Computer Science and Information Systems 18(3):1041–1056 https://doi.org/10.2298/CSIS200620019L

Identifying Key Node in Multi-region Opportunistic Sensor Network based on Improved TOPSIS

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Abstract. The topology of multi-region opportunistic sensor networks is evolving, and it is difficult to identify the key nodes in the networks by traditional key node identification methods. In this paper, a novel method based on the improved TOPSIS method is proposed to identify the key node from the ferry node. The dynamic topology information is represented by the graph model which is modeled by the temporal reachable graph. Based on the temporal reachable graph, three attributes are constructed to identify the key node, which are average degree, betweenness centrality and message forwarding rate. The game theory with a combination weighting method is employed to combine the subjective weight and objective weight, so as to obtain the combined weight of each attribute. The TOPSIS method is improved by the combined weight. The key node is identified by the improved TOPSIS. The experiments in three simulation situations show that, compared with the TOPSIS method and MADM_TOPSIS method, the proposed method has better accuracy for the key node identification in the network.

Keywords: multi-region opportunistic sensor network, key node, combination weight, TOPSIS.

1. Introduction

Multi-region opportunistic sensor networks (MOSNs) are a type of self-organizing network which can collect sensor data through the movement of nodes and encounters between nodes. Part of the concept of MOSNs is derived from mobile ad hoc networks (MANETs) and delay-tolerant networks (DTNs), such as the Intermittent links, temporal paths, real-time messages, etc. [1] MOSNs consist of nodes and links between nodes. The node that has the greatest influence on the network structure and function is called a key node. The events that the key node is attacked or failed may lead the networks to be paralyzed. By identifying the key node, MOSNs can be optimized in advance to improve its security and robustness. Hence how to accurately and efficiently identify the key node in MOSNs is a hot topic.

Aim at solving this problem, lots of indicators have been proposed [2], such as degree centrality [3], betweenness centrality [4], eigenvector centrality [5], Katz centrality [6], etc. Although these methods can identify the key nodes in complex networks from different perspectives, the adaptability and accuracy are easily affected by the factors such as the network structure and scale. On this basis, some researchers combine multiple indicators to identify the key nodes, thereby improving applicability and stability. The reference [7] defines four parameters to represent the influence of a node in social networks. The direct influence spread and indirect influence spread are used to indicate the influence of a node on other nodes. The direct overlaps and indirect overlaps reflect the conflict between nodes. Then, the technique for order preference by similarity to an ideal solution (TOPSIS) is used to combine these parameters to obtain the influence of each node. Fei et al. [8] believe that the interaction between nodes follows the inverse-square law, and the node importance is evaluated by combining the degree centrality of nodes and the distance between nodes. The experiments show that the accuracy of the method is higher than some well-known centrality indicators.

The location of a node in the network determines its importance. Korn et al. [9] are inspired by the fact that the H-index quantifies the contribution of scholars in informatics and use the H-index to evaluate the node importance. If a node has n neighbor nodes whose degree is not less than n, then the H-index of the node is n. Kitsak et al. [10] use K-shell to judge the location of nodes in the network and think that the nodes in the core location usually are more important. The Ks of each node is determined by separating the nodes from the network according to the order of residual degrees from small to large, and it considers fully the global characteristics of nodes. But the K-shell is not suitable for some special networks such as the tree networks and star networks. When the node remaining degree is less than the current number of iterations, the iteration cannot be carried out properly. Lü et al. [11] propose that the H-operation based on the degree centrality converges to the Ks of the node. The view can avoid possible errors in the K-shell process and improve the monotonicity of the evaluation results. Based on the reference [11], Shao et al. [12] propose an important node identification method based on the H-operation in dynamic networks. This method takes the smaller value in the past H-index and the present Ks as the initial value of the H-operation, so that the important nodes can be found quickly at every moment.

