{k\epsilon_0}. \quad (55)$$

For the constant profile case, the optimal forwarding threshold is computed as

$$\mu_k = \left(1 - \frac{1}{k}\right) \mu_{k-1} + \frac{\rho}{k} \cdot (x_k Q(x_k) - \mu_{k-1})^+ \quad (56)$$

where ρ is given by (32).

7. Experimental work and results

In this section we test the selective message forwarding schemes in different scenarios. All simulations have been conducted using Matlab.

7.1 Sensor network

The scenario of an isolated energy-limited selective transmitter node can be found in (Arroyo-Valles et al., 2009). Although it provides useful insights, from a practical perspective a test case with a single isolated node is too simple. For this reason, we simulate a more realistic scenario consisting of a network of nodes. Experiments have been conducted considering both optimal selective transmitters and optimal selective forwarders (with both local and global optimization). Results focused on the optimal selective transmitters are presented in Section 7.1.1 while results for both selective transmitters and forwarders are presented in Section 7.1.2. Before starting the analysis of those results, we first describe part of the simulation set-up that is common for all the numerical tests run in this Section.

1. All nodes deployed in the sensor network are identical and have the same initial resources except for the sink, that has rechargeable batteries (thus it does not have energy limitations). This static unique sink is always positioned at the right extreme of the field. We will consider that $P_I = 0$, $E_T = 4$, $E_R = 1$ and $E_I = 0$. Sources are selected at random and keep transmitting messages of importances x to the sink until network lifetime expires. Network lifetime is defined as the number of time slots achieved before the sink is isolated from its neighboring nodes. In order to simulate a more realistic set up, the parameters of the two distributions considered (uniform and exponential) will be adjusted so that $x_k \in [0, 10]$ (with $x_k = 0$ representing a silent time).
2. Nodes are considered as neighbors if they are placed within the transmission radius, which for simplicity reasons and due to power limitations is assumed to be the same for all nodes (i.e., a Unit Disk Graph model is assumed). Since nodes can only transmit messages inside their coverage area, they have geographical information about their own position, the location of their neighbors and the sink coordinates. It is naturally assumed that coverage areas are reciprocal, which is common when having a single omnidirectional antenna. Under this assumption nodes can listen to the channel and detect retransmissions of neighboring nodes before retransmitting the message again, in case a loss is detected, or discard it.
3. Performance is assessed in terms of the importance sum of all messages received by the sink, the mean value of these received importances, the number of transmissions made by origin nodes and the network lifetime (measured in time slots).
4. Experimental results are averaged over 50 different topologies which contain different samples of the two previous importance distributions.

7.1.1 Sensor network composed of selective transmitters

In this scenario, the sensor network is considered as a square area of 10×10 , where 100 nodes have been uniformly randomly deployed. The initial energy of the nodes is set to $E = 200$ units. Regarding to the transmitting schemes implemented, four different types of sensors are compared.

- *Type NS* (Non-Selective): Non-selective node. The threshold is set to $\mu = 0$, so that it forwards all messages.
- *Type OT* (Optimal Transmitter): Optimal selective node. Threshold μ is computed according to (16) and (19), where nodes know the source importance distribution $p(x)$.
- *Type CT* (Constant Threshold): Asymptotically optimal selective node. The sensor node establishes a constant threshold which is set to the asymptotic value of the optimal threshold given by (33).
- *Type AT* (Adaptive Transmitter): Adaptive selective node. The threshold is also computed following (16) and (19). Nevertheless, the node is unaware of $p(x)$ and it uses the Gamma distribution estimation strategy, proposed in (Arroyo-Valles et al., 2009).

The routing algorithm implemented by the network follows a greedy forwarding scheme (Karp & Kung, 2000). Although the disadvantages of the greedy forwarding algorithm are well-known (e.g., when the number of nodes close to the sink is small or there is a void), we choose this algorithm due to its simplicity, which will contribute to minimize its influence on the final results. This way, we can gauge better the effect of implementing our optimal selective schemes in a network, which indeed is the main objective of the simulations. It is worth

re-stressing that we are not proposing a new routing algorithm but a forwarding scheme with a selective mechanism and therefore, this scheme can also be integrated into other more efficient routing algorithms. Periodical “keep alive” beacons are sent to keep nodes updated. Link losses have also been included and so, the algorithm is made more robust by establishing a maximum number of retransmissions before discarding the message, which has been set to 5 in our simulations.

