



WSN Lifetime Optimization through Controlled Sink Mobility and Packet Bufferization

Tifenn Rault, Abdelmadjid Bouabdallah, Yacine Challal

► To cite this version:

Tifenn Rault, Abdelmadjid Bouabdallah, Yacine Challal. WSN Lifetime Optimization through Controlled Sink Mobility and Packet Bufferization. The 4th Global Information Infrastructure and Networking Symposium, 2013, Trento, Italy. pp.1569808017. hal-00871203

HAL Id: hal-00871203

<https://hal.science/hal-00871203>

Submitted on 9 Oct 2013

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

WSN Lifetime Optimization through Controlled Sink Mobility and Packet Bufferization

Tifenn Rault, Abdelmadjid Bouabdallah, Yacine Challal
Université de Technologie de Compiègne - CNRS
Heudiasyc UMR 7253
BP 20529
60205 Compiègne, France

Abstract—Maximizing the lifetime of energy constrained wireless sensor networks is a very challenging issue. It has been demonstrated that the use of a mobile sink can significantly increase the network lifetime by balancing the load among nodes. However, in existing solutions, nodes either send their data through multihop towards the sink or store the data until the sink comes at the node's vicinity, which usually requires an infinite buffer capacity. In this paper, we propose a new approach in which nodes send their data through multihop towards the sink, but they have the possibility to bufferize data while waiting the sink coming closer (not necessarily at node's radio range), which exempts more sensors from relaying these data. This strategy allows to save energy, while ensuring there is no data loss due to buffer overflow.

We modelize the problem of optimizing WSN lifetime with limited buffer capacity and controlled mobile sink using a Linear Program (LP). For arbitrary topologies, our LP determines the sink sojourn times at each possible locations, the data transfer rates between nodes and the bufferized packets quantities. Compared to previous models, our solution achieves better lifetime and enables to generate and transmit more data to the mobile sink. We show that this lifespan prolongation does not results in an increased energy consumption at nodes level. Finally, the numerical results give useful indications for network dimensioning in terms of buffer capacity and link capacity.

I. INTRODUCTION

In Wireless Sensor Networks architectures using a unique static base station, sensor nodes located close to the base station deplete their battery faster than other sensor nodes, leading to an early disconnection of the network. This is due to the fact that all traffic is forwarded towards the Base Station (or Sink) which induces a workload of few nodes closed to the sink. To increase the network lifetime, one of the efficient solution is to balance the load among nodes using a mobile base station which moves in the network to collect nodes information. Moreover, this kind of operation can be envisioned in many effective applications, such as collecting data from WSN deployed in an agricultural unit using a mobile sink embedded in aerial drone or motorized agricultural engine.

The sink mobility can be *controlled* or *uncontrolled*. For the uncontrolled solution, the mobile sink moves randomly in the monitored region, while the controlled mobile sink can only move along a pre-defined trajectory. Finding the optimal trajectory that maximizes the network lifetime is very challenging. Indeed, the maximum lifetime can only be achieved

by solving optimally two joint problems: a *scheduling* problem that determines the sojourn times of the sink at different locations, and a *routing* problem which defines the path that will be used by the collected data to reach the mobile sink in an energy-efficient way [2], [1]. In other words, routing and mobility are strongly interrelated because the routing strategy greatly influences energy consumption and as the sink moves, paths will change.

However, in existing joint scheduling and routing problem solutions, the considered routing paradigm is a *pure multihop forwarding*, as nodes continuously send data towards the mobile sink. It results in higher energy expenditure compared to a *pure direct communication* approach where the mobile sink visits each sensor and retrieves data through single-hop. Indeed, direct communications enable a minimum energy consumption at each node, but only at the expense of an increased data delivery delay. One solution to trade-off energy and latency is to consider hybrid routing schemes which combine single-hop and multi-hop communication strategies. Nevertheless, in hybrid solutions data are either bufferized while waiting the sink passage or sent through multihop towards the mobile sink. But in real scenario, nodes may experiment data loss due to buffer overflow while waiting the sink coming into the node's vicinity. Instead, we propose to offer nodes the possibility to delay their transmissions, but not necessarily to wait until the sink is at a one-hop proximity. The idea is to allow nodes to bufferize data while waiting the sink to come closer to the node (not necessarily at the node), which would relieve more nodes from relaying these data. We also ensure that there is no data loss due to buffer overflow.

In this paper, we develop a new Linear Programming model for the joint scheduling and routing problem with limited buffer capacity. Our solution achieves better lifetime compared to previous works and assesses the efficiency of the delayed communication paradigm. The LP resolution determines the sink sojourn times at visited nodes, the data transfer rates and the packets bufferization for arbitrary topologies. Furthermore, the numerical experiments provide valuable clues to the future design of a distributed routing protocol and a sink mobility control policy. The paper is organized as follows. In the next section we review existing solutions regarding joint sink mobility and routing problem for lifetime prolongation via controlled mobile sink. Then in section III we present the

network model and our optimization problem formulation. In Section IV we report numerical results of the proposed model and show how far our approach outperforms existing schemes in terms of lifetime. Finally, Section V concludes the paper.

