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Fault-tolerant topology with lifetime optimization for underwater wireless sensor networks

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Abstract. Recently, underwater wireless sensor networks were proposed to explore underwater environment for scientific, commercial and military purposes. However, the limited energy of nodes is a challenge for underwater wireless sensor networks. To prolong the lifetime of battery-limited underwater wireless sensor networks, in this paper, a fault-tolerant topology that can effectively extend the network lifetime is proposed. Initially, the influence of node residual energy and load on node lifetime is analysed. Later the lifetime model of underwater wireless sensor networks is established, and the value range of node load adjustment coefficient satisfying network lifetime is obtained. Finally, the scale-free fault-tolerant evolution model with network lifetime optimization is built based on node residual energy and load case. In addition, simulation experiments are performed to validate performances of the new topology generated by the evolution model built. The results show that the new topology structure can balance the energy consumption of the nodes and prolong the network lifetime effectively, and has good fault tolerance.

Keywords. Underwater wireless sensor networks; residual energy; node load; network lifetime; fault tolerance.

1. Introduction

As an important part of the underwater Internet of Things (IoT), underwater wireless sensor networks (UWSNs) is attracting the interest of many researchers [1–3]. UWSNs are typically self-organized wireless networks, which consist of a large number of multi-functional underwater micro-sensor nodes with acoustic communication links [4]. The UWSNs can accurately monitor real-time underwater environment and can be widely applied to marine exploration, aquaculture, water quality monitoring and so on [5, 6]. However, the node batteries usually cannot be easily replaced under water; when the solar energy is hardly being exploited, the energy of the nodes in UWSNs is limited [7]. Moreover, the random failure nodes caused by complicated underwater environment have a serious impact on UWSNs performance [8]. Therefore, it is very important to improve the energy efficiency and fault tolerance of UWSNs.

The topology structure is the important foundation for UWSNs. The topology structure for UWSNs has to be not only of general characters of self-organizing network, but also consider the limited node energy, the effect of failure nodes to the whole network and so on. A reasonable topology structure for UWSNs can prolong the lifetime and improve the fault tolerance of the network. However, at present, most energy-saving topologies for UWSNs consider not only the residual energy of nodes and ignore the load of nodes. The load of nodes has an important influence on network energy consumption. The nodes with high load easily die due to energy depletion and then the network lifetime is reduced. Therefore, it is necessary to consider the node load during topology generation. The scale-free topology has strong fault tolerance for random node failure. The scale-free structure was originally used for terrestrial wireless sensor networks (TWSNs), but researchers later found that scale-free structure can apply also for UWSNs [9]. Thus, the fault tolerance for random node failure in UWSNs can be improved by the topology generated based on the scale-free evolution mechanism.

Based on this analysis, in this work, the node load case and residual energy in UWSNs are both considered in the process of scale-free evolution. Based on node residual energy and load case, the UWSNs lifetime model is built and the relationship between network lifetime and load

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adjustment coefficient is obtained. Through quantitative analysis, we can solve for the value range of node load adjustment coefficient that meets the required network lifetime. Then the fitness function is established on the basis of the node residual energy and load with adjustment coefficient. The scale-free evolution model with fitness function is presented. In the afore-mentioned evolution model, the generated topology can effectively balance the energy consumption and prolong the network lifetime; meanwhile, the random node failure can be tolerated effectively.

The rest of this paper is organized as follows. Section 2 discusses related works. Section 3 builds the UWSNs lifetime model. Section 4 presents the evolution model of the ELBF (Energy-Load Balanced and Fault-tolerant) topology and analyses the degree distribution characteristics. Section 5 gives the results of simulation. Finally, this paper is summarized in section 6.

