In-network Data Aggregation Route Strategy Based on Energy Balance in WSNs

Bin Zhang, Wenzhong Guo*, Guolong Chen
College of Mathematics and Computer Sciences
Fuzhou University
Fuzhou 350108, China
zhangb2366@163.com, guowenzhong@fzu.edu.cn, fzucgl@163.com

Jie Li
Faculty of Engineering, Information and Systems
University of Tsukuba
Tsukuba Science City, 305-8573, Japan
lijie@cs.tsukuba.ac.jp

***Abstract*—In-network data aggregation in wireless sensor networks (WSNs) can reduce data redundancy in the process of data gathering and therefore decrease energy consumption. Since aggregation cost sometimes can not be neglected in some realistic applications, it is important how to construct an effective route strategy which optimizes not only communication cost but also aggregation cost. In addition, we further study how to adaptively adjust route structure to avoid some nodes' premature death. To solve the above problems, we introduce heuristic algorithms based on discrete particle swarm optimization (DPSO). And the notions of mutation and crossover operators in genetic algorithm are incorporated into the discrete procedure of PSO, which can not only keep the diversity of population, but also make offspring population maintain the preferable characteristics. Experimental results show that our algorithms can effectively reduce energy consumption and trade off energy consumption and network lifetime, compared with other tree routing algorithms.**

***Keywords*—WSNs; route; data gathering; data aggregation; PSO**

I. INTRODUCTION

WSNs are one of the most important technologies changing the world in that such networks could provide a variety of applications. The basic function of WSNs is to collect and return data from each sensor node in respective monitored area, so data gathering is a key operation for WSNs to extract useful information from the operating environment. Recent studies [1, 2, 19] show that data aggregation, a process dealing with several data to obtain what data are more suitable for user needs, is particularly useful in eliminating the data redundancy and reducing the communication load. Since wireless sensor nodes are powered by batteries and usually deployed in some harsh environments, it is unrealistic to replace the batteries. Therefore it is a critical problem how to construct a route structure with data aggregation to improve the energy efficiency and extend the lifetime of network.

Energy-efficient routing algorithm for data gathering is a major concern in WSNs. Routing tree structures were adopted in many previous works [3, 4, 5, 7, 8] to collect data: a sensor node transmits its data and the data from its child nodes to its parent node. In [3], the authors considered the problem of correlated data gathering by a network with a sink node and a tree-based communication structure, and proved that minimum-energy data gathering problem is NP-complete and declared that the optimal result is between Shortest Path Tree (SPT) and Traveling Salesman Problem (TSP). In [4], the authors proposed an optimal algorithm called MEGA for foreign-coding and an approximate algorithm called LEGA for self-coding. In MEGA, all nodes first send their gathered data to the sink node via the Minimum Spanning Tree (MST) and then each encoding node sends its respective encoded data to the sink node through the SPT rooted at the sink. In LEGA, the sink node broadcasts its packet to its neighbor nodes and each node sends its data to the sink node by the constructed SLT. By constructing the Shallow Light Tree (SLT), LEGA achieves a $2(1+\sqrt{2})$-approximation of the optimal data gathering route. Khan and Pandurangan [5] proposed a scheme, called NNT, which is a variant of using greedy algorithm to construct minimum Steiner tree. NNT builds a slightly suboptimal tree with low energy complexity, and it is proved that NNT can be used to design a simple dynamic algorithm for maintaining a low-cost spanning tree.

However, those above literatures only pay attention to transmission cost in building routing tree, neglecting the cost in aggregating correlated data. In some practical applications, aggregation cost may be greater than transmission cost, such as image aggregation [6]. Therefore, in addition to transmission cost, aggregation cost can significantly affect routing decisions when involving data aggregation. Luo [7] put forward the MFST algorithm, which is applied to collect data with aggregation by an energy-efficient method in WSNs. MFST takes both transmission cost and aggregation cost into account, and chooses aggregation nodes based on the quantity of data generated by each node. Luo [8] further proposed an improved algorithm of MFST, called AFST. AFST dynamically decides whether to proceed with data aggregation when each relay node transmits data, rather than merely optimize data transmission route.

In this paper, we also include aggregation cost in [7] as another dimension to the space of routing optimization for correlated data. In order to minimize the total energy consumption, an optimal routing algorithm requires jointly optimizing both transmission cost and aggregation cost. On the one hand, since this problem is NP-hard, we design a heuristic algorithm based on DPSO to find approximations to the minimum cost tree. On the other hand, considering that nodes on the constructed tree consume respective energy unevenly so that some nodes may deplete energy earlier ending up with premature death while others' energy is surplus, causing the imbalance of energy consumption, which motivates us to design an adaptive aggregation strategy that not only optimizes current communication load, but also puts additional stress on each node's remaining energy to effectively prolong the lifetime of network. The problem is a multi-objective optimization problem, which is NP-hard as well, and we adopt the phenotype sharing function to appraise the routing tree. Finally our algorithms are compared with other classical tree routing algorithms, such as SPT, MST, SLT and Greed algorithm to construct minimum Steiner tree, and an extensive set of simulations show that proposed algorithms can effectively decrease energy consumption and achieve a good balance between energy consumption and the lifetime of network.

The rest of this paper is organized as follows: In section 2, the system model and problem formulation are described in detail, and then we present our proposed methodology and strategy in section 3. In section 4, we compare our algorithms with other algorithms and evaluate the performance of them. Finally, concluding remarks are made in section 5.

