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Weak node protection to maximize the lifetime of wireless sensor networks

MAO Yuxing[1,*], ZHAO Huiyuan[1], and YAN Dongmei[2]

1. State Key Lab of Power Transmission Equipment & System Security and New Technology, Chongqing University, Chongqing 400044, China;
2. Science and Technology Enterprise Group of Chongqing University, Chongqing 400044, China

Abstract: Wireless sensor networks (WSN) provide an approach to collecting distributed monitoring data and transmiting them to the sink node. This paper proposes a WSN-based multi-hop network infrastructure, to increase network lifetime by optimizing the routing strategy. First, a network model is established, an operating control strategy is devised, and energy consumption characteristics are analyzed. Second, a fast route-planning algorithm is proposed to obtain the original path that takes into account the remaining energy of communicating nodes and the amount of energy consumed in data transmission. Next, considering the amount of energy consumed by an individual node and the entire network, a criterion function is established to describe node performance and to evaluate data transmission ability. Finally, a route optimizing algorithm is proposed to increase network lifetime by adjusting the transmission route in protection of the weak node (the node with low transmission ability). Simulation and comparison experimental results demonstrate the good performance of the proposed algorithms to increase network lifetime.

Keywords: wireless sensor network (WSN), multi-hop transmission, routing, network lifetime, energy efficient.

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1. Introduction

A wireless sensor network (WSN) is an ad-hoc multi-hop wireless network consisting of many static or moving sensors. It is designed to collaboratively sense, collect, transmit, and process data from monitored objects within network coverage and subsequently send data to the network owner. WSN provides mankind with a practical and effective approach for sensing the outside world and transmitting the message. WSN plays an important role for the internet of things (IoT), which is widely used in many areas.

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*Corresponding author.
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In WSN application scenarios, many sensor nodes are distributed over a large region to process a tremendous volume of data. In addition, the battery capacity, storage capacity, processing capacity, and communication bandwidth of the nodes are limited, thus imposing constraints on the quality of service (QoS) in WSN. QoS criterions in WSN encompass the network's lifetime, coverage, transmission rate, and delay. One of the major factors that influence these criterions is node power control. Most of the energy in sensor nodes is consumed during data transmission, and the amount of energy consumption increases exponentially with transmission distance. Thus, multi-hop transmission is an effective way to reduce energy consumption and enhance load balancing between nodes. By studying the topology of the multi-hop network and optimizing the transmission routes, we can control the transmission power of the nodes, enhance the power balance between nodes, delay node failures, and increase network lifetime.

Methods for forming and controlling multi-hop ad-hoc WSN topology have been studied in the literature. In this topology, the network is usually represented by a directed acyclic graph (DAG) consisting of sensing terminals, a cluster head (CH), and a sink. The focus areas of this study of WSN topology are on network operation mechanisms, node clustering algorithms, and route planning for data transmission.

Many effective application algorithms have been proposed for network modeling and node clustering [1 – 5]. Heinzelman et al. [1] proposed a low energy adaptive clustering hierarchy (LEACH) protocol. LEACH partitions the network communication process into several transmission cycles, selects the head for each cycle stochastically, and follows the rotation strategy. The problem with this approach is that the remaining energy of nodes is not considered. Also, its performance is limited due to the assumption that all nodes can communicate with the head. Shin et al. [2] proposed a balanced clustering algorithm (BCA) for irregularly deployed WSNs. In BCA, each node computes the probability of becoming CH based on the number of nodes in the sensed region, the coverage of each cluster has the same size, and idle redundant nodes are set to sleep mode. In this way, repetitious steps in sensing and transmission are avoided, resulting in alleviated energy consumption and increase of network lifetime. Elhabyan et al. [4] proposed two linear programming algorithms that address clustering and routing problems through particle swarm optimization (PSO). Their clustering method aims to find the best set of cluster heads that maximize energy efficiency, connection quality, and network coverage. In their routing algorithm, the optimal path tree was found through the use of particle coding and fitness function. This scheme has an advantage over other algorithms in terms of measurement reliability and packet transmission rate at the CH. Some researchers have attempted to increase network lifetime by optimizing node distribution and scheduling of transmission slots [6 – 8]. Zhang et al. [7] proposed to balance energy consumption and increase network lifetime through non-uniform data distribution. The game theory has been used to achieve a trade-off between energy consumption and the provision of relaying service at nodes in [8]. Hu et al. [9] used the unscented Kalman filter (UKF) to track and coordinate the network based on an energy balance to facilitate target tracking and node localization. Hou [10] proposed a model that considers the end-to-end delay constraints and delivery ratio requirements of flows jointly, and developed a framework for designing feasibility-optimal policies. Assaf et al. [11] proposed a localization algorithm that is able to accurately locate the sensor nodes owing to a new low-cost implementation.

Path planning is critical in network topology. Due to its ability to reduce energy consumption, prevent data conflicts, and increase data packet transmission rates, the effective transmission path has drawn a lot of attention [12 – 19]. Karp and Kung proposed a greedy perimeter stateless routing (GPSR) algorithm in 2000 for the wireless datagram network in [12]. GPSR determines the path for data forwarding by jointly considering the position of routing nodes and the destination of packets in WSN. GPSR has two modes: greedy forwarding and edge forwarding. GPSR has become the ancestor of many subsequent studies. Xia et al. [13] proposed a gradient based routing (GBR) protocol based on the fact that data always flows to the sink in WSN. GBR protocol defines a gradient for the node based on the distance between the node and the sink, the number of hops, and the energy consumption. While sending data to the sink, each node chooses an upstream node with a small gradient to forward data. The authors in [15] proposed a distributed energy sensing algorithm which plans the routes based on the remaining energy and node coverage. The authors in [18] proposed a hybrid routing strategy to prevent the energy of the hot spot from being exhausted rapidly in WSN. In [19], Hua et al. studied a partition-based routing algorithm and attempted to increase network lifetime through optimization of data aggregation. Some researchers in [20] have attempted mainly studying the use of compression-aware methods to improve the data fusion and compression abilities for extending the network life.

In recent years, more efficient methods have been proposed to address the lifetime maximization problem of WSN [21 – 28]. Xu et al. [23] proposed a cooperative communication method to improve the spatial diversity and maxmize the lifetime for data aggregation. Frezzetti and Manfredi [25] adopted the data compression method based on compressive sensing theory to prolong the lifetime of WSN. They proposed a two-layer controller that ensures efficient signal reconstruction and high network lifetime. Kim [26] proposed a load balancing scheme that balances the energy consumption of the sensor nodes and maximum network lifetime by applying the sub-network management in WSNs. The anthors in [28] proposed an evaluation framework as a benchmark for performance evaluation of routing algorithms based on its ability to specify the optimal performance of increasing network lifetime through the distributed routing strategy. Hou et al. [29] considered a two-tier WSN, and proposed multisession flow routing solutions which split flows to different paths during transmission to extend network lifetime.

This paper uses the DAG-based multi-hop WSN architecture to collect sensor data, studies the network model and routing algorithms, proposes a criterion function for node performance, and increases network lifetime by optimizing the transmission paths in protection of weak nodes. The remainder of the paper is organized as follows. Section 2 describes the system model, which includes discussion on the application scenario and network model; Section 3 proposes a fast route planning algorithm based on remaining energy and energy consumed for data transmission; Section 4 presents a path optimizing strategy, which includes the definition of the performance criterion function and the development of the path optimizing algorithm in protection of weak nodes; Section 5 simulates the proposed algorithm and evaluates performance; Section 6 concludes the paper.

2. System model

In this paper, a WSN-based communication network is constructed to meet the application needs of data collection and transmission using ZigBee terminals. The monitoring devices are deployed at the places where sensing data is collected and sent via the ZigBee module. The network follows the tree-like topology and the coordinator, router, and monitoring terminals are all implemented using the DRF1605H ZigBee module as shown in Fig. 1. They form a tree-like topology that collects data and sends it to the sink. The network coordinator is the sink and is connected to a host PC. The PC is the control center of the WSN and is responsible for route planning, slot allocation, network control, data aggregation, and long-distance data transmission.

