Research Article

A Topology Construct and Control Model with Small-World and Scale-Free Concepts for Heterogeneous Sensor Networks

Lifang Liu,1 Xiaogang Qi,2,3 Jilong Xue,4 and Mande Xie5

1 School of Computer Science and Technology, Xidian University, Xi’an 710071, China
2 School of Mathematics and Statistics, Xidian University, Xi’an 710071, China
3 The State Key Laboratory of Complex Electromagnetic Environmental Effects on Electronics and Information System, Luoyang 471003, China
4 Department of Computer Science, Peking University, Beijing 100083, China
5 School of Computer and Information Engineering, Zhejiang Gongshang University, Hangzhou, Zhejiang 310018, China

Correspondence should be addressed to Mande Xie; xiemd@zjgsu.edu.cn

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Topology construction and control is a vital technique in wireless sensor networks. In this paper, based on small-world and scale-free concepts of complex network theory and considering the characteristics of wireless sensor network, a topology model with small-world and scale-free concepts for heterogeneous sensor network is presented. This work is achieved by applying heterogeneous sensors and preferential attachment mechanism. Furthermore, the topology evolution algorithm is designed. Finally, we simulate the network characteristics, and simulation results are consistent with the theoretic analysis and show that topologies of wireless sensor network built by this model have small-world and scale-free feathers and can significantly improve energy efficiency as well as enhance network robustness, leading to a crucial improvement of network performance.

1. Introduction

Wireless sensor network (WSN) consists of spatially distributed autonomous sensors to monitor physical or environmental conditions, such as temperature, sound, vibration, pressure, motion, or pollutants, and to cooperatively transmit their data through the network to a sink node. Today WSNs are more and more widely used in a variety of industrial and consumer applications, such as industrial process monitoring and control, machine health monitoring, environment and habitat monitoring, health care applications, home automation, and traffic control [1].

In military and warfare applications, WSNs are deployed in hostile monitoring environment and the sensor node is with limited energy support. Energy exhaustion and natural damage of some sensor nodes often lead to the failure of the whole network. Construction and control of topology as a vital technique plays an important role to conquer these problems in WSNs. The main purpose of construction and control of topology is to achieve a higher communication quality, have efficient energy use and strong robust topology through power control, have important network node selection, remove unnecessary communication links, and so on.

Most topology models are based on some network theories such as random graph theory and complex network theory. The complex networks widely exist in real world such as electrical power grids, global transport networks, coauthorship and citation networks, and so on. As an interdisciplinary research area, complex networks arouse worldwide attention [2–4]. Two most typical network models in complex network theory are small-world network and scale-free network [4, 5]. The small-world network has two independent structural features: (i) a small average shortest path length and (ii) a large clustering coefficient [6]. By applying small-world theory in topology construction of WSNs, the network performance will be improved in querying data efficiency, energy efficiency, network lifetime, and so forth [7]. A scale-free network is a network whose node's
degree follows a power law distribution, and the scale-free topology characteristics have a higher robustness to endure the random failure [8]. However, few people study how to construct WSN topology with small-world and scale-free characteristics at the same time.

In this paper, considering the characteristics of WSNs, such as residual energy, degree saturation, and maximum communication radius of sensor, a topology model with small-world and scale-free concept (TMSSC) is proposed based on wireless heterogeneous sensor networks, and the topology evolution algorithm is designed. Topology constructed by this model not only has higher energy efficiency and transmission efficiency but also has higher robustness to endure the random failure.

The rest of the paper is organized as follows. Section 2 in this paper introduces the background of small-world networks and scale-free networks and their application in WSNs. Section 3 describes the TMSSC model and its algorithm, and also the network characteristic is analyzed. Finally, the simulation results analysis and conclusion are, respectively, presented in Sections 4 and 5.

2. Related Works

2.1. Small-World Networks in WSNs. Two main characteristics of small-world network are small average shortest path length and large clustering coefficient, which are the most important factors affecting the network performance. Helmy proposed a small-world concept wireless network through randomly adding a little of logical links to WSNs [9]; this leads to a small average shortest path length of networks, and then he proved that small-world network phenomenon also exists in wireless networks with spatial properties.