II. System Model and Problem Formulation

A. Network Model

In this paper, we consider a wireless sensor network composed of n nodes uniformly and randomly distributed in the areas of monitored regions. Since typical mode of communication in data aggregation involves multiple data source nodes and one sink node, without lost of generality we assume there are $k(k\leq n)$ source nodes and one sink node. Node u can receive the data from node v if node u is within the communication range of node v; otherwise, they have to communicate with each other through multi-hop wireless links [9]. We model a WSN as an undirected graph $G(V,E)$, where V is a finite set of sensor nodes, and E is defined as the wireless connection between nodes.

B. Correlation and Data Aggregation

As mentioned previously, data from multiple child nodes along the routing tree can be aggregated in order to reduce the communication load of network. The aggregation process is essential a process of data compression and the compression ratio is related to data correlation and redundancy. Due to the uncertainty of the ratio in different application scenarios, [7] used an abstract parameter ρ to denote the data reduction ratio due to aggregation. To be more specific, if node u is a child node of node v in the constructed routing tree and u transmits its data to v, we can summarize the aggregation function at node v as

$$\omega(v)=\left(\omega(u)+\varpi(v)\right)\left(1-\rho_{uv}x_{uv}\right) \tag{1}$$

where $\varpi(v)$ and $\omega(v)$ denote the data amount of node v before and after aggregation respectively, and $x_{uv}\in\{0,1\}$ denotes whether aggregation process occurs between node u and node v. That is to say, if node v is an aggregation point, the data amount of v after aggregating income data of node u is $\omega(v)=\left(\omega(u)+\varpi(v)\right)\left(1-\rho_{uv}\right)$; otherwise, $\omega(v)=\left(\omega(u)+\varpi(v)\right)$.

C. Energy Model

Here, we will jointly consider two aspects of costs: communication cost and aggregation cost.

We will use the following radio communication model[10] to calculate the energy consumption for sending and receiving data. The energy model can be respectively represented by the formula (2) and formula (3):

$$E_T(u,v)=\left(\alpha+\beta*{d_{uv}}^2\right)*\omega(u) \tag{2}$$

$$E_R(u,v)=\alpha*\omega(u) \tag{3}$$

where α is the energy consumed by each sending node to send each bit of data, or each receiving node to receive each bit of data. β is the energy consumption in the amplification circuit for forwarding each bit of data. d_{uv} is the distance between node u and node v. $\omega(u)$ is the data amount transmitted from node u. So for edge $e=(u,v)$, the communication cost $t(e)$ of edge e is given by

$$t(e_{uv})=\left(2\alpha+\beta*{d_{uv}}^2\right)*\omega(u) \tag{4}$$

Here we discuss two node types: aggregation points and non-aggregation points. If node v is a non-aggregation point, it will merely consume energy to transmit data and receive data; if not, it should further consume energy to aggregate its own data and the data from its child nodes. That is to say, besides communication cost, in this paper we also include an aggregation cost model which is presented in [8]. And we use formula (5) to represent the cost for fusing the data of node u and v.

$$f(e_{uv})=q*\left(\omega(u)+\varpi(v)\right) \tag{5}$$

where q indicates average unit aggregation cost and it is dependent on the type of data to be aggregated and data correlation. $\omega(u)$ and $\varpi(v)$ are data amount from u and v own data amount before aggregation.

D. Lifetime Model

Network lifetime [11] is concerned with the period in which the network can maintain its desired functionality. It can be defined as the time till the first node in the network dies, called nodal lifetime; meanwhile it can also be defined as the time till a proportion of nodes die. And we will use the former "definition" as sensor network lifetime in the subsequent discussion in the rest of this paper.

For each sensor node in the network, its energy consumption may involve many factors. For simplicity, here we neglect the impact of other secondary factors and only attach importance to three main factors: transmitting data, receiving data and aggregating data. Therefore for an undirected graph $G(V,E)$, the nodal lifetime of node $v(v\in V)$ can be described as follow:

$$l(G,v)=\frac{E_r(v)}{\sum f+\sum E_T+\sum E_R} \quad (6)$$

where $E_r(v)$ indicates residual energy of node v. $\sum E_T$, $\sum E_R$ and $\sum f$ are energy of node v used to transmit data, receive data and aggregate data if it is a aggregation point. According to previous description, a network ends up with the first node depleting its energy. So we can easily formulate network lifetime as follows [12]:

$$l(G)=\min_{v\in V} l(G,v) \quad (7)$$

From the above formulas, it can be obviously seen what kinds of factors are significant to the uneven energy consumption issue, helping us to explore a more effective algorithm to extend network lifetime in the right direction.

E. Problem Formulation

In this paper, we want to achieve two optimization objectives. Given an undirected graph $G(V,E)$, source node set S and sink node t, we assume G' is a connected subgraph of G and energy consumption of G' is given by

$$E(G')=\sum_{e\in E'_f}\left(f(e)+t(e)\right)+\sum_{e\in E'_n} t(e) \quad (8)$$

E'_f is edge set where the end node of each edge is an aggregation point. E'_n is edge set where the end node of each edge is a non-aggregation point. Our first goal is find a near-optimal subgraph G^* that at least contains node set S and sink node t such that

$$G^*=\arg\min_{G'} E(G') \quad (9)$$

It has been shown that the aforementioned problem is NP-hard [8].