II. RELATED WORKS

In this section we review existing works related to the use of a controlled mobile sink for lifetime prolongation in WSN.

Wang et al. [3] consider a bi-dimensional square grid topology and give a linear programming model for determining the sink sojourn times at each node that induce the maximum network lifetime. In their approach, authors assume that half of the work load of each node flows along its horizontal and vertical links towards the current location of the mobile sink. Thus, their LP formulation only solves the scheduling problem while the routing problem is solved offline by imposing the pre-defined routing strategy.

Papadimitriou et al. [2] extend the work of Wang et al. by turning the constants of the model into variables. Their LP formulation finds the sink sojourn times and the transfer rates between neighboring nodes that maximize the network lifetime. Note that in [2] and [3], the visiting order of the mobile sink is not important since the data generation rate at each node is independent of time and the traveling time between two locations is considered negligible. However, with other assumptions, the problem integrates a new dimension which is to determine the visiting order of the sink.

Basagni et al. [4] introduce new constraints: the minimum sojourn time at each sojourn location, the maximum distance the sink can travel while moving from one site to another and the energy cost for building new routes when the sink moves. They propose a Mixed Integer Linear Programming (MILP) model that determines the sink's path and its sojourn times at the different locations while the routing protocol remains a parameter. Then they propose a simple decentralized routing protocol called GMRE: after spending the minimal time at a location, the mobile base station decides to change its location or to stay based on the residual energy of the neighboring nodes of potential future sites.

In [5], Liang et al. consider a mobile sink that must start from and return to a given location to periodically recharge petrol or electricity. They introduce new constraints about this total tour distance, the maximum distance between two consecutive movements and the minimum sojourn time at each location. However, the routing protocol is predefined and does not appear as a variable in the MILP formulation. Because of the complexity of the resulting MILP they introduce a near optimal heuristic algorithm.

Luo et al. [6] propose a distributed protocol to control sink mobility based on the LP developed in [3]. In an initialization phase, the sink visits all possible locations for a sampling period to collect the power consumption records from all nodes. At the end of this phase, the sink is able to perform the LP. In the operation phase, the sink goes through each location determined by the LP and still continues to collect information

in order to obtain a better estimation and regularly resolve the LP.

Luo et al. [7] prove the NP-hardness of the joint sink mobility and routing problem for lifetime maximization with multiple mobile sinks. They also present an algorithm to solve the problem involving a single sink and then generalized it to approximate the problem with multiple sinks.

Gandham et al. [8] consider that the network lifetime is split into equal periods of time called *rounds* and that multiple mobile base stations stay fixed at feasible locations during a round. Then, at the beginning of each round, a base station computes an Integer Linear Program (ILP) that gives the new location of all the base stations and the flow of information at each node for the duration of the round. It is not exactly a joint routing and scheduling problem as the time spent by each sink at a location is predefined by the round length.

As explained in the introduction, these research works rely on a pure multihop forwarding paradigms, while other approaches have been proposed to compute a mobile sink trajectory for single-hop data collection, which maximizes the network lifetime at the expense of an increased latency. Somasundara et al. [9] and Gu et al. [10] were interested in networks of sensors operating at different sampling rates and propose a solution to schedule the sink movement so that there is no data loss due to buffer overflow. However, the routing strategy is limited to direct communication with the mobile base stations. Rao et al. [11] develop distributed algorithms to compute the sink trajectory for single-hop data collection in order to reduce the average collection delay. They determine a trip for the mobile base station so that the trip distance is minimized and the MBS comes within the radio range of every sensor during its trip, without necessarily being colocated to sensors.

Some hybrid routing schemes that combine direct and multihop communication strategies with a MBS have been proposed. Rao and Biswas solution [12] computes the minimum-distance trajectory so that while the MBS moves along this path, it comes within up to k hop reach of all network nodes. They define some Designated Gateways (DG) nodes that can reach the sink in 1-hop when it passes close to them. A DG buffers data from other nodes that are at most $k-1$ hop away from it, and uploads these collected data to the MBS. Even if the solution enables a trade-off between energy and latency, it results in a uneven distribution of the energy consumption among nodes. Indeed, the energy consumption of a node depends on the number of hops that separates it from its assigned DG. Moreover, DGs are supposed to have an infinite buffer capacity. Sugihara and Gupta [13] propose a framework that combines direct communication and multihop forwarding which aims at planning a MBS motion to minimize the data delivery delay. Because of the NP-hardness of the problem, they propose to solve several subproblems: i) a forwarding subproblem that gives the information transfer rates of each node given a limit on their energy consumption, ii) a path selection subproblem that determines a trajectory so that the MBS travels within each node's communication range at least

TABLE I
COMPARING VARIABLES OF DIFFERENT MODELS

	Pure multihop					
Variables	[3]	[2]	[5]	[4]	[7]	[8]
sojourn times	+	+	+	+	+	-
visiting order	-	-	+	+	-	+
routing	-	+	-	-	+	+

	Pure single hop			Hybrid			
Variables	[9]	[10]	[11]	[12]	[13]		
sojourn times	+	+	+	+	-	-	+
visiting order	+	+	+	+	-	+	-
routing	-	-	-	-	+	-	-

once, iii) a joint speed control and scheduling problem that gives the schedule of data collection from each node and its speed displacement along the path so that it can collect all the data from all sensor nodes.

