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A Lifetime-Enhancing Method for Directional Sensor Networks with a New Hybrid Energy-Consumption Pattern in Q-coverage Scenarios

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Abstract: An important issue in directional sensor networks (DSNs) is how to prolong the network lifetime in Q-coverage scenarios where each target point may have different coverage requirements. When the Q-coverage requirement is met, it is an effective way to maximize the network lifetime by controlling energy consumptions. Unlike the existing results where only the sensing energy consumption is considered, this paper proposes a new hybrid energy consumption pattern, which reflects the reality of energy consumptions more closely. In such a pattern, both sensing and communication energy consumptions are considered. By combining scheduling and clustering technologies to control these two kinds of energy consumptions in each round, a new lifetime-enhancing method (NLEM) is devised to prolong the network lifetime. First, a sensing direction scheduling algorithm for Q-coverage is proposed to make different sensing direction sets meet the coverage requirement of each target point. Then, a new cluster head selection algorithm and an inter-cluster communication algorithm are developed to select an optimal cluster head set and achieve multi-hop communication, respectively. Simulation results demonstrate the effectiveness of the NLEM in prolonging the network lifetime for DSNs in Q-coverage scenarios.

Keywords: network lifetime; Q-coverage; energy consumption; sensing direction scheduling; cluster head selection; inter-cluster communication

1. Introduction

Directional sensor networks (DSNs) have wide applications in many fields such as traffic safety monitoring, industrial and agricultural control, resident monitoring, and urban environment monitoring [1]. Network lifetime is an important factor that is directly related to the monitoring quality in DSNs [2]. To solve the network lifetime maximization problem in Q-coverage scenarios, a precondition is that a set of given target points $P = \{p_1, p_2, \dots, p_m\}$ has to be covered by $Q = \{q_1, q_2, \dots, q_m\}$ sensor nodes such that the target point p_i ($1 \leq i \leq m$) is covered by at least q_j ($1 \leq j \leq m$) sensor nodes, where Q consists of different constants. Due to the limited energy of directional sensor nodes, it is a challenging problem to prolong the network lifetime by controlling energy consumptions when the Q-coverage requirement is met [3].

To reduce the energy consumption in Q-coverage scenarios, some conventional methods have been proposed to control the sensing energy consumption generated by collecting and addressing the monitoring data [3–5]. However, the communication energy consumption is not considered in these methods, which is generated during the process of data transmission. In practical monitoring environments, great communication energy consumption also notably shortens the network lifetime

because of excessive redundant data communication [6]. Thus, it is necessary to control both sensing and communication energy consumptions in order to maximize the network lifetime.

Taking the above-mentioned explanations into consideration, this paper proposes a new hybrid energy consumption pattern of DSNs, where both sensing and communication energy consumptions are considered. Based on this pattern, the network lifetime maximization problem is investigated in Q-coverage scenarios. Assume that the network lifetime is divided into multiple rounds. In each round, active sensor nodes rotate their sensing direction to meet the Q-coverage requirement, and each node collects the same amount of video data. To prolong the network lifetime, it is necessary to control two kinds of energy consumptions when the coverage requirement of each target point is met in each round.

For the sensing energy consumption optimization, it is important to utilize the scheduling technology to make different sensing direction sets meet the Q-coverage requirement. During the past decades, many scheduling optimization methods have been proposed to control the sensing energy consumption. Among them, some are only suitable for the situations where the network consists of omni-directional sensor nodes [7–12]. With the development of video sensing technology and surveillance networks, many methods have been proposed for the situations where sensor nodes are directional. According to different coverage requirements, most of the methods mainly focus on basic coverage [13–17] and k -coverage scenarios [18,19]. However, the scheduling optimization method for DSNs is very scarce in Q-coverage scenarios.

For the communication energy consumption optimization, the cluster is one of the most effective layering technologies that reduces the energy consumption by controlling the data redundancy. The process of clustering network is shown in Figure 1. In the clustered DSN, there are many groups called clusters, and each cluster includes a cluster head and multiple member nodes. Many clustering optimization methods have been proposed to control the communication energy consumption. Most of the existing ones are based on the single-hop communication, and they mainly include two categories: meta-heuristic [20–28] and nature-inspired methods [29–36]. Although a few clustering methods based on multi-hop communication have been proposed in recent years [37–39], they are only suitable for small-scale networks.

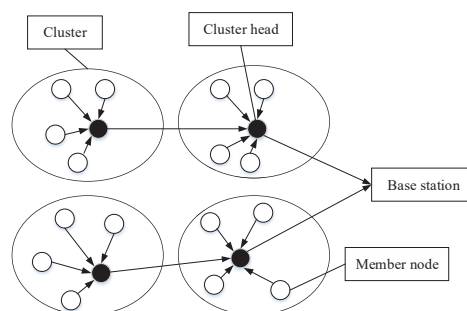


Figure 1. Cluster-based directional sensor network.

Motivated by the above discussions, this paper proposes a new lifetime-enhancing method (NLEM), which combines scheduling and clustering technologies to prolong the network lifetime for DSNs with a hybrid energy consumption pattern in Q-coverage scenarios. Simulation experiments under different situations indicate that the NLEM has a better effect on prolonging the network lifetime than other methods.

The main contributions of this paper are summarized as follows:

1. A new hybrid energy consumption pattern that considers both sensing and communication energy consumptions is proposed in Q-coverage scenarios. Based on this pattern, a lifetime-enhancing method is developed to prolong the network lifetime by controlling two kinds of energy consumptions when the Q-coverage requirement is met.

