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Connected Model for Opportunistic Sensor Network Based on Katz Centrality

Jian Shu[1], Lei Xu[1], Shandong Jiang[1], and Lingchong Meng[1]

Internet of Things Technology Institute, Nanchang Hangkong University
Nanchang 330063,China
shujian@nchu.edu.cn
18270717228@163.com
{306315953,282733193}@qq.com

Abstract. Connectivity is an important indicator of network performance. But the opportunistic sensor networks (OSNs) have temporal evolution characteristics, which are hard to modelled with traditional graphs. After analyzing the characteristics of OSNs, this paper constructs OSNs connectivity model based on time graph theory. The overall connectivity degree of the network is defined, and is used to estimate actual network connectivity. We also propose a computing method that uses the adjacency matrix of each snapshot. The simulation results show that network connectivity degree can reflect the overall connectivity of OSNs, which provide a basis for improving the OSNs performance.

Keywords: opportunistic sensor networks, connectivity, network connectivity degree, time graph.

1. Introduction

Opportunistic sensor networks (OSNs) are a type of self-organized network [13] that does not require complete communication paths between source and destination. They utilize contacting opportunities of ferry nodes to achieve data communication so that they can attain the regional information with low cost. They also have high delay, frequent split and intermittent connection characteristics, which are derived from the delay tolerant networks (DTNs).

The trait of the non-fully connection [17] make OSNs dispose the difficult problems when the networks are splitting. Therefore they have a wide application prospect in the hostile environment such as wildlife monitoring, emergency rescue, battlefield information collection, remote networking, vehicle network and so on. After the deployment of nodes, in order to analyze the operating condition of each node and the change of network, we should not only excavate the data from the networks, but also have a further measurement on the connectivity of the OSNs. So it has a great significance for us monitoring network and describing the link of the nodes.

Our research on OSNs connectivity seeks to improve network performance and the success rate of message delivery. We can change the delopyment of nodes and optimize the network design through the overall connectivity model. The key to analyzing connectivity lies on establishing a suitable model and comparing with the message delivery rate. It can also help the network administrator to analyze the condition of the nodes and the environment being monitored.

As shown in Fig. 1, due to the restriction of the regional terrain, the sensing areas are separated into many sub-regions. These sub-regions can only send the messages to the sink node by ferry nodes. The topology and the connectivity change frequently because of the intermittent connection between sub-regions and ferry nodes. Accordingly, it is hard to model OSNs and obtain the connectivity of the whole network accurately using the traditional graph.

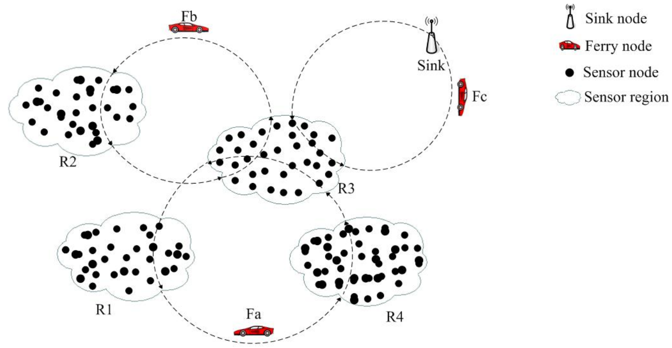

Fig. 1. The scenario of OSNs

In static networks, the links between nodes are stable and the network can be embodied into an undirected static graph by graph theory. So the node degree, the betweenness centrality and the density of the nodes can be obtained through the end-to-end path used to describe the connectivity and the robustness of the network. However, in OSNs, the physical condition and the invalidation of the nodes will lead to a spare distribution of nodes. The frequent mobility of the nodes may lead the end-to-end path becoming invalid for extended periods, which can make it difficult to describe the link relation of the nodes accurately. In this paper we define overall network connectivity with time graph theory by analyzing the opportunistic connection of nodes, and the overall connectivity can be verified through the Opportunistic Network Environment simulator(ONE).

The rest of this paper is structured as follows. In section 2, the previous research that has been performed in this area is analyzed. We propose the definitions of the time graph and the overall network connectivity in the section 3. In section 4, our experimental studies and results are presented. The concluding remarks are summarized in Section 5.

2. Related Works

In the ad hoc network, static graphs are mainly used to study the influence of node degree, the node density and the communication radius on the network connectivity. Based on the percolation-theory Kong et al. [15] found that the dynamic network has the upper and lower bounds on the critical density when it has a phase transition, and the propagation delay between the node has linear correlation with the Euclidean distance.The asymptotic critical transmission radius for k-connectivity in a wireless ad hoc network where nodes are uniformly and independently distributed in a unit area was studied in [26] , which applied the critical transmission radius to obtain an accurate upper bound for critical k-connectivity neighbor number.

