Load Balancing Techniques for Lifetime Maximizing in Wireless Sensor Networks

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ABSTRACT

Energy consumption has been the focus of many studies on Wireless Sensor Networks (WSN). It is well recognized that energy is a strictly limited resource in WSNs. This limitation constrains the operation of the sensor nodes and somehow compromises the long term network performance as well as network activities. Indeed, the purpose of all application scenarios is to have sensor nodes deployed, unattended, for several months or years.

This paper presents the lifetime maximization problem in *"many-to-one"* and *"mostly-off"* wireless sensor networks. In such network pattern, all sensor nodes generate and send packets to a single sink via multi-hop transmissions. We noticed, in our previous experimental studies, that since the entire sensor data has to be forwarded to a base station via multi-hop routing, the traffic pattern is highly non-uniform, putting a high burden on the sensor nodes close to the base station.

In this paper, we propose some strategies that balance the energy consumption of these nodes and ensure maximum network lifetime by balancing the traffic load as equally as possible. First, we formalize the network lifetime maximization problem then we derive an optimal load balancing solution. Subsequently, we propose a heuristic to approximate the optimal solution and we compare both optimal and heuristic solutions with most common strategies such as shortest-path and equiproportional routing. We conclude that through the results of this work, combining load balancing with transmission power control outperforms the traditional routing schemes in terms of network lifetime maximization.

1. Introduction

Advances in wireless networking, micro-fabrication and embedded microprocessors have enabled a new generation of massive-scale sensor networks suitable for a range of environmental, commercial and military applications. Imagine a set of small electronic devices, autonomous, equipped with sensors and able to communicate wirelessly. Together, they form a wireless sensor network able to monitor an area or phenomenon of interest, provide useful information through the combination of measures taken by the various sensors and then transmitted via the wireless medium. This new technology promises to revolutionize the way we live, work and interact with the physical environment [1]. Today, these tiny and cheap sensors may be literally strewn on roads, structures, walls or machines, creating a sort of a second digital skin which can detect a variety of physical phenomena. Many areas of application are considered including detection and monitoring of disasters, environmental monitoring and biodiversity mapping, intelligent building, precision agriculture, monitoring and preventive maintenance of machinery, medicine and health-care, intelligent transport and logistics.

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Wireless sensor networks are often characterized by a very dense and large-scale deployments in resource constrained environments. The constraints include limited capacity of processing, storage and especially energy since they are mainly powered by batteries. Battery recharging in sensor networks is sometimes impossible because of the number of nodes, but more often for the simple reason that this operation is practically or economically unattainable. It is widely accepted that energy limitation is an inevitable question in the design of wireless sensor networks because it imposes strict constraints on network operations. In fact, the energy consumption of sensors plays an important role in the network lifetime that became the dominant performance criterion in this area. Indeed, if we want the system operating in a satisfactory mode, as long as possible, these energy constraints require us to compromise between various activities at both the node and network levels.

Several research studies have emerged with a main goal: optimization of nodes energy consumption through the use of innovative conservation techniques to improve network performance, including lifetime maximizing. In general, saving energy is ultimately to find the best trade-off between the different energy-consuming activities. The literature on wireless sensor networks recognizes that radio is a prominent consumer of energy [2,3].

Minimizing energy consumption is a key goal in many multi-hop wireless networking systems, especially when the nodes of the network are battery powered. This requirement has become increasingly important for wireless sensor networks. Wireless sensor networks differ from other types of multi-hop wireless networks by the fact that, in most cases, the sensor data has to be delivered to a single sink or base station (*BS*). Clearly, one of the primary concerns is the lifetime of the network. Although different definitions of lifetime exist [4], certainly a sensor network has to be considered dead whenever it is no longer able to forward any data to the *BS*. We can settle for a definition where network lifetime is the time span from the deployment to the instant when the network is considered nonfunctional. The moment when a network can be considered nonfunctional is, however, application-specific, for example, the instant when the first sensor dies, a percentage of sensors die, or the loss of coverage occurs [5].

1.1. Our contributions

The energy balance problem is especially relevant in large-scale WSNs with many-to-one traffic pattern and static nodes, in order to maximize the lifetime of already deployed sensor network. This paper consider this problem within two scenarios of 2-D grid network topologies: one with a base station in the corner; and another one with a base station in the center of the grid. We assume that the network lifetime corresponds to the moment when the first node dies. To ensure that this moment will be the latest possible, we focus our study on traffic load and energy consumption balancing strategies.

First, we mathematically derive an optimal solution based on load balancing technique. As the optimal solution is centralized and being calculated in special cases, we propose on-line distributed heuristic trying to approximate the optimal case. This heuristic combines load balancing with transmission power control in order to find the good traffic proportions between the nodes to ensure a best balancing of their energy consumption. Moreover, we compare both of the optimal solution and the heuristic with other routing techniques, namely, *equiproportional* and *shortest-path* routing.

1.2. Organization

The reminder of this paper is organized as follows: Related work is summarized in Section 2. Section 3 states the problem of energy-balancing. Section 4 presents the problem formulation and the assumptions we made in our study. In Section 5, we detail an optimal solution. A transmission power control based heuristic approaching the optimal solution is presented in Section 6. In Section 7, we take a step back to discuss both of the optimal and the heuristic solutions and compare them to conventional schemes like shortest-path and equiproportional routing. Section 8 summarizes the main conclusions of our research, and presents a set of open issues and research challenges.

2. Previous work

Minimizing energy consumption is a major objective in several multi-hop wireless networks, especially when the nodes are powered by batteries. This need has become hugely important for WSNs which differ from other types of multi-hop networks by the fact that in most cases, data of sensor nodes must be transmitted to a single sink or Base Station.

Numerous research studies have been conducted in order to propose algorithms, protocols, and solutions reducing energy consumption in communications to extend the lifetime of the network. Anastasi et al. provide a good survey in [6]. In order to maximize the sensor network lifetime two major techniques can be employed: the introduction of sleep/active modes for sensors and the use of energy efficient routing. Extensive research has been carried out on energy efficient data gathering and information dissemination in sensor networks. Well-known energy efficient protocols were developed, such as LEACH [7]. LEACH organizes sensor nodes into clusters to fuse data before transmitting to the *BS*. PEGASIS [8] improved the LEACH by considering both metrics of energy consumption and data-gathering delay. Other routing schemes for maximizing network lifetime were presented in [9]. Another important technique used to prolong the lifetime of sensor networks is the introduction of switch on/off modes for sensor nodes. Carle et al. pointed out in [10] that the best method for conserving energy is to turn off as many sensors as possible, while still keeping the system functioning.

Some efforts have been made recently to analyze the upper bound of sensor networks lifetime. Haenggi [11], analyzed four strategies based on a Rayleigh fading link model to balance the energy consumption of the nodes.

These analyzes are restricted to one-dimensional chains of N nodes.

Bhardwaj et al. [12,13] studied the upper bound of the lifetime of data gathering sensor networks. They assume a randomly distributed data source in a region with a given pdf and the data sink is located at a fixed point. They calculate the minimum power required to transmit a bit from the source to the sink and then compute the upper bound of the network lifetime based on the minimum power consumption. In [14], authors investigated the upper bounds on network lifetime extension. They illustrated the trade-off between node density and network lifetime for a cell-based energy conservation technique in wireless ad hoc networks. Along these analytical studies, authors consider different network topologies and they state various assumptions that does not allow any comparison.

Coleri et al. [15] investigate the lifetime of sensor networks where sensors are organized in a tree-based multi-hop networks. They analyze the lifetime of nodes in four different groups based on their distances to the data sink using the finite automata technique. However, their analysis is primarily on the lifetime of individual nodes instead of that of the network. Duarte-Melo et al. [16] proposed a hierarchical clustering technique to extend sensor network lifetime. They calculated the mathematical expectation of sender-to-receiver distance, the authors gave numerical results on estimated lifetime and optimal network cluster number.

