Wireless Pers Commun (2013) 68:303–319
DOI 10.1007/s11277-011-0453-x

Sink Node Placement Strategies for Wireless Sensor Networks

Fengchao Chen · Ronglin Li

Published online: 15 November 2011

Abstract In wireless sensor networks (WSNs), all the data collected by the sensor nodes are forwarded to a sink node. Therefore, the placement of the sink node has a great impact on the energy consumption and lifetime of WSNs. This paper investigates the energy-oriented and lifetime-oriented sink node placement strategies in the single-hop and multiple-hop WSNs, respectively. The energy-oriented strategy considers only the minimizing of the total energy consumption in the networks, while the lifetime-oriented strategy focuses much more on the lifetime of the nodes which consume energy fastest. Using a routing-cost based ant routing algorithm, we evaluate the performances of different placement strategies in the networks. Simulation results show that the networks with lifetime-oriented strategy achieve a significant improvement on network lifetime.

Keywords Wireless sensor networks · Sink node placement · Network lifetime · Energy consumption

1 Introduction

Wireless sensor networks (WSNs) consist of large numbers of low-power and low-cost sensor nodes which are deployed in a designated region. Each node can gather information within its sensing range, and then transmits data to its neighboring nodes. The information collected by all nodes is finally forwarded to the base station, which is called the sink node.

The deployment of communication nodes is one of most important factors that affect the lifetime in WSNs. Recently, the research efforts pay much attention to the deployment of sensor nodes (SNs) [1,2] and relay nodes (RNs) [3–6]. However, the deployments of SNs and RNs are not easy to carry out since most of the communication nodes are out of our reach and their distributions are uncontrollable. The sink node placement is easier to be controlled and it is also essential for prolonging the network lifetime.

F. Chen (✉) · R. Li
School of Electronic and Information Engineering, South China University of Technology, Guangdong 510640, China
e-mail: fengchao_chen@163.com

In this paper, we focus on WSNs with a single static sink node. If the sensor nodes are uniformly deployed in a regular geometric region, such as a circular region or a rectangular region, the sink node will be placed at the center of the region. Most researches and simulations were carried out based on this placement strategy. Efrat et al. [7] and Jun and Hubaux [8] applied the P-Median Problem (PMP) model to determine the sink node placement, which was proved to be non-deterministic polynomial-time hard (NP-hard). It has been proved in [8] that the center of the circle is the optimal position for a base station in WSNs, but the conclusion is only suitable for the uniform deployment of nodes. In [9], the sink node position was chosen to maximize the combined weight of data flows so that the energy consumption could be reduced. Pan et al. [10] proposed a generic two-tiered WSNs model and focused on the topology of base-stations and application nodes. The network lifetime was evaluated by the average bit-stream rate and the distance between all sensor nodes and the sink node. However, the energy hole [11,12] in WSNs was not considered in the above-mentioned papers. Luo et al. [13] used the PMP model to formulate the placement problem of multiple sink nodes and implemented the solution with an iterative algorithm. However, the placement of the sink nodes need to be predetermined for some selected points. The research in [14] determined the sinks placement by calculating the number of sensor nodes whose data were relayed by a neighboring node of the sink. The minimum of the objective function in the strategy was then found to approximate the PMP model. However, this algorithm is not steady in WSNs with dynamic routing protocol. Guney et al. [15] used mixed-integer linear programming formulations to describe the integrated model of the sink location and routing problem. The sensing field was divided into many grids and the nodes were arranged at the grid points. The solution minimized the total energy consumption and balanced the data flow in the networks, but it did not consider the residual energy of the sensor nodes and could not work with dynamic routing.

In this paper, we propose some sink node placement strategies to prolong the network lifetime in homogeneous WSNs. First, we introduce the energy-oriented and lifetime-oriented placement strategies in single-hop WSNs. Second, we introduce the energy-oriented and lifetime-oriented placement strategies in multi-hop WSNs. Finally, the performances of different sink node placement strategies are evaluated combined with the routing-cost based ant routing algorithm. The paper is organized as follows. Section 2 discusses the sink node placement strategies in single-hop WSNs. Section 3 discusses the sink node placement strategies in multi-hop WSNs. In Sect. 4, we simply analyze the routing-cost and use it to construct the heuristic factor in the ant routing algorithm. In Sect. 5, we show the performances of different sink node placement strategies. Finally a conclusion is drawn in Sect. 6.

2 Sink Node Placement Strategies in Single-Hop WSNs

In this section, we present a model of the networks, and provide two strategies to find an optimal position for the sink node. The sink node placement problem is discussed in single-hop WSNs, and then the objective function $g(x, y)$ of energy-oriented strategy and lifetime-oriented strategy are analyzed. Finally our goal is to minimize $g(x, y)$.

2.1 Model and Definitions

Network Model

In this paper, we assume that there is only one static sink node in the networks, and the sensor nodes with the same data generation rate are deployed randomly in a convex region S. We also assume that the distribution of sensor nodes meets both the coverage and the connectivity requirements of the networks.

Energy Model

For the energy model, we only consider energy consumption for data transmitting and receiving. Let $E_{TX}(d)$ and E_{RX} denote energy consumption of transmitting and receiving 1-bit data, respectively. The first order radio model in [16] is adopted, and we have

$$E_{TX}(d) = E_{elec} + \varepsilon_{amp} d^2 \tag{1}$$

$$E_{RX} = E_{elec} \tag{2}$$

where d is the transmitting distance, E_{elec} is the energy consumed by the transmitter or the receiver, and ε_{amp} is the amplification coefficient.

Network Lifetime

There are different definitions of the network lifetime proposed in [17,18]. Here we choose the n-of-n lifetime metric adopted in [18], that is, the network lifetime ends as soon as the first node fails.