2. For the sensing energy consumption optimization, a Q-coverage sensing direction scheduling algorithm is devised to make different sensing direction sets accomplish the coverage task in each round. In this algorithm, both residual energy and total coverage probability are considered to make the minimal number of nodes with sufficient residual energy meet the Q-coverage requirement.
3. For the communication energy consumption optimization, a new cluster head selection algorithm, which considers total residual energy and average intra-cluster distance, is first proposed to select an optimal cluster head set from inactive nodes. Then, an inter-cluster communication algorithm based on the weight function is designed to achieve multi-hop communication.

The rest of the paper is organized as follows. The preliminaries are presented in Section 2. Section 3 formulates the problem under investigation. Section 4 describes our proposed method. In Section 5, the simulation experiment is conducted to evaluate the performance of the method. The conclusion of this paper is presented in Section 6.

2. Preliminaries

2.1. Network Model

To simplify the problem analysis in this paper, some assumptions about the monitoring scenario are given as follows.

- (1) Each sensor node is stationary and can rotate the sensing direction.
- (2) Each sensor node has two work modes: active mode and inactive mode.
- (3) Each sensor node can become the cluster head or member node.
- (4) Each sensor node can reduce data redundancy by data fusion.
- (5) All sensor nodes can guarantee the network connectivity.

2.2. Directional Probability Sensing Model

Different from the conventional sensing model, which has the same sensing probability within the circle sensing range, a directional probability sensing model is considered in this paper. According to Figure 2, the probable sensing area of a directional sensor node S is denoted by the five-tuple $(L, R_1, R_2, \vec{D}, \alpha)$. Here, L is the position of node, R_1 is the certain sensing radius, R_2 is the uncertain sensing radius, \vec{D} is the sensing direction, and α is the sensing angle.

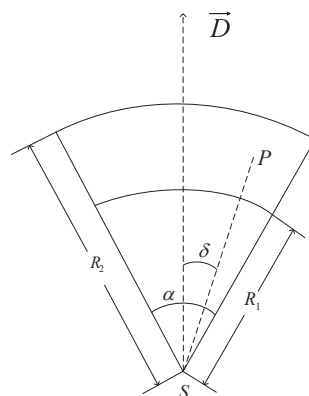


Figure 2. Directional probability sensing model.

The coverage probability that the sensor node S provides to the target point P is given as follows.

$$p = \begin{cases} 1, & \text{dis}(S, P) \leq R_1, \quad \delta \leq \alpha/2 \\ e^{-\lambda(\text{dis}(S, P) - R_1)^\gamma}, & R_1 < \text{dis}(S, P) \leq R_2, \quad \delta \leq \alpha/2 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where δ is the absolute included angle between \vec{SP} and \vec{D} and λ and γ are scalars satisfying $0 < \lambda < 1$ and $0 < \gamma < 1$.

2.3. Energy Consumption Model

During the process of the network operation, directional sensor nodes first collect and address the monitoring data, and then, they send these data to the BS. The energy consumption model mainly includes two parts: sensing and communication energy consumption models.

In the sensing energy consumption model, the energy that each sensor node consumes to collect and address the monitoring data is the same in each round, and the energy is given as the following equation.

$$E_{SX} = E_{S0} \quad (2)$$

where E_{S0} is a constant, and it is generally determined by the sensing characteristics of the sensor node.

The communication energy model used in this paper is the same as the one in [20]. In this model, the transmitter consumes energy to run the radio electronics and the power amplifier. The receiver consumes energy to run the radio electronics. The total energy that each sensor node consumes to transmit l bit data is given by Equation (3).

$$E_{TX}(l, d) = \begin{cases} l \cdot E_{elec} + l \cdot \varepsilon_{fs} \cdot d^2, & d < d_0 \\ l \cdot E_{elec} + l \cdot \varepsilon_{mp} \cdot d^4, & d \geq d_0 \end{cases} \quad (3)$$

where E_{elec} is the energy consumed per bit to run the transmitter or the receiver circuit. ε_{fs} and ε_{mp} are the power amplification energy consumption coefficients in different energy consumption modes. d_0 is the threshold transmission distance.

The energy consumption of the receiver to receive l bit data is given by:

$$E_{RX}(l) = l \cdot E_{elec} \quad (4)$$

where E_{elec} depends on several factors such as digital coding, modulation, filtering, and signal spreading.

3. Network Lifetime Maximization Problem Statement

To prolong the network lifetime in Q-coverage scenarios, we combine scheduling and clustering technologies to control sensing and communication energy consumptions. This section describes the process of the scheduling sensing direction, the process of the clustering network, and the problem formulation.

3.1. Process of Scheduling Sensing Direction

The process description of scheduling sensing direction is described in Figure 3. In the Q-coverage scenario, there are seven target points $p_1 \sim p_7$ and twenty-six directional sensor nodes $s_1 \sim s_{26}$, where the coverage requirement of each target point is $pr_1 = pr_2 = pr_3 = 1$, $pr_4 = pr_5 = 2$, and $pr_6 = pr_7 = 3$. The directional sensor nodes have two work modes: active and inactive mode, and they are stationary and can rotate direction. In order to meet the Q-coverage requirement, it is important to activate partial nodes and rotate their sensing direction to cover target points. Let the network lifetime be divided into multiple rounds. In each round, each active directional sensor node collects the same amount of video data, and we schedule different sensing direction sets to accomplish the Q-coverage task in order to reduce the sensing energy consumption.