However, the topology of complex networks usually is changing, the nodes and edges may appear or disappear at any time, and the network is called a temporal network [13]. In recent years, some researchers have begun to identify the key node in the temporal network. Zhang et al. [14-18] model MANETs as time-varying graphs to represent the topology of temporal networks. Based on the previous research, Zhang et al. [19] define a new metric called criticality that can measure node importance accurately in MANETs, and the experiments show that attacking the key node identified by the criticality has a greater impact on network performance than some centrality indexes. Based on the view that the node importance depends on their neighbors, the reference [20] proposes a temporal information aggregation process to identify the key node in temporal networks. Arrigo et al. [21] utilize the sparse version of dynamic communicability matrix to estimate node importance and rank for nodes, and the experiments show that this method can rank the list of highly central nodes accurately with a lower level of storage, and the cost is only linearly with the number of time points. Abbas et al. [22] divide the data into past time window and future time window based on user-object binary networks, to identify and predict the key node (the popular or important objects in the future) in e-commerce networks and social networks. Xiao et al. [23] predict the most powerful persuaders based on machine learning in social networks. The reference [24] proposes coverage centrality in temporal networks. It is found that the most of nodes with high centrality are located in a small time window near a certain time. The majority of information in temporal networks is only transmitted by the minority of nodes, and there is a bottleneck period in the transmission process.

Different from the general temporal networks, there are three types of nodes in MOSNs, which are sink node, ferry node, and sensor node. The sink node collects all of the messages generated from the sensor region and sends them to the server. The ferry node walks along fixed or random routes in the sensor region and forwards the messages from the sensor region to the sink node. The sensor node is fixed in the sensor subregion and generates the messages that contain sensor data. The key node must be found from the ferry node. The main contributions of this paper are as follows:

(1) The dynamic topology information is represented by the graph model which is modeled by the temporal reachable graph. Based on the temporal reachable graph, three attributes are constructed to identify the key node, which are average degree, betweenness centrality and message forwarding rate.

(2) The TOPSIS method is improved by the combined weight. The game theory with a combination weighting method (GTCW) is employed to combine the subjective weight and objective weight, so as to obtain the combined weight of each attribute.

(3) This paper uses the simulator ONE to conduct simulation experiments in three experimental scenarios. The simulation results show that compared with methods such as the TOPSIS method and MADM_TOPSIS method, the method proposed in this paper has better accuracy for the key node identification in MOSNs.

The paper is organized as follows: The problem description and definitions about the temporal reachable graph are presented in section 2. The key node identification method based on the improved TOPSIS (GTCW_TOPSIS) is introduced in section 3. The experiments and results are shown in section 4. The conclusion and prospect are given in section 5.

2. Problem Description and Definitions

2.1. Problem Description

Due to various reasons such as node damage, signal attenuation, and geographical environment, the sensor region of MOSNs may be divided into multiple subregions in practical application. MOSNs consist of one sink node, several sensor nodes, and several ferry nodes. The sink node is fixed and used to collect the sensor data from sensor nodes. The sensor node is placed in the sensor region and senses environmental conditions. The ferry node moves between the sink node and the sensor region, and forwards the messages from the sensor region to the sink node by the "carry-store-forward" mechanism. The process of communication is as follows: Firstly, the ferry node receives the messages from the sensor region when it passes through the sensor region. Then, the ferry node saves the messages in the cache unit it encounters with other ferry nodes or the sink node. Finally, the ferry node sends the messages to the sink node.

In order to reduce the complexity of the research, a sensor subregion is regarded as a region node instead of considering every sensor node separately. Compare with the sensor node, the ferry node plays a vital role in the communication between the region node and the sink node, and the topology of MOSNs changes with the location of the ferry node. It is obvious that the ferry node is the most valuable node besides the sink node, so the key node is selected among the ferry nodes. As shown in fig. 1, some sensor nodes collect data in the region node R_1, the ferry node F_1 serves as a bridge to deliver messages between the region node R_1 and R_4, and when F_1 encounters with F_2, it will send the messages received from R_1 to F_2. The event that F_1 is damaged is likely to cause the region node R_1 to be separated from the network.

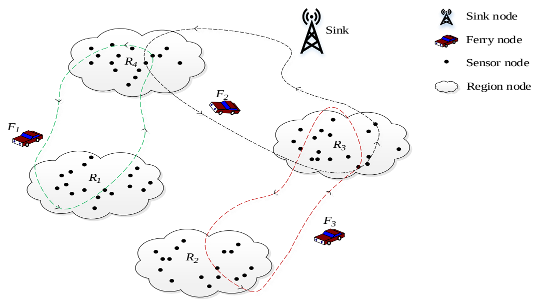

Fig. 1. The scenario graph of MOSNs

2.2. Definitions

In order to realize the effective transmission of sensor data, through the mechanism that location of the ferry node changes, the network structure of MOSNs is frequently changed. Aiming to represent the dynamic topology information and reduce the temporal information loss, the temporal reachable graph is used to model MOSNs.