2.2 Energy-Oriented Strategy

Let N denote the number of sensor nodes, and node i $(i = 1, 2, \ldots, N)$ is deployed independently at (U_i, V_i) in the region S with a probability density function $f(u, v)$. In some small scale WSNs, each node sends message to the sink directly. We should choose an optimal position (x, y) for the sink, so that the expected value of total transmitting energy consumption in the networks reaches minimum. The objective function is given by

$$g(x, y) = E\left[\sum_{i=1}^{N} E_{TX}(D_i)\right] \tag{3}$$

where D_i is a random variable, and it means the distance between (x, y) and (U_i, V_i), that is

$$D_i = d(x, y, U_i, V_i) = \sqrt{(x - U_i)^2 + (y - V_i)^2} \tag{4}$$

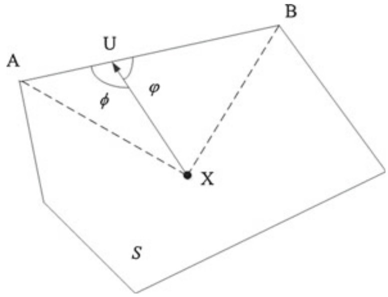
Because (U_i, V_i) $(i = 1, 2, \ldots, N)$ is independent, applying (1), (3) and (4), we have

$$\begin{aligned} g(x, y) &= E\left[\sum_{i=1}^{N} E_{TX}\left(\sqrt{(x - U_i)^2 + (y - V_i)^2}\right)\right] \\ &= N \int\int_{(u,v)\in S} E_{TX}\left(\sqrt{(x - u)^2 + (y - v)^2}\right) f(u, v)\, du dv \\ &= N \int\int_{(u,v)\in S} \left\{E_{elec} + \varepsilon_{amp}\left[(x - u)^2 + (y - v)^2\right]\right\} f(u, v)\, du dv \end{aligned} \tag{5}$$

Finally, the aim is to find minimization of $g(x, y)$. Here we can use the particle swarm optimization (PSO) algorithm [19] to find the optimal placement. Another way to solve the problem is shown as follows. We can differentiate (5) with respect to x and y, and then set the result to 0, that is

$$\partial g/\partial x = 0, \partial g/\partial y = 0 \tag{6}$$

Fig. 1 S is a convex polygon in lifetime-oriented strategy



We have

$$\int\int_{(u,v)\in S} 2\varepsilon_{amp}\,(x-u)\, f\,(u,v)\, du dv = 0,\quad \int\int_{(u,v)\in S} 2\varepsilon_{amp}\,(y-v)\, f\,(u,v)\, du dv = 0 \tag{7}$$

Therefore, the solution can be computed as follows.

$$x = \int\int_{(u,v)\in S} uf\,(u,v)\, du dv,\quad y = \int\int_{(u,v)\in S} vf\,(u,v)\, du dv \tag{8}$$

It means that the optimal placement of the sink is the center of gravity of region S.

2.3 Lifetime-Oriented Strategy

When the sink node is placed at the center of gravity, the total energy consumption is minimal. However, the sensor nodes consume energy in different speeds. The node which is farthest from the sink consumes energy fastest and has a shortest lifetime. Our goal of this strategy is to find a proper position for the sink node, which minimizes the fastest energy consumption in S. It can be formulated as

$$\begin{aligned} g\,(x,y) &= \max_{(u,v)\in S} E_{TX}\left(\sqrt{(x-u)^2+(y-v)^2}\right) \\ &= \max_{(u,v)\in S} \left\{E_{elec} + \varepsilon_{amp}\left[(x-u)^2+(y-v)^2\right]\right\} \end{aligned} \tag{9}$$

Because the sensor nodes are deployed randomly, (9) means that we should first find the farthest point from the sink in S.

When S is a convex region, it is obvious that the farthest point belongs to the boundary of the region. In particular, when S is a convex polygon (see Fig. 1), we assume that X is the coordinate of the sink; A and B are two adjacent vertices of S; U (U$\neq$A and U$\neq$B) is a point on the boundary AB. In Fig. 1, we have $\phi \geq 90°$ or $\varphi \geq 90°$, that is, XA or XB is longer than XU. Therefore, when S is a polygon, the farthest point from the sink is one of the vertices.

Finally, we set $g\,(x,y)$ to be the farthest distance between the sink and the boundary point of S, and use the PSO algorithm to find the minimum of the object function.

3 Sink Node Placement Strategies in Multi-Hop WSNs

A multi-hop case is much more popular than a single-hop case in WSNs. However, the solution is more complicated.

In WSNs, there are two methods to estimate the total energy consumption of the networks per unit of time.

The first method is carried out by adding the energy consumption of each node. The amount of data transmitting and data receiving of each node per unit of time is estimated. Then (1) and (2) are used to compute the energy consumption of each node, and finally the total energy consumption per unit of time of all nodes can be estimated.

In the second method is carried out by adding the energy consumption of each route. Firstly, the data generation rate of each node is estimated. Then the energy consumption per unit of time on the route from each source node to the sink is computed. Finally, the total energy consumption per unit of time is the sum of the energy consumption of each route.

Since the nodes are deployed randomly, it is difficult to compute energy consumption of the sensor nodes. In this paper, the placement strategies are analyzed based on the second method. We give approximate solutions for the energy-oriented strategy and the lifetime-oriented strategy, which are different from solutions in the sing-hop WSNs.

3.1 Energy-Oriented Strategy

Vincze et al. [14] has made a simple analysis of the energy-oriented strategy in multi-hop WSNs. In this section we only depict the same strategy in a stochastic distribution case.

Applying (1) and (2), we can compute the energy consumption of node when it forwards 1-bit data in an h hops route.

$$\delta_m = \begin{cases} E_{TX}(d_m) = E_{elec} + \varepsilon_{amp} d_m^2, & m = 0 \\ E_{RX} + E_{TX}(d_m) = 2E_{elec} + \varepsilon_{amp} d_m^2, & m = 1, 2, \ldots, h-1 \end{cases} \tag{10}$$

where d_m is the transmitting distance of the mth hop, and δ_m is 1-bit energy consumption of data forwarding. In (10), the source node ($m = 0$) transmits the data, while other relay nodes ($m = 1, 2, \ldots, h-1$) receive and then transmit the data. The energy consumption of the sink node is neglected.

