Available online at www.sciencedirect.com
ScienceDirect
Computer Networks 50 (2006) 3564–3584
Computer Networks
www.elsevier.com/locate/comnet

Understanding optimal data gathering in the energy and latency domains of a wireless sensor network

U. Monaco [a,*], F. Cuomo [a], T. Melodia [b], F. Ricciato [c], M. Borghini [a]

[a] INFO-COM Department, University of Rome "La Sapienza", Via Eudossiana 18, 00184 Rome, Italy
[b] Broadband and Wireless Networking Laboratory – Georgia Institute of Technology, Atlanta, GA 30332, United States
[c] Forschungszentrum Telekommunikation Wien (ftw.), Donau City Strae 1, 1220 Wien, Austria

Received 14 October 2005; received in revised form 17 February 2006; accepted 20 February 2006
Available online 30 March 2006

Responsible Editor: S. Palazzo

Abstract

The problem of optimal data gathering in wireless sensor networks (WSNs) is addressed by means of optimization techniques. The goal of this work is to lay the foundations to develop algorithms and techniques that minimize the data gathering latency and at the same time balance the energy consumption among the nodes, so as to maximize the network lifetime. Following an incremental-complexity approach, several mathematical programming problems are proposed with focus on different network performance metrics. First, the static routing problem is formulated for large and dense WSNs. Optimal data-gathering trees are analyzed and the effects of several sensor capabilities and constraints are discussed, e.g., radio power constraints, energy consumption model, and data aggregation functionalities. Then, dynamic re-routing and scheduling are considered. An accurate network model is proposed that captures the tradeoff between the data gathering latency and the energy consumption, by modeling the interactions among the routing, medium access control and physical layers.

For each problem, extensive simulation results are provided. The proposed models provide a deeper insight into the problem of timely and energy efficient data gathering. Useful guidelines for the design of efficient WSNs are derived and discussed.

Keywords: Wireless sensor networks; Energy-latency trade-offs; Mathematical programming/optimization

1. Introduction

Wireless sensor networks (WSN) [1] are composed of small miniaturized devices with limited sensing, processing and computational capabilities. Wireless sensors can be densely deployed across the monitored area, and enable a broad range of applications such as environmental monitoring, monitoring of fire and earthquake emergencies, vehicle tracking, traffic control and surveillance of city districts.

In typical applications, sensors monitor their neighboring area, extract information, and send

* Corresponding author. Tel.: +39 06 47825184; fax: +39 06 48930606.
E-mail address: monaco@infocom.uniroma1.it (U. Monaco).

1389-1286/$ - see front matter © 2006 Elsevier B.V. All rights reserved.
doi:10.1016/j.comnet.2006.02.003

the sensed data to remote sinks that reconstruct the characteristics of the phenomenon being monitored [1]. Since wireless sensors are typically low-cost, low-power and short-range devices, multi-hop routes are used to relay data from the monitored area to the sink. These paths are typically built on-demand (*reactive routing*) or dynamically pre-computed (*proactive routing*) [2]. In the former case, path computation is triggered by the occurrence of specific events or upon request from the application; in the latter, the routes are determined before they are actually used. The aggregate of multi-hop paths used to relay data from the sensors to the sink can be seen as a *data-gathering tree*.

In this context, data aggregation has been proposed as an essential paradigm for routing in WSNs [3]. Data aggregation mechanisms are aimed at reducing the energy consumption of the network nodes by exploiting data correlation. This relies on the assumption, true in many practical cases, that data sensed by different sensors are to some extent spatially correlated [4], hence data can be aggregated as they are forwarded by the sensor network. This in-network processing avoids the sending of individual data items and decreases the sensor network energy consumption. The amount of energy saved by the in-network aggregation depends both on the considered aggregation model, i.e., the correlation level among sensed data, and on the topological characteristics of the sensor network (cluster-based, tree-based, etc.). The achievable improvement in energy efficiency in adopting a correlation aware aggregation tree as opposed to a correlation unaware tree is discussed in detail in [5]. This paradigm shifts the focus from the traditional *address-centric approaches* (finding short routes between pairs of addressable end-nodes) to the so-called *data-centric approach* (finding routes from multiple sources to a single destination and allowing in-network consolidation of redundant data). For this reason, data-gathering trees are also referred to as *data-aggregation trees* (DA-trees in the following).

Intuitively, due to the dense sensor deployment, many different DA-trees can be constructed to relay data from the event area to the sink. The choice of a particular DA-tree greatly affects several key performance metrics of the WSN such as network lifetime, energy consumption, network availability, and end-to-end delay. In fact, the characteristics of different DA-trees may differ in many domains, primarily with respect to energy consumption (i.e., the energy needed to gather sensed data to the sink), and with respect to the introduced latency (i.e., the time needed to deliver data to the sink). According to the requirements of the sensor network application, energy-oriented or latency-oriented design approaches should be preferred by the network designer.

The objective of this paper is to provide a wide-ranging analysis of the impact of different network design strategies for data gathering. To this aim, we define several optimization problems in the energy-latency domain and tackle them with a multi-target approach. To design the optimization framework we considered quasi-ideal network condition by implementing a time scheduling that avoids collisions at the MAC layer and by assuming negligible transmission errors as well as ideal data correlation. The mathematical framework proposed here allows the WSN designer to foresee the impact of different design choices on optimal DA-trees as a function of different performance targets. The presented results will help researchers gain a deeper understanding of the fundamental characteristics of WSNs in the energy-latency domains.

To better discern the effects of the assumptions about the scenario and to gain a deeper insight into optimal data gathering in WSNs, we follow an incremental-complexity approach. First, we consider a simple reference model where data flow routes do not change over time and *multi-path routing* is allowed. We refer to this model as *static routing*. We consider different Linear Programming (LP) problems, with different energy-oriented objectives. Moreover, we account radio transmission range constraints and assess the effects of the sensor energy consumption model in the selection of the optimal data gathering trees. We show that in the hypothesis of splittable traffic the energy consumption at all nodes can be perfectly equalized so as to maximize the network lifetime, with optimal routing patterns that involve two next-hops for each node – one close to the transmitter, the other closer to the sink.

According to the incremental-complexity approach, we further address the problem of finding the optimal data-aggregation trees in WSNs. We solve instances of the optimization problem when only a subset of all the sensors are data sources. In particular, we assess the energy consumption savings caused by data aggregation events and analyze the main characteristics of the DA-trees. Finally, we further extend the model and consider *dynamic* *re-routing*, i.e., new data paths are calculated for each subsequent monitored event, and the scheduling of data packets and the interference between neighboring nodes at the MAC layer. The objective is to devise optimal strategies to balance the node energy consumption in time and maximize the network lifetime while maintaining a low data gathering latency. We define two different optimization strategies, one primarily *latency-oriented*, and another primarily *energy-oriented*. We observe that the latency-oriented strategy minimizes the time needed to gather the event features for each event. Moreover, it achieves a comparable behavior in terms of energy consumption and network lifetime with respect to the energy-oriented strategy.

The following of the paper is organized as follows. In Section 2 we review the related literature on the topic. Section 3 introduces the general network model. Section 4 presents different formulations of the optimal data gathering with static routing problem, while the model defined to investigate the problem of dynamic re-routing is presented in Section 5. In Section 6 we provide numerical results, while in Section 7, we draw the main conclusions and outline future work.

2. Related work

Considerable previous work has considered the problem of minimizing the energy consumption of a WSN, from several different perspectives. For example, energy-efficient broadcasting and multicasting in wireless networks was discussed in [6], where heuristic solutions were presented. The problem was subsequently proven to be NP-Complete [7].

Chang and Tassiulas [8,9] formulated the maximum lifetime routing problem for a WSN as a multi-commodity flow integer linear program, and propose heuristic algorithms to determine approximate solutions. In [10], a distributed algorithm is presented to determine the maximum lifetime, based on the Garg–Koenemann [11] algorithm for multicommodity flows. In [12], a heuristic near-optimal solution is proposed for the problem of maximum lifetime routing that can be computed in polynomial time. In [13], Bhardwaj and Chandrakasan explore the fundamental bounds of WSN lifetime and examine feasible role assignments (FRA) of nodes as a means of maximizing the lifetime of aggregating as well as non-aggregating sensor networks. In [14], the authors formulate the maximum lifetime routing problem as a maximum concurrent flows problem, and propose a distributed routing algorithm that finds the optimal solution within an asymptotically small relative error, hence providing lower bounds on its performance. In [15], the maximum lifetime routing problem is formulated as a linear program and sub-gradient algorithms are used to solve it in a distributed manner. The resulting algorithms have low computational complexity and are guaranteed to converge to an optimal routing scheme that maximizes the network lifetime. In [16], Sadagopan and Krishnamachari formulate the problem of maximizing the data extraction of a sensor network. Although maximum data extraction is related to maximizing lifetime of the network, in maximum data extraction the network operates until the energy in all nodes is depleted, not until the first node exhausts its energy. While the authors in [16] propose a heuristic based on the Garg–Koenemann algorithm, in [17] a similar problem is solved with a distributed sub-gradient algorithm. In [18], Hou et al. study the network capacity problem by trying to maximize the amount of bit volume that can be generated by the entire network under a network lifetime requirement. In [19], the authors formulate the problem of determining the extension of the local topology knowledge ranges that minimize the energy consumption of a sensor network operating with geographical routing as an integer linear program.

In general, in the above papers, the routing issue is dealt with exclusively from an energy consumption standpoint. Conversely, in this paper we extend the analysis to the latency domain. This allows us to investigate energy-latency trade offs for optimal data gathering in WSNs. This problem has been previously investigated in [20]. There, the focus was on minimizing the energy consumption given a time constraint, by leveraging physical layer modulation scaling techniques. However, the problem of finding the minimum latency data-gathering tree was not investigated.

Tightly related with energy minimization in sensor networks is the problem of data aggregation. In-network aggregation has been considered in several previous works (see [5] and references therein). The gain of data aggregation on energy savings, and hence on network lifetime, firstly depends on the assumed data correlation model, i.e., the level of spatial correlation among sensed data and the kind of aggregation that can be performed on it. In [21], non-ideal data aggregation (e.g., partially correlated data) and distortion constraints are considered. The authors propose an analytical framework to assess the effects of the data correlation on the performance of clustering algorithms and show that there is a trade-off between total energy consumption and network lifetime. In particular, the increase in network lifetime mentioned by the authors of [21] derives from the clustering algorithm and it is due to the general energy saving provided by data aggregation. An ideal aggregation model is considered in [22], where a distributed timing method is proposed to achieve efficient data aggregation. According to the proposed mechanism, each sensor determines the time it has to wait for receiving data from its neighbors, before forwarding aggregated data towards the sink. The proposed solution is independent from the routing protocol and can be applied over a general data-gathering tree. Conversely, in this paper we propose a framework to analyze optimal data gathering in WSNs. In particular, we jointly consider routing and data aggregation. Moreover, we explicitly account for energy balancing as an effective means aimed at maximizing the network lifetime. Hence, the results presented in this work can be assumed as reference performance bounds for distributed implementation schemes such as the solution proposed in [22], which are within the scope of the assumptions that we consider. As a final remark, in this work we assume an ideal data correlation model. However, the proposed framework can be used as the foundation for further studies aimed at accounting more complex in-network processing functions and partially correlated data scenarios.

