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EBTM: AN ENERGY-BALANCED TOPOLOGY METHOD FOR WIRELESS SENSOR NETWORKS

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Abstract. *This work proposes a new energy-balanced topology method (EBTM) for wireless sensor networks (WSNs), based on the modern complex network theory. Due to the limited energy and transmission ability of sensor nodes, the next link node in EBTM is chosen according to not only conventional features – the residual energy and the node degree, but also new features – the transmission energy consumption and the transmission pressure between two nodes. Hence, a flow pressure estimation model is established and inconsistent initial edge weights are introduced in this paper, which result in various nodes-selected strategies in different regions. Moreover, in order to better adapt to diverse demands in reality, tunable parameters for the new method are proposed. In the experiments, EBTM is compared with BA, EAEM and FASF, and the experimental results show that EBTM outperforms the other algorithms with longer network lifetime and better robustness.*

Keywords: Energy balance, Robustness, Topology, Flow pressure estimation model, WSNs

1. Introduction.

Wireless sensor networks (WSNs) consist of hundreds of low-cost and battery-powered sensors [1]. Due to the limited battery power, sensors die over time, which degrades the network density and impacts the reliability of network [2-5]. This requires an optimized design of topologies for WSNs, so as to obtain better robustness and longer lifetime.

Barabasi et al. [6] proposed the first scale-free model, i.e., the BA model, which was proven to be robust against random removal or failure of nodes [7,8]. Recent advances in the studies of complex networks motivated the research that adopts scale-free topologies for WSNs [9,10]. However, a scale-free network typically results in a small amount of nodes with much higher degree than the others, which causes unbalanced energy consumption of the sensor nodes. Therefore, constructing an energy-balanced topology of WSNs became the study focus recently to prolong the lifetime of networks [11-15]. EAEM [16] constructed the topology according to the node degree and the residual energy of each sensor node, which extended the lifetime of WSNs in contrast with BA networks. Similar to the EAEM, EABA [13] was proposed by the same two factors, and tunable parameters were introduced to construct flexible and varied topologies. However, in WSNs, the main energy consumption occurs in flow transmission and reception related to the associated sensor nodes during each network operation. Therefore, FASF [17] was proposed to take such energy consumption of network operations into account, which achieved a better balanced energy consumption in WSNs. Simulations indicated that this model improved connectivity and lifetime of networks.

However, two crucial factors of the energy consumption in WSNs, which were totally or partially missed in previous models, should be considered in practice. First, during each network operation, the transmission distance between two nodes and size of each traffic flow decide the consumed energy, such that both long distance transmission and big traffic flow could produce a big amount of energy consumption and result in a quicker dead of nodes [18-20]. Second, not all the edges are operating at the same time during networks operating; thus, the node degree cannot represent the real traffic pressure on each node. In this work, a novel energy-balanced topology method (EBTM) is proposed, which considers not only the conventional features of the residual energy consumption and the node degree, but also the new features of the transmission energy consumption and transmission pressure between two nodes. In order to better predict the transmission pressure of nodes, we propose a new estimation model of flow pressure. Moreover, considering the energy consumption of network operation, inconsistent initial edge weights are applied in topology evolution. Simulation experiments prove that, compared with BA, EAEM and FASF, the proposed EBTM not only increases lifetime of networks but also obtains better robustness.

This paper is organized as follows. In Section 2, the concepts of BA model and BBV model are outlined. Section 3 introduces the energy model. In Section 4, the prediction of traffic flow model is proposed, and then the new energy-balanced topology method is presented. In Section 5, simulation results are provided, along with comparisons to three state-of-the-art methods, in terms of network lifetime and robustness. Section 6 concludes this paper.

2. Related Works.

Two well-known evolutionary algorithms are often used in the topology construction for wireless sensor networks, i.e., BA model and BBV model. In this section, basic evolution models with related works in wireless sensor networks are briefly reviewed.

2.1. BA model.

The BA model is the first scale-free evolution model proposed in 1999. By including two evolving mechanisms, i.e., network growth and preferential attachment [6,21], BA model evolves the scale-free network with exponent. Lots of studies showed that scale-free network exhibits strong robustness against random failures attacks. The steps of BA model are as follows.

1) Network initialization: start with a set of m_0 nodes connected with each other.

2) Network growth: at every step time a new node with m ($m \leq m_0$) links joins the network.