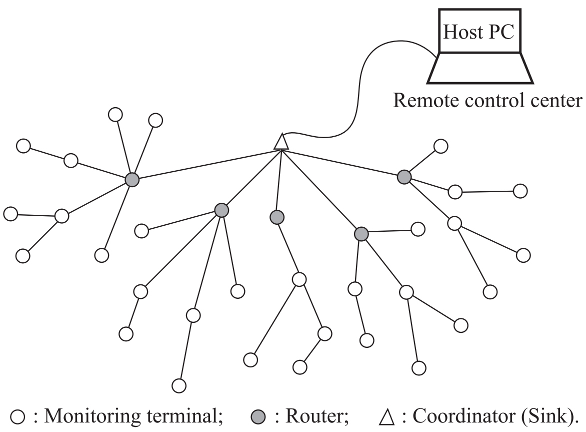


Fig. 1 WSN framework for monitoring data aggregation

The ZigBee communication terminal is a critical network transmission device, all ZigBee nodes have set up the PAN ID, communication channels, transmission baud rates, and user-defined addresses. The control center knows the user-defined addresses, spatial locations, and sensor types of all nodes. The PC sets up the network parameters, plans the transmission paths, and generates network topologies based on node locations and transmission requirements. The coordinator broadcasts topology information to all routers and terminals in the network. Each route and terminal stores the transmission address and distance of the upstream node. The stored data will be utilized as the criterion for selection of the desired node and adjustment of power during data transmission.

Based on the design of the network model, operating conditions of the network are given below:

(i) The network has a tree-like topology with the sink as the root. The root also serves as the coordinator for the ZigBee network.

(ii) All nodes, except the sink, can forward data and serve as a routing or terminal node. In addition to forwarding data, the router needs to send data from its sensor.

(iii) The energy of the router and terminal is fixed and cannot be replenished. The transmission power is controllable and can be adapted to transmission distance. The network will be regarded as failure if any node is unable to transmit data due to exhaustion of energy.

(iv) Network operation is partitioned into multiple cycles, and all nodes send packets only once in a cycle.

(v) All nodes are physically fixed. The host PC knows the location and original energy of each node, and has the ability to compute the remaining energy for each node during each cycle. The host dynamically plans the network during each cycle and broadcasts it to each router and terminal using the coordinator, and activates a transmission cycle.

(vi) Control information is also used as the criterion for clock synchronization. The router and terminal adapt the timing parameter to their locations in the topology and send data packets during the assigned slots.

This paper focuses on dynamic planning of network topology. During each transmission cycle, network paths can be optimized by jointly considering the remaining energy and the total energy consumed in data transmission. The criterion function is defined to evaluate the performance of a node in protection of weak nodes. By doing so, we can increase network lifetime.

3. Path planning based on remaining energy

3.1 Network topology and energy consumption analysis

In this paper, we assume the WSN communication system is consisting of N sensor nodes and a sink, the network model can be represented with a DAG $G(V, E)$, where V denotes a set of $N+1$ nodes and E denotes the set of edges representing the transmission paths. In DAG, all nodes have only one upstream node. Thus, E consists of N edges. The N transmission nodes are numbered $1, 2, \dots, N$ and the sink is numbered $N+1$, so $G(V, E)$ can be uniquely represented by the vector $\boldsymbol{r} = (r_1, r_2, \dots, r_N)^{\mathrm{T}}$, where r_i denotes the upstream node of i and $r_i \in \{1, 2, \dots, N+1\}$.

In the case of data transmission over a short distance, the energy consumptions of nodes in WSN include the energy consumed by the receiving circuit, the sending circuit, and the energy consumed due to attenuation. Without considering multi-path attenuation, the energy can be represented as

$$E = (E_{T-elec} + E_{R-elec} + E_{amp} \times d^2)\mathrm{packet}_{\mathrm{size}} \quad (1)$$

where E_{T-elec} andE_{R-elec} denote the energy consumed by the sending circuit and receiving circuit, respectively. E_{amp} denotes the power amplification coefficient of the attenuation model, d denotes distance between source and desired node, and $\mathrm{packet}_{\mathrm{size}}$ denotes the size of a packet.

Let P_d represent the packets generated by all sensors during each transmission cycle and let P_c represent the information from the control center. Reception of the message P_r and transmission of the message P_t at node i can be expressed as

$$\begin{cases} P_r = (T_i - 1) \cdot P_d + P_c \\ P_t = T_i \cdot P_d \end{cases} \tag{2}$$

where T_i denotes the number of packets to be sent by node i and $T_i - 1$ denotes the number of packets that node i needs to forward as a router. In addition to the forwarded data, the sent data also encompasses the data from the sensor in the node itself. Consider that node i sends the data to the upstream node r_i; let $d_{i,ri}$ represent its transmission distance, i.e., the distance between i and r_i. Based on (1), the energy consumption E_i of i is given as

$$E_i = (E_{T-elec} + E_{amp} \times d_{i,r_i}^2)P_t + E_{R-elec}P_r. \tag{3}$$

Based on the topology, vector $\boldsymbol{r}$ is used to analyze the number of packets T_i sent by node i. Let p_{ji} represent the probability that node j sends data to node i. This is formulated as

$$p_{ji} = \begin{cases} 1, & r_j = i \\ 0, & r_j \neq i \end{cases} \tag{4}$$

where $j \in \{1, 2, \dots, N\}$ and $i \in \{1, 2, \dots, N, N+1\}$.

If node i is the router, then the number of packets that need to be forwarded can be computed as shown in

$$T_i = \sum_{j=1}^{N} p_{ji}T_j + 1. \tag{5}$$

Since the upstream node of any node cannot be the node itself, i.e., $p_{ii} = 0$, $i \in \{1, 2, \dots, N\}$, (5) can be rewritten as

$$T_i - \sum_{\substack{j=1 \\ j \neq i}}^{N} p_{ji}T_j = 1. \tag{6}$$

Define the vector $\boldsymbol{T} = (T_1, T_2, \dots, T_N)^{\mathrm{T}}$ and $\boldsymbol{b} = (1, 1, \dots, 1)^{\mathrm{T}}$. Then (6) can then be rewritten as

$$\boldsymbol{AT} = \boldsymbol{b} \tag{7}$$

where $\boldsymbol{A}$ is an $N \times N$ matrix consisting of p_{ji}. Component $\boldsymbol{A}$ can be obtained directly using (4) and the vector $\boldsymbol{r}$:

$$\boldsymbol{A} = \begin{bmatrix} 1 & -p_{21} & \cdots & -p_{N1} \\ -p_{12} & 1 & \cdots & -p_{N2} \\ \vdots & \vdots & \ddots & \vdots \\ -p_{1N} & -p_{2N} & \cdots & 1 \end{bmatrix}. \tag{8}$$

It is known from (7), that $\boldsymbol{T} = \boldsymbol{A}^{-1}\boldsymbol{b}$, so the number of packets sent by each node (denoted by T_i) can be computed. Based on (2) and (3), the total amount of energy consumption E_i of node i and E_t of the network can be given as

$$\begin{cases} E_i = (E_{T-elec} + E_{R-elec} + E_{amp} \times d_{i,r_i}^2)\cdot \\ \qquad P_dT_i + (P_c - P_d)E_{R-elec} \\ E_t = \sum\limits_{i=1}^{N} E_i \end{cases}. \tag{9}$$

3.2 Planning of the original path

From the analysis above, it can be seen that the energy consumption E_i and the total amount of energy consumption E_t can be obtained as long as the spatial location of the node and the topology vector $\boldsymbol{r}$ are known. By considering both the remaining energy of the node and the amount of energy consumed in data transmission, we propose a fast routing algorithm, the algorithm can sequentially determine the upstream node of each node to form an original network topology.

In our network model, if the distance between the node and the sink is less than the maximum transmission distance $d_{\max}$, then the sink is defined as its upstream node. Otherwise, additional nodes are required to function as relays. There are three principles for our path planning algorithm:

(i) All nodes are sorted based on remaining energy and the distance from the sink. Then, the nodes are chosen one by one to plan their upstream nodes. Nodes with more remaining energy and nearer to the sink are probably assigned transmission path firstly.

(ii) Upstream nodes must be chosen from nodes whose transmission distance is no more than the limit and whose transmission path has been specified.

(iii) If there are multiple choices for upstream nodes, choose the optimal one according to the remaining energy and the amount of energy needed to send data to the sink.

The three principles jointly consider remaining energy and distance from the sink, thereby enabling the node with more energy and near distance to be chosen first as the upstream node, implying that the amount of energy needed to send data from the node to the sink is minimized.

According to the second principle, it is possible that a node does not meet the specified conditions. Therefore, path planning can be completed after several rounds of planning. The node whose path cannot be planned can be extended to subsequent rounds, until path planning of all N nodes is completed. The steps of the algorithm are as Algorithm 1.