Other techniques such as random routing proposals exist in the literature. In [17], authors consider a grid topology where each node sends data to all its neighbors with a blind (regardless of destination) routing probability of $\frac{1}{4}$. Slama et al. [18] associate a neighborhood discovery protocol with random routing to minimize the overall energy consumption. This problem is NP-complete. Authors propose heuristics for general cases. However, random routing is often tailored to "Mostly-on" functioning where nodes should be "ON" to receive any packet (nodes are subject to idle listening) and involving also overhearing.

Our point of view is different as we propose solutions taking into account application, topology and sharing the traffic with minimum signaling in order to optimize the network lifetime. In this work we design and analyze several energy balancing strategies in a regular grid topology with uniformly deployed and stationary nodes. We take into account different transmission power levels to calculate the traffic proportions of each node in order to extend the network lifetime. Furthermore, we derive an optimal solution to balance node energy consumptions and maximize the network lifetime.

3. Problem statement and network model

In multi-hop WSNs where all sensor nodes transmit data to the base station, the bottleneck around this sink represents the major constraint. This limits the network performance, particularly the network lifetime. Indeed, as all the sensor data has to be forwarded to the base station (Sink) via multi-hop routing, the traffic pattern is highly non-uniform, putting a high burden on the sensor nodes close to the base station.

The origin of this work comes from an intensive experimental study with real sensors. In [19] we deployed nodes in different topologies (grids and straight-lines). We studied the impact of transmission power on the network topology and link quality (LQI) between nodes. While the multi-hop routing algorithm was based on link quality, the first observation is that all the sensor nodes try to connect with the closest nodes to the base station to send their data. Indeed, we consider the Fig. 1 which depicts a possible arrangement of the sensor nodes. A priori and without appropriate measures, we identify the most critical nodes in the network. Apparently, the burden on the nodes close to the base station is considerably higher than on the nodes that are far away. They will die quickly, rendering the network useless. In this paper, we propose and discuss strategies to ensure maximum lifetime of the network by balancing the energy load as equally as possible.

3.1. Energy model

The First-Order Radio Model proposed in [7] has been widely used for measuring energy consumption in wireless communications. In this model, the energy spent by the transmission of one data bit over distance d is $e_{tx}(d) = e_{elec} + e_{amp} \cdot d^k$, where e_{elec} is the energy spent by transmitter electronics, e_{amp} is the energy consumed by the transmitting amplifier and $k(k \leqslant 2)$ is the propagation loss exponent. When receiving data, only the receiving circuit is invoked and, thereby, the energy spent by receiving one bit data is $e_{rx} = e_{amp}$. In this study, we do not consider the energy consumption for data sensing since all nodes have uniform data generation rate and the energy spent by sensing has been balanced among all nodes. Compared with data communication, the energy dissipated by data aggregation is much smaller, and is not taken into account.

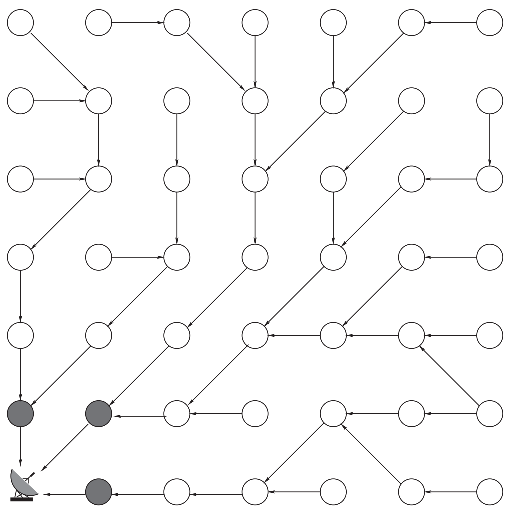


Fig. 1. A many-to-one traffic pattern impact in a 2-D grid topology with *BS* in the corner.

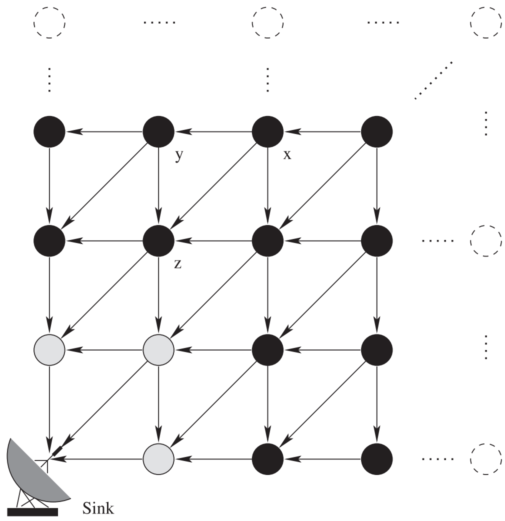


Fig. 2. A 2-D regular grid topology with a base station in the corner.

The energy consumption is proportional to $d_{xz}^{k}, k \geqslant 2$. When $k = 2$, if receiving energy is ignored, we can see that the same amount of energy is consumed by sending packet (transmission energy) via multi-hop along the grid edge and direct hop along the diagonal line with 45° angle. For example, consider the following energy costs of one packet sending: e_{xy}, e_{yz}, and e_{xz}. As shown in Fig. 2, $e_{xy} + e_{yz} = e_{xz}$, according to the Pythagorean Theorem. However, when $k > 2$, the direct diagonal hop consumes more energy than multi-hop along the grid edge. If the receiving energy consumption is taken into account, the benefit from multi-hop transmission on the grid edge is diminished because it involves energy consumption on relaying nodes.

4. Problem formulation

Before presenting in details our solution, we introduce the following notations (Table 1).

4.1. Assumption of our model

For easier understanding of our proposal in the remainder of this paper, we make some reasonable assumptions in the case of a grid network with all-to-sink traffic pattern, as follows:

- Nodes are uniformly distributed in a grid topology with size $N = M \times M$, consequently, the density is uniform throughout the entire network (Fig. 1). It is a reasonable since the grid topology is widely studied in WSN. The main reason is that several application areas use regular topologies as 2D grids: precision agriculture, trucks and warehouses monitoring, urban networks, etc.
- Each node generates constant bit rate (CBR) data and sends to the *BS* through multi-hop routes.
- We plan to make a hop by hop routing and load-sharing between the accessible nodes. Indeed, Load sharing is possible without signaling protocol. Basically, we can make calculations early in the life of the network (calculations may be made by the *BS*) and transmit these proportions to the different sensors.
- "Mostly-off" network pattern is better than "Mostly-on" one, that is why we prefer to refer to proportions rather than probabilities because the load-sharing by probabilistic routing is costly and requires "Mostly-on" nodes. Consequently, in "mostly-on" networks, the transmission power has a major impact on the over-consumption of energy due to overhearing.
- Sleep/wakeup scheduling is assumed to be perfect without neither collision nor retransmission.
- Sensor nodes have two different transmission ranges of d and $\sqrt{2}d$ meters.
- According this well-known formula given by [20]: $P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 L d^n}$, we assume that each node uses two transmission power levels TPL_1 for range d and TPL_2 for $\sqrt{2}d$.
- Since energy consumption (E) when transmitting is proportional to transmission power P_{tx}, (Eq. (1) in [21]) we assume: $E(\mathrm{TPL}_2) \simeq 2 \times E(\mathrm{TPL}_1)$

Table 1
Index of symbols used in the formulation.