3. Network model

We consider a multi-hop WSN with one sink and N sensors uniformly distributed in a square sensor field. The network of sensors is modeled as an undirected graph $\mathscr{G}(\mathscr{N},\mathscr{E})$, where $\mathscr{N}$ represents the set of vertexes (sensor nodes) $v_1, v_2, \ldots, v_N$, with $N = |\mathscr{N}|$, and $\mathscr{E}$ represents the set of links among nodes. We denote by d_{ij} the Euclidean distance between sensors v_i and v_j (also simply referred to as i and j for simplicity), while d_i denotes the distance between sensor v_i and the sink. Each sensor is characterized by a maximum transmission range R_{T} that accordingly defines the set C_i of neighbors for the sensor i. We adopt the *unit disk graph* communication model, where a link $\epsilon_{ij} \in \mathscr{E}$ if and only if v_i and v_j are within distance R_{T}, which is assumed to be equal for all nodes. A subset of the sensors $\mathscr{S} \subseteqq \mathscr{N}$, with $S = |\mathscr{S}|$ (referred to as *sources*) generates information that has to be relayed to the *sink*, referred to as O. We assume that transmitting one unit of information from sensor i to sensor j requires a power which is a function of d_{ij}^{α} with $2 \leqslant \alpha \leqslant 5$. We will further specify the energy model in the following sections. Unless otherwise specified, we assume free space attenuation $\alpha = 2$. More details regarding the considered network scenarios, and specifically of the advanced features, e.g., data aggregation, will be given in Section 4 as they are introduced.

4. Optimal data gathering with static routing

In this section, we provide different problem formulations for finding optimal data-gathering trees with static routing, i.e., data paths do not change with time. Since the problem of optimal data gathering in WSNs can be formulated as a classical network flow transportation problem [23], we rely on a set of simplifying assumptions that keep the complexity of the problem low, thus preventing it from becoming NP-Complete [24].

The presented formulations for optimal data gathering are aimed at analyzing the energy consumption in different practical application scenarios, e.g., field monitoring, and target tracking [25]. In particular, in Section 4.1 we consider the field monitoring scenario where all sensors generate and relay uncorrelated data to the sink to produce a complete view of the monitored field. This problem does not consider data aggregation. Then, in Section 4.2, we assume that only a subset of the nodes senses an event. In this case, we extend the problem formulation to include data aggregation mechanisms.

4.1. Problem formulation without data aggregation

We consider the problem of finding static data-gathering trees in WSNs with the following assumptions:

- Sensors can arbitrarily split the traffic that they generate/relay and accordingly transmit it to several different neighbors (multi-path routing). This results in the linear relaxation of the routing variables, also referred to as "splittable traffic" [26].
- Sensors do not perform data aggregation.
- Sensors communicate through an ideal channel, i.e., packet losses do not occur.

- Sensors implement a contention-free MAC protocol, in other words in this section we focus on finding optimal data gathering trees only from a routing perspective by assuming that an optimal scheduling is later achieved over the resulting gathering trees (see Section 5 for a joint routing/scheduling formulation of the optimal data gathering problem).

Moreover, without loss of generality, we assume a continuous-time transmission of information, so that we can define the following quantities:

- g_i is the information flow *generated* by sensor i and destined to the sink;
- all sensors generate the same amount of information towards the sink, i.e., $S = N$ with $g_i = g$, $\forall i \in \mathcal{N}$;
- l_{ij} is the information flow *transmitted*[1] from sensor i to sensor j.

The energy consumption per bit at the physical layer is modeled as

$$E^{\text{trans}} = E^{\text{trans}}_{\text{elec}} + \beta d^{\alpha}, \quad E^{\text{rec}} = E^{\text{rec}}_{\text{elec}}, \tag{1}$$

where E^{trans} and E^{rec} are the energy consumption at the transmitter and receiver devices of a sensor, respectively. In particular, $E^{\text{trans}}_{\text{elec}}$ and $E^{\text{rec}}_{\text{elec}}$ [J/bit] are *distance independent* terms that take into account overheads of sensor electronics (PLLs, VCOs, bias currents, etc.) and digital processing. The term βd^{α} takes into account the radiated power; β is a constant [J/(bit m$^{\alpha}$)]. As in [27], we assume that $E^{\text{trans}}_{\text{elec}} = E^{\text{rec}}_{\text{elec}} = E_{\text{elec}}$.

The overall expression for the total energy consumption at sensor i becomes:

$$E_i = \sum_{j \in C_i} \left[(\beta d^{\alpha}_{ij} + E_{\text{elec}}) \cdot l_{ij} + E_{\text{elec}} \cdot l_{ji} \right], \tag{2}$$

where $\beta d^{\alpha}_{ij} + E_{\text{elec}}$ is the energy wasted to transmit l_{ij} bits to sensor j and E_{elec} takes into account the energy consumed for the reception of l_{ji} bits from sensor j.

With such positions, the objective of minimizing and/or balancing the network energy consumption can be achieved by optimally controlling the fraction of information (therefore, of energy) transmitted by each sensor to each of its neighbors, which defines the multi-path routing strategy for the whole network. Hence, the optimization problem consists of finding, for all sensor pairs (i,j), the set of variables l_{ij} that minimize the energy consumption. Two objective functions can be considered leading to different problems, namely:

- minimizing the maximum energy consumption of the network $E_{\max} = \max_{i \in \mathcal{N}} \{E_i\}$. We refer to this strategy as ROM_{E} (*Routing Optimization Maximum Energy*);
- minimizing the total energy consumption of the network $E_{\text{tot}} = \sum_{i=1}^{N} E_i$. We refer to this strategy as ROT_{E} (*Routing Optimization Total Energy*). Since minimizing the total energy consumption E_{tot} is equivalent to minimizing the mean energy consumption $E_{\text{mean}} = \frac{1}{N} E_{\text{tot}}$, in the rest of the paper we will consider E_{mean}.

These two objectives are conflicting and a trade-off is in place between them. In the following we provide a Linear Programming (LP) formulation for the general case of mixed optimization, where the objective function to be minimized is a linear combination of $E_{\max}$ and E_{mean}. By tuning the coefficient γ in (3) one can shift from a pure ROM_{E} formulation ($\gamma = 1$) to ROT_{E} ($\gamma = 0$).

Problem 1 (*Static routing without data aggregation*)

Minimize:

$$\gamma E_{\max} + (1 - \gamma) \cdot \frac{1}{N} E_{\text{tot}}. \tag{3}$$

Subject to:

$$l_{ij} \geqslant 0, \quad \forall j \in C_i, \ \forall i \in \mathcal{N}, \tag{4}$$

$$\sum_{j \in C_i} (l_{ij} - l_{ji}) = g_i, \quad \forall i \in \mathcal{N}, \tag{5}$$

$$E_i = \sum_{j \in C_i} \left[(\beta d^{\alpha}_{ij} + E_{\text{elec}}) \cdot l_{ij} + E_{\text{elec}} \cdot l_{ji} \right], \quad \forall i \in \mathcal{N}. \tag{6}$$

Since we assume a single sink and we do not consider data coding/aggregation, the information flow is additive (constraint (5)). Hence, we do not need to discriminate between information flows originated by different sensors and Problem 1 reduces to a single-commodity flow problem.

4.2. Problem formulation with data aggregation

In this section, we extend Problem 1 to account for data aggregation mechanisms. We assume that

[1] Note the different usage of terms *transmitted* and *generated*.

all the sensed data generated by different sources in $\mathcal{S}$ can be aggregated, e.g., by performing simple data fusion operations such as min, max, mean, or logical OR, AND, XOR over the relayed data. Hence, a sensor receiving two packets of size g bits generated by different sources can aggregate the data in a single g-bit packet.

The problem of finding DA-trees is tackled by introducing a new set of variables x_{ij} that represent the *aggregated* flow transmitted from sensor i to sensor j (e.g., the flow that derives from the data aggregation process carried out by sensor i). Moreover, to prevent different flows generated by the same sensor from being aggregated, sources of the routed flows need to be discriminated. For this purpose, the l_{ij} variables in Problem 1 are replaced by the l_{ij}^s variables which represent the information flow *transmitted* from sensor i to sensor j and *generated* by sensor s (multi-commodity flow problem). Moreover, because of the splittable traffic hypothesis packets of different size can be received by a sensor along the route to the sink. When this occurs, we assume that data aggregation can be still performed and only one packet, whose size is equal to the size of the largest received packet, will be relayed. Using the same notation introduced above, we can introduce the new formulation of the problem, which we refer to as *static routing with data aggregation* or Problem 2.

Problem 2 (*Static routing with data aggregation*)

Minimize:

$$\gamma E_{\max} + (1-\gamma)\cdot\frac{1}{N}E_{\text{tot}}. \tag{7}$$

Subject to:

$$E_i = \sum_{j\in C_i}\left[(\beta d_{ij}^{\alpha} + E_{\text{elec}})\cdot x_{ij} + E_{\text{elec}}\cdot x_{ji}\right],\quad \forall i\in\mathcal{N}, \tag{8}$$

$$\sum_{j\in C_s}(l_{sj}^s - l_{js}^s) = g,\quad \forall s\in\mathcal{S}, \tag{9}$$

$$\sum_{i\in C_O}(l_{iO}^s - l_{Oi}^s) = g,\quad \forall s\in\mathcal{S}, \tag{10}$$

$$\sum_{(i,j)}(l_{ij}^s - l_{ji}^s) = 0,$$

$$\forall s\in\mathcal{S},\ \forall (i,j): \{i\in\mathcal{N}, j\in C_i\}, \tag{11}$$

$$0\leqslant l_{ij}^s\leqslant x_{ij},\quad \forall s\in\mathcal{S},\ \forall (i,j): \{i\in\mathcal{N}, j\in C_i\}. \tag{12}$$

Constraint (8) defines the energy consumption at each node, according to the energy model in (1). Eqs. (9)–(11) express conservation of flows [23], while Eq. (12) allows aggregation of data generated by different sources in $\mathcal{S}$.

5. Optimal data gathering with dynamic re-routing

In this section, we further detail our network model to include scheduling at the MAC layer and to account for the latency associated to each DA-tree. The new model captures the interdependencies between the network and medium access control layers, and thus allows studying the latency of the data gathering process. We also analyze *dynamic scenarios*, where optimal DA-trees are determined sequentially for different events, thus taking into account the evolution of the residual energy at each sensor.

We consider a scenario with *multiple events*. For each event, the sensors in $\mathcal{S}$ generate information (e.g., one data packet) to be delivered to the sink. For each event, we calculate a new DA-tree from sources to sink. The goal of the DA-tree selection is twofold: on one side the DA-tree should balance the residual energy of the network nodes; on the other side the scheduling on this DA-tree should minimize the latency. Since the calculated DA-trees are different for each event, depending on the residual energy at the nodes, we refer to this procedure as *re-routing*. We model a collision-free scheduling of data transmissions on the DA-trees at the MAC layer. To do so, we require that transmissions from sensors within reciprocal radio range be scheduled in different *MAC periods* (referred to as time slots in the following). Multiple time slots are thus required to gather the information generated by the sensors in $\mathcal{S}$ at the sink. We further assume that each sensor is characterized by a *sensing range* R_S. Let us introduce the following definitions.

Definition 1. In the multiple-event case, the *lifetime* of the WSN is the *maximum number of events* that can be observed at the sink before at least one sensor in $\mathcal{S}$ loses its connectivity to the sink.

Definition 2. The network *latency* T_{Sch} for an event is the total number of time-slots required to gather the information generated by the sensors in $\mathcal{S}$ for that event, where $\mathcal{T} = \{1,\ldots,T_{\text{Sch}}\}$ is the set of time slots required to deliver the data measured by the sensors in $\mathcal{S}$ to the sink.

