A Forward-connection Topology Evolution Model in Wireless Sensor Networks

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Abstract: The stability and reliability of the topology structure play an important role in the efficiency of the data collecting for wireless sensor networks. In this paper, a topology evolution model is proposed. The model considers the directionality of the data flow, and adopts the forward connectionism to ensure the neighbor nodes of each node. Furthermore, the model considers the balanced energy overhead in each communication path, adopts the energy balanced mechanism to compute the connection probability to the neighbor nodes. Meanwhile, the process of topology evolution is distributed and the communication radiuses of all sensor nodes are limited. A theoretical analysis exhibits that the model has power-law distribution of node degrees. Simulation shows that the proposed topology evolution model make energy overhead more balanced, and prolongs the lifetime of the network.

Keywords: wireless sensor networks; topology evolution; energy balanced mechanism; power-law distribution

1 Introduction

Wireless sensor networks (WSNs) are a kind of wireless networks which are constructed by plenty of sensor nodes. WSNs can gather the data from its monitoring physical or environment conditions (e.g. the temperature, the sound etc.) and send their data to the destination (Base Station) directly or via multi-hop [1,2]. WSNs cover a wide range of applications, since it is easily deployed and self-organized, such as environmental monitoring, military target tracking, natural disaster relief and health monitoring, and so on [3,4]. On the other hand, WSNs are weakness in processing capability and storage capacity. Especially, when the WSNs are deployed in a harsh environment that people hardly reach, the nodes are difficultly recharged and replaced, and it leads to the limited energy sensor nodes. Therefore, establishing a model which can prolong the lifetime of WSNs efficiently is a very important issue.

The study of complex networks has become a common focus of many branches of science since the end of last century [5,6]. The complex networks study the characteristics of the networks, which can describe many systems in nature, such as the cooperative networks, social networks and so on. Most complex networks are scale-free networks, which are robust against random removal or failures of nodes. Recently, complex network is used to study connectivity, fault tolerant and topology evolution of the wireless sensor networks.

In this paper, we proposed a forward-connection topology evolution model for wireless sensor networks. Different from existing schemes, in the proposed model, a node sends the data to those nodes that are nearer to the base station than itself.

The remainder of this paper is organized as follows. In Section 2, the related work is summarized. In Section 3 and 4, an algorithm of forward-connection topology evolution model is proposed and analyzed. In Section 5, the simulation to present the features of the networks generated by the proposed algorithms is provided. Finally, the conclusion of this paper is given.

2   Related works

The topology evolution models can be divided into two types roughly: the cluster-based and the non-cluster-based. In the non-cluster-based topology evolution models, all the nodes transit the data by a chain, a tree and so on to the base station. These models are used to some small WSNs or the single type nodes.

In 2002, S. Lindsey et al. [7] proposed PEGASIS (Power-Efficient Gathering in Sensor Information Systems) model, an optimal chain-based protocol, which can reduce the energy consumption. But if a middle node in the chain is drained, all the nodes behind the drained node $can't$ transmit the data to the base station. In 2003, H. O. Tan et al. [8] improved the PEGASIS Model, and proposed PEDAP algorithm. The algorithm is near to optimal minimum spanning tree based routing schemes.

In 2003, Xiang Y L et al. [9] considered how the transmission range is related with the number of nodes in a fixed area such that the resulted network can sustain k fault nodes with high probability. Then they presented a localized method to control the network topology.

In 2005, Thallner et al. [10] presented an improvement of topology control algorithm for dynamic networks and low power devices, which provided an improvement of topology control algorithm for dynamic networks and low power devices.

In 2006, Abhishek et al. [11] proposed an approximation algorithm, which used additional relay nodes to construct a fault-tolerant backbone network. On the other hand, the cluster-based topology evolution models divide the WSNs into the inner-cluster layer and inter-cluster layer. These two layers usually possess the self-similarity. These models are used to some large or mixed WSNs.

In 2000,W. R. Heinzelman et al. [12] presented an LEACH protocol which is able to distribute energy dissipation evenly throughout the sensors, doubling the useful system lifetime for the networks we simulated. But the LEACH protocol is not fit for the huge WSNs and the WSNs which have the unbalanced energy for each node.