There has been a growing interest in the dense networks. For example, using computer simulations, paper [29]obtained a probability distribution graph of k-vertex-connectivity by casting the nodes randomly in sensor network. Using regression analysis, regression formula of the average connectivity of network and the empirical equation of 3-connected networks were presented. They also discussed the effect on the connectivity by the boundary nodes. These studies have a certain reference for deploying nodes. However, it is difficult to analyze the topology of sparse network like OSNs, which may undergo splitting for an extended period.

The topology of dynamic networks changes frequently with time, making them difficult to model using static methods. Therefore, they are usually modelled using probability statistics. For example, paper [28] utilized the snapshot method and used the network's average node degree per unit time as an estimation of the mobile network's overall connectivity. A correlation function describing the number of nodes, the node transmission radius and the network connectivity are obtained through curve fitting analysis, which provides the basis for deploying the nodes. Paper [18] studied the connectivity of the mobile ad-hoc networks (MANETs) under the Random Waypoint RWP mobility model in arbitrary convex region. The critical transmitting range is acquired when the network is k-connected, and MANETs have a high requirement for node fault tolerance. Guo L et al. [10] investigated three fundamental characteristics (the node degree distribution, the average node degree and the maximum node degree) of MANETs in presence of radio channel fading. The results are very useful in the study of improving connectivity and the routing protocols. The premise of the MANETs connectivity research is to ensure a complete end-to-end path, which makes the connectivity and the node degree of the network unsuitable for use in OSNs.

Derived from DTNs, OSNs share many similar characteristics. In [11] Harras K A et al. pointed out that the increasing use of wireless devices has created new challenges such as network partitioning and intermittent connectivity. Accordingly, delay tolerant mobile networks (DTMNs) have been proposed to achieve inter-regional communication using a dedicated set of messengers. Additionally, several classes of messenger scheduling algorithms have been developed to improve connectivity and performance. In recent years, with the development of the dynamic network research [1][2][22][24][21][8], characteristics used to analyze static networks have increasingly been applied to dynamic networks. For example, paper [19] referred to the time-varying graph(TVG). [6] Casteigts et al. studied the strongly connected components in time-varying graph and proposed a method to calculate the temporal diameter of the dynamic network. Paper [7] proposed a method to solve the temporal diameter of dynamic network. It proved that the mobile nodes have the "small world" characteristic in opportunistic network-shorter temporal diameter lead to higher network connectivity. A new temporal distance metric composed of the shortest path and the clustering coefficient was proposed in paper [25]. They demonstrated that, compared with the metrics used with static graphs, this metric can obtain the temporal characteristics more accurately by using a time-varying graph. Paper [27] proposed a new dynamic coding control mechanism to exploit the connection opportunities and optimize network resources. Paper [23] presented a systematic approach to the interdependencies and constructed analogies for the various factors that affect and constrain wireless sensor networks. However, parameters such as connected component and network diameter do not accurately reflect the overall network connectivity of OSNs.

In order to characterize the connectivity of OSNs precisely, we use the time graph to model the connectivity, and propose the methods to estimate the connectivity based the OSNs' characteristics. A series of time windows are obtained via snapshots, which are then transformed into adjacency matrices. The adjacency matrix set is then used to calculate overall network connectivity.

3. Connectivity Modeling

3.1. Time-Graph Model

In order to obtain the dynamic topology information, the time factor should be considered. Give a dynamic network trace starting at t_{min} and ending at t_{max}. Let $G_t^w(t_{min}, t_{max})$ be a time graph, the snapshot sequences can be expressed as $G_{t_{min}}, G_{t_{min+w}}, \cdots, G_{t_{max}}$, where w is the size of each window in terms of a time unit. Viewed from an abstract level, the topology in OSNs is a series of time windows in a continuous sequence.

Each node is deployed using the wireless sensor network method for monitoring the environment in paper [12]. The density and connectivity in these regions are higher than other simulations, so we can abstract the sensing region into a super node to simplify analysis. The snapshots at t_1, t_2, t_3, t_4 can be viewed from the Fig. 2.