But without considering the imbalance of energy consumption, the constructed routing tree may result in premature death of some nodes, energy hole problem [13] and so on. On the basis of (9), we further consider nodal remaining energy and dynamically adjust routing strategy to balance nodal energy, effectively prolonging network lifetime. So our second goal is to find a feasible subgragh G' considering nodal remaining energy such that

$$\begin{cases} \min E(G') \\ \max l(G') \\ s.t.\quad E(G')\le \varepsilon E(G^*) \end{cases} \quad (10)$$

Notice that ε denotes maximal permissible times of energy consumption of G' to G^* and it is a variable that is set by us. Above problem is a multi-objective optimization problem, which is NP-hard as well because the solving of optimal subgraph G^* is NP-hard.

III. ALGORITHM

A. Basic Particle Swarm Optimization

PSO is a population based search problem, where each particle is defined as a potential solution to a problem in a D-dimensional space, with the ith particle represented as $X_i = (X_{i1}, X_{i2}, \ldots, X_{iD})$. Each particle adjusts its position according to its own flying experience and its neighboring particles' flying experience, close to the minimum. Algorithm records two "*best*" values: one is historically best position (*pbest*) of each particle and the best position (*gbest*) of all particles in the population. Based on these two values, each particle updates its velocity according to the following equations:

$$v_{id}^{t+1}=w\times v_{id}^{t}+c_1r_1\left(p_{id}-x_{id}^{t}\right)+c_2r_2\left(p_{gd}-x_{id}^{t}\right) \quad (11)$$

$$x_{id}^{t+1}=x_{id}^{t}+v_{id}^{t+1} \quad (12)$$

where t is the iteration index, d is the number of dimensions, w is inertia weight, c_1 and c_2 are acceleration factors, r_1 and r_2 are random numbers in the range [0…1].

B. Discrete Particle Swarm Optimization

Since the previously mentioned optimization goals are not only NP-hard but also discrete problems, standard PSO is no appropriate for those above problems and some modifications must be done to the standard PSO.

1) Representation of particles

As our objective is to construct an efficient routing tree structure, we adopt Prufer sequence in literature [14] to represent a labeled tree T whose vertexes are numbered from 1 to n.

Procedure: Encoding

Step 1: Let j be the smallest labeled leaf vertex in the T.

Step 2: Set k to be the first digit in the Prufer sequence if k is incident to j.

Step 3: Remove j and the edge connecting j and k from T.

Step 4: Repeat above steps till only one edge is left and produce the Prufer sequence in order.

Procedure: Decoding

Step 1: Let P be a Prufer sequence, and Q be the set of all vertexes not included in P.

Step 2: Let j be the vertex with smallest label in Q, and k be the leftmost digit in P. Add the edge connecting j and k into the tree. Remove j from Q and k from P. If k does not occur anywhere in Q, put it into Q.

Step 3: Repeat above steps till no digits are left in P.

Step 4: If no digits remain in P, there are exactly two vertexes in Q. Add the edge connecting remaining vertexes into the tree.

2) Discrete procedure of PSO

The notion of mutation operator in GA [15, 16] is incorporated into the first part of (11).

$$A_i^t=F_1(X_i^{t-1},w)=\begin{cases} M(X_i^{t-1}), r_1<w \\ X_i^{t-1}, \text{otherwise} \end{cases} \quad (13)$$

where F_1 indicates the mutation operator with the probability of w.

The second and third parts of (11) all adopt the notion of crossover operator in GA.

$$B_i^t = F_2(A_i^t, c_1) = \begin{cases} C_p(A_i^t), r_2 < c_1 \\ A_i^t, \text{otherwise} \end{cases} \tag{14}$$

$$X_i^t = F_3(B_i^t, c_2) = \begin{cases} C_g(B_i^t), r_3 < c_2 \\ B_i^t, \text{otherwise} \end{cases} \tag{15}$$

where F_2 and F_3 indicate the crossover operators with the probability of c_1 and c_2 respectively.

Then we can get the following formula:

$$X_i^t = F_3(F_2(F_1(X_i^{t-1}, w), c_1), c_2) \tag{16}$$

3) *Fitness value function*

The mutation and crossover operators can not only preferably keep the diversity of population, but also make offspring population keep the preferable characteristics. The difficulty of DPSO is how to define the fitness function of individuals.

For the problem (9), we just use the energy consumed by the constructed tree, namely the formula (8), to evaluate relative merits of each particle.

But the problem (10) is a multi-objective optimization one, so we can not merely use single objective value like energy or lifetime to evaluate the particle. To our knowledge, there are a lot of methods to deal with multi-objective optimization problems such as the *weighted-sum* method, the *utility-function* method and so on. In this paper, Pareto method in [17] is adopted to comprehensively compute the fitness of the particle.

Definition 1 Target Distance fd_{ij}: fd_{ij} is the distance between the two particles i and j. Supposed that the distance has m dimensions which are noted as f_1dij、f_2dij、…、f_mdij respectively, and

$$fd_{ij} = f_1dij + f_2dij + \ldots + f_mdij = \left|f_1\left(x^i\right) - f_1\left(x^j\right)\right| + \left|f_2\left(x^i\right) - f_2\left(x^j\right)\right| + \ldots + \left|f_m\left(x^i\right) - f_m\left(x^j\right)\right|, i \neq j. \tag{17}$$

Definition 2 Dominance Measure $D(i)$: $D(i)$ denotes the state of domination the ith particle with respect to the current population, and

$$D(i) = \sum_{j=1}^{p} nd(i, j) \tag{18}$$

where $nd(i,j)$ is one if particle j dominates particle i, and zero otherwise.

