Xu *et al. J Wireless Com Network* (2021) 2021:188
https://doi.org/10.1186/s13638-021-02062-7

EURASIP Journal on Wireless Communications and Networking

RESEARCH Open Access

Evaluation method of node importance in temporal satellite networks based on time slot correlation

Rui Xu[1,2], Xiaoqiang Di[1,2,3*], Xiongwen He[4] and Hui Qi[1,2]

*Correspondence: dixiaoqiang@cust.edu.cn
[1] School of Computer Science and Technology, Changchun University of Science and Technology, Changchun 130022, China
Full list of author information is available at the end of the article

Abstract

Temporal satellite networks can accurately describe the dynamic process of satellite networks by considering the interaction relationship and interaction sequence between satellite nodes. In addition, the measurement of node importance in satellite networks plays a crucial role in understanding the structure and function of the network. The classical supra-adjacency matrix (SAM) temporal model identifies the key nodes in the temporal network to some extent, which ignores the differences of inter-layer connectivity relationships leading to the inability to reflect the dynamic variations of satellite nodes. Therefore, the evaluation method based on time slot correlation is proposed to measure the importance of satellite nodes in this paper. Firstly, the correlation coefficient of time slot nodes is defined to measure the coupling relationship of adjacent time slots. Secondly, the dynamic supra-adjacency matrix (DSAM) temporal network model is proposed considering the correlation between adjacent time slots and the characteristics of link time. Finally, the node importance ranking results in each time slot and a global perspective are obtained by utilizing the eigenvector centrality. Experimental simulations of the Iridium and Orbcomm constellations demonstrate that the DSAM method has a relatively accurate recognition rate and high stability.

Keywords: Temporal satellite network, Time slot coefficient, Supra-adjacency matrix, Eigenvector centrality, Key nodes

1 Introduction

With the maturing technology and decreasing cost of various links in the satellite industry chain, many commercial companies have launched satellite Internet development plans, among which Starlink, Telesat, and OneWeb are at the forefront of the industry. Moreover, the data shows that 2,460 satellites are operating in orbit worldwide in 2019. A large number of satellites are interconnected by inter-satellite links to constitute a satellite network. At the same time, the satellite network holds the characteristics of periodicity and time-varying. After launching into orbit, satellites usually face the following three problems. To begin with, satellite nodes are poorly concealed and easily detected and predicted which leads to being easily damaged by anti-satellite satellites, laser weapons, and other weapons. Next, due to satellite systems being in an extremely

Springer Open

© The Author(s), 2021. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

harsh space environment, satellite nodes and inter-satellite links are prone to random failures at any given moment. Finally, this situation that the failure of satellite nodes cannot be repaired will have serious consequences on the regional satellite network such as reduced connectivity, performance degradation, and even paralysis of the entire network [1]. Therefore, analyzing the topology of the satellite network and mining the key nodes in the satellite network is of great significance for the construction and improvement of the satellite network, as well as ensuring the reliability and security of the satellite network [2, 3]. Recently existing research recognizes that identifying key nodes can play an important role in addressing the issue of solving practical problems in satellite networks. Zhang et al. [4] develop a temporal centrality-balanced traffic management scheme that accounts for the temporal features of the networks based on temporal centrality. Zhang et al. [5] find a feasible scheme that a dependent failure approach is presented to identify the faulty links in satellite networks so as to overcome the limitations of traditional independent failure methods by means of node importance evaluation. Wang et al. [6] discover similarities between the agile earth observation satellites (AEOSs) redundant targets scheduling problem and the node centrality ranking problem and propose a fast approximate scheduling algorithm (FASA) which is helpful in AEOSs scheduling problems by introducing the theory of complex networks. Zhou et al [7] design an intelligent backup multi-path ant colony routing algorithm (IMB-ACR) to set backup routes for original routes containing key satellite nodes, thus improving the anti-destructive and resilient ability of satellite networks while reducing time overhead.

In recent years, scholars have conducted a series of studies on the evaluation of satellite node importance around the network structure characteristics of satellite networks [4–11]. Some of these scholars carry out research from the perspective of static networks, abstracting satellite networks into static networks connected by points and edges, and then obtaining the importance of satellite nodes based on their location importance, propagation dynamics characteristics, and dependencies between nodes [5–8]. Despite the progress of such methods, real satellite networks change continuously over time, and the links between satellite nodes are intermittently disconnected and connected over time, which makes the above static network-based studies considerably limit the effectiveness and reliability of the research results for application in real satellite networks. Therefore, scholars have started to consider identifying the importance of satellite network nodes from the perspective of temporal networks. The most important feature of the temporal network is the introduction of time attributes. With the addition of time attributes, the traditional static topology is also changing, presenting a situation that the correlation between nodes is not constant but appears and disappears intermittently with time [12]. Temporal networks can reflect the real system more accurately and have the properties of causality and dynamism that static networks do not have [13, 14]. Another part of scholars divides the satellite network into time slices to obtain the topology of all time slices. For a certain time slice, the betweenness centrality in complex network theory is selected to identify the key nodes, which is the ratio of the shortest path through the nodes in the satellite network to the shortest path of the whole network, and the higher the betweenness value of a node, the more important the node is [4, 9–11]. Although this type of method can well identify the key nodes of a certain time slice, it ignores the interaction relationship and interaction sequence between satellite

nodes within different time slices, and cannot reflect the inter-layer coupling relationship between different time slices.

To address the above problems, the evaluation method of node importance in temporal satellite networks based on time slot correlation is proposed, which can completely represent the structural characteristics and time-varying features of temporal satellite networks. The main advantages and contributions of this paper are summarized as follows.

(1) The time slots are obtained by merging adjacent time slices with the same topology, which contribute to the accurate identification of stable topologies and survival periods within the operating cycle.
(2) Time slot correlation is proposed to accurately depict the connection relationship between nodes in adjacent time slots.
(3) The DSAM temporal network model based on time slot correlation is proposed to properly depict the temporal satellite network, which takes into account the connection relationship of nodes within time slots, the connection relationship between nodes in adjacent time slots, and the variability of the time duration of adjacent time slots.
(4) The evaluation method of node importance in temporal satellite networks based on time slot correlation is proposed, which evaluates the importance of nodes in satellite networks from each time slot as well as the global perspective separately. Through experimental analysis, the method has a relatively accurate recognition rate.

The rest of the paper is structured as follows: Sect 2 cites the recent related works to our work. Section 3 introduces preliminaries. Then, Sect. 4 focuses on the proposed method to identify the key nodes based on time slot correlation in temporal satellite networks. Next, the experimental results and discussions are presented in Sect. 5. Finally, results and discussion are provided in Sect. 6.

2 Related works

Currently, identifying key nodes is one of the research hotspots in the field of network science research which is also attracted the attention of scholars. Many traditional algorithms have been derived from the perspective of network topology, including degree centrality (DC) [15], betweenness centrality (BC) [16], closeness centrality (CC) [17], eigenvector centrality (EC) [18], k-shell centrality (KS) [19]. However, the real complex networks are constantly evolving and changing, and the interaction between nodes in the network is intermittent and time-varying. As a result, the traditional identification method of key nodes based on the static network is no longer reliable. In order to overcome the shortcomings of traditional methods, a series of key node identification algorithms suitable for temporal networks is proposed. Temporal degree centrality focuses on the volatility of degree values of nodes in a temporal network during the time change, which is measured by obtaining the mean value of degree values at different time points [20]. Wang et al. [21] take the standard deviation of the degree value at different time points based on the time window model and

use the deviation value to sort the importance of the nodes in order to obtain the volatility characteristics of the degree value. Tang et al. [22] not only reconsider the path and distance in the temporal network based on the time window graph model but also analyze the evolution of the network from a local and global perspective and propose temporal paths and temporal distances. Tang et al. [23] propose the calculation method of temporal betweenness centrality and temporal closeness centrality based on betweenness centrality and closeness centrality in static networks, which needs to consider not only the calculation of shortest paths in independent window graphs but also the duration of information retained by nodes related to shortest paths in adjacent window graphs. KIM et al. [24] propose the betweenness centrality and closeness centrality of nodes combined with temporal network characteristics based on the temporal network model of obvious path flow. In the temporal network represented by an ordered multi-layer graph, Taylor et al. [25] firstly construct a supra-adjacency matrix containing inter-layer relations and intra-layer relations with a dimension of NT× NT. Then they calculate the principal eigenvector of the supra-adjacency matrix. Finally, they map the eigenvector to an N×T matrix and analyze the matrix to dynamically identify important nodes at different times. In the temporal network, GARAS et al. [26] create snapshots of the network and propose the identification method of key node based on K-shell, which first performs K-shell decomposition in different blocks separately and obtains the instantaneous kernel values of the nodes, then feeds the dynamic kernel values into the static network, and finally analyzes the kernel values of the edges in the network so as to obtain the global temporal kernel values of the nodes.