Based on the results of Helmy [9], Cavalcanti et al. improved the connectivity of wireless ad hoc networks by using small-world characteristics [10]. A few of sensor nodes with high energy and strong communication capability called H-sensor are introduced in this paper. Results show that H-sensors can improve the connectivity of networks significantly.

Research results by Chitradurga and Helmy [11] show that the average path length can significantly be decreased by adding shortcuts in the network. Specially, the length of shortcut just needs to be 25% to 40% of the diameter of a network with 1000 uniform distribution of sensor nodes; the average shortest path length of the modified network can reach 60% to 70% as that of original one.

Hawick paid attention to network coverage, fault tolerance, and sensor network lifetime by applying small-world theory [12]. Results show that adding a few of random links among sensor nodes can not only decrease the average path length but also decrease the number of isolated clusters, which lead to a great improvement of network coverage and lifetime.

2.2. Scale-Free Networks in WSNs. As the recent research focus, scale-free networks in WSNs are mostly improved by BA network model, which was proposed by Barabási and Albert [4]. This model is based on two important characteristics:

(i) growth: the scale of the network is expanding;
(ii) preferential attachment: the new node is more inclined to join with those nodes with higher degree.

BA scale-free network did not take spatial properties into consideration, so many scholars improved this model. For example, Saffre et al. [13] proposed an algorithm to build network topology with scale-free concept using local geographic information of sensor. Literature [8] proposed a topology evolution of WSNs among cluster heads by random walkers. Topology built by this model has a scale-free characteristic and better robustness, but this paper takes little consideration in communication features of WSNs, which might lead to a limited utility.

3. TMSSC Topology Evolution Model

In this section, we firstly introduce the topology model with small-world and scale-free concept (TMSSC) in heterogeneous wireless sensor networks, which consist of large number of sensors (L-sensor) and a small portion of super sensors (H-sensor). Firstly, some model assumptions are introduced. Then, we define some concepts and notations which may be used. Finally, the TMSSC topology evolution model is proposed and the algorithm is designed. Also, the dynamic characteristics of topology analysis are shown in this section.

3.1. Model Assumption. In our model, we assume the sensor networks consist of large portion of L-sensors and small portion of H-sensors. The H-sensors are equipped with high energy and strong communication capability and can communicate with H-sensor and L-sensor by using the different radios, respectively, in which one radio is responsible for long-distance communication and one is responsible for short-distance communication as equipped on the L-sensors.

In order to keep the symmetry of the network after adding H-sensor in WSNs, we assume that if an H-sensor \( v_i \) connects to another node \( v_j \); it should at least satisfy the following conditions:

\[
\begin{align*}
  d(v_i, v_j) &\leq L_{\text{high}}, & \text{if } v_j &\in H\text{-sensor}, \\
  d(v_i, v_j) &\leq L_{\text{low}}, & \text{if } v_j &\in L\text{-sensor},
\end{align*}
\]

where \( d(v_i, v_j) \) is the Euclidean distance between node \( v_i \) and node \( v_j \) and \( L_{\text{high}} \) and \( L_{\text{low}} \) are communication radius of H-sensor and L-sensor, respectively. With the situation of \( v_i \) being an L-sensor, the condition is that the distance between 2 nodes just is less than the communication radius \( L_{\text{low}} \).

Finally, we assume that the network topology management mechanism is achieved by using clustering. Clustering topology has the advantages in topology management, energy use, data fusion, and so on. This paper employs the HEED clustering algorithm which takes into consideration both the residual energy and communication cost [14]. So we assume
that TMSSC topology model is built by using the cluster head nodes.

