Prolonging the Lifetime of Large Scale Wireless Sensor Networks via Base Station Placement

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***Abstract*—Network lifetime is a critical design goal of any battery operated large scale wireless sensor networks (WSNs). In this paper, we investigate how to prolong the lifetime of large scale WSNs via optimal placement of base stations (BSs). With multiple BSs placed, the sensor nodes can send their data to nearby sinks and may reduce energy consumption of relaying packets for other sensor nodes. Due to the high cost of BSs and geographical constraints in WSNs, we can only place a limited number of BSs in a few candidate locations. Considering wireless transmission features and flow routing, we formulate this base station placement (BSP) problem in WSNs into a mixed integer nonlinear programming (MINLP) problem. In view of the NP-hardness of the formulated problem, we develop the heuristic algorithm to pursue feasible solutions. Through extensive simulations, we show that the solutions found by the proposed algorithm are close to the optimal one and the proposed scheme is effective in prolonging the lifetime of large scale WSNs.**

I. Introduction

During the last decade, wireless sensor networks (WSNs) have attracted intensive attention due to its enormous application potential in battlefield surveillance, environmental monitoring, biomedical observation and other fields [1]–[6]. A WSN, consisting of a number of sensor nodes (SNs), is usually required to provide *in situ*, unattended and real-time observations over a vast area. The SNs are endowed with a multitude of sensing modalities (e.g., temperature, pressure, light, magnetometer, infrared and etc.) and are normally powered by batteries. Although there have been significant improvement in processing and computing designs, advances in battery technology still lag behind. Since energy depletion disables the operation of SNs and leads to transmission failures of perceived data in WSNs, energy efficient design is needed for prolonging network lifetime.

In existing literature, there have been many research efforts on prolonging the lifetime of WSNs, where the lifetime refers to the maximum time that all SNs in a WSN remain alive until one or more SNs drain up their energy [2]–[5]. For example, Xie et al. in [2] proposed to employ a wireless charging vehicle periodically traveling inside a WSN to charge SNs wirelessly. As long as a proper cycle and charging time are chosen, they claimed that the WSN would never die. In [3], Hou et al. studied how to extend the lifetime of WSNs through placing aggregation and forwarding nodes (AFNs). AFNs aggregate the collected data from SNs and forward the aggregated data to the sink (i.e., the BS) via the backbone network of AFNs. In this way, the SN's energy consumption of relaying packets for other SNs is saved, and correspondingly the lifetime of WSNs is prolonged. With a joint consideration of lifetime extension, connectivity and fault-tolerance, Tang et al. investigated a similar relay node placement problem in [6]. Given multiple BSs, in [4], Hou et al. investigated the optimal BS selection for anycast routing to maximize the lifetime of WSNs.

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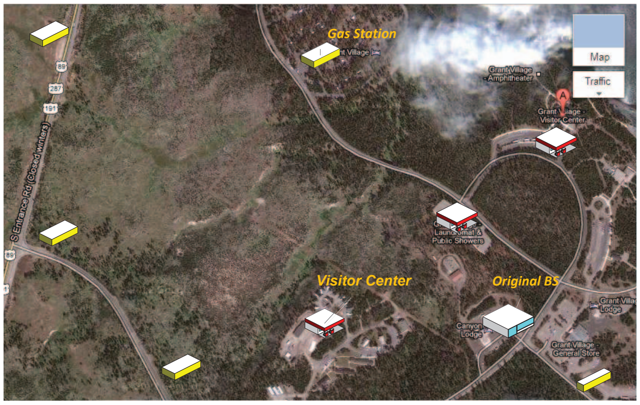
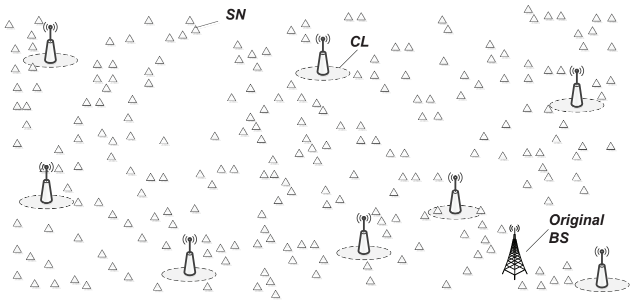
However, most prior schemes may not be applicable for large scale WSNs, especially for those deployed in harsh environments or difficult terrains (e.g., dense forest, mountains, etc.). Specifically, a wireless charging vehicle can charge the nearby SNs along the selected routes, but it cannot provide energy to the SNs deep inside the monitoring area. Besides, deploying an amount of AFNs in large scale WSNs may be extremely difficult due to the large, varying and complex terrains. Moreover, for a large scale WSN, if all sensed data swarms to a single BS, certain relaying SNs may run out of their power fast, which may disfunction the network in a very short time.