Applying (10), we can compute the total energy consumption Θ_i in the networks when the source node i transmits 1-bit data to the sink.

$$\Theta_i = (2H_i - 1)\, E_{elec} + \varepsilon_{amp} \sum_{m=0}^{H_i - 1} D_{im}^2 \tag{11}$$

where D_{im} and H_i are random variables of transmitting distance and hops, respectively.

However, it is difficult to compute (11) precisely in WSNs with random distribution, so two approximations are given as follows.

(1) The hops of the route are proportion to the distance between the source node and the sink, that is

$$H_i = cD_i \tag{12}$$

where D_i is the distance between the source node i and the sink, and $c(c > 0)$ is a constant.

(2) The expected value of D_{im}^2 is a constant, and it is independent of H_i, that is

$$ED_{im}^2 = \sigma \tag{13}$$

where $\sigma(\sigma > 0)$ is a constant.

According to the network model, each sensor node has the same probability density function $f(u, v)$. Therefore, in the energy-oriented strategy, $g(x, y)$ can be depicted as

$$\begin{aligned} g(x, y) &= E\left[\sum_{i=1}^{N} \Theta_i\right] = E\left\{\sum_{i=1}^{N}\left[(2H_i - 1)E_{elec} + \varepsilon_{amp}\sum_{m=0}^{H_i-1} D_{im}^2\right]\right\} \\ &= \sum_{i=1}^{N}\left(2E_{elec}EH_i + \varepsilon_{amp}ED_{im}^2 EH_i - E_{elec}\right) \\ &= \left(2E_{elec} + \varepsilon_{amp}\sigma\right)NcED_i - NE_{elec} \end{aligned} \tag{14}$$

We notice that $\left(2E_{elec} + \varepsilon_{amp}\sigma\right)Nc > 0$, so $g(x, y)$ can be simplified as

$$g(x, y) = ED_i = \int\int_{(u,v)\in S} \sqrt{(x-u)^2 + (y-v)^2} f(u, v)\, dudv \tag{15}$$

The PSO algorithm can be used to find the optimal place of the sink. The iterative method can also solve the problem [20]. (15) is differentiated with respect to x and y, and the result is set to be 0, that is

$$\begin{cases} N\int\int_{(u,v)\in S} \frac{2(x-u)}{\sqrt{(x-u)^2+(y-v)^2}} f(u, v)\, dudv = 0 \\ N\int\int_{(u,v)\in S} \frac{2(y-v)}{\sqrt{(x-u)^2+(y-v)^2}} f(u, v)\, dudv = 0 \end{cases} \tag{16}$$

Finally, the iterative formulae are

$$\begin{cases} x \leftarrow \dfrac{\int\int_{(u,v)\in S} \frac{uf(u,v)}{\sqrt{(x-u)^2+(y-v)^2}} dudv}{\int\int_{(u,v)\in S} \frac{f(u,v)}{\sqrt{(x-u)^2+(y-v)^2}} dudv} \\ y \leftarrow \dfrac{\int\int_{(u,v)\in S} \frac{vf(u,v)}{\sqrt{(x-u)^2+(y-v)^2}} dudv}{\int\int_{(u,v)\in S} \frac{f(u,v)}{\sqrt{(x-u)^2+(y-v)^2}} dudv} \end{cases} \tag{17}$$

3.2 Lifetime-Oriented Strategy

The above solution finds the placement which makes the energy consumption minimal. However, it is usually not the optimal solution for the lifetime in WSNs. For example, when the coordinate of the solution is in an area where the sensor density is very low, it means that there will not be enough sensor nodes near the sink to relay the data and thus the network lifetime will be shorter. We prefer to choose a placement in an area where the sensor density is higher even if the energy consumption in the networks is not minimal.

Let R_c denote the communication range of the node, and region S_i is the communication region of the sink node, that is

$$S_i = \left\{(u, v) | (u, v) \in S, \sqrt{(u-x)^2 + (v-y)^2} \le R_c\right\} \tag{18}$$

Region S_o is defined as $S_o = S - S_i$.

Considering the solution of energy hole problem in [1], the number of sensor nodes in S_i must be more than that in S_o in order to achieve the subbalanced energy depletion. However, in most of the time, the deployment of sensor nodes cannot follow a geometric distribution, so the sensor nodes in S_i usually fail faster. The objective function should take into account both the total energy consumption and the sensor density near the sink. According to the energy-oriented strategy, we should make the total distance between all sensor nodes and the sink as short as possible to reduce the energy consumption. On the other hand, the networks should have enough sensor nodes in S_i to prolong the network lifetime. Therefore, $g(x, y)$ in the lifetime-oriented strategy can be described as follows.

$$g(x, y) = E\left[\frac{\sum_{i=1}^{N} D_i}{M(x, y)}\right] \tag{19}$$

where the random variable $M(x, y)$ is the amount of sensor nodes in S_i.

If the connectivity of the networks is fulfilled, there must be at least one sensor deployed in S_i, that is, $M(x, y) \geq 1$. The probability that a sensor is deployed in S_i can be written as

$$p = \int\int_{(u,v)\in S_i} f(u, v)\, dudv \tag{20}$$

where $q = 1 - p$ is the probability that the sensor is deployed in S_o.