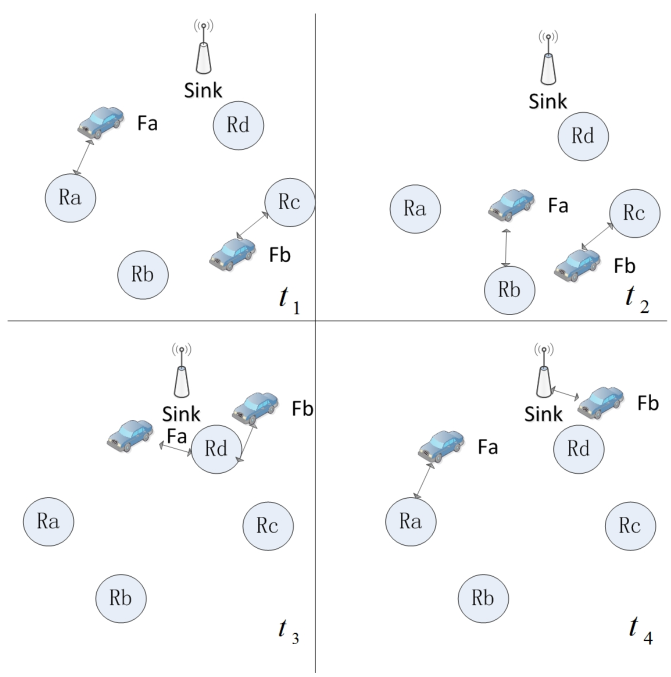

Fig. 2. The snapshots at t_1,t_2,t_3,t_4

Definition 1:Time graph G_t^w

Let G_t^w, $G_{t_{min}}$, $G_{t_{min+w}}$, $\cdots$, $G_{t_{max}}$ denote the ordered graphs under a series of increasing discrete times from t_{min} to t_{max}, and $G(t) = (V(t), E(t))$ denotes the subgraph at the t moment, where $V(t)$ and $E(t)$ are the vertex set and edge set in t moment respectively. For $\forall t \in [t_0, t_\tau], |V(t)| = N$, where N is the number of nodes in network.

N remains approximately invariant during the operation of the network, so we can combine the link information which is acquired from the snapshots and identify the time the link appears. As shown in Fig. 3, although the network is not connected in each snapshot, it can forward the sensing messages from the four sensing regions R_a, R_b,R_c,R_d to the sink node via ferry nodes.

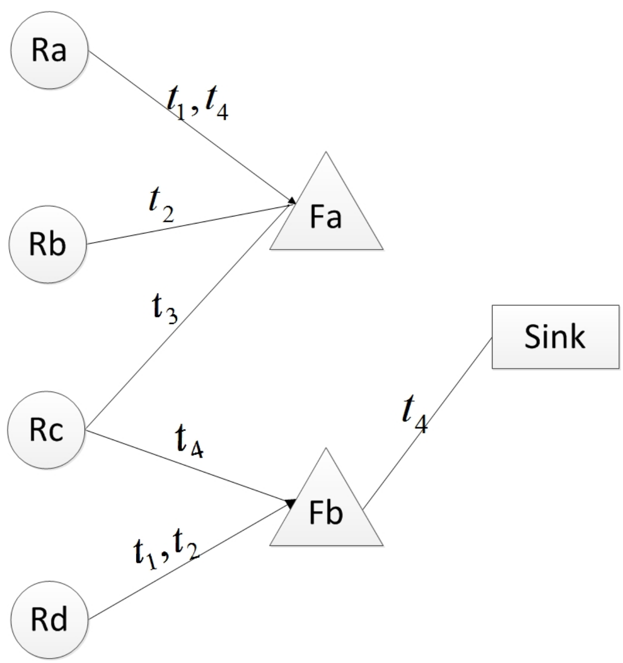

Fig. 3. Time graph model in snapshots corresponding to Fig.2

The transmission paths of the message have typical time-tropism characteristics in the time graph, so we can't use the tradition path to describe it. According to the Fig. 3,the temporal path is defined as follows.

Definition 2:Temporal Path

Let $\{n_1, n_2, n_3, \cdots, n_m\}$ be a set of non-repetitive nodes in $G_{t_{min},t_{max}}$ from t_{min} to t_{max}. If there are non-decreasing time series in $\{t_{min} + w, t_{min} + 2w, \cdots, t_m\}$, for arbitrary two nodes p and q, denoting $n_1 \equiv p$,$n_m \equiv q$, it can be concluded that the temporal path has been existed from p and q, which can be expressed as $R_{pq}(t_{min} + w, t_m)$. In this case, no temporal path exists if $R_{pq}(t_{min} + w, t_m) = \infty$.

The connectivity situation can be reflected by the temporal path as shown in Fig. 3, indicating that the sensing messages can't forward from R_a to R_d.

Definition 3:Temporal Distance

For arbitrary two nodes i and j, temporal distance is the shortest temporal path between i and j from t_0 to t_τ, which is defined as $D_{ij}(t_0, t_\tau)$.

$$D_{ij}(t_0, t_\tau) = Min\{(R_{ij}(t_0, t_\tau))\}. \quad (1)$$

Connectivity efficiency is a metric used to analyze the effectiveness of the static networks [16]. John [25] extended it into dynamic networks and redefined the efficiency of the nodes in a period of time. In this paper, we define the connectivity efficiency based on the characteristics of OSNs, the formula is denoted as follows.

