COOPERATIVE DATA CENSORING FOR ENERGY-EFFICIENT COMMUNICATIONS IN
SENSOR NETWORKS

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ABSTRACT

Signal processing algorithms in Wireless Sensor Networks claim for energy efficiency because of node energy scarcity. Tailored to this scenario, in this paper we develop energy-efficient cooperative strategies for selective communications. Cooperation among nodes is exploited in order to optimize energy consumption while guaranteeing good overall performance. The analysis of representative scenarios reveals that cooperative selective nodes yield a good performance in both network lifetime and quality of the transmitted information under different network conditions.

1. INTRODUCTION

A characteristic of Wireless Sensor Networks (WSNs) is their ability to operate with autonomy when sensors are resource constrained. Specifically, the need to operate for long periods under energy limitations is a primary concern. Therefore, signal processing algorithms should be designed based on energy conservation principles. A first step to address optimum designs is to properly quantify both costs (energy) and benefits (overall network performance and quality of the transmitted information).

Thus, when the potential benefits of transmitting information messages do not compensate for the subsequent communication energy cost, we may consider discarding it. This is the key idea behind selective communications: each sensor node is able to make autonomous decisions about transmitting or not available data to its neighbors based on certain criteria. The transmit/no transmit dilemma is also the basis of censoring networks in distributed detection, proposed by [1], and later adapted to WSNs [2]. In these works, (energy, or other kind of) resource constraints are quantified using free parameters, whose assignment (usually made a priori) is not trivial as they establish a trade-off between application performance and energy saving.

Based on the aforementioned ideas, in previous works [3, 4] we proposed adaptive low-complexity information-based statistical models for energy-efficient selective communications for WSNs. We even analyzed their suitability in a specific and realistic signal processing scenario: target tracking [5]. In these works, the optimization along the whole lifetime was mathematically stated using Markov Decision Processes (MDPs), mainly motivated by its recent application to weigh up the trade-off among different performance parameters (energy consumption, delay, communication efficiency, throughput, etc.) in WSNs [6, 7].

However, the independent optimization at each node does not guarantee an overall performance optimization, even if neighborhood information is taken into account. Each node should also consider in its decision-making process the savings and energy consumptions of all the nodes involved in a transmission. In this paper we propose a first approach to a selective transmission algorithm where nodes work cooperatively to achieve the overall performance optimization. The analysis of simplified but representative scenarios will show that the performance gain due to the use of cooperative nodes is high compared to that obtained with other selective schemes for different traffic rates and number of nodes.

The rest of the paper is organized as follows: Section 2 describes the model for WSN. The selective forwarding policy and the cooperative strategy are stated in Section 3. Numerical simulations are shown in Section 4. Conclusions in Section 5 wrap-up this paper.

2. SENSOR MODEL

2.1. State vector

For the purpose of the analysis that follows, we consider a sensor network as a collection of nodes $\mathcal{N} = \{n | n = 1, \ldots, N\}$, and a sink (node $N + 1$) to whom all messages are forwarded. The network state will be characterized by at least two variables:

- $e_k$: a $N$-dimensional vector of available energies (battery levels) at time $k$. 

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• $x_k$: importance of the message to be sent at time $k$. The importance is a measurement of the significance, priority, relevance or utility of messages generated by sensors.

The network state vector is defined as $s_k = (e_k, x_k)$, and it contains all and only the information that is available at the network to make a decision at time $k$.

The “time” variable $k$ does not represent physical time, but a counter of epochs. An epoch is every time period that starts when a message is originated at any sensor node, ends when any node discards the message or when the message arrives to its final destination, and contains all time instants devoted to receive, process and (eventually) forward these data.