Definition 3. The *sensing coverage* of the network is the portion of the area that is monitored by the sensors, i.e., that is within the sensing range of at least one sensor that has not depleted its battery.

We propose two different strategies for the data gathering problem, namely:

- *latency-oriented:* The primary objective is to minimize the latency, while the secondary objective is to balance the energy consumption among nodes (R^2OB_L – *Re-Routing Optimal Balancing, Latency-oriented*);
- *energy-oriented:* The primary objective is to balance the energy consumption among nodes, while the secondary objective is to minimize the latency (R^2OB_E – *Re-Routing Optimal Balancing, Energy-oriented*).

Algorithms 1 and 2 describe the procedure to solve R^2OB_L and R^2OB_E, respectively. Both strategies solve the ILP introduced in the following, referred to as T_{Sch} *DA-tree problem*, for each event.

Given a topology, a set of sources, and a number of time slots T_{Sch}, the solution of the T_{Sch} *DA-tree problem*, if it exists, consists of an optimal DA-tree, according to the objective function, and a feasible scheduling of data transmissions from sources to sink in T_{Sch} time slots.

Suppose that the residual energy of sensor i is $E^i_{\text{res}}(n)$ at the nth event. We calculate the mean $\overline{E}(n)$ of the residual energies at event n:

$$\overline{E}(n) = \frac{1}{N}\sum_{i=1}^{N} E^i_{\text{res}}(n). \tag{13}$$

Then, for each link (i,j) we compute e_{ij}, which is equal to the minimum between the residual energy at sensors i and j after the $(n+1)$th event, if link (i,j) is used to relay data for the $(n+1)$th event. Hence,

$$e_{ij}(n+1) = \min\left(E^i_{\text{res}}(n) - E^{\text{trans}}_{ij}, E^j_{\text{res}}(n) - E^{\text{rec}}_{ij}\right). \tag{14}$$

Finally, we define the cost matrix for re-routing strategies, where the generic element c_{ij} has the form

$$c_{ij} = \left|e_{ij}(n+1) - \overline{E}(n)\right| \tag{15}$$

that represents the distance of the residual energy after the $(n+1)$th event, $e_{ij}(n+1)$, from the current mean residual energy of the network $\overline{E}(n)$.

We represent the scheduling of transmissions with a set of matrices F^t, one for each time slot $(1 \leqslant t \leqslant T_{\text{Sch}})$. The element f^t_{ij} in F^t equals 1 if and only if a transmission occurs on link (i,j) during time slot t. With the definitions above, along with those in Section 3, we can formulate the ILP as follows.

Problem 3 (T_{Sch} *DA-tree*)

Minimize:

$$c_{\text{tot}} = \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{N}}\sum_{j\in C_i} f^t_{ij}\cdot c_{ij}. \tag{16}$$

Subject to:

$$\sum_{t\in\mathcal{T}}\sum_{j\in C_i} f^t_{ij} = 1, \quad \forall i\in\mathcal{S}, \tag{17}$$

$$1 \leqslant \sum_{t\in\mathcal{T}}\sum_{i:O\in C_i} f^t_{iO} \leqslant |\mathcal{S}|, \tag{18}$$

$$\sum_{t\in\mathcal{T}}\sum_{i:O\in C_i} f^t_{iO} = 0, \tag{19}$$

$$\sum_{j\in C_i} f^t_{ij} \leqslant \sum_{\tau=1}^{t-1}\sum_{k:i\in C_k} f^\tau_{ki}, \quad \forall t\in\mathcal{T}: t>1,\ \forall i\in\mathcal{N}\setminus\{\mathcal{S}\cup O\}, \tag{20}$$

$$\sum_{j:i\in C_j} f^t_{ji} \leqslant \sum_{\tau=t+1}^{T_{\text{Sch}}}\sum_{k\in C_i} f^\tau_{ik}, \quad \forall t\in\mathcal{T}: t<T_{\text{Sch}},\ \forall i\in\mathcal{N}\setminus O, \tag{21}$$

$$\sum_{j\in C_i} f^1_{ij} = 0, \quad \forall i\in\mathcal{N}\setminus\mathcal{S}, \tag{22}$$

$$\sum_{i:j\in C_i} f^{T_{\text{Sch}}}_{ij} = 0, \quad \forall j\in\mathcal{N}\setminus O, \tag{23}$$

$$\sum_{j\in C_i}(f^t_{ij} + f^t_{ji}) \leqslant 1, \quad \forall t\in\mathcal{T},\ \forall i\in\mathcal{N}, \tag{24}$$

$$N\cdot\sum_{j\in C_i} f^t_{ij} + \sum_{k\in C_i}\sum_{m:k\in C_m} f^t_{mk} \leqslant N, \quad \forall i\in\mathcal{N},\ \forall t\in\mathcal{T},\ m\neq i. \tag{25}$$

Eq. (16) is the objective function of the problem, and represents the total cost of the network for the event. This is obtained by weighing all transmissions, represented by the elements in F^t, for each $t \leqslant T_{\text{Sch}}$, with the cost associated with a transmission on that link. Remember that the cost matrix measures the gap between the forecasted residual energy at the sensors and the current mean residual energy of the network, so as to balance the energy consumption.

Note that the DA-tree can be seen as a union of flows, each departing from a source sensor and converging to the sink. A flow is the set of transmissions from a source to the sink. Constraints (17)–(21) express conservation of flows. In particular, constraint (17) requires that each source transmit only once. Constraint (18) imposes that the sink receive at least one and no more than $|\mathcal{S}|$ flows, while constraint (19) requires that the sink does not generate a flow. Constraints (20) and (21) are related to relay sensors. If a relay sensor transmits a packet in a time slot $t^* \geqslant 1$, it must have previously received the packet from another sensor in a time slot $t \leqslant t^*$. Constraint (22) allows only source sensors to transmit during the first time slot, and constraint (23) imposes that the sink receives the information during the last time slot. The MAC constraints are defined by (24) and (25). According to (24), each sensor can transmit to or receive from only one sensor in each time-slot. Constraint (25) is introduced to account for a collision-free MAC protocol, i.e., MAC collisions never occur in the resulting DA-trees. To this aim, we impose that when a sensor i is transmitting to a sensor j, no other sensors in the range of j can transmit, as it would interfere with the reception at j.

5.1. Latency-oriented optimization (R^2OB_L)

On the basis of this ILP formulation the latency-oriented algorithm (see Algorithm 1) solves instances of T_{Sch} *DA-tree* with increasing T_{Sch} (e.g., $T_{\text{Sch}} = 3, 4, 5, \ldots$ time slots). The first instance of T_{Sch} *DA-tree* that admits solution defines the minimum latency T_{Sch}, the relevant DA-tree and the minimum-latency scheduling for the considered scenario. The value T_{Sch} is initialized to the minimum possible latency for the considered topology, which is equal to

$$T^{\text{Start}} = \max(h, T), \tag{26}$$

where h is the hop distance of the farthest source from the sink, and T is such that

$$|\mathcal{S}| \leqslant \sum_{i=0}^{T-1} 2^i. \tag{27}$$

The second member in Eq. (27) represents the maximum number of sources that can send their data towards the sink in T time slots.

Algorithm 1. $\text{R}^2\text{OB}_\text{L}$

event $\leftarrow 0$;
while all sources are connected **do**
  event $\leftarrow$ *event* $+ 1$;
  Calculate T^{Start};
  $T_{\text{Sch}} \leftarrow T^{\text{Start}}$;
  found $\leftarrow$ *false*;
  repeat
    Solve an instance of T_{Sch} *DA-tree* for the *event* (see Problem 3);
    if solution does not exist in T_{Sch} time slots **then**
      $T_{\text{Sch}} \leftarrow T_{\text{Sch}} + 1$;
    else
      found $\leftarrow$ *true*;
    end if
  until (not *found*);
  Update residual energy at each sensor;
end while
network_lifetime $\leftarrow$ *event*;

5.2. Energy-oriented optimization (R^2OB_E)

The $\text{R}^2\text{OB}_\text{E}$ finds the optimal DA-tree for each event giving priority to the energy aspects. To this aim, it performs two steps. First, it selects the DA-Steiner-tree [28] with the link costs defined by (15). Then, it computes the T_{Sch} *DA-tree* in the minimum T_{Sch} on the DA-Steiner-tree calculated in the previous step. In this way, during the first step the algorithm finds the tree that best balances the energy consumption, while at the second step it solves

Algorithm 2. $\text{R}^2\text{OB}_\text{E}$

event $\leftarrow 0$;
while all sources are connected **do**
  event $\leftarrow$ *event* $+ 1$;
  Calculate the *DA-Steiner-tree* with costs c_{ij} defined in Eq. (15) for the *event*;
  Calculate T^{Start};
  $T_{\text{Sch}} \leftarrow T^{\text{Start}}$;
  found $\leftarrow$ *false*;
  repeat
    Solve an instance of T_{Sch} *DA-tree* only for $\forall (i,j)/\epsilon_{ij} \in$ *DA-Steiner-tree*;
      if solution does not exist in T_{Sch} time slots **then**
        $T_{\text{Sch}} \leftarrow T_{\text{Sch}} + 1$;
      else
        found $\leftarrow$ *true*;
      end if
  until (not *found*);
  Update residual energy at each sensor;
end while
network_lifetime $\leftarrow$ *event*;

Problem 3 with the additional constraint $f_{ij}^t = 0$, $\forall t \in \mathscr{T}$, $\forall (i,j)$ s.t. $\epsilon_{ij} \notin$ DA-Steiner-tree.

6. Analysis of the results

We analyze the results relative to the optimization problems presented in the previous sections. In particular, in Sections 6.1 and 6.2 we present results related to the optimization problems presented in Section 4, while in Section 6.3 we discuss results related to the models and algorithms presented in Section 5. For ease of understanding in Table 1 we report a summary of the notation introduced in the previous sections. The objective is to investigate the basic interactions between routing and the resulting latency and energy consumption. In the following we assume a $30\,\text{m} \times 30\,\text{m}$ square terrain with the sink located in the upper-right corner of the region. As in [27] we set $E_{\text{elec}} = 570\,\text{nJ}$, $\alpha = 2$, while β is dependent on the maximum transmission range (R_{T}) of the radio device ($\beta = 740/36\,\text{nJ/m}^2$). Without loss of generality, we consider $g = 1$ bit.

6.1. Static routing – Problem 1

We implemented the optimization problem described in Section 4.1, with the objective function given in (3), in AMPL [29], and used the CPLEX solver [30], which implements the simplex algorithm to solve linear problems. We considered several scenarios, with different topologies and sensor densities. To better understand the dependencies of the optimal DA-trees from the energy model, we first analyze Problem 1 by assuming that the term $E_{\text{elec}} \cong 0$ in Eq. (2) then we include also values of $E_{\text{elec}} > 0$.

6.1.1. Case of $E_{elec} = 0$

Here, we report the main characteristics of the data-gathering trees with reference to a sensor network with $N = 200$ sensors. We initially set the radio transmission range $R_{\text{T}} = d^{\max} = 30\sqrt{2}\,\text{m}$. Fig. 1 reports the per-sensor energy consumption E_i for all sensors as a function of the distance from the sink d_i, for different objective functions (i.e., different values of γ in Eq. (3)).