In these hybrid routing schemes, data are either bufferized while waiting the sink passage or sent through multihop towards the mobile sink. But in real scenario, nodes may experiment data loss due to buffer overflow while waiting the sink coming into the node's vicinity. To overcome this limitation, in our solution we address the joint scheduling and routing problem by taking into consideration hybrid communication schemes. Nodes can forward their data through multihop towards the mobile sink, and they can also bufferize a certain amount of data while it does not exceed their buffer capacity. So, the network lifetime is improved. We describe in the next section our system model and give our optimization problem formulation.

III. SYSTEM MODEL

A. Model formulation

In this section, we propose a modelization for the lifetime prolongation of a WSN with a controlled mobile base station. We define a Linear Programming model that determines for a given topology: the sink sojourn times at different locations, the data flows between neighboring nodes, and the packets bufferization. Thus, we obtain both the optimal sink mobility displacement and the optimal data routing scheme that maximize the lifetime of a specified network.

We consider that the wireless sensor network is composed of a set N of static sensor nodes and one mobile sink s collecting the information. The sensors are randomly deployed to monitor their physical surroundings and generate a constant data rate $Q_i > 0, i \in N$. We denote by L the set of possible locations of the sink, not necessarily colocated with the sensors. We also assume that $K = (l_1, l_2, l_3, \dots, l_{|L|-1}, l_{|L|})$ is an ordered list of sink visiting locations, i.e. the sink will first visit l_1 and then l_2 and so on. We will later detail the implication of this assumption at the end of this section. The sink sojourns at the location l_k for a time duration $t_{l_k} \geq 0$ and change its position from one location to another with a negligible traveling time as considered in [3], [2], [7].

The set $S_i^{l_k} \subseteq N \cup \{s\}$ represents the nodes (either sensors or the sink) that are in the transmission range of sensor $i \in N$

for a given location $l_k \in K$ of the sink. Note that the only possible difference between two sets $S_i^{l_{k1}}, S_i^{l_{k2}}$ is the sink s .

Every sensor sends its data either through multihop towards the sink or via direct communication if the sink is in the nodes's vicinity. We consider that $q_{ij}^{l_k} \geq 0$ represents the data rate transmission from node i to its neighboring node $j \in S_i^{l_k}$ when the sink is at the location $l_k \in K$. Additionally, each sensor has the possibility to buffer a certain amount of data while this quantity does not exceed its buffer capacity $W_i \geq 0$. $w_i^{l_k} \geq 0$ corresponds to the amount of data contained in the buffer of the sensor $i \in N$ at the end of the sink sojourn time at location $l_k \in K$. Additionally, we denote by $R_{ij}(i \in N, j \in S_i^{l_k})$, the capacity of the link (i, j) . It is a constant quantity that upper bounds the transmission rates $q_{ij}^{l_k}$.

We consider that each sensor has an initial energy E_i and we suppose that the main factors of energy consumption are data reception and transmission. We denote by e_{ij}^T the energy consumption of sensor i to transmit a data unit to its neighboring node j and by e_{ji}^R , the energy consumption of sensor i when receiving a data unit from its neighboring node j .

We suppose that the sink has an unlimited energy and keeps moving until the end of the network lifetime, which is defined as the time until the first node dies due to energy depletion. The objective of our optimization problem is to find the optimal routing strategy and the optimal sojourn times at each sink location so that the network lifetime is maximized for a given order of visited locations. In the following, we give the formulation of the problem of maximizing the network lifetime and then derive a Linear Programming model.

$$\max \sum_{l_k \in K} t_{l_k} \quad \text{subject to} \quad (1)$$

$$t_{l_k} \geq 0, \quad l_k \in K \quad (2)$$

$$q_{ij}^{l_k} \geq 0, \quad i \in N, j \in S_i^{l_k}, l_k \in K \quad (3)$$

$$w_i^{l_k} \geq 0, \quad i \in N, l_k \in K \quad (4)$$

$$\sum_{l_k \in K} \sum_{j \in S_i^{l_k}} e_{ij}^T q_{ij}^{l_k} t_{l_k} + \sum_{l_k \in K} \sum_{j: i \in S_j^{l_k}} e_{ji}^R q_{ji}^{l_k} t_{l_k} \leq E_i, \quad i \in N \quad (5)$$