2.2. Actions, policies and state dynamics

At time $k$, the network must make a decision $d_k$ about sending or not the current message. The message is sent if $d_k = 1$, while it is discarded if $d_k = 0$. A forwarding policy $\pi = \{d_1, d_2, \ldots \}$ is a sequence of decision rules, which are functions of the state vector; i.e.,

$$d_k = d_k(s_k) = d_k(e_k, x_k).$$ (1)

Nodes consume energy at each time epoch by an amount that depends on the taken actions. We will express the available energy at time $k$ recursively as

$$e_{k+1} = e_k - d_k c_{1,k} - (1 - d_k)c_{0,k},$$ (2)

where $c_{1,k}$ contains the energy consumed at each node when the network decides to transmit the message, and $c_{0,k}$ contains the energy consumed when the message is discarded. The latter may include the cost of sensing the data (if the sensor is the source of the message), the cost of data reception when data come from other nodes or the cost of idle states if there is no data to transmit. Parameter $c_{1,k}$ accounts for all the previous costs plus the cost of forwarding the message. In general, we assume that energy consumption may depend on $x_k$ and may have some random components, so that $c_{1,k}$ and $c_{0,k}$ are stochastic processes. This way we can deal with scenarios with fading, packet losses, retransmissions, etc. Also, we assume that the sequence of importance values, $x_k$, is statistically independent, and independent of $e_{k-n}$ or $d_{k-n}$, for any $n > 0$. Finally, we consider that $x_k$ is zero when nodes are in idle state. This equivalence is useful for mathematical convenience.

2.3. Rewards

Let $q_k \in \{0, 1\}$ denote the success index (a binary variable taking value 1 if the message at time $k$ is successfully delivered to its destination, and zero otherwise). The reward at time $k$ for a network that decides to transmit a message with importance $x_k$ is $r_k = x_k q_k$. Therefore, the selective forwarding policy is chosen in order to maximize the total expected reward, defined as

$$T = \mathbb{E}\left\{ \sum_{i=0}^{\infty} d_i r_i \right\} = \mathbb{E}\left\{ \sum_{i=0}^{\infty} d_i q_i x_i \right\}. \quad (3)$$

Note that, since nodes have limited energy resources, the sum in (3) only contains a finite number of nonzero values.

3. OPTIMAL SELECTIVE STRATEGIES

3.1. A single node analysis

The tuple defined by $(\mathcal{S}, \mathcal{A}, P, r)$, where $\mathcal{S}$ is the set of states, $\mathcal{A} = \{0, 1\}$ is the set of possible decisions (actions), $P$ is a transition probability defining the state dynamics (according to (2)) and $r$ is the reward function, has the structure of a MDP.

Before facing the network optimization problem based on (3), we will first analyze a single node scenario. If the WSN contains a single node, energy is a scalar variable ($e_k = e_k$). In such a case, the optimal selective strategy is given by the following:

**Theorem 1** Let $\{x_k, k \geq 0\}$ be a statistically independent sequence of importance values, and $e_k$ the energy process given by (2). Consider the sequence of decision rules in the form

$$d_k = u(Q_k(e_k, x_k) x_k - \mu_k(e_k, x_k)),$$ (4)

where $Q_k(e_k, x_k) = \mathbb{E}\{q_k|e_k, x_k\}$ is the success probability and threshold $\mu_k$ is defined recursively through the pair of equations

$$\mu_k(e, x_k) = \mathbb{E}\{\lambda_{k+1}(e - c_{0,k}) - \lambda_{k+1}(e - c_{1,k})|x_k\},$$

$$\lambda_k(e) = \mathbb{E}\{\lambda_{k+1}(e - c_{0,k})\} + \mathbb{E}\{Q(e, x_k) x_k - \mu_k(e, x_k)^+\} u(e).$$ (6)

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

Sequence $\{d_k\}$ is optimal in the sense of maximizing $T$ (given by (3)), among all sequences in the form $d_k = d_k(e_k, x_k)$.

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

$$\lambda_k(e) = \sum_{i=k}^{\infty} \mathbb{E}\{d_i q_i x_i|e_k = e\}. \quad (7)$$

The proof of this theorem can be found in [4]. Note that (5) and (6) state a forward recursion ($\lambda_k$ vs. $\lambda_{k+1}$), which makes the direct application of these equations impossible
in a general non-stationary environment, because in order to compute \( \lambda_0 \) the importance distribution \( \forall k \) should be known at time \( k = 0 \).

