Energy-efficient Selective Forwarding for Sensor Networks

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***Abstract*—In this paper a new energy-efficient scheme for data transmission in wireless sensor networks is proposed. It is based on the idea of selective forwarding: sensor nodes only transmit the most relevant messages, discarding the least important ones. To do so, messages are assumed to be graded with an importance value, and a forwarding threshold, which depends on the sensor consumption patterns, the available energy resources and the information obtained from the neighborhood, is applied to these values. In this approach, the sensor decision also depends on the expected behavior of neighboring nodes, so as to maximize not only the transmission efficiency, but also the performance of the whole communication up to the destination node. Simulation results show that the proposed scheme increases the network lifetime, and maximizes the global importance of the messages received by the sink node.**

***Index Terms*—selective forwarding, energy-efficiency, message importance, sensor networks**

I. Introduction - Problem Motivation

Wireless Sensor Networks are attracting a growing interest from several research communities, motivated by the large amount of theoretical and practical applications [1] as well as the technological challenges that this field presents [2]. Some of these challenges arise from the energetic limitations of network nodes. Sensors must work in an autonomous manner, without any other energy source than batteries (which are often not rechargeable) or the energy captured from the environment (which states many technological difficulties [3]). Therefore, optimizing the energy consumption is of fundamental importance in order to increase the network lifetime.

Many solutions, both software and hardware, have been proposed in the literature to optimize energy use. In terms of energy consumption, the wireless exchange of data, i.e., the communication process, dominates over functions such as processing and sensing [4]. In addition, radio consumes a non negligible amount of energy in reception and idle mode [5]. Some algorithms exploit the fact that most of the time, the network is only sensing its environment waiting for an event to happen. Thus, significant energy saving may be obtained by putting the node in sleep mode, so that the node is temporally disconnected from the network and originates a topology change [6]. However, nodes in sleeping mode can not act as relays in a multihop network and, somehow, it is necessary to reach a trade-off between network connectivity and energy saving. Other energy management schemes focus on the use of power scheduling to reduce energy consumption in the physical layer [7]. Data aggregation is also another basic distributed data processing procedure for saving energy and reducing medium access layer contention. However, the intrinsic trade-off between energy and delay in aggregation operations imposes a crucial question on nodes to decide optimal instants for forwarding their samples [8]. Other proposals concentrate their efforts on proposing energy-efficient algorithms, for network coverage, medium access control protocols and routing (see e.g. [9], [10], [11]) to extend network lifetime. Data reduction strategies, aimed at reducing the amount of data sent by each node, also reduce power consumption. One common approach consists of selecting among all data produced by the sensor network, a subset of sensor readings that is delivered to the sink. Sometimes, nodes are required to report their readings to the sink if the value falls outside or inside a certain interval. Other approaches [12] exploit spatio-temporal correlation among data. [13] presents an adaptive approach based on an efficient prediction technique using the LMS (*Least Mean Squares*) adaptive algorithm.

Messages are frequently graded in sensor networks. 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. It is not difficult to find scenarios where messages are graded, specially in monitoring and security fields [14]. For instance, in [15], message priority is assigned depending on the importance of the event when monitoring the temperature of pumps in a water pumping station. A design of a flood warning system is presented in [16]. It uses a set of sensor nodes to collect readings of water level and a grid-based flood predictor model is required to carry out extensive processing to generate the data importance, which is determined with experts' help.

Message importance can have an effect on the management of the transmission queues in sensors in order to establish prioritized transmission mechanisms. Some algorithms such as DAIDA [17] or WPDD [18], follow this line.

Some mechanisms that discard messages depending on their priority have also been proposed: IDEALS [19], PGR [20] or the approach presented in [21] are some examples, to name a few. Moreover, other routing algorithms as [22], LPGR [23] and Q-PR [24] consider decision models that utilize information about message values and the available energy resources at each node, in order to make an efficient energy use.

Summarizing, energy in sensor networks can be saved by making importance-driven decisions about message transmission, in an autonomous and self-organized manner. In 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.

Starting from a statistical approach to the selective forwarding problem, in this paper we show that if all transmitted messages in a sensor network are graded in some way (by some measure of information, importance, utility or relevance, for instance), a selective transmission strategy may let nodes maximize their efficiency as information forwarders. Efficiency is measured as the sum of importance values of all messages forwarded by a node with success.

Our statistical model takes into account the communication efficacy, measured in terms of successful receptions at the neighboring nodes or at the final sink node, or even the efficiency of the overall communication (from the source node to the sink, through all intermediate forwarding nodes). To do so, we integrate, in the node decision processes, some information about the state of the neighboring nodes. Before transmitting a message, each node evaluates its belief that some of its neighboring nodes will forward a message toward destination, and makes a forwarding decision according to this. We show that this selective forwarding scheme, which combines energy considerations and message importance with the expected neighbor's behavior, improves the global performance in terms of quantity and quality of the messages that really arrive at the destination node. The proposed method could eventually be incorporated into many existing routing protocols. Besides, our approach can be easily integrated with a variety of existing data collection approaches, including schemes that support in-network data aggregation.