In 2003, S. Bandyopadhyayet al. [13] proposed a distributed, randomized clustering algorithm to organize the sensors into clusters in a wireless sensor network. They then extended this algorithm to generate a hierarchy of cluster heads and observe that the energy savings increase with the number of levels in the hierarchy.

In 2004, Ossama et al. [14] proposed HEED protocol, which selected cluster heads periodically according to the node residual energy. The HEED protocol can prolong the lifetime of WSN.

Recently, the evolution models which combine the complex networks come up.

In 2009, Li J C et al. [15] proposed an evolving model among the cluster heads of WSN. The model is based on the random walker theory, and exhibits a power-law distribution.

In 2009, Zhu et al. [16] presented two self-organized energy-efficient models for WSNs. The first model constructed evolving network considering the connectivity and remaining energy of each node. The second model considered the energy consumption balance of the whole network.

In 2011, Xiao G Q et al. [17] proposed a topology evolution TEBAS, which introduces fitness and local world and more suitable for WSNs than ERW (Topology Evolution by Random Walker).

In 2012, Ya Q W et al. [18] studied the influence of node failure on the performance of WSN, and different immunization strategies were given.

In 2012, Xiao J L et al. [19] considered the energy-aware mechanism, and proposed a new topological evolving model based on the complex network theory. They found that node energy distribution had the weak effect on the degree distribution.

In the practical applications, a node sends the data to the others that are nearer to the base station than itself. This kind of connection reduces the energy consumption and the delay of transmission. Based on this connection, a forward-connection topology evolution model is proposed, which considers both the forward-connection mechanism and the energy-balanced mechanism. Analysis and simulation show that the network exhibits well robustness, a power-law degree distribution and a long lifetime.

3   Forward-connection topology evolution model

The model uses the cluster network which contains three kinds of nodes: base station, cluster heads and cluster nodes. The network is divided into two layers: inner-cluster and inter-cluster. In the inner-cluster, data are sent to the cluster head, and the cluster head verifies the data integrity to restrict the range of compromised node. In the inter-cluster, data are sent to the base station, and the integrity is verified at the base station. Furthermore, a mechanism is proposed to locate the compromised node. SPPDA model can be divided into initialization, key distribution, inner-data aggregation and inter-data aggregation.

In this section, a forward-connection mechanism is considered. Meanwhile, the energy of each node in a path should be kept balance. It means that there is no node which energy is less than others. Then, an energy balanced mechanism is considered, which prolong the lifetime of the path.

In WSNs, most energy of sensor nodes was used in data transmission. So, it′s assumed that the higher energy a node has, the greater connection probability the node holds in this model. Besides, referred to the evolution principles of complex networks, preferential attachment of the nodes is present in the processes of the topology evolution. Meanwhile, considering the relationship between the distance and the energy consumption, a threshold of communication radius should be set, which decides the communication probability between two nodes. The probability equals zero when the distance of two nodes is larger than the threshold. And the closer of two heads are, the larger probability connects to these heads is. Here, $d_{j,max}$ is used to represented the communication radius of node j, and d_{max} is the communication radius of the node whose energy is E_{max}, then $d_{j,max} = \frac{E_j}{E_{max}} d_{max}$.

Since each node in the network are homogenous, the initial node actual does not exist in the theory of distributed mechanism, which is considered in this paper. All nodes will send a message to its surrounding node when the topology evolution begins. According to the time of index, the node sends agreement to the earliest request, and refuses to the rest. The messages that nodes sent are direction in the evolution. Then a directed network is considered, where the direction shows the direction of data flow.