Instead of placing AFNs or selecting a designated BS, in this paper, we propose to prolong the lifetime of large scale WSNs via BS placement. The BSs can be mobile BSs or small APs. Considering the cost and difficulty of BS placement in geographically constrained fields, we assume only a limited number of BSs can be placed in certain candidate locations (CLs). Taking the Yellowstone National Park in Fig. 1(a) for example, the CLs can be visitor centers, gas stations and grocery stores. With a given number of BSs placed in selected locations, the manageability of the network is increased, and the energy dissipation at each SN for long distance transmission as well as packet relaying is reduced. In parallel with that, the lifetime of WSNs is extended. Our main contributions are summarized as follows.

- We propose to prolong the lifetime of large scale WSNs via BS placement. With the objective of maximizing the lifetime, we mathematically formulated the BS placement (BSP) in WSNs under energy provision and flow routing constraints into a mixed integer nonlinear programming (MINLP) problem.
- Since the formulated MINLP problem is NP-hard to solve, we develop a heuristic algorithm for solutions and analyze its complexity. If there is a feasible solution, it yields a lower bound of the MINLP optimization.



(a) Skyview of the Yellowstone National Park with only one BS.



(b) Toy topology with candidate locations for BS placement.

Fig. 1. A brief illustration of BS placement in WSNs.

- Through extensive simulations in both grid topology and random topology, we show that the feasible solution obtained by the proposed heuristic algorithm is close to the optimal one. Compared with the random BSP approach and the original WSN with one BS, the proposed BSP scheme is much better in terms of prolonging network lifetime of large scale WSNs.

The remainder of the paper is organized as follows. In Section II, we introduce the network configuration and corresponding models. Based on those models, we mathematically present the BSP problem in Section III. Due to the NP-hardness of the formulated problem, in Section IV, we provide a heuristic algorithm for feasible solutions. We conduct the performance evaluation in Section V, and conclude the paper in Section VI.

II. Network Model

A. Network Configuration

We consider a WSN consisting of $\mathcal{N} = \{1, \cdots, n, \cdots, N\}$ SNs and one original BS as shown in Fig. 1(b). SNs can be application-specific sensors (e.g., pressure sensors, humidity sensors, temperature sensors, video sensors, etc.) deployed at targeted region for sensing/monitoring applications. The SN collects data and aims to send the generated information to the sinks through multi-hop communications. So, the energy consumption of each SN mainly comes from two parts: (i) sending its own sensed information, and (ii) forwarding (or relaying) packets for other SNs. To save the energy consumption of the SN's packet relaying and prolong the network lifetime, we try to place some BSs (e.g., mobile BS or small APs) into the large scale WSN. Due to the cost of placing the BS and geographical constraints in certain difficult terrains (e.g., dense forest, mountains, etc.), we assume that only a limited number of BSs, say M BSs, can be placed in certain CLs. Taking the Yellow Stone National Park for example, those CLs could be visitor centers, grocery stores, restaurants or gas stations along the roads as shown in Fig. 1(a) and 1(b). Denote the CL set by $\mathcal{L} = \{0, 1, \cdots, l, \cdots, L\}$, where CL 0 represents the site of the existing original BS. Then, we have $M \le L$.

B. Power Consumption Model

We assume SNs have exponentially distributed residual energy, denoted by $\mathcal{E} = \{e_1, e_2, \cdots, e_i, \cdots, e_N\}$ $(i \in \mathcal{N})$, by the time we place new BSs into the network. For SNs, the dominant source of power consumption is the energy used for wireless communications (i.e. receiving data and transmitting) [1]. The power dissipation at a receiver [7] can be modeled as

$$p_r(j, i) = \rho \cdot f_{ji}, \tag{1}$$

where $p_r(j, i)$ is the power consumption for SN i $(i \in \mathcal{N})$ as a receiver, when it receives data from SN j $(j \in \mathcal{N})$, ρ is power consumption coefficient for receiving data, which is a constant, and f_{ji} is the bit rate from j to i.