The rest of the paper is organized as follows. Section II-A describes the context, the sensor model and exposes the selective forwarder, obtaining a general formula to compute the threshold for the selective forwarder. Section III presents the algorithmic design, i.e., the manner in which we are estimating some parameters required to compute the optimal forwarding policy. Section IV shows the experimental study and results for a sensor network considering different importance distributions and different kinds of sensor networks. Finally, the paper ends with some concluding remarks and some pointers to future work in Section V.

II. Selective Forwarding

A. Scenario

Consider a static sensor network as a collection of nodes $\{n_i, i = 0, \ldots, N-1\}$. The dynamics of each sensor node n_i 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.
- x_k : Importance of the message to be sent at time k. It reflects the "external input" to the node.

For mathematical convenience we assume that if, at time k, the node does not receive any request to transmit, then $x_k = 0$, which means that a silent time is formally equivalent to a request to transmit a zero-importance message. So, true messages will have $x_k > 0$.

We assume that the network routing algorithm (whatever it is) has defined (possibly, in a decentralized manner) a set of neighbors for each node, in such a way that, any sensor node holding a message has to make a decision, d_k, about forwarding the message to one of its neighbors, or not. We take $d_k = 1$ if the message is sent, and $d_k = 0$ if the node decides to discard it. In our simulations, we assume that a pre-established *sink* node is the final destination of all messages in the network, but it is important to remark that our mathematical model does not make specific assumptions about the final destination of the message or the algorithm that each sensor has to use to select the next hop in the communication path.

In general, sensor nodes decrease their batteries at each time slot according to their current action: message reception, transmission or idle state. We consider three constant parameters:

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

Note that, for simplicity reasons, we assume that the energy expended when the sensor node acts as the source of the message is the same than the energy consumption caused by a message reception, E_R. Extending the model to a more general situation is not difficult, but it complicates the mathematical formulation without providing a further insight on the behavior of the selective forwarding scheme proposed in this paper.

Note also that the assumption of constant energy consumption for any transmission is a reasonable approximation if information is sent in packets of the same size and transmission power remains unchanged as well. In addition, we assume that E_T, E_R and E_I are constant with k and they are perfectly known by the sensor node.

According to this, the available energy at time k can be expressed recursively as

$$e_{k+1} = e_k - d_k E_{RT} - (1 - d_k) I_{x_k > 0} E_R - (1 - d_k) I_{x_k = 0} E_I \tag{1}$$

where $E_{RT} = E_R + E_T$ and I_α is an indicator function equal to 1 if condition α holds and zero otherwise. In this work, we consider that the energy consumed at the idle state is negligible, and $E_I \approx 0$.

Note that, if $e_k < E_T$, the sensor node does not have enough energy to transmit any message, and $d_k = 0$.

B. Routing with Selective Forwarders

Since each message must travel through several nodes before arriving to destination, the message transmission is completely successful if the messages 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 requested to forward. If d_k denotes the decision at node i, and q_k denotes the decision at neighboring node j, the transmission is said to be locally successful through j if $d_k = 1$ and $q_k = 1$.

We define the cumulative sum of the importance values of all messages transmitted with local success from a given node at time k as

$$s_k = \sum_{i=0}^{k} d_i q_i x_i, \tag{2}$$

In this paper, we take

$$s_\infty = \lim_{k\to\infty} s_k \tag{3}$$

as the goal to be maximized by each node. Our approach is statistical, and we will maximize, at each time the conditional expected value of this amount. To do so, we make three main assumptions:

- The importance distributions, $p_k(x_k)$, k=0,...,∞, are known. This is essential for our theoretical analysis, but not for a practical implementation of the forwarding policy. In the experiments, p_k is estimated iteratively at each node based on the observed message flow.
- The sequence of importance distributions is statistically independent.
- Each node knows its energy resources, and constants E_T and E_R are known.

Each node makes a decision at time k is a (deterministic) function of the available energy, e_k, and x_k in order to maximize $E\{s_\infty|e_k, x_k\}$ taking into account that E_R and E_T are known constants.

