Nodes Non-uniform Deployment with Energy Harvesting in Linear WSN

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Abstract. Aiming at the problem that the network lifetime declines in linear WSN powered by battery, node energy model with energy harvesting (EH) and prediction is constructed. Based on the model, the multi-sink WSN network is deployed in an optimal non-uniform way. The mathematical expressions of the average packet delivery ratio and throughput density of the optimal deployment strategy are deduced theoretically. The performances of the average packet delivery ratio, throughput density, network lifetime, and residual energy ratio are simulated in EH-WSN and WSN, as well as the ratio $q$ and the signal-to-interference noise ratio (SINR) threshold $\theta$. The results show that the lifetime of EH-WSN is prolonged by adjusting the ratio $q$ and the SINR threshold $\theta$, compared with WSN powered by battery. The proposed strategy has good scalability, suitable for the non-uniform deployment in linear EH-WSN, especially with a large number of nodes and a long distance.

1. Introduction

Wireless sensor network (WSN) is constituted of plenty of sensor nodes that can perceive and collect the data in the surroundings. The processed data is transmitted to sink node in the way of wireless communication [1]. The linear WSN is widely used in tunnels, railways and other long-distance monitoring areas because of its special topological structure [2]. Generally, the data is transmitted to the sink node in multi-hop way [3]. The closer these nodes are to the sink, the greater the amount of data forwarded and the more energy consumed, resulting in the 'energy hole' problem of linear WSN [4]. When some nodes in the network run out of energy, the entire network fails.

With the development of ambient power harvesting (APH) technology, researchers have used APH to apply energy (solar energy, vibration energy, etc.) to WSN [5], effectively extending the lifetime. The nodes in the WSN convert the energy collected in the surrounding into electrical energy, forming an energy harvesting wireless sensor network (EH-WSN). In view of the problem that the energy consumption of node is too fast, which results in the decline of lifetime, the paper [6] proposes an exponential weighted moving average algorithm to predict the energy, assuming that the same time slot collects the same energy in several days, but the prediction error is large when the weather suddenly changes. Paper [7] proposes a trapezoidal energy model, which divides the network into energy consumption, energy storage and the stabilization period. But, the model is too simple to be applied to the case of abrupt weather change. In [8], a linear WSNs network deployment scheme based on the increasing proportional sequence is proposed, which improves network energy balance and the lifetime. However, the node hasn’t energy collection device and can’t supply energy.
In this paper, an improved weather conditioned moving average (WCMA) is introduced, and WSN node energy model with energy collection and prediction function is proposed. Based on the model, the multi-sink WSN network is deployed in an optimal non-uniform way. Combined with node energy prediction model and free space path loss model, we obtain the proposed strategy effectively improves the performance of the network, and more suitable for long distance linear WSN.

2. System Model

2.1. Linear WSN nodes deployment model

The one-dimensional linear WSN model is illustrated in Figure 1. The network is composed of the sensing nodes and the sink nodes, among which the sensing node with data collection, calculation, communication and solar energy collection. The energy of the sink node is not limited. A linear multi-sink WSN is formed by the non-uniform deployment of $k$ sensing nodes between two sink nodes in the proportional sequence with the common ratio $q$. The $d_i$ represents the distance between node $i=1$ and left sink node. $S$ means the distance between two sink nodes. Moreover, node $i$ transmits the collected data to the sink nodes on both sides in a multi-hop manner.

\[ S = \frac{d_i (1 - q^{k+1})}{1 - q} \]  \hspace{1cm} (1)

Then the distances from node $i$ to $S_1$ and $S_2$ are respectively shown as:

\[ d_{i,S_1} = \frac{d_i (1 - q^i)}{1 - q} \]  \hspace{1cm} (2)

\[ d_{i,S_2} = S - \frac{d_i (1 - q^i)}{1 - q} \]  \hspace{1cm} (3)

2.2. Node energy harvesting and prediction model

The energy model of node is shown in Figure 2. Each harvesting cycle $n$ includes a harvesting phase, characterized by the harvesting rate $\eta P_{m+1}$ ($\eta$ is the charging efficiency of the battery), and the super capacitor capacity $E_f$ (initial energy), and the consumption phase characterized by the power consumption levels. In this paper, only the energy dissipation during data processing and data transmission is considered, and the power consumption of the processor is recorded as $P_u$; The power consumption of the transceiver is recorded as $P_o$, which depends on the transmission power $P_t$.