Definition 3 Sharing Function $sh(fd_{ij})$:

$$sh\left(fd_{ij}\right) = \begin{cases} 1, & if\ fd_{ij} \leq \sigma_s \\ 0, & otherwise \end{cases} \tag{19}$$

where σ_s is a sharing parameter.

Definition 4 The Neighbor Density Measure $N(i)$: $N(i)$ associated with particle i is defined as

$$N(i) = \sum_{j=1}^{p} sh\left(fd_{ij}\right) \tag{20}$$

Definition 5 The Fitness of A Given Particle $F(i)$: $F(i)$ is then defined as

$$F(i) = \left(1 + D(i)\right) \times \left(1 + N(i)\right) \tag{21}$$

Since the value of formula (21) may be multi-value, we should choose proper leader particles from personal best and global best with same values to direct the movement of particle. A proper mechanism of choosing leader particles [18] can help to find more Pareto solutions in a shorter time.

C. *Algorithm Overview*

The overview of our strategy can be described as follow:

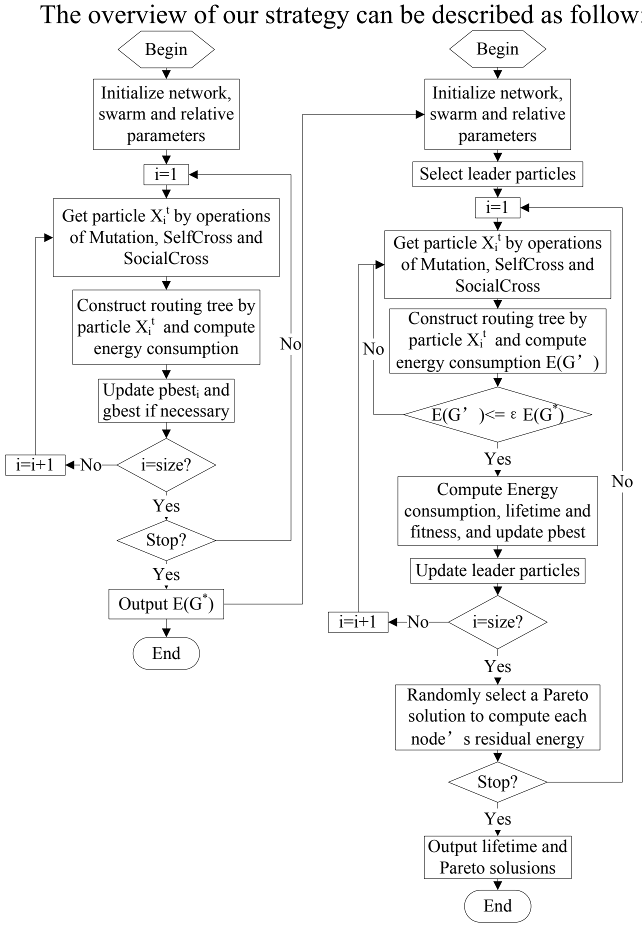


Fig. 1. The flow chart of our strategy

As we can see, our route strategy is divided into two stages. We need to achieve a near-optimal subgraph G^* through DPSO algorithm and apply $E(G^*)$ to optimize network lifetime further.

IV. EXPERIMENTAL STUDY

In this section, the performances of the improved discrete PSO method applied to network optimization in the aspects of energy and lifetime are observed through lots of simulations, which are implemented in MATLAB. And we compare proposed algorithms with other previous tree routing algorithms, such as SPT, MST, SLT and Greed Steiner, with respect to several metrics.

TABLE I. PARAMETER TABLE

Symbol	Definition	Value
σ_s	A sharing parameter whose dimensions equal to the number of objectives	[0.01 0.01]
α	The energy consumed by sending each bit of data	50nJ/bit
β	The energy consumption in the amplification circuit for forwarding each bit of data	100pJ/bit/m^2
w_0	The data amount sent by each source node	400bit
r_s	The correlation range	50m
ρ	The correlation coefficient between two nodes in an approximated spatial model	ρ=1-d/r_s while $d<r_s$, ρ=0 otherwise
r_c	The maximum communication range of each sensor node	From 15m to 50m
n	Number of nodes	50
k	Number of source nodes	7 and 15
q	Average unit aggregation cost	20nJ/bit and 80nJ/bit
ε	Maximal permissible times of energy consumption of G' to G^*	From 1 to 1.5
E_r	The initial energy of each relaying node	2mJ

Without lost of generality, we generate 50 sensor nodes randomly distributed in a 50m×50m region with k source nodes and one sink node. And we initialize each relative parameter as TABLE I.