In order to obtain the optimal forwarding policy, we express the accumulated importance recursively as

$$s_\infty = s_{k-1} + \sum_{i=k}^{\infty} d_i q_i x_i \tag{4}$$

so that

$$\begin{aligned} E\{s_\infty|e_k, x_k\} &= E\{s_{k-1}\} + d_k E\{q_k|e_k, x_k\} x_k + \\ &+ \sum_{i=k+1}^{\infty} E\{d_i q_i x_i|e_k, x_k\} \end{aligned} \tag{5}$$

Taking into account that d_k is a deterministic function of e_k and x_k, we can write, for any $i > k$,

$$\begin{aligned} &E\left\{d_i q_i x_i|e_k, x_k\right\} = \\ &= (1-d_k) E\left\{d_i q_i x_i|e_k, x_k, d_k = 0\right\} \\ &+ d_k E\left\{d_i q_i x_i|e_k, x_k, d_k = 1\right\} \\ &= (1-d_k) E\left\{d_i q_i x_i|e_{k+1} = e_k - E_R, e_k\right\} \\ &+ d_k E\left\{d_i q_i x_i|e_{k+1} = e_k - E_{RT}, e_k\right\}, \end{aligned} \tag{6}$$

replacing (6) into (5) the expected accumulated importance can be written as

$$\begin{aligned} E\{s_\infty|e_k, x_k\} &= E\{s_{k-1}\} + \\ &+ (1-d_k) \sum_{i=k+1}^{\infty} E\{d_i q_i x_i|e_{k+1} = e_k - E_R, e_k\} \\ &+ d_k x_k Q_k(x_k, e_k) \\ &+ d_k \sum_{i=k+1}^{\infty} E\{d_i q_i x_i|e_{k+1} = e_k - E_{RT}, e_k\} \end{aligned} \tag{7}$$

where $Q_k(x_k, e_k) = E\{q_k|e_k, x_k\} = P\{q_k = 1|e_k, x_k\}$. With the goal of maximizing $E\{s_\infty|e_k, x_k\}$, the transmitter must select $d_k = 0$ or $d_k = 1$ depending on the relative size of the factors multiplying d_k and $(1 - d_k)$ in (7). Therefore,

$$d_k = u(x_k Q_k(x_k, e_k) - \mu_k(e_k)) u(e_k - E_{RT}) \tag{8}$$

where $u(\cdot)$ is the step function and the decision threshold is given by

$$\mu_k(e_k) = (\lambda_{k+1}(e_k - E_R) - \lambda_{k+1}(e_k - E_{RT})) \tag{9}$$

where

$$\lambda_k(e) = \sum_{i=k}^{\infty} E\{d_i q_i x_i|e_k = e\} \tag{10}$$

Note that $\lambda_k(e)$ represents the increment of the total importance that can be expected at time k. It can be computed recursively by noting that, for any $i > k$,

$$\begin{aligned} &E\{d_i q_i x_i|e_k\} = \\ &= Pr\{d_k = 0|e_k\} E\{d_i q_i x_i|e_k, d_k = 0\} \\ &\quad + Pr\{d_k = 1|e_k\} E\{d_i q_i x_i|e_k, d_k = 1\} \\ &= Pr\{d_k = 0|e_k\}) E\{d_i q_i x_i|e_{k+1} = e_k - E_R, e_k\} \\ &\quad + Pr\{d_k = 1|e_k\} E\{d_i q_i x_i|e_{k+1} = e_k - E_{RT}, e_k\} \end{aligned} \tag{11}$$

Therefore

$$\begin{aligned} \lambda_k(e) =& E\{d_k q_k x_k|e_k = e\} \\ &+ Pr\{d_k = 0|e_k = e\} \\ &\times \sum_{i=k+1}^{\infty} E\{d_i q_i x_i|e_{k+1} = e - E_R\} \\ &+ Pr\{d_k = 1|e_k = e\} \\ &\times \sum_{i=k+1}^{\infty} E\{d_i q_i x_i|e_{k+1} = e - E_{RT}\} \\ =& E\{d_k q_k x_k|e_k = e\} \\ &+ Pr\{d_k = 0|e_k = e\} \lambda_{k+1}(e - E_R) \\ &+ Pr\{d_k = 1|e_k = e\} \lambda_{k+1}(e - E_{RT}) \\ =& E\{d_k q_k x_k|e_k = e\} + \lambda_{k+1}(e - E_R) \\ &+ Pr\{d_k = 1|e_k = e\} \\ &\cdot (\lambda_{k+1}(e - E_{RT}) - \lambda_{k+1}(e - E_R)) \end{aligned} \tag{12}$$

and, using (9)

$$\lambda_k(e) = \lambda_{k+1}(e - E_R) + E\{d_k q_k x_k | e_k = e\} - Pr\{d_k = 1 | e_k = e\}\mu_k(e) \quad (13)$$

Taking into account that $Pr\{d_k = 1|e_k = e\} = E\{d_k|e_k = e\}$, and using (8), we get

$$\begin{aligned}
\lambda_k(e) =& \lambda_{k+1}(e - E_R) + u(e - E_{RT}) \\
& \cdot E\{u(x_k Q_k(x_k, e_k) - \mu_k(e)) q_k x_k | e_k = e\} \\
& - E\{u(x_k Q_k(x_k, e_k) - \mu_k(e))\} u(e - E_{RT}) \mu_k(e) \\
=& \lambda_{k+1}(e - E_R) + u(e - E_{RT}) \\
& \cdot E\{(q_k x_k - \mu_k(e)) u(x_k Q_k(x_k, e_k) - \mu_k(e)) | e_k = e\} \\
=& \lambda_{k+1}(e - E_R) + u(e - E_{RT}) \\
& \cdot E\{(x_k Q_k(x_k, e_k) - \mu_k(e)) \cdot \\
& \quad \cdot u(x_k Q_k(x_k, e_k) - \mu_k(e)) | e_k = e\} \qquad (14)
\end{aligned}$$