3) Preferential attachment: a new node n selects m old nodes to establish links with a probability proportional to node degree. The probability for node i which will be linked is given as:

$$\prod_i = \frac{k_i}{\sum_j k_j} \tag{1}$$

where k_j ($j = 1, 2, \ldots$) is the node degree for every node in the existing network. The proportion of vertices of degree k follows a power law distribution $P(k)$. It has been proven that the scale-free network has a surprising degree of tolerance against random failures; thus, topology for WSNs based on scale-free theory has received great concern.

However, the network lifetime is reduced due to the unbalanced energy consumption in BA network. Many researches devote to extending the lifetime of networks by optimizing the probabilistic formula [12,13,16,17] in preferential attachment. In [16], an energy-aware evolution model (EAEM) is proposed to better energy efficiency. Consider both the residual energy and node degree for each node. The probability that node i will be selected is given as:

$$\prod_i = \frac{f(E_i)k_j}{\sum_{j \in localarea} f(E_j)k_j} \tag{2}$$

where E_i and E_j are residual energy for node i and node j. $f(E)$ is an increasing function here and the form could be such as E, $\sqrt{E}$. In EAEM, Equation (2) reduces the probability that a low-energy node evolves into a high degree node; thus, EAEM prolongs the network lifetime compared with BA networks.

2.2. **BBV model.** Due to the influence of various parameters, network links between any two nodes are heterogeneous in reality. Thus, BBV weighted network model is proposed [22] to form the novel topology. The steps of BBV model are as follows.

1) Network initialization: start with a set of m_0 nodes connected and a few edges ($w = w_0$). Here, w_0 is the initial weight and w is weight of links between nodes.

2) Network growth: at every step time a new node with m ($m \leq m_0$) links joins the network.

3) Preferential attachment: a new node n selects m old nodes to establish links with a probability as follows:

$$\prod_i = \frac{s_i}{\sum_j s_j} \tag{3}$$

where the vertex weight s_i is defined as the sum of edge weights connected to it: $s_i = \sum_{j \in \Theta_i} w_{ij}$, w_{ij} is the edge weight between node i and node j, and Θ_i is the set of neighbor nodes which directly connect to node i.

4) Update the node weights and edge weights: as shown in Figure 1, with the addition of a new node, node weight and edge weight of neighbor will be calculated again.

$$w_{ij} \rightarrow w_{ij} + \Delta w_{ij} \tag{4}$$

$$\Delta w_{ij} = \lambda \frac{w_{ij}}{s_i} \tag{5}$$

Here, λ is a positive or negative increment. After repeat steps 2) $\rightarrow$ 4), the whole network evolution is completed. Considering the weighted edges in network, BBV is more fit for WSNs.

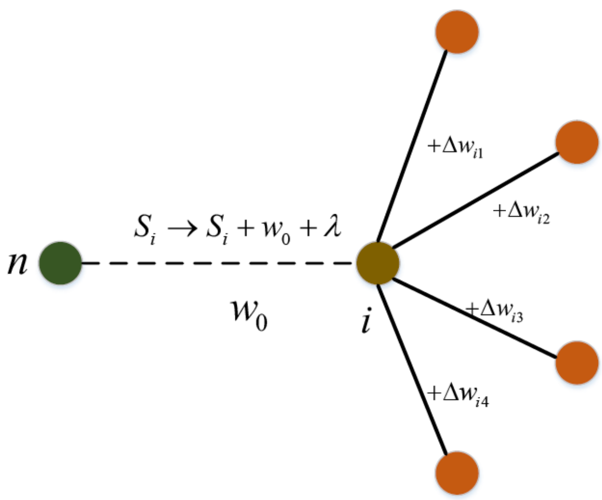

FIGURE 1. Weight network of WSNs

Based on BBV model and BA model, FASF model is proposed in [17]. FASF introduces the special deterministic attachment in the network growth: when node i is selected by the preferential selection (BA) and its degree is k_i, deterministic attachment algorithm will search the current network to find out all nodes which have the same degree k_i, and then choose the minimum weight node calculated by BBV to link to. The steps of FASF are as follows.

1) Initialization: the network contains m_0 nodes randomly linked to each other. The initial weight of each edge according to BBV model.

2) Growth: at each time a new node is added into the network and linked to m nodes, and each of the m nodes is selected through the following three steps.

(a) Preferential selection: the probability of node i to be selected in this step depends on its degree k_i according to BA model.

(b) Deterministic attachment: suppose that node i is selected in step (a) and its degree is k_i, then search the network to find out all nodes that have a degree of k_i. Calculate the weight of these nodes (include node i) and then choose the one with the minimum weight to link to the newly added node.

(c) Weight updating: after the node has been added into the network, update the weight of edges/nodes using Equation (4) and Equation (5).