Definition 4:Connectivity Efficiency

$$E_{ij}(t_0, t_\tau) = \begin{cases} 0, & D_{ij}(t_0, t_\tau) = \infty \\ \frac{t_\tau - D_{ij}(t_0, t_\tau)}{t_\tau}, & D_{ij}(t_0, t_\tau) < t_\tau \end{cases} . \quad (2)$$

Where $D_{ij}(t_0, t_\tau)$ represents the temporal distance between i and j. If $E_{ij}(t_0, t_\tau)$ has a bigger value, it means two nodes can form a link in shorter time, and that means a good connectivity between two nodes.

Definition 5:Region Connectivity Efficiency

The mean of the connectivity efficiency of all the nodes in the sensing region is the region connectivity efficiency from t_0 to t_τ , so it can be defined as follows:

$$R_{ij}(t_0, t_\tau) = \frac{1}{N_{R_i}(N_{R_i} - 1)} \sum_{ij} E_{ij}(t_0, t_\tau). \quad (3)$$

Where N_{R_i} is the number of nodes in sensing region R_i .

The region connectivity efficiency can reflect connectivity situation in sensing region.

3.2. The Connectivity of the Whole Network

In OSNs, the sink node is the center node. If a network with good connectivity, each sensing region has good connectivity with the sink node. At this moment, it acts as the core of the network. It is different from sensing nodes and ferry nodes, as it has an obvious centrality. After considering the relationship between the region and the sink node, we use the Katz centrality to reflect the centrality of sink node. Katz Centrality [20][4][14] originates from the social network analysis (SNA) and represents the degree of which one node influenced others. Paper [9] expanded the Katz Centrality to the dynamic network and found that it is extremely suitable for use with sparse networks such as MANETs, Social networks, OSNs and so on. Paper [5] utilized the Katz centrality to assess the capacity of nodes transmitting the messages to the sink node.

Definition 6:Adjacency matrix

Let G(V,E) be an undirected graph, with $V = \{v_1, v_2, \cdots, v_n\}$ the set of nodes and $E = \{e_1, e_2, \cdots, e_m\}$ the edge set . Its adjacency matrix is denoted as follows.

$$A = (a_{ij})_{n\times n}, a_{ij} = \begin{cases} 1, (v_i, v_j) \in E \\ 0, otherwise \end{cases} . \quad (4)$$

In the adjacency matrix A, the m-order power represents the number of paths between nodes with length m, and m also concludes the number of repeated nodes or edges.

$$A \times A \times \cdots \times A = (A^m)_{i,j} = k(m, k \in \mathbf{Z}^+)\,. \tag{5}$$

Then we should say that there are a total number of k walks with length of m from node i to node j. For any arbitrary node pair i and j, the corresponding number of walks of length $m = 1, 2, 3 \cdots$ is

$$(A^1)_{ij}, (A^2)_{ij}, (A^3)_{ij}, (A^4)_{ij}, \cdots\ . \tag{6}$$

The total number of walks with length no more than m from node i to all the other nodes in graph G is

$$\sum_{j}^{n} (\sum_{k=1}^{l} A^k)_{i,j}\ . \tag{7}$$

Generally, those nodes with longer walk length away from the source node may have less compact on the source node. This fact motivated the derivation of Katz Centrality. In this paper, we denote $\alpha(0 < \alpha < 1)$ as the impact factor. Let node j be a l-degree neighbor of node i. The impact factor of node i to node j is assigned with α^l, denoting $S = I + \alpha A + \alpha^2 A^2 + \alpha^3 A^3 + \cdots$. Let $\rho(A)$ represents the spectral radius of A, when $\alpha < 1/\rho(A)$, S is converged to $(I - \alpha A)^{-1}$, so the Katz centrality of i is define as:

$$\sum_{j=1}^{N} [(I - \alpha A)^{-1}]_{ij}\ . \tag{8}$$

The 'Dynamic Walk' in the temporal network is defined as below.

Definition 7:Dynamic walks

In a non-decreasing time series $t_1 \leqslant t_2 \leqslant \cdots \leqslant t_l$, a dynamic walk of length l consists of a sequence of edges $i \to v_1, v_1 \to v_2, \cdots, v_m \to v_{m+1}, v_l \to j$, that are composed of the dynamic walks only if the r_{th} snapshot satisfies $A_{im,im+1}{}^{[r]} \neq 0$.