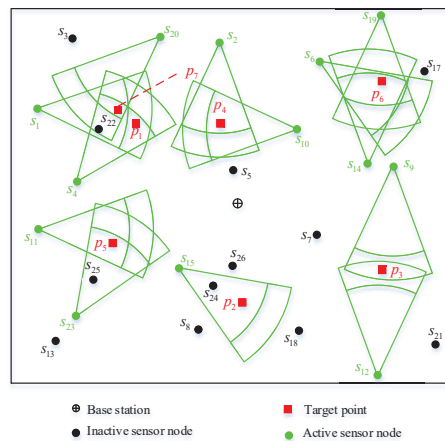


Figure 3. Process description of scheduling sensing direction.

3.2. Process of the Clustering Network

To control the communication energy consumption, it is necessary to utilize the clustering technology to optimize the structure of the network. The process of the clustering network is shown in Figure 4. Considering multi-hop communication, the process mainly includes two parts: cluster head selection and inter-cluster communication. After scheduling a sensing direction set to meet the Q-coverage requirement, the work mode of each directional sensor node is determined. A certain number of inactive nodes is selected as cluster heads of active nodes. Figure 4a shows that the sensor node set $\{s_5, s_7, s_{17}, s_{22}, s_{25}\}$ is selected as the cluster head set $\{ch_1, ch_2, ch_3, ch_4, ch_5\}$. The active nodes select the nearest cluster heads to join in so as to form clusters. The multi-hop communication includes two modes. As shown in Figure 4b, some cluster heads such as ch_1, ch_2, ch_5 directly send their received data to the BS. Other cluster heads ch_3, ch_4 are farther away from the BS, and they send data to the next-hop cluster heads.

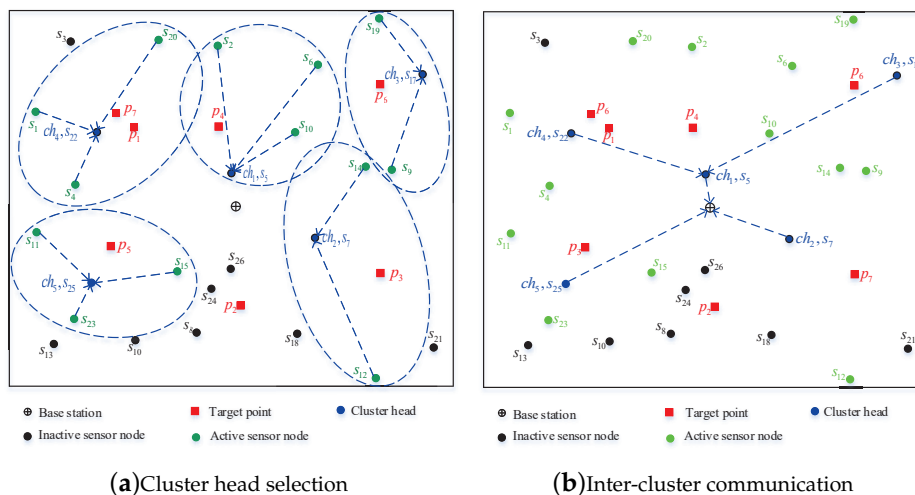


Figure 4. Process description of the clustering network.

3.3. Problem Formulation

3.3.1. Terminology

In order to simplify the understanding, we give some terminology as follows.

1. S: sensor node set, i.e., $S = \{s_1, s_2, \dots, s_n\}$.

2. P : target point set, i.e., $P = \{p_1, p_2, \dots, p_m\}$.
3. Q : coverage requirement of target points, i.e., $Q = \{q_1, q_2, \dots, q_m\}$.
4. c_i : possible number of sensing directions of sensor node s_i , $1 \leq i \leq n, 1 \leq c_i < \infty$.
5. $sd_{i,j}$: j^{th} sensing direction of sensor node s_i .
6. $x_{i,j,k}$: coverage probability that the j^{th} sensing direction of sensor node s_i can provide to target point p_k , $1 \leq i \leq n, 1 \leq j \leq c_i, 1 \leq k \leq m$.
7. SS : status of the sensor node, i.e., $SS = \{ss_1, ss_2, \dots, ss_n\}$. If sensor node s_i is active, $ss_i = 1$. Otherwise, $ss_i = 0$.
8. SE : residual energy of the sensor node, i.e., $SE = \{se_1, se_2, \dots, se_n\}$.
9. SDS : status of each sensor direction, i.e., $SDS = \{sds_{i,j} | 1 \leq i \leq n, 1 \leq j < c_i\}$. If sensing direction $sd_{i,j}$ is chosen to accomplish the coverage task, $sds_{i,j} = 1$. Otherwise, $sds_{i,j} = 0$.
10. CH : cluster head set, i.e., $CH = \{ch_1, ch_2, \dots, ch_t\}$.
11. CE : residual energy of the cluster head, i.e., $CE = \{ce_1, ce_2, \dots, ce_t\}$.
12. l_j : The number of sensor nodes in cluster j .
13. $dis(s_i, p_j)$: The distance between directional sensor node s_i and target point p_j .

3.3.2. Integer Programming Formulation for the Network Lifetime Maximization Problem in Q-Coverage Scenarios

To prolong the network lifetime in Q-coverage scenarios, it is important to control both sensing and communication energy consumptions when the Q-coverage requirement is met. Solving the following three new models yields the maximal network lifetime.