Definition 1: The temporal reachable graph $G = \{G_1, G_2, G_3, \cdots, G_L\}$ is a set that is composed of several ordered graphs during the observation period $[0, T]$, where L is the number of temporal reachable subgraphs, $G_l = (V_l, E_l, W_l), l = 1,2,3, \cdots, L$ is the l_{th} temporal reachable subgraph. V_l is the node set in G_l, and it consists of the sink node S, the ferry node set F and the region node set R, E_l is the edge in G_l, W_l is the edge weights set in G_l. The key node will be found in F.

Definition 2: The set W_l in $G_l = (V_l, E_l, W_l)$ is defined in (1):

$$W_l = \left\{w_{ab}^l \,|\, \forall a, b \in V_l \ and \ (a, b) \in E_l\right\} \tag{1}$$

In which w_{ab}^l is the number of connections between the node a and the node b in G_l. According to the Definition 1 and 2, considering the changes of the network structure in each time window, the subnet in the interval $[t_{l-1}, t_l]$ is aggregated as G_l, the temporal reachable subgraph sequence $\{G_1, G_2, G_3, \cdots, G_L\}$ are shown in fig. 2.

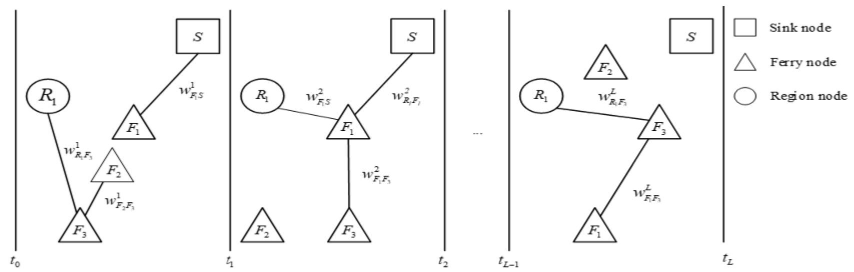

Fig. 2. Temporal reachable subgraphs

As shown in Fig. 2, in G_1 and G_L, there are two edges between R_1 and F_3, $w^1_{R_1F_3}$ and $w^L_{R_1F_3}$ are the edge weight between R_1 and F_3, and there is not edge between R_1 and F_3 in G_2. In summary, the edge weight is aggregated at every temporal reachable subgraph to construct the temporal reachable graph, and as shown in Fig. 3.

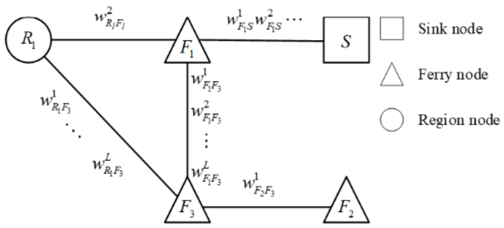

Fig. 3. Temporal reachable graph

Definition 3: In MOSNs, the messages eventually are aggregated to the sink node along the temporal reachable path. As for the region node R_i and the sink node S, if there is an edge sequence $[R_i, x_1], [x_1, x_2], [x_3, x_2], \dots, [x_{n-1}, S]$ that exists in the network G, the sequence is a temporal reachable path from R_i to S. In Fig. 3, the messages can be transmitted from R_1 to S by two temporal reachable paths: $R_1 \to F_1 \to S$ and $R_1 \to F_3 \to F_1 \to S$. Different from the traditional path, the edges that make up a temporal reachable path must follow the order of time, which results in lower usability of paths than that in static networks. Hence, the temporal reachable path is applied to representing the information of message transmission. The temporal reachable paths are shorter, the communication and interaction are easier between a pair of nodes.

3. Identifying Key Node

In this section, we define three attributes of the ferry node as indicators, then calculate the combination weight by the game theory with a combination weighting method [26]. Based on the above model, we propose a method named GTCW_TOPSIS to identify the key node.