In the ROT_{E} case, ($\gamma = 0$, Fig. 1(d)) it is known that an extremal solution of the problem in (3) exists [23], with either $l_{ij} = 0$ or $l_{ij} = g$ for each (i,j) pair. This solution represents single-path data routing (non-splittable traffic) from each source towards the sink, i.e., each sensor selects only *one* next hop and transmits all the traffic that it relays/generates to that next hop. Since the energy consumption of a sensor is proportional to d_{ij}^{α} ($E_{\text{elec}} = 0$), ROT_{E}

Table 1
Summary of the notation

Symbol	Description
$\mathscr{N}$	Set of sensor nodes
$\mathscr{S}$	Set of data sources
g	Generated information flow [bit]
l_{ij}	Transmitted information flow from i to j [bit]
l_{ij}^s	Transmitted info flow from i to j, generated by s [bit]
x_{ij}	Aggregated information flow from i to j [bit]
E_{elec}	Distance independent energy consumption [nJ]
E_i	Total energy consumption at i [nJ]
E_{tot}	Network total energy consumption [nJ]
$E_{\max}$	Network maximum energy consumption [nJ]
C_i	Set of neighbors of i
R_{T}	Radio transmission range [m]
α	Free space attenuation factor
β	Per-bit energy transmission factor
γ	Objective function weight coefficient
d_{ij}	Distance from i to j [m]
T_{Sch}	Event latency [s]
$\mathscr{T}$	Set of time slots
$E_{\text{res}}^i(n)$	Residual energy of i, at nth event [nJ]
$e_{ij}(n)$	Minimum residual energy between i and j after nth event [nJ]
c_{ij}	Link (i,j) cost
f_{ij}^t	Scheduling variable for link (i,j) at time slot t

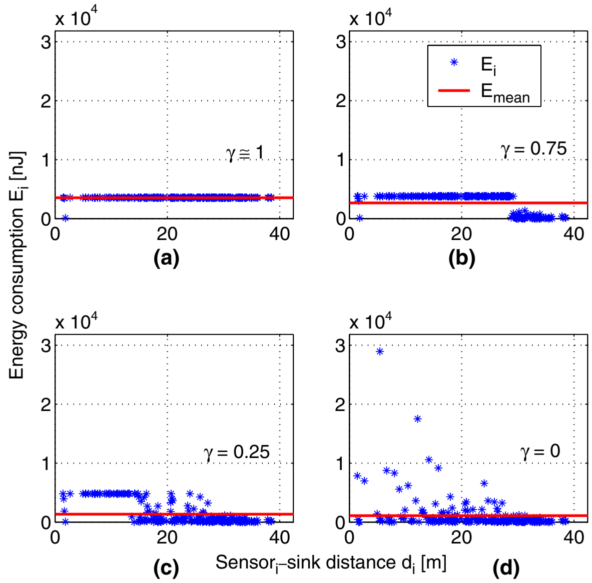

Fig. 1. Per-sensor energy consumption E_i versus d_i for different optimization strategies. ROM_{E} (a), mixed optimization (b) and (c), ROT_{E} (d).

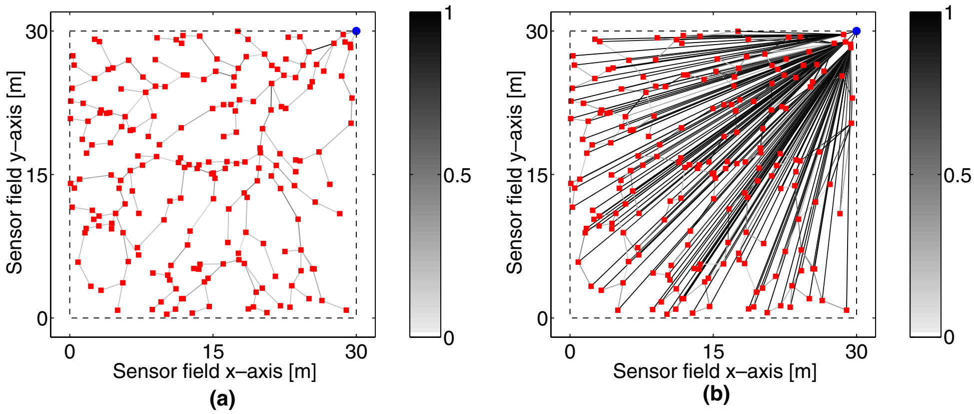

Fig. 2. Optimal data-gathering trees for different optimization strategies, case of $E_{elec} = 0$. (a) ROT_E; (b) ROM_E.

minimizes the distance between each pair of sensors along the data-gathering paths, i.e., each next hop is the closest node to the corresponding transmitting sensor towards the sink. Therefore, "exterior" sensors (i.e., sensors far from the sink) only consume energy to transmit the data they generate, while "interior" sensors (i.e., sensors close to the sink) also relay data for other sensors. Hence, the ROT_E strategy entails a higher energy consumption E_i for interior sensors.

When $\gamma > 0$, a mixed $E_{max} - E_{tot}$ optimization is performed, and the optimal data-gathering trees are computed to reduce the maximum energy consumption E_{max}, at the price of a higher E_{tot}. For $\gamma \cong 1$ (ROM_E, Fig. 1(a)), Problem 1 results in the min–max formulation. The objective of minimizing the maximum energy consumption implies that all sensors consume almost the same amount of energy ($E_i = E_{max} \simeq E_{mean}$). In the considered WSN, ROM_E reduces the maximum energy consumption E_{max} by a factor 8 with respect to ROT_E, at the cost of E_{tot} being more than three times higher. Fig. 2(a) and (b) shows the optimal data-gathering trees in the ROT_E and ROM_E case, respectively. The color[2] of each link indicates the normalized energy consumption E_{ij}/E_{max} (white corresponds to $E_{ij} = 0$ and black $E_{ij} = E_{max}$), while the sink is placed in the upper-right corner of the field. It can be noted that in the ROT_E case each sensor selects one near next hop, while in the ROM_E case, energy balancing produces also *far* transmissions to occur alongside *near* transmissions. Note that *far* transmissions absorb the highest fraction of the total energy.

To better understand how data flows are routed, we report for each transmission of l_{ij} bits from sensor i to sensor j the distance of the receiver from the sink d_j as a function of the distance of the transmitter from the sink d_i, for ROT_E and ROM_E (Fig. 3(a) and (b), respectively). All points close to the bisector correspond to short steps *towards* the sink ($d_i \cong d_j$), on the other hand points distant from the bisector correspond to long steps in the direction of the sink (a step is as long as d_i overcomes d_j). Since almost all the transmissions take place towards the sink, points close to the bisector represent *near* transmissions, while the others are *far* transmissions. The color of each point indicates the normalized energy consumption E_{ij}/E_{max}.

As previously discussed, in the ROT_E case each sensor selects only *one close next hop* along the path towards the sink ($d_i \cong d_j$). In particular, we found that 70% of the times the next hop j of sensor i is the closest with $d_j < d_i$ at distance $d^i_{near} = \min_{j \in C_i}(d_j)$, and 95% of the times it is distant up to $2 \cdot d^i_{near}$. As a consequence, sensors closer to the sink need to relay a higher amount of data, thus consuming more energy (see dark points in Fig. 3(a) and links in the upper-right corner of Fig. 2(a)).

Conversely, when the ROM_E strategy is adopted, *far* transmissions also occur (points with $d_j \simeq 0$ m in Fig. 3(b)). These transmissions are directed to the sink or to sensors closer to it (which we refer to as *far next hops*), and are responsible for most of the energy consumption. Load balancing among nodes is also achieved by means of these *far* transmissions, i.e., each sensor tries to "spend" E_{max}

[2] For color version of figures, reader is referred to the web version of this article.

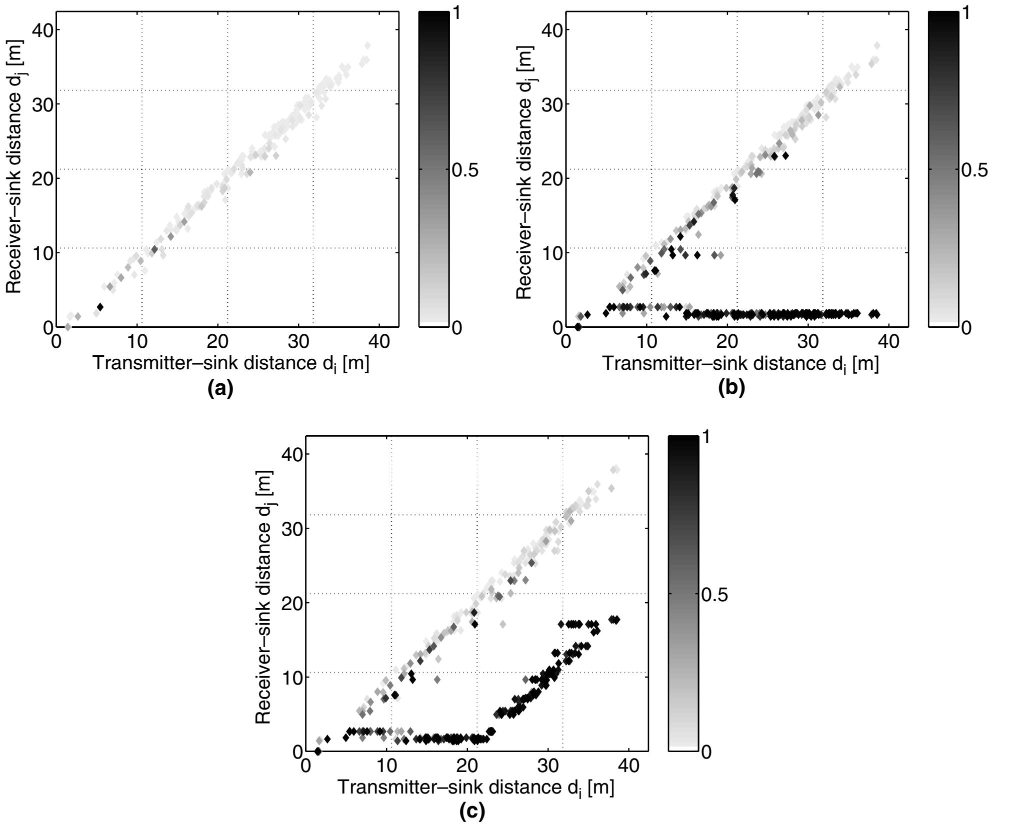

Fig. 3. Distance of the receiver from the sink (d_j) as a function of the distance of the transmitter from the sink (d_i) for all the transmissions, case of $E_{\text{elec}} = 0$. The color of each point represent the normalized energy consumption $E_{ij}/E_{\max}$. (a) ROT_E ($R_\text{T} = d^{\max}$); (b) ROM_E ($R_\text{T} = d^{\max}$); (c) ROM_E ($R_\text{T} = 21$ m).

units of energy by routing data over multiple near and far next hops. An interesting point regards the distribution of the number of next hops selected by each sensor. In fact, constraint (4) in Section 4 potentially allows its value to reach N, i.e., each sensor can potentially send information to all its neighbors. Instead, we found that the number of next hops is always very limited: approximately 10% of the sensors select only 1 next hop, 83% select 2 next hops, and 7% transmit to 3 next hops. In particular, when 2 next hops are selected, transmissions are almost always directed to one *near next hop*, to which most of the data is transmitted, with low energy consumption; and to one *far next hop*, to which a smaller amount of data is transmitted, but with most of the energy consumption. The choice of the optimization strategy also has an impact on the *network lifetime*. If we consider a strict lifetime definition, i.e., the network dies when the first sensor depletes its energy, in the ROT_E case the network lifetime is highly influenced by the unbalanced use of energy in the sensors. Conversely, in the ROM_E case all sensors deplete their batteries at the same time, which in most practical applications leads to the extended network lifetime.