1. Sensing direction scheduling optimization model: For a given target point set and directional sensor node set, it is necessary to schedule different sensing direction sets to meet the Q-coverage requirement alternately. According to the different coverage requirements of each target point, we activate partial directional sensor nodes and choose one sensing direction to accomplish the coverage task. When choosing the active nodes, it is important to guarantee sufficient residual energy and activate the minimal number of nodes. Therefore, the sensing direction scheduling problem is described as follows.

Minimize:

$$F_1 = \frac{A_num}{\sum_{i=1}^n se_i \cdot ss_i} \quad (5)$$

subject to:

$$\sum_{i=1}^n \sum_{j=1}^{c_i} x_{i,j,k} \cdot sds_{i,j} \geq q_k, \forall k, 1 \leq k \leq m \quad (6)$$

where A_num is the total number of active nodes and $\sum_{i=1}^n se_i \cdot ss_i$ is the total residual energy. Equation (6) shows that the coverage requirement of each target point should be met.

2. Cluster head selection optimization model: To select an optimal cluster head set from inactive sensor nodes, it is important to consider energy and distance parameters in order to control the communication energy consumption. For the cluster head selection, we mainly consider following two energy efficiency parameters.

- (1) Total residual energy ratio of cluster head candidates:

During the process of data transmission, cluster heads consume much more energy than member nodes. It is important to guarantee sufficient residual energy of cluster heads. The first objective function is defined as the total residual energy ratio of cluster head candidates.

$$f_1 = \sum_{i=1}^n (se_i \cdot ss_i) / \sum_{j=1}^k ce_j \quad (7)$$

where $\sum_{i=1}^n (se_i \cdot ss_i)$ is the total residual energy of active sensor nodes and $\sum_{j=1}^t ce_j$ is the total residual energy of cluster head candidates in the current round.

(2) Average intra-cluster distance:

In a clustered network, member nodes consume energy to communicate with cluster heads. It is necessary to reduce the distance between member nodes and cluster heads. The second objective function is defined as the average intra-cluster distance.

$$f_2 = \frac{1}{t} \sum_{j=1}^t \frac{1}{l_j} \sum_{i=1}^{l_j} dis(s_i, ch_j) \quad (8)$$

where $dis(s_i, ch_j)$ is the distance between sensor node s_i and cluster head ch_j .

The above objective functions are not strongly conflicting with each other, so it is wise to give the cluster head selection optimization function as a linear combination. The cluster head selection optimization problem is summarized by the following.

Minimize:

$$F_2 = \alpha \cdot f_1 + (1 - \alpha) \cdot f_2 \quad (9)$$

subject to:

$$0 < \alpha < 1 \quad (10)$$

where the α is a constant given by the importance of the two objective functions.

3. Inter-cluster communication optimization model: Inter-cluster communication mainly includes two modes. If the distance between the cluster head and BS d is no more than the threshold distance d_m , the cluster head directly communicates with the BS. If d is over d_m , the cluster head establishes inter-cluster multi-hop routing to communicate with the BS, and the next-hop cluster head is determined by an inter-cluster weight function. The weigh function depends on the following three factors.

(1) Inter-cluster distance:

A cluster head ch_i should select its next-hop cluster head ch_j that is not far away from it. Therefore, the first factor is defined as the inter-cluster distance, i.e., $dis(ch_i, ch_j)$.

(2) Residual energy of the next-hop cluster head:

To control the overall communication energy consumption during the process of data transmission, a cluster head should consider the next-hop cluster head ch_j with more sufficient residual energy, i.e., ce_j .

(3) Number of member nodes in the next-hop cluster:

To reduce the load of the next-hop cluster head, a cluster head ch_i needs to select its next-hop cluster head ch_j with fewer relative member nodes. The third factor is the number of member nodes in the next-hop cluster, i.e., $c_num(j)$.

Taking the three factors into consideration, the inter-cluster communication problem is described as follows.

Minimize:

$$F_3 = \omega_1 \cdot dis(ch_i, ch_j) + \omega_2 \cdot (1 - ce_j) + \omega_3 \cdot c_num(j) \quad (11)$$

subject to:

$$\omega_1 + \omega_2 + \omega_3 = 1 \quad (12)$$

$$0 < \omega_1, \omega_2, \omega_3 < 1 \quad (13)$$

where F_3 is a linear combination of the three relative inter-cluster communication factors. When F_3 is minimized, the optimal inter-cluster communication is achieved.

4. Proposed Lifetime-Enhancing Method

To prolong the network lifetime in Q-coverage scenarios, our proposed method mainly includes two parts: the Q-coverage sensing direction scheduling optimization method and the multi-hop communication-based clustering optimization method.

4.1. Q-coverage Sensing Direction Scheduling Optimization Method

To control the sensing energy consumption when the Q-coverage requirement is met, our proposed method schedules different sensing direction sets to accomplish the Q-coverage requirement in each round. First, we propose a sensing direction partition algorithm to divide the sensing direction of each node into several non-coincidence directions. Then, we design a sensing direction scheduling algorithm to set up the sensing direction set so as to meet the Q-coverage requirement.

4.1.1. Sensing Direction Partition Algorithm

In this section, we utilize a sensing direction partition algorithm to divide the sensing direction of each sensor node into several non-coincidence directions. For each sensor node, we need to make different sensing directions cover different target point sets. Figure 5 is an example of the sensing direction partition.