Algorithm 1 The preliminary path planning method

Initialize: $d_{\max}$, $r_i = -1$, compute $d_{i,j}$, $d_{i,S}$, E_r^i for all i

All nodes are sorted by E_r^i (descend), $d_{i,S}$ (ascend)

```
Set round_flag=true
while(round_flag)
  round_flag=false
  for i = 1, 2, ..., N
    t ← the ith index number of the sorted nodes
    if r_t != −1
      break
    end if
    if d_{t,S} < d_max
      r_t = N + 1, E_t = (E_{T−elec} + E_amp × d_{t,s}^2) P_d
      round_flag=true
      break
    end if
    Get the index number set of optional nodes j
        Subject to d_{t,j} < d_max && r_j != −1
    if the set is empty
      break
    else
      Compute the energy consumption E_t corresponding to all js in the set
      E_t = (E_{T−elec} + E_{R−elec} + E_amp × d_{t,j}^2) P_d + E_j
    end if
    All js in the set are sorted by E_r^j (DESC),
    E_t (ASC)
    r_t ← the first j in the sorted set
    round_flag=true
  End for
End while
```

4. Strategy for dynamically optimizing transmission paths

Nodes are selected based on the specified sequence for path planning and the upstream node cannot be changed after it is determined. In this context, under the routing algorithm discussed in Section 3.2, nodes close to the sink may be depleted of energy rapidly. This algorithm cannot address the hot spot problem effectively, therefore, the path produced by this algorithm can only be used as the original path. This section defines a criterion function to evaluate node data transmission ability and proposes an optimization strategy by protecting the weak nodes in the original network topology to increase the lifetime of the overall network.

4.1 Definition of the criterion function

After the network topology is obtained, the vector $\boldsymbol{r}$ is known and enables us to compute the energy consumption of all nodes E_i and the total amount of energy consumption E_t using (9) $(i = 1, 2, \dots, N)$. Let E_r^i denote the remaining energy of i after the previous cycle, and E_r^t denote the total amount of the remaining energy. The criterion function F_i for i is defined as follows:

$$F_i = \alpha \cdot \frac{E_i}{E_r^i} + \beta \cdot \frac{E_t}{E_r^t} \tag{10}$$

where α and β are weights and $\alpha + \beta = 1$. F_i jointly considers the energy consumption of i and the total amount of energy consumption. A large value of F_i implies that node i occupies a large proportion of the remaining energy and the total amount of energy consumption in the network is high. In this case, this node with large value of F_i may be exhausted first and can become a network bottleneck. Further analysis of (10) is performed as

$$F_i = \alpha \cdot \frac{E_i}{E_r^i} + \beta \frac{E_t}{E_r^t} = \alpha \cdot \frac{E_i}{E_r^i} + \beta \frac{\sum\limits_{j=1}^{N} E_j}{E_r^t} = \left(\frac{\alpha}{E_r^i} + \frac{\beta}{E_r^t} \right) E_i + \frac{\beta}{E_r^t} \sum_{\substack{j=1 \\ j \neq i}}^{N} E_j. \tag{11}$$

Let $\boldsymbol{F} = [F_1, F_2, \dots, F_N]^{\mathrm{T}}$ denote the attribute vector, which consists of the attribute value of each node computed using the criterion function. Let $\boldsymbol{E} = [E_1, E_2, \dots, E_N]^{\mathrm{T}}$. Equation (11) can be written in matrix form as

$$\boldsymbol{F} = \boldsymbol{D}\boldsymbol{E} \tag{12}$$

where $\boldsymbol{D}$ is an $N \times N$ constant matrix:

$$\boldsymbol{D} = \begin{bmatrix} \dfrac{\alpha}{E_r^1} + \dfrac{\beta}{E_r^t} & \dfrac{\beta}{E_r^t} & \cdots & \dfrac{\beta}{E_r^t} \\ \dfrac{\beta}{E_r^t} & \dfrac{\alpha}{E_r^2} + \dfrac{\beta}{E_r^t} & \cdots & \dfrac{\beta}{E_r^t} \\ \vdots & \vdots & \ddots & \vdots \\ \dfrac{\beta}{E_r^t} & \dfrac{\beta}{E_r^t} & \cdots & \dfrac{\alpha}{E_r^N} + \dfrac{\beta}{E_r^t} \end{bmatrix}. \tag{13}$$

The node corresponding to the largest value of $\boldsymbol{F}$ is regarded as the weak node, and its value is called the feature value of the network, denoted by C, i.e., $C = \|\boldsymbol{F}\|_\infty$. Generally, the communicating hot spot close to the sink is likely a weak node, which should be protected during path planning. In this paper, we propose an adjustment to the network topology such that the loads of the weak nodes are shifted to other nodes in order to improve energy consumption balance, resulting in a reduced feature value C and an increased network lifetime.

4.2 Path optimization algorithm for protection of weak nodes

After the original network topology is determined, the attribute vector $\boldsymbol{F}$ can be used to obtain the feature value of the network and the location of weak nodes. This subsection proposes a network topology optimizing scheme to protect weak nodes and to reduce the feature value C. If node i becomes a weak node, i.e., $C = F_i$, this means that node i is energy intensive. Its attribute value F_i can be decreased by reducing E_i. It is clear from (9) that with other parameters (e.g., P_c and P_d) being the same, there is no way of decreasing T_i and $d_{i,ri}$ except by changing the network topology. Fig. 2 shows the details of path optimization. The value of $d_{i,ri}$ can be reduced by changing the upstream node of node i to shorten its transmission distance, as shown in Fig. 2(d). Reducing T_i is equivalent to reducing the number of packets sent by node i. This can be achieved by reducing the number of downstream nodes, as shown in Fig. 2(b) and Fig. 2(c).

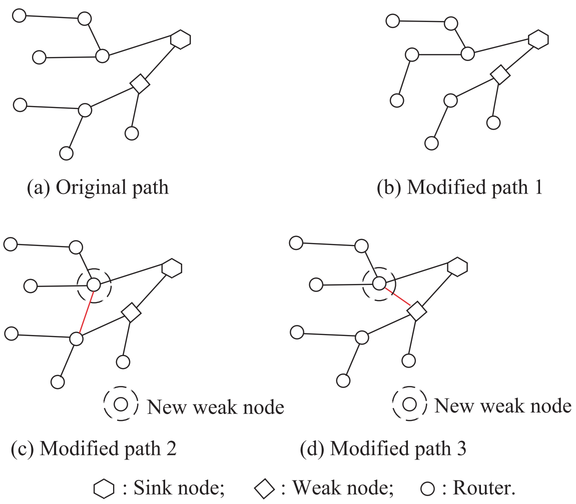


Fig. 2 Changing the transmission path to protect the weak point

From Fig. 2, it can be observed that by changing the upstream and downstream nodes of the weak node, we can alleviate the energy consumption of the weak node along the existing path and reduce its attribute value F_i. Adjusting the path will inevitably increase the load of other nodes, making it possible to generate a new weak node, as shown in Fig. 2(c) and Fig. 2(d). Even worse, the new weak node may have a higher attribute value, resulting in an increased feature value C of the entire network, thus worsening network performance. An optimization algorithm is needed to reduce C gradually during path adjustment.

Based on the above analysis, the value of F_i can be alleviated by decreasing T_i or $d_{i,ri}$, this can be achieved by changing the upstream node or reducing the incoming nodes of node i. If node i is the weak node, let S_i denote the set of these nodes that not only node i, but also all nodes pass node i while transmitting the data to the sink. Changing the upstream node of any node in S_i may reduce F_i. If only the upstream node of node i is changed, then T_i remains constant. If the upstream node of other nodes in the set is changed, the new upstream node must not be in S_i, otherwise T_i will remain constant.

Let $flag(i)$ represent a flag that node i has been processed. Based on vector $\boldsymbol{r}$, the method for constructing S_i is given by Algorithm 2.