Four key simplifications may serve to find simple approximations to the optimal selective strategies. (1) The statistical distributions of \( x_k, q_k, c_{0,k} \) and \( c_{1,k} \) are stationary (i.e., they do not depend on \( k \)). In such a case, it can be shown [4] that the threshold function \( \mu_k \), the residual importance \( \lambda_k \) and the success probability \( Q_k \) do not depend on \( k \) (so we can remove subindex \( k \)). (2) The success probability does not depend on \( e \) for \( e \) large enough, so we can write \( Q(e, x_k) = Q(x_k) \). Provided that nodes have enough energy to transmit information, the transmission success is independent of the specific value of the available energy (and only depends on other external factors, like the path loss probability). (3) The empirical observations in [3] show that, under the stationarity assumption, no matter what the importance distribution is, the threshold function \( \mu(e, x_k) \) is approximately constant (independent of \( e \)) for large \( e \). Finally (4), the energy consumption \( c_{0,k} \) or \( c_{1,k} \) is independent of the message importance. Under these conditions, the asymptotic value of the threshold function \( \mu = \lim_{e \to \infty} \mu(e, x) \) can be computed as the unique solution of (see [4])

\[
\mu = \rho E\{(c_1 - c_0) | x > 0\},
\]

where

\[
\rho = \frac{E\{c_1\} - E\{c_0\}}{E\{c_0\}}.
\]

Parameter \( \rho \) represents the relative cost increment caused by the decision \( d_k = 1 \). If the energy parameters in (9) are unknown, they can be estimated from data provided that nodes can measure the current energy consumption of its sensing and communication processes.

The main idea behind the selective forwarding algorithms is to replace the optimal rules in Theorem 1 by their asymptotic approximations based on (8). Our experimental work in [3] suggests that this is a good choice provided that there is enough energy for a reasonable number of transmissions.

The optimal threshold depends on the distribution of message importances, which in practice may be unknown. To bypass this problem, we can try to estimate \( \mu \) in (8) and replace the threshold function by its asymptotic limit. The estimation can be done in real time based on the available information at time \( k \), \( \{(x_{\ell}, q_{\ell}), \ell = 0, \ldots, k\} \), using [4]

\[
\mu_k = \left( \frac{k-1}{k} \right) \mu_{k-1} + \frac{\rho}{k} (x_k Q(x_k) - \mu_{k-1})^+.
\]

Finally, the success probability, \( Q(x) \), can also be estimated from data based on the success of previous transmissions. In a single-hop network, the success of a transmission can be known from the acknowledgments (ACKs) provided by the sink during the communication protocol.

### 3.2. Cooperation in networks

In a multi-hop network, the design of optimal selective communication strategies becomes a much harder problem, because the decision to send a message from a source node to a destination requires the coordination with all nodes in the way, and the information required to make optimal decisions may be spread along the network.

In [4], the problem is solved by using independent selective strategies at each node. This way, each node maximizes the importance sum of all messages it successfully sends (or forwards) to destination. Nodes behaving in this way will be named Local Forwards (or LF nodes) in the following. Despite each node pursues a different optimization criterion, they do not behave uncoordinatedly: if a message originated at node A is refused by node B in the way to destination, the success probability estimated by node A and all the nodes from A to B changes, and future transmit/discard decisions will be influenced by this rejection. Thus, the selective strategies used by a single node influence the transmission policies of other nodes, which has an overall coordination effect.

However, as we will see in Section 4, a network of LF nodes may be far from optimal. A collection of local optimizers is not a global optimizer. The design of globally optimal selective strategies for general networks is not an easy problem. In a network of nodes with finite resources, the scenario is no longer stationary: even though nodes behave stationarily using constant thresholds, as soon as a node depletes batteries, a change in the information flow to neighbor nodes arises.

Our approach in this paper is based on the idea of looking for optimal strategies at least up to the first node depletion. The key idea is to assume that nodes closer to destination can be expected to die first. This, for instance, can be reasonable if all nodes in the network have the same initial battery, similar average consumption patterns (\( E\{c_0\} \) and \( E\{c_1\} \)) and all messages are routed through fixed routes (at least, up to the first node depletion).