In recent years, scholars have started to conduct a series of studies on node importance identification in temporal satellite networks. Zhang et al. [27] summarize the temporal network types and representation methods to establish a network model of temporal networks, and select space information networks as simulation objects to demonstrate the advantages of temporal networks in the study of vulnerability. Zhang et al. [8] propose an improved method to evaluate the importance of satellite nodes, where the importance of a satellite node depends on the location of the satellite and the contribution value of its neighboring nodes. The position of a node is determined by its betweenness, and the contribution value is influenced by the betweenness and closeness of its neighboring nodes. Zhu et al. [9] select node betweenness, node closeness, and node distance as node importance metric parameters to propose a node importance evaluation method in the steady-state satellite network, and finally combine the topological graph weights to derive the node importance evaluation algorithm in satellite time-varying networks. Wei et al. [10] redefine the concept of satellite node closeness centrality to measure the closeness between nodes in a satellite network, thus proposing a method to evaluate the importance of satellite nodes based on closeness centrality, which is simple and effective. Wang et al. [11] use the time-cumulative graph techniques (C-TVG) to model satellite networks and propose a method to identify key nodes in LEO satellite networks (PKN), which uses the betweenness as an indicator to quantify the importance of satellite nodes. The above methods ignore the inter-layer coupling relationship between different time slices, and thus cannot accurately depict the temporal satellite network.

The SAM model is an effective means to identify key nodes in a temporal network, which takes into account the structural evolution and dynamics of the temporal network and can effectively avoid the above problems. However, only a fixed parameter is applied to represent the inter-layer relationships between adjacent times without measuring the differences in the connectivity relationships between adjacent time nodes in the construction of the hyper-connectivity matrix. Since the movement of satellite nodes is periodic and the corresponding topological structure of adjacent time may be the same in satellite networks, merging adjacent time slices with the same structure helps to reduce the computational cost. The research of this paper can be summarized as follows. In the first instance, a series of time slots are generated by merging adjacent time slices with the same structure, so that the node correlation coefficients of time slots can be utilized to express the connection relationship of nodes in different time slots. In the next place, the dynamic supra-adjacency matrix (DSAM) is constructed according to the time slot correlation. Afterward, the importance values of nodes in each time slot are obtained by the method of eigenvector centrality which is utilized to analyze the trend of node importance values over time. To wind up with, the node importance values from the global perspective are obtained according to the different proportion of time slots.

3 Preliminaries

3.1 Modeling of temporal satellite networks

Satellite networks are characterized by highly dynamic changes in network topology, frequent changes in inter-satellite links, and multiple types of services, etc. Therefore, the connectivity of inter-satellite links is only considered without involving the specific services on the links when constructing the topology of the satellite network. According to the periodic characteristics of satellite networks, the topology of satellite networks is finite and shows regular changes within a cycle. Therefore, the temporal satellite network is modeled as $G = (T, S)$, where T represents the observation time of the satellite network. The value range of T is $[T_B, T_E]$, where T_B and T_E respectively represent the start time and end time of the observation. T is usually chosen for one full cycle of constellation operation. $S = \{S_1, S_2, S_3, \ldots, S_n\}$ denotes the set of time slices, where S_i denotes the network topology corresponding to the i-th time slice.

The time slice S_i is usually denoted by the triplet $S_i = (V_i, E_i, T_i)$, which is a processing method for static networks. Since inter-satellite link communication is mutual in satellite networks, an undirected graph is used to represent the time slice S_i, in which satellites are abstracted as nodes and inter-satellite connected links are abstracted as edges. Although the positions of satellite nodes in the satellite constellation change dynamically, the number of satellite nodes always remains the same. Hence there are a consistent number of V_i in any time slice S_i. In the time slice S_i, the links between satellite nodes are continuously connected, regardless of information such as connection duration and frequency. In most cases, the entire observation time is divided equally into N consecutive non-overlapping time slices, and the duration of each time slice S_i is equal which is defined as $T_i = (T_E - T_B)/N$, the value of i belongs to $[1, N]$. A temporal satellite network can be composed of a series of dynamically changing time-slice topologies. Moreover, the topology of each time slice can be represented by an adjacency matrix. In the time slice S_i, $a_{mn}(T_i)$ is defined as the element of the corresponding adjacency matrix $A^{(T_i)}$,

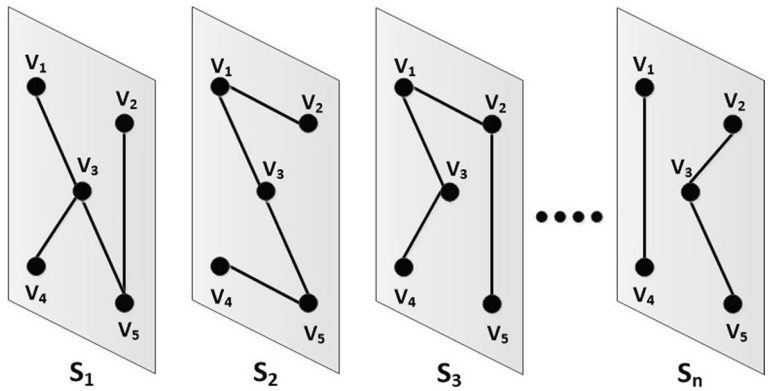

Fig. 1 Satellite network topology based on time slices

	V_1	V_2	V_3	V_4	V_5	V_1	V_2	V_3	V_4	V_5	V_1	V_2	V_3	V_4	V_5
V_1	0	0	1	0	0	0	1	1	0	0	0	1	1	0	0
V_2	0	0	0	0	1	1	0	0	0	0	1	0	0	0	1
V_3	1	0	0	1	1	1	0	0	0	1	1	0	0	1	0
V_4	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0
V_5	0	1	1	0	0	0	0	1	1	0	0	1	0	0	0

T_B t=1 t=2 t=3 T_E

Fig. 2 Representation of the adjacency matrix in the case of equal length of time slices

which is utilized to represent the connection relationship between node m and node n. If there is a link between node m and node n, $a_{mn}(T_i)$ is represented by 1, otherwise, it is represented by 0. Combining the data of each time slice in the satellite network in Fig. 1, the corresponding adjacency matrix can be obtained, as shown in Fig. 2.