Summarizing, the decision threshold and the expected residual importance can be computed recursively through the pair of equations

$$\mu_k(e) = \lambda_{k+1}(e - E_R) - \lambda_{k+1}(e - E_{RT}) \quad (15)$$

$$\begin{aligned}
\lambda_k(e) =& \lambda_{k+1}(e - E_R) \\
& + E\{(x_k Q_k(x_k, e_k) - \mu_k(e))^+\} u(e - E_{RT}) \quad (16)
\end{aligned}$$

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

The initial value can be computed using (10), and taking into account that, if the available energy is below E_T, no transmissions are possible, so that

$$\lambda_k(e) = 0, \qquad \text{for any } k \text{ and } e < E_T. \quad (17)$$

It is interesting to combine (8) and (9) to express the optimal decision as

$$d_k = u\left(Q_k(x_k, e_k) - \frac{\mu_k(e)}{x_k}\right) u(e_k - E_{RT}) \quad (18)$$

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 [22], [23].

Fig. 1 shows a sensor network and the inner mechanism of a node to make a decision about the transmission of messages: a forwarding threshold, which depends on the consumption patterns, the available energy resources and the information from neighboring nodes, is applied to the importance value of messages.

III. Algorithmic Design

In practice, in order to apply the optimal forwarding policy given by (15) and (16) in a sensor network, we need to estimate $Q_k(x_k, e_k)$ and the importance distributions, $p_k(x_k)$. To do so, we make two additional assumptions:

- The network's behavior is stationary or slowly varying, in such a way that each node can estimate $p_k(x_k)$ from the sequence of importance values observed in messages processed by the node.

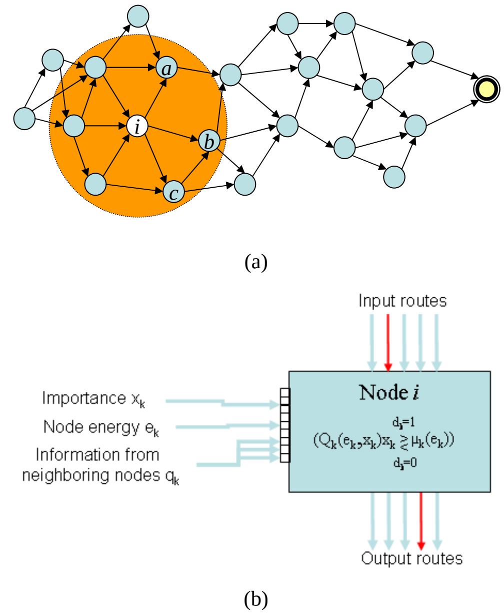

Fig. 1. (a) A sensor network. The shaded circle shows the coverage area of node i (if no obstacles are considered and sensor antennas are omnidirectional, the coverage area of i will be represented by a circle whose center is the node i, UDG Model). All nodes inside the circle (unless i) is the set of neighbors. Each time node i receives a message, it should make a decision about forwarding or not the current message. (b) A sensor node and the threshold mechanism of the selective forwarder to make a decision about message transmission.

- Function $Q_k = E\{q_k|x_k, e_k\}$ does not depend on e_k. This is a reasonable assumption, since q_k is the (eventual) decision of the neighboring node that will receive the message if $d_k = 1$, and e_k is the energy at the node currently holding the message. Since the neighboring node does not know e_k, we can expect that its (eventual) decision will not be influenced by the energy resources of the transmitting node.

A. Estimating the importance distribution

The true importance distribution at each node is estimated by means of the parametric estimate of $p(x)$ given by the Gamma distribution with parameters θ and v,

$$p(x|v, \theta) = x^{v-1} \frac{e^{-x/\theta}}{\theta^v \Gamma(v)} \qquad x, v, \theta > 0. \quad (19)$$

The use of the gamma distribution is motivated by the fact that it is a two-parameter distribution for which thresholds can be computed analytically. Despite the fact that a non-parametric estimate does not depend on the distribution assumption, this procedure requires storing all importance values at each time. Therefore, it may be computationally expensive given that the estimator's computational cost grows linearly with regard to the number of observations, which also increases with time.

Let $\hat{\theta}$ and $\hat{v}$ denote the Maximum Likelihood (ML) estimate of θ and v parameters, respectively.