$$w_i^{l_k} = \sum_{j: i \in S_j^{l_k}} t_{l_k} q_{ji}^{l_k} + t_{l_k} Q_i - \sum_{j \in S_i^{l_k}} t_{l_k} q_{ij}^{l_k} + w_i^{l_{k-1}}, \quad i \in N, k \in \{0, 1, \dots, |L|\} \quad (6)$$

$$w_i^{l_0} = 0, \quad i \in N \quad (7)$$

$$\sum_{i \in N} Q_i t_{l_k} + \sum_{i \in N} w_i^{l_{k-1}} - \sum_{i \in N} w_i^{l_k} = \sum_{j: s \in S_j^{l_k}} t_{l_k} q_{js}^{l_k}, \quad l_k \in K \quad (8)$$

$$q_{ij}^{l_k} \leq R_{ij}, \quad i \in N, j \in S_i^{l_k}, l_k \in K \quad (9)$$

$$w_i^{l_k} \leq W_i, \quad i \in N, l_k \in K \quad (10)$$

The objective function (1) maximizes the network lifetime, i.e. the sum of the sojourn times of the mobile sink at all locations. Constraints (2), (3) and (4) assure the non-negativity of sojourn times t_{l_k} , the rates $q_{ij}^{l_k}$ and the quantities $w_i^{l_k}$. Constraint (5) states that the energy consumed in sensor i for transmission and reception must not exceed its initial energy E_i .

Constraints (6) and (8) correspond to flow constraints with buffer capacity. The left part of the inequality in constraint (6) represents the amount of data bufferized by node i when the sink sojourns at the location l_k for a duration t_{l_k} . It is equal to the difference between the amount of data the node has to transmit (i.e. the data received from its neighboring nodes, its own generated data and the data previously bufferized) and the amount of data it effectively transmits. Note that we have introduced an artificial state l_0 and we impose in constraint (7) $w_i^{l_0} = 0$ to represent the fact that at the beginning of the network operation buffers are empty. Similarly, we can set $w_i^{l_L} = 0$ to impose that buffers are empty at the end of the network lifetime.

Constraint (8) assures that at any time t_{l_k} , the sink is the final destination of all the data transmitted by nodes, which consist in the data generated by all nodes and their previously bufferized data minus the data bufferized at t_{l_k} .

Constraint (9) ensures that at any time the flow information rates going through a link (i, j) do not exceed the capacity of the link (i, j) .

Constraint (10) states that at any time, the amount of data bufferized at node i should not exceed its buffer capacity W_i .

By defining $\hat{q}_{ij}^{l_k} = t_{l_k} q_{ij}^{l_k}$ as the amount of data transmitted from sensor i to its neighboring node j during time t_{l_k} , the optimization problem can be expressed as a Linear Programming model:

$$\max \sum_{l_k \in K} t_{l_k} \quad \text{subject to} \quad (11)$$

$$t_{l_k} \geq 0, \quad l_k \in K \quad (12)$$

$$\hat{q}_{ij}^{l_k} \geq 0, \quad i \in N, j \in S_i^{l_k}, l_k \in K \quad (13)$$

$$w_i^{l_k} \geq 0, \quad i \in N, l_k \in K \quad (14)$$

$$\sum_{l_k \in K} \sum_{j \in S_i^{l_k}} e_{ij}^T \hat{q}_{ij}^{l_k} + \sum_{l_k \in K} \sum_{j: i \in S_j^{l_k}} e_{ji}^R \hat{q}_{ji}^{l_k} \leq E_i, \quad i \in N \quad (15)$$

$$w_i^{l_k} = \sum_{j: i \in S_j^{l_k}} \hat{q}_{ji}^{l_k} + t_{l_k} Q_i - \sum_{j \in S_i^{l_k}} \hat{q}_{ij}^{l_k} + w_i^{l_{k-1}}, \quad i \in N, k \in \{0, 1, \dots, |L|\} \quad (16)$$

$$w_i^{l_0} = 0, \quad i \in N \quad (17)$$

$$\sum_{i \in N} Q_i t_{l_k} + \sum_{i \in N} w_i^{l_{k-1}} - \sum_{i \in N} w_i^{l_k} = \sum_{j: s \in S_j^{l_k}} \hat{q}_{js}^{l_k}, \quad l_k \in K \quad (18)$$

$$\hat{q}_{ij}^{l_k} \leq R_{ij}, \quad i \in N, j \in S_i^{l_k}, l_k \in K \quad (19)$$

$$w_i^{l_k} \leq W_i, \quad i \in N, l_k \in K \quad (20)$$

B. The sink visiting order

Our LP finds the optimal solution of the joint scheduling and routing problem with packets bufferization for a given ordered list of visiting positions K . To find the optimal solution of the general problem without a predefined sink trajectory, we can run the LP for each possible ordered list of $|L|$ locations. However, this corresponds to run the LP for each possible permutation of a list of size $|L|$ which is equal to $|L|!$ times. When the possible locations of the mobile sink is restricted to a few number of sites, it is conceivable. However, as the number of possible locations grows we need to study the impact of fixing a visiting order on the lifetime performance.