However, the formula (7) can't be applied to calculate the repetitive walks when calculating the temporal path. When using meeting opportunities to achieve the message transmission, the sensing messages may appear as repetitive nodes or edges on the transmission direction. So, we can calculate the number of the dynamic walks of length l from t_1 to t_l, multiplying the number with the influence factor α. The dynamic walks with length l can be obtained as follows

$$\alpha^l A(t_1)A(t_2)\cdots A(t_l)(t_1 \leqslant t_2 \leqslant \cdots \leqslant t_l\,)\,. \tag{9}$$

Considering all possible dynamic walks, when $\alpha < mint_m \rho(A(tm))$,

$$Q = [I - \alpha A(t_1)]^{-1}[I - \alpha A(t_2)]^{-1} \cdots [I - \alpha A(t_l)]^{-1}\ . \tag{10}$$

In OSNs, we should consider the reachability of nodes message. In this paper we just consider the message reachability of each sensing region. The calculation is defined as:

$$C = \frac{1}{N_R} \sum_{i \in R} Q_{iS}\ . \tag{11}$$

Where N_R is the number of the sensing regions in OSNs.

When the network has better performance, the overall network connectivity calculated by formula (11) grows to a bigger value. In order to reflect the connectivity of the current network more accurately, we need to eliminate the influence of the dimension, the variation of the variables and the numerical value, and standardize the overall network connectivity from 0 to 1.Firstly, a logarithmic function transformation method is used to compress the variable scale of the overall network connectivity. The formula is defined as follows, in which C indicates the connectivity of the whole network. C^1 is the compressed value calculated by the logarithmic function transformation method.

$$C^1 = lg(C) \ . \tag{12}$$

After compression of the connectivity, the deviation standardization is adopted to map the connectivity into $[0, 1]$

$$C^* = \frac{C^1 - min}{max - min} \ . \tag{13}$$

Where max and min are the maximum value and the minimum value of the sample data.

(1) Selection of sliding time-window

In order to facilitate network connectivity monitoring, it is very important to understand that connectivity changes over time. Due to the time-evolution characteristics of OSNs, one can obtain the connectivity by computing dynamic walks over different time. So the sliding time-window is utilized to compute the current connectivity.We calculate the success rate of the message delivery in t_2,t_3,t_4,... and find that the temporal paths have relation with the time to live(TTL) of the messages. In this way, if OSNs have better connectivity, there will be more dynamic walks to the sink node, which means more messages can be delivered to the sink nodes. But if the OSNs have bad connectivity, it may exists some dynamic walks which the arrival time is [t_3,t_4] and the departure time is [t_1,t_2] . If we just count the interval [t_1,t_2] and [t_2,t_3] , we can not find dynamic walks in this two interval. And it causes the lower success rate of the message delivery. Therefore we redefined the effective interval in this paper. As it shows in the Fig. 4, the sliding time-window length is 2, which is used to compute the connectivity from t_2 to t_5. The sliding time-window decides the effective time of the dynamic walks in the network.

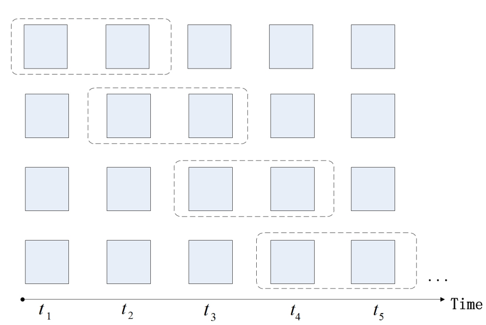

Fig. 4. the sliding time-window with the length 2

(2) Adjacency matrix sequences generation algorithm

Topology information can be acquired from continuous snapshots. However, in OSNs, due to the small number of ferry nodes and sensing regions, there are many non-connected nodes in snapshots and invalid critical-link, such as the link between ferry nodes to sink node, which affect the accuracy of OSNs connectivity.

In this paper, snapshots are generated by the communication records of the ferry nodes. The records are converted into adjacency matrix sequences, which are used as the input parameter for calculating OSNs connectivity, including the ID of the communication nodes, starting and ending time and the like. ONE can provide the format of the record of nodes as shown in Fig. 5.

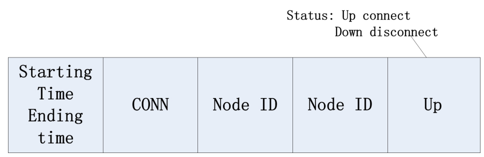

Fig. 5. Node communication record format in ONE

The adjacency matrices are generated from the record of ferry node F_a. In this algorithm, the number of adjacency matrices are determined by the interval time of each snapshot and the statistical period of simulation. The specific algorithm is described as algorithm 1.