3.1   Forward-connection mechanism

In forward-connection mechanism, the forward neighbors of each node are confirmed. The mechanism is divided into two steps. In the first step, the neighbors of sending node are confirmed. In the second step, if the base station is the neighbor of sending node, the sending node has no forward neighbors, because the sending node transmits the data to the base station directly. If the base station is not the neighbor of sending node, the neighbor nodes whose distance

to the base station is smaller than the sending node are selected. These neighbor nodes are the forward neighbors of sending node. As shown in Figure 1, point O is the base station. Point I is the sending node. Line OA, OI and OB is the distance between sending node and the base station. Lind IA and IB is the communication radius of the sending node. Point P is a neighbor of sending node. Then, a conclusion to confirm the forward neighbors is given as follows.

Conclusion: if $\angle PIO$ is less than 60 degree, P is the forward neighbor of sending node.
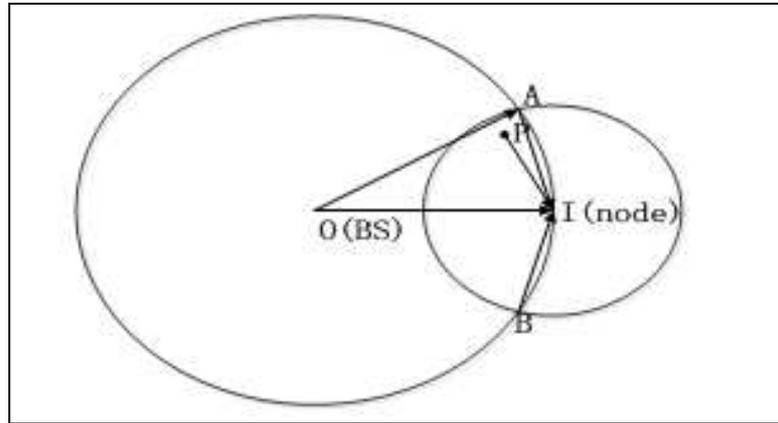
Figure 1: Forward-connection mechanism

Proof: The forward neighbors of sending node exist. So, we have $OA > AI$, then $\angle OIA > \angle AOI$. On the other hand, $OA = OI$, so $\angle OIA = \angle IAO$.In $\triangle \; AIO$, $\angle AIO + \angle IAO + \angle AOI = 180°$. So, $180° = \angle AIO + \angle IAO + \angle AOI < \angle AIO + \angle IAO + \angle AIO = 3\angle AIO$. That is $\angle AIO > 60°$. In the same way, we have $\angle OIB > 60°$.   □

According to the conclusion, the forward neighbors of each node can be confirmed easily.

3.2 Energy-balanced path mechanism

In energy-balanced mechanism, the neighbors of sending node in two hops are considered. In this paper, an energy-balanced element is used to judge the level of the energy-balanced. And a threshold ŚĹ is used to distinguish the high energy nodes and the low energy nodes. If the energy of a forward neighbor ϵ is larger than the energy of sending node, this forward neighbor is a high energy node. Node i is one of the forward neighbors of sending node. N is the number of the forward neighbors of node$i$, and N_ϵ is the number of the high energy nodes of node i. Thus, the energy-balanced element of node i can be counted as $\delta_i = \frac{N_\epsilon}{N}$.

3.3 Model of evolution network

In this model, a network is modeled as a directed graph $G(V, E)$, where nodes are represented as the set of vertices V and the links as the set of edges E. The number of sensor nodes is defined as $|V| = N$. In the topology evolution networks, there are two rules of the distributed and local-world topology evolution model which is R-1 (growth) and R-2 (preferential attachment) is given as follows:

R-1:After the node i is selected, this node sends the message to other nodes in its local-world, which means the circle area is within the maximum communication radius $d_{j,max}$ of the head i.

The nodes send agreement to the earliest request, and refuses to the rest.

The evolution ends when each node succeed to connect other nodes actively.

R-2: Until the each node in its local-world returns the agreement to the request node, the request node connects m edges to these nodes with the probability $\Pi_{i \rightarrow j}$. If the number of the nodes is less than m, it connects all of the nodes. $\Pi_{i \rightarrow j}$ represents the probability of a head j connected to head i. The probability $\Pi_{i \rightarrow j}$ depends on the connectivity, the distance of two nodes and the threshold of node i. The form of $\Pi_{i \rightarrow j}$ is $\Pi_i = \frac{E_j \delta_j k_j}{\sum_{l \in \Lambda_i} E_l \delta_l k_l}$, where $\bigwedge_i$ is the local-world of node i.