A. The First Simulation

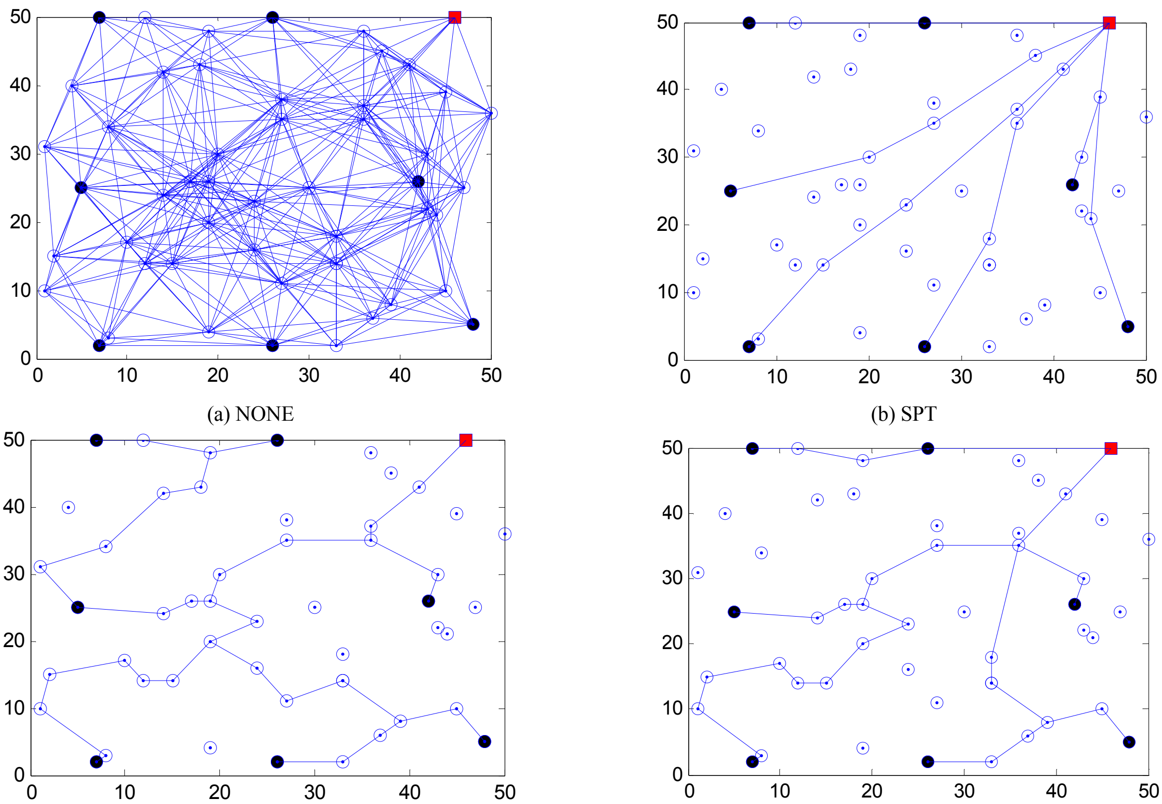
In this simulation, we consider how to construct an optimal routing tree with respect to minimum energy consumption.

Firstly, we set k to be 7, r_c to be 20m and q to be 80nJ/bit to simulate a network, and the tree structures derived by SPT, MST, SLT, Greed Steiner and Our Algorithm are shown in fig. 2. In each picture, red solid square, black solid circles and hollow circles respectively represent the sink node, source nodes and other relay nodes. And data aggregation occurs where information streams intersect.

Secondly we set k to be 7 and q to be 20nJ/bit and 80nJ/bit respectively. By varying r_c from 15m to 50m, we can control the connectivity of the network. The results are shown in fig. 3.

Thirdly we change network structure with k set to 15 and q set to 20nJ/bit and 80nJ/bit respectively. The results are shown in fig. 4.

According to above pictures, we can see MST is to construct an optimal routing structure for the whole graph, wasting precious energy on data aggregation and transmission at unnecessary relaying nodes. While SPT is to construct shortest paths from the sink node to each source. It is not optimal for the subgraph which at least contains the sink node and source nodes, resulting in wasting energy on redundant data transmissions. As SLT reconstructs the tree structure derived by MST, it is a hybrid tree structure balancing MST and SPT, achieving a middle performance between them. Greed Steiner uses a greedy strategy to construct the Steiner minimum tree and achieve better performance.