3) Node/link failure and compensation: at each time some node will be deleted and the loss is compensated by adding new edges for each remove link.

In FASF the deterministic attachment could balance the node weight in the network, which prolongs the network lifetime. Thus, FASF gets a better energy efficiency for wireless sensor networks compared with BBV model.

Although EAEM and FASF enhance the performance of scale-free networks on WSNs compared with BA and BBV respectively, two crucial factors of the energy consumption in WSNs, which were totally or partially missed in these two models. First, in wireless sensor networks, transmission distance and information size play very crucial roles in energy consumption, such that both long distance transmission and big traffic flow could produce a big amount of energy consumption and result in a quicker dead of nodes, causing the instability of network. Second, during networks operating, not all the edges in topology will stay operating at the same time; thus, the same degree nodes may have various traffic load. In order to estimate the traffic pressure on each node with the absence of parameters, the characteristics of information transmission of WSNs shall be taken into account.

Moreover, in FASF, the initial edge weights are uniform w_0, which is not appropriate in reality. Considering transmission distance and transmission pressure, the inconsistent initial edge weights w_{ij} for each link are proposed in this paper.

3. **Energy Model of the Network.** Before the new balanced evolution model is introduced, we shall discuss the energy consumption in wireless sensor networks first. In wireless sensor networks, the free space model and the multi-path fading channel model are two different ideal radio models [23-26]. When the distance between the transmitter and receiver is less than some positive threshold value d_0, the algorithm adopts the free space model (d^2 power loss). Otherwise, it adopts the multi-path fading channel model (d^4 power loss) [27]. The energy spent for sending an l-bit packet over distance d is:

$$E_T(l, d) = \begin{cases} lE_{elec} + l\varepsilon_{fs}d^2 \\ lE_{elec} + l\varepsilon_{fmp}d^4 \end{cases} \tag{6}$$

Here, E_{elec} is the unit energy dissipation for transmitter electronics or receiver electronics, ε_{fs} is the amplifier energy in the free space model while ε_{fmp} is the one in the multi-path fading channel model. For the experiments described in this paper, the communication energy parameters are set as: $E_{elec} = 50\text{nJ/bit}$, $\varepsilon_{fs} = 10\text{pJ/bit/m}^2$ and $\varepsilon_{fmp} = 0.0013\text{pJ/bit/m}^4$.

When the data transmission distance is larger than threshold d_0, the energy consumption would rise extremely, so the maximum transmission radius of sensor nodes is d_0 in this paper.

From the free space model, we could clearly find out two main factors play important roles in energy consumption, i.e., transmission distance and size of transmission data. However, before the construction of networks, related information may not be acquired. In this paper, two definitions for rough estimate of the two factors are proposed, which are beneficial for topology evolution in terms of energy balance.

Definition 3.1. *Based on the energy model, the transmission consumption estimation* e_{ij} *between node* i *and node* j *is defined:*

$$e_{ij} = E_{elec} + \varepsilon_{fs} d_{ij}^2 \tag{7}$$

Here, d_{ij} *is the distance between node* i *and node* j*.*

Definition 3.2. *In wireless sensor networks, information flows to the sink through the relay transmission. As shown in Figure 2, we define transmission pressure for node* i*: the size of all probable data that node* i *need directly or indirectly to transmit.*

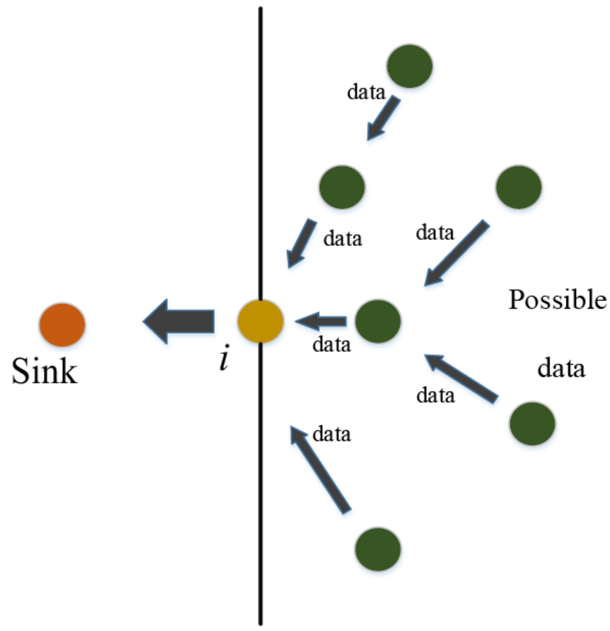

Figure 2. Data estimation (transmission pressure) of sensor node

4. **Energy-Balanced Topology Method.** Based on the energy model of the WSNs, two aspects are of most importance for the node energy consumption: the transmission pressure and consumption, which can be essentially quantified in the following subsection. Traditionally, the flow estimation methods can be classified into two categories: the node degree is used in the first category of methods to estimate flow pressure; however, during network operation, not all the edges of one node are transmitting information; estimating transmission pressure only by the node degree can lead to the wrong results. On the other hand, the inverse of the distance, from the sink to the node, is used in the second