3.4　Model of evolution network

In a network, the energy consumptions in each node are different according to the different distances and the amount of data. The route is constructed by the initial energy. Then, the energy is consumed when the nodes send the data to the base station. And the remaining energy in each node is changed. So, the local-reconstruction is needed when the network runs for a while.

In this section, two local-reconstruction mechanisms are provided which are initiative local-reconstruction mechanism and passive local-reconstruction mechanism. The initiative local-reconstruction mechanism is a centralized reconstruction, and the local-reconstruction require is sent by the node that has a lower energy. The passive local-reconstruction mechanism is a distributed reconstruction. And the local-reconstruction require is sent by the node that whose parent node has a lower energy. These two mechanisms are proposed as follows:

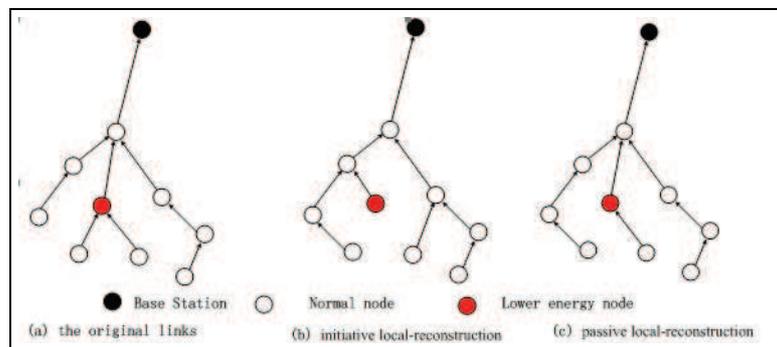**The initiative local-reconstruction**

Figure 2: Local-reconstruction mechanisms

In initiative local-reconstruction, when a node that has a lower energy exists in the network, this node determines the nodes that need to change the routes in its neighbors. Then, this node sends the local-reconstruction requests to these nodes. The nodes that receive the requests delete the link from the lower energy node. Finally, these nodes connect to other nodes with the evolution model above. Figure2(b) shows the initiative local-reconstruction.

Algorithm1 shows the algorithm of initiative local-reconstruction. N_i is the lower energy node, NF_i is the parent node of node N_i, NS_i is the set of son nodes with node N_i.

The Initiative Local-Reconstruction

In passive local-reconstruction, each node determines whether it needs reconstruction according to the rate between the node and its parent node. A node need, it sends the local-reconstruction requests to its parent when necessary. Then, the parent node deletes the link between them after receiving the requests. Lastly, this node connects to other nodes with the

Algorithm 1. Algorithm of initiative local-reconstruction

Set the threshold δ_1 and δ_2
Node N_i
For all the nodes in the wireless sensor network
if N_i is a leaf node then
        if $E(N_i) < \delta_1$ then
            Delete the connection of its parent node
            Use the evolution model to choose a new parent node
        else
            if $E(N_i) < \delta_2$ then
                Delete the connection of its parent node
                Set its energy-balanced element of node N_i to 0
                Use the evolution model to choose a new parent node
                Send the reconstruction message to all of its son nodes NS_i
            else
                if $\delta_2 < E(N_i) < \delta_1$ then
                    Send the reconstruction message to all of its son nodes NS_i
                end if
            end if
        end if
end for
Nodes in NS_iSet
For all the nodes in the NS_iset
Delete the connection of node N_i
Set its energy-balanced element of node N_i to 0
Use the evolution model to choose a new parent node

Figure 3: Algorithm of initiative local-reconstruction

Algorithm 2. Algorithm of passive local-reconstruction

Set the threshold δ_1
For all the nodes in the wireless sensor network
Each node i
Get the energy of the parent node of node i: $E(P_i)$
$E(i)$ is the energy of node i
if $E(P_i)/E(i) < \delta_1$ then
    Delete the connection of its parent node
    Set its energy-balanced element of node N_i to 0
    Use the evolution model to choose a new parent node
end for

Figure 4: Algorithm of passive local-reconstruction

evolution model above. Algorithm 2 shows the passive local-reconstruction.Figure.2(c) shows the algorithm of initiative local-reconstruction. N_i is the lower energy node, NF_i is the parent node of node N_i, NS_i is the set of son nodes with node N_i.