The conditional probability density function of the node which is deployed in S_i can be given as

$$f_i(u, v) = f(u, v|\,(u, v) \in S_i) = \begin{cases} \frac{f(u,v)}{\int\int_{(u,v)\in S_i} f(u,v)dudv} = \frac{f(u,v)}{p}, (u, v) \in S_i \\ 0,\ \text{others} \end{cases} \tag{21}$$

The conditional probability density function of the node which is deployed in S_o can be given as

$$f_o(u, v) = f(u, v|\,(u, v) \in S_o) = \begin{cases} \frac{f(u,v)}{\int\int_{(u,v)\in S_o} f(u,v)dudv} = \frac{f(u,v)}{q}, (u, v) \in S_o \\ 0,\ \text{others} \end{cases} \tag{22}$$

Because $M(x, y) \geq 1$, without loss of generality, we assume that node 1 must be deployed in S_i and is subject to $f_i(u, v)$. Therefore, the probability that there are $(i + 1)\,(i = 0, 1, \ldots, N - 1)$ sensor nodes deployed in S_i is

$$p_i = P(M(x, y) = i + 1) = C_{N-1}^{i} p^i q^{N-1-i} \tag{23}$$

Let $A(x, y)$ and $B(x, y)$ denote the expected value of $D_i (i = 1, 2, \ldots, N)$ in S_i and S_o, respectively, that is

$$\begin{aligned} A(x, y) &= E[D_i|\,(U_i, V_i) \in S_i] \\ &= \int\int_{(u,v)\in S_i} \sqrt{(x-u)^2 + (y-v)^2} f_i(u, v)\, dudv \\ &= \frac{1}{p}\int\int_{(u,v)\in S_i} \sqrt{(x-u)^2 + (y-v)^2} f(u, v)\, dudv \end{aligned} \tag{24}$$

$$\begin{aligned}B(x,y) &= E\left[D_i\,|\,(U_i,V_i)\in S_o\right]\\ &= \int\int_{(u,v)\in S_o}\sqrt{(x-u)^2+(y-v)^2}\,f_o(u,v)\,dudv\\ &= \frac{1}{q}\int\int_{(u,v)\in S_o}\sqrt{(x-u)^2+(y-v)^2}\,f(u,v)\,dudv \qquad (25)\end{aligned}$$

When $M(x,y)=m(m\geq 1)$, the conditional expectation in (19) is given by

$$\begin{aligned}E\left[\frac{\sum_{i=1}^{N}D_i}{M}\middle|M=m\right] &= E\left[\frac{\sum_{(U_i,V_i)\in S_i}D_i+\sum_{(U_i,V_i)\in S_o}D_i}{M}\middle|M=m\right]\\ &= \frac{mE\left[D_i\,|\,(U_i,V_i)\in S_i\right]+(N-m)\,E\left[D_i\,|\,(U_i,V_i)\in S_o\right]}{m}\\ &= A+\frac{N-m}{m}B \qquad (26)\end{aligned}$$

where M, A and B are the abbreviation of $M(x,y)$, $A(x,y)$ and $B(x,y)$, respectively. Applying (26), the objective function (19) can be computed as follows.

$$\begin{aligned}g(x,y) &= p_0E\left[\frac{\sum_{i=1}^{N}D_i}{1}\middle|M=1\right]+p_1E\left[\frac{\sum_{i=1}^{N}D_i}{2}\middle|M=2\right]+\cdots\\ &\quad +p_{N-1}E\left[\frac{\sum_{i=1}^{N}D_i}{N}\middle|M=N\right]\\ &= \sum_{i=0}^{N-1}p_iE\left[\frac{\sum_{i=1}^{N}D_i}{M}\middle|M=i+1\right]=\sum_{i=0}^{N-1}p_i\left[A+\frac{N-(i+1)}{i+1}B\right] \qquad (27)\end{aligned}$$

Substitute (23) into (27), and we notice that $p+q=1$. Then

$$\begin{aligned}g(x,y) &= A\sum_{i=0}^{N-1}C_{N-1}^{i}p^iq^{N-1-i}+B\sum_{i=0}^{N-1}\frac{N-i-1}{i+1}C_{N-1}^{i}p^iq^{N-1-i}\\ &= A+\frac{qB}{p}\sum_{i=1}^{N-1}C_{N-1}^{i}p^iq^{N-1-i}\\ &= \frac{Ap+Bq}{p}-B\frac{q^N}{p} \qquad (28)\end{aligned}$$

Substitute (24) and (25) into (28), and we have

$$\begin{aligned}g(x,y) &= p^{-1}\left[\int\int_{(u,v)\in S_i}\sqrt{(x-u)^2+(y-v)^2}\,f(u,v)\,dudv\right.\\ &\quad \left.+\int\int_{(u,v)\in S_o}\sqrt{(x-u)^2+(y-v)^2}\,f(u,v)\,dudv\right]\\ &\quad -p^{-1}q^{N-1}\int\int_{(u,v)\in S_o}\sqrt{(x-u)^2+(y-v)^2}\,f(u,v)\,dudv\\ &= p^{-1}\int\int_{(u,v)\in S}\sqrt{(x-u)^2+(y-v)^2}\,f(u,v)\,dudv\\ &\quad -p^{-1}q^{N-1}\int\int_{(u,v)\in S_o}\sqrt{(x-u)^2+(y-v)^2}\,f(u,v)\,dudv\end{aligned}$$

$$= p^{-1} E D_i - p^{-1} q^N E\left[D_i | (U_i, V_i) \in S_o\right] \tag{29}$$

Finally, $g(x, y)$ can be computed by (20), (25) and (29). Then the PSO algorithm is used to find the optimal solution.

4 Ant Routing Algorithm

In Sect. 3, it is mentioned that the sensor nodes are deployed in the region with a probability density function $f(u, v)$ in the multi-hop WSNs. It means that the node densities may be heterogeneous in different directions of the sink. For example, when the left node density of the sink is larger than the right side, the problem is that whether the energy is consume faster in the right side so that the network lifetime becomes shorter, even the amount of sensor nodes in S_i is large enough. Therefore, it is important that the route can avoid the nodes with less residual energy, and the networks can achieve energy balance in different directions and make full use of all the energy in S_i.

There are many classical routing algorithms in WSNs, such as *Directed Diffusion* algorithm in [21], *LEACH* algorithm in [16], and so on. According to the above sections, we prefer a flat routing algorithm which chooses a route according to the energy distribution in the networks. The ant routing algorithm constructed by the residual energy of the sensor nodes or hops information is adopted in this paper [22,23]. First of all, we improve the ant routing algorithm in WSNs, so that it can reflect the route characteristics more objectively.