3.1. Three Attributes of Ferry Node

Definition 4: In the subgraph G_l, the average degree AD_{F_i} of the ferry node F_i is defined in (2):

$$AD_{F_i} = \frac{\sum_{j=1}^{N}\sum_{l=1}^{L}\omega_{F_iR_j}^{l}}{L} \tag{2}$$

In (2), L denotes the number of the temporal reachable subgraph, N is the number of nodes in the network. The average degree reflects the relation with the surrounding nodes. In general, the greater the average degree, the more important the ferry node.

Definition 5: The betweenness centrality BC_{F_i} of F_i is defined in (3):

$$BC_{F_i} = \sum_{j=1}^{|R|}\frac{g_{R_jS}^{F_i}}{g_{R_jS}} \tag{3}$$

Where R_j is a region node in the network, S is the sink node, g_{R_jS} denotes the number of the temporal reachable path from R_j to S, $g_{R_jS}^{F_i}$ denotes the number of the the temporal reachable path through F_i in g_{R_jS}. The betweenness centrality reflects the ability that the ferry node affects the message transmission paths from the region node to the sink node. The larger the betweenness centrality, the more important the ferry node.

Definition 6: The message forwarding rate MFR_{F_i} of F_i is defined in (4):

$$MFR_{F_i} = \frac{m_{F_i}}{\sum_{j=1}^{|R|} m_{R_j}} \tag{4}$$

Where m_{R_j} denotes the total number of the messages forwarded from F_i to S, M_b denotes the total number of the messages generated by R_j, the message forwarding rate reflects contribution of the ferry node to message delivery in MOSNs.

3.2. Attribute Weights

The subjective weight ω_1 and objective weight ω_2 of the attributes are obtained by the analytic hierarchy process (AHP) and entropy method respectively. By constructing a basic weight set $W = \{\omega_1, \omega_2\}$, the combination weight is defined in (5):

$$\omega = \sum_{k=1}^{2}\alpha_k\omega_k^T, \omega_k \in W \tag{5}$$

The combination weights consist of ω_1 and ω_2, where α_k is the weight coefficient of different ω_k. Then, we minimize the deviation of ω and ω_k, as show in (6):

$$min\|\sum_{k=1}^{2}\alpha_k\omega_k^T - \omega_h^T\|_2 \tag{6}$$

According to the differential nature of the matrix, equation (7) is the condition that optimizes the first derivative of (6):

$$\sum_{k=1}^{2}\alpha_k\omega_h\omega_k^T = \omega_h\omega_h^T \tag{7}$$

The corresponding linear equation as shown in (8):

$$\begin{bmatrix} \omega_1\omega_1^T & \omega_1\omega_2^T \\ \omega_2\omega_1^T & \omega_2\omega_2^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} \omega_1\omega_1^T \\ \omega_2\omega_2^T \end{bmatrix} \tag{8}$$

The weight coefficient vector (a_1, a_2) is obtained in (8), and we normalize (a_1, a_2) according to [27]:

$$\alpha^* = \frac{\alpha_k}{\sum_{h=1}^{2}\alpha_h} \tag{9}$$

Finally, the weight coefficient normalized vector α^* is substituted into (5), and the combination weight ω^* is calculated in (10):

$$\omega^* = \sum_{k=1}^{2}\alpha_k^*\omega_k^T \tag{10}$$

3.3. Estimation Algorithm

In this paper, the key node is identified by a new method called GTCW_TOPSIS. The steps used to identify the key node in MOSNs are as follows:

(1) Construct normalized decision matrix

It is assumed that there are n ferry nodes in the network so that the corresponding solution set denoted by $F = \{F_1, F_2, F_3, \dots, F_N\}$, the attributes of each ferry node are denoted by the attribute set $A = \{\alpha_1, \alpha_2, \alpha_3\}$, where α_1 is AD, α_2 is BC, α_3 is MFR. The decision matrix is expressed as (11):

$$X = \left(x_{ij}\right)_{n\times 3} \tag{11}$$

Where x_{ij} $(i = 1,2,3,\cdots,n; j = 1,2,3)$ is the j_{th} attribute of the i_{th} ferry node.