Let define

$$s_k = \frac{1}{k+1}\sum_{\ell=0}^{k} x_\ell \tag{20}$$

$$t_k = \frac{1}{k+1}\sum_{\ell=0}^{k} \ln\left(x_\ell\right) \tag{21}$$

Finding the maximum in the log-likelihood function with respect to both parameters, we get

$$\hat{\theta} = \frac{s_k}{\hat{v}} \tag{22}$$

and $\hat{v}$, whose implicit equation $\ln(\hat{v})-\psi(\hat{v}) = \ln(s_k)-t_k$ does not have a closed-form solution for $\hat{v}$, can be approximated as [25]

$$\hat{v} \approx \frac{3-z+\sqrt{(z-3)^2+24z}}{12z} \tag{23}$$

where $z = \ln(s_k) - t_k$. Closer approximations requires numerical techniques to obtain the ML estimates of v, so that the Newton-Raphson iteration method then gives [26]

$$\hat{v} = \hat{v} - \frac{\ln(\hat{v}) - \psi\left(\hat{v}\right) - z}{1/\hat{v} - \psi'(\hat{v})} \tag{24}$$

where $\psi'\left(\cdot\right)$ denotes the trigamma function (the derivative of the digamma function $\psi\left(\cdot\right) = \Gamma'\left(\cdot\right)/\Gamma\left(\cdot\right)$).

B. Estimating Q_k

Since we assume that each node can listen if a neighboring node re-transmits the messages it has just sent, we can estimate function Q_k from the observed sequence of neighbor's decisions, $\{q_k\}$ and the observed sequence of importance values, $\{x_k\}$. To do so, we follow a similar approach to that in [22], [23], by using the parametric model

$$Q_k(x_k, w, b) = P\{q_k = 1|x_k, w, b\} = \frac{1}{1+\exp(-wx_k - b)} \tag{25}$$

Note that, for positive values of w, Q_k increases monotonically with x_k, as expected from the node's behavior. We estimate parameters w and b via ML (maximum likelihood) using stochastic gradient learning rules

$$\begin{aligned} w_{k+1} &= w_k + \rho(q_k - Q_k(x_k, w_k, b_k))x_k \\ b_{k+1} &= b_k + \rho(q_k - Q_k(x_k, w_k, b_k)) \end{aligned} \tag{26}$$

where ρ is the learning step.

IV. Experiments and results

In this section, numerical results related to the proposed selective forwarding scheme are provided to highlight energy efficiency. Performance is assessed in terms of the sum of the importance of all received messages, the mean value of the importance of received messages, the number of transmitted messages and the network lifetime. Network lifetime is measured in terms of the number of time slots achieved before the sink is isolated from its neighboring nodes, i.e, there is no available path to reach the destination.

For that purpose, one hundred sensor nodes have been uniformly deployed at random in a 10 x 10 square units area. In our simulations, nodes in the sensor network have the same initial resources. Nodes are provided with $E = 200$ units of energy, except for the sink, which is the most critical device in the network because it is in charge of merging all the information before processing it. A static sink has been considered and it is always placed at the right extreme of the field. Sources, chosen at random, generate and transmit messages of different importances until network lifetime expires.

Nodes must make a decision about transmitting or not a certain message when comparing the importance value of a message with the forwarding threshold, according to (8). Messages with importance x_k are generated stochastically at different source nodes according to different importance distributions $p(x)$ (uniform, exponential and Pareto), which are independent of k. Free parameters in distributions have been adjusted to delimit message importance values (x_k) from 0 to 10 to set up a more real scenario, and where $x_k = 0$ means a silent time, as it was mentioned in Section II-A. So that $x_k \sim U(0, 10)$ for the first distribution type and $a = 1.8$ for the exponential distribution, $a = 2.5$ for the Pareto. Nodes can be capable of knowing the importance distribution of messages for a specific application while it is impossible to have such an information in other cases. In the latter case, nodes should estimate $p(x)$ in real time insofar as nodes receive importance distribution samples, as described in Section III-A.

For comparative purposes, we propose simulations with different kind of sensors:

- $Type\ NS$: Non-selective sensor node, it forwards all the received messages, no matter which its importance value is.
- $Type\ T$: Selective transmitter sensor node. This sensor is the particular case of (3) 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 sum of importance values of all messages transmitted by the node, no matter if they are forwarder by the neighboring node or not.
- $Type\ F1$: Selective forwarder sensor node based on the sources' importance distribution. This sensor type knows the importance distribution $p(x)$ and computes the forwarding threshold according to (15) and (16). So that it considers the influence of neighboring nodes decisions as well as the remaining energy level and the consumption patterns.
- $Type\ F2$: Selective forwarder sensor node, which estimates the importance distribution $p(x)$. Since nodes do not always have the knowledge of $p(x)$, they should estimate it based on received samples in real time. Moreover, transmission policies in neighboring nodes may alter and change the importance distribution at some nodes, so that this sensor type reflects this real and common scenario.

Transmission and reception consumption values are equal in all nodes in the network. Values are set up to $E_T = 4$,

$E_R = 1$ units, respectively. Energy spent while nodes are in idle state is set to $E_I = 0$, as mentioned in Section II-A.