4.1 Basic Ant Colony Algorithm

The basic ant colony algorithm can be simply described by two rules, that is, the node transition rule and the updating rule [24].

The node transition rule defines the probability p_{ij}^k to select node j as the next hop when the forward ant k locates in node i.

$$p_{ij}^k = \begin{cases} \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta}, & j \in N_i^k \\ 0, & \text{others} \end{cases} \tag{30}$$

where N_i^k is the set of neighboring nodes which have not been visited. τ_{il} ($l \in N_i^k$) is a pheromone value on the link (i, l), and η_{il} is a heuristic factor. α and β are parameters that control the relative importance of τ_{il} and η_{il}.

When node i receives a backward ant from its neighboring node j, it uses pheromone updating rule to update the pheromone information. In this paper we adopt the updating rule in AntNet [25]. As the pheromone of node j increases, the pheromone of other neighboring node evaporates in the following manner:

$$\tau_{ij} \leftarrow \begin{cases} \tau_{il} + \rho(1 - \tau_{il}), & l = j \\ \tau_{il} - \rho\tau_{il}, & l \in N_i^k, \quad l \neq j \end{cases} \tag{31}$$

where ρ is an evaporation coefficient.

4.2 Routing-Cost Based Ant Routing Algorithm

We assume that the energy consumption of the sink node can be neglected. The networks select a route of h hops to transmit data from source to destination, and each node in this route consumes energy to forward message. Therefore, the cost of forwarding the message should be determined by the energy information of h nodes on the route.

Here we provide some definitions to compute the routing-cost.

Value of node V_m:

$$V_m = \frac{1}{E_m} \tag{32}$$

where E_m is the residual energy of the node of the mth hop. In WSNs, the node with less energy has more value. In other words, as time passes by, the value of the node increases.

Node cost of data forwarding ω_m:

$$\omega_m = \frac{1}{E_m - \delta_m} - \frac{1}{E_m} = \frac{\delta_m}{E_m\left(E_m - \delta_m\right)} \tag{33}$$

where δ_m is 1-bit energy consumption of data forwarding, which is defined in (10). Node cost is defined as the difference between the node value after data forwarding and the node value before data forwarding. The node with less energy will cost more value to forward data.

Routing-cost of data forwarding γ:

$$\gamma = \sum_{m=0}^{h-1} \omega_m = \sum_{m=0}^{h-1} \frac{\delta_m}{E_m\left(E_m - \delta_m\right)} \approx \sum_{m=0}^{h-1} \frac{\delta_m}{E_m^2} \tag{34}$$

Routing-cost is the sum of all the node cost on the route. Because energy consumption of data forwarding is often far less than the residual energy, that is $\delta_m << E_m$, the equation can be simplified as (34).

From (34) we can notice that the nodes with less energy on the route have much more impact on the routing-cost. The cost of data forwarding increases as a route of less energy or a route of more hops is chosen. In accordance with routing-cost, the networks can choose a route of fewer hops, and make a detour to avoid the low energy area.

Finally, the heuristic factor η_{ij} can be constructed by γ^{-1}.

$$\eta_{ij} = \frac{\gamma_j^{-1}}{\sum_{l\in N_i^k} \gamma_l^{-1}} = \frac{\left[\sum_{m=0}^{h_j-1} \frac{\delta_m^{R_l}}{\left(E_m^{R_j}\right)^2}\right]^{-1}}{\sum_{l\in N_i^k}\left[\sum_{m=0}^{h_l-1} \frac{\delta_m^{R_l}}{\left(E_m^{R_l}\right)^2}\right]^{-1}} \tag{35}$$

where R_l is the optimal route from neighboring node l to the sink, and γ_l is the routing-cost of R_l. $\delta_m^{R_l}$ and $E_m^{R_j}$ are the 1-bit energy consumption and residual energy on the mth hop of R_l, respectively. Therefore, the route with less routing-cost can be selected with a larger probability.

Finally (30) and (35) are used to construct the ant routing algorithm in WSNs.

5 Performance Evaluation

In this section, we evaluate the sink node placement strategies in the sing-hop WSNs and multi-hop WSNs, respectively. The routing-cost based ant colony routing algorithm is adopted in the multi-hop case. Here we set $\alpha = 1$ and $\beta = 3$ in (30) to adapt to the dynamic energy distribution. Evaporation coefficient ρ is set to be a moderate value of 0.5. In the following simulations, we assume that the initial energy of each sensor node is 1 J. E_{elec} and ε_{amp} in the energy model (1) and (2) are set to be 50 nJ and 100 pJ/m^2, respectively.

In the objective functions (5), (9), (15) and (29), it is usually not easy to compute the integration, even if $f(u, v)$ is very simple and S is a regular figure. An approximate solution should be found for $g(x, y)$.

We divide the sensing region S into grids, and there are N_g crossover points. The weight of each point (u_k, v_k) $(k = 1, 2, \ldots, N_g)$ is $f(u_k, v_k)$. Here we take the objective function (29) for example. The discrete function can be expressed as

$$\begin{aligned} g(x, y) = p^{-1} \sum_{i=1}^{N_g} \left[(x-u_i)^2 + (y-v_i)^2\right] f(u_i, v_i) \\ -p^{-1} q^{N-1} \sum_{(u_i, v_i) \in S_o} \left[(x-u_i)^2 + (y-v_i)^2\right] f(u_i, v_i) \end{aligned} \tag{36}$$

where p and q can be computed as follows.