2. Related works

The problem of energy limit for UWSNs has been extensively studied. In recent years, the scholars have been focusing on energy efficiency in UWSNs. Goyal *et al* [10] improved UWSNs lifetime by appropriate selection of cluster head, cluster size and routing scheme. Ahmed *et al* [11] proposed a cooperative transmission scheme for UWSNs to enhance the network lifetime. Kartha and Jacob [12] considered the UWSNs lifetime maximization and proposed a mobile sink-based data collection scheme that can extend network lifetime. The energy efficiency is considered during investigating weak k-barrier coverage problem in UWSNs in [13]. Uyan and Gungor [14] deployed the mixed integer programming model to optimize encryption decision cases, which leads to an improved network lifetime. Zhou *et al* [15] analysed the solution of the optimal network flow at each link that maximizes the network lifetime. However, these studies mainly extended the UWSNs lifetime from the aspects of communication, network protocol, network security, network node deployment and so on. In addition, the energy efficiency of UWSNs is greatly related to the topology structure [16]. A reasonable topology structure is one of the efficient solutions for saving energy and prolonging lifetime in UWSNs. Thus it is significant to research the topology, which can improve network lifetime.

Research on topology with lifetime optimization in UWSNs gradually attracts the attention of scholars. Hong *et al* [17] built the energy consumption model and proposed a topology control algorithm with energy balance (TCEB). TCEB improved the energy utilization and extended the network lifetime effectively. He *et al* [18] considered the residual energy of the nodes in the game model and proposed potential game topology control algorithm. Liu and Liu [19] described the topology recovery problem and proposed an approximate topology recovery algorithm. This algorithm can obtain a well-constructed topology that has less energy consumption, and longer UWSN lifetime. He *et al* [20] analysed topology reconfiguration to optimize network connectivity and coverage, and reduce the network energy consumption. Diao and Wang [21] implement dormancy strategy on nodes with high redundancy in UWSNs, which can effectively reduce network energy consumption and prolong network lifetime. However, these algorithms do not consider the load of nodes in the process of building the topology in UWSNs. The nodes with high load easily die due to energy depletion, and then the network lifetime is reduced. In addition, these researchers do not consider the random failure caused by complex underwater environment, which decreases network performance and even causes network failure.

Researchers found that the scale-free structure can strongly tolerate the random node failure [22, 23]. Liu *et al* [24] applied the scale-free structure in UWSNs based on the topology formation algorithm (TFA) and verified that the underwater random failure nodes can be effectively tolerated. However, the special heterogeneous property of the scale-free topology can lead the nodes with larger degree in scale-free topology to easily die due to excessive load. Based on these existing problems, we consider the node load case and residual energy in the process of scale-free evolution to generate fault-tolerant topology with lifetime optimization.

3. UWSNs lifetime model

UWSNs lifetime strongly depends on the lifetime of the single node that constitutes the network [25]. In this section, the lifetime of node in UWSNs is analysed quantitatively. Later UWSNs lifetime model is built, and the value range of load adjustment coefficient satisfying network lifetime can be obtained by analysing the influence of load adjustment coefficient on network lifetime.

3.1 *Node lifetime model*

In UWSNs, the lifetime of node usually depends on the residual energy and the load of the node. The node load is the total data traffic that the node itself needs to send and forward to other nodes per unit time. The node degree determines the corresponding node load [26]; generally, nodes with large degree carry more load. Therefore, the load of the node in UWSNs can be expressed as follows:

$$L_i(t) = L + k_i^{\beta} L \quad (\beta \geqslant 0) \tag{1}$$

where L is the data traffic that the node i itself needs to send to other nodes. $k_i^{\beta} L$ is the data traffic that the node i forwards to other nodes, in which k_i is the degree of the node i and β is load adjustment coefficient.

Due to the different media between the underwater environment and air, the communication mode of UWSNs is different from that of TWSNs. TWSNs mainly rely on radio waves for data transmission. However, because radio does not work in water, acoustic communications have to be employed in UWSNs. As we all know, the energy of the network node is mainly consumed in the process of communication. As a result, the traditional energy consumption in TWSNs cannot be applied to UWSNs. In this paper, the average energy consumption of the node in UWSNs is analysed by the underwater acoustic propagation model [27].