category of methods to estimate transmission pressure, but the relationship between such distance and transmission pressure is not a simple inverse which could be complex. Given this, we introduce a new model of transmission pressure model, along with transmission consumption, which gives rise to our energy-balanced topology method.

4.1. **Transmission pressure, transmission consumption, inconsistent initial edge weights and tunable parameters.** In WSNs, all the information will flow to the sink eventually through multiple hops [28]. For the node, the shorter distance is from the sink, the bigger transmitted data volume can be.

The function of WSNs is to monitor and acquire information from the entire region. Each sensor node is sensing data from some region, receiving data from other connected nodes, and transferring data to the next hop node at the current time. We assume that every sensor node monitors fixed information from a unit area. Hence, the size of monitored information is proportional to the monitored area. In addition, we assume that the sensors are distributed uniformly and randomly in the entire area; the number of nodes is proportional to the area size. Thus, we can estimate roughly the transmission or flow pressure for each node as follows:

$$PM = S_T/S_N \tag{8}$$

where S_T gives the probable information area for transmission or relay transmission and S_N represents the node area. Following the equation proposed above, the transmission pressure of nodes in area N could be calculated with the ration of two areas, i.e., S_T and S_N. Wireless sensor network is a unique reality of network, and all information will eventually flow to the sink. Considering the special character in this paper, the information area for node i could be approximately considered that all the area is farther than node i to the sink. Detailed calculation method for transmission pressure will be introduced as follows.

As shown in Figure 3, we divide the whole square region into $n+1$ sub-regions: n ring-like areas and the complementary sub-region A. Since the nodes of region A usually do not need to forward information from the other nodes, we assume that the flow pressure of region A is constant. Nodes of region A only need to transmit the monitored information, while the nodes in the adjacent region B are required to transmit not only the information collected in region B but also the information received from region A.

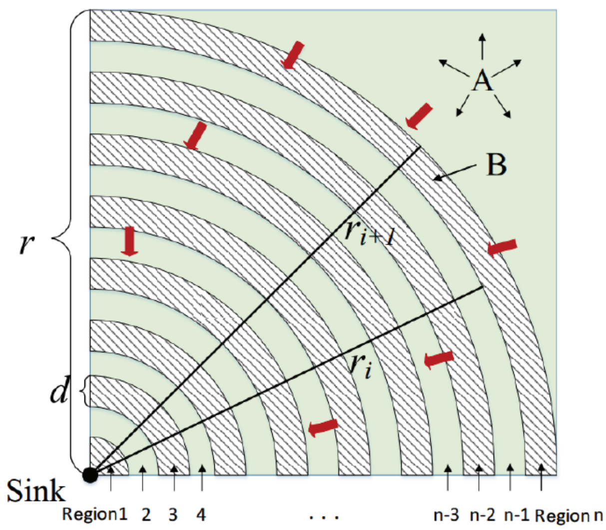

FIGURE 3. Flow pressure estimation model for WSNs

The total information of region B needs to be transmitted or relay transmitted is represented by the total area $S_P = S_B + S_A$, where S_B and S_A are the areas of region B and A respectively. Let $r = nd$ and $r_{i+1} = r_i + d$.

Therefore, the flow pressure of region B is:

$$PM_B = S_P/S_B = \frac{r^2 - 0.25r_{n-1}^2\pi}{0.25\pi\left(r_n^2 - r_{n-1}^2\right)} \tag{9}$$

In general, the flow pressure for each section area is:

$$PM_i = \frac{r^2 - 0.25r_i^2\pi}{0.25\pi\left(r_{i+1}^2 - r_i^2\right)} = \frac{r^2 - 0.25r_i^2\pi}{0.25\pi(2r_id + d^2)} \tag{10}$$

We could approximately replace the r_i by the $D_{(j,\sin k)}$, and then the flow estimation function for each node j is given by

$$PM_j \approx \frac{r^2 - 0.25D_{(j,\sin k)}^2\pi}{0.25d^2\pi + 0.5d\pi D_{(j,\sin k)}} \tag{11}$$

where the distance between node j and sink is $D_{(j,\sin k)}$.