3.2 SAM temporal network model

The eigenvector centrality for static networks is to obtain the importance value of each node by calculating the principal eigenvector of the adjacency matrix. Further, Taylor et al. [25] propose the SAM model by integrating the inter-layer and intra-layer relationships in the temporal network. On the basis of the SAM model, the joint centrality of the node-time layer pair is used to express the centrality of node i in the time layer t, and the marginal node centrality and the marginal time layer centrality are respectively represented as the importance of nodes and time layers. So that key nodes in different time layers can be dynamically identified. The SAM model is composed of $T \times T$ block matrices, all of which are $N \times N$ matrices. Among them, the main diagonal reflects the intra-layer connectivity and contains T block matrices, which are represented by the adjacency relations $A^{(1)}$, $A^{(2)}$, $A^{(3)}$, ..., $A^{(T)}$ of different time layers in the temporal network. Besides, the 1-th diagonal and -1-th diagonal reflect the inter-layer connectivity, both containing $T-1$ block matrices, and the closeness of the inter-layer connectivity can be adjusted with parameter ω. The SAM temporal network model is as follows.

$$A = \begin{bmatrix} A^{(1)} & \omega I & 0 & \cdots \\ \omega I & A^{(2)} & \omega I & \ddots \\ 0 & \omega I & A^{(3)} & \ddots \\ \vdots & \ddots & \ddots & \ddots \end{bmatrix}. \tag{1}$$

In Eq. (1), $A^{(t)}$ is the intra-layer connection relationship of the corresponding time layer at time t, which are all $N \times N$ adjacency matrices sequentially distributing on the main diagonal. The value of t is between [1, T]. Moreover, $T - 1$ elements ωI form the 1-th diagonal and $-$ 1-th diagonal, which are used to reflect the inter-layer connection relationship of adjacent time layers. I is a unit matrix of $N \times N$ and the parameter ω takes values in the range [0.1,1.0]. All other elements in matrix A are 0.

4 Methods

4.1 Merging identical time slices

According to the setting in Chapter 2, time slices S_1, S_2, ..., S_n with the same duration are adopted in this paper to describe the time-varying characteristics of the satellite network. In a satellite network, the links between satellite nodes are connected and disconnected with a certain regularity, and thus the topology of time slices formed by these nodes has a survival period. During the survival period, no link connection or disconnection occurs between satellite nodes to keep the topology stable, and the duration of the survival period may be one or more time slices. The adjacent time slices with the same topology can be merged to obtain the time slot sequence P_1, P_2, ..., P_n whose duration of survival is denoted as TS_i. The above process can be shown in Fig. 3, where there are a series of time slices S_1, S_2, ..., S_n with equal time. Assuming that the duration of each time slice is 1s, a series of time slots P_1, P_2, ..., P_m are obtained after merging adjacent time slices with the same topology. At the same time, the corresponding duration of each time slot is obtained as $TS_1, TS_2, \ldots, TS_m$.

Within the observation range T of the satellite network, the time slot sequence reflects the evolution of the satellite network over time. Besides, the uneven distribution of the time slot survival duration also reflects the variability of the weights of each time slot. Therefore, the weight of each time slot can be set as w_i, and the weight matrix composed of each time slot can be expressed as follows.

$$W = \left[w_1, w_2, w_3, \ldots\right] = \left[\tfrac{TS_1}{T}, \tfrac{TS_2}{T}, \tfrac{TS_3}{T}, \ldots\right]. \tag{2}$$

4.2 Time slot correlation

In the temporal network, the coupling relationship of adjacent time slots can be measured by local correlation, and the indicators from the local perspective can be divided into two categories. For one thing, the first type of metrics is measured from the nodes' own neighbors on the adjacent time slots, including the common neighbor (CN) [25] and the normalized metrics derived from CN. For another, the second type of metrics is measured from the perspective of common neighbors of nodes on adjacent time slots. In

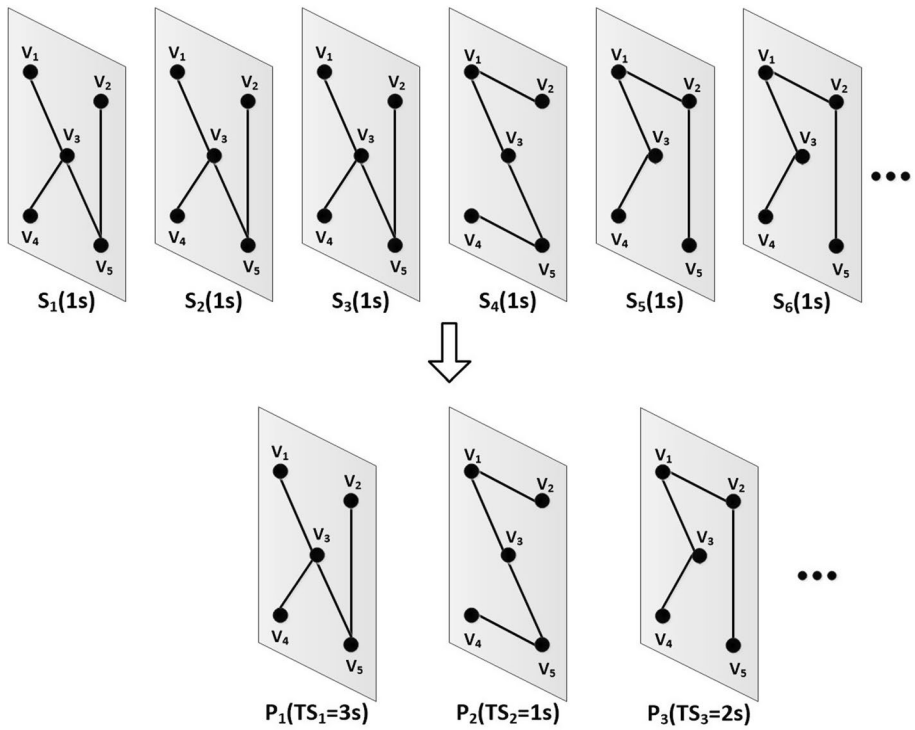

Fig. 3 Diagram of merging identical time slices

this paper, the above two factors are comprehensively measured to obtain the correlation coefficient of time slot nodes which is as follows.

$$C_j(t, t+1) = \frac{\sum_i a_{ij}(t) a_{ij}(t+1)}{min\left[\sum_i a_{ij}(t), \sum_i a_{ij}(t+1)\right]}. \tag{3}$$

Where $a_{ij}(t)$ and $a_{ij}(t+1)$ respectively denote the elements in the adjacency matrix corresponding to the adjacent time slots P_t and P_{t+1}. If there is a link between node i and node j in the time slot P_t, $a_{ij}(t) = 1$. Otherwise, $a_{ij}(t) = 0$. If there is simultaneously a link between node i and node j in the time slots P_t and P_{t+1}, $a_{ij}(t)a_{ij}(t+1) = 1$. Otherwise, $a_{ij}(t)a_{ij}(t+1) = 0$.

In a temporal satellite network, the correlation coefficient of time slot nodes reflects the adjacency relationship between nodes in adjacent time slots and the possibility of continuous occurrence of nodes. When the coefficient is large, there is a stable link between the satellite nodes in two adjacent time slots, and most of the satellite nodes that work continuously remain online for a long time. When this coefficient is small, the proportion of continuously working satellite nodes as well as stably existing links in two adjacent time slots is small, which reflects that the topological structure of the satellite network changes drastically. A diagonal matrix is constructed to represent the time slot correlation based on the correlation of adjacent time slot nodes, as shown in Eq. (4).

$$C^{(t,t+1)} = \begin{bmatrix} C_1(t,t+1) & & & 0 \\ & C_2(t,t+1) & & \\ & & \ddots & \\ 0 & & & C_N(t,t+1) \end{bmatrix}. \tag{4}$$

In Eq. 4), $C_j(t,t+1)$ is the correlation coefficient of adjacent time slot nodes, which indicates the correlation of node j in time slot t and time slot $t+1$. These node correlation coefficients are all on the diagonal. On the contrary, the remaining elements are denoted by 0.