In the underwater acoustic propagation model, the underwater acoustic attenuation is expressed as

$$A(d) = d^{\lambda}\alpha^{d} \tag{2}$$

where d is the communication distance of the node, λ is the energy spreading factor (its value is usually the constant 1) and $\alpha = 10\alpha^{\alpha(f)/10}$ is a frequency-dependent term obtained from the absorption coefficient $\alpha(f)$. The absorption coefficient $\alpha(f)$ can be calculated based on Thorp's expression [28] as follows:

$$\alpha(f) = 0.11\frac{f^2}{1+f^2} + 44\frac{f^2}{4100+f^2} + 2.75\times10^{-4}f^2 + 0.003 \tag{3}$$

where f is the carrier frequency.

Suppose the minimum power required for a node in UWSNs to successfully receive a packet is P_0. In order to ensure normal communication between the node i and its neighbour nodes, the minimum transmission power of the node i is calculated as

$$P_t = A(d)P_0. \tag{4}$$

According to Eq. (1), the node i receives $(k_i^{\beta}L)$ bit data and sends $L_i(t)$ bit data per unit time. Then the energy consumed by the node i to receive and send data per unit time is, respectively

$$E_r = E_{elec}k_i^{\beta}L, \tag{5}$$

$$E_t = E_{elec}L_i(t) + P_tL_i(t) \tag{6}$$

where E_r is the energy consumed by node to receive data, E_t is the energy consumed by node to send data and E_{elec} is the data fusion energy consumption per bit.

Then the energy consumed by the node i per unit time satisfies Eq. (7):

$$\begin{aligned} E_i(t) &= E_r + E_t \\ &= E_{elec}k_i^{\beta}L + [E_{elec} + P_0A(d)]L_i(t) \\ &= [2E_{elec} + P_0A(d)]L_i(t) - E_{elec}L \\ &= pL_i(t) + q \end{aligned} \tag{7}$$

where $p = 2E_{elec} + P_0A(d)$ and $q = -E_{elec}L$; p and q are constants after the network model is given. It can be seen from Eq. (7) that the load of nodes determines their energy consumption in the network. Substituting Eq. (1) into Eq. (7), we can obtain

$$E_i(t) = pL(1 + k_i^{\beta}) + q. \tag{8}$$

This equation shows that the higher the degree of a node, the more the energy it consumes, the more likely the node dies due to energy exhaustion. The node lifetime depends on the residual energy E_i and the energy consumption $E_i(t)$ per unit time of the node. Hence, the node lifetime can be expressed as

$$T_{node} = E_i/E_i(t) = \frac{E_i}{pL(1+k_i^{\beta})+q}. \tag{9}$$

Thus, the node lifetime model in UWSNs is as shown in Eq. (9). From Eq. (9), we can find that the node lifetime in UWSNs depends on the residual energy and load of the node. The larger the residual energy and the smaller the load of the node, the longer the lifetime of the node; the smaller the residual energy and the larger the load of the node, the shorter the lifetime of the node.

3.2 *Network lifetime model*

Suppose that all nodes except sink node have the same initial energy in UWSNs. Based on the node lifetime we analysed in section 3.1, we know that the nodes with the largest degree will die first due to the energy exhaustion. The failure of the node with the largest degree may result in the disconnection of many communication links in UWSNs, and the UWSNs cannot complete task normally. In light of these facts, in this paper, UWSNs lifetime is defined to be the time at which the first node dies due to energy exhaustion. Then the UWSNs lifetime can be expressed as

$$T_{net} = \min(T_{node}). \tag{10}$$

In this paper, we focus on the shallow water environments since most current underwater IoT applications are located in inland lakes and rivers, e.g. aquaculture and water quality monitoring. In the shallow water environments, the three-dimensional network can be mapped into a two-dimensional network [17]. Assume that N nodes are uniformly deployed in monitoring field G (the area of G is S); from to the probability theory, the probability density function of the node coordinates (x, y) is

$$g(x,y) = \begin{cases} 1/S, & (x,y)\in G, \\ 0, & else. \end{cases} \tag{11}$$

Then the relationship between the number k_i of nodes covered by the communication area G_i of the node i and its communication distance d can be calculated as

$$k_i = N\iint_{G_i} g(x,y)dxdy = N\frac{\pi d^2}{S}. \tag{12}$$

The expression between the maximum node degree k_{max} and the maximum communication distance d_{max} of the initial network node satisfies the following formula:

$$k_{max} \leqslant N\pi d_{max}^2/S. \tag{13}$$

Thus, the maximum load that a single node in UWSNs needs to carry can be described as follows:

$$L_{max}(t) = L + k_{max}^{\beta}L \leqslant L + (N\pi d_{max}^2/S)^{\beta}L. \tag{14}$$