C. The routing graph

Once we solve the linear model, we define the *routing graph* $G_k(V, E_k)$ as the directed graph obtained for each location l_k of the mobile sink, so that $V = N$ and there exist an edge $(i, j) \in E_k$ if and only if $\hat{q}_{ij}^{l_k} > 0$ and edges are valued by the quantity $\hat{q}_{ij}^{l_k}$. We observe that there could be cycles in the routing graph G_k . We could have introduced additional constraints in the LP to prevent cycle formation. However, the number of constraints would be equal to the number of cycles in the topology, which can grow exponentially with the number of nodes in case of dense network.

Instead, we propose to suppress cycles after solving the LP, by applying Johnson's algorithm [14]. We first detect all the elementary cycles present in the routing graph in time bounded by $O((V + E)(c + 1))$, where c is the number of elementary circuits in the routing graph. Then, for each cycle, we subtract to all edges of the cycle, the minimum value associated with them. In this way, one edge is set to 0 and the cycle is suppressed. The flow validity is still ensured since

for a node, we suppress the same incoming and outgoing number of data.

Note that the existence of such cycles does not influence the maximum achievable lifetime. Indeed, the solver maximizes the network lifetime, but for sensors that have remaining energy after optimization, it can create cycles involving them. Intuitively, a cycle consumes energy uselessly and would not be possible for nodes whose energy constrains the problem. Thus, when suppressing cycles, we only affect the node's remaining energy but not the network lifetime.

IV. NUMERICAL RESULTS

A. Description of the compared models

In what follows, we compare our solution denoted OPT-B with an approach proposed in the literature, we will call OPT.

- 1) **OPT**: This is the LP model proposed by Papadimitriou and Georgiadis [2] which provides the optimal solution of the joint routing and scheduling problem without packet bufferization. It determines the sojourn times of the sink at each possible sink locations and the information transfer rates between neighbor nodes for each position of the mobile sink. We add a constraint $\sum_{i \in N} Q_i t_{l_k} = \sum_{j: s \in S_{j_k}^{l_k}} \hat{q}_{j_k}^{l_k}, l_k \in K$ to specify that the sink is the final destination of all generated packets in the network (which is missing in the original formulation). The number of variables in this model is in order of $O(L + dNL)$ where d is the average number of neighbors per node.
- 2) **OPT-B**: This is the LP model proposed in section III which provides the optimal solution to the joint routing and scheduling problem with packet bufferization for a given order of visited locations. It determines the sink sojourn times, the data transfer rates and the packets bufferization rates. In our model the number of variables is in order of $O(L + (d + 1)NL)$ where d is the average number of neighbors per node.

B. Scenario and parameters settings

We compare the performances of the above two models for various network sizes with respect to lifetime, which is defined as the time until the first sensor dies. We use the same values as in [3] for the initial energy ($E = 1.35$ Joules), the energy cost of one transmission/reception ($e = 0.62e^{-6}$ Joules/bit) and the data generation rate ($\lambda = 1$ Bit/sec). In every scenario, parameters W_i and R_{ij} are set identic for all nodes and all links, and we specify these values. The possible locations of the sink s are the nodes, i.e. $L = N$. Note that this scenario implies an important number of variables in the order of $O(N^2)$, because the number of possible locations is equal to the number of nodes. For OPT-B, nodes are visited in the increasing order of their identifier. In fact, it corresponds to a random displacement of the mobile sink from one location to another.

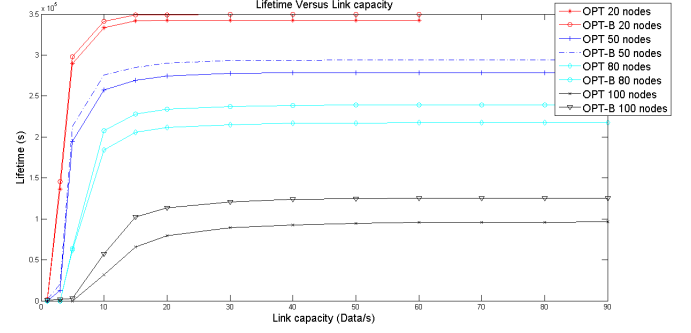


Fig. 1. Achievable lifetime for various link capacity and various network size

We solved the LP models with CPLEX¹ and the constraints are generated in C++. We consider arbitrary topologies (nodes uniformly distributed within a square area) with various network sizes (20,50,80,100,150,200 nodes).

C. Results

We first study the impact of the buffer capacity W_i and the link capacity R_{ij} parameters on the network lifetime. We then investigate the improvement of OPT-B over OPT in terms of network lifetime and nodes' residual energy. We further compare the pause time distribution of the two models. Finally we highlight how buffers are used by nodes in OPT-B.