Symbol	Definition
BS	Base station whose energy is unbounded
Ω	Set of all the sensors, and $N = M \times M = \lvert\Omega\rvert$
e_{tx}	Energy required for transmitting one data unit
e_{rx}	Energy required for receiving one data unit
$\lambda_g^{(i)}$	Traffic generated by the node i
$\lambda_r^{(i)}$	Traffic received by the node i
$\Lambda^{(i)}$	Overall traffic load sent by the node i
$L_{Network}$	Network lifetime
T_i	Node lifetime, $i \in \Omega$
TPL	Transmission power level
$\mathbb{P}$	Stochastic matrix of traffic proportions
p_{ji}	Traffic proportion sent by node j to i
$E^{(i)}$	Energy consumed by the node i

4.2. Network lifetime definition

Network lifetime is the time span from the deployment to the instant when the network is considered nonfunctional. When a network should be considered nonfunctional is, however, application-specific. It can be, for example, the instant when the first sensor dies, a percentage of sensors die, the network partitions, or the loss of coverage occurs [5]. Among all existing definitions in the literature (cf. for example in [22]), we chose to adopt the first one, i.e., the period until the first node depletes all its energy. Obviously, when the traffic is rather sporadic (e.g. alarms) regardless of its position when a node dies, this represents a major failure because there is a non covered part of the area. In this regard, there are other definitions of lifetime related to coverage and application. In this paper we opted for a general example application context. The nodes send regular traffic requiring load balancing because of the large number of packets. Given our assumption model, the critical nodes are those near the Sink because all traffic generated is relayed to the sink by them. Therefore, the network lifetime depends on the lifespan of these nodes. Indeed, the death of one of them will accelerate the death of the other two because their load will be increased considerably. Therefore, if we consider $T^{(i)}$ the lifetime of the node $i \in \Omega$, then the network lifetime may be expressed as follows:

$$L_{Network} = \min_{i \in \Omega} T_i \quad (1)$$

This definition makes the selected scenario analysis tractable. Maximizing the network lifetime is equivalent to maximizing the minimum node lifetime. Moreover, extend the time the first node dies ensures that the maximum energy consumption of each node is minimized. That is to load balance network traffic so that no node is exposed to high energy consumption. Our idea is then to implement simple routing mechanisms with different strategies that will be illustrated in the next section.

Remark 1. Determine the maximum lifetime of the first node that fails amounts to minimizing the maximum energy E consumed by the sensor nodes of the network.

4.3. Formulation

The problem can be formulated as follows: Let $N = M \times M$ be the total number of nodes and $\Lambda = (\Lambda^{(1)}, \Lambda^{(2)}, \ldots, \Lambda^{(N)})$ the vector of output traffic rates of all nodes in the network. The load $\Lambda^{(i)}$ of the node i can be written as follows: $\Lambda^{(i)} = \lambda_g^{(i)} + \sum_j \Lambda^{(j)} p_{ji}$, with $\lambda_g^{(i)}$ as the traffic generated by i itself (we assume that each node has a constant traffic rate λ_g) and p_{ji} is the traffic proportion sent by node j to i (p_{ij}=0 means that is node i is not connected to node j). Thus we can write: $\Lambda = \lambda_g \mathbb{1} + \Lambda \mathbb{P}$

$\mathbb{1}$ is the identity vector and $\mathbb{P}$ is the stochastic matrix of traffic proportions between the nodes.

$$\mathbb{P} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \cdots & \cdots & \cdots & \cdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{pmatrix}$$

The matrix is obtained under the following constraint: $\sum_{j=1}^{N} p_{ij} = 1, \forall i,j \in \{1 \ldots N\}^2$

Let $\mathbb{Q}$ be the matrix of costs taking into account the transmission power between each pair of nodes:

$$\mathbb{Q} = \begin{pmatrix} q_{11} \cdot p_{11} & q_{12} \cdot p_{12} & \cdots & q_{1N} \cdot p_{1N} \\ q_{21} \cdot p_{21} & q_{22} \cdot p_{22} & \cdots & q_{2N} p_{2N} \\ \cdots & \cdots & \cdots & \cdots \\ q_{N1} p_{N1} & q_{N2} p_{N2} & \cdots & q_{NN} p_{NN} \end{pmatrix},$$

q_{ij} is the transmission power level used by node i to reach node j.

To maximize the network lifetime we must minimize the energy consumption of the critical nodes (those nodes consuming more energy in the network).

Let $E^{(i)}$ be the energy consumed by sensor node i in the network, $\Lambda^{(i)}$ the outgoing traffic, $\lambda_r^{(i)}$ the incoming traffic, and the vector $\mathbb{1} = (1, \ldots, 1)$ the normalized traffic generated by each node. Now, we introduce q_{ij} as the transmission power and assume that the energy consumption of one receiving packet is normalized to 1 unit.

$$E^{(i)}(\mathbb{P}) = \lambda_r^{(i)} + \sum_j \Lambda^{(i)} p_{ij} q_{ij}$$

Then the problem is defined as follows:

$$E^* = \min_{\mathbb{P}} \|E(\mathbb{P})\|_\infty \quad (2)$$

This problem is nonlinear with linear constraints. An analytical solution, when the sensors are placed on a grid topology and where the maximum transmission power used q_{ij} is equal to 2 is shown in Fig. 5. The optimal case can be obtained when the three neighboring nodes of the *BS* (*BS* is placed in the corner of the grid) consume the same energy as we shall demonstrate in Section 5.

5. Proposed optimal solution

We present an optimal case to balance the energy consumption of the critical nodes in a 2-D grid topology with a base station in a corner. Due to the nodes range, the overburdened sensors are those near to the base station. Indeed, they will deliver all traffic from other nodes: $\psi_r = (N-4)\lambda_g$ as the received traffic; and $\psi_s = (N-1)\lambda_g$ as the overall traffic to send. We note $\phi_s = N-4$ the rest of the sensor nodes.

For the remainder of our analysis, let us associate coordinates to each node: (i,j) as in Fig. 3 and let:

$E_{rx,(i,j)}$ be the receiving energy of the node (i,j).

$E_{tx,(i,j)}$ be the transmitting energy of the node (i,j).

$E_{(i,j)}$ be the overall energy consumption of the node (i,j).

For the energy consumption while receiving, the direct neighbors of the *BS* will consume at least:

$$E = E_{rx,min} = (N-4)\lambda_g \cdot P_1 = \phi_s \lambda_g \cdot P_1 \quad (3)$$

where P_1 is the receiving power at a distance d (reception power has been normalized to 1 unit).

- Let p be the traffic proportion coming directly from the node "(2,2)", and for symmetry reasons, $\frac{1-p}{2}$ the traffic proportion which enters through the nodes "(1,2)" and "(2,1)".
- Let q be the traffic proportion sent by "(2,2)" directly to the *BS*, and $\frac{1-q}{2}$ which is sent respectively to the nodes "(1,2)" and "(2,1)".

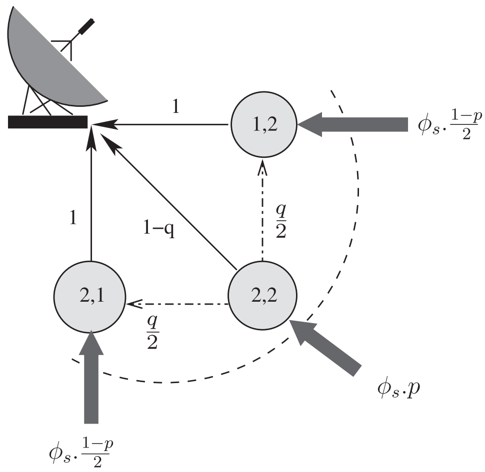


Fig. 3. Optimal case analysis: incoming traffic load on the closest nodes to the base station.