4   Analysis

Degree distribution is an important and useful feature for a given complex networks. The degree distribution of this network is analyzed by the mean field theory.

We assumed that N is the total number of the nodes in the WSNs, and these nodes are uniformly distributed in the WSNs. Some important parameters are defined in Table 1.

Table 1: Definition of important parameters

Parameters	Definition
N	Number of nodes in a network
d_{max}	The maximum communication radius0
M	Numbers of new edges which a new node connect at every time step
k_i	Number of links connected to node i
d_{max}	60 600 150 200
E	Remaining energy of a node
L	Number of nodes in every new comer's local-area
t_i	Time of node i newly introduced into the network

The evolution process described in this paper adopts the distributed mechanism, which can describe the real evolution processing more efficiently. Actually,the nodes can not begin to send the message at the very same time/concurrently, so it can be approximately regarded the process as follows.

R-1: Starting with one node and m edges, at each step, a new node with m edges was added. The node can connect with all the nodes surrounding.

R-2: When a new node comes into the network, it will choose some nodes in its local-world to connect with the probability $\prod_{i \to j}$. During each unit of time, m new edges are formed.

So we get

$$\frac{\partial k_i}{\partial t} \approx \frac{mL_i \prod_{j \to i}}{N} = \frac{mL_i E_j \delta_j k_i}{N \Sigma_{l \in \Lambda \Lambda_j} E_l \delta_l k_l} \qquad (1)$$

Here, L_i is the number of nodes which can connect to node i.

According to the mean field theory [20]:

$$\sum_{l \in \Lambda_j} E_l \delta_l k_l = L_j \bar{E} \bar{\delta} \langle k \rangle \qquad (2)$$

Similarly, L_j is the number of nodes in the new comer's (node j) local-world. $\bar{E}$ is the mean value of the local-world energy, and $\langle k \rangle$ is the average degree of local-world. In a large scale network, the average degree can be calculated as

$$< k >= \frac{1}{t+1} = \varepsilon_j m \qquad (3)$$

Where l is the number of edges connected to the node that has joined. it's not a fixed number while it satisfied the equation:$0 \leq l \leq (t+1)m$, $\varepsilon_j m$ is the mean degree of the network after node j joined. The ϵ_j increases when time t increases constantly.

So it's simply defined as $\epsilon_j = \frac{t}{N}$.

Combine three equations above, we get

$$\frac{\partial k_i}{\partial t} = \frac{L_i \delta_i E_i}{L_i \bar{e} \bar{\delta}} \frac{k_i}{t} \tag{4}$$

We set

$$\frac{L_i \delta_i E_i}{L_i \bar{e} \bar{\delta}} = g \tag{5}$$

Then we have

$$\frac{\partial k_i}{\partial t} = g \frac{k_i}{t} \tag{6}$$

Solving this differential equation, we get $k_i(t) = Ct^g$. Since $k_i(t_i) = m_i$, thus we have

$$k_i(t) = \frac{m_i}{t_i^g} t^g \tag{7}$$

The probability that a node has connectivity $k_i(t)$ smaller than k is

$$P(k_i(t) < k) = P(\frac{m_i}{t_i^g} t^g < k) = 1 - P(t_i < (\frac{m_i}{k})^{\frac{1}{g}} t) \tag{8}$$

Assume that we add the nodes to the network at equal time intervals, the probability density at the time is $f(t_i) = \frac{1}{t+1}$, therefore, we get

$$P(k_i(t) < k_{in}) = 1 - P(t_i < (\frac{m_i}{k_{in}})^{\frac{1}{g}} t) = 1 - \frac{t}{t+1} (\frac{m_i}{k_{in}})^{\frac{1}{g}} \tag{9}$$