Based on Eq. (8), the energy consumed by the node with the maximum load per unit time in the UWSNs can be obtained as

$$\begin{aligned} E_{max}(t) &= pL_{max}(t) + q \\ &\leqslant p[L + (N\pi d_{max}^2/S)^{\beta}L] + q. \end{aligned} \tag{15}$$

In UWSNs, the node with maximum load is the first to die due to energy exhaustion. Thus, the shortest lifetime of failure node caused by energy exhaustion can be expressed as follows:

$$\begin{aligned} T'_{node} = E_i/E_{max}(t) &= \frac{E_i}{pL_{max}(t) + q} \\ &\geqslant \frac{E_i}{p[L + (N\pi d_{max}^2/S)^{\beta}L] + q}. \end{aligned} \tag{16}$$

Using Eqs. (10) and (16), we can obtain the UWSNs lifetime as

$$T_{net} = \frac{E_i}{p[L + (N\pi d_{max}^2/S)^{\beta}L] + q}. \tag{17}$$

From this analysis, the UWSNs lifetime model can be expressed by Eq. (17). Equation (17) shows that the UWSNs lifetime is affected by residual energy E_i and load adjustment coefficient β. We can adjust β to build the topology structure meeting the required network lifetime. Suppose the required network lifetime is θ; in order to make the network topology meet application requirements, we need to ensure $T_{net} \geqslant \theta$; thus, we obtain

$$\frac{E_i}{p[L + (N\pi d_{max}^2/S)^{\beta}L] + q} \geqslant \theta. \tag{18}$$

Equation (18) can be rewritten as

$$0 \leqslant \beta \leqslant \ln\left(\frac{E_i/\theta - p - qL}{pL}\right)/\ln(N\pi d_{max}^2/S). \tag{19}$$

From Eq. (19), the value range of β can be obtained based on the required network lifetime. Therefore, in order to make the UWSNs lifetime meet the actual demand, the load adjustment coefficient can be adjusted to balance the network load when constructing the network topology. Then the node energy exhaustion failure due to the excessive load can be prevented, and the network lifetime can be improved.

4. ELBF topology generation and characteristics analysis

Based on the UWSNs lifetime, a scale-free evolution model considering node residual energy and load case is proposed in this section. From the evolution model, a fault-tolerant topology with lifetime optimization (ELBF topology) is generated. Later, the degree distribution characteristic of ELBF is analysed to reflect the topological structure properties.

4.1 *ELBF topology evolution model*

Through the analysis in the earlier section, we know that UWSNs lifetime is determined by the residual energy and load of nodes. The larger the residual energy and the smaller the load of the node, the longer the lifetime of UWSNs. Therefore the residual energy E_i and load case k_i^{β} are considered in the process of the ELBF topology evolution. Thus, we establish a fitness function as follows:

$$\mu_i = E_i/k_i^{\beta}. \tag{20}$$

The topology with scale-free properties can be generated on the basis of the preferential connection mechanism. The fitness function is considered in the preferential connection mechanism. Thus, the ELBF topology evolution model is described as follows:

(1) Growth: Initially, there are m_0 nodes in the network. A new node is added to the network in each subsequent time step. The newly added node is connected to the m nodes that already exist on the network, where $m \leqslant m_0$.
(2) Preferential connection: The probability that a new node will be connected to the node i depends on the degree k_i of i, the residual energy of i and load adjustment coefficient β. The preferential connection probability $\Pi(k_i)$ of i is expressed as

$$\prod(k_i) = \frac{\mu_i k_i}{\sum\limits_{j\in local} \mu_j k_j} = \frac{E_i k_i^{1-\beta}}{\sum\limits_{j\in local} E_j k_j^{1-\beta}} \tag{21}$$

where *local* is the neighbour nodes in the communication range of the new node.