We repeat the data-gathering tree analysis by limiting the transmission range R_T of the sensors, i.e., $R_\text{T} < d^{\max}$. As expected, in the ROT_E case, until the network is connected, a reduction of the transmission range does not produce significant changes in the optimal data-gathering trees, with respect to those obtained with $R_\text{T} = d^{\max}$, neither in terms of number of the next hops (always one), nor in terms of the mean distance between sensor nodes d_{ij}. On the other hand, the R_T constraint mainly affects the *far* transmissions when the ROM_E strategy is considered. Fig. 3(c) reports the distance of the receiver from the sink d_j as a function of the distance of the transmitter from the sink d_i and the normalized energy consumption for each transmission with $R_\text{T} = 21$ m in the ROM_E case. The key characteristics that we underlined when $R_\text{T} = d^{\max}$ continue to hold, but the constraint on the radio range causes the overall energy consumption to increase. In fact, a short transmission range causes ROM_E to find data-gathering trees similar to the ROT_E case, that is, exterior sensors that cannot directly transmit to the sink increase the load on interior ones, that are thereby forced to consume more energy.

Fig. 4 reports the energy consumption (E_{mean} and E_{max}) as a function of the transmission range R_T for the ROM_E case. Until R_T is big enough to equalize the energy consumption, every sensor consumes the same amount of energy $E_{max} = E_{mean}$ (with E_{max} increasing as R_T decreases), while if R_T decreases below a "critical" range (around 20 m in Fig. 4), the energy consumption cannot be balanced (in this case $E_{max} > E_{mean}$). For small values of the radio range, ROM_E data-gathering trees are similar to ROT_E trees, since every sensor can only transmit data to a *near* next hops. This explains why E_{max} increases, while E_{mean} and E_{tot} diverge.

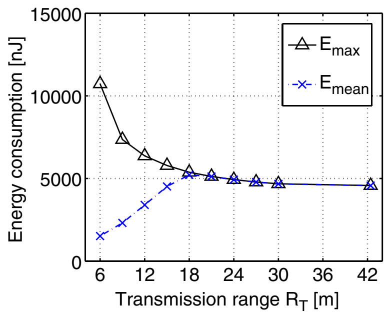

Fig. 4. ROM_E, case of $E_{elec} = 0$ – Mean and maximum energy consumption as a function of the transmission range R_T.

6.1.2. Case of $E_{elec} > 0$

In the following analysis we assess the impact of the distance independent term (E_{elec}) in the energy model of Eq. (2). As expected, the E_{elec} term leads to higher E_{mean} and E_{max}. In particular, we found that with respect to the results shown in Fig. 1, in the ROM_E case E_{max} increases by a factor 3, and in the ROT_E case E_{mean} increases by a factor 6. However, the distance independent term does not affect the main characteristics of the optimization strategies discussed in the previous section. In fact, a perfect equalization of the energy consumption can still be achieved by minimizing the maximum energy consumption (ROM_E), while the ROT_E strategy entails a higher energy consumption E_i for sensors closer to the sink.

In Fig. 5(a) and (b), we report optimal data-gathering trees relative to the case of $E_{elec} > 0$. In Fig. 6(a) and (b), we collect for each transmission of l_{ij} bits the distance of the receiver from the sink d_j as a function of the distance of the transmitter from the sink d_i, for ROT_E and ROM_E, respectively. The color of each point indicates the normalized energy consumption E_{ij}/E_{max}. As in Figs. 2(a), (b) and 3(a), (b), we observe that in the ROT_E case only *near* transmissions occur, and because of the existence of the extremal solution only one *near* next hop is selected. On the other hand in the ROM_E case mainly one *near* and one *far* next hops are chosen in order to equalize the energy consumption. The main difference of the data-gathering trees is the distance of the *near* transmissions. As can be noted in Fig. 6(a) all points close to the bisector are placed around a given distance (about 5 m). This behavior depends on the E_{elec} term and can be explained as follows.

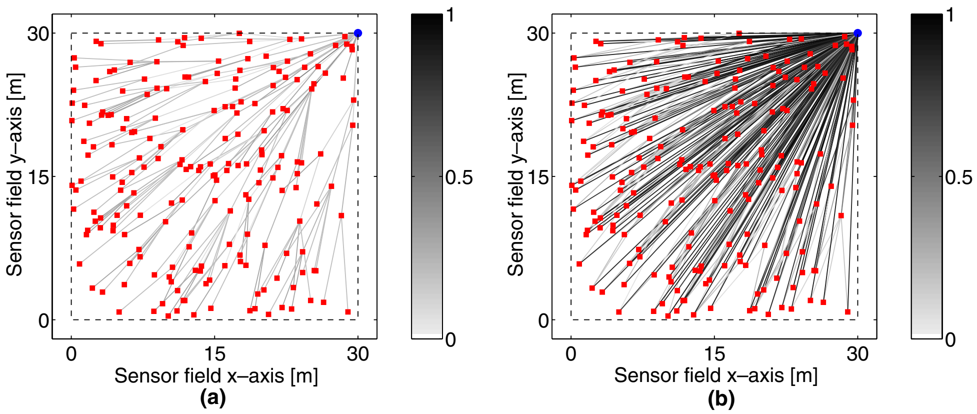

Fig. 5. Optimal data-gathering trees for different optimization strategies, case of $E_{elec} > 0$. (a) ROT_E; (b) ROM_E.

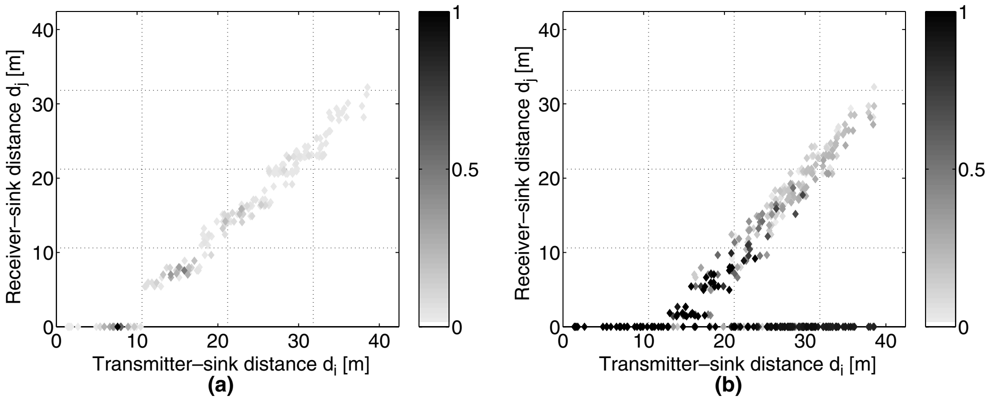

Fig. 6. Distance of the receiver from the sink (d_j) as a function of the distance of the transmitter from the sink (d_i) for all the transmissions, case of $E_{elec} > 0$. The color of each point represents the normalized energy consumption E_{ij}/E_{max}. (a) ROT_E ($R_T = d^{max}$); (b) ROM_E ($R_T = d^{max}$).

Let us consider a simplified scenario in which sensors are homogeneously deployed and aligned along straight lines connecting the sources and the sink, with the distance d_i integer multiple of a base distance d, i.e., $d_i = kd\ \forall i \in \mathcal{N}$, and $d_{ij} = d$ for each couple of neighboring sensors (i,j) along the line.

In the ROT_E case, the base distance is a function of β, α and E_{elec}. It minimizes the energy consumed along each data path. It can be considered as an optimal transmission distance d^{opt}. Due to the single-path data routing behavior of the solution, the minimum energy E_{mean}^{min} is

$$E_{mean}^{min} = \frac{1}{N} \cdot E_{tot}^{min} = \frac{1}{N} \cdot \min_d \left\{ \sum_{i=1}^{N} \frac{d_i}{d} (\beta d^{\alpha} + 2 \cdot E_{elec}) - E_{elec} \right\}, \tag{28}$$

where the last member is the sum of the overall energy consumption of the paths from each source i to the sink. In particular d_i is the total length of the path, d_i/d is the number of hops and $\beta d^{\alpha} + 2 \cdot E_{elec}$ is the energy consumed by each sensor along the path. Since source sensors do not receive data, E_{elec} needs also to be subtracted from each path. Expression (28) is minimized when

$$(\alpha - 1) \cdot d_i \beta (d^{opt})^{\alpha-2} - \frac{2 d_i E_{elec}}{(d^{opt})^2} = 0 \Rightarrow d^{opt} = \sqrt[\alpha]{\frac{2 \cdot E_{elec}}{(\alpha - 1)\beta}}. \tag{29}$$

with the considered parameters, $d^{opt} \approxeq 5$–6 m.

On the other hand, in the ROM_E case, because of the min–max optimization criteria and the multipath data routing, a simple expression for d^{opt} as in Eq. (29) cannot be easily provided. However, as shown in Fig. 6(b), in the ROM_E case d^{opt} seems to be independent of the distance between the transmitter and the sink, and it is higher than the value found in the ROT_E case.

Fig. 7 reports the energy consumption (E_{mean} and E_{max}) as a function of the transmission range R_T for the ROM_E case. From the comparison with Fig. 4 relative to the case of $E_{elec} = 0$, it can be noted that for low R_T values, since data are routed along many hop paths, the distance independent term causes E_{mean} to significantly raise. A perfect energy equalization can be achieved for higher value of the transmission range (here the "critical range" is around 24 m). In fact the E_{elec} term mainly burdens sensors that relay most of the data, i.e., closer to the sink.

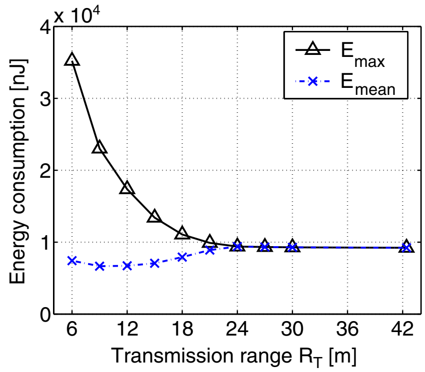

Fig. 7. ROM_E, case of $E_{elec} > 0$ – Mean and maximum energy consumption as a function of the transmission range R_T.

Hence, exterior sensors have to transmit at higher distances to unload nodes closer to the sink and to achieve energy balancing.

In Sections 6.1.1 and 6.1.2 we pointed out that in the ROT_E case sensors closer to the sink deplete their battery faster than the exterior sensors potentially leading to the death of the entire network. According to the specific application scenario and network performance requirements, one of the presented energy-oriented strategies can be chosen to efficiently drive routing mechanisms.

Unexpectedly, we also found that even in the ROM_E case, when energy equalization is achieved, invariant characteristics emerge, i.e., number and position of the selected next hops.