Figure 1 gives the average lifetime achieved by the two models for various link capacity R_{ij} . For each network size and each link capacity, the results are obtained from 50 randomly generated instances. The four curves present identical behaviour. Below a certain link capacity (we denote by R'_{ij}), as the link capacity increases, the network lifetime also increases. This can be explained by the fact that when the link capacity is small, nodes have few opportunities to balance the load between their neighbors, whereas when the link capacity is sufficiently high, nodes can distribute more fairly the load between their neighbors depending on their respective reception and transmission activities. Above R'_{ij} , the maximum lifetime is achieved and do not vary anymore. This is due to the fact that the link capacity is sufficiently high and do not constrain anymore the problem. The optimization problem remains constrained only by the energy consumption limitation (and the buffer capacity for OPT-B). This result is interesting when dimensioning the network. Indeed, it is possible to interpolate for a given network size the minimum optimal R'_{ij} that permits to achieve the maximum lifetime. It is a valuable insight when choosing the appropriate technology standard. In all the following scenarios we set R_{ij} equal to 90 so that the results reflect the energy limitation.

In Figure 2 we study the impact of the buffer capacity W_i on the network operation time for our model OPT-B. As expected, the introduction of a buffer capacity enables to increase the network lifetime and greater is the buffer capacity, higher

¹<http://www-01.ibm.com/software/integration/optimization/cplex-optimizer/>

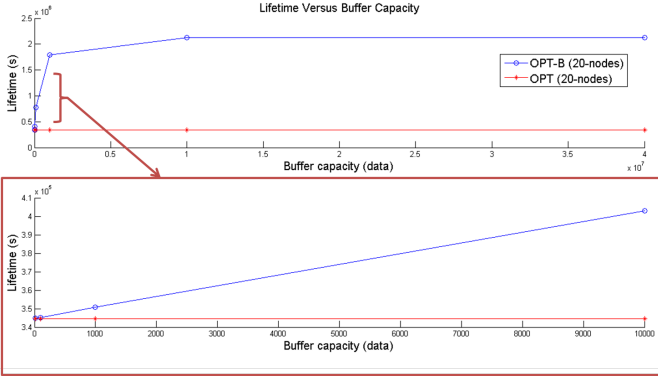


Fig. 2. Achievable lifetime for various buffer capacity in a 20-nodes network

TABLE II
AVERAGE LIFETIME OF OPT AND OPT-B IN ARBITRARY TOPOLOGIES

$ N $	OPT	OPT-B (W=1000)	Improvement
20	344 656	350 663	1.74%
50	297 606	311 367	4.62%
80	212 708	233 836	9.93%
100	94 974	124 017	30.58%
150	56 135	95 349	69.85%
200	41 378	86 570	109.23%

is the improvement. Indeed, for a 20-nodes topology when the buffer capacity is small, e.g. equal to 10 data unit the improvement in lifetime over OPT is quite small. But with a buffer equal to 10000 data unit, the improvement goes to 16.95% over the overall lifetime of OPT. Moreover, with an important buffer capacity in the order of 10^7 data, we observe that the network can achieve a lifetime close to the upper bound $\frac{E_i}{e_{is}} = 2,1774e^6$ which corresponds to the case nodes only have to transmit their own data directly to the sink. In our model this case requires an important buffer capacity as the sink visits a location only once during the network operation time.

Table II compares the maximum average lifetime achieved for six different network sizes (20, 50, 80, 100, 150, 200) of arbitrary topologies. For each network size, it represents the average of the results obtained from 100 randomly generated instances. We can observe that as the network size increases, the improvement in lifetime of OPT-B over OPT also increases. Indeed, for a 20-nodes network the improvement is in the order of 2% while it goes to 109% for a 200-nodes network with a buffer capacity W_i set to 1000 in both cases.

In Table III we compare the balancing of energy depletion among sensor nodes. We recall that E_i denotes the initial energy of sensor $i \in N$. Let E_i^r be the residual energy of i at the end of the network lifetime. For every instance, we compute the percentages of sensors whose residual energy is equal to zero ($E_i^r = 0$), below 25% of the node's initial energy ($E_i^r \leq 0.25E_i$) and below 50% of its initial energy ($E_i^r \leq 0.50E_i$). We then average the corresponding percentages over the 100 instances of each network size. We observe that our solution exhibits nearly the same residual energy percentages as OPT. Because our solution lasts longer, one

TABLE III
COMPARISON OF THE RESIDUAL ENERGY OF THE SENSORS

$ N $	$E_i^r = 0$		$E_i^r \leq 0.25E_i$		$E_i^r \leq 0.50E_i$	
	OPT	OPT-B	OPT	OPT-B	OPT	OPT-B
20	27.95%	27.45%	46.10%	46.05%	59.45%	58.5%
50	39.16%	31.60%	59.86%	57.54%	72.34%	72.76%
80	35.22%	28.01%	56.46%	52.72%	70.22%	72.19%
100	16.92%	14.53%	33.81%	33.14%	47.03%	52.66%

would have expected that at the end of the network operation, nodes have less energy left. Indeed, in our solution much more data are generated and routed towards the sink. However, we can explain the quasi-equivalent residual energy of OPT and OPT-B by the fact that the energy spent in sending more data in OPT-B is compensated by the energy saved for not relaying some of other's packets. We also observe that the average residual energy decreases from 20 to 50 nodes and then increases. This is because above a certain topology size, a single mobile base station is not sufficient to balance efficiently the load among the important number of nodes. Thus there remains more energy in sensors.