The normalized decision matrix is obtained by the vector normalization method according to (12) ~ (13):

$$Y = \left(y_{ij}\right)_{n\times 3} \tag{12}$$

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n}x_{ij}^2}} \tag{13}$$

(2) Construct weighted normalized decision matrix

The combination weight of each attribute is calculated by (5) ~ (10), and the weight of j_{th} attribute is denoted as ω_j^*. The weighted normalized decision matrix E is denoted as (14):

$$E = \left(e_{ij}\right)_{n\times 3} = \left(\omega_j^* y_{ij}\right)_{n\times 3} \tag{14}$$

Where $e_{ij} = \omega_j^* y_{ij}$ $(i = 1,2,3,\cdots,n; j = 1,2,3)$.

(3) Determine the positive ideal solution A^+ and the negative ideal solution A^-

The maximum value of each attribute constitutes a positive ideal solution A^+, and the negative ideal solution A^- is composed of the minimum value of each attribute. As shown in (15) ~ (18).

$$e_j^+ = \max_i\left\{e_{ij} \,\middle|\, i = 1,2,3,\dots,n; j = 1,2,3\right\} \tag{15}$$

$$e_j^- = \min_i \{e_{ij} \,|i = 1,2,3, \ldots, n; j = 1,2,3\} \quad (16)$$

$$A^+ = (e_j^+ | j = 1,2,3) \quad (17)$$

$$A^- = (e_j^- | j = 1,2,3) \quad (18)$$

(4) Calculate the Euclidean-Distance from each solution to A^+ or A^-

The Euclidean-Distance from each solution to A^+ or A^- is the deviation between them.

$$d_i^+ = \sqrt{\sum_{j=1}^{3}(e_{ij} - e_j^+)^2} \quad (19)$$

$$d_i^- = \sqrt{\sum_{j=1}^{3}(e_{ij} - e_j^-)^2} \quad (20)$$

(5) Calculate the closeness from each solution to A^+ and A^-

The closeness of the node i indicates how close the solution is to the positive ideal solution.

$$c_i^+ = \frac{d_i^-}{d_i^+ + d_i^-} \quad (21)$$

Where $0 < c_i^+ < 1$.

(6) Construct closeness set $C^+ = \{c_1^+, c_2^+, c_3^+, \cdots, c_n^+\}$, and the node with the largest c_i^+ is suspected to be a key node.

(7) The steps 1~6 is repeated for k times, the time that each ferry node is identified to be a suspected key node is recorded, and the ferry node with the most times is the key node.

3.4. Verification of Results

The node removal method is utilized to verify the experiment result, and the whole network delivery success rate (WNDSR) of the network which a node is removed is compared with that of the complete network, the process is repeated until all ferry nodes are removed. The WNDSR can be used to reflect the performance of MOSNs. If the event that a node is removed makes the greatest reduction in the WNDSR, the node is the key node.

Definition 7: In MOSNs, the whole network delivery success rate is defined as:

$$WNDSR = \frac{m_S}{\sum_{i=1}^{|R|} M_{R_i}} \quad (22)$$

Where m_S denotes the total number of messages received by the sink node S during the observation period $[0, T]$.

4. Experiments and Analysis

In this section, we use the WNDSR as a basis for identifying the key node and compare the accuracy that the key node is identified by the GTCW_TOPSIS method the TOPSIS method [27] and MADM_TOPSIS method [28] under three different scenarios.

4.1. Experiments

Three scenarios are simulated by the simulator ONE. ONE is an opportunity network simulator developed by the University of Helsinki in Finland. The parameters of the three scenarios are shown in Table 1.

Table 1. The parameters in the three scenarios.

parameter name	value
Radius of region node	50 m
region node cache	20 M
Radius of ferry node	100 m
ferry node cache	50 M
Date transfer rate	250 kB/s
Router	Epidemic Router
Message survival time	10 min

As shown in fig. 4, there are one sink node (s), six ferry nodes (fa, fb, fc, fd, fe and fg) and five region nodes (ra, rb, rc, rd and re) in scenario 1. There are 20 sensor nodes in each region node. Among the six ferry nodes, the movement model of fa, fg, fd and fe is the random way point model, they walk randomly between the sensor region and the sink node, and the movement model of fb and fc is the movement based map model. Without considering the node whose movement model is the random way point model, the movement track of fb passes through re, the movement track of fc passes through ra, fb and fc can communicate with s.