$$p = \sum_{(u,v) \in S_i} f(u_i, v_i) \tag{37}$$

$$q = \sum_{(u,v) \in S_o} f(u_i, v_i) \tag{38}$$

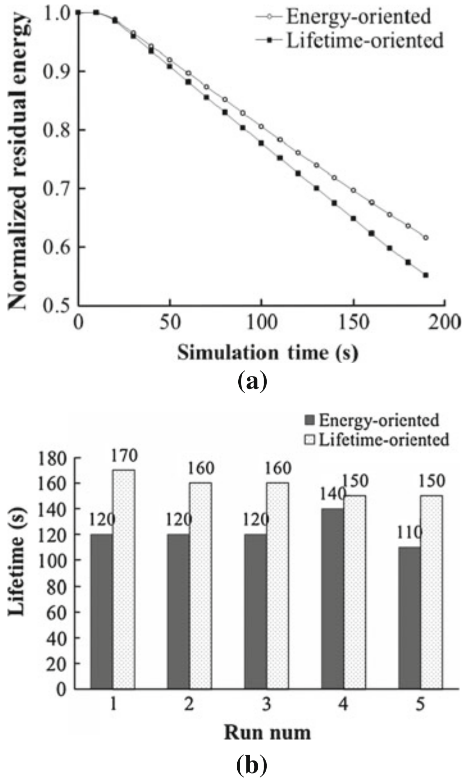
Simulation 1

100 sensor nodes are deployed randomly in a square of $400 \times 400\text{m}^2$. The probability density function shown by (39) complies with triangular distribution in u direction, and it is a uniform function in v direction. Each sensor connects to the sink directly, that is, the networks work on single-hop mode.

$$f(u, v) = \begin{cases} 3.125 \times 10^{-8} \times u, & 0 < u, v \leq 400 \\ 0, \text{ others} \end{cases} \tag{39}$$

We compute the minimum of (5) and (9). The optimal sink node placements are at (267,200) for the energy-oriented strategy, and at (200,200) for the lifetime-oriented strategy. Each strategy runs 5 times with different random seeds for the distribution. Here we choose the average energy consumption and the network lifetime as performance metrics. Figure 2 shows the simulation results in the single-hop case. The average residual energy of the networks at different simulation time in Run 1 is presented by Fig. 2a, and the network lifetime of each run is shown in Fig. 2b. From these figures, we make the following observations. As we predicted, the energy consumption of energy-oriented strategy is lower than that of lifetime-oriented strategy in Fig. 2a. In Fig. 2b, the simulation data are different in each run because of the random distribution, while the networks with the lifetime-oriented strategy always have a longer lifetime. Moreover, in most cases, the lifetime-oriented strategy achieves more than 30% improvement in lifetime when compared with the energy-oriented strategy. Therefore, the simulation shows the better performance of the lifetime-oriented strategy in terms of the network lifetime in the single-hop WSNs.

Fig. 2 Performances of two sink node placement strategies in single-hop case Eq. (39). (**a**) Average of residual energy, (**b**) network lifetime



Simulation 2

370 sensor nodes are deployed randomly in a square of $600 \times 600\text{m}^2$. The probability density function is shown by (40). The source nodes transmit data to the sink node in a multi-hop way.

$$f(u,v) = \begin{cases} \frac{1}{33} \times 10^{-4}, & 0 \le u \le 250 \text{ and } 0 \le v \le 600 \\ \frac{1}{66} \times 10^{-4}, & 250 < u \le 350 \text{ and } 0 \le v \le 600 \\ \frac{1}{33} \times 10^{-4}, & 350 < u \le 600 \text{ and } 0 \le v \le 600 \\ 0, & \text{others} \end{cases} \tag{40}$$

We find the minimum of (15) and (29). The optimal placements are at (300,300) for the energy-oriented strategy, and at (421,300) for the lifetime-oriented strategy. (40) shows that the node density near (300,300) is lower than that near (421,300). Moreover, the node densities are heterogeneous in different directions of the sink, therefore, the routing-cost ant routing algorithm is chosen here to make full use of all the energy in S_i. Figure 3 shows the energy and lifetime performances of different placement strategies in the multi-hop case. Figure 3a shows that in the simulation time [0,100], the networks with lifetime-oriented strategy consume energy slightly faster than the networks with energy-oriented strategy, while the difference between the two curves increases after 100 s. The nodes of energy-oriented strategy in S_i fail faster after 100 s, and the networks have to drop more packets; on the contrary, the nodes of lifetime-oriented strategy in S_i fail slower, and the networks will con-

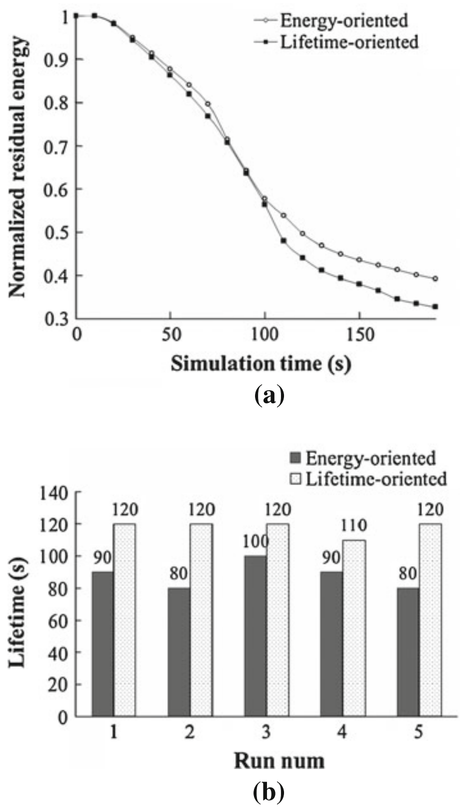


Fig. 3 Performances of two sink node placement strategies in multi-hop case Eq. (40). (**a**) Average of residual energy, (**b**) network lifetime

sume more energy to finish the communication. Figure 3b shows the network lifetime of the two placement strategies. Compared with the energy-oriented strategy, the lifetime-oriented strategy prolong the lifetime by more than 20% in each run. The improvement of lifetime performance is attributed to the high node density in S_i.