The power dissipation at the transmitter can be modeled as

$$p_t(i, j) = c_{ij} \cdot f_{ij}, \tag{2}$$

where $p_t(i, j)$ is the power dissipated at SN i $(i \in \mathcal{N})$ as a transmitter, when it transmits data to node j, f_{ij} is the bit rate from SN i to node j, and c_{ij} is the power consumption coefficient of radio link (i, j). c_{ij} can be modeled as

$$c_{ij} = \beta + \gamma \cdot d_{ij}^{\alpha}, \tag{3}$$

where β and γ are constants, d_{ij} is the distance between SN i and node j, and α is the path loss index $(2 \le \alpha \le 4)$ [7]. Example values for these parameters are β = 50 nJ/b and γ = 0.0013 pJ/b/m^4 (for $\alpha = 4$) [8].

III. The Formulation of BSP Problem

Given the description of the large scale WSN and power consumption models, in this section, we mathematically formulate the BSP problem under energy provision and flow routing constraints with the objective of maximizing the network lifetime.

Let ω_k represent the status of BS placement at CL k $(k \in \mathcal{L})$, where ω_k is a binary variable. ω_k is equal to 1, if CL k is selected to place a BS, and 0 otherwise, i.e.,

$$\omega_k = \begin{cases} 1, & \text{if CL } k \text{ is chosen to place a BS;} \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

Note that ω_0 = 1 since the original BS is already placed at CL 0. As introduced in Section II, we plan to place M BSs in

L CLs in order to prolong the lifetime of large scale WSNs. Thus, we have

$$\sum_{k\in\mathcal{L}} \omega_k = M + 1. \tag{5}$$

With multiple BSs placed, the SN can save the energy of relaying packets for some other SNs, so that the network lifetime can be extended. According to the definition of network lifetime [2], [3], [5], the SN's energy consumption during the lifetime must be less than or equal to its residual energy, which can be modeled as

$$\Big(\sum_{j\in\mathcal{N},j\neq i} p_r(j,i) + \sum_{j\in\mathcal{N},j\neq i} p_t(i,j) + \sum_{k\in\mathcal{L}} p_t(i,k)\Big)\cdot T \le e_i, \tag{6}$$

where T is the network lifetime of the large scale WSN.

With multiple BSs placed, the SNs can route their traffic to nearby sinks/BSs to save the energy of long distance transmissions. As for flow routing, from the SN's side, it is obvious that the incoming data (i.e., data from other SNs and local generated data) rate should be equal to outgoing data (i.e., data to other SNs and to BSs) rate. Denote the local data generating rate of SN i by g_i. The flow balance of the SN is

$$\sum_{j\in\mathcal{N},j\neq i} f_{ji} + g_i = \sum_{j\in\mathcal{N},j\neq i} f_{ij} + \sum_{k\in\mathcal{L}} f_{ik}\omega_k, \tag{7}$$

where $i \in \mathcal{N}$. From the network side, all collected information should finally flow into BSs. That means the local data generating rate for all SNs should be equal to the incoming data rate for BSs. So, the flow balance of the WSN can be written as

$$\sum_{i\in\mathcal{N},k\in\mathcal{L}} f_{ik}\omega_k = \sum_{i\in\mathcal{N}} g_i. \tag{8}$$

Based on the energy provision and flow routing constrains above, the BSP problem for the lifetime maximization of the large scale WSN can be formulated as follows.

$$\text{Maximize:} \quad T \tag{9}$$

s.t.

$$\sum_{j\in\mathcal{N},j\neq i} f_{ji} + g_i = \sum_{j\in\mathcal{N},j\neq i} f_{ij} + \sum_{k\in\mathcal{L}} f_{ik}\omega_k, \quad (i\in\mathcal{N}), \tag{10}$$

$$\sum_{i\in\mathcal{N},k\in\mathcal{L}} f_{ik}\omega_k = \sum_{i\in\mathcal{N}} g_i, \tag{11}$$

$$\Big(\sum_{j\in\mathcal{N},j\neq i} \rho f_{ji} + \sum_{j\in\mathcal{N},j\neq i} c_{ij} f_{ij} + \sum_{k\in\mathcal{L}} c_{ik} f_{ik}\omega_k\Big)\cdot T \le e_i, \quad (i\in\mathcal{N}), \tag{12}$$

$$c_{ij} = \beta + \gamma\cdot d_{ij}^{\alpha} \quad (i,j\in\mathcal{N}, j\neq i), \tag{13}$$

$$c_{ik} = \beta + \gamma\cdot d_{ik}^{\alpha} \quad (i\in\mathcal{N}, k\in\mathcal{L}), \tag{14}$$

$$\omega_k \in \{0,1\} \quad (k\in\mathcal{L}), \tag{15}$$

$$\sum_{k\in\mathcal{L}} \omega_k = M + 1, \tag{16}$$

where ρ, α, β, γ, g_i and e_i are constants, and f_{ij}, f_{ik}, ω_k and T are variables.