From the analysis of UWSNs lifetime in the earlier section, the value range of β can be obtained when the required network lifetime is given. Then the fault-tolerant topology with lifetime optimization based on the ELBF topology evolution model can be generated.

4.2 *ELBF characteristics analysis*

To use the continuous field theory, suppose that the node degree varies continuously with time; the rate of continuous change of k_i based on the afore-mentioned preferential connection mechanism can be expressed as

$$\frac{\partial k_i}{\partial t} = m\prod_{local}(k_i) = m\frac{E_i k_i^{1-\beta}}{\sum\limits_{j\in local} E_j k_j^{1-\beta}}. \tag{22}$$

E_i is a continuous function on the closed interval $[E_{\min}, E_{\max}]$. Then we can obtain

$$E_{min}\sum_{j\in local} K_j^{1-\beta} \leqslant \sum_{j\in local} E_j K_j^{1-\beta} \leqslant E_{max}\sum_{j\in local} K_j^{1-\beta}. \tag{23}$$

From the the intermediate value theorem, there is an $E_\xi \in [E_{min}, E_{max}]$. Then we have

$$\sum_{j\in local} E_j K_j^{1-\beta} = E_\xi \sum_{j\in local} K_j^{1-\beta}. \tag{24}$$

Therefore, Eq. (21) can be rewritten as

$$\prod_{local}(k_i) = \frac{E_i k_i^{1-\beta}}{E_\xi \sum\limits_{j\in local} k_j^{1-\beta}}. \tag{25}$$

We assume that at time t, a new node Δ with transmission radius d_Δ is added into the network. At this moment, the radius of the network is d_t. Because the node deployment in the monitoring area obeys uniform distribution, the probability that the nodes in the communication range of the new node Δ are selected can be denoted by the area ratio $({d_\Delta}^2/2)/{d_t}^2$. Hence $\prod_{local}(k_i)$ is given as

$$\begin{aligned}\prod_{local}(k_i) &= \frac{E_i k_i^{1-\beta}}{E_\xi \sum\limits_{j\in local} k_j^{1-\beta}}\\ &= \frac{1}{2}{d_\Delta}^2/{d_t}^2 \frac{E_i k_i^{1-\beta}}{E_\xi N_t[\frac{1}{2}{d_\Delta}^2/{d_t}^2]\bar{k}_t^{1-\beta}}\\ &= \frac{E_i k_i^{1-\beta}}{E_\xi N_t \bar{k}_t^{1-\beta}}\end{aligned} \tag{26}$$

where N_t and $\bar{k}_t$ are the number and average degree of network nodes at time t, respectively. From the afore-mentioned topology evolution model, at time t, the number of the nodes and edges in the topology generated are $m_0 + t$ and mt, respectively. Hence, we can obtain $\bar{k}_t = 2mt/(m_0 + t)$; if m_0 is very small, then

$$\begin{aligned}\frac{\partial k_i}{\partial t} &= m\frac{E_i k_i^{1-\beta}}{E_\xi(m_0+t)(\frac{2mt}{m_0+t})^{1-\beta}}\\ &= f(E_i, E_\xi)2^{\beta-1}m^\beta \frac{k_i^{1-\beta}}{t}\end{aligned} \tag{27}$$

where $f(E_i, E_\xi) = E_i/E_\xi$. Using the method of separating variables, the solution of this differential equation is

$$k_i(t) = [(f(E_i, E_\xi)2^{\beta-1}m^\beta \ln t + C)\beta]^{\frac{1}{\beta}}. \tag{28}$$

Using the initial conditions $k_i(t_i) = m$, this formula is expressed as

$$k_i(t) = [f(E_i, E_\xi)2^{\beta-1}\beta m^\beta \ln\frac{t}{t_i} + m^\beta]^{\frac{1}{\beta}} \tag{29}$$

The probability $p(k_i(t) < k)$ can be described as

$$p(k_i(t) < k) = p\left(t_i > te^{\frac{m^\beta - k^\beta}{f(E_i,E_\xi)2^{\beta-1}\beta m^\beta}}\right). \tag{30}$$