Figure 3 represents the residual energy distribution at the end of the network lifetime in a 50-nodes and a 100-nodes topology for the two models. It appears that sensors with the most remaining energy are mostly located at the periphery of the network. Furthermore, the relatively high quantity of remaining energy in sensors indicates that it could be pertinent to reconsider the definition of lifetime or to introduce additional mobile base stations.

Figure 4 represents the pause time distribution of the mobile sink in a 50-nodes and a 100-nodes network. An observation already made in [7] is that the mobile sink stops at few different locations in OPT. We have verified that these locations do not specifically correspond to nodes with high degrees nor location with a high node density. It requires further investigation to highlight specific patterns for the sink mobility in this case. For the OPT-B model we observe that the mobile sink stops at almost all the nodes. Regarding the routing graph, we can roughly distinguish the pause times into two categories: *long-time pauses* during which all sensors route their data towards the sink in a tree-like manner and *short-time pauses* during which sensors close to the mobile sink send their bufferized data while more distant sensors bufferized their generated data. It is interesting to note that long-time pauses locations are almost the same as the locations chosen in OPT.

The average buffer utilization depending on the hop-distance of the nodes from the mobile base station location is plotted in Figure 5. The results are averaged over 100 instances for each network size. It appears that the more distant is the base station, the more the node will bufferize data. Indeed, buffers are used to store data while waiting the base station to come closer to the node. Then nodes take advantage of the base station proximity to empty their buffer. This strategy relieves more sensors from relaying other's data and results in an overall energy saving.

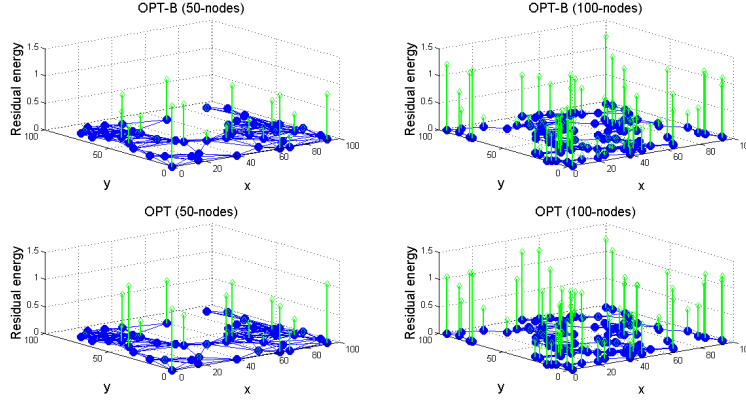


Fig. 3. Residual energy distribution of OPT and OPT-B in a 50-nodes and a 100-nodes network

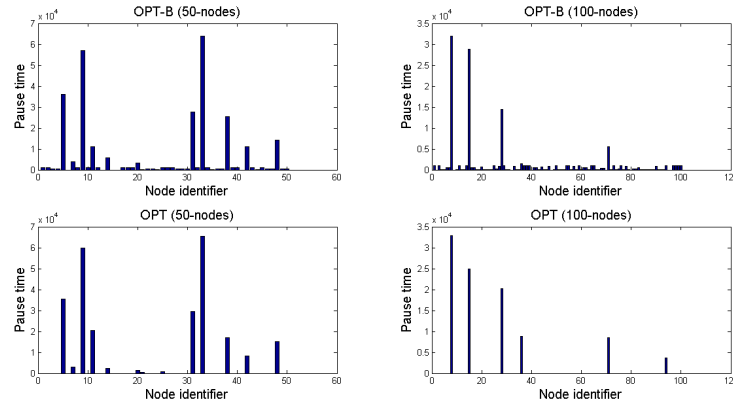


Fig. 4. Pause time distribution of OPT and OPT-B in a 50-nodes and a 100-nodes networks

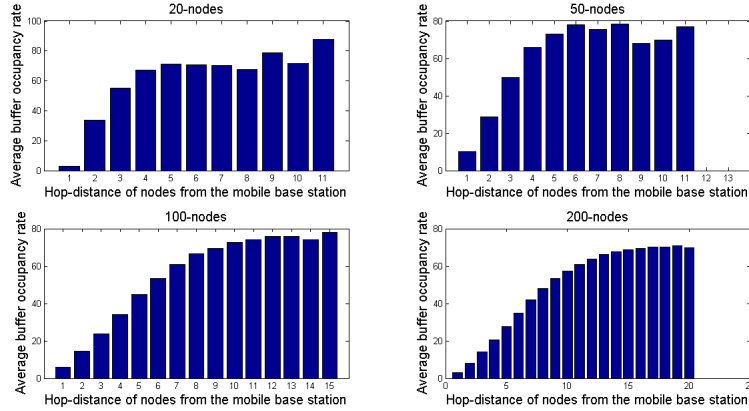


Fig. 5. Average buffer occupancy rates depending on the hop-distance of the nodes from the base station in various network size