3.2. Definitions and Notions

3.2.1. Same Directed Angulation towards Sink $\Phi_{ij}$. Same directed angulation towards sink $\Phi_{ij}$ defines the similarity between the directed angulation of node $v_i$ towards sink and the directed angulation of node $v_j$ towards node $v_j$. Since the goals of all the clustering head nodes are to transmit the collected data to the sink, the waste of communication energy is greatly reduced by taking into account the direction of edges between H-sensors [7]. We assume that the coordinates of node $v_i$ are $(x_i, y_i)$, the coordinates of sink node are $(x_0, y_0)$, the straight line from $v_i$ to sink is $y = m_1x + b_1$, and the straight line from $v_i$ to $v_j$ is $y = m_2x + b_2$; note the angle between two lines as $\theta$; thus, $\tan \theta = (m_1 - m_2)/(1 + m_1m_2)$.

The definition of $\Phi_{ij}$ between $v_i$ and $v_j$ is

$$
\Phi_{ij} = \frac{1}{\tan \theta} = \frac{1 + m_1m_2}{m_1 - m_2}.
$$

If node $v_i$ connects with another node $v_j$ with the probability of $\Phi_{ij}$, all edges in the constructed topology will have the tendency towards sink node. Figures 1(a) and 1(b), respectively, show the topology in which edges between H-sensors are connected with probability $\Phi_{ij}$ and in random mode.

3.2.2. Other Definitions

(i) Degree $k_i$ is the number of edges connected with node $i$.

(ii) Communication radius $L$: the communication radius of L-sensor is $L_{low}$ and the value of H-sensor is $L_{high}$.

(iii) Residual energy $E_i$ is the residual energy of node $i$; a node is death when $E_i = 0$.

3.3. Design of Model and Algorithm. Based on the above definitions and assumptions, we propose the TMSSC topology evolution model according to "preferential attachment" mechanism. The model is described as follows.

3.3.1. Growth. Initially the network just contains a small scale topology which consists of $m_0$ L-sensors, $m_0$ H-sensors, $e_0$ edges, and sink node. Then, choose a new node to join the topology every round. If the node is H-sensor, then add $m_2$ edges between this new node and current topology, and this new node only can connect to H-sensors. If it is L-sensor, add $m_1$ edges between this new node to current topology, and it can connect with any other nodes.

3.3.2. Preferential Attachment. If the new node is an L-sensor, what should be taken into account are energy balance, the degree saturation, and communication radius. Thus, the probability $\Pi_{ij}$ of new node $v_i$ connecting to node $v_j$ in the current topology is formulated as

$$
\Pi_{ij} = \frac{E_jk_i}{\sum_{j=1}^{N_j} E_jk_i} \cdot P\{d(v_i, v_j) \leq L_{low}\},
$$

where $E_j$ and $k_i$, respectively, indicate residual energy and degree of node $v_j$, $N_j$ is the number of L-sensors, $n$ is number of nodes in which degree is saturated, $d(v_i, v_j)$ is the distance of two nodes, and $P[d(v_i, v_j) \leq L_{low}] = \pi L_{low}^2/S.$
Algorithm of TMSSC

Require: Initial topology with \( m_0 \) H-sensors and L-sensors;
(1) \( V = \text{RandomGenerate}(N) \);
(2) \( N_{in} = 2 \times m_0 \);
(3) \( L_{in} = \text{initial 2m}_0 \text{ nodes} \);
(4) for all \( v_i \in V \) do
    (5) broadcastHelloPacket(\( v_i \));
    (6) receiveNeighborInformation();
(7) end for
(8) while \( N_{in} < N \) do
    (9) \( v_j = \text{randomSelect}(V - L_{in}) \);
    (10) for all \( v_j \in \text{Neighbor of } v_i \) do
        (11) \( \Pi_i = \Pi^h_i, v_j \in \text{L-sensor} \)
        (12) if \( \text{random()} \leq \Pi_i \) then
            (13) \( v_j \text{ connect with } v_i \);
            (14) \( L_{in} \leftarrow v_i \);
            (15) \( N_{in} \leftarrow N_{in} + 1 \);
        (16) end if
    (17) end for
(18) end while

Algorithm 1: Algorithm of TMSSC topology evolution model.