In the ELBF topology evolution model only one new node is added to the network for each time step, so t_i obeys uniform distribution. Thus the probability density function of t_i can be expressed as $p(t_i) = \frac{1}{m_0+t}$. Then the degree distribution characteristic of ELBF is shown to be

$$\begin{aligned}\frac{\partial p(k_i(t) < k)}{\partial k} &= \frac{\partial\left(1 - p\left(t_i \leqslant te^{\frac{m^\beta - k^\beta}{f(E_i,E_\xi)2^{\beta-1}\beta m^\beta}}\right)\right)}{\partial k}\\ &= \frac{1}{m2^{\beta-1}f(E_i,E_\xi)}\left(\frac{k}{m}\right)^{-(1-\beta)} e^{\frac{m^\beta - k^\beta}{f(E_i,E_\xi)2^{\beta-1}\beta m^\beta}}.\end{aligned} \tag{31}$$

It can be seen from Eq. (31) that the distribution of the evolution topology depends on the residual energy and load adjustment coefficient of the node when m is given. The energy and load of the topology can be balanced by adjusting the parameter β. Thus the energy depletion failure of the node due to the excessive load of can be avoided, and the topology generated based on the scale-free evolution model can tolerate the random failure nodes effectively.

5. Simulation experiment

5.1 *Simulation environment*

In order to evaluated the performance of the ELBF topology, we choose the energy-efficient TCEB algorithm [17] and the TFA algorithm [24] with good fault tolerance as the comparative algorithms. All experiments in this section were done using Matlab.

In the following experiments, the initial conditions of the network in the three topology algorithms are the same. Assume that each node in the network can complete at least 1500 rounds of data transmission. All experimental results are the average of 100 experiments. The experimental parameters are set in table 1.

5.2 *Topology performance*

In this section, we focus on the network lifetime and fault tolerance of ELBF. It can be seen from the afore-mentioned theoretical analysis that the value of β depends on the actual required network lifetime. When $0 \leqslant \beta \leqslant 1$, the network possesses the scale-free property. For the validity of the experiment, we choose the ELBF topology ($\beta = 0.3$, $\beta = 0.6$, $\beta = 0.9$) to study the topological performance in the following simulations.

The relationship between the residual energy of the nodes and the corresponding node degree can reflect network energy efficiency. In figure 1 the network topology is rebuilt after running 100 rounds, and the residual energy and degree of the nodes in ELBF, TCEB and TFA algorithms are researched. Here, the residual energy is the average residual energy of nodes with degree k.

From figure 1, we observe that the nodes with bigger degree have higher residual energy in the ELBF and TCEB. However, TFA does not have this characteristic. This is because the residual energy of nodes is considered in the process of constructing ELBF and TCEB topologies. The nodes with larger residual energy have higher connection probability, which can balance the energy consumption of the network and improve the network energy efficiency. Figure 1 also shows that energy efficiency of ELBF is better than that of TCEB. The main reason is ELBF evolution model considers the interaction between the residual energy and the node load in the process of preferential attachment, so the topology constructed has better energy efficiency.

In figure 2, the network lifetimes of the three topologies are contrasted. In this paper, UWSNs lifetime is defined as the time for the first node to fail due to energy exhaustion. Thus, in this experiment, the network lifetime is the number of rounds until the first node dies due to energy exhaustion. In each round of experiments, data is transmitted according to the energy consumption model established in section 3.

Table 1. The experimental parameters.

Parameters	Value
Node number N	100
Network size S	200 m$\times$200 m
Maximum transmission radius d_{max}	50 m
Initial energy E_0	3 J
Data fusion energy consumption E_{elec}	8 nJ/bit
Minimum receiving power P_0	0.07 W
Energy spreading factor λ	1
Carrier frequency f	15 kHz
Packet length L	100 bits