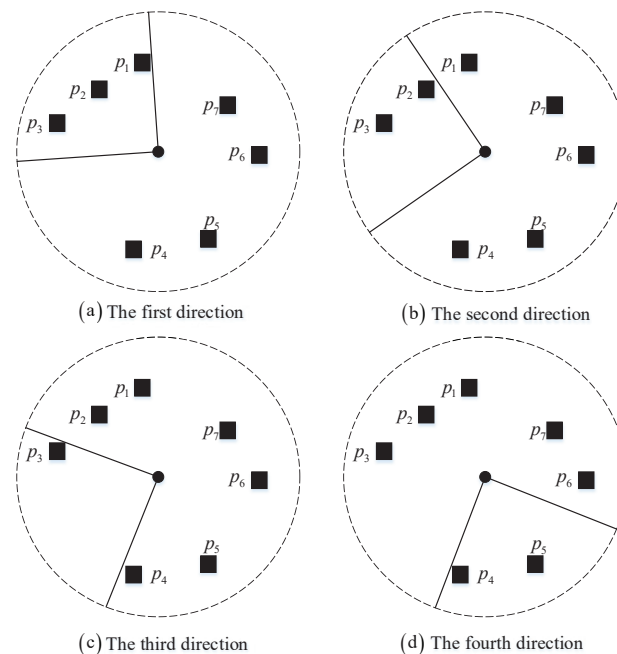


Figure 5. An example of the sensing direction partition.

In Figure 5, seven target points may be covered by sensor node s within its sensing range. The sensing direction is divided into seven parts, and Figure 5 shows the first four examples. If s is in the first sensing direction, the covered target point set is $\{p_1, p_2, p_3\}$. As the second sensing direction, the covered target point set is $\{p_2, p_3\}$. For the third sensing direction, the covered target point is p_3 . When it is in the fourth sensing direction, the covered target point set is $\{p_4, p_5\}$.

The process of conducting sensing direction partition is shown in Algorithm 1. After Algorithm 1 is run, we can require the coverage probability that each sensing direction of all sensor nodes can provide to each target point.

Algorithm 1: Sensing direction partition algorithm.

Input: Sensor node set: $S = \{s_1, s_2, \dots, s_n\}$
 Target point set: $P = \{p_1, p_2, \dots, p_m\}$
Output: Coverage quality that each sensing direction of all sensor nodes can provide to each target point: $x_{i,j,k}$

- 1: **for** $i = 1$ to n **do**
- 2: **for** $j = 1$ to c_i **do**
- 3: **for** $k = 1$ to m **do**
- 4: **if** $dis(s_i, p_j) \leq R_2$ **then**
- 5: Calculate $x_{i,j,k}$ according to Equation (1);
- 6: **end if**
- 7: **end for**
- 8: **end for**
- 9: **end for**

4.1.2. Q-coverage Sensing Direction Scheduling

In this section, we propose a Q-coverage sensing direction scheduling algorithm to make different sensing direction sets accomplish the Q-coverage task in each round. The objective of our proposed algorithm is to activate partial sensor nodes and choose one sensing direction of them to construct sensing direction sets. In order to guarantee sufficient energy, we select the sensing direction of the node with more residual energy to meet the coverage requirement of each target point. If some sensor nodes have the same residual energy, we next consider the sensing direction that provides target points with higher total coverage probability. After one sensing direction is selected, we update the status of the relative sensor node as active because one sensor node can only select one direction.

Algorithm 2 shows the Q-coverage sensing direction scheduling process of sensor nodes. If the practical coverage value pc_k is less than the coverage requirement of target point q_k , we select the sensing direction of the sensor node with higher residual energy to enhance coverage. If there exist sensor nodes with the same residual energy, we next select the one with higher total coverage probability. We constantly select the sensing direction to enhance coverage until the coverage requirement of each target point is met.

4.2. Multi-hop Communication-Based Clustering Optimization Method

After scheduling a sensing direction set of partial sensor nodes to accomplish the Q-coverage task, we next utilize clustering technology to optimize the structure of the network. We first propose a cluster head selection algorithm based on PSO to select a certain number of inactive nodes as the cluster heads of active nodes. Then, we propose an inter-cluster algorithm based on the weight function to achieve multi-hop communication.

4.2.1. Cluster Head Selection Algorithm Based on PSO

To select an optimal cluster head set from all inactive nodes, we utilize particle swarm optimization (PSO) to solve the proposed cluster head selection model. PSO is an evolution optimization technology by utilizing multiple particles to look for the best solution [40]. To accomplish cluster head selection, each particle updates its position and velocity until the optimal cluster head set is found. The pseudocode of the cluster head selection algorithm based on PSO is as follows.

Algorithm 3 shows the process of the cluster head selection based on PSO. Firstly, the network parameters and PSO parameters are initialized, and the fitness function is calculated. Then, each

particle constantly updates its velocity and position to search for a better solution. Finally, the optimal cluster head set is found.

Algorithm 2: Q-coverage sensing direction scheduling algorithm.