Consider, for instance, a single-path network, where all nodes are deployed along a line, in such a way that \( i \)-th node only sends messages to node \( i + 1 \) and receives messages only from node \( i - 1 \). In such a network, the node closer to destination support higher amount of data traffic, and it can be expected to be the first depleting batteries. Under these conditions, though the network state is defined by the vector \( e_k \) and contains the energy available at each node, only the energy at the last node \( N \) is relevant. Under this perspective, we can view the whole network as a single ‘supernode’, and decision costs of transmitting or refusing a message can be computed over the last node. The transmission policy given by (8) and (9) can still be applied with \( E\{c_1\} = P_i E_i + (1 - P_i)(E_i + E_s) \) and \( E\{c_0\} = E_i (1 - P_{s,N}) + P_{s,N} E_s \), where \( P_i \) is the global...
probability of idle state (i.e., 1 - probability of generating a message in the ‘supernode’), \( P_s,N \) is the probability of node \( N \) being the message source, and \( E_i \), \( E_s \), \( E_r \) and \( E_t \) are the average energy consumption for receiving, sensing, transmitting and idle. Applying (9), it is not difficult to show that

\[
\rho = \frac{P_s(E_i + (1-P_s)(E_s + E_r))}{E_i(1-P_s,N) + P_s,N E_s} - 1,
\]

Hence, the cooperative threshold should be computed by node \( N \) (the critical one) using an adaptive rule similar to (10):

\[
\mu_k = \frac{k_0}{k} \mu_{k0} + \frac{P}{k} (x_k Q(x_k) - \mu_{k0})^{+},
\]

where \( k_0 \) is the last epoch when the threshold was updated.

In LF networks \( k = k_0 + 1 \), but now node \( N \) has also to consider in its decision-making process all the messages dropped in the routing path (that is denoted as \( m_n \) with \( n = 1, \ldots, N - 1 \)) since the last threshold update. If \( M \) includes all the decisions \( m_n \) made by nodes, then \( k = k_0 + 1 + M \).

Fig. 1. Protocol of information diffusion in the cooperative selective transmitter.

Fig. 1 shows a simple protocol to share \( \mu_k \) and the needed information to calculate it. Together with a transmitted data, each node propagates the \( M \) value by adding its number of dropped messages since the last transmitted message. With \( M \) and the estimation of \( E_i \) and \( P_{N,N} \), node \( N \) calculates \( \mu_k \), which is then propagated backwards in the routing path (i.e., included in the ACK of any transmission).

4. NUMERICAL EXPERIMENTS AND RESULTS

In this section we analyze the performance of the cooperative selective transmitter in different scenarios through simulations based on Matlab. First, we describe some common features of the experimental setup.

1. We use a simple deterministic energy model in our experiments defined by four constant and known parameters: \( E_i \), \( E_s \), \( E_r \) and \( E_t \) defined in Section 3.

2. All nodes except the sink are assumed homogeneous with the same initial level of battery (equal to 5000 units). The sink is considered to have an unlimited power supply. A network is considered dead under two different criteria: when a node consumes all its battery or when all the sink neighbors consume all their batteries.

3. Messages are generated with traffic rate \( R_s = 1 - R_i \) (packages generated in the network per time slot) and their source nodes are randomly chosen. All of them are forwarded towards the sink and two nodes are able to communicate to each other if they are within their mutual communication range (link losses are not considered in the model).

4. Selective strategies work over any routing algorithm that generates fixed tree topologies. We use greedy forwarding [8] for simplicity. In greedy forwarding each node selects the neighbor geographically closest to the sink as the next hop of the message.

5. In all the experiments we will compare the performance of the new scheme for cooperative selective communications developed in this paper, named Cooperative Transmitter (CooT), with the ‘Full information’ Local Forwarder (LF-FI) presented in [4]. The performance is measured in terms of gain over the Non-Selective transmitter (NS), where no message is censored, considering two merit figures: the total importance received at the sink and the network lifetime (number of time slots up to the network death).