	Total Import. Received Sink	Importance mean value	Number of Transmissions	Network Lifetime
Type NS	1021.92	5.06	688.56	7896.00
Type OT	1388.40	7.49	677.38	8467.90
Type CT	1384.26	7.49	656.92	8441.08
Type AT	1377.22	7.80	720.78	8812.74

Table 1. Averaged performance when the importance values are generated according to a uniform distribution - routing scenario

Simulation results for the scenario composed of selective transmitters are summarized in Tables 1 and 2. The numerical results validate our theoretical claims. As expected, the main conclusion is that the selective transmission scheme outperforms the non-selective one.

	Total Import. Received Sink	Importance mean value	Number of Transmissions	Network Lifetime
Type NS	331.72	1.76	672.84	7798.02
Type OT	610.96	3.84	613.30	8758.00
Type CT	609.45	3.86	596.82	8713.88
Type AT	594.92	4.18	685.98	9309.56

Table 2. Averaged performance when the importance values are generated according to an exponential distribution - routing scenario

Regardless of the distribution tested, both the mean value of the importance of messages received by the sink and the network lifetime are higher when the selective transmission scheme is implemented.

Among the selective policies, *OT* nodes exhibit the best performance. Nevertheless, performance differences among *OT*, *CT* and *AT* are not extremely high. The underlying reason is that decisions made at neighboring nodes and path losses may alter the shape of the original importance distribution. Since *AT* nodes estimate the importance distribution $p(x)$ based on real received data, they are able to correct this alteration. This is not the case of *OT* and *CT* nodes, which calculate μ based on the original distribution, without accounting for the alterations introduced by the network. The existence of a transitory phase through the calculation of the adaptive threshold in the *AT* scheme may also justify small differences with respect to the other non-adaptive selective schemes.

7.1.2 Performance comparison among selective nodes

In this subsection, we compare the performance of different networks each of them comprising a different type of selective nodes, namely:

- *Type NS* (Non-Selective) : Non-selective sensor node, it forwards all the received messages, no matter which its importance value is.
- *Type AT* (Adaptive Transmitter): Adaptive Selective transmitter sensor node. This sensor corresponds to the particular case of (42) taking $q_k = 1$, which is equivalent to assume that the node does not take into account the neighbors' behavior, i.e. it maximizes the importance sum of all messages transmitted by the node, no matter if they are forwarded by the neighboring node or not.
- *Type LAF* (Local Adaptive Forwarder): Local Adaptive Selective forwarder sensor node. This sensor type computes the forwarding threshold according to (45) and (46). It bears in mind the influence of neighboring nodes decisions.
- *Type GAF* (Global Adaptive Forwarder): Global Adaptive Selective forwarder sensor node. The forwarding threshold is set according to (45) and (46); however a_k and A_k are used instead of q_k and Q_k in order to achieve a global network optimization.

Since the transmission policies implemented by each node can (and will) alter the importance distribution originally generated by the sources, all selective types of nodes considered here are adaptive and the forwarding threshold is computed using the asymptotic threshold estimate given by (56).

For illustrative purposes, we simplify the simulation set-up by considering 30 nodes that are equally-spaced placed in a row, so that each sensor can only communicate with the adjoining sensors. This configuration is a simple but illustrative manner of emulating the traffic arriving to a sink, as nodes located close to the sink have to route more messages (both those generated by themselves and the ones arriving from others far-away located). The energy values of the different energy states are the same as the ones used in previous sections. Nodes have the same initial amount of battery, set to 5000. The channel is ideal (loss free path). Parameter η in (50) is set to .005. All nodes generate messages according to the same importance distribution, which is equivalent to say that the source importance distribution is the same for all nodes. Again, results averaged over 50 runs for different importance distributions are listed in Tables 3 and 4. Simulations are stopped when the sink is isolated.

	Total Import. Received	Importance mean value	Number of Receptions	Network Lifetime
Type NS	4989.26	4.99	999.02	1000
Type AT	8158.45	8.28	985.52	2963.42
Type LAF	8210.73	8.33	985.38	3056.90
Type GAF	8209.80	8.33	985.36	3056.64

Table 3. Averaged performance when the importance values are generated according to a uniform distribution

According to the analytical formulation, the non-selective sensor nodes perform worse (regardless of the metrics) than any type of the selective nodes. It is worth mentioning that the

mean value of the messages received by the sink is slightly higher in this scenario than in the precedent which corresponds to an arbitrary topology.