6.2. Static routing – Problem 2

In this section, we present the results relative to the optimization Problem 2 introduced in Section 4.2. Since data aggregation strategies are considered, in the following data-gathering trees are referred to as data-aggregation trees (DA-trees). In Section 4.2 we further assumed that only a subset S of sensors generates data; in particular, due to the large size of Problem 2 we resorted to reduce problem instances when only a set of $S = 5$ sensors acts as data sources. For the sake of comparison, we re-run Problem 1 (case of $E_{elec} > 0$) assuming the same reduced set of data sources (recall that in Section 6.1.2 we assumed $S = N$). Hence, in this section we also report optimal data-gathering trees, i.e., relative to Problem 1 with $E_{elec} > 0$ and $S = 5$, as a term of comparison for the analysis of DA-trees derived by solving Problem 2. We remark that if all sensors are data sources (i.e., $S = N$), the energy consumption of the receiver circuitry is neglected, and all batteries are equally charged, then the minimum spanning tree rooted at the sink minimizes at the same time the total network energy and the maximum energy consumption for a single node. In fact, due to data aggregation, each sensor transmits the same amount of information (e.g., one unit), regardless of the amount of received information. Hence, the energy consumption at each node only depends on the power used to transmit that packet. Therefore, minimizing E_{tot} coincides with minimizing E_{max}, and the minimum spanning tree is the optimal DA-tree for both ROT_E and ROM_E. Moreover, in such case a globally optimal distributed strategy is for each node to transmit data to its closest neighbor, and the node that depletes its battery first is the node whose closest neighbor is the farthest.

Fig. 8(a) and (b) report the per-sensor energy consumption E_i versus d_i, without data aggregation, in the ROM_E and ROT_E case, respectively (note the different scale when data aggregation is in place). In particular E_{mean} is calculated as the mean value of the energy consumption of the transmitting nodes. From the comparison with Fig. 1(a), it can be noted

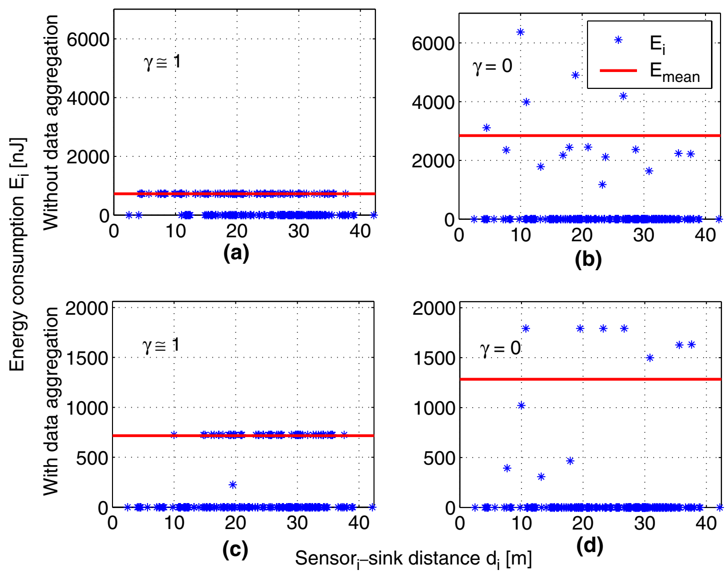

Fig. 8. Per-sensor energy consumption E_i versus d_i for different optimization criteria. ROM_E (a) and (c), ROT_E (b) and (d), *without* data aggregation (a) and (b) and *with* data aggregation (c) and (d).

Table 2
Problem 2 – E_{max} and E_{tot} for different optimization strategies with and without data aggregation

E_{max} [nJ]/E_{tot} [nJ]	ROM_E	ROT_E
Without data aggregation	724.2/55756.9	6370.2/45525.5
With data aggregation	724.2/42227.1	1792.5/14119.3

that when $S \ll N$ energy equalization is achieved over a subset of all the sensors. Moreover, since the data sources are located in the same quadrant, in the ROT_E case the sensors that consume more energy are not necessarily located close to the sink (see Fig. 8(b)). As expected, if data aggregation is permitted (Fig. 8(c) and (d)) the total energy consumption decreases, mainly in the ROT_E case (see Table 2).

In Table 2 we report E_{max} and E_{tot} for all the considered cases. When data aggregation is permitted, in the ROT_E case, the maximum and total energy consumption are reduce to around 72% and 69%, respectively, of the value found without data aggregation. In the ROM_E case, E_{tot} is reduced to around 25% and E_{max} does not change. In fact, since the maximum energy consumption is lower bounded by E_{elec} (each data source needs to send at least 1 bit), data aggregation mechanisms do not produce E_{max} gain, but potentially reduce the overall number of transmitting nodes leading to a lower E_{tot}.

Fig. 9(a) and (b) shows optimal data-gathering trees without and with data aggregation, respectively. In particular data sources are represented by bigger markers. In Fig. 10(a) and (b), we report the distance of the receiver from the sink d_j as a function of the distance of the transmitter from the sink d_i, for the ROM_E case without and with data aggregation, respectively. From the comparison of Fig. 10(b) ($S = 5$) with Fig. 6(b) ($S = N$) it can be seen that the optimal tree characteristics have changed. In fact, when $S = 5$, energy consumption balancing is achieved by routing data over multiple parallel paths (instead of two paths only), and the paths include long detours. Hence each sensor selects a greater number of next hops including nodes that are not in the direction of the sink. Basically, when all sensors generate data, because of the radial symmetry of the routing problem, energy balancing takes place along the direction towards the sink by means of *near* and *far* transmissions. Indeed, if $S = 5$ data are routed over many short hop detours and more sensors relay data generated by a single source. On the other hand, if data aggregation is permitted (Fig. 10(b)), because the overall information routed in the network decreases, also *far* transmissions occur.

In Fig. 11(a) and (b) we report E_{max} and E_{mean} for the transmitting sensors, as a function of the transmission range R_T for the ROM_E case without and with data aggregation, respectively. In particular when data aggregation is avoided the trends of maximum and mean energy are similar to the curves in Fig. 7, but because of energy balancing does not involve *far* transmissions, the "critical range" is lower (around 10 m in Fig. 11(a)). Hence, it is possible to equalize the energy consumption of the transmitting sensors even with a more strict constraint on the transmission range R_T. On the other hand, when data aggregation is considered, the minimum

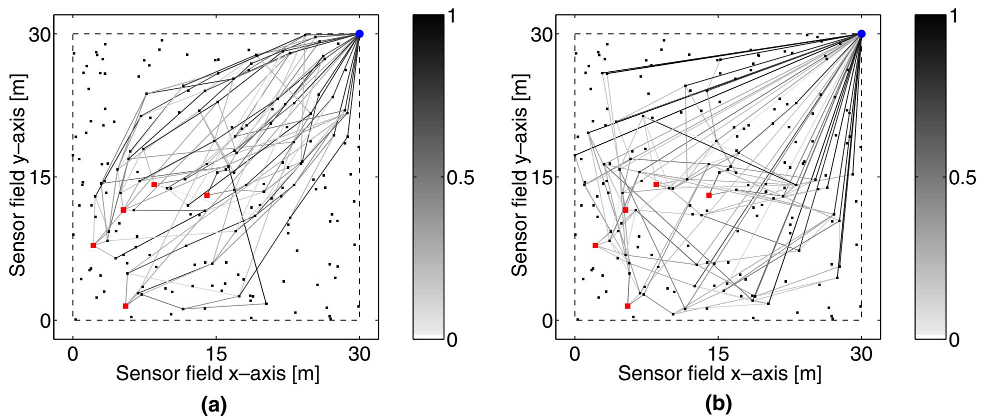

Fig. 9. Optimal data-gathering and data-aggregation trees for different optimization strategies. (a) ROM_E without data aggregation; (b) ROM_E with data aggregation.

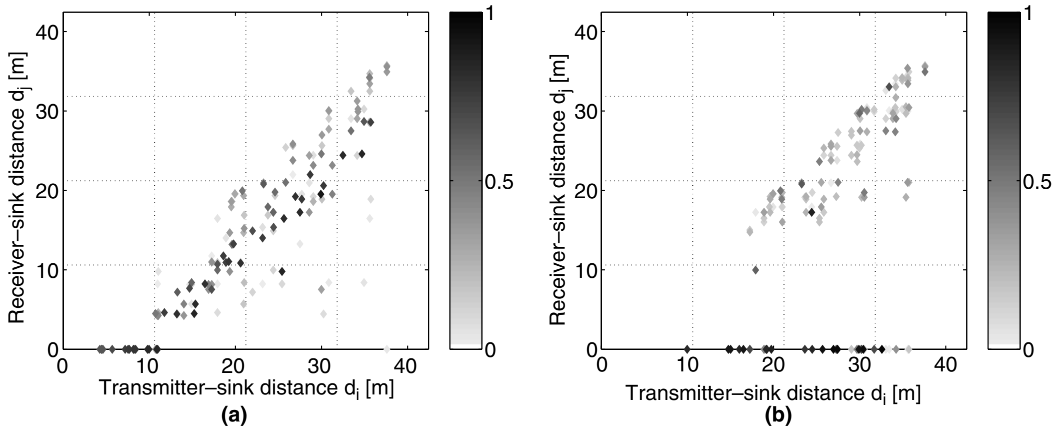

Fig. 10. Distance of the receiver from the sink (d_j) as a function of the distance of the transmitter from the sink (d_i) for all the transmissions. The color of each point represent the normalized energy consumption E_{ij}/E_{max}. (a) ROM_E *without* data aggregation; (b) ROM_E *with* data aggregation.

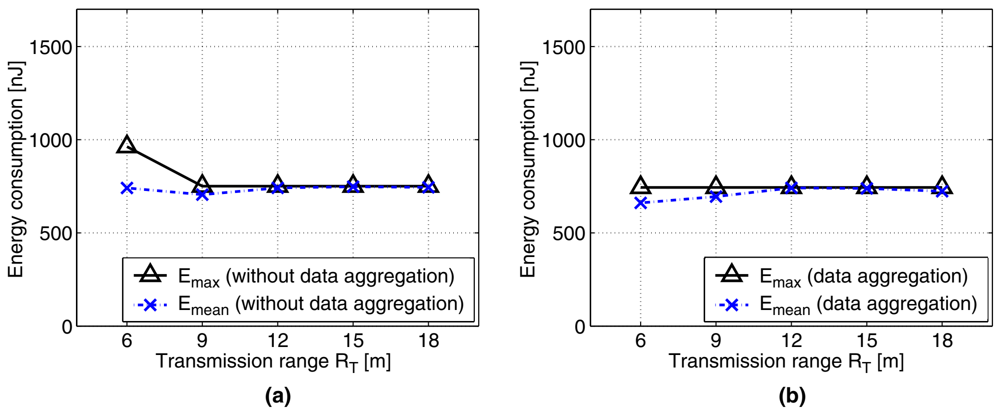

Fig. 11. ROM_E Problem 2 – Mean and max energy consumption as a function of the transmission range R_T. (a) *without* data aggregation; (b) *with* data aggregation.

E_{max} is achieved even with $R_T = 6$ m. In fact, the lower the amount of data to be gathered at the sink, and the lower is the overload on interior sensors caused by the short hops routing behavior. Thus, the overall energy saving produced by data aggregation also results in the improved balance of the energy consumption.

We have shown that even when data aggregation is considered the following statements hold true: ROT_E overloads interior sensors, and ROM_E achieves energy balancing among all transmitting sensors. With respect to the scenario addressed in the previous section, data are routed along multiple parallel paths and include long detours. Then, we have pointed out that data-aggregation also improves the energy balancing capabilities with strict transmission range constraints.

6.3. Dynamic re-routing – Problem 3

In this section we present results related to the R^2OB_L and R^2OB_E optimization strategies, introduced in Section 5. We set $R_T = 5$ m and, as in Section 6.2, we position the sink in the upper right corner of the square, while $S = 5$ sources are placed in the lower left region.