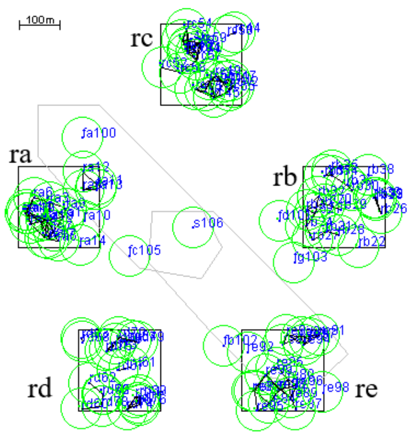

Fig. 4. Scenario 1

As shown in fig. 5, there are one sink node (s), six ferry nodes (fa, fb, fc, fd, fe and fg) and five region nodes (ra, rb, rc, rd and re) in scenario 2. There are 20 sensor nodes in each region node. The movement models of the six ferry nodes are the movement based map model. fc, fe and fg can connect with s directly, fa, fb and fd cannot communicate with s directly, and the movement track of fa and fd passes through ra, rb and rc, the movement track of fb passes through re and rd, the movement track of fc passes through re, the movement track of fe and fg passes through ra.

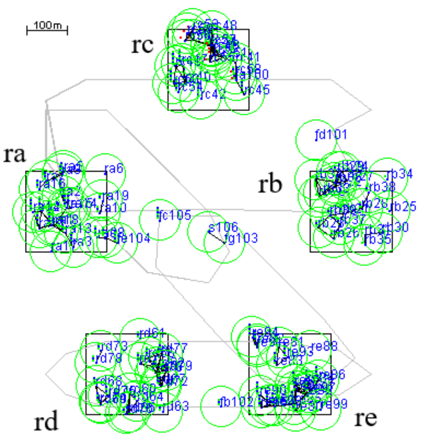

Fig. 5. Scenario 2

As shown in fig. 6, there are one sink node (s), six four nodes (fa, fb, fc and fd) and three region nodes (ra, rb, and rc) in scenario 3. There are 20 sensor nodes in each region node. The movement models of the four ferry nodes all are the movement based map model. Among them, the movement track of fa and fb passes through rb and ra, fc walks between ra and rb, and fb walks between ra and rc.

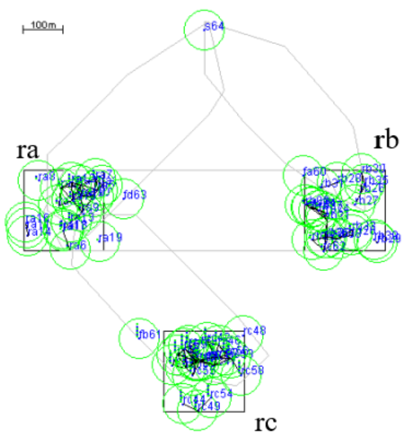

Fig. 6. Scenario 3

4.2. Results

The time window is set to 10 minutes for each experiment, and the experiments are repeated 200 times in each scenario, the results obtained are shown in fig. 7~9.

From fig. 7-9, we imply that the key nodes of scenario 1-3 are fb, fc and fd. The number of identifying the suspected key node by the GTCW_TOPSIS method is more than the others. Although the key node in MOSNs can be identified by the three methods, the effectiveness of the three methods needs to be verified by the WNDSR. If the WNDSR is the lowest, after the key node identified by the GTCW_TOPSIS method is removed, the method proposed in this paper is effective.