Before network construction, abundant information about network is not available. Thus, in Equation (11), the flow pressure estimation model was proposed only based on the value of distance. Although the estimated value may be different from the actual value during network operation, the pressure estimation model still gives big rise to our method.

Besides the transmission pressure, transmission consumption also plays a vital role in energy consumption. Based on Definition 3.1 and the free space model, we could calculate the transmission consumption $[e_{ij}]_{n\times n}$ between any two nodes i and j, where e_{ij} is a fixed energy spent for sending 1-bit data between node i and node j. In this paper, from the view of transmission consumption, energy consumption will be balanced more effective and practical.

In BBV model and FASF model, the initial edge weights are uniform value w_0, which is inappropriate in practice. Considering transmission distance and transmission pressure, the inconsistent initial edge weights w_{ij} for each link are proposed in this paper. During the topology evolution, the initial edge weight between node i and node j, is given by

$$w_{ij} = \frac{E_iE_j}{e_{ij}^{\alpha}(PM_iPM_j)^{\beta}} \tag{12}$$

where E_i and E_j are the respective residual energies of node i and node j, the transmission pressure PM_i and PM_j are given in Equation (10) and Equation (11), and e_{ij} is a fixed energy spent for sending 1-bit data between node i and node j.

In particular, α and β in Equation (12) are two tunable parameters. When the network has a busy traffic, we can increase β to prevent the network congestion: bigger β decreases the selected probability of high transmission pressure node, which could balance the whole network traffic flow. Whereas, we could reduce α as the network needs to ensure the transmission rate: smaller α increases the selected probability of longer transmission distance node, which could effectively reduce the transmission hops from some nodes to the sink. By changing the two parameters, the topology evolution becomes more flexible in real situations.

4.2. **EBTM model.** Different from the traditional weight network model, the edge weight is not just a uniform initialization. Based on the inconsistent initial edge weights in

Equation (12), we could calculate the weights of vertexes in the exiting network through Equation (13).

$$S_i = \sum_{j \in \Theta_i} w_{ij} \tag{13}$$

Here, Θ_i is a set which contains all neighbor nodes of node i in the current network, and the weight of vertex i is S_i.

Based on the weighted network model and EAEM model, energy-balanced topology method for WSNs is proposed. Considering both transmission distance and transmission pressure, the preference attachment between node i and node j is $\prod_{i \to j \in \Theta_i}$, when a new node i is added into the network, $\prod_{i \to j \in \Theta_i}$ is given by

$$\prod\nolimits_{i \to j \in \Theta_i} = \frac{S_j}{\sum\limits_{n \in \Theta_i} S_n} \tag{14}$$

The algorithm of our proposed EBTM is as follows:

1) Network initialization: the initial network contains m_0 nodes randomly linked to each other and $t = 0$.

2) Network growth: at each time-step a new node i is added into the network and linked to m nodes in the current network, which are selected through the following four steps $t = t + 1$.

(a) As the new node i is added into the network, calculate the transmission pressure PM_i of node i and transmission consumption $[e_{ij}]_{(m_0+t)\times(m_0+t)}$ between node i and node j from the current network, here, m_0+t is the total number of nodes in the current network.

(b) Calculate the edge weight w_{ij} between node i and node j from the current network with the parameters from step (a), based on Equation (12).

(c) Calculate the vertex weight S_j for all nodes in the current network based on Equation (13). Each of the m nodes is selected through the preferential attachment as $\prod_{i \to j \in \Theta_i}$ based on Equation (14).

(d) Update the residual energy E_j and the weight S_j for the current network, where the edge weight w_{ij} is calculated by Equation (4) and Equation (5).

3) Network complication: Take d_0 as the threshold, select the nodes that distance from sink is less than the threshold, and then link these nodes to the sink directly.

5. **Simulation and Result Analysis.** To investigate the performance of EBTM, we assume the network has initial interconnected nodes $m_0 = 3$ and a new node with $m = 2$ links joins the networks at every step. In simulations, $\alpha = 1$, $\beta = 1$, the initial energy for each node is $E_i = 3$J, the entire coverage region is $S = 300 \times 300\text{m}^2$, the distribute of nodes in the region is random and uniform, and the LEACH [29] protocol is used for clustering during network operation. We compare BA, EAEM, FASF, and EBTM by three parameters: network lifetime (NL), energy-balanced factor (EBF), and robustness for the network (RN).

The definition and requirement of NL vary under different conditions. In our experiment, we consider the NL is time during the period from the beginning of the network to the death of all nodes. Figure 4 shows the NLs of four topology models in different network sizes. Simulations show that EBTM extends the lifetime of WSNs compared with BA, EAEM and FASF. In particular, EBTM prolongs the lifetime at least 10% compared with FASF.