4.3 DSAM model based on time slot correlation

In the classical SAM temporal network model, the connection relationship of each node in adjacent time is mainly expressed by the parameter ω, ignoring the variability between nodes. On the contrary, the connection relationship of each node in the adjacent time should be treated differently, so as to reflect the characteristics of the dynamic change of the nodes in the satellite network. In this paper, an improved DSAM temporal network model is proposed to portray the interlayer connectivity relationships in adjacent time slots from two aspects. To start with, the time slot node correlation coefficient is utilized to reflect the similarity of the connection relationship between nodes in adjacent time slots. In the next place, the ratio of the duration of the adjacent time slots is utilized to reflect the impact of the previous time slot on the next time slot, which helps to distinguish the variability in the duration of adjacent time slots. So the specific representation of the improved DSAM temporal network model is as follows.

$$A' = \begin{bmatrix} A^{(1)} & \frac{TS_1}{TS_2}C^{(1,2)} & 0 & \cdots \\ \frac{TS_1}{TS_2}C^{(1,2)} & A^{(2)} & \frac{TS_2}{TS_3}C^{(2,3)} & \ddots \\ 0 & \frac{TS_2}{TS_3}C^{(2,3)} & A^{(3)} & \ddots \\ \vdots & \ddots & \ddots & \ddots \end{bmatrix}. \tag{5}$$

Where A' is the supra-adjacency matrix in the DSAM model. $A^{(1)}$, $A^{(2)}$, ..., $A^{(n)}$ is respectively the adjacency matrix corresponding to the time slot P_i, which represents the intra-layer connectivity relations among the time slot sequences $\{P_i\}$ in the satellite network. $C^{(1,2)}$, $C^{(2,3)}$, ..., $C^{(n-1,n)}$ respectively represents the inter-layer connectivity of adjacent time slots, where the time slot correlation coefficients $C^{(i-1,i)}$ in the form of $N \times N$ diagonal matrices denotes the connectivity between adjacent time slots P_{i-1} and P_i. In addition, $C^{(i-1,i)}$) is specifically expressed as $C^{(i-1,i)}) = \mathrm{diag}(C_1(\mathrm{i}-1,\mathrm{i}), C_2(\mathrm{i}-1,\mathrm{i}), \ldots, C_N(\mathrm{i}-1,\mathrm{i}))$. What's more, the ratio $\frac{TS_{i-1}}{TS_i}$ of the duration of adjacent time slots is utilized to measure the degree of influence between time slots. Since the DSAM model only considers the connection relationship of the same node between adjacent time slots, all other elements of the matrix A' are denoted by 0.

Based on the DSAM temporal network model, the temporal network containing four nodes and three time slots is selected as an example, where the duration of the three time

slots are four seconds, twelve seconds, and eight seconds, respectively. The example is shown in Fig. 4, where the connection relationships within the time slots are shown by solid lines, and the connection relationships between adjacent time slots are shown by dashed lines.

$$A' = \begin{bmatrix} 0 & 0 & 1 & 1 & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & \frac{1}{3} & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & \frac{1}{6} & 0 & 0 & 0 \\ \frac{1}{3} & 0 & 0 & 0 & 0 & 0 & 1 & 0 & \frac{3}{2} & 0 & 0 \\ 0 & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{3} & 0 & 1 & 0 & 0 & 1 & 0 & 0 & \frac{3}{2} \\ 0 & 0 & 0 & \frac{1}{6} & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{3}{2} & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{3}{2} & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{3}{2} & 0 & 0 & 1 \end{bmatrix}. \tag{6}$$

Equation (6) represents the supra-adjacency matrix of the DSAM model-based temporal network instance. The three block matrices on the main diagonal correspond to the adjacency matrices generated by each of the three time slots in the instance. The 1-th diagonal and $-$ 1-th diagonal are composed of the diagonal matrices derived from the calculation of the adjacent time slots using $\frac{TS_{i-1}}{TS_i} C^{(i-1,i)}$. Since the connection relationship between non-adjacent time slots is not considered, the elements of other regions are used with 0.

4.4 Evaluating the importance of satellite nodes in each time slot

Eigenvector centrality in the static network is an important indicator for evaluating the importance of nodes in the network, which can be expressed as $EC(v_i) = \lambda^{-1} \sum_{j=1}^{N} a_{ij} e_j$. Where λ is the main eigenvalue of the adjacency matrix A, the corresponding eigenvector is $e = [e_1, e_2, \ldots, e_n]^T$, and a_{ij} represents the connection relationship between node i and node j. This measure considers that the neighboring nodes of a node in the core position will also have higher importance than the general edge nodes. By measuring the

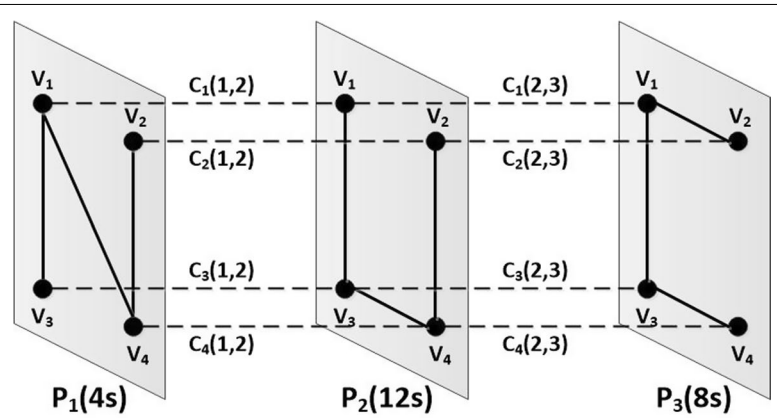

Fig. 4 Example of a temporal network based on the DSAM model

importance of the neighboring nodes directly connected to this node, the importance of this node in the whole network can be reflected [18].

In the temporal satellite network, the eigenvector centrality is exploited to seek the eigenvectors of the super-neighbor matrix A' constructed above and to select the principal eigenvector corresponding to the largest eigenvalue. This principal eigenvector is denoted as $v = \{v_1, v_2, v_3, \ldots, v_{NT}\}^T$, which contains the importance values corresponding to all nodes in each time slot. First of all, $\{v_1, v_2, v_3, \ldots, v_N\}^T$ denotes the eigenvector centrality value of each node in the first time slot. Next, $\{v_{(i-1)N+1}, v_{(i-1)N+2}, v_{(i-1)N+3}, \ldots, v_{iN}\}^T$ denotes the eigenvector centrality value of each node in the i-th time slot. Lastly, $\{v_{(T-1)N+1}, v_{(T-1)N+2}, v_{(T-1)N+3}, \ldots, v_{NT}\}^T$ denotes the eigenvector centrality value of each node in the T-th time slot. Since there are T different time slot vectors, all of which correspond to vector length N, the $(N(t-1)+i)$-th term in vector v can be used to represent the importance of node i in the t-th time slot. Thus, an $N \times T$ matrix of importance values is obtained, which is represented as follows.

$$Ws = \{ws_{it} \mid ws_{it} = v_{N(t-1)+i}\}_{N \times T}. \tag{7}$$

4.5 Evaluating the importance of satellite nodes from a global perspective

In the satellite network, the degree of importance of N nodes in each time slot and the weight of each time slot are considered together to obtain the importance value of each node in the global perspective which is denoted as We.

$$We = \{we_i \mid we_i = \sum_{j=1}^{T} Ws(i,j) \times W(j)\}. \tag{8}$$

Where the matrix W is the weight matrix of each time slot obtained above and Ws is the node importance matrix in each time slot obtained above.

5 Experiments

5.1 Experimental data

Due to the representative structures of the Iridium and Orbcomm constellations, these two constellations are chosen as experimental objects to simulate the low earth orbit (LEO) satellite network. First of all, Iridium is the world's first satellite communication system with global coverage proposed by Motorola. Iridium has become the most mature satellite network supporting inter-satellite links after years of construction. The Iridium constellation consists of 66 LEO satellites and 6 spare satellites. 66 operational satellites are evenly distributed on 6 circular orbital planes with an orbital altitude of 780 km and an orbital inclination of 86.4°. The operational period of the Iridium constellation is about 6000s [28]. Next, Orbcomm is a satellite system that provides global communication services, using a constellation of low-orbit satellites to achieve communication between user terminals and gateways. The Orbcomm constellation contains 35 satellites distributed on 6 orbital planes labeled A, B, C, D, F, and G. On these 6 orbital planes, there are 8, 8, 8, 7, 2, and 2 satellites evenly distributed respectively. The orbital heights of the A, B, C, and D orbital planes are all

827 km, and the orbital heights of the F and G orbital planes are 744 km and 833 km, respectively. The inclination angles of the A, B, C, and D orbital planes are all 45°, and the inclination angles of the F and G orbital planes are 70° and 108°, respectively. The operation period of the Orbcomm constellation is about 5820s [29]. The simulation parameters of the two constellations are shown in Table 1.