If the new node \( v_i \) is an H-sensor, it should consider the angulation towards sink \( \Phi_{ij} \) besides above factors. Because of the longer distance between H-sensors than L-sensors, if the deviation of transmission direction is too large, it will waste energy greatly. Thus, the probability \( \Pi^h_{ij} \) of new node \( v_j \) connecting to node \( v_i \) is formulated as

\[
\Pi^h_{ij} = \frac{\Phi_{ij}k_i}{\sum_{i=1}^{N_i} \Phi_{ij}k_i} \cdot P \left\{ d(v_i, v_j) \leq L_{\text{high}} \right\}, \tag{4}
\]

where \( k_i \) indicate degree of node \( v_i \) and \( N_i \) is the number of H-sensors in current topology. The \( n \) is number of nodes in which degree is saturated, \( d(v_i, v_j) \) is the distance of two nodes, and \( P[d(v_i, v_j) \leq L_{\text{high}}] = \pi L_{\text{high}}^2 / S \).

In order to implement this model, we design the algorithm pseudo code of TMSSC topology evolution model, which is shown in Algorithm 1. This algorithm eliminates the clustering process. More details about clustering algorithm are presented in [14].

3.4. Dynamic Analysis of Topology Evolution. According to mean-field theory [15], we assume that \( k_i \) is continuous, and thus the probability \( \Pi_i \) can be considered as a continuous rate of change of \( k_i \). Consequently, we have the equation for node \( i \) as follows:

\[
\frac{\partial k_i}{\partial t} = (1 - p) m_1 \Pi^l_i + p \cdot m_2 \Pi^h_i, \tag{5}
\]

where \( p \) is the probability of H-sensor connecting to the current topology and \( 1 - p \) is the probability of L-sensor connecting to the current topology; \( \Pi^l_i \) and \( \Pi^h_i \) are formulated as (3) and (4).

Since the continuity of \( E_i \), we have

\[
E_{\min} \sum_{i=1}^{N_i} k_i \leq \sum_{i=1}^{N_i} E_i k_i \leq E_{\max} \sum_{i=1}^{N_i} k_i, \tag{6}
\]

and \( \exists E_t \in [E_{\min}, E_{\max}] \) such that

\[
\sum_{i=1}^{N_i} E_i k_i = E_t \sum_{i=1}^{N_i} k_i. \tag{7}
\]

Similarly, \( \exists \Phi_t \in [\Phi_{\min}, \Phi_{\max}] \) such that

\[
\sum_{i=1}^{N_i} \Phi_i k_i = \Phi_t \sum_{i=1}^{N_i} k_i. \tag{8}
\]

Here we assume that a few nodes have reached the saturation value of degree \( K_{\text{sat}} \). That is, \( n \) is very minimal so that it can be ignored here. At time \( t \), taking into account that \( \sum_{i=1}^{N_i} k_i = 2m_1 t \) and \( \sum_{i=1}^{N_i} k_i = 2m_2 t \), we have

\[
\frac{\partial k_i}{\partial t} = \beta \frac{k_i}{t}, \tag{9}
\]

where

\[
\beta = (1 - p) \frac{E_t \pi L_{\text{low}}^2}{2SE_t} + p \frac{\Phi_t \pi L_{\text{high}}^2}{2S\Phi_t}. \tag{10}
\]

According to the assumptions, the initial condition of above equation is that node \( i \) is added to the topology at time \( t_i \) with connectivity \( k_i(t_i) = (1 - p)m_1 + p \cdot m_2 \); note that \( m = (1 - p)m + p \cdot m_2 \). The solution of this equation is

\[
k_i(t) = m \left( \frac{t}{t_i} \right)^{\beta}. \tag{11}
\]
Using (10), the probability that a node has a connectivity \( k_i(t) \) less than \( k \), \( P(k_i(t) < k) \), can be written as

\[
P \{ k_i(t) < k \} = P \left\{ t_i > \frac{m^{1/\beta}}{k^{1/\beta} t} \right\}, \quad (11)
\]