Algorithm 2 Construction method of set S_i

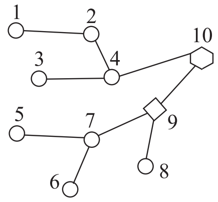
Initialize: $flag(i) = 0$ for all i
$S_i = [i]$; i is a member of S_i
For $k = 1, 2, \dots, N$, s.t. $k! = i \&\& flag(i) = 0$
  $count = 1, t = [\,], t(count) = k, current = r(k)$
    While($current! = i \&\& current! = N + 1$)
      If($flag(current) == 0$)
        $t(+ + count) = current$
        $flag(current) = 1$
      End if
  $current = r(current)$
    End while
    If $(current == i)$
      $S_i \leftarrow S_i \cup t$
    End if
  End for

After the set S_i is determined, we need to change the upstream node of elements in this set. The new upstream node is called the target node. Considering the possibility that a new weak node may occur after path adjustment, we must choose the correct node as the target node. For any node $j \in S_i$, the target node k obtained after path adjustment must meet the distance constraint, i.e., $d_{i,k} < d_{\max}$. At the same time, nodes with a small attribute value should be chosen as the new upstream nodes. However, even if F_k is small, the data sent to node k advances to the sink along the path of k, making it possible to worsen the performance of other nodes along the path. Thus, the performance of all nodes in the path should be considered when deciding on the target node. In this paper, the associated attribute value is used to address the problem above.

Let N_j be the set of neighbors of node j and let L_k be the set of nodes that forward data from k to the sink. Details are as follows:

$$\begin{cases} N_j = \{m | d_{j,m} < d_{\max}\} \\ L_k = \{n | \text{nodes in } k\text{'s path}\} \\ j, k = 1, 2, \dots, N; m, n \in \{1, 2, \dots, N+1\}; j \neq m \end{cases}. \tag{14}$$

Let F_k be the attribute value of node k and R_k be the associated attribute value of node k, which is actually the maximum attribute value among all nodes in the transmission path of k, as shown in (15). For any network topology, if the attribute value F_k of node k is known, then the value of R_k can be found using vector $\boldsymbol{r}$, as shown in Fig. 3.



k	1	2	3	4	5	6	7	8	9	10
F_k	0.56	0.67	0.60	0.75	0.42	0.40	0.74	0.48	0.70	0
R_k	0.75	0.75	0.75	0.75	0.74	0.74	0.74	0.70	0.70	0

⬡ : Sink node; ◇ : Weak node; ○ : Router.

Fig. 3 Comparison of criterion function F_k and associated attribute value R_k

According to the definition of the network model, no energy constraints are imposed on the sink. In Fig. 3, F_k and R_k are set to 0.

$$R_k = \max\{F_n | \forall n \in L_k\} \tag{15}$$

The path is adjusted only when we obtain the set S_i, N_j, and the associated attribute value R_k. Consider that node i is the weak node. Then, for any node $p \in S_i$, its original upstream node r_p is changed to q, i.e., $r_p = q$, where q is determined in (16). There may be more than one node q that meets the criterions. In this case, according to the energy consumption criterion, the node with less energy consumption in the new path is chosen as the upstream node.

$$q = \begin{cases} n | R_n = \min\limits_{m}\{R_m\} | d_{p,m} < d_{p,r_p} | \\ \quad m \in (N_p - S_i), \quad p = i \\ n | R_n = \min\limits_{m}\{R_m\} | m \in (N_p - S_i), \\ \quad p \neq i \end{cases} \tag{16}$$

Changing the upstream node of p in S_i to q can reduce the value of F_i, but it may also result in a new weak node and thus increase the value of C, thereby worsening network performance. A full search strategy is adopted to ensure acceptable network performance and a balance of loads between nodes. We change the upstream node for all source nodes in S_i whose target node q can be found using (16). Let C_{old} denote the feature value of the network before path adjustment. The feature value C is computed after the upstream node of any node is changed. Let $C_{\min}$ denote the minimum value of C and $\boldsymbol{r}_{\text{new}}$ denote the corresponding topology vector. After all nodes are processed and their results are recorded, we can compare $C_{\min}$ with C_{old}. If $C_{\min} < C_{\text{old}}$, the adjustment is valid and $\boldsymbol{r}_{\text{new}}$ is regarded as the original path for the next round of optimization. Otherwise, the path is optimal and the previous path is exactly the final path.

Let $\boldsymbol{r}$ be the path that needs to be optimized and pos be the location of the weak node. The path optimization steps are as Algorithm 3.

Algorithm 3 Optimization method of the path
Initialize: get $\boldsymbol{r}$, E_r^i
Compute E_i, E_t, E_r^i, F_i
Compute C, pos from F_i
$C_{\min} = C, E_{\min} = E, pos_{\min} = pos, \boldsymbol{r}_{\text{best}} = \boldsymbol{r}$
  While(1)
    Compute S_{pos} according to Algorithm 2
    $C_{\text{old}} = C_{\min}$
    For $j = 1, 2, \ldots$, size of (S_{pos})
      $K = S_{pos}(j)$
        Get the new upload node q for k based on (16)
      If exist q
        $temp = r_k, r_k = q$
        Compute E_i, E_t, E_r^i, F_i from new $\boldsymbol{r}$
        Compute C_{new}, pos from F_i
        If($C_{\text{new}} < C_{\min}$)
        $E_{\min} = E, C_{\min} = C_{\text{new}}, pos_{\min} = pos, \boldsymbol{r}_{\text{best}} = \boldsymbol{r}$
        End if
        $r_k = temp$
      End if
    End for
    if ($C_{\text{old}} > C_{\min}$)
      $\boldsymbol{r} = \boldsymbol{r}_{\text{best}}, pos = pos_{\min}$
    Else
      Break
    End if
  End while

5. Numerical simulation

Our proposed algorithms are simulated using Matlab 7.0. Parameters are set up as the following. Sixty data collecting nodes are assumed randomly deployed in a 100 m× 100 m area, and, the sink is located at the coordinate (80, 80). Other parameter settings are given in Table 1 and Table 2. Parameters in Table 1 are fixed and parameters in Table 2 are varied for performance analysis.

Table 1 Fixed parameters for simulation

E_r^i/J	P_c/bit	E_{amp}/(J/bit·m^2)	E_{R-elec}/(J/bit)	E_{T-elec}/(J/bit)
0.05	1 000	10×10^{-12}	50×10^{-9}	50×10^{-9}

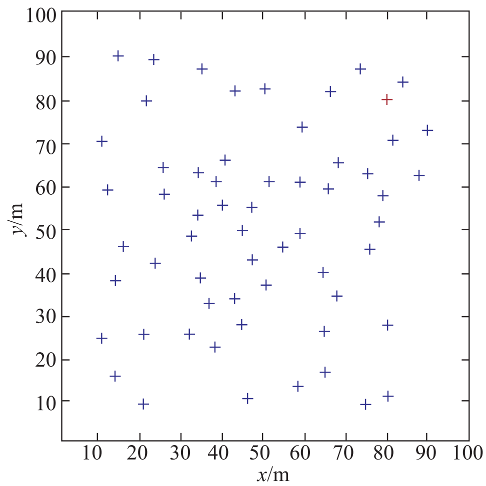
Table 2 Varied parameters for simulation

$d_{\max}$/m	P_d/bit	α	β
30	300	0.8	0.2

5.1 Network performance comparison before and after optimization

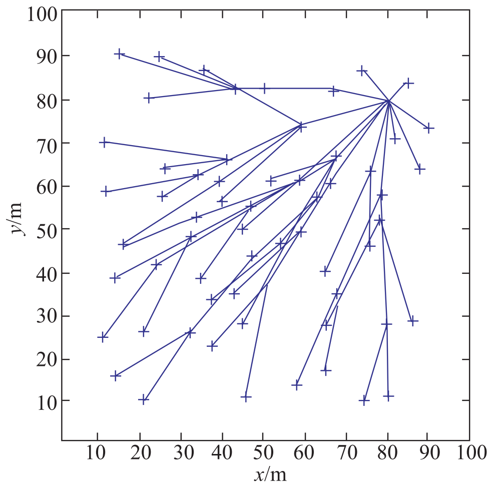
5.1.1 Comparison and analysis of paths

The simulation is first conducted to determine the effectiveness of the proposed path planning and optimization algorithms, as shown in Fig. 4. Fig. 4(a) shows the spatial distribution of communicating nodes, assuming that all nodes are located in the 2-D plane. Fig. 4(b) shows the original path from Algorithm 1. The planning of the original path only considers the remaining energy of the node and the amount of energy consumed in data transmission. Since the remaining energy is the same, energy efficiency is the only criterion. All nodes attempt to find the most energy efficient path. Upstream nodes always advance to the sink. Fig. 4(c) is an optimized version of the path in Fig. 4(b), the feature value of the network is introduced as a criterion, which determines that both the amount of energy consumed for energy transmission and the data transmission load of nodes need to be considered jointly.