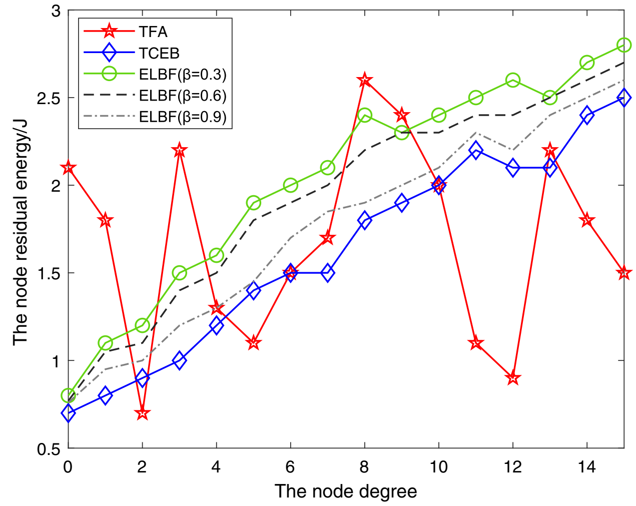

Figure 1. The network energy efficiency contrast.

From figure 2, we can see that the network lifetime of ELBF topology (3500 rounds under $\beta = 0.3$, 3200 rounds under $\beta = 0.6$, 3050 rounds under $\beta = 0.9$) is much longer than that that of TCEB topology (2500 rounds) and TFA topology (1800 rounds), which indicates that the lifetime optimization of ELBF topology is better than those of TCEB and TFA topologies.

Figure 2 also compares the running time of three network topologies under random node failure. For UWSNs, in addition to the node failure caused by the energy exhaustion, the complex underwater environment can also cause random failure of nodes. Considering that the edge nodes have little influence on the topology, in this experiment, the running time of network under random node failure is recorded when 50% nodes in network are unavailable due to random failure caused by harsh underwater environment. As shown in figure 2, in the case of

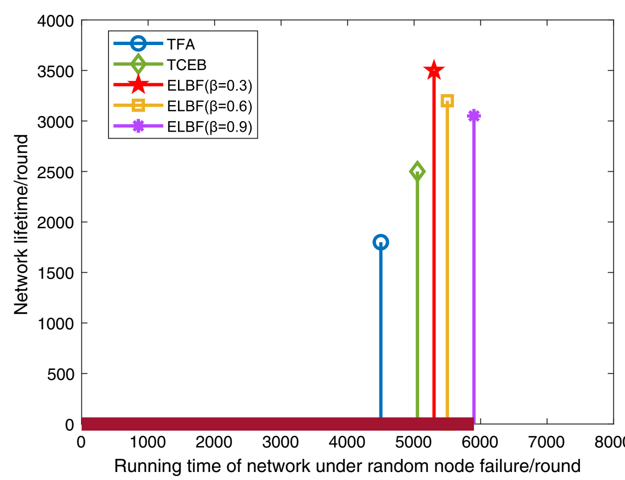

Figure 2. The lifetime contrast of ELBF, TCEB and TFA.

random node failure, the network running time of ELBF topology (5300 rounds under $\beta = 0.3$, 5500 rounds under $\beta = 0.6$, 5900 rounds under $\beta = 0.9$) is longer than that of TCEB topology (5100 rounds) and TFA topology (4500 rounds), which indicates that the ELBF topology can operate longer under random node failure than the TCEB and TFA topologies.

Fault tolerance is one of the most important performances of UWSNs. Generally, the largest connected component ratio is used as the evaluation index of fault tolerance of UWSNs. The largest connected component ratio is the ratio of the size of the largest connected component to the size of whole network (size of a network or a component is defined as the number of nodes included in it). For different network topologies, when the same number of nodes die, the network that has greater largest connected component ratio has better fault tolerance.

In figure 3, the fault tolerances of ELBF, TCEB and TFA topologies are compared. Considering that the failure of the node caused by the complex underwater environment is random, in this experiment, the nodes are removed randomly according to Poisson's rule. In each round of experiments, the number of nodes removed in three topologies is the same.

Figure 3 shows that the largest connected component ratios of ELBF and TFA topologies are much larger than that of TCEB when the same number of nodes are removed, which indicates the ELBF and TFA topologies have better fault tolerance for random failure. This is because both ELBF and TFA topologies are generated based on scale-free evolution model. The scale-free evolution model can tolerate random failure effectively. From figure 3, we also see that the fault tolerance for random failure of ELBF topology is stronger than that of TFA topology. Therefore, the ELBF topology has strong fault tolerance for random node failure.