(a) NONE

(b) SPT

(c) MST

(d) SLT

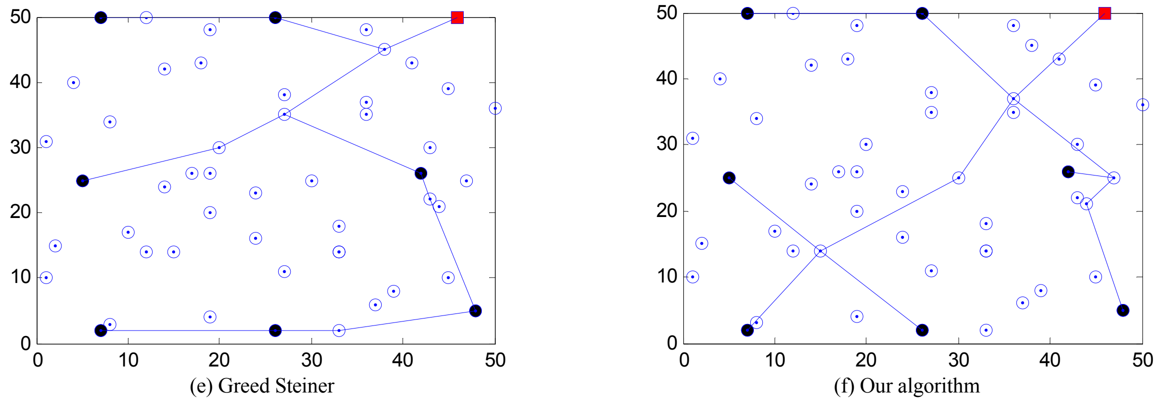


Fig. 2. Routing tree structures

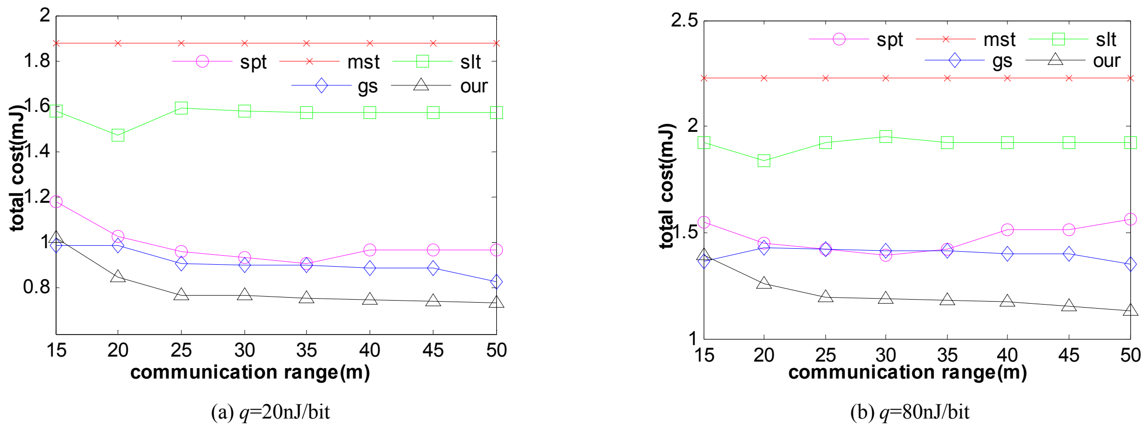


Fig. 3. Impact of r_c to energy consumption when k=7

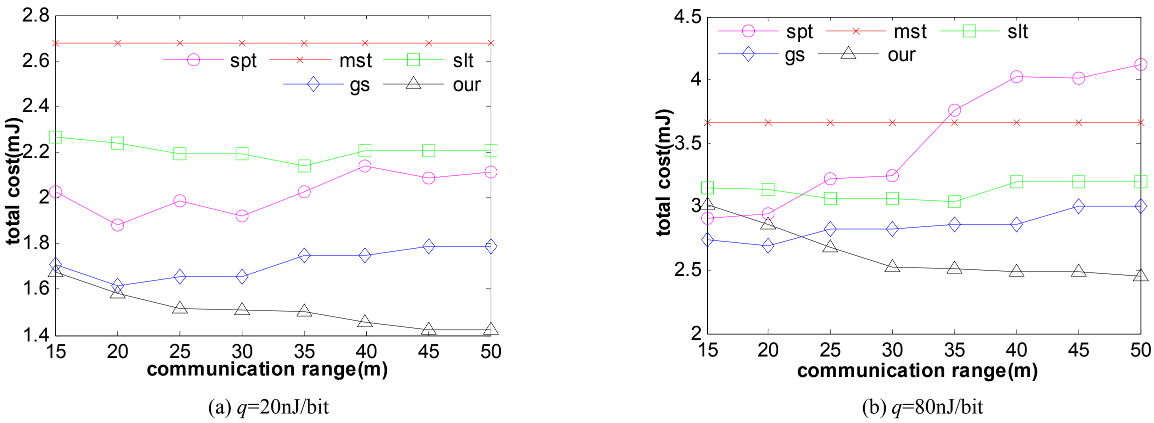


Fig. 4. Impact of rc to energy consumption when k=15

However without considering aggregation cost in the process of tree construction, so energy consumption of Greed Steiner is still relatively high.

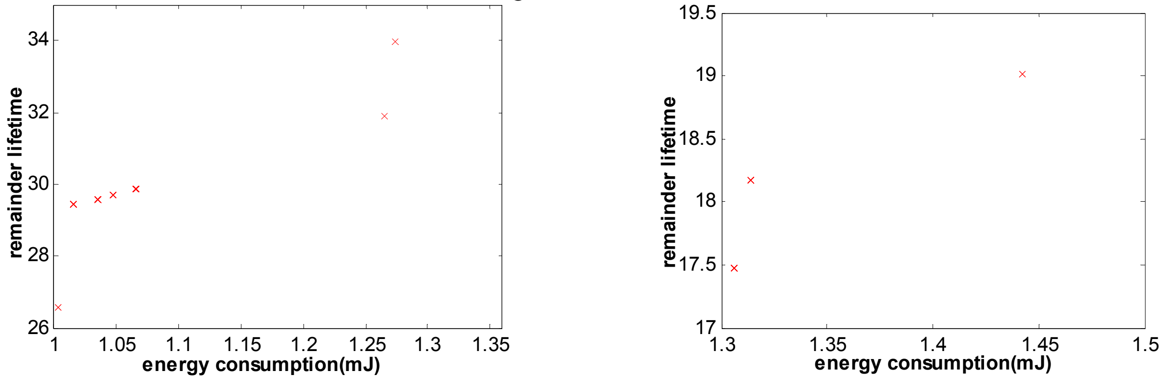
As expected, our algorithm almost outperforms all other algorithms in different communication ranges. It can adapt itself to a variety of situations. In contrast to other algorithms, our algorithm can dynamically change route selection and decide to select which nodes to perform data aggregation according to different network structures and average unit aggregation costs, and it can effectively trade off multi-hop relay benefiting from high data reduction ratio and single-hop transmission benefiting from less unit aggregation cost.