Algorithm 1 Adjacency Matrix Seq Build Algorithm

Input: $facr$: F_a's communication record; $[t_0, t_\tau]$: the simulation time; $\triangle\ t$: the interval time;
Output: $amseq$: Adjacency matrix sequences;

1: Traverse facr . Obtain network connection records $facr^{'}$, counting the number $N_{facr'}$ and the dimension of adjacency matrices d;
2: Set $N_{seq} = \frac{(t_{t\tau} - t_0)}{\Delta t}$;
3: Construct a three-dimensional array with N_{seq} , d, d ,initialize k and other variables;
4: Set k=k+1; **if** k$\leq N_{facr'}$, turn to step 6,**then** turn to step 15;
5: **end if**;
6: **if** facr[k].status, turn to step 9,**then** turn to step 4;
7: **end if**;
8: Set the beginning time begin=facr[k].time;
9: **if** k+1$\leq N_{facr'}$, turn to step 11,**then** set end=t and turn to step 13;
10: **end if**;
11: **if** facr[k+1].status=down, turn to step 15,**then** turn to step 6;
12: **end if**;;
13: Calculate low=$\lfloor$begin/$\triangle\ t\rfloor$ and high=$\lfloor$end/$\triangle\ t\rfloor$
14: Set amseq[low][0][0] to amseq[high][d-1][d-1] into 1 with corresponding position and return to step 4;
15: Output the amseq;

As mentioned above, Algorithm 1 abstracts the sensing region into a super node. So we just need to mark the starting time $begin$ (when the ferry nodes contact with the first node), and the ending time end (when the ferry node disconnect with the last node). Due to the better connectivity in the intra-sensing region, it can be considered that the ferry nodes have a connection with regional nodes in a continuous link state from $[begin, end]$. Then set the corresponding nodes of the adjacency matrices into a link state based on the length of time slots. The adjacency matrices can be obtained by traversing the ferry node communication record, which are used to calculate the overall network connectivity.

4. Simulation Experiment

4.1. Simulation Experiment Parameters and Test Indicators

We simulated opportunistic sensor networks using ONE. The experimental scenario is shown as Fig. 6. There are four sensing regions (Ra, Rb, Rc, Rd), two ferry nodes (Fa, Fb) in the scenario. The sensor nodes have a relatively large radius of communication to ensure the interior of the region having a better connectivity. The ferry nodes collects sensing messages from the sensor nodes according to the fixed route line and delivers the messages to the sink node.

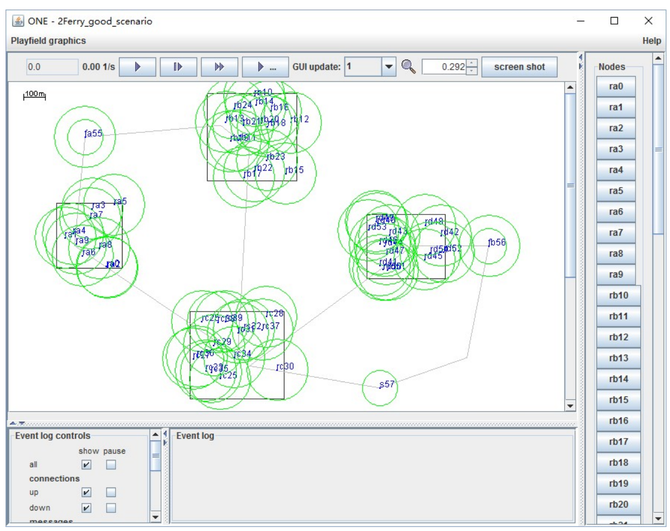

Fig. 6. The scenario of the connectivity of the whole network

The statistic cycle of the simulation is 1200 seconds. During the operation of the network, each sensing area (Ra, Rb, Rc, Rd) will randomly generate a message every 20 seconds. The simulation is carried out for 20 hours. The message delivery rate and the connectivity of the whole network are recorded every 20 minutes. Three connectivity scenarios (good connectivity, general connectivity, poor connectivity) are simulated by adjusting the movement speed of the ferry node. The detailed parameter settings are shown in Table 2.The region sizes are corresponding to the number of region nodes.

Table 1. Experimental parameter settings

Parameter	Value
Simulation time(h)	20
Simulation period(m)	20
Region size(m*m)	300*295,410*400,430*400,360*295
Number of regional nodes(unit)	10,15,15,15
Ferry node communication radius(m)	80
Message generation intervals (s)	20
Fa movement speed(ms)	1-2,2.5-3,5-6
Fb movement speed(ms)	1-2,3-4,5-6s
TTL(s)	1200

Each sensing area (Ra, Rb, Rc, Rd) randomly generates a message every 20 seconds until the end of the simulation. The messages generated in each region are forwarded to the sink node by the ferry nodes, which taken a certain time. As a result, the messages near the end of a statistical cycle time will fail to deliver to the sink node due to the short time of the message generation. This causes a decrease message delivery success rate. In order to calculate the success rate of message delivery accurately, the following statistical method is used to compute the success rate, as shown in Fig. 7.