If we look closely among the selective nodes, the selective forwarding (local or global) yields a better performance than the selective transmission for all the proposed importance distribution types. Nevertheless, looking at the averaged values of the importance sum, the goal metric to be maximized, it is revealed that the improvement, although substantial, is not extreme. The reason stems from the fact that all nodes have an identical source importance distribution. More noticeable differences will appear whenever the nodes generate messages of different importance distributions.

	Total Import. Received	Importance mean value	Number of Receptions	Network Lifetime
Type NS	1755.40	1.76	999.02	1000
Type AT	5526.04	5.99	923.12	11580.70
Type LAF	5612.34	6.11	919.18	12459.76
Type GAF	5612.22	6.11	919.08	12468.58

Table 4. Averaged performance when the importance values are generated according to an exponential distribution

Additionally, the difference is almost unnoticeable when comparing the LAF and GAF nodes (the actual difference depends on the distribution tested). This extremely low difference is due to the effect that nodes tend to propagate their current thresholds to adjoining nodes and, therefore, the local and global optimization are almost coincident.

Figure 5 shows the threshold evolution for Adaptive Transmitters (a) and Local Adaptive Forwarders (b). Going into detail, results in Figure 5(a) point out that each node behaves independently and sets its threshold according to its own available information. The furthest node from the sink sets the lowest threshold, which clearly corresponds to the isolated node scenario given that it only has its own generated traffic. Nevertheless, the subsequent nodes in the network increase their thresholds as a consequence of receiving messages with clipped importances from their previous nodes. Thus, the closer a node is placed to the sink, the larger the threshold value is. On the other hand, LAF nodes in Figure 5(b) follow a similar trend. Again, after a transitory phase, nodes tend to converge to the threshold value established by the nearest node from the sink. This is a reasonable behavior because it would not make sense to transmit a message up to the last but one node and then, discard it for not being important enough. Nodes tend to learn the threshold that the neighbor closer to the sink node is using to ensure that the message to transmit is forwarded, so that in the end, nodes learn the threshold estimated by the nearest node to the sink. Learning the probability of retransmission (Q_k or A_k in case of global optimization) is equivalent to the effect of backward propagating the threshold value to the whole sensor network.

Once the last but one node is isolated, two effects can be observed. The first is related to that node, which is now free to fix its own threshold value according to the messages generated by itself. And the second is related to the remaining nodes in the network. From the moment the network is broken down and there is no manner to reach the sink, nodes located on the isolated side of the breakdown will tend to set a lower threshold since the lack of collaboration is then propagated backwards (the estimation of the probability that a neighbor will re-transmit

the messages decreases). Moreover, since this effect is produced in cascade, nodes will end up adjusting their thresholds to the threshold of the node located next to the breakdown.

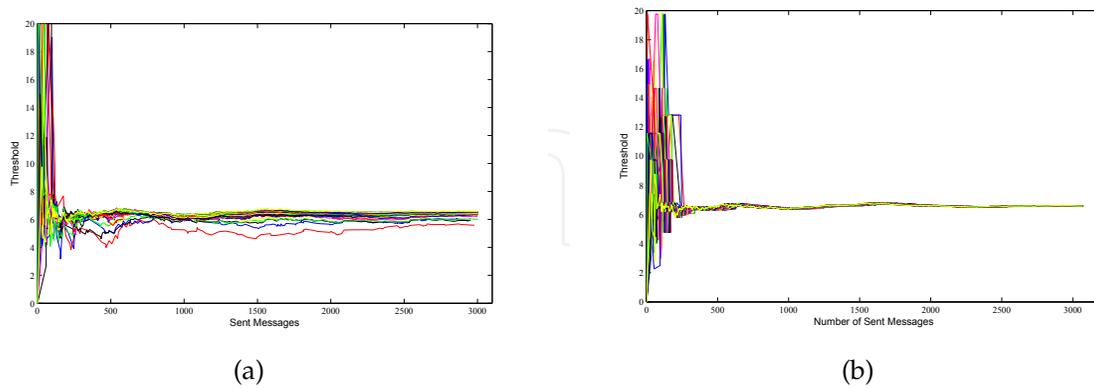


Fig. 5. The decision threshold evolution for Adaptive Transmitters (a) and Local Adaptive Forwarders (b) as a function of the number of sent messages in a simulation run. A network topology of 30 equally-spaced nodes located in a row is considered. A uniform importance distribution $U(0,10)$ is assumed.