Also, we assume that node is added to the system at equal time intervals; the probability density of \( t_i \) is

\[
pd(t_i) = \frac{1}{2m_0 + t}. \quad (12)
\]

By substituting this into (11), we obtain the following equation:

\[
P \{ k_i(t) < k \} = 1 - P \left\{ t_i < \frac{m^{1/\beta}}{k^{1/\beta} t} \right\} = 1 - \frac{m^{1/\beta}}{k^{1/\beta} (t + 2m_0)}. \quad (13)
\]

The probability density for \( pd(k) \) can be obtained using

\[
pd(k) = \frac{\partial P \{ k_i(t) < k \}}{\partial k} = \frac{m^{1/\beta} t}{\beta (t + 2m_0)} \cdot \frac{1}{k^\gamma}, \quad (14)
\]

where \( \gamma = 1 + 1/\beta \). Accordingly, the degree distribution of this topology agrees with power-law distribution; in other words, this topology has scale-free characteristics.

### 4. Network Features and Simulation Results

#### 4.1. Simulation Assumptions

In the simulation, we use a network with a total of 1000 nodes (L-sensors and H-sensors) randomly deployed in a sensor field of 1000 × 1000 m². There is only one sink node located at (0, 0). The communication radii of L-sensors and H-sensors are 60 m and 500 m, respectively. Initial number of nodes \( m_0 = 3 \), every time an edge is added into topology. All results are obtained by \( n \) times simulation, each time the simulation network topologies are different; here \( n = 30 \).

#### 4.2. Small-World Features Evaluation

In this section, we evaluate the average minimum effective path length \( L(k) \) and the clustering coefficient \( \langle C \rangle \). The average minimum effective path length is defined as arithmetic average of the length of the shortest path from each node to sink node. The clustering coefficient of node \( v_i \) is defined as \( C_i = n/(k_i(k_i-1)/2) \), where \( n \) is the number of edges linked between node \( v_i \)'s \( k_i \) neighbor nodes. Thus, the clustering coefficient of network is \( \langle C \rangle = \langle C_i \rangle \).

In each generated topology, we evaluate the average minimum effective path length and the average clustering coefficient of the network. After \( n \) simulations, we obtain the average of these \( n \) results. The values \( \langle C \rangle \) and \( L(k) \) are, respectively, defined as the clustering coefficient and the average minimum effective path length of the WSN topology with H-sensor probability \( p \). The values \( \langle C \rangle(0) \) and \( L(0) \) are defined as the same parameters but for no H-sensor addition. According to simulation results, the ratios of \( \langle C \rangle(p)/\langle C \rangle(0) \) and \( L(p)/L(0) \) are calculated. These ratios clearly show the influence of adding a fraction of H-sensors in the WSN.

#### 4.3. Scale-Free Features Evaluation

We find that when \( p = 0.01 \sim 0.1 \) the network built by TMSSC has small-world features. In this section, we will evaluate the degree distribution function \( P(k) \) of networks with H-sensor probabilities \( p = 0.01 \) and \( p = 0.1 \). In each generated topology, we evaluate the degree distribution of the network. After \( n \) times simulation, we obtain the average values of these \( n \) times results. We can get Figures 3(a), 3(b), 3(c), and 3(d) and use them to evaluate the scale-free characteristics.

Figures 3(a) and 3(b) illustrate the degree distribution of the network, which show that most of the nodes in the network have small degree. For example, the degree of 82.5% nodes is less than 4 in Figure 3(a) and that of 81.9% nodes is less than 3 in Figure 3(b). This characteristic makes the network robust enough to resist the random node failures.