The formulated BSP problem is a mixed integer nonlinear programming (MINLP) problem, which is NP-hard to solve in general [9], [10]. However, when network size is small, we can resort to the brute-force approach to optimally solve that problem. Specifically, we first enumerate every possible scenario, i.e., every possible combination of placing M BSs to L CLs. For each combination, the binary value of ω_k ($k \in \mathcal{L}$) is determined, either 1 or 0, so that $f_{ik}\omega_k$ is f_{ik} or 0. Thus, for each combination, the formulated MINLP problem becomes a Nonlinear Programming (NLP) problem. Although this NLP problem is still NP-hard, the particular structure of the NLP problem allows us to convert it into a LP problem [4], [11]. By multiplying Equation (10) and Equation (11) by T, we can substitute $f_{ij}\cdot T$-variables with F_{ij}-variables, convert the NLP problem into LP problem, and optimally solve it using CPLEX [12]. Finally, we choose the one combination with the maximum lifetime T as the optimal solution. But when network size is large (i.e., the number of SNs, $|\mathcal{N}|$, is big), the computation complexity of this brute-force approach would be huge[1], and we may not find the optimal solution for BSP problem in large scale WSNs. That spurs us to develop the heuristic algorithm to pursuit feasible solutions.

IV. A Heuristic Algorithm for BSP

In this section, we develop a heuristic algorithm called Divide and Brute Force (DBF) to pursuit feasible solutions to the BSP problem, and analyze its complexity.

A. Divide and Brute Force Algorithm

As discussed in Section III, the formulated problem can be optimally solved by brute-force approaches when the network size of the WSN is small. Inspired by this fact, the proposed DBF algorithm tries to divide the overall large-size network into a few small-size subnetworks, and solve the MINLP problem by brute-force approaches in each subnetwork. We briefly list the procedure of the DBF algorithm in Alg. 1.

To reduce the computational complexity, we endeavor to evenly divide the coverage area of the WSN according to the sites of CLs. That is, we try to divide the whole network into $|\mathcal{H}|$ subnetworks, where any two subnetworks have the same or similar number of CLs. The number of BSs to place in a subnetwork, M_i ($i \in \mathcal{H}$ and $M_i \le L_i$), depends on the density of SNs belonging to that subnetwork. Then, within each subnetwork, we have a reduced BSP problem in terms of complexity. Following the solving process presented in Section III, we can find the optimal solution in each subnetwork, determine ω_{k_i}-variables ($k_i \in \mathcal{L}_i$ and $i \in \mathcal{H}$), further set the values of ω_k-variables ($k \in \mathcal{L}$ and $\mathcal{L} = \cup_{i\in\mathcal{H}}\mathcal{L}_i$), and piece up all subnetworks together to obtain the feasible solution. Obviously, this feasible solution yields a lower bound rather than an optimal result, while the computational complexity of BSP problem is significantly reduced. The detailed complexity analysis of the proposed DBF algorithm is presented in the next subsection.

[1]This issue will be further demonstrated in Section IV-B.