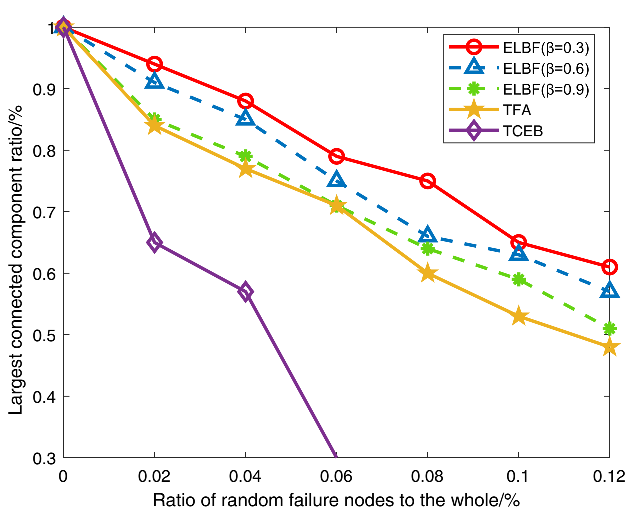

Figure 3. The random failure fault tolerance contrast of ELBF, TCEB and TFA.

In order to verify the fault tolerance of UWSNs for selective node failure due to malicious attacks, in the experiment, the nodes with larger degree are removed in each round of the network operation. Figure 4 gives the relationship between the largest connected component and selective failure nodes in ELBF, TCEB and TFA topologies. In figure 4, we can observe that the largest connected component size of ELBF topology is larger than those of TCEB and TFA topologies when the same nodes die due to malicious attacks. Hence, the influence of selective node failure on ELBF topology is smaller than in TCEB and TFA topologies. Thus the ELBF topology has a certain ability to tolerate selective failure of nodes, which ensures that the network can complete the monitoring task.

6. Conclusion

In this paper, two factors – residual energy and load of node – are considered. Based on the two factors, the network lifetime model of UWSNs is built. Through analysing the influence of residual energy and load of node on the network lifetime, the fitness function for residual energy and load case is established. The fitness function takes into account the scale-free evolution model; thus the nodes with high energy and small load have higher connection probability and the energy of nodes in UWSNs is balanced effectively. Using the the improved evolution model, the fault-tolerant topology ELBF with network optimization is obtained. Simulation experiments demonstrate that the ELBF topology has better energy efficiency and longer lifetime than those of TCEB and TFA topologies, and the ability of the ELBF topology to tolerate node failure is stronger than those of TCEB and TFA topologies. The lifetime and fault tolerance of UWSNs can be improved effectively by the ELBF topology.

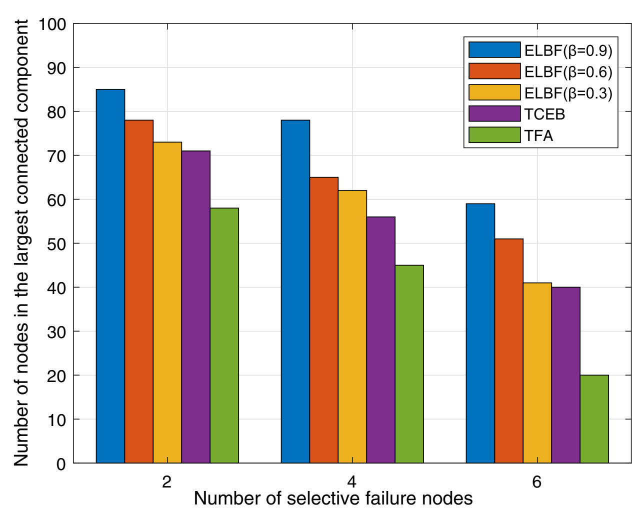

Figure 4. The topology selective failure fault tolerance contrast.

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List of symbols

N	Node number
S	Network size, m× m
$d_{\max}$	Maximum transmission radius, m
E_0	Initial energy, J
P_0	Minimum receiving power, W
L	Packet length, bit
f	Carrier frequency, kHz
E_{elec}	Data fusion energy consumption, nJ/bit
λ	Energy spreading factor

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