The probability density function of the degree of a node with remaining energy E is

$$P(k_{in}) = \frac{\partial P(k_i(t) < k_{in})}{\partial k_{in}} = \frac{t m_i^{\frac{1}{g}}}{t+1} k_{in}^{-(1+\frac{1}{g})} \tag{10}$$

Here,$g = \frac{L_j E_{\,j} \delta_j}{L_j \bar{E} \bar{\delta}}$

Therefore, the distribution has a power-law form with degree exponent $\gamma = -(1+\frac{1}{g})$ in the network. Thus, we can organize WSNs with scale-free feature in this energy-aware algorithm. This algorithm can not only make the network evolution in energy-efficient, but also improve the network reliance against random errors, which is an inherent advantage of most scale-free networks. Especially, when the distributions of energy and nodes are uniform distribution, it is got that $g \approx (1 - d(i,j)/d_{j,max})$, which is obvious that $\gamma < -2$, and if d_{max} is big enough, the degree exponent $\gamma \to -2$.

5   Simulations

In the evolution of the network, we assume that the cluster heads have been selected, and the network has 1000 cluster heads. These cluster heads are randomly deployed over a 600 meters ×600 meters. The network parameters are listed in Table 2.

In the simulation of lifetime and network-efficiency, we compare three kinds of aggregation tree: the tag aggregation tree [21] (Tag aggregation tree), the tag aggregation tree with forward-connection evolution model and the FCTag tree with reconstruction.

5.1   The degree distribution

Table 2: Main settings in simulation

Parameters	Setting
Area	600×600
N	1000
m	2 6 15 30
E	Random in [0.8 1]
d_{max}	60 600 150 200

In the analysis, there are two parameters influence the degree distribution: d_{max} and m. The following simulation shows the influence of d_{max} and m on the evolving network.

The influence of d_{max}

In this section, the influence of d_{max} is discussed. Four different value of d_{max} are listed in table 2 (m=3).

As shown in Figure 5, when d_{max} is small,$f < 1$, so the exponent $\gamma < -2$. When d_{max} gets larger, f closes to 1, then the exponent γ closes to -2. Besides, Figure 1 also shows that when the d_{max} increases constantly, the maximum in-degree get larger. This is because the larger the communication radius is, the more likely be connected by other nodes.

The Influence of m

In this section, the influence of m is discussed with different m ($d_{max} = 120$).

As shown in Figure.6, when m is small, the process of preferential attachment works well, and a node is connected randomly, the network exhibits a power-law degree distribution. When m gets larger, the process of preferential attachment is limited. It leads to the reduction of the randomness of the connection. So the degree distribution can′t obey the power-law form well. Especially, when m is larger than the neighbors, the node will connect all nodes surrounding, which is independent of the preferential attachment.