Input: Sensor node set: $S = \{s_1, s_2, \dots, s_n\}$
 Target point set: $P = \{p_1, p_2, \dots, p_m\}$
Output: Status of each sensor node: $SS = \{ss_1, ss_2, \dots, ss_n\}$

- 1: Get coverage quality that each sensing direction can provide to the target point
- 2: according to **Algorithm 1**.
- 3: **while** $(\sum_{i=1}^n \sum_j^{c_i} x_{i,j,k} \cdot sds_{i,j} \geq q_k, \forall k, 1 \leq k \leq m)$ is not met. **do**
- 4: **for** $k = 1$ to m **do**
- 5: **if** $pc_k < q_k$ **then**
- 6: **for** $i = 1$ to n **do**
- 7: **if** $(ss_i == 0) \ \&\& \ (se_i > 0)$ **then**
- 8: **for** $j = 1$ to c_i **do**
- 9: **if** $ps_k == 0$ **then**
- 10: $ps_k = i$; %Select sensor node.
- 11: $pd_k = j$; %Select sensing direction.
- 12: **else if** $ps_k \neq 0$ **then**
- 13: **if** $se_i > se_{pd_k}$ **then**
- 14: $ps_k = i$;
- 15: $pd_k = j$;
- 16: **else if** $se_i == se_{pd_k}$ **then**
- 17: **if** $stc_{i,j} > stc_{ps_k, pd_k}$ **then**
- 18: $ps_k = i$;
- 19: $pd_k = j$;
- 20: **end if**
- 21: **end if**
- 22: **end if**
- 23: **end for**
- 24: **end if**
- 25: **end for**
- 26: **end if**
- 27: **end for**
- 28: **end while**

Algorithm 3: Cluster head selection algorithm based on PSO

Input: Sensor nodes set: $S = \{s_1, s_2, \dots, s_n\}$
 Status of sensor nodes: $SS = \{ss_1, ss_2, \dots, ss_n\}$
 Size of swarm: num
 Dimensions of particles: $dim = t$
 Maximal number of iterations: $maxnum$

Output: Optimal cluster head set: $CH = \{ch_1, ch_2, \dots, ch_t\}$

- 1: Initialize particle $P_i, \forall i, j, 1 \leq i \leq num, 1 \leq j \leq dim = t$
- 2: $X_{i,j}(0) = (x_{i,j}(0), y_{i,j}(0))$ %The possible positions of the cluster heads
- 3: **for** $i = 1$ to n **do**
- 4: (1) Calculate $F_2(P_i)$ %According to Equation (9)
- 5: (2) $P_{besti} = P_i$
- 6: **end for**
- 7: $G_{best} = \{P_{besti} | F_2(P_{besti}) = \min(F_2(P_{besti}), \forall i, 1 \leq i \leq num)\}$
- 8: **for** $t = 1$ to $maxnum$ **do**
- 9: **for** $i = 1$ to num **do**
- 10: (1) Update velocity and position of P_i
- 11: (2) Calculate $F_2(P_i)$, and update P_{besti} and G_{best}
- 12: (3) Output the optimal cluster head set G_{best}
- 13: **end for**
- 14: **end for**

4.2.2. Inter-Cluster Communication Algorithm

In order to achieve multi-hop communication, it is important to solve the multi-hop communication optimization model. If the distance between the cluster head and BS is no more than the threshold value, it directly communicates with the BS. If the distance is over the threshold value, it sends video data to the next-hop cluster head. The pseudocode of the inter-cluster communication algorithm based on the weight function is shown in Algorithm 4.

Algorithm 4: Inter-cluster communication based on the weight function.

Input: Sensor node set: $S = \{s_1, s_2, \dots, s_n\}$
Cluster head set: $CH = \{ch_1, ch_2, \dots, ch_t\}$
The residual energy of cluster heads: $CE = \{ce_1, ce_2, \dots, ce_t\}$
Output: Next-hop cluster head id: $CN = \{cn_1, cn_2, \dots, cn_t\}$

```

2:   if  $dis(ch_i, BS) > d_m$  then
3:      $temp = \infty$ 
4:     for  $j = 1$  to  $n$  do
5:       if  $i \neq j$  then
6:         Calculate  $F_3$ 
7:          $cn_i = j$ ; select  $j$  as the next-hop cluster head
8:       end if
9:     end for
10:  end if
11:end for

```

Algorithm 4 shows the process of the inter-cluster communication between cluster heads. After the weight function is calculated, each cluster head selects another one with the minimum weight value as the next-hop cluster head. When each cluster head out of the threshold distance determines its next-hop cluster head, we can achieve optimal inter-cluster communication.

5. Simulation Experiment

5.1. Simulation Parameters

In this section, we conduct simulation experiments to verify the performance of our proposed method in MATLAB. The network parameters and PSO parameters are in Tables 1 and 2, and these parameters are given by referring to [20,40]. When we compare NLEM with other methods, the simulation parameters are the same. In our experiment, we randomly deploy N directional sensor nodes with certain sensing radius R_1 and uncertain sensing radius R_2 ($R_2 = R_1 + 5$). The sensing angle of sensor nodes is A , and the initial energy is E_0 . There are M target points in the monitoring area, and their coverage requirements vary from one to four.

5.2. Performance Evaluation

We evaluated the performance by conducting simulation experiments in different scenarios. The network lifetime was the number of rounds until the Q-coverage requirement was not met. We compared our proposed method with existing ones and discussed the parameter effect on the performance. There was no other optimization method that considered prolonging the network lifetime when the Q-coverage requirement was met in hybrid energy consumption DSNs. To verify the advantage of our method, we compared it with existing scheduling optimization methods and clustering optimization methods, respectively.