Simulation 3

300 sensor nodes are deployed randomly in a square of $600 \times 600\text{m}^2$. The probability density function is shown in (41). The node density increases as u increases. The source nodes transmit data to the sink node in a multi-hop way.

$$f(u, v) = \begin{cases} \frac{u}{324} \times 10^{-6} + \frac{1}{54} \times 10^{-4}, & 0 < u, v \leq 600 \\ 0, & \text{others} \end{cases} \tag{41}$$

In Simulation 3 we compare the performances of different sink node placements. This simulation shows the trade-off between total energy consumption and sensor density near the sink node in the multi-hop case. Figure 4 illustrates energy consumption and the network lifetime of three sink node placements, that is, the center of the sensing region, the placement computed by energy-oriented strategy and the placement computed by lifetime-oriented strategy. The corresponding coordinates of these three positions are (300,300), (343,300) and (417,300). In Fig. 4a, the difference of energy consumption between the three strategies is slight, and is similar to the result of Simulation 2. The energy-oriented strategy has the best

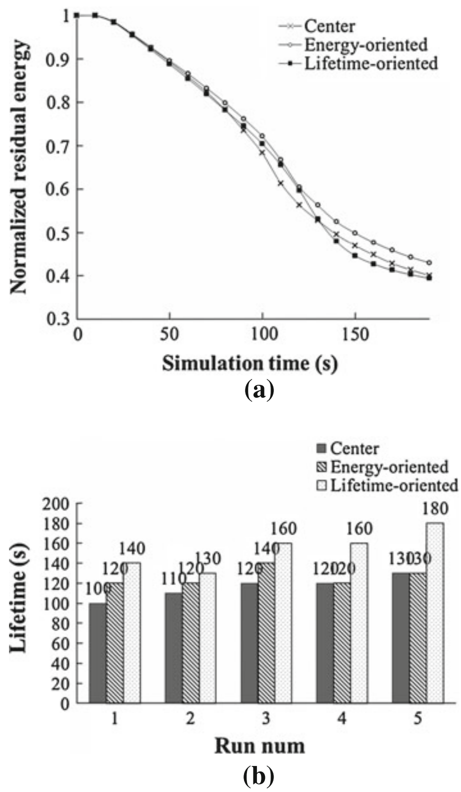


Fig. 4 Performances of three sink node placement strategies in multi-hop case Eq. (41). (**a**) Average of residual energy, (**b**) network lifetime

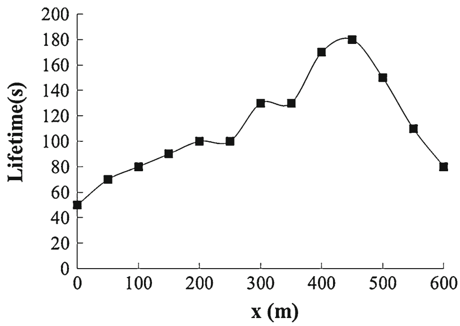


Fig. 5 The network lifetime of different positions in multi-hop case ($y = 300\,\text{m}$) Eq. (41)

energy performance. In the first 120 s, the networks with lifetime-oriented strategy consume energy slightly faster than the networks with energy-oriented strategy; while after 120 s, the difference between these two curves increases because the networks with lifetime-oriented strategy drop fewer packets and consume more energy to finish the communication. In Fig. 4b, it is clear that the lifetime-oriented strategy has the best lifetime performance, and in most cases, it shows more than 30% improvement compared with the center strategy. The energy-oriented strategy just has a slightly better lifetime performance than the center strategy.

Figure 5 shows the network lifetime when the sink node is placed at different positions in Simulation 3. Here we change the x-coordinate of the sink node from 0 to 600 m, and simulate the networks every 50 m. The y-coordinate is set to be 300 m constantly. According to the x-coordinates decided by the two placement strategies, that is, (343,300) and (417,300), the curve in Fig. 5 can be divided into three parts. First, we notice that from 0 to 343 m of the x-coordinate, the total energy consumption decreases and the sensor density increases, therefore the network lifetime increases. Second, when the sink moves from 343 to 417 m of the x-coordinate, both the total energy consumption and the sensor density increase. Due to the high sensor density, the network lifetime increases too. Third, when the sink moves from 417 to 600 m of the x-coordinate, the lifetime decreases even if the sensor density increases in this range. This is because the energy consumption of the networks increases as the x-coordinate of the sink node keeps far away from 343 m. We can notice that the optimal placement in Fig. 5 is consistent with the solution of the lifetime-oriented strategy.

6 Conclusions

In this paper we have explored the sink node placement problem and proposed strategies to find the optimal position from a perspective of the network lifetime in the single-hop WSNs and multi-hop WSNs, respectively. We adopt a routing-cost based ant routing algorithm to simulate the networks. The simulations show that the lifetime-oriented strategy generally outperforms the energy-oriented strategy in terms of network lifetime. In addition, simulation results suggest that the sink node placement strategy in the multi-hop WSNs should seeks a trade-off between the total energy consumption and the sensor density in S_i, so that the network lifetime can reach maximum.

The lifetime-oriented strategy shows significant advantage of prolonging the network lifetime in single-sink WSNs. However, the research on multi-sink WSNs is more complicated and needs further investigation.

Acknowledgments This work was supported by the National Natural Science Foundation of China (NSFC 60871061), the Guangdong Natural Science Foundation (GDSF 8151064101000085), and the Specialized Research Fund for the Doctoral Program of Higher Education (SRFDP 20080561).