With regard to the routing algorithm, since our goal is to analyze the nodes' behavior in a sensor network when selective forwarders are considered, the greedy forwarding algorithm has been selected. In this way, a simple algorithm has been chosen, which enables us to obtain useful conclusions without complicating the model. In the particular case of a selective forwarding sensor network, when a node decides not to transmit a certain message, it evaluates the transmission decision with other neighboring nodes having a positive advance towards the sink before discarding the message. It is important to remark that we are not proposing a new routing algorithm but a forwarding scheme with a selective mechanism that also takes into account information coming from the environment, specifically from neighboring nodes. Therefore, this model can be integrated into other more efficient routing protocols.

Derived from the chosen routing algorithm, location information is available at nodes. It allows them to exploit the geographical information to reach the sink node greedily, by selecting the message's next hop as the neighbor geographically closest to the message destination and this process is repeated until the sink is reached. Moreover, nodes can forward messages inside its coverage area as a result of considering a Unit Disk Graph model. As nodes have power restrictions, they can only send messages within its transmission radius. Given that sensors have omnidirectional antennas and coverage areas are reciprocal, neighboring nodes are able to listen to all transmissions made inside the forwarder's coverage area and so update their information.

In order to make the routing algorithm more robust under channel losses, a maximum number of retransmissions before discarding a message is established. This value has been set to 5 in simulations.

Experimental results are averaged over 50 different topologies which contain different samples of the three previously aforementioned importance distributions.

TABLE I
AVERAGED PERFORMANCE WHEN IMPORTANCE IS GENERATED ACCORDING TO A UNIFORM DISTRIBUTION

	Total Import. Received	Importance mean value	Number of Transmissions	Network Lifetime
Type NS	1148.40	5.04	730.72	3977.12
Type T	1680.06	7.48	728.62	7938.10
Type F1	1723.39	7.56	957.92	8322.34
Type F2	1766.40	7.82	982.96	9241.46

Table I, II and III show network performance results for a uniform, exponential and Pareto importance distributions.

As it was anticipated in Section I, the selective forwarding nodes yield a better performance than the non-selective model in terms of the considered metrics. As the mathematical formalism has been obtained considering $E_I = 0$, the different networks with every type of sensor are almost able to transmit the same amount of messages, although it is slightly higher for the selective forwarder sensor networks ($F1 - type$ and $F2 - type$ sensor networks).

TABLE II
AVERAGED PERFORMANCE WHEN IMPORTANCE IS GENERATED ACCORDING TO AN EXPONENTIAL DISTRIBUTION

	Total Import. Received	Importance mean value	Number of Transmissions	Network Lifetime
Type NS	366.29	1.76	707.66	3746.22
Type T	805.81	3.84	708.86	12492.80
Type F1	828.71	3.94	928.12	13187.66
Type F2	850.58	4.19	956.2	15513.24

TABLE III
AVERAGED PERFORMANCE WHEN IMPORTANCE IS GENERATED ACCORDING TO A PARETO DISTRIBUTION

	Total Import. Received	Importance mean value	Number of Transmissions	Network Lifetime
Type NS	257.02	1.17	726.72	3842.28
Type T	1269.88	5.76	729.78	50262.66
Type F1	807.76	3.71	910.30	19304.96
Type F2	818.43	3.90	944.82	21317.48

At first glance at Table I, II and III, it can be clearly noted that the sum of the importances of all messages forwarded by neighboring nodes, the term that we wanted to maximize, and therefore, the sum of the importances of all received messages is lower in $NS - type$ sensor networks than in the others, whatever the importance distribution is. If we analyze results comparing the non-selective sensor networks with the $F1 - type$ sensor networks, the latter multiplies by one and a half, on average, the sum of received importances achieved by the former in the uniform importance distribution, doubles the sum in the exponential distribution and multiplies by four the sum in the Pareto distribution. Besides, as it is expected from their own nature, the mean value of the received messages is higher in the selective sensor networks than in the non-selective ones: between 7.48 and 7.82 for the selective forwarder networks with the uniform importance distribution against 5.04 for the $NS - type$ sensor networks, between 3.84 and 4.19 against 1.76 for the exponential importance distribution and between 3.71 and 5.76 against 1.17 when message's importance follows a Pareto distribution. Furthermore, it is noteworthy mentioning how network lifetime is extremely increased in the selective sensor networks, so as energy resources last longer, one of the challenges pursued in sensor networks. Thus, while network lifetime is approximately the same in non-selective sensor networks, it lasts longer in selective forwarder networks whose importance distribution is Pareto or exponential than uniform. Network lifetime is enlarged 2 times in the uniform distribution, 3.5 times in the exponential and 5 times in the Pareto distributions, when $F1 - type$ and $NS - type$ sensor networks are compared.