Algorithm 1 DBF Pseudocode

```
Divide the WSN into H = {1, ··· h, ··· , H} subnetworks.
Identify the number of SNs N_i, CLs L_i and BSs M_i to
  place in each subnetwork i (i ∈ H).
for all i ∈ H do
    List the set C_i of all possible combinations for placing
      M_i BSs into K_i CLs in subnetwork i.
    Rewrite the MINLP formulation into LP in each
      combination q (q ∈ C_i), and solve the converted LP
      problem.
    Compare the optimal solutions T_i^q of different com-
      binations, and find q* = argmax_{q∈C_i} (T_i^q).
    Determine ω_{k_i} (k_i ∈ L_i) with the combination q*.
end for
Determine ω_k with ω_{k_i} (k ∈ L and L = ∪_{i∈H} L_i).
Rewrite the MINLP formulation into LP with determined
  ω_k values, solve the converted LP, and output the solution
  as the lower bound to the original MINLP.
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B. Complexity Analysis

We start with the complexity analysis of the brute-force approach without network division. Firstly, we list all possible combinations of placing M BSs into L CLs, i.e., $C_L^M = \frac{L!}{M!(L-M)!}$. As for each combination, the converted optimization is a LP problem. The LP problem's inherent computational complexity is $\mathcal{O}(A^3 \cdot B)$ as demonstrated in [13], where A is the number of constraints or variables in the problem, whichever is larger, and B is the number of binary bits required to store the data. Since the number of variables is $\mathcal{O}(N^2)$ and is larger than the number of constraints $\mathcal{O}(N)$, the complexity of solving the converted LP problem is $\mathcal{O}(N^6 \cdot B)$. As a result, the overall complexity is $\mathcal{O}(\frac{L!}{M!(L-M)!} \cdot N^6 \cdot B)$ for the brute-force approach without network division. As for DBF algorithm, the WSN is partitioned into $|\mathcal{H}| = H$ subnetworks and the complexity for solving the reduced BSP problem in the subnetwork is $\mathcal{O}(\frac{(\frac{L}{H})!}{(\frac{M}{H})!(\frac{L-M}{H})!} \cdot (\frac{N}{H})^6 \cdot B)$ by average. Thus, the complexity of the proposed DBF algorithm is $\mathcal{O}(\frac{(\frac{L}{H})!}{(\frac{M}{H})!(\frac{L-M}{H})!} \cdot (\frac{N}{H})^6 \cdot B \cdot H)$, which is significantly reduced compared with that of the brute-force approach without network division.

V. Performance Evaluation

A. Simulation Setup

To evaluate the performance of the DBF algorithm, we consider placing BSs into WSNs with different network sizes (i.e., $|\mathcal{N}|$, the number of SNs) under different topologies. In particular, we consider placing $M = 4$ BSs into $L = 6$ CLs, where the sites of CLs are already fixed according to geographical constraints. The SN can communicate with other SNs that are located within its transmission range, which is 200 (m). For illustrative purposes, the residual energy at SN i is randomly generated following a uniform distribution with $e_i \in [6, 12]$ (kJ) [14], and the local data generating rates of SN i and j ($\forall i, j \in \mathcal{N}$) are set to be the same with $g = 9$ (kb/s). For the other parameters, we have $\alpha = 4$, $\beta = 50$ nJ/b, and $\gamma = 0.0013$ pJ/b/m^4 [8]. Based on the simulation settings above, we conduct simulations to study BSP problem under the grid topology/random topology, where SNs are uniformly/randomly distributed within 500×500 (m^2) area. In addition, all the relaxed/converted LP optimization involved in simulations are solved by CPLEX [12].