In Fig. 12(a), the lifetime of the network, as defined in Definition 1 in Section 5, is depicted with varying number of sensors, from 75 to 200. Although it can be seen that R^2OB_E guarantees a slightly longer lifetime, the two approaches yield comparable results in terms of lifetime. Fig. 12(b) compares the final sensing coverage of the network, i.e., the sensing coverage after the event that determines the "death" of the network, according to

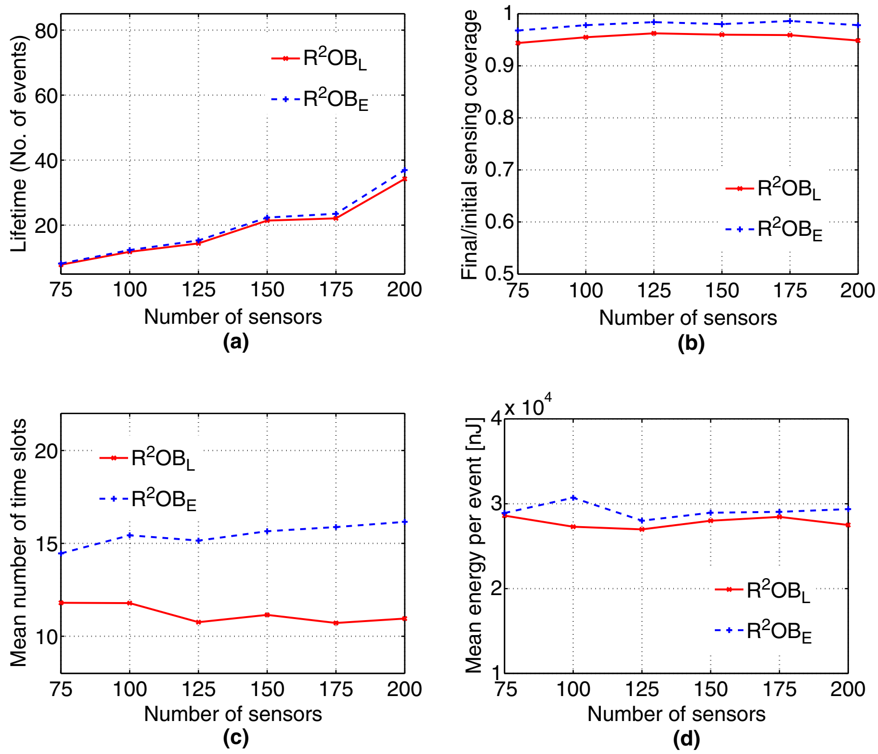

Fig. 12. Performance analysis of R^2OB_L and R^2OB_E as a function of the number of sensors. (a) Lifetime; (b) sensing coverage ratio; (c) mean latency per-event; (d) mean energy per-event.

the definition given in Section 5. We assume a sensing range of each sensor equal to $R_S = 2$ m. When a sensor depletes its battery, it cannot monitor the area around it. Hence, the sensing coverage potentially decreases after each event. At the end of each optimization run, we compute the final sensing coverage with respect to the initial sensing coverage. The value of the final sensing coverage is high for both approaches, but as expected R^2OB_E performs slightly better. Conversely, R^2OB_L achieves a lower mean per-event latency (Fig. 12(c)) and a lower mean energy consumption (Fig. 12(d)), as compared to R^2OB_E.

Fig. 13(a) and (b) shows the variation of the latency and of the energy consumption, respectively, throughout the lifetime of the network, for R^2OB_L and R^2OB_E. For both approaches, the mean energy consumption varies considerably from event to event, by alternatively increasing and decreasing. This is caused by the objective function (16) in the optimization problem in Section 4, which tends to level the residual energy of the sensors by distributing the energy consumption over time and space. For the first event, the DA-tree with minimum energy cost is selected, since all sensors have the same energy. This DA-tree stretches over the imaginary line connecting the region where the sources are located and the sink. For the following events, the trees become alternatively wider, i.e., they tend to be built on nodes that are further away from this line, and then they get closer to that line again. This way, the energy consumption can be distributed over the whole region. This can be also seen in Fig. 14(a) and (b), which shows the relevant DA-trees. Similarly, the latency of R^2OB_E shows an "accordion-like" behavior. Indeed, the latency increases when the tree becomes wider and vice versa. Conversely, the latency is monotonically increasing in R^2OB_L.

This makes in general the R^2OB_L approach preferable to R^2OB_E as far as concerns the metrics considered by now. In fact, while in terms of energy consumption the two approaches lead to similar results, R^2OB_L assures a more predictable behavior and lower latency. But when the focus is on how the energy consumption is distributed, R^2OB_E outperforms R^2OB_L. Fig. 13(c) reports the value of the objective function in Problem 3. This figure is dual

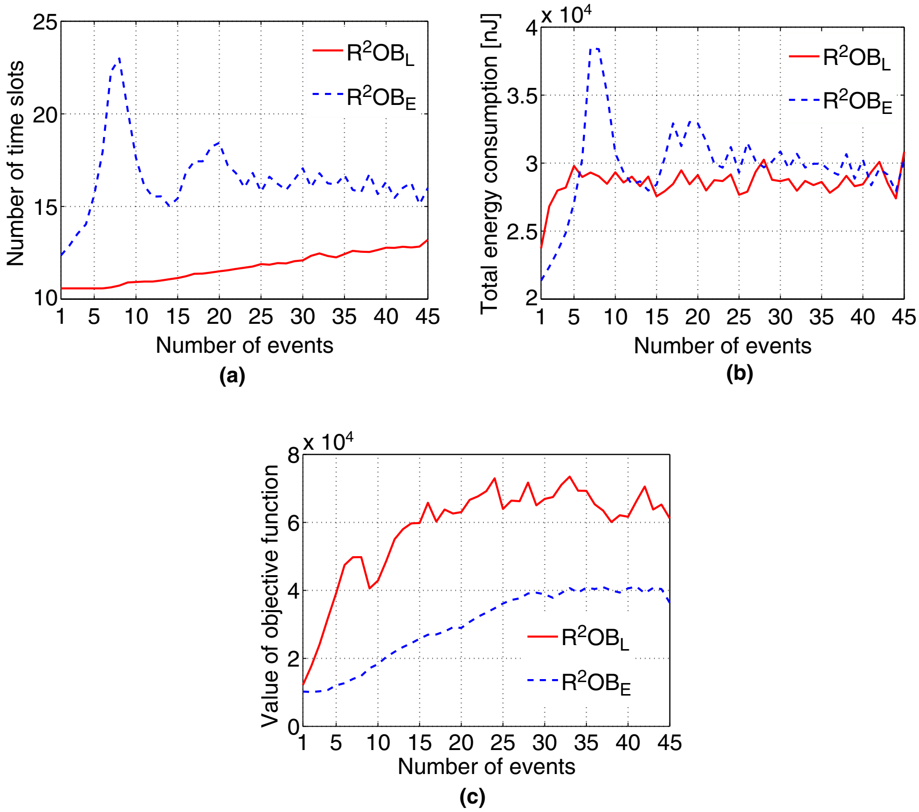

Fig. 13. Performance analysis of R^2OB_L and R^2OB_E as a function of the number of events. (a) Latency; (b) total energy consumption; (c) objective function.

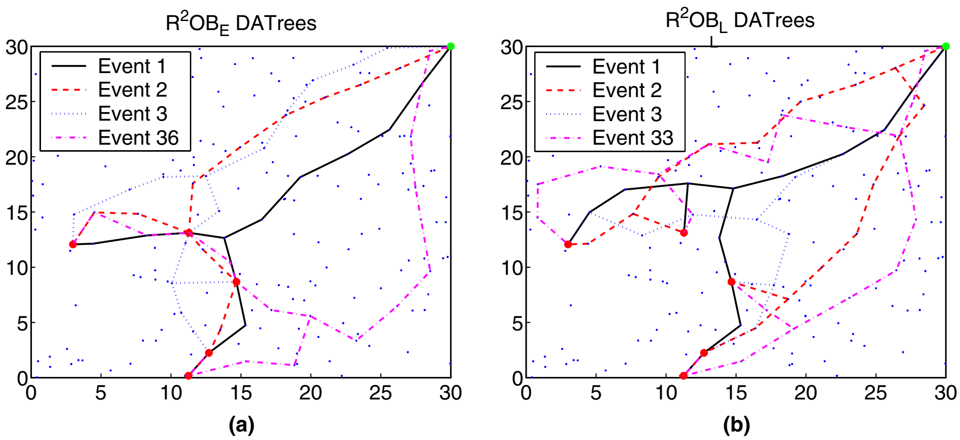

Fig. 14. Selection of DA-trees for R^2OB_E (a) and R^2OB_L (b).

to Fig. 13(a). In fact, while in R^2OB_L the main goal is to minimize the latency, R^2OB_E tries to distribute the energy consumption among the nodes. In this case, R^2OB_E presents a more predictable behavior.

The final distribution of the residual energy for both approaches is depicted in Fig. 15(a), i.e., the spatial distribution of the residual energy on the monitored area when the network dies, according

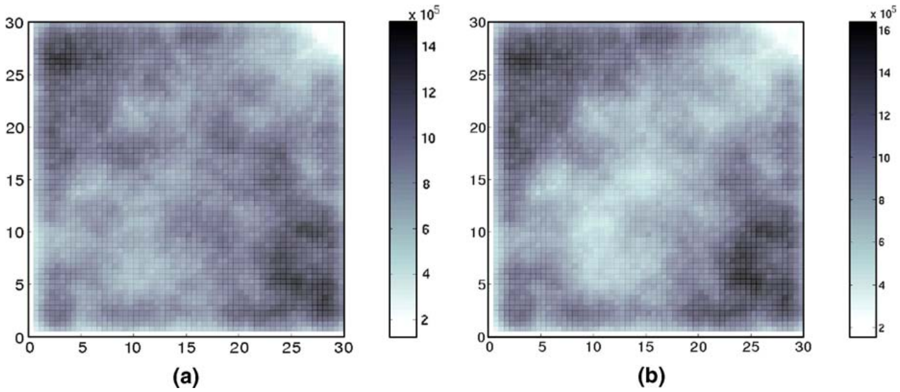

Fig. 15. Spatial energy distribution after the last event for R^2OB_E (a) and R^2OB_L (b).

to Definition 1 in Section 5. The color of each point represents the sum of the residual energies of all sensors covering that point. Darker colors represent regions that reside within the sensing range of sensors with higher energy, while a white region represents an uncovered portion of the terrain. To reduce the impact of the network density, the results are averaged on all the simulations. In fact, in particular scenarios spatial energy distribution could be poorly uniform because of the initial network topology. Spatial energy distribution offers a way to evaluate the network status at the end of its lifecycle. The WSN can be better reused to monitor all the region if the energy is better distributed. R^2OB_L presents a hole in the center of the region and higher peaks at the borders when compared to R^2OB_E, that shows a more uniform energy distribution.

Fig. 16 depicts the cumulative distribution functions of the spatial residual energies of the sensor nodes for both strategies. The more the curve is similar to a step, the better the energy is distributed. As expected, R^2OB_E shows a sharper transition than R^2OB_L, i.e., the residual energies of the nodes in the R^2OB_E case are more evenly distributed. Note that the spacial averaging operation smoothens the slope of the two curves. Hence, the cumulative distribution functions of the sensor energy spacial distribution is even more divergent.