![Figure 1. Linear WSN nodes deployment model.](image)

![Figure 2. Energy model of sensor node.](image)

![Figure 3. Node energy harvesting prediction model.](image)
The structure of node with energy harvesting and prediction is illustrated in Figure 3. The energy harvesting module uses the WCMA algorithm proposed by Pioron J R to predict the solar energy [9]. The WCMA takes an $E$ matrix of size $D \times M$ that stores energy values of $M$ time slots for previous $D$ days [10]. $E(d,m)$ stands for the energy value of present day at $m$ time slot; $M_D(d,m+1)$ is the average energy value of previous $D$ days at $m+1$ time slot, which expression is given as follows:

$$M_D(d,m+1) = \frac{\sum_{i=0}^{d-1} E(i,m+1) }{D} \tag{4}$$

$GAP_i$ indicates the weather change in present day is related to the past $D$ days. The expression is:

$$GAP_i = V \cdot Y \sum Y \tag{5}$$

Where a vector $V = [u_1, u_2, \ldots, u_L]$ that comprises the quotient of the energy value of past $L$ time slots at present day and the average energy value during the past $D$ days for those time slots. Therefore, $u_i$ is:

$$u_i = \frac{E(d,m-L+l-1)}{M_D(d,m-L+l-1)} \tag{6}$$

Besides, for pay more attention to the nearest values in time, we define vector $Y = [y_1, y_2, \ldots, y_L]$ to weight these values with the distance to the genuine point. Thus, we can computer $\gamma_l = l/L$.

Finally, the energy value on present day at $m+1$ time slot predicted by WCMA is formulated as follows, where, $\lambda \in [0,1]$ is a weighting factor.

$$P_{m+1} = \lambda E(d,m) + \left(1-\lambda \right) \cdot GAP_i \cdot M_D(d,m+1) \tag{7}$$

### 3. Performance Analysis

Above all, assuming the data packet size is $S$ bits, the transmission rate is $\alpha$ bps and the power consumption is $P_r+P_u$. The energy consumed when transmitting a data packet of duration $t_d = \frac{S}{\alpha}$ is $(P_r+P_u)t_d$. We assume that the remaining energy at the end of the harvesting cycle $n$ is $E_n$. Thus:

$$E_n = E_{n-1} + \eta P_{m+1} (t_h + t_d) - (P_r + P_u)t_d \tag{8}$$

Supposing that when $E[E_n]=E[E_{n-1}]$, the energy is kept in a steady state, the time of the energy harvesting phase can be obtained as follows:

$$t_h = \frac{(P_r + P_u) - \eta P_{m+1}}{\eta P_{m+1}} t_d \tag{9}$$

Then the time of the harvesting cycle can be formulated as:

$$T_h = E[t_t] + t_h = \frac{P_r + P_u}{\eta P_{m+1}} t_d \tag{10}$$

Taking the free space path loss model, we obtain the receive powers of node $i$ at $S_1$ and $S_2$ as:

$$P_{i,S_1} = \frac{KP_i}{d^\gamma_{i,S_1}} = \frac{KP_i}{(d_{i,S_1}^\gamma)} \tag{11}$$

$$P_{i,S_2} = \frac{KP_i}{d^\gamma_{i,S_2}} = \frac{KP_i}{(S - d^\gamma_{i,S_2})} \tag{12}$$

Where $K$ is the propagation factor; $\gamma (2 \leq \gamma \leq 4)$ is the path loss exponent;

For the harvesting cycle, when the transmission intervals overlap of node $i$ and node $j$, the node $i$ will be interfered by node $j$ during data transmission, and the probability of interference is shown as:

$$p_{ij} = \frac{2t_d}{t_h + t_d} = \frac{2\eta P_{m+1}}{P_r + P_u} \tag{13}$$

When node $i$ transmits the collected data to the sink, the total interference power can be computed:
\[ I_{s} = \sum_{j=l_{s}} P_{s_{j}} \] \hspace{1cm} (14)

Then the SINR of node \( i \) at sink is obtained as follows, where \( N_0 \) represents the receiver noise.

\[
\text{SINR}_{i,s} = \frac{P_{i,s}}{I_{i,s} + N_0} \cdot \frac{KP}{I_{i,s} + N_0} \cdot \frac{1}{d_i(1-q^i)^\gamma} \cdot \frac{1}{I_{i,s} + N_0} \] \hspace{1cm} (15)

\[
\text{SINR}_{i,s} = \frac{P_{i,s}}{I_{i,s} + N_0} \cdot \frac{KP}{I_{i,s} + N_0} \cdot \frac{1}{S - d_i(1-q^i)^\gamma} \cdot \frac{1}{I_{i,s} + N_0} \] \hspace{1cm} (16)

Only when the SINR exceeds the threshold \( \theta \), the data from the node \( i \) can be accurately received at least one sink, and this occurs with probability, \( P_{\text{succ,}i} \), given by, where \( P_{i,s} = P(\text{SINR}_{i,s} \geq \theta) \).

\[
P_{\text{succ,}i} = P_{i,s} + P_{i,s} + P_{i,s} + P_{i,s} \geq P_{i,s} + P_{i,s} - P_{i,s} - P_{i,s} \] \hspace{1cm} (17)

Definition of average packet delivery ratio: the average packet delivery ratio is the probability that a single sensing node successfully sends packets at the sink node [11]. Its expression is shown by:

\[
DR = \frac{\sum_{i=1}^{k} P_{\text{succ,}i}}{k} \] \hspace{1cm} (18)

Because each node sends data on average in the harvesting cycle \( T_i \) seconds, the throughput as:

\[
R_i = \frac{P_{\text{succ,}i}}{T_i} \] \hspace{1cm} (19)