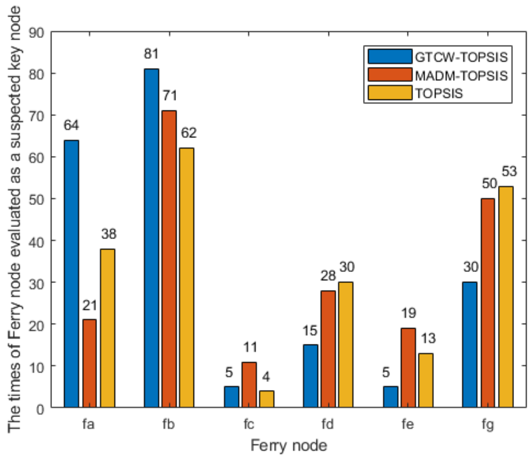

Fig. 7. The results of scenario 1

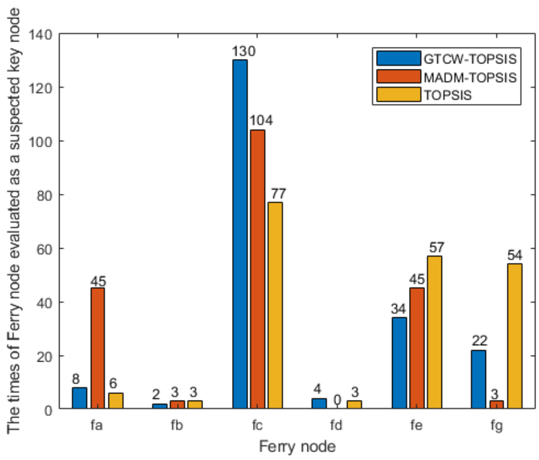

Fig. 8. The results of scenario 2

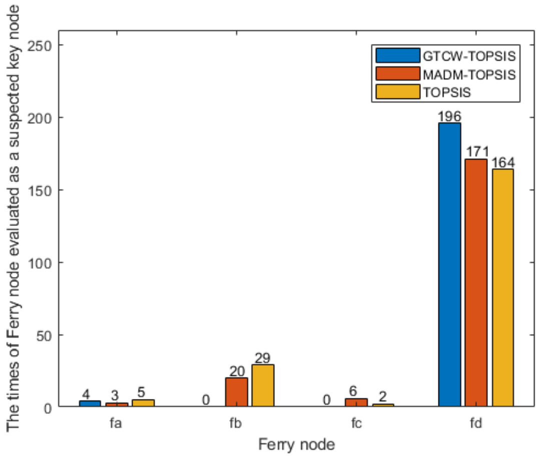

Fig. 9. The results of scenario 3

4.3. Verification

In the experiments, we remove a ferry node every 200 minutes and compute the WNDSR of the remaining network until every node is removed once. Aiming to reduce the error caused by randomness, the simulation experiments are repeated 10 times. The WNDSR is shown in fig. 10-12, wsall denotes the WNDSR before removing ferry nodes, wsda denotes the WNDSR after the fa is removed, wsdb denotes the WNDSR after the fb is removed, the significance of wsdc, wsdd, wsde and wsdg is same as wsda and wsdb.