STK (Satellite Tool Kit) is an analysis tool developed by Analytical Graphics and widely used in the aerospace field, which can fully support complex space environment simulation extrapolation and analysis evaluation, and provide detailed analysis results and realistic space visualization functions [4]. MATLAB is commercial mathematical software from MathWorks for data analysis, wireless communication, and other fields [9].In this paper, STK and MATLAB are selected as experimental and analytical tools to analyze the Iridium and Orbcomm constellations. A series of different time slots are obtained by comparing the topologies of adjacent time slices and merging the same time slices in the operational periods of these constellations. In order to conserve calculation time, the time slots with a survival period lower than five seconds are eliminated and the time slots with a survival period greater than or equal to six seconds are screened out. As a result, 259 and 235 time slots are obtained for the Iridium and Orbcomm constellations, respectively.

5.2 Assessment methods

The methods commonly used to evaluate the degree of importance of nodes include those based on the ability to disseminate information in the network [30] and those based on the vulnerability and robustness of the network [14]. In satellite networks, the degree of importance of a node is evaluated by measuring the degree of change in network connectivity after the node is deleted. When a node is deleted, the greater the change in network connectivity, the higher the importance of the deleted node. On the contrary, the importance of this node is low.

Network efficiency is one of the important methods for evaluating network connectivity [31, 32]. After removing the nodes and all the edges connected in the network, some paths in the network are forced to break and cause the shortest path between some nodes to become larger, which leads to an increase in the average path length of the whole network and affects the connectivity of the nodes in the network. The specific form of network efficiency is as follows.

Table 1 Iridium and Orbcomm simulation parameters

Parameters	Iridium	Orbcomm
Orbit height/km	780	827, 744, 833
Inclination/(°)	86.4	45, 70, 108
Number of tracks	6	6
Total number of satellites	66	35
Operation cycle/s	6000	5820

$$\eta = \frac{1}{N(N-1)} \sum_{i,j \in V} \frac{1}{d_{ij}}. \tag{9}$$

where N is the total number of nodes in the network, and d_{ij} is the shortest path between nodes in the satellite network.

In order to verify the effect of the DSAM method on the evaluation of the importance of nodes in the satellite network,the results obtained by the DSAM method are compared and analyzed with the SAM method and the literature [11] respectively. By deleting some specific nodes in the satellite network, the scenario where the satellite network encounters random attacks is simulated. The difference in network efficiency before and after the node is deleted is used as the criterion for judging the importance of the node, so the difference in network efficiency is expressed as $\Delta\eta = |\eta - \eta_0|$. η_0 denotes the network efficiency in the initial state, and η denotes the network efficiency after the node is removed. Moreover, a larger value of $\Delta\eta$ indicates a greater change in network efficiency after the node is removed, reflecting the greater importance of the node in the satellite network.

5.3 Effectiveness analysis of DSAM model

For the two satellite network data of Iridium and Orbcomm introduced in Sect. 5.1, the ranking results in each time slot are calculated and obtained based on the DSAM model, SAM model, and PKN model [11]. Further, the ranking results are compared so as to evaluate the accuracy of each method in mining the key satellite nodes. First, on the basis of the DSAM model and SAM model, the eigenvector centrality is calculated for each time slot of the temporal satellite network, respectively, so as to obtain the node importance ranking results of the DSAM method and SAM method ($\omega \in$[0.1,1.0]) for each time slot. Next, the PKN method selects the betweenness as the evaluation index to quantify the importance of satellite nodes with the aim of obtaining the results of node importance ranking for each time slot. Then, the node deletion method is selected as the benchmark ranking method to also calculate the node importance ranking results for each time slot of the temporal satellite network. Finally, the ranking results of each time slot obtained by the DSAM method and the other methods are compared with the results of the benchmark ranking to calculate the Spearman correlation coefficient, which mainly measures the degree of correlation between the two sequences in order to test the effect of DSAM method more intuitively.

The Spearman correlation coefficient [33] is used to evaluate the degree of correlation between the ranking results obtained by this method and the benchmark ranking results. The larger the Spearman value is, the more accurate the sorting result of the method is. The Spearman values for two sequences of sorting results $X = \{x_1, x_2, x_3, \ldots, x_n\}$ and $Y = \{y_1, y_2, y_3, \ldots, y_n\}$ can be calculated by the following equation, where X denotes the sorting result obtained by DSAM or other methods at a certain time slot, Y denotes the benchmark sorting result at the same time slot, and $\overline{x}$ and $\overline{y}$ denote the average of the values in X and Y, respectively.

$$\rho = \frac{\sum_{i=1}^{N}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \overline{x})^2 \sum_{i=1}^{N}(y_i - \overline{y})^2}}. \tag{10}$$

In this paper, the first experiment is conducted and analyzed on the Iridium constellation. The DSAM method, SAM method ($\omega \in$[0.1,1.0]), and PKN method are sorted separately in each of the 259 time slots of the Iridium constellation. Afterward, the Spearman values are calculated by comparing the ranking results of the above three methods with the benchmark ranking results, as shown in Fig. 5.

In Fig. 5, the horizontal and vertical coordinates represent the 20 intervals into which Spearman's range of values is divided and the number of time slots in the current interval respectively, and the total number of time slots corresponding to each algorithm is 259. The range of Spearman value is [− 1,1]. The Spearman value in the range of [0,1] indicates that the two sides of the comparison are positively correlated, while the Spearman value in the range of [− 1,0] indicates that the two sides of the comparison are negatively correlated. The closer the Spearman value is to 1, the more similar the algorithm is to the sorting result of the benchmark sort, reflecting the higher node importance identification rate of the algorithm. Conversely, the closer the Spearman value is to − 1, the more irrelevant the algorithm is to the ranking result of the benchmark ranking, reflecting the lower node importance recognition rate of the algorithm. (1) The distribution of Spearman values of SAM method is not uniform for different parameters ω. For some parameters ω, the SAM method has more time slots with positive Spearman values. On the contrary, for other parameters ω, the results are more in the number of time slots in negative correlation. (2) The Spearman values obtained by the PKN method are mostly distributed around 0, where most of the time slots correspond to Spearman

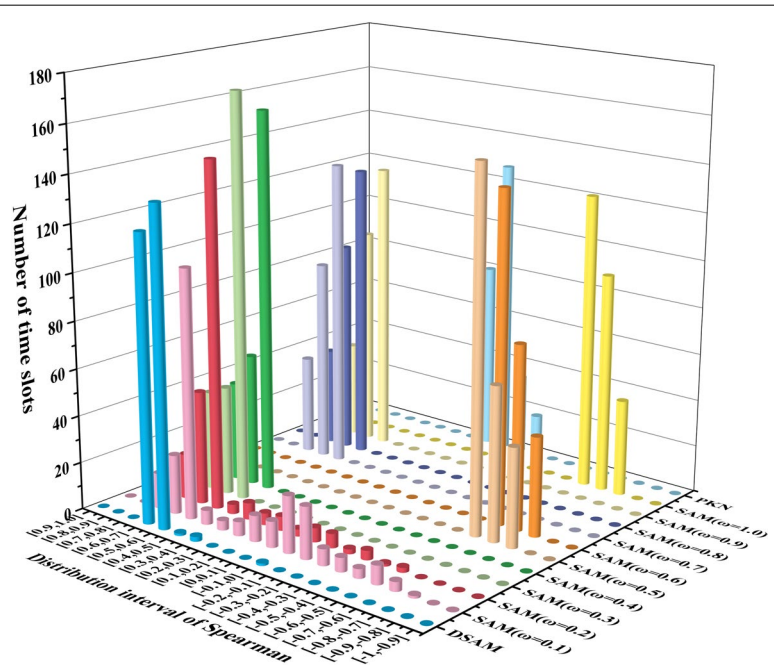

Fig. 5 Distribution of Spearman values calculated for the 259 time slots of Iridium

values in [0,0.2] and a few of them are in [− 0.2,0]. (3) The Spearman values obtained by the DSAM method for each time slot are mostly positively correlated, and most of the Spearman values are located at [0.5,1.0]. Further analysis is performed in Table 2.