In order to enhance the advantages of using selective forwarding schemes, a new scenario is proposed. In this case, nodes generate messages according to an exponential distribution, but the source importance distribution is different in every node so that parameter a follows an exponential trend, too. Remark that the manner of selecting parameter a implies that message importance $x_k \notin [0,10]$ any more. For concision, Table 5 lists results only for the AT and LAF cases.

	Total Import. Received	Importance mean value	Number of Receptions	Network Lifetime
Type AT	11229.32	13.92	811.60	27014.90
Type LAF	11763.35	14.37	825.48	28583.16

Table 5. Averaged performance when the importance values are generated according to an heterogeneous exponential distribution

In summary, numerical results corroborate that selective forwarding sensor nodes are more energy-efficient than their non-selective counterparts. On the one hand, the selective forwarding schemes significantly increase the network lifetime. On the other hand, they also allow high importance messages to reach the sink when batteries are scarce.

8. Conclusions

This chapter has introduced an optimum selective forwarding policy in WSN as an energy-efficient scheme for data transmission. Messages, which were assumed to be graded with an importance value and which could be eventually discarded, were transmitted by sensor nodes

according to a forwarding policy, which considered consumption patterns, available energy resources in nodes, the importance of the current message and the statistical description of such importances.

Forwarding schemes were designed for three different scenarios (a) when sensors maximize the importance of their own transmitted messages (selective transmitter); (b) when sensors maximize the importance of messages that have been successfully retransmitted by at least one of its neighbors (selective forwarder with local optimization); and (c) when sensors maximize the importance of the messages that successfully arrive to the sink (selective forwarder with global optimization). Interestingly, the structure of the optimal scheme was the same in all three cases and consisted of comparing the received importance and the forwarding threshold. The expression to find the optimum threshold varies with time and is slightly different for each scenario. It is worth remarking that the developed schemes were optimal from an importance perspective, efficiently exploited the energy resources, entailed very low computational complexity and were amenable to distributed implementation, all desirable characteristics in WSN.

The three schemes have been compared under different criteria. From an overall network efficiency perspective, the first scheme performed worse than its counterparts, but it required less signaling overhead. On the contrary, the last scheme was the best in terms of network performance, but it required the implementation of feedback messages from the sink to the nodes of the WSN. Numerical results showed that for the tested cases the differences among the three schemes were small. This suggests that the second scheme, which is just slightly more complex than the first one and performs evenly with the third one, can be the best candidate in most practical scenarios.

Finally, suboptimal schemes that operate under less demanding conditions than those for the optimal ones were also explored. Under certain simplifying operating conditions, a constant forwarding threshold which did not change along time and entailed asymptotic optimality, was also developed and closed-form expressions were obtained. The gain of the selective forwarding policy compared to a non-selective one was quantified and it was proved to have a strong dependence on energy expenses (transmission, reception and idle), the frequency of idle times and the statistical distribution of importances. Going further, as nodes are integrated in a sensor network, information coming from the neighborhood was incorporated into the statistical model and thus, an expression for the optimal forwarding threshold was obtained, which turned into a general expression of the optimal selective transmitter. Finally, for cases where the importance distribution of messages was unknown (or it varied with time), a blind algorithm, which is based on the received messages, caught this distribution on-the-fly and required less computational complexity, was proposed.

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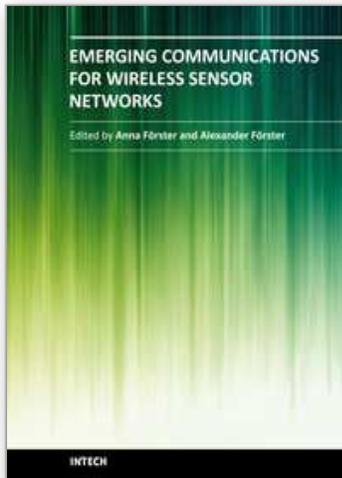
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Wireless sensor networks are deployed in a rapidly increasing number of arenas, with uses ranging from healthcare monitoring to industrial and environmental safety, as well as new ubiquitous computing devices that are becoming ever more pervasive in our interconnected society. This book presents a range of exciting developments in software communication technologies including some novel applications, such as in high altitude systems, ground heat exchangers and body sensor networks. Authors from leading institutions on four continents present their latest findings in the spirit of exchanging information and stimulating discussion in the WSN community worldwide.

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