Going into detail, we now compare the three types of selective forwarders. Except for the Pareto distribution, the $F2-type$ selective sensor networks outperforms the other two types. So, $F2-type$ sensors make the networks last longer at the same time that maximize the sum of the received messages and increase the importance mean value of the received messages.These sensor networks yield a slightly better performance than the $F1-type$ sensor networks. It is a reasonable result given that $F1-type$ sensors are only based on the sources' importance distribution while $F2-type$ sensors have to estimate the real importance distribution arriving at each node in the network, and so consider selective transmission policies applied by previous nodes. However, $F1-type$ sensors clearly perform better than the non-selective nodes and even than the $T-type$ selective sensors, which do not take into account the behavior of neighboring nodes.

Fig. 2 illustrates the number of times that source nodes decide not to transmit a certain message according to the decision threshold. The value appearing at the top of the bars represents the importance mean value of the non-sent messages. In agreement with the results previously exposed in Table I, II and III, the non-selective sensors transmit all generated messages and so the forwarding threshold is set to 0. Forwarding sensor networks ($F1$ and $F2-type$) have the most restrictive threshold among the selective sensor types (except for the Pareto distribution) and therefore, they have the highest number of times of non-transmission decisions. $T-type$ sensors have a slightly worse performance than the other two selective schemes since they do not consider information coming from neighboring nodes in the transmission's decision.

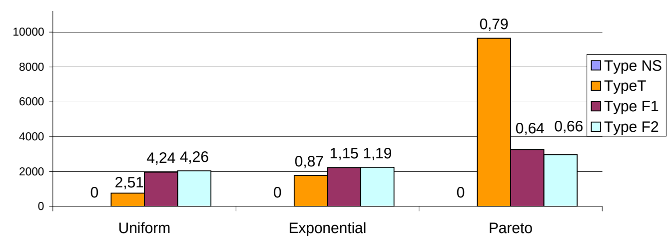

Fig. 2. Number of times that source nodes decide not to transmit a certain message and the importance mean value of the non-sent messages for the different kind of sensors: non-selective nodes, the asymptotical selective transmitter ($T-type$), and the two types of selective forwarders ($F1$ and $F2-type$) when three types of importance distributions are considered.

In summary, the behavior of selective sensor networks are energy-efficient compared with the non-selective one, allowing the formers to obtain a huge increase in network lifetime at the same time that maximizes the communication efficacy up to the sink node, and therefore, notably improves the global performance.

V. Conclusions

Starting from a mathematical formulation of the selective forwarding problem, this paper derives a theoretically optimal forwarding policy that maximizes (statistically) the sum of the importance values of all messages transmitted by a node that are also forwarded by its neighbors. Our simulation work shows that selective transmission strategies based on our model can significantly improve the overall network performance measured as the sum of the importance values arriving at the sink node. This also means that the number of highest priority messages arriving to the sink node is higher than that of a non-selective forwarding scheme.

The mathematical model of the sensor network used in this paper makes several simplifying assumptions, that should be carefully examined in practical scenarios. Our simulations show that some of them (like the assumption that the importance distributions and the function Q_k are known) may be overcome if nodes are allowed to estimate some model parameters during operation. Other assumptions may require a further work in order to extend the model to more general scenarios. For instance, the assumption that the importance sequence is statistically independent may not hold in scenarios with data aggregation, or a in situation where messages may be fragmented in packets with equal size. In these cases, we may assume some local correlations, whose effect on the forwarding scheme should be analyzed.

Finally, this work is based on the assumption that idle energy is negligible and so we have disregarded the energy consumption due to this node state. As we know that it is a feeble supposition since it is sometimes comparable to reception consumption, future work also includes the study of the selective forwarding schemes when idle state is considered. It may affect node decisions and therefore, global performance in a sensor network.

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References

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A Survey on Sensor Networks," *IEEE Comm. Magazine*, vol. 40, no. 8, pp. 102–114, Aug. 2002.

[2] Q. Jiang and D. Manivannan, "Routing Protocols for Sensor Networks," in *Proc. 1st IEEE Consumer Comm. and Networking Conf. (CCNC '04)*, Jan. 2004, pp. 93–98.

[3] J. Paradiso and T. Starner, "Energy scavenging for mobile and wireless electronics," *IEEE Trans. Pervasive Computing*, vol. 4, no. 1, p. 1827, 2005.

[4] K. Sohrabi, J. Gao, V. Ailawadhi, and G. Pottie, "Protocols for self-organization of a wireless sensor network," *IEEE Personal Commu.*, vol. 7, no. 5, p. 1627, Oct. 2000.

[5] W. Ye and J. Heidemann, "Medium Access Control in Wireless Sensor Networks," Information Sciences Institute, University of Southern California, Tech. Rep. ISI-TR-580, Oct. 2003.

[6] C. Schurgers, V. Tsiatsis, and M. Srivastava, "STEM: Topology management for energy efficient sensor networks," in *Proc. IEEE Aerospace Conf.*, vol. 3, 2002, pp. 1099 – 1118.

[7] J. Xiao, S. Cui, Z. Luo, and A. Goldsmith, "Power scheduling of universal decentralized estimation in sensor networks,."