In Table 2, the distribution of Spearman values corresponding to the DSAM method and the other methods is shown. Analysis of the distribution of Spearman values corresponding to each method reveals the following situations. (1) The range of parameter ω in the SAM method is [0.1,1.0], and the distribution of Spearman values corresponding to SAM methods with different parameters is very different. When the parameter ω is set of [0.3,0.4,0.7,0.8,0.9], the Spearman values corresponding to the SAM method are mostly in positive correlation and have high similarity with the results of the node deletion method. When the parameter ω is set of [0.5,0.6,1.0], the Spearman values corresponding to the SAM method are all in negative correlation. When the parameter ω is set of [0.1,0.2], the proportion of Spearman values corresponding to SAM methods in negative correlation is 44.02% and 17.76%, respectively. (2)By analyzing the results obtained by the PKN method, it is found that the Spearman values of 79.92% of the time slots are in positive correlation, but they are all in [0,0.2], indicating that the similarity between the method and the benchmark ranking results is not high. Therefore, the PKN method does not have a high recognition rate for the importance of nodes in the Iridium constellation. (3) Among the results obtained by the DSAM method, 46.72% of the Spearman value corresponding to the DSAM method is in the interval of [0.6,1.0], which is higher than that of the SAM method corresponding to most of the parameters ω. A total of 99.61% of the Spearman values are in the interval of positive correlation, which is also higher than most of the SAM methods corresponding to parameter ω. On the contrary, only 0.39% of the Spearman values are left in negative correlation. Meanwhile, the DSAM method is superior to the PKN method. It can be seen that the DSAM method has a higher recognition rate for the Iridium constellation data.

In the next step, the Orbcomm constellation is experimented with and analyzed according to the above method. The DSAM method, SAM method ($\omega \in$[0.1,1.0]), and PKN method are sorted separately in each of the 235 time slots of the Orbcomm

Table 2 Statistics of Spearman values calculated for 259 time slots of Iridium

Methods	[0.7,0.8]	[0.6,0.7]	[0.5,0.6]	[0,0.5]	[− 0.5,0]	[− 1,− 0.5]
DSAM	0	121	134	3	1	0
SAM($w = 0.1$)	15	25	105	38	63	13
SAM($w = 0.2$)	19	48	146	25	19	2
SAM($w = 0.3$)	42	46	171	0	0	0
SAM($w = 0.4$)	42	56	161	0	0	0
SAM($w = 0.5$)	0	0	0	0	0	259
SAM($w = 0.6$)	0	0	0	0	0	259
SAM($w = 0.7$)	42	86	131	0	0	0
SAM($w = 0.8$)	42	91	126	0	0	0
SAM($w = 0.9$)	41	94	124	0	0	0
SAM($w = 1.0$)	0	0	0	0	0	259
PKN	0	0	0	207	52	0

constellation. Afterward, the Spearman values are calculated by comparing the ranking results of the above three methods with the benchmark ranking results, as shown in Fig. 6.

In Fig. 6, the horizontal and vertical coordinates represent the 20 intervals into which Spearman's range of values is divided and the number of time slots in the current interval respectively, and the total number of time slots corresponding to each algorithm is 235. (1) Analyzing the results of the SAM algorithm at different parameters ω, the distribution of Spearman values corresponding to each time slot is not uniform. However, the Spearman values corresponding to most time slots are distributed around 0 from an overall view. (2) The Spearman values obtained by PKN method are all in positive correlation, and the number of time slots with Spearman values in [0.5,0.6] is the largest. (3) The Spearman values of each time slot obtained by the DSAM method are mostly in the following four intervals [0.6,0.7], [0.5,0.6], [0.4,0.5], [− 0.6,− 0.5], where the first three intervals are positively correlated and the last one is negatively correlated. Further analysis is performed in Table 3.

The Spearman values of the DSAM and other methods sorting results with the benchmark sorting results are shown in Table 3. Analysis of the distribution of Spearman values corresponding to each method reveals the following situations. (1) When the parameters ω is set of [0.3,0.4,0.8,0.9], most of the Spearman values of the time slots corresponding to the SAM method are less than 0.5 and a large proportion of them are in negative correlation, which reflects that the results of the SAM method and the node deletion method are not very similar. When the parameter ω is set of [0.1,0.2,0.5,0.6,0.7,1.0], the proportion of Spearman values of the time slots corresponding to the SAM method in [0.5,1.0] can reach up to 25.53%. (2) The Spearman values of each time slot obtained by the PKN method are in positive correlation, and 60% of the

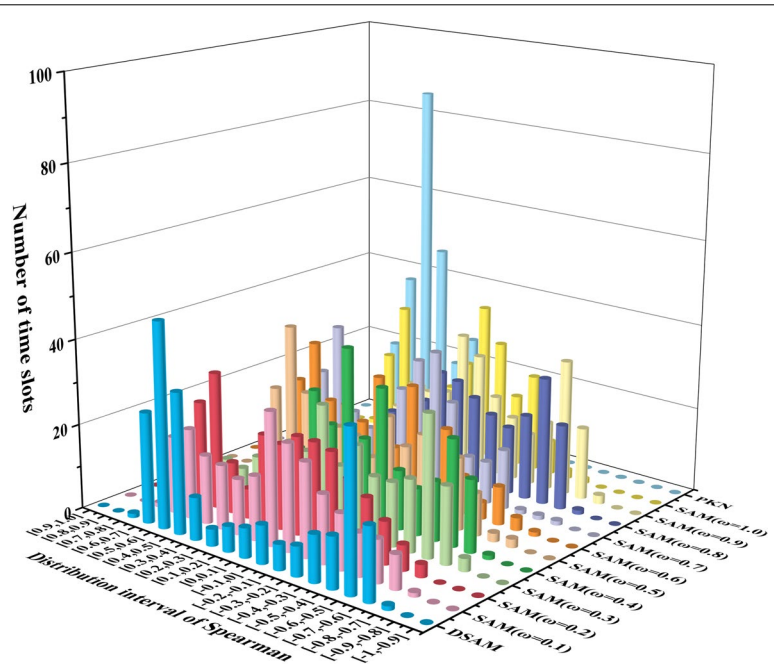

Fig. 6 Distribution of Spearman values calculated for the 235 time slots of Orbcomm

Table 3 Statistics of Spearman values calculated for 235 time slots of Orbcomm

Methods	[0.7,0.8]	[0.6,0.7]	[0.5,0.6]	[0,0.5]	[− 0.5,0]	[− 1,− 0.5]
DSAM	1	26	48	60	45	55
SAM($w = 0.1$)	1	18	21	90	86	19
SAM($w = 0.2$)	1	24	32	83	86	9
SAM($w = 0.3$)	2	8	7	81	83	54
SAM($w = 0.4$)	0	0	1	101	90	43
SAM($w = 0.5$)	2	21	37	77	84	14
SAM($w = 0.6$)	1	21	31	89	80	13
SAM($w = 0.7$)	1	21	33	88	89	3
SAM($w = 0.8$)	0	2	6	77	99	51
SAM($w = 0.9$)	0	0	2	92	90	51
SAM($w = 1.0$)	1	19	32	103	79	1
PKN	19	37	85	92	2	0

time slots correspond to Spearman values lies in [0.5,1.0], which indicates that the PKN method has a high similarity with the benchmark ranking results. Therefore, the PKN method can accurately identify the importance of nodes in the Orbcomm constellation. (3) 31.91% of Spearman values of the time slots corresponding to DSAM methods are in [0.5,1.0], which is higher than those corresponding to SAM methods with all parameters ω. Besides, a total of 57.45% of the time slots corresponding to Spearman values are in the positive correlation interval. Moreover, the PKN method is superior to the DSAM method in each interval of [0,1]. Therefore, it shows that the recognition rate of DSAM method for Orbcomm constellation data is higher than that of SAM method and lower than that of PKN method.