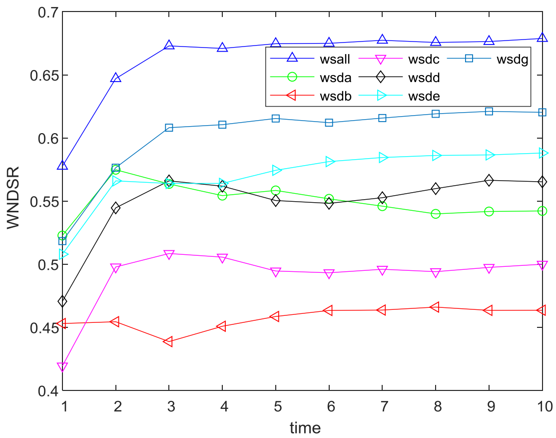

Fig. 10. WNDSR of scenario 1

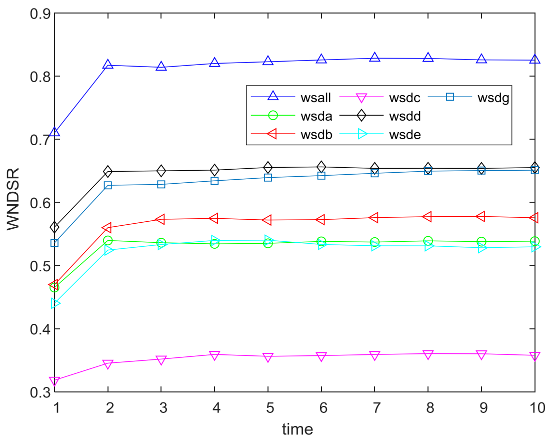

Fig. 11. WNDSR of scenario 2

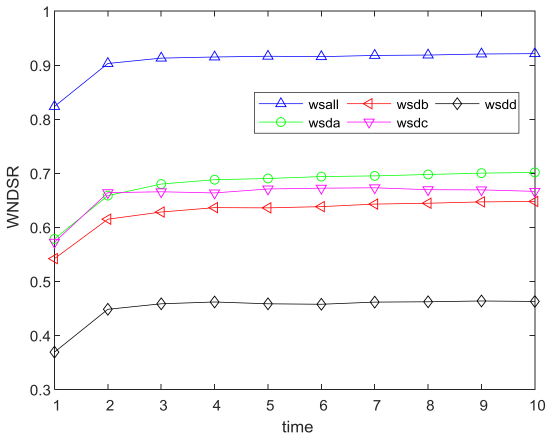

Fig 12. WNDSR of scenario 3

In fig. 10, the removal of fb notably reduces the WNDSR, therefore fb is the key node. As in fig. 11, the removal of fc leads to a crucially decrease of the WNDSR, therefore fc is the key node. From fig. 12, it shows that the removal of fd significantly reduces WNDSR, therefore fd is the key node. In summary, the results show that the key nodes identified by the method proposed all align with the real key node in the scenario 1~3. It can verify that identifying the key node in MOSNs by the method proposed is feasible. It can be seen from Fig. 4-6, the time that the key node is identified by the TOPSIS method and MADM_TOPSIS method is significantly less than the proposed method, which indicates that the proposed is the best in the three methods.

4.4. Accuracy

According to fig. 7~9, the accuracy of the GTCW_TOPSIS method, TOPSIS method and MADM_TOPSIS method are shown in fig. 13. There are some ferry nodes that move with the random way point model in scenario 1, so the accuracy of the three methods is similar. In scenario 2 and scenario 3, the accuracy of the GTCW_TOPSIS method is 65% and 98%, which is obviously higher than the TOPSIS method and MADM_TOPSIS method.

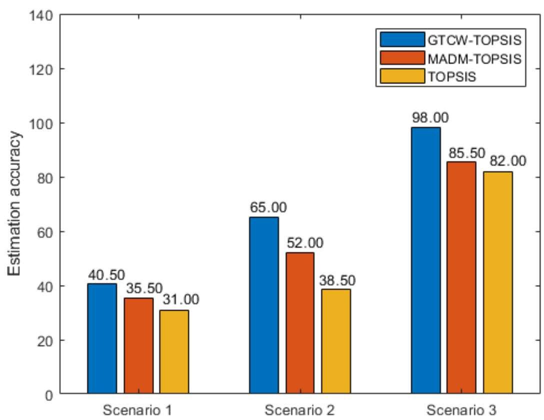

Fig. 13. Estimation accuracy

5. Conclusions

Aiming to identify the key node in MOSNs, first of all, we focus on the characteristics that the topology changes frequently, and use the temporal reachable graph to model MOSNs. Based on this model, the average degree is defined to reflect the activity of the ferry node in the network. The betweenness centrality is defined to reflect the ability of the ferry node to control the path between the region node and the sink node. The messages forwarding rate is defined to reflect the contribution on delivering messages generated by the region node to the sink node. Secondly, we use the average degree centrality, the betweenness centrality and the messages forwarding rate as the attributes of identifying the key node, the subjective weight and objective weight of each attribute are obtained by the AHP method and the entropy method respectively, and the GTCW method is used to calculate the combination weight of each attribute. Thirdly, we use the combination weight to construct the decision matrix and identify the key node in MOSNs by the TOPSIS method. Finally, the experiments in three scenarios are used to verify the effectiveness and evaluate the performance of the GTCW_TOPSIS method. In the future, we will further analyze the characteristics of MOSNs to propose more node importance attributes and apply the method based on the GTCW_TOPSIS method to other dynamic networks.

Acknowledgment. This paper is supported by the National Natural Science Foundation of China (62062050, 61762065, 61962037), the Natural Science Foundation of Jiang Province (20202BABL202039), and the Innovation Foundation for Postgraduate Student of Jiangxi Province (YC2019028).

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Received: December 20, 2019; Accepted: May 02, 2020