Definition of throughput density: the throughput density is the number of packets received by sink node per second [12]. Its expression is shown as:

\[
D = \frac{\sum_{i=1}^{k} R_i}{S} \] \hspace{1cm} (20)

4. Simulation Experiment

4.1. Performance analysis of EH-WSN and WSN

In this section, using matlab to simulate and analyse the average packet delivery ratio, throughput density, network lifetime and node residual energy ratio of EH-WSN and WSN nodes non-uniform deployment strategy. The parameters of experience are shown in Table 1.

| Table 1. Experience parameters. |
|----------------------------------|
| Parameters          | Values         |
| \( S_d \) (bytes)   | 100            |
| \( \alpha \) (kbps) | 250            |
| \( N_0 \) (dBm)     | 0              |
| \( \gamma \)        | 2              |
| \( K \)             | 3.1623x10^-6   |
| \( P_u \) (mW)      | 24             |
| \( \eta \)          | 0.32           |

Figure 4 compares the average packet delivery ratio and throughput density of the network when the number of deployed nodes \( k=50, 100, 150, 200, 250 \), respectively. It can be observed that the average
packet delivery ratio and throughput density decrease with the increasing $k$. This is because when the number of nodes increases, the interference between nodes rises correspondingly, and the sink node’s probability successfully receiving the packet decreases, thus affecting the performance of the network. Obviously, the average packet delivery ratio and throughput density of EH-WSN are higher than that of WSN. Moreover, with the increase of $k$, the change trend of average packet delivery ratio and throughput density tends to be gentle. Therefore, the EH-WSN non-uniform deployment strategy proposed in this paper has better scalability and is suitable for the linear network with more nodes.

The network lifetime, as shown Figure 5, can be known that the lifetime of the EH-WSN is larger than the lifetime of the WSN. Besides, with the increase of deployment node $k$, the change of EH-WSN lifetime tends to be flat, and the gap of lifetime between EH-WSN and WSN non-uniform deployment strategies increases accordingly. Figure 5 also shows the ratio of the remaining energy of the node to the initial energy at the end of the network lifetime. We can obtain the EH-WSN has less residual energy at the end of the lifetime. But for the WSN non-uniform deployment strategy, the remaining energy of the node shows a larger increase as the number of nodes is increased, which has a lower energy utilization rate.

4.2. The effect of the common ratio $q$ and the threshold $\theta$ on the EH-WSN

In Figure 6, the average packet delivery ratio and throughput density of EH-WSN are analyzed when $\theta=5$, $q = 0.2, 0.4, 0.8$. It can be known that for a given threshold $\theta$, with the increase of $q$, the average packet delivery ratio and throughput density reduce correspondingly. This is because the increase of $q$ affects the distance between sensor nodes, and the distance between two sink nodes increases correspondingly, which makes the average packet delivery ratio and throughput density decrease.

The lifetime and residual energy ratio of EH-WSN are demonstrated in Figure 7 when $\theta=5$, $q=0.2, 0.4, 0.8$. As can be seen from Figure 7, for a fixed threshold $\theta$, the lifetime of the network reduces with the increasing $q$. This is because the increase of $q$ leads to the increases in the distance between nodes, and more energy is consumed during data transmission, which results a decline of the network lifetime. Figure 7 also demonstrates that the remaining energy of the node increases and the energy utilization rate is lower with $q$ increases.

Figure 8 evaluate the average packet delivery ratio and throughput density of EH-WSN when $q=0.4$, $\theta=2.5, 10$. We can observe that for a fixed common ratio $q$, the average packet delivery ratio and throughput density of the network decrease with the rise of threshold $\theta$. This is because the rise of threshold $\theta$ reduces the network’s tolerance to interference, so the average packet delivery ratio and throughput density decline accordingly, too.
Finally, the network lifetime and residual energy ratio of EH-WSN are depicted in Figure 9 when \(q=0.4, \theta=2,5,10\). For a given common ratio \(q\), the lifetime of EH-WSN increases with the rising threshold \(\theta\), because as the rise of threshold \(\theta\), the average packet delivery ratio and throughput density of the network decrease, the energy consumed by the network in data transmission decreases, thus prolonging the network lifetime. On the other hand, along with the rise of threshold \(\theta\), the residual energy of node declines and has a higher energy utilization rate is shown in Figure 9.

5. Conclusion

This paper proposes an optimal non-uniform, multi-sink deployment network model for linear WSN with solar energy harvesting. Combined with node energy prediction model and free space path loss model, the performances of the average packet delivery ratio, throughput density, network lifetime, and residual energy ratio are studied in EH-WSN and WSN under different node numbers, as well as the common ratio \(q\) and threshold \(\theta\). The simulation results show that by adjusting the common ratio \(q\) and threshold \(\theta\), the average packet delivery ratio and throughput density of the EH-WSN non-uniform deployment strategy are higher than the WSN, and it extends the lifetime of the network and improves the energy utilization rate.
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