6. All the experimental results are averaged over 50 simulations, with different topologies and traffic patterns.

4.1. Line topology

Firstly, we consider a network with line topology, where all the nodes lie uniformly distributed in a line, with the sink node placed at one end. Unless differently specified, in all the experiments the message importance follows an exponential distribution. This represents a feasible environment where there are a lot of messages of small relevance and a few of higher one.


In this case the energy costs are set to the following values: \( E_i = 0.05 \) and \( E_s = E_r = E_t = 4 \).

From Fig. 2, where we illustrate the behavior of the three schemes (NS, LF and CooT) with respect to the traffic rate, and Fig. 3, where we show their behavior with respect to the number of nodes, we observe that the CooT scheme beats the LF for all the considered traffic rates and number of nodes. It obtains a higher gain over NS, both in the
Fig. 2. Performance of CooT, LF and NS schemes in terms of the averaged total importance received at the sink and network lifetime for different traffic rates and equal active state costs. Over each sample the traffic rate is indicated.

averaged total received importance and in the lifetime. Furthermore, the performance of CooT and LF in terms of the total received importance decreases when the traffic rate decreases. Moreover, when the traffic rate and the number of nodes decrease, the difference in the total received importance of both schemes is smaller, whereas the difference in network lifetime is higher. Finally, if the number of nodes keeps increasing, the total received importance reaches a local maximum at around 25 nodes, which typically is higher than the maximum number of hops allowed by the routing protocols.

4.1.2. Case B: Different active state costs.

The results above reflect the performance of the different selective schemes when the transmitting, receiving and sensing energy costs are the same. In this section we consider the same setup of case A, but having different active state costs: \( E_i = 0.05 \), \( E_t = 4 \) and \( E_s = E_r = 1 \).

Fig. 4 shows that the behavior of the selective schemes is very similar to the one in case A: the lower the traffic rate is, the lower the gain obtained by a selective scheme is. The biggest difference with case A is that now the performance of LF improves and becomes similar to the one of the CooT. This result is not surprising since in [4] it is stated that the best performance of LF scheme is obtained when \( E_t >> E_r \). Anyway, despite this slight improvement, it is worth using CooT in this kind of scenarios because its overhead is almost the same that the one of LF.

Fig. 3. Performance of CooT, LF and NS schemes in terms of the averaged total importance received at the sink and network lifetime for different number of nodes and equal active state costs. Over each sample the number of nodes is indicated.

4.2. Random topology

The second scenario is a network where 100 nodes are randomly deployed, following a uniform spatial distribution. We consider that all the nodes are homogeneous with the energy consumption model of case A. In Fig. 5 we show the performance for NS, LF, CooT schemes for a traffic rate of 0.2 (1 message generated every 5 time slots) under two different death criteria:

1. The network dies when any of its nodes consumes all its batteries.

2. The network dies when all the sink neighbors consume all their batteries and hence the sink is disconnected.

This figure shows that, despite the low traffic rate, the performance of the CooT is significantly better than the one of the LF under the first criterion. Besides, a high gain in terms of the total received importance with respect to the NS is obtained. Under the second criterion, the CooT is not optimal, and the average performance is similar to the one of the LF. This happens because, once the network topology starts to change due to the death of a few nodes, the last node is not the critical one in terms of energy consumption. Results for higher traffic rates (i.e., 1 message generated per time slot or higher) will improve, as it was obtained for the line topology network.
5. CONCLUSIONS

This paper has introduced a new cooperative selective communication strategy to optimize the overall energy consumption in WSN. In this scheme all the nodes involved in the transmission try to optimize the energy consumption of the most critical node of the transmission chain, the last one. Its performance has been compared with the previously developed local forwarder scheme under two different criteria: total importance received at sink and network lifetime. In the simplified scenario of a line topology, the cooperative transmitter obtained a considerably higher gain in both criteria with respect to the non-selective scheme for different network and traffic conditions. In a more general setup the improvement in performance was not significant unless the network dies when any node run out of batteries.

On the contrary, under a different death criterion, as the network topology varies along its lifetime, the good performance of the scheme was not assured. Hence, future work will be focused on developing adaptive cooperative strategies for those scenarios where the batteries of the sink neighbors are not critical.

6. REFERENCES