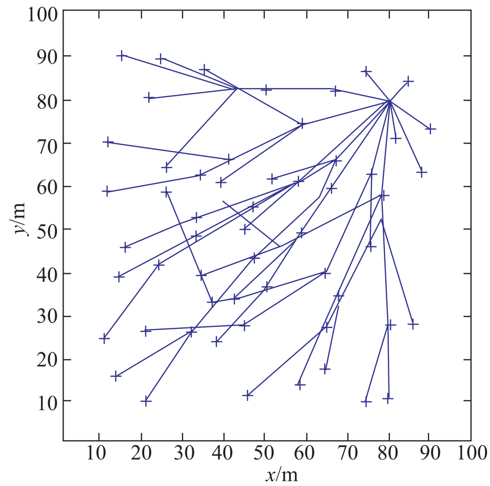


+ : Rouber; + : Sink.

(a) Distribution of nodes



(b) Path planning with no optimization



(c) Path optimization result for (b) (α=0.6, β=0.2)

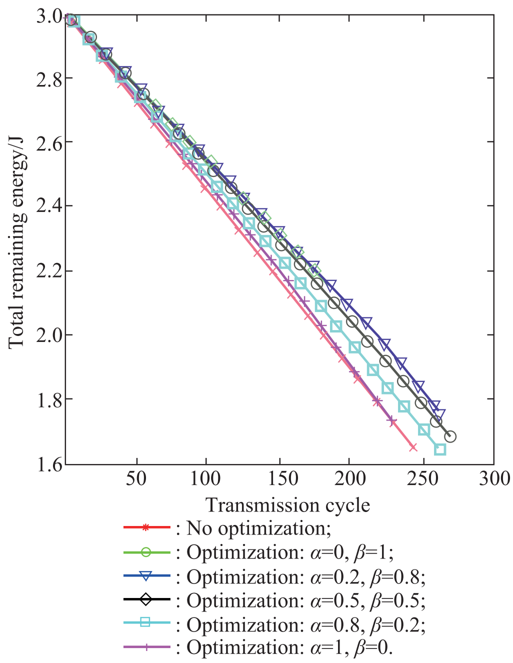
Fig. 4 Path planning for nodes with the same remaining energy

Therefore, the path optimization may cause longer paths that may increase energy consumption, but it is helpful in addressing the hot spot problem.

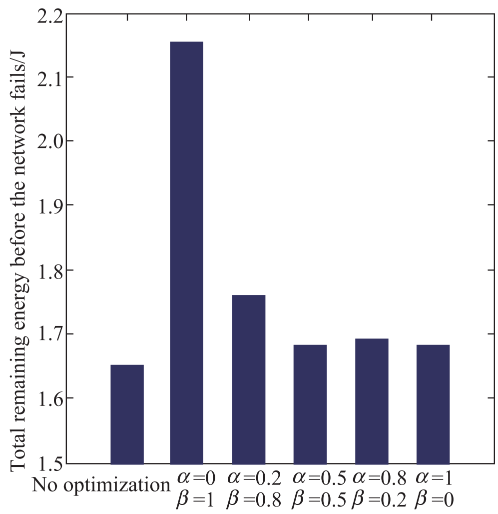
5.1.2 Analysis of energy consumption during each cycle

We treat energy consumption as a function of optimizing parameters, and the impact of optimization parameters on total energy consumption is analyzed in Fig. 5. Fig. 5(a) shows that the total amount of energy consumption during each cycle varies with the optimization parameters. A maximum amount of energy is consumed when the path is not optimized, so the remaining energy decreases rapidly. In the case of optimizing the transmission path, the energy consumption decreases with the value of β increasing, and the remaining energy decreases more slowly with transmission cycles. The amount of energy consumption reaches the lowest level when $\beta = 1$. In cases where optimization is not done, or, optimization is done but with no protection of the weak node, the amount of energy consumption is almost the same per transmission cycle at the early and late periods of the lifetime. In other optimization cases, paths may be designed to bypass the weak node, resulting in more energy consumption. Thus, in the late period of the lifetime, the amount of energy consumption per cycle increases.

Due to non-uniform energy consumption among nodes, a small amount of energy consumption per transmission cycle does not mean that the lifetime is long. Fig. 5(b) shows the total amount of remaining energy before the network fails with varying optimization settings. In the case of $\beta = 1$ optimization, although the amount of energy consumption is small, the hot spot bottleneck is neglected. As a result, the lifetime is short and the amount of energy remaining before the network fails is much larger than that in other cases. If the path is not optimized, the amount of energy remaining before the network fails reaches the lowest level. This is not due to the large lifetime of the network, but mainly because the amount of energy consumed per cycle is large.



(a) Total remaining energy varing with transmission cycle

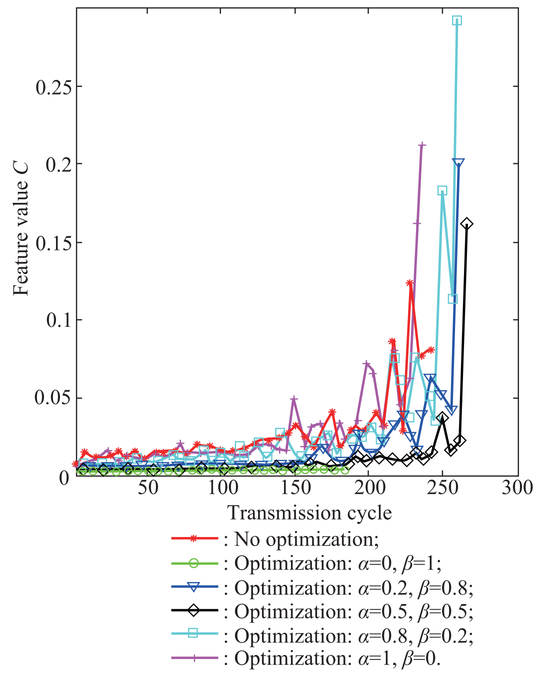


(b) Total remaining energy before network fails varing with different optimization settings

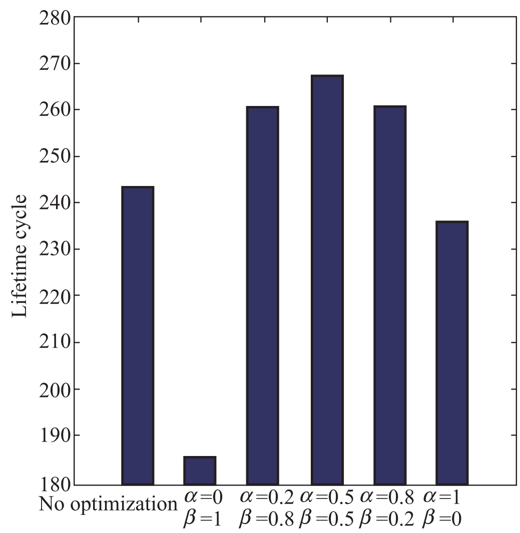
Fig. 5 Energy consumption as a function of transmission cycle

5.1.3 Impact of criterion function on lifetime

One of the major contributions of this paper is increasing network lifetime by optimizing the routing protocol based on the attribute value of the communicating node. Fig. 6 shows the impact of different optimization parameters on lifetime. Fig. 6(a) shows the variation of feature values with transmission cycle during lifetime under each optimization setting. The feature value increases with overall lifetime, with occasional fluctuations. This implies that the data transmission ability of the weak node worsens gradually and approximates to the level of failure. Fluctuations indicate that the workload of the node is more balanced by protecting the weak node. It is clear from Fig. 6(a) that in the case of $\beta = 1$, the definition of the criterion function only considers the total amount of energy consumption, ignoring the energy consumption of each node.



(a) Feature value varing with transmission cycle



(b) Lifetime cycle varing with different optimization settings

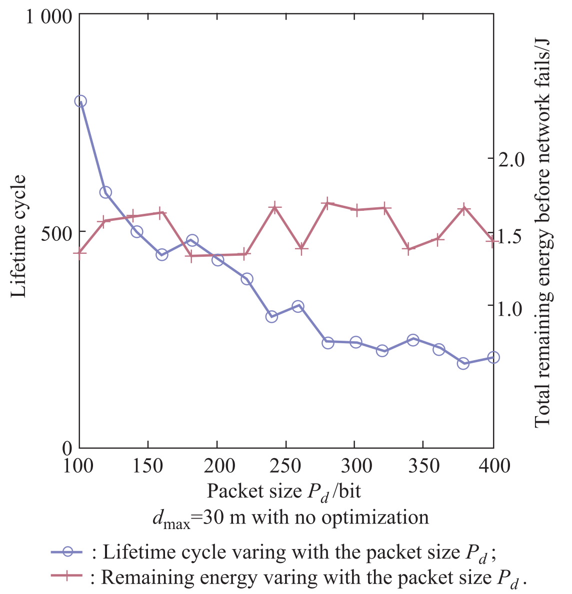
Fig. 6 Feature value C and lifetime cycle corresponding to different optimization settings

The hot spot of the network makes no contribution to the attribute value, thus the network has the lowest feature value and does not fluctuate. In the case of $\beta = 0.5$ optimization, the feature value increases slowly and the network shows the greatest overall performance.