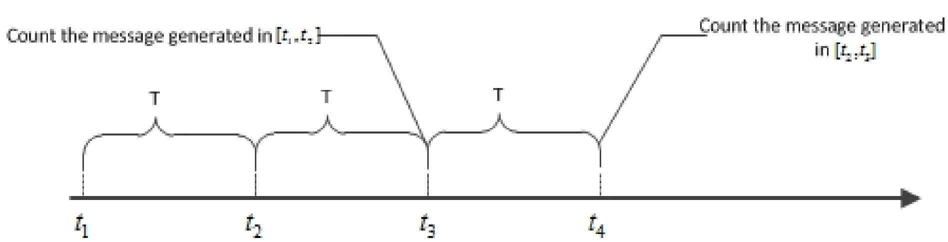

Fig. 7. The statistics of the success of the delivery

The success rate of message delivery at t_3 is generated in the time period $[t_1, t_2]$. Messages are delivered to the sink node in the time period $[t_1, t_3]$. If the sink node receives the sensing messages generated in the time period $[t_2, t_3]$, during the time period $[t_1, t_3]$, it does not count the number of the received message at the current time (t_3), and the packet is counted as the number at the next time (t_4).

In order to verify the overall network connectivity applicability, another experiments was designed in the simulation. We change the static node in regions into mobile nodes with different communication radius (20m, 40m, 60m, 80m) to simulate a network, in which sensing region is extended. The experimental scenario is shown as Fig.6. The detailed parameter settings are shown in Table 2.

Table 2. Experimental parameter settings

Parameter	Value
Simulation time(h)	20
Simulation period(m)	20
Region size(m*m)	600*450,580*390,575*400,610*395
Number of regional nodes(unit)	35,30,20,30
Ferry node communication radius(m)	70
Message generation intervals (s)	20

4.2. Experimental Results

We input the adjacency matrix sequences generated by algorithm 1 into the program and use Matlab to calculate the overall network connectivity. The connectivity of the whole network is shown in Fig. 8.The real success rate of message delivery simulated by ONE is shown in Fig. 9.The message delivery success rate is the important index to represent the real connectivity of the network in paper [3]. So we have compared it with the connectivity calculated in this paper.

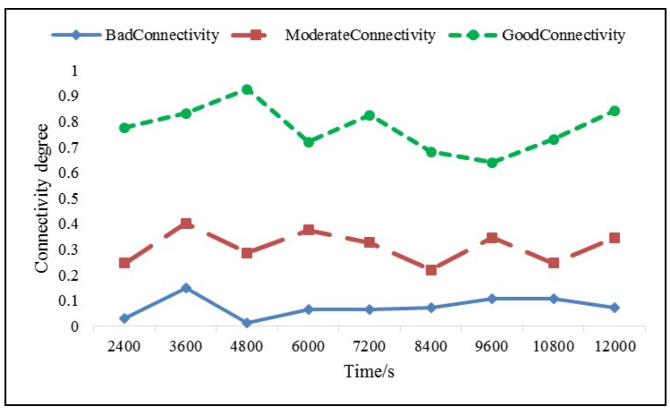

Fig. 8. The simulation effect of the connectivity of the whole network

In Fig.8, the connectivity degree in three connectivity scenarios (good connectivity, general connectivity, poor connectivity) are divided into three different ranges obviously. It can be seen from Figs. 8 and Fig. 9 that the calculated network connectivity is in good agreement with that of the real network. Therefore, the defined model can estimates the network connectivity.

Then we design another experiment to verify the applicability. We extend the sensing region and change the static nodes into mobile nodes in sensing region.By changing the radius of the sensing nodes, the simulation results can be seen from Figure.10, Fig.11 and Fig.12.

Compared Fig.10 and Fig.11, with the decrease of node communication radius in regions, region connectivity efficiency is also decreasing and the message can not spread