5.2   Lifetime

In the simulation of lifetime, we assume that all sensor nodes have an initial energy which is 0.5J. The data packet size is 1000 bits. There is not an exact definition in lifetime for a WSN. Some papers use the round when the first drained node appears. Some papers use the round when a certain ratio of drained nodes appears. Some papers use the round when the network canĄŻt cover the monitor area. In this paper, we just run the network for a certain round (here
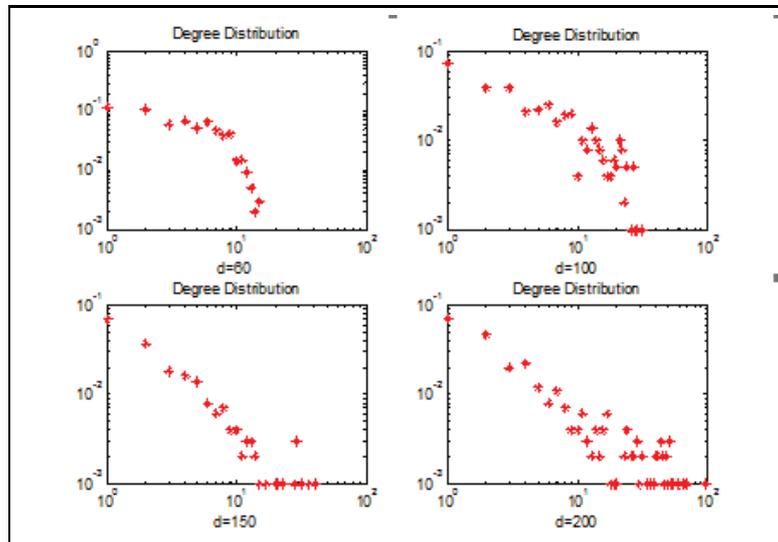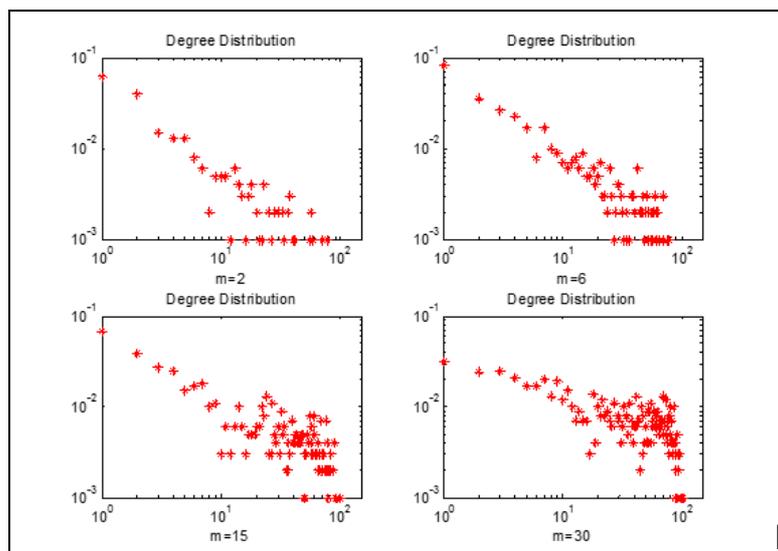
Figure 5: The influence of d_{max}

Figure 6: The influence of m

uses the 1500 round), and we observe the changing rule in different aggregation tree. We deem an aggregation tree has a longer lifetime if the drained nodes increase slower. Nodes consume energy both in sending and receiving data according to [22]. In this paper, we use the model that the pass loss exponent is 2. The model is as follows:

A k-bit data packet is transmitted and the energy consumption of sending node is given by $E_t = \varepsilon_1 \times k + \varepsilon_2 \times d^2 \times k$, d is the distance between the two sensor nodes, and $\varepsilon_1 = \frac{50nJ}{bit}, \varepsilon_2 = \frac{100pJ}{bit \cdot m^2}$ .A k-bit data packet is transmitted, and the energy consumption of receiving node is given by $E_\gamma = \varepsilon_1 \times k$

Without Local-Reconstruction

As shown in Figure 7, the dotted line is the lifetime of Tag aggregation tree. The solid line is FCTag aggregation tree. Obviously, in the dotted line, the first drained node appears at the 592th round. In the solid line, it appears at 737th round. This shows that the FCTag aggregation tree consumes the energy more balance than the Tag aggregation tree.

Another key point appears at about the 1280th round. Two lines intersect. And after this point, the number of drained nodes in dotted line is larger than that in solid line. It means that, after some round, the energy consumption in our model is more unbalance than the pure tag aggregation tree.

The point of intersection appears normal and reasonable. There are two reasons for the point. Firstly, the FCTag aggregation tree is constructed according to the energy and the position of nodes at that time. With the network running, the energy decreases which make the FCTag aggregation tree is no longer suit for the network now.

Secondly, the idea of FCTag aggregation tree is that, when the nodes transmit the data, the nodes that have large energy use more energy, and the nodes that have low energy use less energy. So the nodes that have low energy can run more round, but it makes the nodes that have large energy run less round. In fact, the FCTag aggregation tree has large total energy consumption in one round than Tag.

In the first reason, a local-reconstruction mechanism can solve it well. But the second reason is because of the idea of our model. Finally, the point of intersection is difficult to remove, but it can be delayed.