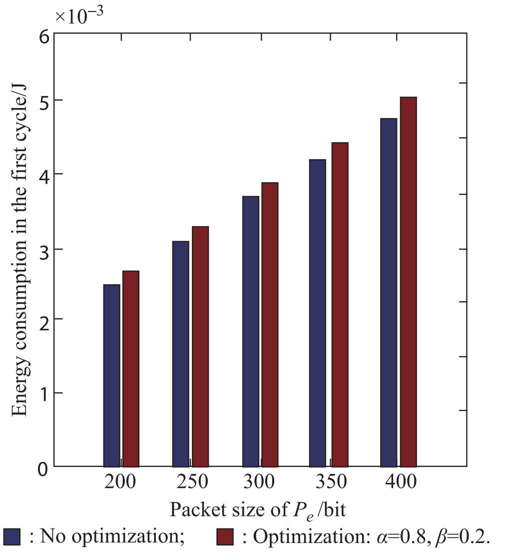
Fig. 6(b) shows the network lifetime with varying optimization settings given the same original conditions. In the case of optimization with $\beta = 1$, network lifetime is shorter than that under any other optimization settings, including the lifetime achieved without any optimization. This is because the original route planning considers the remaining energy of each node, but global optimization is not carried out. The optimization strategy with $\beta = 1$ adjusts the path, but neglects the energy consumption of each node. Thus, despite alleviating total energy consumption, it inevitably causes the hot spot problem and an imbalance of energy consumption among nodes, shortening network lifetime. Furthermore, with $\alpha = 1$ and $\beta = 0$, lifetime is also short, implying the necessity of considering the total amount of energy consumption during path planning. The network under the optimization settings of $\alpha = 0.5$ and $\beta = 0.5$ has the longest lifetime, indicating that the energy consumption of each node is equally important to the total amount of energy consumption during path planning.

5.2 Impact of packet size on network performance

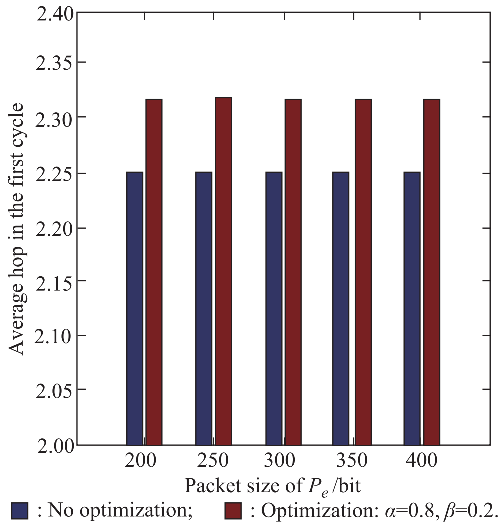
The impact of the packet size on network performance is also analyzed and the results are shown in Fig. 7. The packet containing the control message is fixed after its format is defined and it does not need to be sent via the routing node.



(a) Lifetime and remaining energy before network fails varying with packet size



(b) Energy consumption in the first cycle varing with packet size



(c) Average hop in the first cycle varing with packet size

Fig. 7 Performance of network as a function of packet size

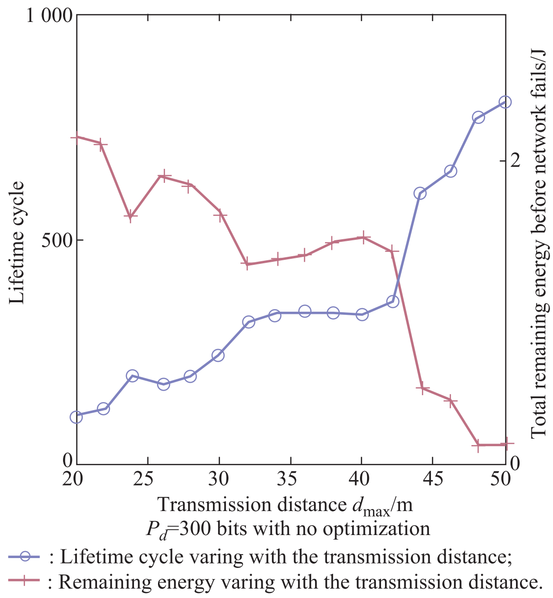
We only consider variations of the packet P_d from sensors. The impact of the packet size on network lifetime, the amount of energy remaining before a network fails, the energy consumption per cycle, and the average number of hops in a multi-hop route are analyzed.

Fig. 7(a) shows a non-optimized original path, where the horizontal axis represents the packet size, the left vertical axis represents lifetime, and the right vertical axis represents energy remaining before a network fails. The figure shows that lifetime decreases with an increase in the packet size, except for occasional fluctuations. This is due to the fact that planning the original path considers the remaining energy and the total amount of energy consumption, so the planned paths vary depending on the packets. The planned path is not optimal, thus it is sometimes possible that lifetime increases with the packet size. In fact, this can be verified by the vertical coordinate, which represents energy remaining before a network fails; the increase in lifetime leads to a decrease in energy remaining.

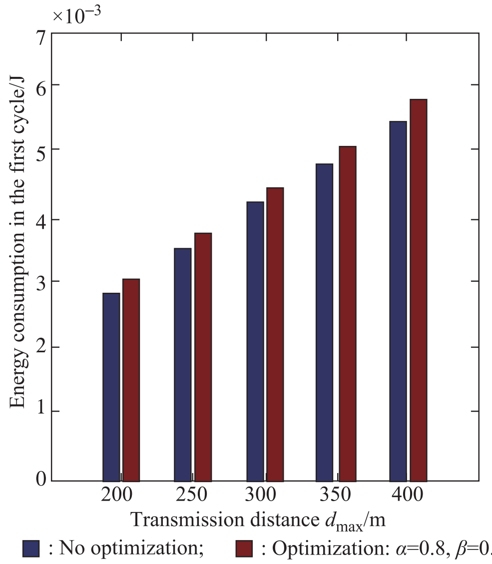
Fig. 7(b) shows the impact of the packet size on energy consumption in the first cycle. More energy is consumed in the first cycle with an increase in the packet size. The figure also shows that optimizing the path leads to more energy consumption. This is because some nodes increase the number of hops in their paths to bypass weak nodes, thereby consuming more energy. Fig. 7(c) shows the impact of the packet size on the number of hops. The average number of hops is independent of the packet size. The average number of hops after path optimization is higher than that when the path is not optimized. This is consistent with the theoretical analysis.

5.3 Impact of transmission distance on network performance

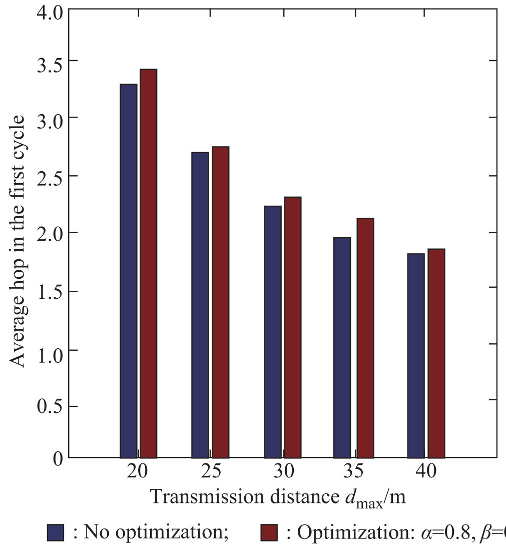
Finally, we simulate the impact of transmission distance on network performance. Due to complexity of the network environment in actual applications, the coverage of nodes is limited, highlighting the need to analyze the impact of transmission distance on network performance. We discuss the impact of transmission distance on network lifetime, the amount of energy remaining before a network fails, the energy consumption per cycle, and the average number of hops. Fig. 8(a) shows that lifetime decreases with transmission distance. When transmission distance exceeds 40 m, lifetime decreases quickly.