[8] Z. Ye, A. Abouzeid, and J. Ai, "Optimal Policies for Distributed Data Aggregation in Wireless Sensor Networks," in *Proc. 26th IEEE Int'l Conf. on Computer Communications (INFOCOM 2007)*, May 2007, pp. 1676–1684.

[9] M. Bhardwaj, T. Garnett, and A. P. Chandrakasan, "Upper bounds on the lifetime of sensor networks," vol. 3, June 2001, pp. 785–790.

[10] W. Ye, J. Heidemann, and D. Estrin, "An energy-efficient MAC protocol for wireless sensor networks," vol. 3, June 2002, pp. 1567–1576.

[11] J. N. Al-Karaki and A. E. Kamal, “Routing techniques in wireless sensor networks: A survey,” vol. 11, no. 6, Dec. 2004, pp. 6–28.

[12] S. Goel and T. Imielinski, “Prediction-based monitoring in sensor networks: taking lessons from MPEG.”

[13] S. Santini and K. Rmer, “An Adaptive Strategy for Quality-Based Data Reduction in Wireless Sensor Networks,” in *Proc. 3rd Int’l Conf. on Networked Sensing Systems (INSS 2006)*, May 2006.

[14] E. Sabbath, A. Majeed, K. Kang, K. Liu, and N. AbuGhazaleh, “An Application Driven Perspective on Wireless Sensor Network Security,” in *Proc. 2nd ACM Int’l Workshop on Quality of service and security for wireless and mobile networks (Q2SWinet’06)*, Oct. 2006, pp. 1–8.

[15] G. Merrett, N. Harris, B. Al-Hashimi, and N. White, “Energy Controlled Reporting for Industrial Monitoring Wireless Sensor Networks,” in *Proc. 5th IEEE Conf. on Sensors*, Oct. 2006, pp. 892–895.

[16] J. Zhou, D. D. Roure, and S. Vivekanandan, “Adaptive Sampling and Routing in a Floodplain Monitoring Sensor Network,” in *Proc. IEEE Int’l Conf. on Wireless and Mobile Computing, Networking and Communications (WiMob’2006)*, June 2006, pp. 85–93.

[17] J. Qiu, Y. Tao, and S. Lu, *Grid and Cooperative Computing*. Springer Berlin / Heidelberg, 2005, vol. 3795/2005, ch. Differentiated Application Independent Data Aggregation in Wireless Sensor Networks, pp. 529–534.

[18] F. Dressler, “Weighted Probabilistic Data Dissemination (WPDD),” Dept. of Computer Science 7, University of Erlangen, Germany, Tech. Rep. TR-05/06, Dec. 2006.

[19] G. Merrett, B. Al-Hashimi, N. White, and N. Harris, “Information Managed Wireless Sensor Networks with Energy Aware Nodes,” in *Proc. NSTI Nanotechnology Conf. and Trade Show (NanoTech ’05)*, May 2005, pp. 367–370.

[20] S. J. Mujumdar, “Prioritized Geographical Routing in Sensor Networks,” Master’s thesis, Vanderbilt University, Tennessee, May 2004.

[21] J. Rivera, G. Bojorquez, M. Chacon, G. Herrera, and M. Carrillo, “A Fuzzy Message Priority Arbitration Approach for Sensor Networks,” in *Proc. North American Fuzzy Information Processing Society (NAFIPS ’07)*, June 2007, pp. 586–591.

[22] R. Arroyo-Valles, A. García-Marqués, J. Vinagre-Díaz, and J. Cid-Sueiro, “A Bayesian Decision Model for Intelligent Routing in Sensor Networks,” in *Proc. 3rd IEEE Int’l Symp. on Wireless Comm. Systems (ISWCS ’06)*, Sept. 2006.

[23] R. Arroyo-Valles, A. García-Marqués, and J. Cid-Sueiro, “Energy-aware Geographic Forwarding of Prioritized Messages in Wireless Sensor Networks,” in *Proc. 4th IEEE Int’l Conf. on Mobile Ad-hoc and Sensor Systems (MASS ’07)*, Oct. 2007.

[24] R. Arroyo-Valles, R. Alaiz-Rodríguez, A. Guerrero-Curieses, and J. Cid-Sueiro, “Q-Probabilistic Routing in Wireless Sensor Networks,” in *Proc. 3th Int’l Conf. on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP ’07)*, Dec. 2007.

[25] M. Maddah, W. W. III, S. Warfield, C. Westin, and W. Grimson, “Probabilistic Clustering and Quantitative Analysis of White Matter Fiber Tracts,” in *Proc. 20th Int’l Conf. on Information Processing in Medical Imaging (IPMI 2007)*, July 2007, pp. 372–383.

[26] S. Choi and R. Wette, “Maximum Likehood Estimation of the Parameters of the Gamma Distribution and Their Bias,” *Technometrics*, vol. 2, no. 4, pp. 683–690, Nov. 1969.