Local-Reconstruction

In this part, we simulated the lifetime with Tag aggregation tree and FCRTag aggregation tree.

In the Figure 8, the dotted line is the lifetime of Tag aggregation tree, the solid line is FCRTag aggregation tree. It shows that when a local-reconstruction mechanism is considered in the FCTag aggregation tree. The lifetime of the network is better. The drained node appears in 737th round too. And obviously, there is no intersected point before the 1500th round. But in fact, these two lines are getting more and more near when the round increasing. So it can be inferred that there is an intersected point after 1500th round.
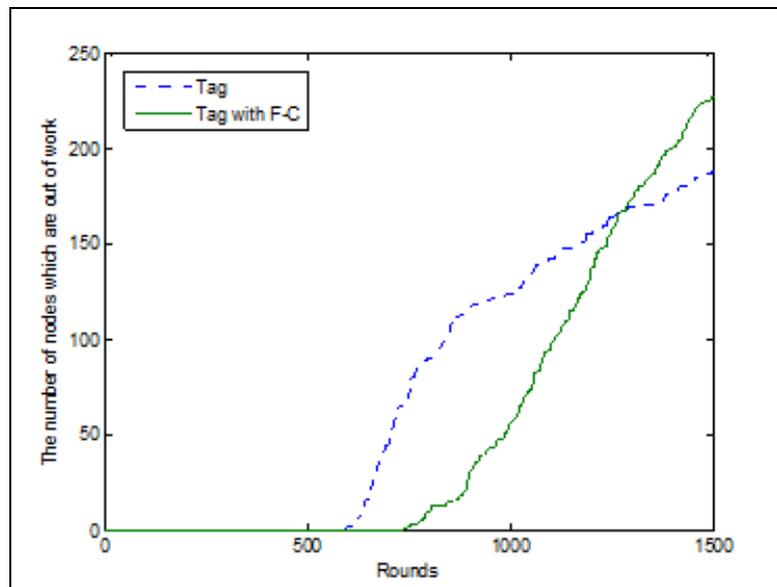
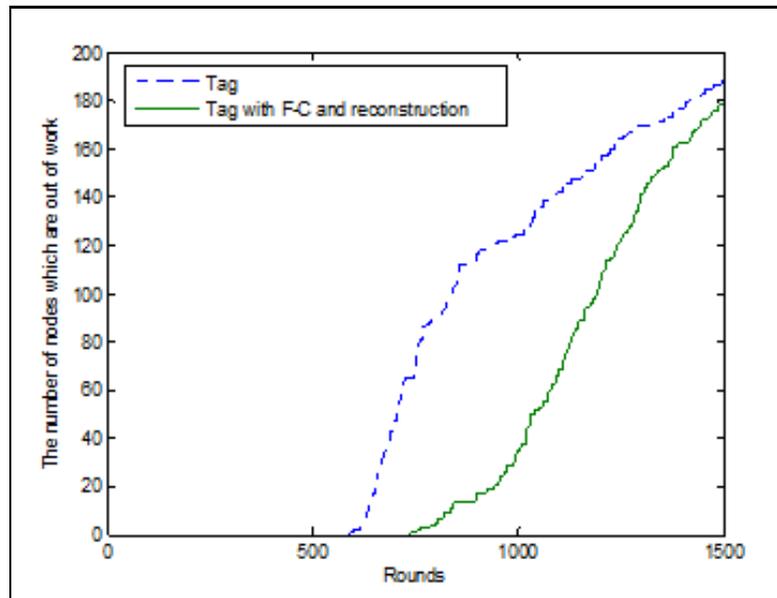Figure 7:   The lifetime without local-reconstruction

Figure 8:   The lifetime with local-reconstruction

Conclusions and future work

In this paper, we present a new secure privacy-preserving data aggregation model, which adopts a mixed data aggregation structure of tree and cluster. The proposed model verifies the data integrity both at the cluster nodes and the base station. Meanwhile, the model gives a mechanism to locate the compromised nodes. Finally, the detail analysis shows that this model is robust to many attacks, and has lower communication overhead.

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