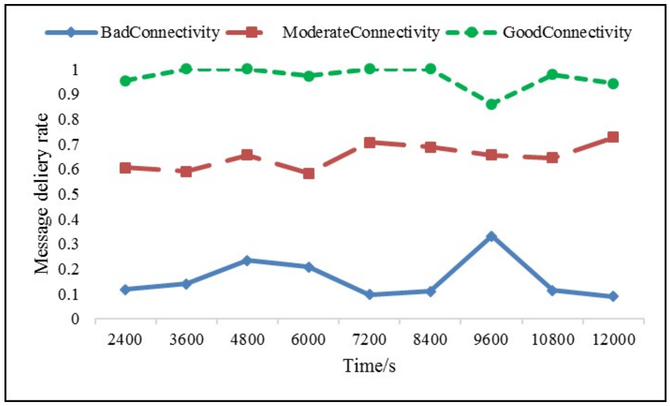

Fig. 9. The success rate of the message delivery

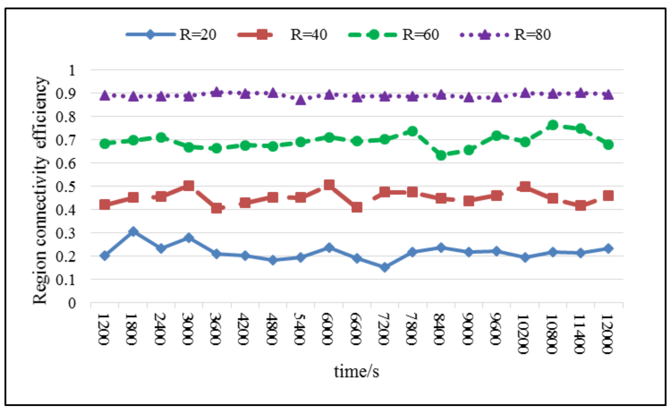

Fig. 10. Simulation results of network region connectivity efficiency

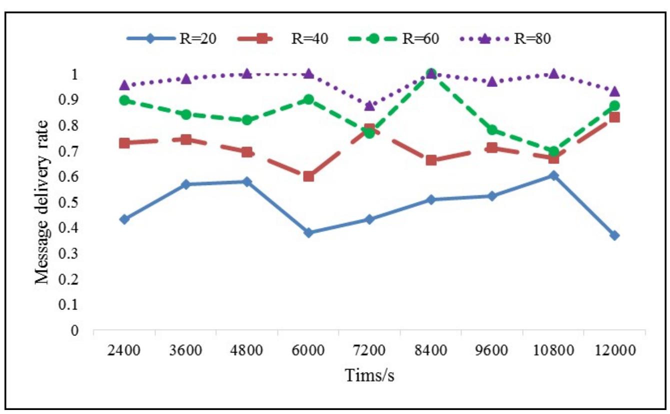

Fig. 11. Simulation results of network message delivery rate

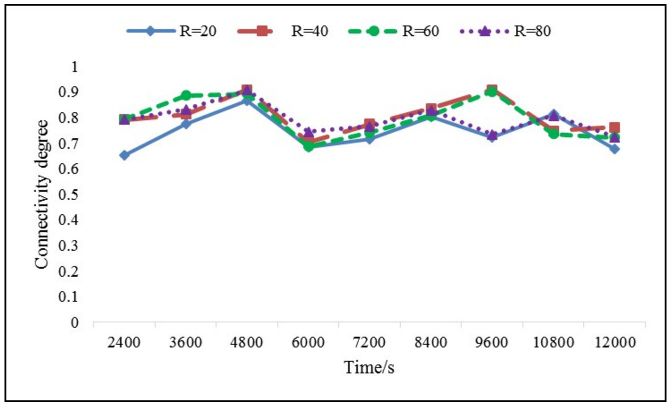

Fig. 12. Simulation results of network connectivity degree

throughout the region when message generates. Although ferry node have gone through the region, it could not obtain all the sensing messages in the region. It causes the decline of the success rate of the message delivery. As it can be seen from the Fig.10, Fig.11 and Fig.12, it can be found that when the connectivity efficiency is better, the calculated overall connectivity is in good agreement with the real network connectivity. The whole network connectivity defined in this paper can reflect the network connectivity in two different scenarios, which shows that the defined connectivity is applicable.

5. Conclusion

Network connectivity is an important metric for measuring network performance. The connectivity of OSNs has a time-evolution characteristic, which makes it difficult to model it with traditional graph models. In this paper, considering the central characteristics of the sink node, the connectivity of OSNs is modelled by time graph, according to the characteristics of OSNs. We define the connectivity of the network based on Katz Centrality in the end. The experimental results show that the proposed network connectivity model can reflect the connectivity of the whole network in different scenarios.

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Jian Shu is a full Professor at the Nanchang Hangkong University, in China. He received his bachelor degree and master degree in computer science from the Northwestern Polytechnical in 1985 and 1990. His research interests include internet of things, machine learning, and software engineering.

Lei Xu received the Bachelor degree in electronic and information engineering from the Jiangxi University of Science and Technology, Ganzhou, China, in 2015. He is currently a postgraduate, School of Software, Nanchang Hangkong University, Nanchang, China. His research is focused on opportunistic sensor networks.

Shandong Jiang received the Bachelor degree in software engineering from the Nanchang Hangkong Univerisity, Nanchang, China, in 2013. He is currently a postgraduate, School of Software, Nanchang Hangkong University, Nanchang, China. His research is focused on opportunistic sensor networks.

Lingchong Meng received the Bachelor degree in communication engineering from the Qingdao Agricultural University, Qingdao, China, in 2014. He is currently a postgraduate, School of Software, Nanchang Hangkong University, Nanchang, China. His research is focused on opportunistic sensor networks.

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