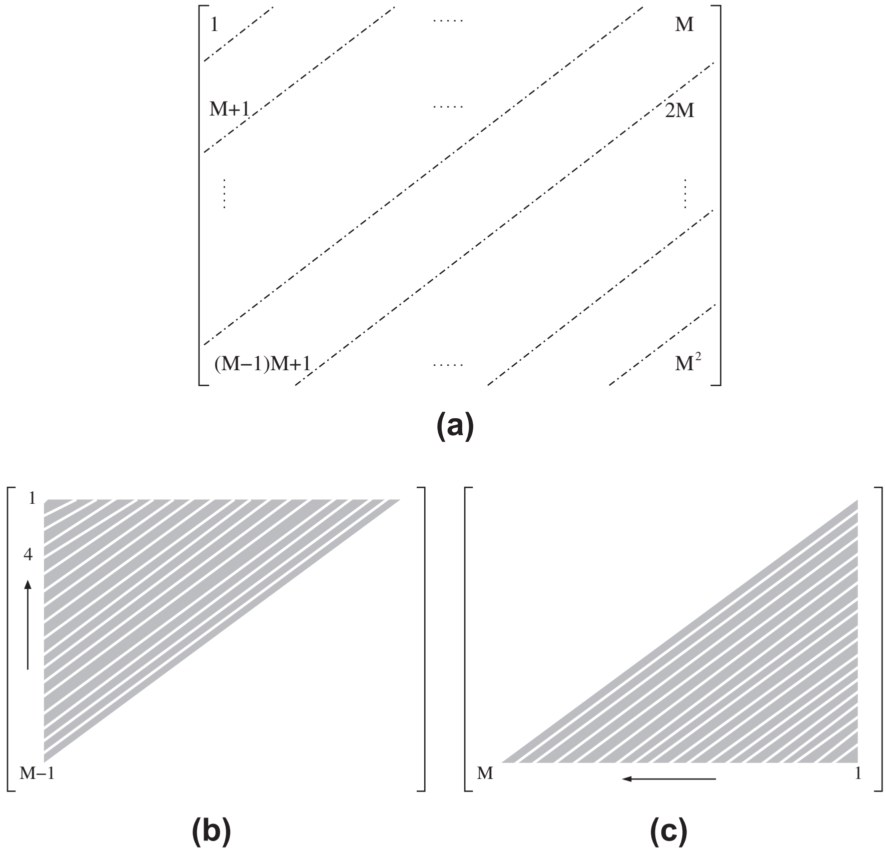


Fig. 4. Optimal case analysis: figure (a) shows the diagonals of the grid. Figure (b) distinguishes the diagonals “4” to “M-1” above the main diagonal. (c) Distinguishes the diagonals from “1” to ”M” below the main diagonal.

- Sending message from “(1,2)” to “(2,2)” has no interest because transmitting from “(1,2)” to “(2,2)” is as expensive as sending directly to the base station and it will cost certainly to the node “(2,2)” itself.

We obtain:

$$E_{rx,(1,2)} = E_{rx,(2,1)} = \frac{1-p}{2}\lambda_g P_1 \phi_s + \lambda_g P_1 \{1 + p\phi_s\}\frac{1-q}{2}$$
$$E_{tx,(1,2)} = E_{tx,(2,1)} = E_{rx,(1,2)} + \lambda_g P_1$$
$$\frac{E_{(1,2)}}{\lambda_g P_1} = 2 + \phi_s - q(1 + p\phi_s)$$
$$\frac{E_{(2,2)}}{\lambda_g P_1} = 1 + 2p\phi_s + q(1 + p\phi_s)$$

Thus, we look for minimizing the maximum energy consumption of the nodes “(1,2)”, “(2,1)” and “(2,2)”. Since $E_{(1,2)} = E_{(2,1)}$, the problem is written as follows:

$$\eta^* = \min_{p,q \in (0,1)^2} \max(E_{(1,2)}, E_{(2,2)}) \quad (4)$$

which lead to a linear problem by putting $x = q(1 + p\phi_s)$. It can easily derived that:

$$p^* = \frac{\phi_s - 1}{4\phi_s};\ q^* = 1 \quad (5)$$

with: $\eta^* = E^*_{(1,2)} = E^*_{(2,2)} = \lambda_g\left\{2 + \frac{3(\phi_s - 1)}{4}\right\}$

This value is a lower bound of E^*. Moreover, the questions that arise are: *can this minimum be reached? Are we sure that no other node will consume more energy?*

So, the objective function (4) becomes:

$$\eta^* = \min_{\mathbb{P}}(E(\mathbb{P})) \quad (6)$$

where

$$E(\mathbb{P}) = \max_{i,j} E_{(i,j)}$$

and $\mathbb{P}$ is the stochastic matrix of the traffic proportions.

$$E^* \geqslant E^*_{(1,2)}$$

To answer the above questions, we look for a matrix of proportions that leads to this lower bound. We design a solution where the energy is the same for all nodes located on the same diagonal (Fig. 4). Now, we proceed in Tables 2 and 3, to the analysis of the traffic and the energy consumption in each diagonal. For information, the energy values in the tables are divided by λ_g.

The nodes consume at most M.

$$\frac{E_{(1,2)}}{\lambda_g} = \frac{5 + 3\phi_s}{4} = \frac{3M^2 - 7}{4} > M \text{ if } M > 2.$$

The energy consumed by the nodes on the diagonals “4” to $(M-1)$ above the main diagonal (Fig. 4b) is shown in Table 3.

Table 2
Diagonals "1" to "M" below the main diagonal (Fig. 4c).

Diag.	Number of nodes	Total receiving	Received per node	Transmitted per node	Energy
1	1	0	0	1	1
...	...	...	...	...	...
k	k	$\frac{k(k-1)}{2}$	$\frac{k-1}{2}$	$\frac{k-1}{2}+1$	k
...	...	...	...	...	...
M	M	$\frac{M(M-1)}{2}$	$\frac{M-1}{2}$	$\frac{M-1}{2}+1$	M

$\frac{2M^2}{k} - k$ is a decreasing function of k and energy (E) maximum for $k = 4$.

$\frac{2M^2}{4} - 4 = \frac{2M^2-16}{4} < \frac{3M^2-7}{4}$.

Therefore, outside the base station range, nodes consuming more energy are those located on the 4th diagonal. They consume less than the nodes within the range.

For the 3rd diagonal, we are able to find propositions satisfying the Eq. (5) (Refer to Fig. 5), node (3,1) respectively (1,3) sends to node (2,1) respectively (1,2).

We finally obtain:

$E_{(3,1)} = E_{(1,3)} < E_{(2,1)} = \eta^*$.

The maximum for (1,2), (2,1) and (2,2) is η^*.

By applying the calculation rules proposed in the two tables, we obtain the routing proportions illustrated in Fig. 5, at the same time the matrix $\mathbb{P}$ for which: $E(\mathbb{P}) = \eta^*$ and finally:

$$E^* = \lambda_g \left(\frac{3N-7}{4}\right) \tag{7}$$

Remark 2. For the deployment considerations of the optimal solution, all calculations can be carried out by the Base Station that transmits routing decisions to the various nodes (e.g. with flooding), we can proceed it by techniques of topology discovery. We can even pre-program the sensor nodes with the routing information.

6. Proposed load balancing heuristic

The optimal solution is obtained only for a grid topology, so we propose a heuristic which can be used in more general contexts. We propose a heuristic that attempts to improve the traffic load balancing to increase the lifetime of the network. This heuristic distributes the contributions of each node beginning from the *BS* by considering them as proportional to the transmission power of each node. We consider only the nodes within the same range. A neighbor node is said downstream (resp. upstream) from another node if it is closest to (resp. farthest from) the base station. The heuristic illustrated by Fig. 6 works in the following steps:

Table 3
Diagonals "4" to "$M - 1$" above the main diagonal (Fig. 4b).