5.2.1. Comparison with Scheduling Optimization Methods

In this experiment, we compared our proposed method with existing scheduling optimization methods and discussed the parameter effect. There was no other scheduling optimization method that was directly related to the Q-coverage in DSNs. We set the genetic algorithm-based method (GCABM) and greedy algorithm-based method (GYABM) in [16] as the basic algorithms respectively to solve the network lifetime maximization problem in Q-coverage scenarios. In order to show the advantage of our proposed method, we compared the NLEM with GCABM and GYABM under the circumstance that the clustering optimization method was the same one proposed in this paper. We considered several parameters' effect on the performance while fixing other parameters as default values.

Table 1. Network parameters.

Parameter	Default Value
Monitoring area	$50 \times 50 \text{ m}^2$
BS position	(25, 25)
N	200
M	60
R_1	16 m
R_2	21 m
A	30°
d_0	87 m
d_m	30 m
E_0	1 J
E_{elec}	50 nJ/bit
ε_{fs}	10 pJ/bit/m ²
ε_{mp}	0.0013 pJ/bit/m ⁴
Packet length	4000 bits
Message size	500 bits

Table 2. PSO parameters.

Parameter	Value
Number of particles	30
c_1	2
c_2	2
ω	[0, 1]
D	[0, 200]
V_{max}	2π
Number of iteration	500

Figure 6 shows the relationship between the network lifetime and two sensing parameters. As shown in Figure 6a, the network lifetime gradually improved when the certain sensing radius increased from 10 to 20. The performance difference among the three methods began to increase after the sensing radius was over 12. In Figure 6b, the sensing angle varied from 10 to 110, and the sensing angle had no big effect on the performance. This was due to the fact that the number of the sensing directions of each node was fixed according to Algorithm 1, and a larger sensing angle did not obviously reduce the number of active nodes when the Q-coverage requirement was met.

Figure 7 shows the relationship between the network lifetime and two scale parameters. In Figure 7a, the network lifetime and the performance difference among three methods gradually improved as the number of sensor nodes increased. This was due to the reason that NLEM scheduled more suitable sensing direction sets to meet the Q-coverage requirement when there were enough nodes. In Figure 7b, the performance difference by three methods gradually decreased after the number of target points was over 60. This was due to the reason that the selectable sensing direction sets decreased when there were too many target points.

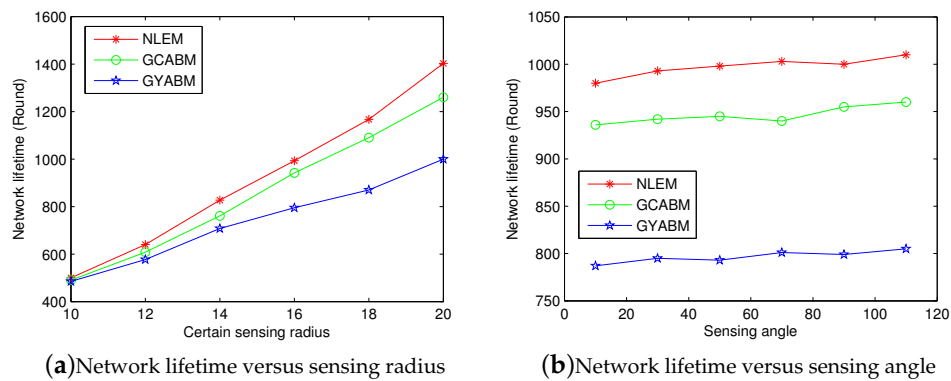


Figure 6. Network lifetime versus sensing parameters. NLEM, new lifetime-enhancing method.

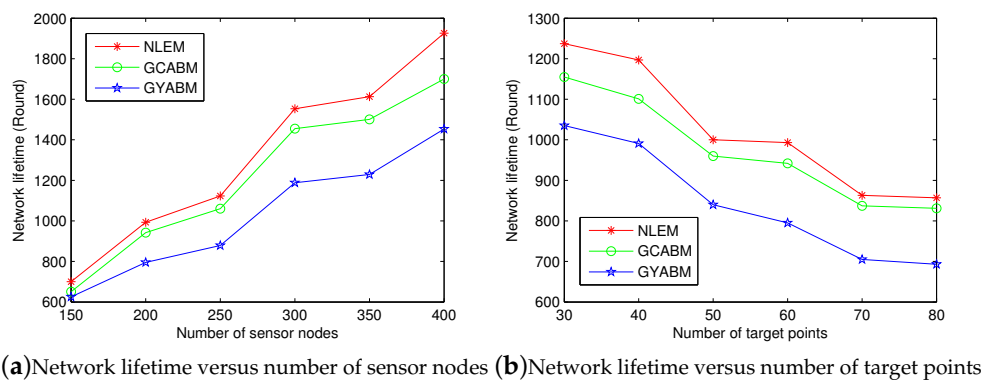


Figure 7. Network lifetime versus scale parameters.

From the above figures, it could be concluded that the performance of NLEM was better than GCABM and GYABM. Compared to the other two methods, the average increase by our method was 6.7% and 30.7%, respectively. This was due to the reason that the NLEM took more consideration of the residual energy of sensor nodes than the total coverage probability. In hybrid energy consumption DSNs, sufficient residual energy was more important than total coverage probability. NLEM selected the sensor node with the highest residual energy to meet the coverage requirement, and the other ones may select the sensor node with low energy and high total coverage probability.