References

1. Wu, X. B., Chen, G. H., & Das, S. K. (2008). Avoiding energy holes in wireless sensor networks with nonuniform node distribution. *IEEE Transactions on Parallel and Distributed Systems, 19*(5), 710–720.
2. Li, Q. Q., Yang, M., Jin, Y., Zheng, J., Jiang, Y. T., & Zeng, J. Z. (2009). Load-similar node distribution for prolonging network lifetime in PMRC-based wireless sensor networks. *Communication and Networking, 56*, 384–393.
3. Xu, K. N., Hassanein, H., Takahara, G., & Quanhong, W. (2010). Relay node deployment strategies in heterogeneous wireless sensor networks. *IEEE Transactions on Mobile Computing, 1*(28), 145–159.
4. Misra, S., Hong, S. D., Xue, G. L., & Tang, J. (2010). Constrained relay node placement in wireless sensor networks: Formulation and approximations. *IEEE-ACM Transactions on Networking, 18*(2), 434–447.
5. Lloyd, E. L., & Guoliang, X. (2007). Relay node placement in wireless sensor networks. *Computers, IEEE Transactions, 56*(1), 134–138.
6. Kaur, T., & Baek, J. (2009). A strategic deployment and cluster-header selection for wireless sensor networks. *IEEE Transactions on Consumer Electronics, 55*(4), 1890–1897.
7. Efrat, A., Har-Peled, S., & Mitchell, J. S. B. (2005). Approximation algorithms for two optimal location problems in sensor networks. In *Broadband networks, 2005. BroadNets 2005. 2nd international conference on* (pp. 767–776), Boston, USA, 3–7 October 2005.
8. Jun, L., & Hubaux, J. P. (2005). Joint mobility and routing for lifetime elongation in wireless sensor networks. In *INFOCOM 2005. 24th annual joint conference of the IEEE computer and communications societies. Proceedings IEEE* (pp. 1735–1746), Fédérale de Lausanne, Switzerland, 13–17 March 2005.

9. Bogdanov, A., Maneva, E., & Riesenfeld, S. (2004). Power-aware base station positioning for sensor networks. In *INFOCOM 2004. 23rd annualJoint conference of the IEEE computer and communications societies*, Hong Kong, China, 7–11 March 2004.
10. Pan, J. P., Cai, L., Hou, Y. T., Shi, Y., & Shen, S. X. (2005). Optimal base-station locations in two-tiered wireless sensor networks. *IEEE Transactions on Mobile Computing, 4*(5), 458–473.
11. Li, J., & Mohapatra, P. (2005). An analytical model for the energy hole problem in many-to-one sensor networks. In *Vtc2005-Fall: 2005 IEEE 62nd vehicular technology conference, Proceedings* (pp. 2721–2725), Dallas, USA, 25–28 September 2005.
12. Li, J., & Mohapatra, P. (2007). Analytical modeling and mitigation techniques for the energy hole problem in sensor networks. *Pervasive and Mobile Computing, 3*(3), 233–254.
13. Luo, D. D., Zhao, H., Bi, Y. G., Lin, K., Zhang, X. Y., Yin, Z. Y., et al. (2007). Multiple sink nodes' deployment based on PMP in WSNs. In *Pervasive computing and applications, 2007. ICPCA 2007. 2nd international conference on*, Birmingham, UK, 26–27 July 2007.
14. Vincze, Z., Vida, R., & Vidacs, A. (2007). Deploying multiple sinks in multi-hop wireless sensor networks. In *2007 IEEE international conference on pervasive services*, Istanbul, Turkey, 15–20 July 2007.
15. Guney, E., Aras, N., Altinel, I. K., & Ersoy, C. (2010). Efficient integer programming formulations for optimum sink location and routing in heterogeneous wireless sensor networks. *Computer Networks, 54*(11), 1805–1822.
16. Heinzelman, W. R., Chandrakasan, A., & Balakrishnan, H. (2000). Energy-efficient communication protocol for wireless microsensor networks. In *System sciences, 2000. Proceedings of the 33rd annual Hawaii international conference on* (pp. 1–10), Cambridge, USA, 4–7 January 2000.
17. Chen, Y. X., & Zhao, Q. (2005). On the lifetime of wireless sensor networks. *Communications Letters, IEEE, 9*(11), 976–978.
18. Dietrich, I., & Dressler, F. (2009). On the lifetime of wireless sensor networks. *ACM Transactions on Sensor Networks, 5*(1), 1–39.
19. Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Neural networks, 1995. Proceedings of IEEE international conference on* (pp. 1942–1948), Washington, DC, USA, Nov/Dec 1995.
20. Leon, C. (1963). Location-allocation problems. *Operations Research, 11*(3), 331–343.
21. Intanagonwiwat, C., Govindan, R., & Estrin, D. (2000). Directed diffusion: A scalable and robust communication paradigm for sensor networks. In *Proceedings of MobiCom 2000. Sixth annual international conference on mobile computing and networking* (pp. 56–67), Boston, USA, 6–11 August 2000, Acm.
22. Zhang, Y., Kuhn, L. D., & Fromherz, M. P. J. (2004). Improvements on ant routing for sensor networks. In *4th international workshop on ant colony optimization and swarm intelligence (ANTS 2004)* (pp. 154–165), Brussels, Belgium, 5–8 September 2004.
23. Xie, H., Zhang, Z. G., & Zhou, X. G. (2009). A novel routing protocol in wireless sensor networks based on ant colony optimization. In *2009 international conference on environmental science and information application technology* (pp. 646–649), Wuhan, China, 04–05 July 2009.
24. Colorni, A., Dorigo, M., & Maniezzo, V. (1991). Distributed optimization by ant colonies. In *Proceedings of the 1st European conference on artificial life* (pp. 134–142), Paris, France.
25. Di Caro, G., & Dorigo, M. (1998). AntNet: Distributed stigmergetic control for communications networks. *Journal of Artificial Intelligence Research, 9*(1), 317–365.

Author Biographies

Fengchao Chen received the B.S. degree in School of Physics and Telecommunication Engineering, South China Normal University, in 2004 and 2007, respectively. He is currently working toward the Ph.D. degree in School of Electronic and Information Engineering, South China University of Technology. His current research interests include routing algorithm and sink node placement strategies in wireless sensor networks.

Ronglin Li received the B.S. degree in electrical engineering from Xi'an Jiaotong University, China, in 1983, and the M.S. and Ph.D. degrees in electrical engineering from Chongqing University, in 1990 and 1994, respectively. He is a Professor in School of Electronic and Information Engineering, South China University of Technology. His research interests include new design techniques for antennas in mobile and satellite communication systems, phased arrays and smart antennas for radar applications, wireless sensors and RFID technology, electromagnetics and information theory.