Diag.	Number of nodes	Total receiving	Received per node	Transmitted per node	Energy
$M-1$	$M-1$	$M_2 - \frac{M(M-1)}{2}$	$\frac{M^2}{M-1} - \frac{M}{2}$	$\frac{M^2}{M-1} - \frac{M}{2} + 1$	$\frac{2M^2}{M-1} - (M-1)$
...	...	...	...	...	...
k	k	$M_2 - \frac{k(k+1)}{2}$	$\frac{M^2}{k} - \frac{k+1}{2}$	$\frac{M^2}{k} - \frac{k+1}{2} + 1$	$\frac{2M^2}{k} - k$
...	...	...	...	...	...
4	4	$M^2 - 10$	$\frac{M^2}{4} - \frac{5}{2}$	$\frac{M^2}{4} - \frac{5}{2} + 1$	$\frac{2M^2}{4} - 4$

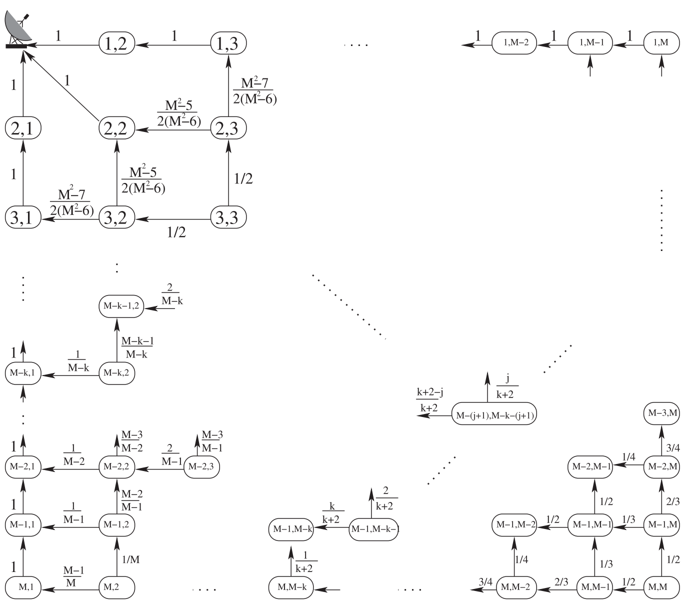
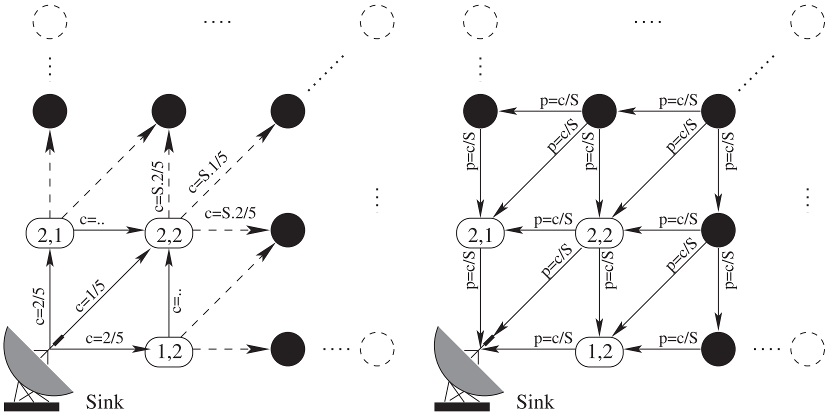


Fig. 5. Stochastic matrix for the optimal solution.



(a) Contributions calculation (b) Proportions calculation

Fig. 6. Load balancing heuristic. (c link contribution and S sum of contributions.)

1. Starting with the base station, we calculate for each node the contribution of each of its upstream neighbors, taking into account the power of these neighbors to reach it. For example, the *BS* has three downstream neighbors: "(1,2)", "(2,2)", and "(2,1)" (with transmission power level 2) so the contributions are respectively $\frac{2}{5}, \frac{1}{5}$ and $\frac{2}{5}$ (Fig. 6).
2. We sum the contributions that nodes receive from their upstream neighbors and impute them to each upstream neighbor. For instance, the node "(2,2)" gets three contributions, one from *BS*, one from node "(1,2)", and one from node "(2,1)" (Fig. 6). Let S be the sum of these three contributions. Finally "(2,2)" distributes the contributions for its upstream neighbors.

The heuristic is also described by the following algorithm. We note $V(j)$ the neighborhood of node i and $d(i,j)$ the distance from i to j. In our example, the weight $W(j,i) \propto d^2(j,i)$.

Algorithm 1. Load Balancing Heuristic

Require: $G(N,A)$, $V = \{v_i\}$, $i \in \Omega$
ensure: Proportion(i,j)
Contributions calculation
forall $i \in \Omega$ **do**
forall $j \in \Omega$ **do**
if $j \in V(i)$ et $d(i,SB) < d(j,SB)$ **then**
Contribution$(j,i) \leftarrow$ *SumContributions*$(i) \times$ $W(j,i)$
SumContributions(j) *SumContributions*(j) + *Contribution*(j,i)
endif
endfor
endfor
Proportions calculation
forall $j \in \Omega$ **do**
Proportion(i,j) *Contribution*(i,j)/ *SumContributions*(i)
endfor
Return Proportion(i,j)

7. Performance evaluation

In this section, we examine the performance of the proposed solutions. In different configurations, we have examined their effectiveness, their energy-efficient load balancing, and their lifetime maximizing. In order to establish whether the proposed optimal solution and heuristic really have a positive impact on the network lifetime, we compared them to two conventional techniques.

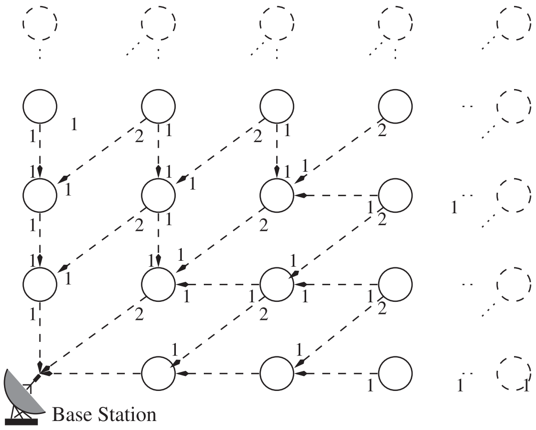
7.1. Comparison

We compared the performance of the optimal solution and the heuristic with shortest-part and equiproportional routing techniques which are described as follows.

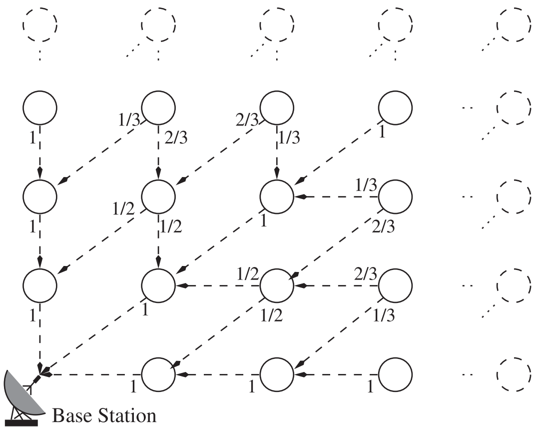
7.1.1. Shortest path routing

A common method to prevent neighbors from consuming energy is to choose the shortest-path or share the load between the shortest-paths when the node has several shortest-paths, it is thus similar to a load sharing as proposed by OSPF (*Open Shortest Path First*). In the context of energy conservation the shortest-path is the path that have the lowest cost in terms of energy consumption. However, this involves a first signaling phase to identify these paths and consequently, consume additional energy. In the case of the grid topology shown in Fig. 7a, we notice that the nodes on the two border lines leading to the base station transmit their data always in the direction of their boundary line. While the shortest-paths of the rest, is often to take the diagonal link or go to the main diagonal of the grid. Clearly, we can conclude that the most critical node will be the one on the main diagonal close to the base station. Fig. 7a showing the shortest-path algorithm, also shows the transmitting and receiving costs. We found that the traffic is directed as follows:

- Nodes on the both sides converging towards the *BS* always send their data in the border direction through the border nodes.
- All the other nodes send their data either in diagonal, they try to reach the main diagonal in the direction of the *BS*.



(a) Tx and Rx costs



(b) Routing proportions

Fig. 7. Shortest-path strategy

Furthermore, we must determine for each node the number of the possible shortest-paths through each of its neighbors in order to balance the traffic load (Fig. 7b). We analyze the results of this strategy later.

7.1.2. Equiproportional routing

By analogy with the equiproportional routing, we also considered equiproportional routing where nodes decide to distribute locally the traffic proportions equally among their upstream neighbors. We remind that the idea of a probabilistic routing is rejected because of the "mostly-Off" selected model.