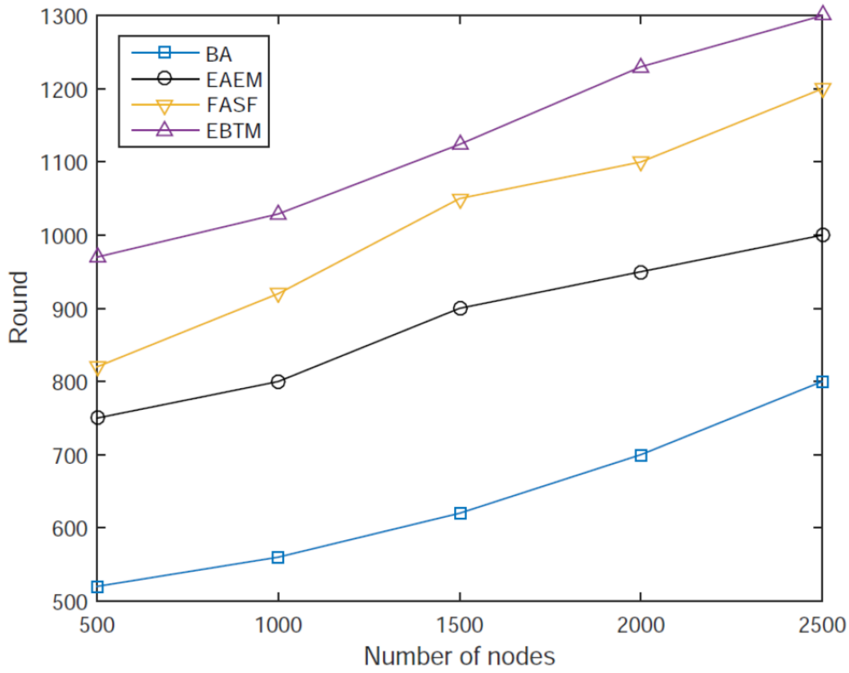

FIGURE 4. Comparison of network lifetime

To measure the balance of energy consumption of the proposed topology, EBF is defined in [16] as the standard deviation of the nodes' residual energy

$$EBF = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[E_i(t) - E_{avg}(t)\right]^2}}{E_{avg}(t)} \tag{15}$$

where N is the number of all network nodes, $E_i(t)$ is the residual energy of node i at round t and $E_{avg}(t)$ is the average residual energy of all nodes.

With 997 steps of evolution, topology with 1000 sensor nodes was built. The energy balanced factors (EBF) in four different models, i.e., BA model, EAEM model, FASF model and EBTM model, were shown in Figure 5. Compared with the other three state-of-the-art models, EBF of EBTM keeps a lower state. In other words, EBTM achieves more balanced energy consumption.

The robustness of a network (RN) is defined as its ability to against node failures under random attack and deliberate attack. To test this quality, average path length (APL) was introduced, which is defined as $APL = \frac{1}{N(N-1)}\sum d_{ij}$, where d_{ij} is the smallest number of hops from node i to node j and N is the total number of nodes in the network.

In order to test the robustness of our evolution network, we simulate the AHS under two different attack conditions. Under random attack, nodes in the network will be randomly selected and removed. Relatively, under deliberate attack, high degree node will be preferred to be selected and removed. Figure 6 shows APL performance comparison of BA, EAEM, FASF and EBTM under random attack. In Figure 6, the beginning performance of EBTM is not particular great among the four models. However, as the percentage of the nodes removed increases, EBTM is getting ahead compared with other models. This result indicates that EBTM exhibits a similar high robustness with the scale-free against random attack.

Figure 7 shows APL performance comparison of BA, EAEM, FASF and EBTM under deliberate attack. Compared to random attacks, the network operation has been seriously