(a) Lifetime and remaining energy before network fails varying with transmission distance



(b) Energy consumption in the first cycle varing with transmission distance



(c) Average hop in the first cycle varing with transmission distance

Fig. 8 Impact of transmission distance on network performance

This is because the amount of energy consumed in data transmission is proportional to the square of distance; energy consumption increases substantially after the distance reaches a threshold, resulting in reduced lifetime. Energy remaining before a network fails is also related to lifetime. The energy remaining increases with a decrease in lifetime, as shown by the curve of the right vertical coordinate in Fig. 8(a). Fig. 8(b) shows that energy consumption decreases with maximum transmission distance limitation increasing. The reason behind this is that our network model considers the energy consumption of the circuit, which decreases with a decrease in the number of hops. Meanwhile, the increase in transmission distance leads to an increase in the amount of energy consumed in data transmission per hop, but the increment is marginal compared to the case of short-distance multi-hop transmission. This observation implies that it is necessary to increase transmission distance appropriately without compromising communication reliability during network planning. Fig. 8(c) shows the impact of transmission distance on the average number of hops. An increase in transmission distance reduces the number of hops in the multi-hop network. This figure also proves that, when using the optimizing algorithm for protection of weak nodes, the average number of hops needed to deliver data to the sink increases. This is consistent with the theoretical analysis.

5.4 Network performance comparison with other related works

For further evaluation of the proposed method, some related algorithms in literature are chosen for comparison test. Even though there are lots of study focusing on the lifetime of WSN, most of them cannot be adopted for comparison due to their unique characteristics with a specific scenario. Since our study is applied to gather the surveillance information of the power system, a control center will be built to analyze the operation state of the power system. The control center can be served as the sink node, and, there is no energy limited with it. Furthermore, there are high performance computers working together with the sink node. Besides concentrating the information of the monitoring and metering appliances within the monitoring area, the control center can analyze the energy consumption and complete the path planning for the sensor nodes according to the previous tasks.

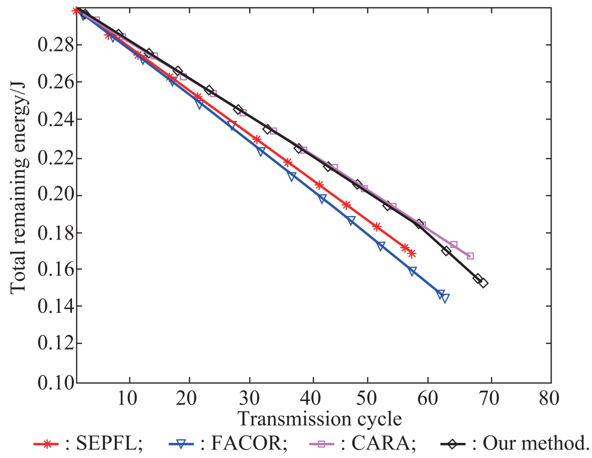
We investigate a lot of literatures to seek the routing algorithm with the similar application scenario of ours, which is described in Section 2. We choose three latest literatures called stable election protocol fuzzy logic (SEPFL) [21], connectivity aware routing algorithm (CARA) [24], fuzzy ant colony optimization routing (FACOR) [27] for comparison test. The routing protocol called SEPFL [21] is proposed based on fuzzy logic control, in which, the stable election protocol is used for cluster head election to improve the lifetime and throughput of the WSN. Jain proposed a CARA [24] based on the concept of Betweenness centrality. Betweenness centrality is used to calculate the connectivity factor of a node. By preserving the highly connected nodes at the previous round, the network lifetime is enhanced. In addition, Amiri et al. [27] proposed a routing protocol based on FACOR. The transmission path is determined inspired by the foraging behavior of ants, meanwhile, the fuzzy logic is applied for the ants to choose the optimal path.

In order to evaluate the performance of our method comparing with the chosen methods, the simulation parameters should be setup uniformly for each scheme. Thus, the original conditions and parameters defined in the literatures may be modified. For simulations, 60 nodes randomly deployed in an area of 100 m×100 m have been considered. The common parameters of E_{amp}, E_{R-elec} and E_{T-elec} should not be changed, which are presented in Table 1. The other parameters are reassigned in Table 3. The optimal parameters α and β in our method are both set to 0.5. We write the Matlab programs for each algorithm according to the literatures.

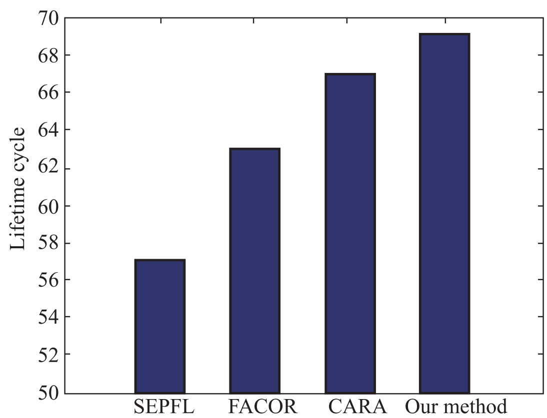
Table 3 Parameters for comparison test

E_r^i/J	P_c/bit	$d_{\max}$/m	p_d/bit
0.05	80	30	128

Firstly, we focus on the energy consumption varying with transmission cycle. The experimental results are shown in Fig. 9. In Fig. 9(a), it can be seen that the energy cost in each transmission cycle in our method is close to that of the CARA method, but less than SEPFL and FACOR.



(a) Total remaining energy varing with transmission cycle

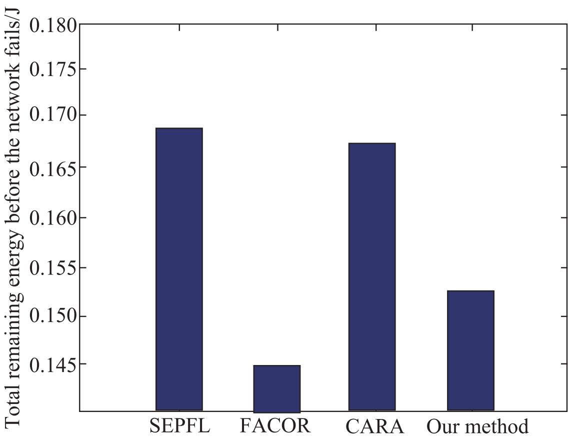


(b) Lifetime cycle of different methods

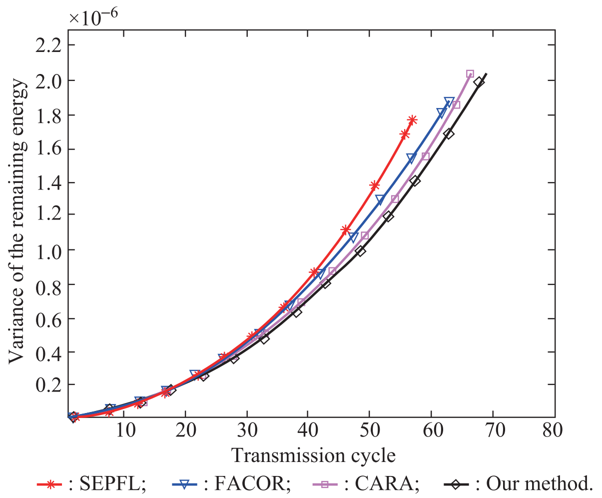
Fig. 9 Energy consumption as a function of transmission cycle

In our method, when an upstream path is planned for a node, the total energy consumption from the node to sink is considered instead of the energy consumption of the node itself. Thus, the total remaining energy decreases slowly in our method. Overall, less energy consumption in transmission cycle will lead to longer network lifetime. Fig. 9(b) presents the lifetime cycle, which is defined as the transmission rounds before the first failure node appears. The lifetime cycle of SEPFL, FACOR, CARA and ours are 57, 63, 67 and 69, respectively. It demonstrates the good performance of our method.

Then, we analyze the relation between the remaining energy and the lifetime. The conformity of energy distribution among the sensor nodes is also a critical factor to network lifetime. That is why the total remaining energy of FACOR decreases more rapidly than SEPFL, but the lifetime of FACOR is longer. We present the total remaining energy before the network fails and the energy conformity among the nodes in Fig. 10.