B. Results and Analysis

As shown in Fig. 2(a) and Fig. 3(a), when the network size is small ($|\mathcal{N}| \leq 100$), we compare the optimal solution derived by the brute-force approach with the solution derived by the proposed DBF in grid topology and random topology, respectively. From the results, we find that although the DBF algorithm provides a lower bound to the BSP problem, the solution derived by DBF is very close to the optimal one.

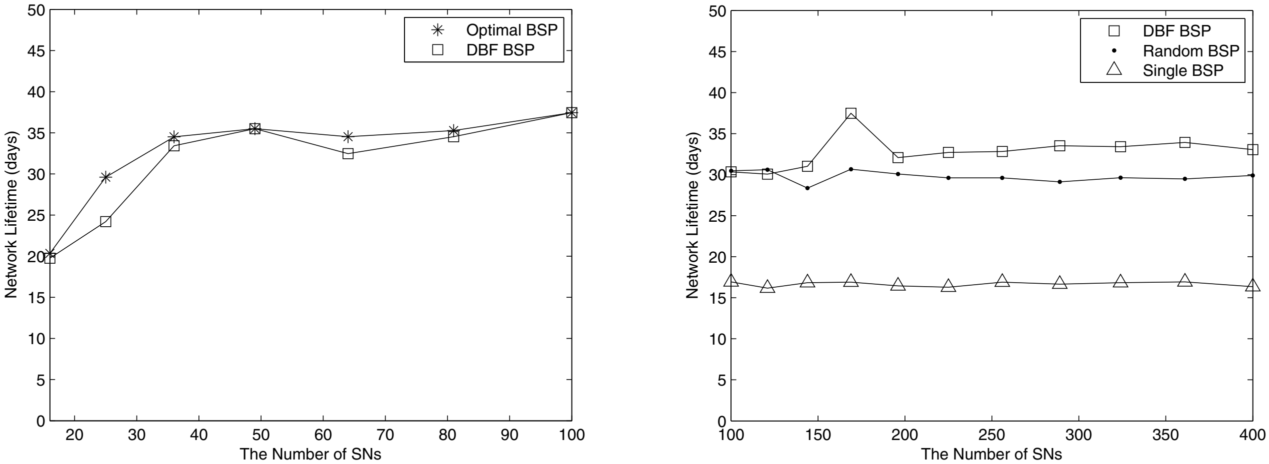
For the large scale WSN where the complexity of the brute-force approach is unacceptably high, we compare the DBF BSP with two other BSP schemes, i.e., the random BSP and the optimal single BSP[2] [5], respectively, and present the results in Fig. 2(b) and Fig. 3(b). It is not surprising that the DBF BSP is much better than optimal single BSP in either grid or random topology. The reason is that with more BSs placed, the SNs can deliver their data to nearby BSs and relay less traffic for other SNs, so that the energy consumption of SNs is reduced and the lifetime of the WSN is effectively prolonged. DBF BSP also outperform random BSP in both topologies. That is because when selecting the CLs to place BSs, DBF considers both energy provision and networking factors, such as the residual energy of SNs, the flow routing, the density of SNs, etc., which have great impact on the lifetime of WSNs.

Another observation is that lifetime T is not monotonic with network size N. More SNs indicate shorter distance between SNs, leading to less energy consumption for long-distance transmission, while more SNs also generate more data flows, leading to more energy consumption in data relaying. Thus, when the number SNs increases, lifetime is not necessarily prolonged or shortened.

VI. Conclusion

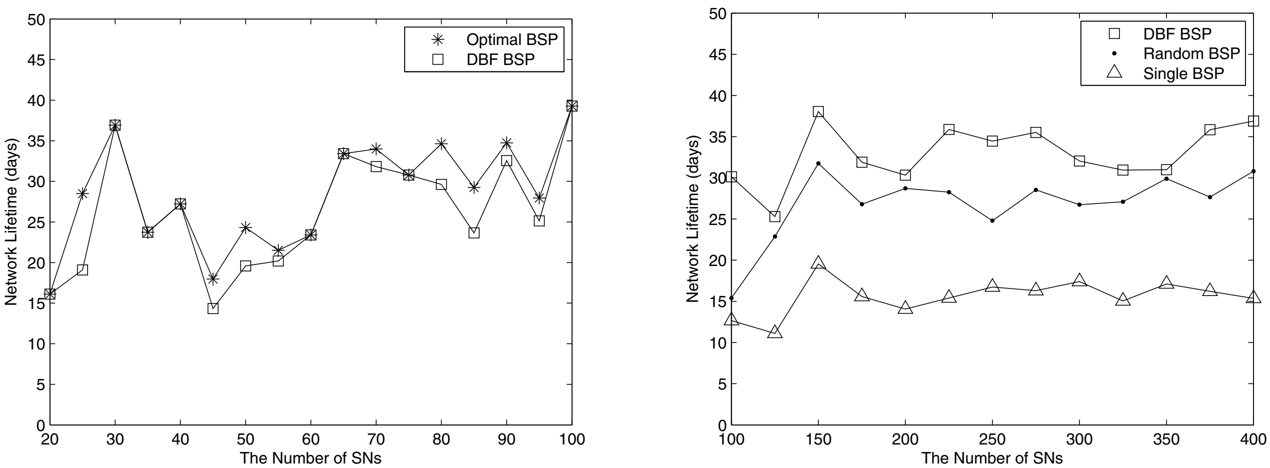
In this paper, we have studied how to extend the lifetime of large scale WSNs via BSP. Considering the features of WSNs, we have mathematically formulated the BSP problem under energy provision and flow routing constraints into a MINLP problem. Due to the NP-harness of the MINLP problem, we have developed a heuristic algorithm, DBF, for feasible solutions. Through extensive simulations, we have shown that the proposed DBF algorithm yields close-optimal solutions, outperforms other BSP algorithms, and is effective in prolonging the lifetime of the large scale WSN.

[2]We strictly follow the proposed BSP scheme in [5], and optimally place the single BS regardless of the geographical limitation.



(a) Network lifetime comparison between the optimal BSP and DBF BSP. (b) Network lifetime comparison with three different BSP methods.

Fig. 2. Network lifetime of the WSN: grid topology.



(a) Network lifetime comparison between the optimal BSP and DBF BSP. (b) Network lifetime comparison with three different BSP methods.

Fig. 3. Network lifetime of the WSN: random topology.

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