V. CONCLUSION

In this paper, we gave a novel Linear Programming model for data collection in a wireless sensor network with a controlled mobile base station and limited buffer capacity. our solution always achieves higher network lifetime compared to existing solutions and demonstrates the efficiency of the delayed communication paradigm. The numerical experiments

are insightful for the future design of a distributed routing protocol and a sink mobility control policy. Depending on their distance to the mobile base station, nodes will tend to bufferize or transmit their data. The sink will stop at almost all the sensors. Long-time pauses will result in the construction of a routing tree towards the sink and during short-time pauses the sink will only collect data from the closest nodes. Moreover,

given a network size, the numerical results can be used to dimension the buffer capacity and the link capacity.

REFERENCES

- [1] J. Luo and J.-P. Hubaux, "Joint mobility and routing for lifetime elongation in wireless sensor networks," in *Proceedings IEEE 24th Annual Joint Conference of the IEEE Computer and Communications Societies.*, vol. 3. IEEE, 2005, pp. 1735–1746.
- [2] I. Papadimitriou and L. Georgiadis, "Maximum Lifetime Routing to Mobile Sink in Wireless Sensor Networks," *Proceedings of the 13th IEEE International Conference on Software, Telecommunications and Computer Networks (SoftCom 2005)*.
- [3] Z. Wang, S. Basagni, E. Melachrinoudis, and C. Petrioli, "Exploiting Sink Mobility for Maximizing Sensor Networks Lifetime," in *Proceedings of the 38th Annual Hawaii International Conference on System Sciences (HICSS 2005)*.
- [4] S. Basagni, A. Carosi, E. Melachrinoudis, C. Petrioli, and Z. Wang, "A New MILP Formulation and Distributed Protocols for Wireless Sensor Networks Lifetime Maximization," in *2006 IEEE International Conference on Communications*. IEEE, 2006, pp. 3517–3524.
- [5] W. Liang, J. Luo, and X. Xu, "Prolonging Network Lifetime via a Controlled Mobile Sink in Wireless Sensor Networks," in *IEEE Global Telecommunications Conference (GLOBECOM 2010)*. IEEE, Dec. 2010, pp. 1–6.
- [6] J. Luo, J. Panchard, M. Piorkowski, M. Grossglauser, and J.-P. Hubaux, "MobiRoute : Routing towards a Mobile Sink for Improving Lifetime in Sensor Networks," in *Second IEEE International Conference on Distributed Computing in Sensor Systems*, 2006.
- [7] J. Luo and J.-P. Hubaux, "Joint Sink Mobility and Routing to Maximize the Lifetime of Wireless Sensor Networks: The Case of Constrained Mobility," *IEEE/ACM Transactions on Networking*, vol. 18, no. 3, pp. 871–884, Jun. 2010.
- [8] S. Gandham, M. Dawande, R. Prakash, and S. Venkatesan, "Energy efficient schemes for wireless sensor networks with multiple mobile base stations," in *Proceedings of the 46th IEEE Global Telecommunications Conference Workshops (GlobCom 2003)*.
- [9] A. A. Somasundara, A. Ramamoorthy, and M. Srivastava, "Mobile element scheduling for efficient data collection in wireless sensor networks with dynamic deadlines," in *Proceedings of the 25th IEEE International Real-Time Systems Symposium (RTSS 2004)*.
- [10] Y. Gu, D. Bozdag, E. Ekici, F. Ozguner, and C. Lee, "Partitioning based mobile element scheduling in wireless sensor networks," in *Proceedings of the 2nd IEEE Conference on Sensor and Ad Hoc Communications and Networks (SECON 2005)*.
- [11] J. Rao, T. Wu, and S. Biswas, "Mobile element scheduling for efficient data collection in wireless sensor networks with dynamic deadlines," in *Proceedings of the 2008 IEEE Conference on Wireless Communications and Networking (WCNC 2008)*.
- [12] J. Rao and S. Biswas, "Network-assisted sink navigation for distributed data gathering: Stability and delay-energy trade-offs," *Computer Communications*, vol. 33, no. 2, pp. 160–175, Feb. 2010.
- [13] R. Sugihara and R. Gupta, "Optimizing Energy-Latency Trade-Off in Sensor Networks with Controlled Mobility," in *Proceedings of The 32nd IEEE International Conference on Computer Communications (INFOCOM 2009)*.
- [14] D. B. Johnson, "Finding all the elementary circuits of a directed graph," *SIAM Journal on Computing*, vol. 4, no. 1, pp. 77–84, 1975.