Analysis of the experimental results of the above two constellations reveals the following situation. When the parameter ω is set of [0.3,0.4,0.7,0.8,0.9] in the Iridium constellation, the results obtained by the SAM method are very similar to the node deletion method. When the parameter ω is set of [0.3,0.4,0.8,0.9] in the Orbcomm constellation, the similarity between the result obtained by the SAM method and the node deletion method is very low. These data illustrate that SAM methods with the same parameter ω have a great difference in node importance identification for different constellations and that the use of a fixed value ωI for different satellite constellations to represent the interlayer connectivity between time slots is highly contingent. Meanwhile, the PKN method has very dissimilar results for the identification of Iridium and Orbcomm constellations, which shows that the method is unstable for the identification of node importance in satellite networks. On the contrary, the DSAM method obtains a high agreement between the ranking results and the baseline ranking results when processing the data of two constellations, which indicates that the DSAM method can describe the Iridium and Orbcomm constellations more accurately and has a consistently high node importance identification rate.

5.4 Functional analysis of DSAM model

Due to the time-varying and periodic characteristics of temporal satellite networks, the links between satellite nodes change frequently during the operation cycle of the

constellation, and there are often situations such as disconnection of existing connections or establishment of new connections. Therefore, DSAM method and PKN method are applied to select key nodes from a global perspective and analyze the operation of the links associated with these key nodes during the operating cycle of the constellation. The experimental methods are as follows. (1) To begin with, the importance degree of the 66 satellite nodes in the Iridium constellation is analyzed from a global perspective with the above two methods, and the TOP 10%, 20%, 30% of nodes (TOP 7, 13, 20 nodes) are selected as key nodes. Then, the number of relevant links of key nodes in 259 time slots is counted separately and their proportion in the total links is calculated, as shown in Fig. 7. (2) Firstly, the nodes in the TOP 10%, 20%, 30% importance ranking (TOP 4, 7, 11 nodes) in the Orbcomm constellation are selected as key nodes by adopting the method above. Afterward, the number of links associated with the key nodes in 235 time slots is counted as well as the percentage of the relevant links is calculated, as shown in Fig. 8.

In Fig. 7, the horizontal and vertical coordinates represent the interval of the proportion of links related to key nodes and the number of time slots in the current interval respectively, and the total number of time slots corresponding to both methods is 259. Analyzing the three subfigures in Fig. 7, the following findings can be derived. (1) The results corresponding to TOP 10% nodes are shown in subfigure a. The percentage of relevant links in 57.92% of the time slots is at [0.2,0.3], while no time slots are at [0.2,0.3] for the DSAM method, reflecting that the PKN method outperforms the results corresponding to the DSAM method. (2) The results corresponding to TOP 20% nodes are shown in subfigure b. The percentage of relevant links in 11.20% and 40.93% of the time slots are at [0.5,0.6] and [0.4,0.5] respectively, while the corresponding percentages in PKN method are 0 and 47.88%, reflecting that the DSAM method outperforms the corresponding results of PKN method. (3) The results corresponding to TOP 30% nodes are shown in subfigure c. The percentage of relevant links in 14.29% and 36.68% of the time slots are at [0.7,0.8] and [0.6,0.7] respectively, while the PKN method corresponds to 0 and 56.37%, reflecting that the DSAM method outperforms the results corresponding to the PKN method. In summary, the DSAM method has more links than the PKN algorithm for the key nodes (TOP 20% and TOP 30%) identified in the Iridium constellation. On the contrary for the TOP 10% nodes, the PKN method is better than the DSAM method.

Analyzing the three subfigures in Fig. 8, the following findings can be derived. (1) The results corresponding to the TOP 10% nodes are shown in subfigure a. The percentage of relevant links in 5.11% and 94.89% of the time slots are at [0.3, 0.4] and [0.2,0.3] respectively, while the PKN method corresponds to 0 and 100%, reflecting that the DSAM method outperforms the results corresponding to the PKN method. (2) The results corresponding to TOP 20% nodes are shown in subfigure b. The percentage of relevant links in 96.17% and 3.83% of the time slots are at [0.4, 0.5] and [0.3,0.4] respectively, while the PKN method corresponds to 33.19% and 66.81%, reflecting that the DSAM method outperforms the results corresponding to the PKN method. (3) The results corresponding to the TOP 30% nodes are shown in subfigure c. The percentage of relevant links in 88.94% and 11.06% of the time slots are at [0.6,0.7] and [0.5,0.6] respectively, while the percentages corresponding to the PKN method are 4.68% and 95.32%, reflecting the superiority of the DSAM method over the results corresponding to the PKN method. In