7.2. Results

To calculate the energy consumption of the "shortest-path", the "equiproportional" and the "heuristic" techniques, we implemented, in C language, the algorithms associated with each strategy. This can be achieved by the construction of a linear system, but we preferred to merge and automate the calculation of proportions and the traffic flow to get the energy consumptions. The calculation is simple, with an initial traffic λ_g for each node, we unroll the traffic from the farthest node (in the back of the grid) to the base station. The traffic is shared according to the calculated proportions by ascending diagonal per diagonal. In addition to these strategies we used a simulated annealing method to approximate the optimum and to find the routing proportions.

7.2.1. Distribution of the energy consumptions in the grid

Initially, we calculated the consumption of each node according to the tree strategies: "shortest-path routing", "equiproportional routing", and the "heuristic". This is to verify the position of critical nodes on the one hand and compare the three strategies on the other hand. The topology considered here is a 2-D grid of 10×10 nodes. The nodes are numbered line by line (0–9, 10–19, etc.). Fig. 8 shows the distribution of energy consumption depending on the node position in the grid.

We observe that the nodes consuming more energy are the ones close to the Base Station, then those at the beginning of each matrix line or on the diagonal (for example node 11 in "shortest-path" routing). Fig. 8 shows the distribution of energy consumption according to the position of the node in the matrix grid. First, we can see easily that the most consuming nodes are those near to the base station, then those at the beginning of each grid line. Furthermore, the results show a clear advantage in favor of the load balancing heuristic.

7.2.2. Consumption of the critical nodes

From Fig. 8, we can see that the critical nodes in the three strategies are respectively the node "1" (corresponding to "(1,2)") for the heuristic and the equiproportional routing, and the node "11" (corresponding to "(2,2)", on the diagonal) for the shortest-path routing. Those nodes consumed the largest amounts of energy corresponding respectively to 90,107, 98,782 and 133,817 units. This denotes an energy gain first for the heuristic then for the equiproportional routing compared to the shortest-path algorithm.

Then, we compared all the strategies to the optimal case. We compared the calculated results for the three previous strategies to the optimal solution. According to the previous study, it is clear that the problem for a network of $M \times M$ nodes is to calculate the matrix of the traffic proportions that approximate the optimal solution and satisfies the Eq. (7). Thus, we programmed the calculations of all the strategies to compare the consumption of critical nodes.

Remark 3. The lifetime optimization problem being defined as a nonlinear problem with linear constraints, we also present the results obtained by the simulated annealing method. With this method, we obtain the proportions of traffic very close to the optimal case. Subsequently, we compared all the strategies to the optimal solution. In Fig. 9, we note that the shortest-path and the equiproportional routing are the most consuming, especially when the number of nodes is very large.

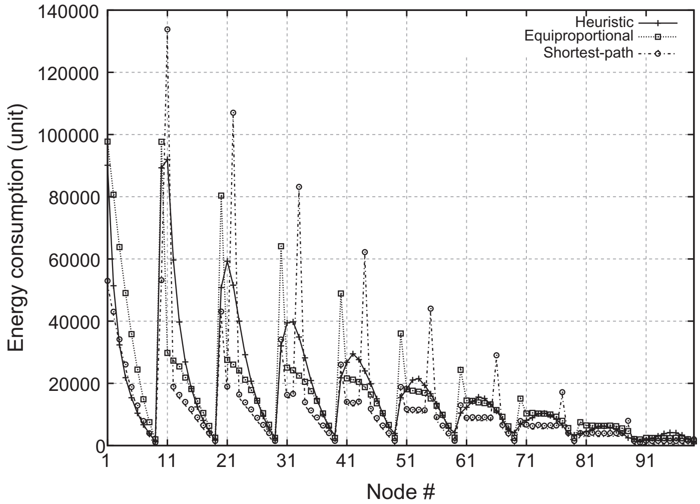


Fig. 8. Energy consumed by each node in a grid of 10×10 nodes, each node generates 1000 packets. Node "0" is the *BS* and. (Energy consumption is normalized.)

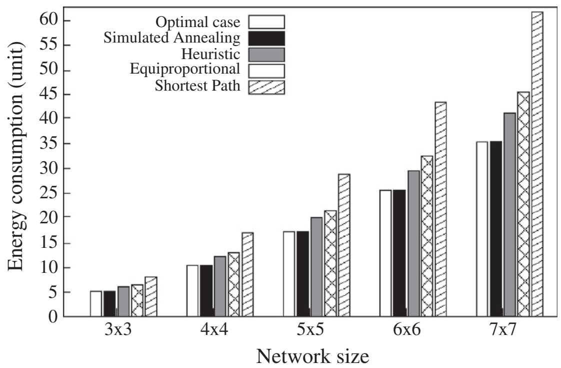


Fig. 9. Energy consumption with $\lambda_g = 1$.

7.2.3. Lifetime

The network lifetime in each strategy can be easily inferred from the Fig. 10a–d. In these figures, we have plotted the energy consumption of each node in the grid by a node in the network based on generated traffic λ_g by each node. We note that the optimal solution outperforms the traditional routing schemes in terms of network lifetime maximizing. Indeed, such a shortest-path routing has heavy consequences on the network lifetime. Furthermore, a close look into the results shown in the Fig. 10a, d, and c reveals that the maximum energy consumption decrease with the heuristic by 38% compared to the shortest-path. In addition, even the equiproportional routing scheme has a 20% increase of maximal energy consumption compared to the heuristic, because the nodes share their traffic regardless of the transmission power. Besides, the heuristic results are not as far from those of the optimal solution because the difference is around 13%.

7.2.3.1. Discussion. The proposed methods for energy balancing maximizes the network lifetime for two main reasons:

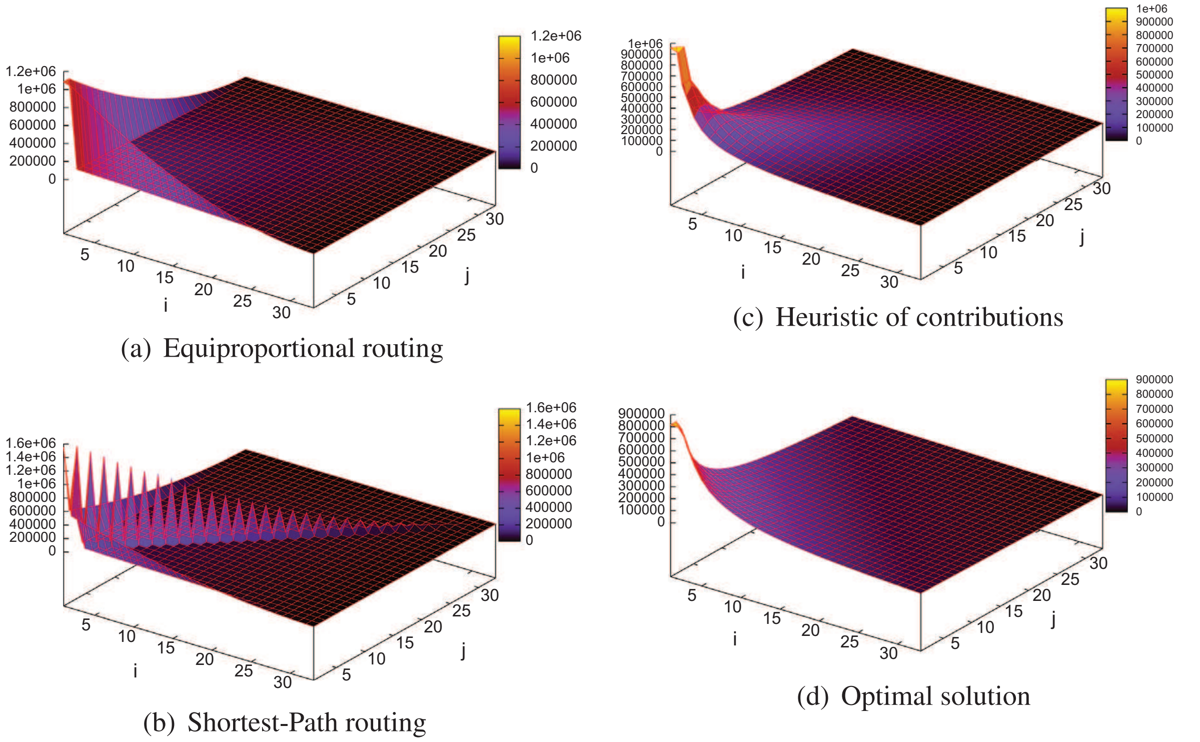
- First, it is stated in this paper that data routing using the proposed policies consumes less energy, at critical nodes, than classical routing strategies such equiproportional or shortest-path routing but are only concerned by each packet individually.
- Secondly, an optimal routing control can also be associated with our methods. In fact, routes may be pre-calculated once at all by the *BS* (this assumes that the overall network topology is known) and distributed by unicast or broadcast to all the network nodes. In this way, the control overhead is minimized.