5.2.2. Comparison with the Clustering Optimization Method

In this experiment, we compared our method with existing clustering optimization methods and discussed the parameter effect. The performance of NLEM was compared with multi-hop communication-based MENCin [37] and single-hop communication-based nCRO-ECAin [35] under the circumstance that the Q-coverage scheduling optimization method was the same one proposed in this paper. Besides, we considered several parameter effects on the performance while other parameters were default values.

Figure 8 shows the relationship between the network lifetime and two sensing parameters. Figure 8a indicates that the network lifetime by the three methods gradually improved with the increase of the sensing radius. The sensor node with a larger sensing radius covered more target points within its sensing range. In Figure 8b, as the sensing angle increased from 10 to 110, the network lifetime had no big change, and NLEM had a stable advantage over other optimization methods.

Figure 9 shows the relationship between the network lifetime and two scale parameters. Figure 9a indicates that the network lifetime by the three methods gradually improved as the number of sensor nodes increased. In Figure 9b, the number of target points varied from 30 to 80, and the network

lifetime gradually dropped with the increase of the number of target points. This was due to the reason that more target points needed to activate more sensor nodes to accomplish the Q-coverage task.

From the above four figures, it could be observed that our NLEM had an advantage over the other two methods. Compared to MENC and nCRO-ECA, the NLEM obtained an average increase of 11.2% and 28.5%, respectively. This was due to fact that the NLEM used the energy efficiency cluster head selection model and the inter-cluster communication model based on the weight function to control the communication energy consumption.

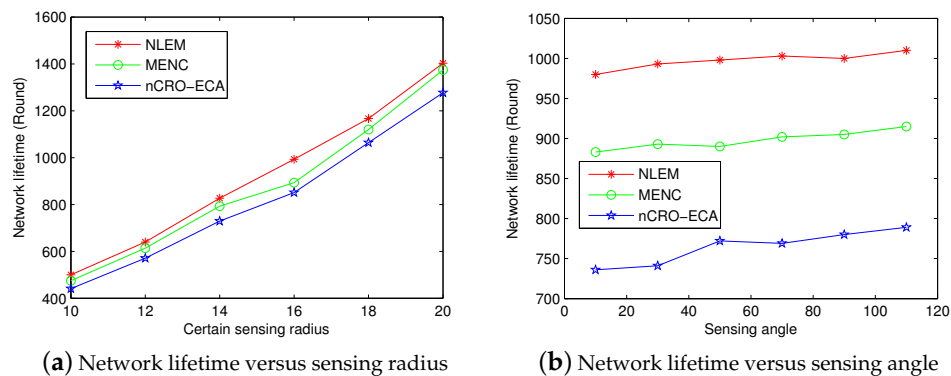


Figure 8. Network lifetime versus sensing parameters.

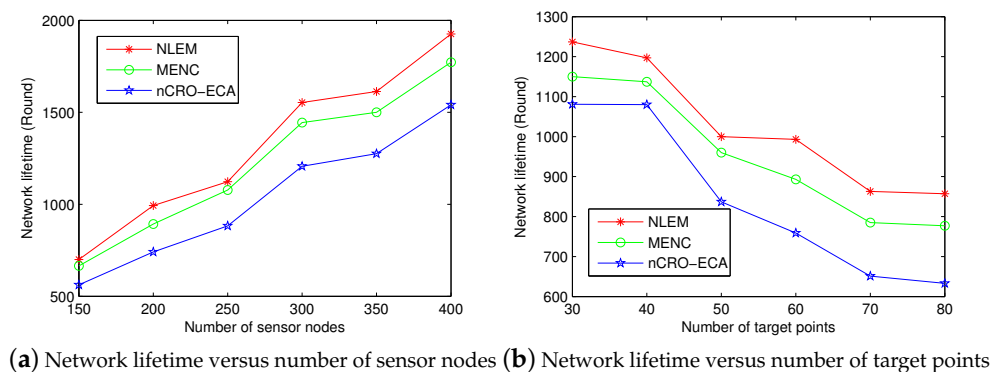


Figure 9. Network lifetime versus scale parameters.

In summary, the experiment results indicated that NLEM effectively prolonged the network lifetime when the Q-coverage requirement was met in hybrid energy consumption DSNs. This method combined scheduling and clustering technologies to control sensing and communication energy consumptions at the same time. Compared to existing scheduling and clustering optimization methods, our method guaranteed a longer network lifetime.

6. Conclusions

This paper proposed a new lifetime-enhancing method for hybrid energy consumption DSNs in Q-coverage scenarios. Our goal was to prolong the network lifetime when the coverage requirement of each target point was met. For the sensing energy consumption optimization, a Q-coverage scheduling optimization algorithm that considered residual energy and total coverage probability was developed to accomplish the coverage task. For the communication energy consumption optimization, an energy efficiency algorithm was first proposed to select an optimal cluster head set from inactive nodes. Then, an inter-cluster communication algorithm was designed to achieve multi-hop communication.

Simulation experiments were conducted to verify the advantage of NLEM. In terms of the sensing energy consumption optimization, the comparison with existing scheduling optimization methods indicated that NLEM obtained a 6.7% and 30.7% increase of the network lifetime, respectively. In terms of the communication energy consumption optimization, the comparison with existing clustering optimization methods showed that the average increase of the network lifetime by the NLEM was 11.2% and 28.5%, respectively. It could be concluded that the proposed method effectively prolonged the network lifetime in Q-coverage scenarios.

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