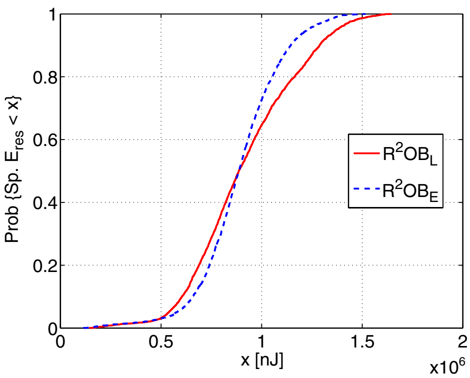

Fig. 16. Cumulative distribution function of the spatial energy distribution for R^2OB_X.

7. Conclusions and future work

In this paper, we dealt with the problem of optimal data gathering in WSNs by combining data aggregation, re-routing and scheduling.

We followed an incremental complexity approach. First, we considered a simple reference model where data routes do not change over time and multi-path routing is allowed. We considered different problem instances each referring to a different practical application scenario. We presented different energy-oriented optimization strategies and we compared the relative performance in term of energy consumption and data-gathering trees characteristics. In particular the effects of different assumptions that we considered at each step, i.e., energy consumption model, transmission range constraints and data aggregation capabilities, are assessed in the selection of optimal routing trees. We showed that when all sensors generated data the energy consumption at all nodes can be equalized so as to maximize the network lifetime, with optimal routing patterns that involve two next hops for each node – one close to the transmitter, the other closer to the sink. Conversely if only a subset of all the sensors acts as data sources energy balancing can be achieved by means of routing sensed data over parallel longer paths. In this case we exposed that data aggregation mechanisms can significantly improve energy savings and equalize energy consumption even when sensors have a limited transmission range.

Then, we further extended the model and considered dynamic re-routing and scheduling as means to balance the energy consumption in time and maximize the network lifetime, while maintaining a low data gathering latency. In fact, lifetime vs. latency emerges as the relevant trade-off in the dynamic scenario. We proposed and compared two different algorithms for optimal re-routing. We found that the R^2OB_L algorithm displays better latency over R^2OB_E with comparable performances regarding energy consumption. However, the R^2OB_E approach is shown to be preferable in scenarios where the application requires that the energy consumption be evenly distributed among the network nodes.

The proposed algorithms rely on a centralized view of the global network state. As a natural extension to this work, our future efforts will address distributed algorithms that can scale to large network size and automatically adapt to changes in the set of sources and to node mobility. While the objective of guaranteeing even energy consumption seems to be distributively achievable by accepting a certain degree of suboptimality, we believe that further study is needed to understand how to reproduce the characteristics of minimum-latency trees with local routing decisions at each individual node. The proposed models, by jointly describing collision-free scheduling, routing and data aggregation, can help researchers to get useful insights into this problem.

References

[1] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, Wireless sensor networks: a survey, Computer Networks 38 (4) (2002) 393–422.

[2] J. Al-Karaki, A. Kamal, Routing techniques in wireless sensor networks: a survey, IEEE Wireless Communications 11 (6) (2004) 6–28.

[3] B. Krishnamachari, D. Estrin, S. Wicker, The impact of data aggregation in wireless sensor networks, in: Proceedings of IEEE DEBS 2002, Vienna, Austria, 2002.

[4] M.C. Vuran, O.B. Akan, I.F. Akyildiz, Spatio-temporal correlation: theory and applications for wireless sensor networks, Computer Networks 45 (3) (2004) 245–259.

[5] Y. Zhu, K. Sundaresan, R. Sivakumar, Practical limits on achievable energy improvements and useable delay tolerance in correlation aware data gathering in wireless sensor networks, in: Proceedings of IEEE SECON 2005, Santa Clara, CA, USA, 2005, pp. 328–339.

[6] J.E. Wieselthier, G.D. Nguyen, A. Ephremides, On the construction of energy-efficient broadcast and multicast trees in wireless networks, in: Proceedings of IEEE INFOCOM 2000, Tel Aviv, Israel, 2000.

[7] M. Cagali, J.P. Hubaux, C. Enz, Minimum energy broadcast in all-wireless networks: NP-completeness and distribution issues, in: Proceedings of ACM MOBICOM 2002, Atlanta, GA, USA, 2002.

[8] J.H. Chang, L. Tassiulas, Routing for maximum system lifetime in wireless ad-hoc networks, in: Proceedings of 37th Annual Allerton Conference on Communication, Control, and Computing, 1997.

[9] J.H. Chang, L. Tassiulas, Energy conserving routing in wireless ad-hoc networks, in: Proceedings of IEEE INFOCOM 2000, 2000, pp. 22–31.

[10] J.H. Chang, L. Tassiulas, Fast approximation algorithms for maximum lifetime routing in wireless ad-hoc networks, in: Proceedings of IEEE Networking 2000, vol. 1815, 2000, pp. 702–713.

[11] N. Garg, J. Koenemann, Faster and simpler algorithms for multicommodity flow and other fractional packing problems, in: Proceedings of 39th Annual Symposium on Foundations of Computer Science, 1998, pp. 300–309.

[12] K. Kalpakis, K. Dasgupta, P. Namjoshi, Maximum lifetime data gathering and aggregation in wireless sensor networks, University of Maryland Technical Report.

[13] M. Bhardwaj, A.P. Chandrakasan, Bounding the lifetime of sensor networks via optimal role assignments, in: Proceedings of IEEE INFOCOM 2002, New York, USA, 2002.

[14] A. Sankar, Z. Liu, Maximum lifetime routing in wireless ad-hoc networks, in: Proceedings of IEEE INFOCOM 2004, Hong Kong SAR, PR China, 2004.

[15] R. Madan, S. Lall, Distributed Algorithms for Maximum Lifetime Routing in Wireless Sensor Networks, in: Proceedings of IEEE Globecom 2004, Dallas, Texas, USA, 2004.

[16] N. Sadagopan, B. Krishnamachari, Maximizing data extraction in energy-limited sensor networks, in: Proceedings of IEEE INFOCOM 2004, Hong Kong SAR, PR China, 2004.

[17] W. Ye, F. Ordez, A sub-gradient algorithm for maximal data extraction in energy-limited wireless sensor networks, in: Proceedings of the Symposium on Wireless Sensor Networks, in IEEE WirelessCom 2005, Maui, Hawaii, USA, 2005.

[18] Y.T. Hou, Y. Shi, H.D. Sherali, Rate allocation in wireless sensor networks with network lifetime requirement, in: Proceedings of ACM MobiHoc 2004, 2004.

[19] T. Melodia, D. Pompili, I.F. Akyildiz, Optimal local topology knowledge for energy efficient geographical routing in sensor networks, in: Proceedings of IEEE INFOCOM 2004, Hong Kong SAR, PR China, 2004.

[20] Y. Yu, B. Krishnamachari, V.K. Prasanna, Energy-latency tradeoffs for data gathering in wireless sensor networks, in: Proceedings of IEEE INFOCOM 2004, Hong Kong S.A.R., P.R. China, 2004.

[21] M. Lotfinezhad, B. Liang, Effect of partially correlated data on clustering in wireless sensor networks, in: Proceedings of IEEE SECON 2004, Santa Clara, CA, USA, 2004, pp. 172–181.

[22] I. Solis, K. Obraczka, In-network aggregation trade-offs for data collection in wireless sensor networks, Technical Report, UCSC Inter-Networking Research Group (i-NRG), August 2003.

[23] R.K. Ahuja, T.L. Magnanti, J.B. Orlin, Network Flows: Theory, Algorithms, and Applications, Prentice Hall, Englewood Cliffs, NJ, 1993.
[24] M.R. Garey, D.S. Johnson, Computers and Intractability: A Guide to the Theory of NP-Completeness, W.H. Freeman & Co, New York, 1990.
[25] C. Gui, P. Mohapatra, Power conservation and quality of surveillance in target tracking sensor networks, in: ACM International Conference on Mobile Computing and Networking (MOBICOM), Philadelphia, PA, USA, 2004.
[26] K. Kar, M. Kodialam, T.V. Lakshman, Minimum interference routing of bandwidth guaranteed tunnels with MPLS traffic engineering applications, IEEE Journal on Selected Areas in Communications 18 (12) (2000) 2566–2579.
[27] W. Heinzelman, A. Chandrakasan, H. Balakrishnan, An application-specific protocol architecture for wireless microsensor networks, IEEE Transactions on Wireless Communications 1 (4) (2002) 660–670.
[28] F. Hwang, D. Richards, P. Winter, The Steiner Tree Problem, North-Holland, Amsterdam, 1992.
[29] R. Fourer, D.M. Gay, B.W. Kernighan, AMPL: A Modeling Language for Mathematical Programming, Duxbury Press/Brooks/Cole Publishing Company, 2002.
[30] CPLEX solver, <http://www.cplex.com>.

Ugo Monaco received the "Laurea" degree in Telecommunications Engineering from the University of Rome "La Sapienza", Italy, in 2002. Currently he is Ph.D. student in the Networking Group of the INFOCOM Department of the same university. His main research interests are in Wireless Sensor Networks, network optimization techniques and Traffic Engineering, IP/MPLS multi-domain routing.

Francesca Cuomo received her "Laurea" degree in Electrical and Electronic Engineering in 1993, magna cum laude, from the University of Rome "La Sapienza", Italy. She earned the Ph.D. degree in Information and Communications Engineering in 1998". Since 1996 she is an Assistant Professor at the INFOCOM Department of this University. She teaches at the University of Rome "La Sapienza" courses in Telecommunication Networks. She has advised numerous master students in computer science, and is the advisor of three Ph.D. students in Networking at Rome University "La Sapienza".

Her main research interests focus on: Modeling and Control of broadband integrated networks, Signaling and Intelligent Networks, Architectures and protocol for fixed an mobile wireless networks, Mobile and Personal Communications, Quality of Service guarantees and real time service support in the Internet and in the radio access, Reconfigurable radio systems and Wireless ad-hoc and sensor networks. She has authored over 40 peer-reviewed papers published in prominent international journals and conferences. She has served on technical program committees and as reviewer in several international conferences and journals including ACM Wireless Mobile Internet Workshop, IEEE ICC and GLOBECOM , Med-Hoc-Net 2004, WONS 2005, WICON 2005, IEEE VTC spring 2005, IEEE Trans. on Wireless Communications, IEEE Journal on Selected Areas on Communications, IEEE Transactions on Mobile Computing.

Tommaso Melodia received the "Laurea" degree in Telecommunications Engineering from the University "La Sapienza", Rome, Italy, in 2001. He is currently pursuing his Ph.D. and working as a research assistant at the Broadband and Wireless Networking Laboratory, Georgia Institute of Technology, Atlanta. His main research interests are in Wireless Ad Hoc and Sensor Networks, Wireless Sensor and Actor Networks, Underwater Acoustic Sensor Networks, Personal and Mobile Communications.

Fabio Ricciato received the "Laurea" degree in Electrical Engineering and the Ph.D. in Telecommunications from the University La Sapienza of Rome, respectively, in 1999 and 2003. He has collaborated with CoRiTeL in several national projects and one EU project (IST-AQUILA). Since 2004 he is a Senior Researcher at the Forschungszentrum Telekommunikation Wien (ftw.) where he leads a research project on traffic measurements in 3G networks. His research interests are in the networking area for wireless and backbone technologies, including QoS, Traffic Engineering, Resilience, Traffic Measurements and Analysis, Network Security.

Marco Borghini received his "Laurea" degree (M.Sc.) in Electronic Engineering in December 2004, magna cum laude, from "La Sapienza" University of Rome. He developed his graduation thesis on topics concerning optimization of data gathering and routing in wireless sensor networks. Now he collaborates with the Infocom Department of "La Sapienza" University of Rome involved in the same research area.