7.3. A topology case with BS in the center of the grid

Fig. 11 shows the second scenario that we considered in which the Base Station is located at the center of the grid. Here, a regular topology and two transmission power levels are considered. Thus, the critical nodes are those close to the Base Station as observed in our results. However, this is probably not the case of arbitrary topologies or a non-uniform traffic.

As shown in Fig. 13a–d, the traffic load is concentrated on the nodes close to the base station and it is distributed symmetrically on the nodes surrounding it. The network lifetime can be inferred from the position of critical nodes in the four Fig. 13a–d. Using an equiproportional routing (Fig. 13a), the load of traffic is concentrated on the nodes located on the column and row with the Base Station is the crossing point. It is quite normal because if we decompose the grid into four blocks each way, each having the base station at the corner, then these critical nodes are boundary nodes of two adjacent blocks.

For the shortest-path routing (Fig. 13b), the nodes located at the two diagonals of the grid nodes are added to previous ones. We interpret this as a slight improvement over the number of nodes; the greater the traffic is balanced.



(a) Equiproportional routing

(b) Shortest-Path routing

(c) Heuristic of contributions

(d) Optimal solution

Fig. 10. Distribution of energy consumptions in a grid of 33 × 33 nodes with *BS* in the corner. *i* and *j* are the coordinates of the node $n_{i,j}$ in the grid. The vertical axis represents the energy consumption of each node $n_{i,j}$ in the grid.

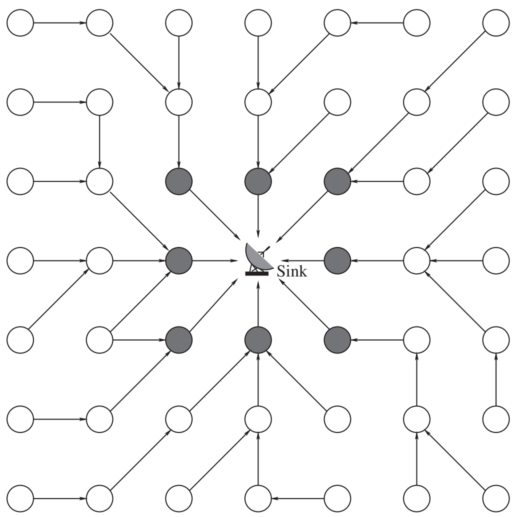


Fig. 11. A many-to-one traffic pattern impact in a 2-D grid topology with *BS* in the center.

We get more enhancements with our heuristic (Fig. 13c) since the load is distributed over all the nodes situated on the two crowns around the Base Station. Finally, the results plotted in Fig. 15 lead to the same conclusions. We implemented the algorithms of the three strategies and we calculated the maximum energy consumed by each node. Similarly to the first case (*BS* in the corner of the grid), we compared the strategies of shortest-path and equiproportional routing with the heuristic and the optimal solution that we derived for this case.

The optimal solution that we derived with the same approach used in Section 5 leads to the optimum:

$$E^* = \lambda_g\left(\frac{3N-13}{10}\right) \tag{8}$$

Proof. As shown in Fig. 12, we can deduce that all traffic arriving on the critical nodes around the *BS* is (for symmetry reasons):

$$4\lambda_r + 4\lambda'_r = \lambda_g(N-9) \tag{9}$$

Furthermore, in the optimal case of energy consumption, a critical node on a diagonal (sending with a *TPL* = 2) consume the same amount as another critical node on the vertical or the horizontal axis. So, we get:

$$E^* = \lambda_r + (\lambda_r + \lambda_g) = \lambda'_r + 2(\lambda'_r + \lambda_g) \tag{10}$$

Then, by combining the formulas (9) and (10) we obtain (8).

The results of the optimal solution in this second scenario are depicted in Fig. 13d. As we can see, the energy consumption of the node is better balanced in the grid compared to the conventional routing schemes. In this scenario, we note once again that the load balancing by the optimal solution gives better performance in terms of

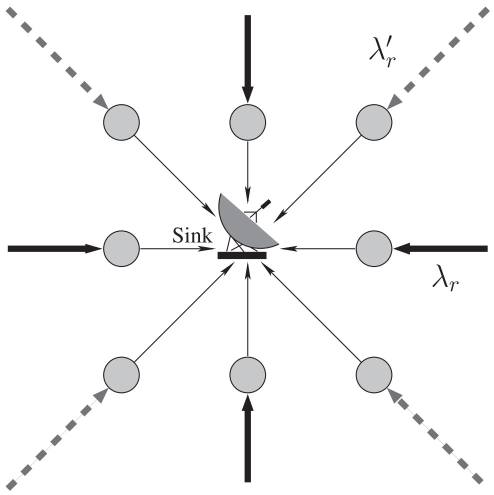


Fig. 12. Optimal case analysis in a 2-D grid topology with *BS* in the center.

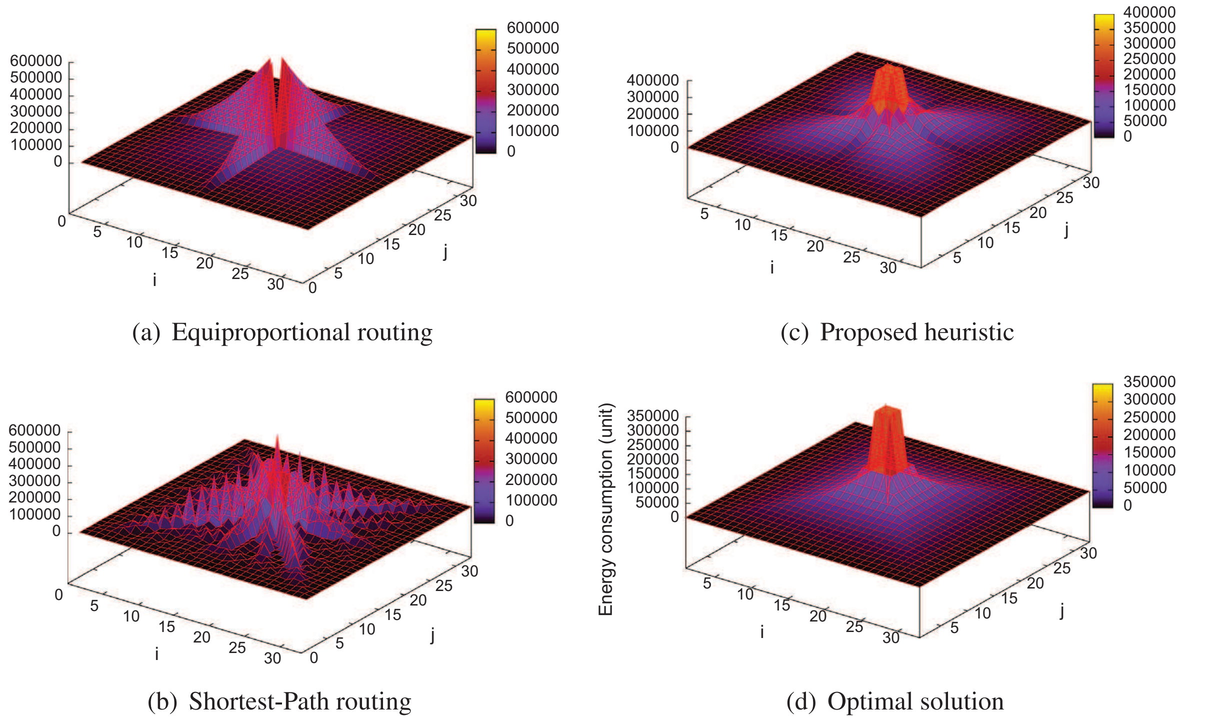
network lifetime. Indeed, as shown in the Fig. 13a–c, the maximal energy consumption decreased by 33% with the heuristic compared to the shortest-path or the equiproportional routing.