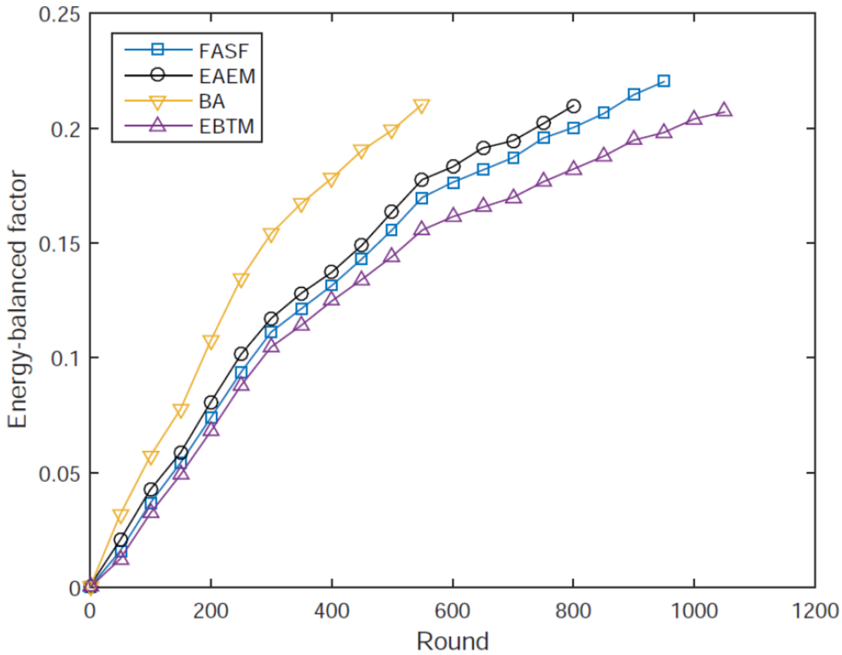

Figure 5. Comparison of EBF

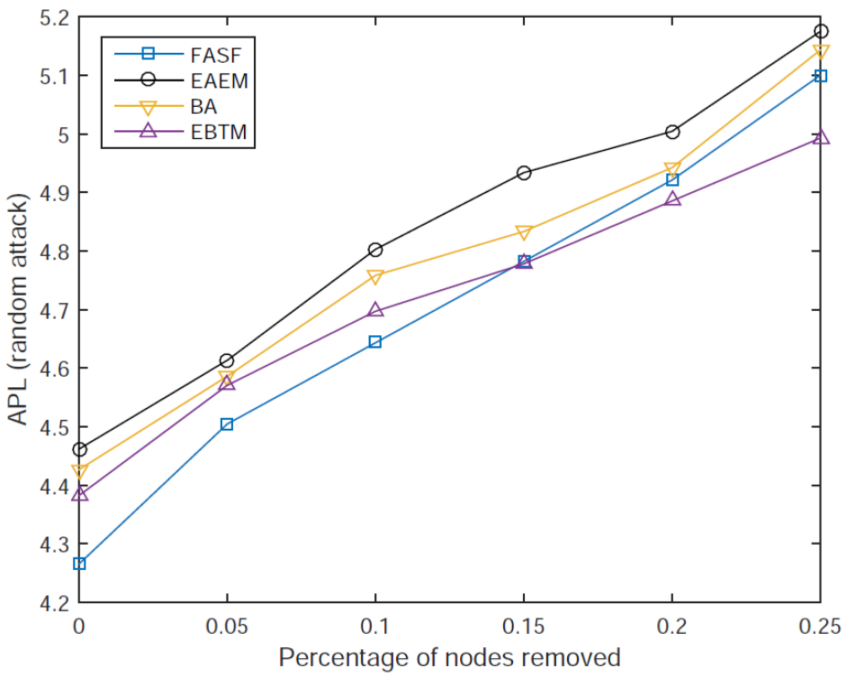

Figure 6. Comparison of APL under random attack

affected under deliberate attack. In Figure 7, APL performance of EBTM was superior to the conventional models. As 15% nodes with high degree were removed in the network, the APL of EBTM network is less than FASF 10.2%. Thus, the normal operation of the entire network was guaranteed well on the EBTM topology.

In EBTM, different tunable parameters could construct diverse types of networks. Figure 8 shows APL performance comparison of four different pairs of parameters in varying scales of the networks. With the scale of networks raising, the four values of APLs are increasing, which is because the average node degree in the simulations is constant. In