(a) Total remaining energy before network fails of different methods



(b) Variance of the remaining energy varing with transmission cycle

Fig. 10 Remaining energy and the variance of the node

The energy conformity is expressed by calculating the variance of the remaining energy. It can be seen in Fig. 10(a) that the total remaining energy of SEPFL is more than other methods, but its lifetime is the shortest one. Fig.10(b) shows that the energy variance of SEPFL increases with the transmission cycle more rapidly than others. On the other hand, since the weak node protection strategy is adopted in our study, the best performance of conformity is achieved in our method. This is the foundation that our routing algorithm can prolong the network lifetime.

6. Conclusions

This paper proposes a WSN-based method for collecting monitoring data from the sensors distributed in a large area. Our work is focused on network routing issues for improving the availability of the WSN. In this paper, the ZigBee wireless communication module is used as the transmission terminal to collect monitoring data. Algorithms for path planning and optimization are proposed that increase network lifetime by balancing energy consumption between nodes. A criterion function is defined to evaluate node data transmission ability in order to find and protect weak nodes in the network, resulting in improved balance in energy consumption among nodes and increased network lifetime. In addition to studying optimization of path parameters and the corresponding performance, this paper analyzes the impact of packet size and transmission distance on network performance. The efficiency of our method is also demonstrated through comparison test with some related works. The proposed network strategy can be adapted to different applications in the future.

References

[1] HEINZELMAN W R, CHANDRAKASAN A, BALAKRISHNAN H. Energy-efficient communication protocol for wireless microsensor networks. Proc. of the 33rd Annual Hawaii International Conference on System Sciences, 2000: 223 – 233.

[2] SHIN H, MOH S, CHUNG I, et al. Equal-size clustering for irregularly deployed wireless sensor networks. Wireless Personal Communications, 2015, 82(2): 995 – 1012.

[3] KUILA P, JANA P K. Energy efficient clustering and routing algorithms for wireless sensor networks: particle swarm optimization approach. Engineering Applications of Artificial Intelligence, 2014, 33(1): 127 – 140.

[4] ELHABYAN R S Y, YAGOUB M C E. Two-tier particle swarm optimization protocol for clustering and routing in wireless sensor network. Journal of Network and Computer Applications, 2015, 52(C): 116 – 128.

[5] SHARMA S, JENA S K. Cluster based multipath routing protocol for wireless sensor networks. ACM SIGCOMM Computer Communication Review, 2015, 45(2): 14 – 20.

[6] PAN M S, LIU P L. Low latency scheduling for convergecast in ZigBee tree-based wireless sensor networks. Journal of Network and Computer Applications, 2014, 46: 252 – 263.

[7] ZHANG H B, SHEN H. Balancing energy consumption to maximize network lifetime in data gathering sensor networks. IEEE Trans. on Parallel and Distributed Systems, 2009, 20(10): 1526 – 1539.
[8] ALSKAIF T, ZAPATA M G, BELLALTA B. Game theory for energy efficiency in wireless sensor networks: latest trends. Journal of Network and Computer Applications, 2015, 54(C): 33 – 61.
[9] HU X Q, HU Y H, XU B G. Energy-balanced scheduling for target tracking in wireless sensor networks. ACM Trans. on Sensor Networks, 2014, 11(1): 21.
[10] HOU I H. Packet scheduling for real-time surveillance in multihop wireless sensor networks with lossy channel. IEEE Trans. on Wireless Communications, 2015, 14(2): 1071 – 1079.
[11] ASSAF A E, ZAIDI S, AFFES S, et al. Low-cost localization for multihop heterogeneous wireless sensor networks. IEEE Trans. on Wireless Communications, 2016, 15(1): 472 – 484.
[12] KARP B, KUNG H T. GPSR: greedy perimeter stateless routing for wireless networks. Proc. of the 6th Internatioanl Conference on Mobile Computing & Networking, 2000: 243 – 254.
[13] LI X, CHEN X, GUAN X H. A new gradient-based routing protocol in wireless sensor networks. Proc. of the International Conference on Embedded Software and Systems, 2005, 5(4): 318 – 325.
[14] VELMANI R, KAARTHICK B. An efficient cluster-tree based data collection scheme for large mobile wireless sensor networks. IEEE Sensors Journal, 2015, 15(4): 2377 – 2390.
[15] AMGOTH T, JANA P K. Energy and cverage-awre routing algorithm for wireless sensor networks. Wireless Personal Communications, 2015, 81(2): 531 – 545.
[16] BARCELÓ M, CORREA A, VICARIO J L, et al. Joint routing, channel allocation and power control for real-life wireless sensor networks. Transactions on Emerging Telecommunications Technologies, 2015, 26(5): 945 – 956.
[17] GUPTA H P, RAO S V, YADAV A K, et al. Geographic routing in clustered wireless sensor networks among obstacles. IEEE Sensors Journal, 2015, 15(5): 2984 – 2992.
[18] ABDULLA A E A A, NISHIYAMA H, KATO N. Extending the lifetime of wireless sensor networks: a hybrid routing algorithm. Computer Communications, 2012, 35(9): 1056 – 1063.
[19] HUA C Q, YUM T S P. Optimal routing and data aggregation for maximizing lifetime of wireless sensor networks. IEEE/ACM Trans. on Networking, 2008, 16(4): 892 – 903.
[20] EBRAHIMI D, ASS C. Network coding aware compressive data gathering for energy-efficient wireless sensor networks. IEEE/ACM Trans. on Sensor Networks, 2015, 11(4): 1 – 24.
[21] TAMANDANI Y K, BOKHARI M U. SEPFL routing protocol based on fuzzy logic control to extend the lifetime and throughput of the wireless sensor network. Wireless Network, 2016, 22(2): 647 – 653.
[22] KIM D, KIM H, LI D, et al. Maximum lifetime dependable barrier-coverage in wireless sensor networks. Ad Hoc Networks, 2016, 36(1): 296 – 307.
[23] XU H L, HUANG L, SUN H. Maximum lifetime data aggregation for wireless sensor networks with cooperative communication. International Journal of Sensor Networks, 2016, 20(3): 187 – 198.
[24] JAIN A. Betweenness centrality based connectivity aware routing algorithm for prolonging network lifetime in wireless sensor networks. Wireless Networks, 2016, 22(5): 1605 – 1624.
[25] FREZZETTI A, MANFREDI S. A two-layer controller scheme for efficient signal reconstruction and lifetime elongation in wireless sensor networks. IEEE Sensors Journal, 2016, 16(7): 2172 – 2179.
[26] KIM H Y. An energy-efficient load balancing scheme to extend lifetime in wireless sensor networks. Cluster Computing, 2016, 19(1): 279 – 283.
[27] AMIRI E, KESHAVARZ H, ALIZADEH M, et al. Energy efficient routing in wireless sensor networks based on fuzzy ant colony optimization. International Journal of Distributed Sensor Networks, 2014, 16(1): 579 – 597.
[28] HABIBI J, AGHDAM A G, GHRAYEB A. A framework for evaluating the best achievable performance by distributed lifetime efficient routing schemes in wireless sensor networks. IEEE Trans. on Wireless Communications, 2015, 14(4): 3231 – 3245.
[29] HOU Y T, SHI Y, PAN J, et al. Maximizing the lifetime of wireless sensor networks through optimal single-session flow routing. IEEE Trans. on Mobile Computing, 2015, 5(9): 1255 – 1266.

Biographies

MAO Yuxing was born in 1967. He received his B.S. and M.S. degrees in Radio Electrical Department from Beijing University, China, in 1989 and 1992, respectively. He got his Ph.D. degree in electrical engineering from Chongqing University, China, in 2004. He worked as a visiting scientist in the Center for Pattern Recognition and Machine Intelligence, Concordia University, Canada, for one year in 2005. He is a senior member of China Society of Image and Graphics. He is currently a professor in School of Electrical Engineering, Chongqing University. His research interests include image processing and computer vision, and wireless sensor networks. He has published more than 40 papers in these fields.
E-mail: myx@cqu.edu.cn

ZHAO Huiyuan was born in 1993. She received her B.S. degree in Dalian Jiaotong University, China. She is currently a graduate student in School of Electrical Engineering, Chongqing University. Her research interest lies in wireless sensor network and power system.
E-mail: 479393530@qq.com

YAN Dongmei was born in 1967. She received her B.S. degree in Yanshan University, China, in 1989. She got her M.S. degree in Chongqing University in 2004. She is a deputy general manager in Science and Technology Enterprise Group of Chongqing University.
E-mail: ydmcd@cqu.edu.cn