Figure 2 illustrates the average minimum effective path length and the clustering coefficient of the network when changing the value of the probability \( p \). We find that the average minimum effective path length and clustering coefficient are not changed when probability \( p = 0.001 \), because those few H-sensors do not contribute too much to reduce the above parameters. When \( p \) is close to 0.01, a network with small-world characteristics can be generated, the average minimum effective path length is reduced to 16.7% of that in the original network, and clustering coefficient is 80.4% of that in the original network. When \( p > 0.1 \), the average minimum effective path length does not reduce significantly. However, the clustering coefficient reduces quickly. All these results show that when \( p = 0.01 \sim 0.1 \), the average minimum effective path length is reduced quickly, the clustering coefficient changed a little, and the network has the small-world features.
Owing to its scale-free structure, the random node failures cannot affect the network's performance significantly. Figures 3(c) and 3(d) illustrate the above degree distribution in double logarithmic coordinates; we find that the degree distribution of networks built by TMSSC approximately obeys the power law distribution, and this agrees with the dynamic analysis results. In other words, the networks built by TMSSC have scale-free features.

4.4. Network Performances

4.4.1. Energy Efficiency. Compared with the BA model, TMSSC takes into consideration the energy balance. So, WSNs built by TMSSC perform a higher energy efficiency than the networks built by BA model under the same conditions. Under same assumptions with Section 4, we evaluate the energy efficiency by the survival nodes percentage by the BA and TMSSC model. In each deployed network, a random initial energy is given to each node. We build the two different topologies by TMSSC and BA model and run the network simulation, respectively. Every 5 rounds, we rebuild the networks and record the number of survival nodes. After n simulations, we obtain the average of these n results; see Figure 4(a). Another simulation is used to evaluate the impact of different number of H-sensors on the network lifetime; see Figure 4(b).

According to Figure 4(a), we illustrate that the survival nodes percentage changes over running time. We find that the TMSSC is better than the BA model. When it runs at 200 rounds, the survival nodes percentages of TMSSC and BA are 69.9% and 65.2%, respectively, because of the contribution of energy balance in TMSSC. Furthermore, in order to evaluate
the energy efficiency with different probability of H-sensors of TMSSC, we run another simulation by adding $p = 0, 0.001, 0.1$ H-sensors into the same network, respectively, and the comparison under these three situations is shown in Figure 4(b). By adding H-sensor probability $p = 0.01$, the survival nodes percentage is improved by 9.8% than that in the original network when simulation runs at 200 rounds. When $p = 0.1$, the value is increased to 25.2%. Above results show that the network life time and the network energy efficiency can be highly improved by adding a fraction of H-sensors into WSNs.

### 4.4.2. Network Robustness

According to the analysis in Section 3, the topology built by TMSSC is with a scale-free feature. Networks with this characteristic have a higher robustness to resist the random node failures. In this section, we investigate the network robustness by using the concept of largest effective component $S$, which defines the largest component containing sink node in a WSN. We use the ratio $S(f)/S(0)$ to analyze the network robustness of randomly removing a fraction $f$ of nodes in sensor network, where $S(0)$ is the original network with no node removed. We compare the robustness of three network topologies which are, respectively, built by BA model and TMSSC model with $p = 0.01$ and $p = 0.1$; the results are shown in Figure 5.

Figure 5 shows that networks built by TMSSC have a better performance on robustness against random node failures than BA model, and the robustness is improved by increasing H-sensors. In addition, this curve shows that the generated network has the characteristic of scale-free network. After randomly removing a little fraction of nodes, the network works well. When $p = 0.01$, there have been 14% of nodes removed from the network and the largest effective component is 80.1% of the original size. So, network built by TMSSC model has the scale-free properties and can resist the random node failures.

### 5. Conclusion

In this paper, we firstly present a topology model with small-world and scale-free concepts for heterogeneous sensor
networks, and this model is achieved by the preference attachment mechanism and the heterogeneous sensor networking. Secondly, we design the topology evolution algorithm and give a dynamic analysis of topology evolution. Finally, we give an extensive simulation to evaluate the topology characteristics and network performances. Simulation results agree with theoretic analysis and show that WSNs topology built by this model has the small-world and scale-free characteristics. Also, the generated sensor networks by this method have higher energy efficiency and the stronger robustness against the random node failures and can highly improve the network performance.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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