B. *The Second Simulation*

In this simulation, we further consider nodal remaining energy. We fix rc to 50m, and set k to be 7 and q to be 20nJ/bit and 80nJ/bit respectively.

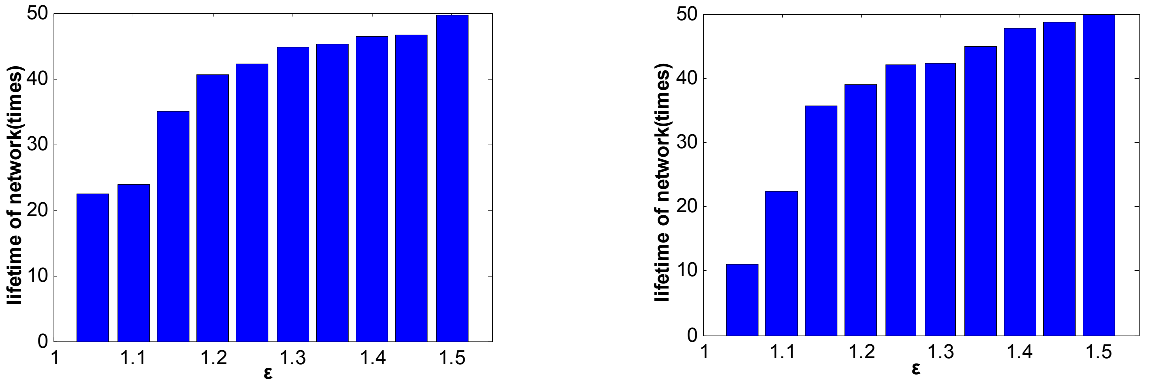
As previously mentioned, problem (10) is a multi-objective optimization problem and its Pareto optimal solutions are multiple. Fig. 5 presents all Pareto optimal solutions in a certain stage where each node is left with different energy, with ε to be 1.5 and q to be 20nJ/bit and 80nJ/bit respectively.

Furthermore, we study the impact of ε on the performance of our algorithm. By varying ε from 1 to 1.5, we can observe the change of network lifetime obviously. As shown in fig. 6, with the increase of ε, the network lifetime becomes longer.



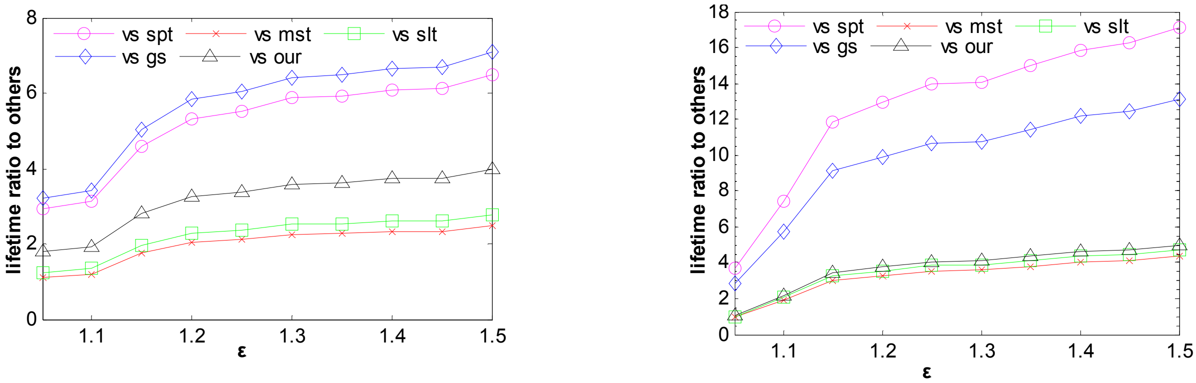
(a) q=20nJ/bit (b) q=80nJ/bit

Fig. 5. Pareto Front when ε=1.5



(a) q=20nJ/bit (b) q=80nJ/bit

Fig. 6. Impact of ε on network lifetime



(a) q=20nJ/bit (b) q=80nJ/bit

Fig. 7. Lifetime ratio of our algorithm to other algorithms

As we see, a small increase of ε may lead to huge extension of lifetime. We further compare our algorithm with others. As shown in fig. 7, with the increase of ε, the lifetime ratio of our algorithm to other algorithms increases drastically. These algorithms include not only SPT, MST, SLT and Greed Steiner, but also our algorithm adopted in the first simulation. While other algorithms throughout use the consistent nodes to transmit or aggregate data despite the fact that some nodes own little energy and other nodes have vast energy remained, resulting in some nodes' premature death, our algorithm can adjust itself to select an optimal route which can balance the total energy consumption and nodal remaining energy, effectively extending network lifetime.

V. CONCLUSION

In this paper, we design discrete PSO-based algorithms to construct an optimal routing tree structure in the process of data gathering with aggregation, considering not only communication cost but also aggregation cost. In addition we further adaptively adjust route strategy according to each nodal remaining energy. The simulation results show that our algorithms can provide a route structure with lower energy consumption while considering aggregation cost, and can trade off communication load and lifetime while considering nodal remaining energy further.

In future work, we will pursue to optimize more other aspects of performance while constructing route structure, such as delay and fault-tolerant ability.