Moreover, even the optimal solution outperforms the heuristic (a difference of 10%), the results show a significant enhancement in energy saving in favor of the heuristic compared to shortest-path or equiproportional routing schemes. Hence, the results depicted in Fig. 13c emphasizes the need to take into account the heterogeneity in terms of transmission power in the load balancing according to the cost in order to better balance the energy consumption of the nodes.

7.3.1. Traffic varying

To better understand how all the strategies behave when the traffic load increases, we varied λ_g from 1000 to 10,000 packets. The results are presented in Fig. 14 for a scenario with a base station in the corner of the grid and in Fig. 15 for the scenario with a base station in the center of the grid. In these figures, we plotted the maximum energy consumed by a node in the network based on generated traffic λ_g by each node. As expected, the energy consumption grows linearly when λ_g increases in all the strategies. However, the traditional routing schemes do not maximize the network lifetime. Indeed, such a shortest-path routing has heavy consequences on the network lifetime. Besides, we have kept the same scale between the two Figs. 14 and 15 to highlight a subsidiary result that comes from comparison of the two figures. We note that the network will have a longer lifetime when the base station is in the center of the grid.

Furthermore, in order to experiment our strategies, we implemented a proportion based protocol for load balancing and lifetime maximization in WSN [23]. The experiments were performed with TmoteSky sensors[24], a platform smaller than a business card. It includes a microcontroller operating at 8 MHz, 48 K of ROM, 10 K of RAM, a 2.4 GHz ZigBee wireless transceiver, and a USB interface for device programming and logging. More details on the implementation approach are described on [23].



(a) Equiproportional routing

(c) Proposed heuristic

(b) Shortest-Path routing

(d) Optimal solution

Fig. 13. Distribution of energy consumptions in a grid of 33 × 33 nodes with *BS* in the center. *i* and *j* are the coordinates of the node $n_{i,j}$ in the grid. The vertical axis represents the energy consumption of each node $n_{i,j}$ in the grid.

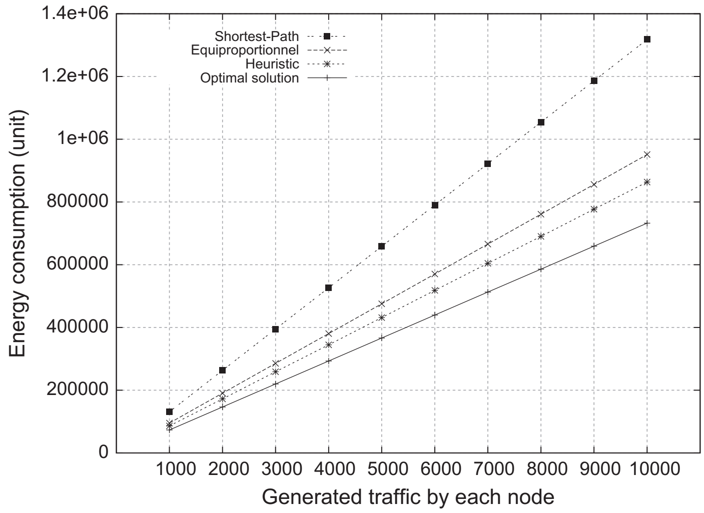


Fig. 14. Maximum energy consumption by a node in a grid topology of (10×10) with *BS* in the corner.

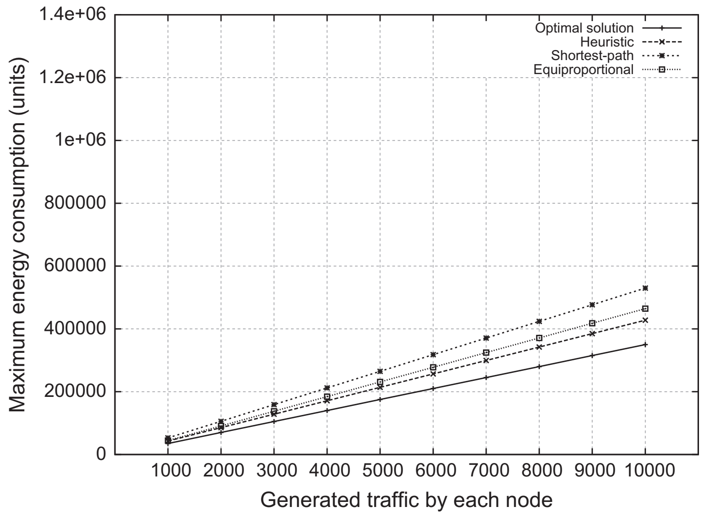


Fig. 15. Maximum energy consumption by a node in a grid topology of (10×10) with *BS* in the center.

7.4. Case of irregular topologies

For irregular topologies a neighboring discovery protocol may be associated to the load balancing method. It is not optimal, but it is a distributed policy. This policy may also be enhanced using additional signaling in order to prevent sensor nodes' loss or to detect some new critical nodes, which appear for a given physical reason or for another. This signaling will allow calculating again the proportions of the messages to send between the remaining valid sensor nodes.

Furthermore, we can discuss our techniques according to the well-known LEACH routing protocol. LEACH is a cluster-based protocol, it uses randomized rotation of roles of cluster heads to consume energy evenly. The advantage of leach is the data aggregation achieved by the cluster heads. Thus, the number of transmitted packets is reduced. In this work we proposed load balancing techniques independently of data aggregation or data gathering aspects. Otherwise the lifetime of the network will be further maximized. Our techniques can be easily combined to such aspects. However, the major inconvenient of LEACH is the geographic scope. As the intra-cluster topology is a star and the cluster heads are directly connected to this Sink, the covered area is limited because of the transmission range limitation. In contrast, our techniques can be deployed regardless of the geographical area since they are based on robust calculations for multi-hop routes.

8. Conclusion

In this paper we analyzed lifetime maximization strategies based on load-balancing. Our idea is that protocols with simple mechanisms can be designed for more balanced routing to ensure a longer network lifetime. This study explore ways to maximize a sensor network lifetime. After defining the problem within a specific scenario, we presented an optimal solution extending the network lifetime. In addition to the optimal solution we proposed a load-balancing heuristic based on transmission power control. Our proposals have been compared to conventional mechanisms such as ‘‘shortest-path’’ and ‘‘equiproportional’’ routing. The load balancing with the proposed heuristic is not optimal in the cases studied but can be evaluated taking into account the additional signaling plans. Our simulation results show that both of optimal solution and heuristic outperform the traditional routing schemes in terms of network lifetime.

Finally, this study showed through simple examples the superiority of the proposed solutions compared to conventional routing schemes. As a research perspective to this work, we think that it would be a challenging to consider other scenarios with different transmission power levels. We can also generalize the presented methods to reflect an uneven distribution of energies or uneven generated traffic rates. Moreover, all of the studied mechanisms may enter in the design of a routing protocol. Indeed, a power control based protocol can be combined with our mechanisms to improve the network lifetime.

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