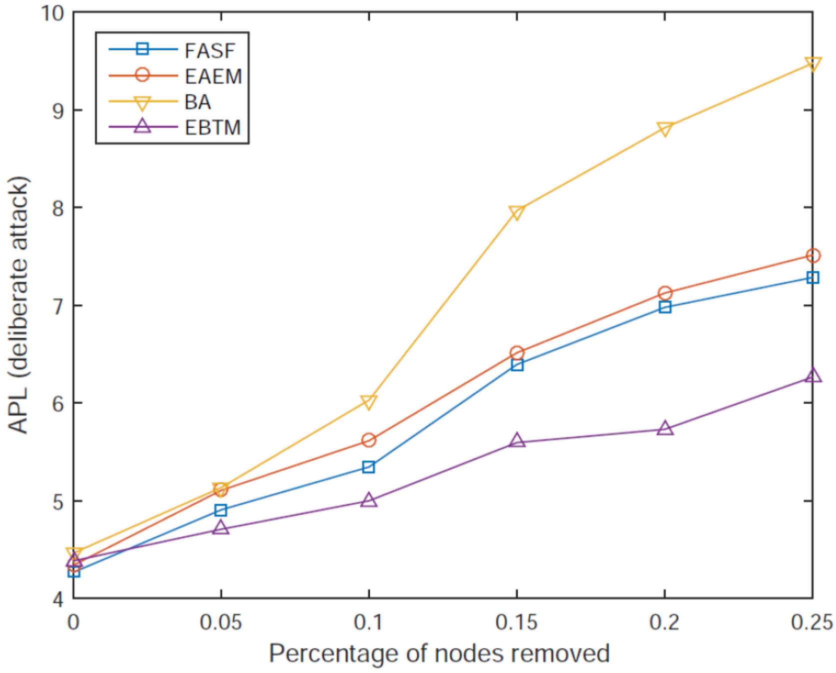

FIGURE 7. Comparison of APL under deliberate attack

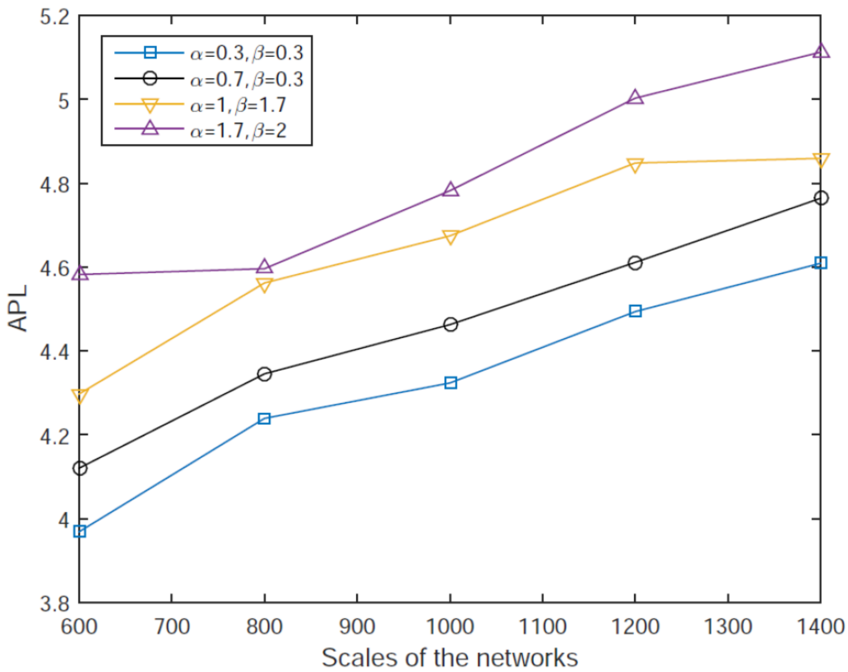

FIGURE 8. Comparison of sensitivity for the tunable parameters

Figure 8, the values of APL were sorted in increased sort turn: ($\alpha = 0.3$, $\beta = 0.3$), ($\alpha = 0.3$, $\beta = 0.7$), ($\alpha = 1.0$, $\beta = 1.7$), ($\alpha = 1.7$, $\beta = 2.0$). It reveals that tunable parameters could regulate the network structure and smaller parameters may have better APLs.

The above simulations show that EBTM outperforms BA, EAEM, and FASF in terms of prolonging lifetime for WSNs, and keeps a high degree of tolerance against deliberate and random attack.

6. **Conclusion.** In this paper, an energy-balanced topology method (EBTM) is proposed for wireless sensor networks (WSNs). Different from the conventional method, in EBTM, the preferential selection of the next link chosen to not only the node degree and residual energy but also the transmission energy consumption and transmission pressure. Thus, inconsistent initial edge weights are proposed based on two estimate model and tunable parameters are introduced to meet various requirements in reality. In order to test the survivability of this topology, we simulated the network lifetime, energy balance factor and network robustness compared with the state-of-the-art methods, e.g., BA, EAEM and FASF. Both results showed that our method outperformed BA, EAEM and FASF in terms of both network lifetime and robustness to deliberate attacks.

Although our topology method (EBTM) achieves better performance in WSNs than the previous algorithms, e.g., BA, EAEM and FASF, the topologies of WSNs are not stable as the network operating. In the future work, growth and deletion mechanism may be taken into account during the topology evolution, which will make the network structure more flexible and practical.

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