ACKNOWLEDGMENT

This paper is supported by the National Natural Science Foundation of China under Grant No. 61103175 and No.11271002; the Key Project of Chinese Ministry of Education under Grant No.212086 and No. 210110; the Technology Innovation Platform Project of Fujian Province under Grant No. 2009J1007; the Key Project Development Foundation of Education Committee of Fujian Province under Grand No. JA11011; the Fujian Province High School Science Fund for Distinguished Young Scholars under Grand No.JA12016.

REFERENCES

[1] S. Ozdemir and Y. Xiao, "Secure data aggregation in wireless sensor networks: A comprehensive overview," *Computer Networks*, vol. 53, no. 12, pp. 2022-2037, Aug. 2009.

[2] S. Mohanty and D. Jena, "Secure Data Aggregation in Vehicular-Adhoc Networks: A Survey," *Procedia Technology*, vol. 6, pp. 922-929, 2012.

[3] R. Cristescu, B. B. Lozano, M. Vetterli and R. Wattenhofer, "Network Correlated Data Gathering With Explicit Communication: NP-Completeness and Algorithms," *IEEE/ACM TRANSACTIONS ON NETWORKING*, vol. 14, no. 1, pp. 41-54, FEB. 2006.

[4] P. V. Rickenbach, "Energy-Efficient Data Gathering in Sensor Networks [D]," *Swiss: ETH ZURICH*, 2008.

[5] M. Khan, G. Pandurangan and V. S. Anil Kumar, "Distributed Algorithms for Constructing Approximate Minimum Spanning Trees in Wireless Networks," *IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS*, vol. 20, no. 1, pp. 124-139, 2009.

[6] M. Chen, V. Leung and S. Mao, "Directional controlled fusion in wireless sensor networks," *Mobile Netw. Appl.*, vol. 14, no. 2, pp. 220-229, Apr. 2009.

[7] H. Luo, YH. Liu and S. K. Das, "Routing Correlated Data with Fusion Cost in Wireless Sensor Networks," *IEEE TRANSACTIONS ON MOBILE COMPUTING*, vol. 5, no. 11, pp. 1620-1632, NOV. 2006.

[8] H. Luo and J. Luo, "Adaptive Data Fusion for Energy Efficient Routing in Wireless Sensor Networks," *IEEE TRANSACTIONS ON COMPUTERS*, vol. 55, no. 10, pp. 1286-1299, OCT. 2006.

[9] S. Kolli and M. Zawodniok, "A dynamic programming approach: Improving the performance of wireless networks," *Journal of Parallel and Distributed Computing*, vol. 71, no. 11, pp. 1447-1459, NOV. 2011.

[10] YH. Zhu, WD. Wu, J. Pan and YP. Tang, "An energy-efficient data gathering algorithm to prolong lifetime of wireless sensor networks," *Computer Communications*, vol. 33, no. 5, pp. 639-647, MAR. 2010.

[11] Z. Li, Y. Peng, DJ. Qiao and WS. Zhang, "LBA: Lifetime Balanced Data Aggregation in Low Duty Cycle Sensor Networks," *in Proceedings of IEEE INFOCOM*, pp. 1844-1852, 2012.

[12] DJ. Luo, XJ. Zhu, XB. Wu and GH. Chen, "Maximizing Lifetime for the Shortest Path Aggregation Tree in Wireless Sensor Networks," *in Proceedings of IEEE INFOCOM*, pp. 1566-1574, 2011.

[13] J. Jia, J. Chen X. Wang and L. Zhao, "Energy-Balanced Density Control to Avoid Energy Hole for wireless sensor network," *International Journal of Distributed Sensor Networks*, 2012.

[14] WZ. Guo, J. H. Park, L. T. Yang, A. V. Vasilakos, NX. Xiong and GL. Chen, "Design and Analysis of a MST-Based Topology Control Scheme with PSO for Wireless Sensor Networks," *in Proceedings of IEEE Asia-Pacific Services Computing Conference*, pp. 360-367, 2011.

[15] WZ. Guo, NX, Xiong, A. V. Vasilakos, GL. Chen and CL. Yu, "Distributed k-connected Fault-Tolerant Topology Control Algorithms with PSO in Future Autonomic Sensor Systems," *International Journal of Sensor Networks*, vol. 12, no. 1, pp. 53-62, 2012.

[16] WZ. Guo, NX. Xiong, HC. Chao, S. Hussain and GL. Chen, "Design and analysis of self-adapted task scheduling strategies in wireless sensor networks," *Sensors*, vol. 11, no. 7, pp. 6533-6554, Jun. 2011.

[17] GL. Chen, SL Chen, WZ. Guo and HW. Chen, "The Multi-criteria Minimum Spanning Tree Problem Based Genetic Algorithm," *Information Sciences*, vol. 177, no. 22, pp. 5050-5063, Nov. 2007.

[18] F. Neumann, M. Laumanns, "Speeding Up Approximation Algorithms for NP-hard Spanning Forest Problems by Multi-objective Optimization," *Electronic Colloquium on Computational Complexity*, Report No. 29, 2005.

[19] WZ. Guo, NX. Xiong, A. V. Vasilakos, GL. Chen and HJ. Cheng, "Multi-source Temporal Data Aggregation in Wireless Sensors Networks," *Journal of wireless Personal Communications*, vol. 56, no. 3, pp. 359-370, 2011.