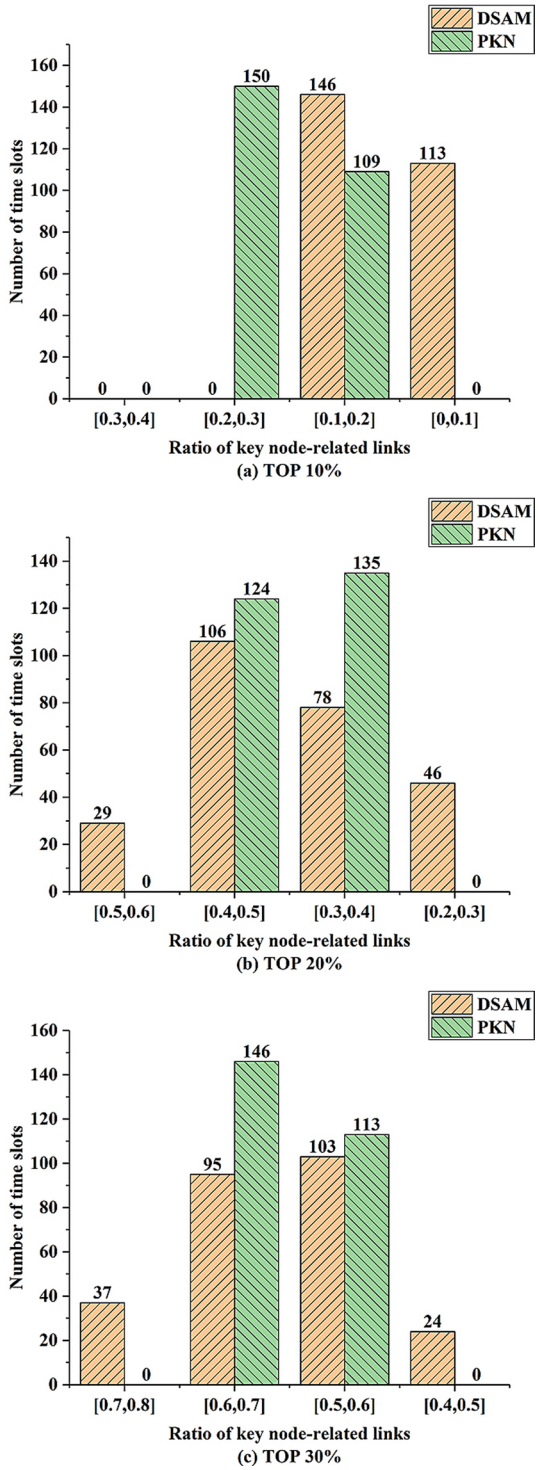

Fig. 7 The ratio of key node related links in each time slot in Iridium

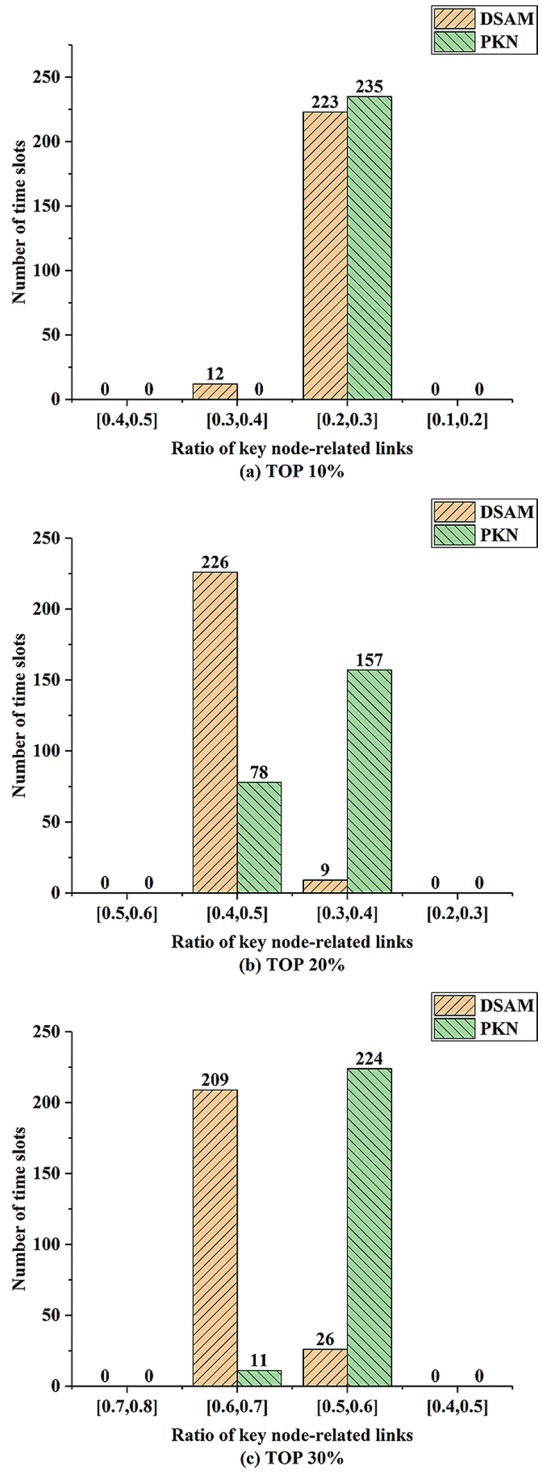

Fig. 8 The ratio of key node related links in each time slot in Orbcomm

summary, it can be seen that the key nodes identified by the DSAM method have more links than the PKN method in the Orbcomm constellation.

Since the links between satellite nodes are the basis for inter-satellite operations. The more inter-satellite links satellite nodes have, the more services they can undertake [34, 35]. By analyzing the experimental results of the Iridium and Orbcomm constellations, it can be found that in most cases the key nodes identified by the DSAM method have more links than those identified by the PKN method. The key nodes identified from a global perspective using the DSAM method can constitute a larger number of links with a smaller number of nodes, and a larger number of links represents that the associated nodes will take on more service functions. Thus, the functionality of the DSAM method is demonstrated from the satellite service perspective.

6 Results and discussion

Identifying key satellite nodes in temporal satellite networks is of great significance for studying the structure and function of satellite networks. Hence, a method based on the DSAM model is proposed to identify the key nodes in the temporal satellite network, which takes into account the connection relationship of nodes within time slots, the connection relationship between adjacent time slots, and the survival duration of time slots. Through experiments for the Iridium and Orbcomm constellations, it is concluded that the DSAM method is more stable than the other methods and can more accurately identify the key nodes in each time slot of the network. Moreover, the key nodes identified by the DSAM method from the global perspective have more links than the PKN method in each time slot, indicating that these key nodes are involved in more satellite services in data communication and are more important from the functional perspective. In the future, satellite networks will develop into large or giant networks. Therefore, the inter-satellite links will be more complicated and the functions performed by individual satellites will be more diverse, which puts forward higher requirements for identifying key nodes in the satellite network.

Abbreviations

SAM: Supra-adjacency matrix; DSAM: Dynamic supra-adjacency matrix; DC: Degree centrality; BC: Betweenness centrality; CC: Closeness centrality; EC: Eigenvector centrality; KS: K-shell centrality; TVGs: Time-varying graphs; AEOSs: Agile earth observation satellites; FASA: Fast approximate scheduling algorithm; CN: Common neighbor; LEO: Low earth orbit; IMB-ACR: Intelligent backup multi-path ant colony routing algorithm; C-TVG: Time-cumulative time-varying graph; PKN: Protect the key nodes; STK: Satellite Tool Kit.

Acknowledgements

Not applicable.

Author's contributions

RX established the model and finished the writing of this manuscript. RX and XD proposed the idea and completed the theoretical derivation. HQ participated in algorithm simulation. XD and HX proofread the manuscript. XH and HQ gave good suggestions on the innovation of the paper. All the authors read and approved the final manuscript.

Funding

This research was supported in part by the National Key Research and Development Program of China under Grant No. 2018YFB1800303 and the Science and Technology Planning Project of Jilin Province under Grant No. 20200401105GX.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
All authors agree to submit this version and claim that no part of this manuscript has been published or submitted elsewhere.

Competing interests
The authors declare that they have no competing interests.

Author details
[1]School of Computer Science and Technology, Changchun University of Science and Technology, Changchun 130022, China. [2]Jilin Province Key Laboratory of Network and Information Security, Changchun University of Science and Technology, Changchun 130022, China. [3]Information Center, Changchun University of Science and Technology, Changchun 130022, China. [4]Beijing Institute of Spacecraft System Engineering, Beijing 100094, China.

Received: 2 June 2021 Accepted: 21 October 2021
Published online: 05 November 2021

References

1. L. Zemanová, C. Zhou, J. Kurths, Structural and functional clusters of complex brain networks. Phys. D **224**, 202–212 (2006)
2. L. Lü, D. Chen, X.L. Ren et al., Vital nodes identification in complex networks. Phys. Rep. **650**, 1–63 (2016)
3. T. Rogers, Assessing node risk and vulnerability in epidemics on networks. EPL **109**, 28005 (2015)
4. Z. Zhang, C. Jiang, S. Guo et al., Temporal centrality-balanced traffic management for space satellite networks. IEEE Trans. Veh. Technol. **67**, 4427–4439 (2018)
5. X. Zhang, Z. Zhang, Link fault identification using dependent failure in wireless communication networks. Electron. Lett. **52**, 163–165 (2016)
6. X.W. Wang, Z. Chen, C. Han, Scheduling for single agile satellite, redundant targets problem using complex networks theory. Chaos Soliton. Fract. **83**, 125–132 (2016)
7. R. Zhou, Q. Zhang, Y. Tao et al., Intelligent multipath backup ant colony routing algorithm of satellite network based on betweenness centrality. In: 2020 IEEE Computing, Communications and IoT Applications (ComComAp), Beijing, China (2020)
8. X.J. Zhang, Z.L. Wang, Z.X. Zhang et al., Finding most vital node in satellite communication network. Appl. Mech. Mater. **635–637**, 1136 (2014)
9. L. Zhu, S. Fang, Q. Hu et al., Evaluation method for time-varying satellite topology network node importance. Systems Engineering and Electronic [in Chinese] **39**, 1274–1279 (2017)
10. D. Wei, Y. Qin, Z. Kong et al., The important node assessment method of satellite network based on near the center. In: 2016 International Conference on Network and Information Systems for Computers (ICNISC), Wuhan, China (2016)
11. S.Q. Wang, Y.J. Zhao, H. Xie et al., Pkn: Improving survivability of leo satellite network through protecting key nodes. In: 2019 15th International Conference on Emerging Networking EXperiments and Technologies(CoNEXT '19), Orlando, USA (2019)
12. P. Holme, J. Saramaki, Temporal networks. Phys. Rep. **519**, 97–125 (2012)
13. I. Scholtes, N. Wider, R. Pfitzner et al., Causality-driven slow-down and speed-up of diffusion in non-markovian temporal networks. Nat. Commun. **5**, 5024 (2013)
14. A. Li, S.P. Cornelius, Y.Y. Liu et al., The fundamental advantages of temporal networks. Science **358**, 1042–1046 (2017)
15. R. Albert, H. Jeong, A.L. Barabasi, Error and attack tolerance of complex networks. Nature **406**, 378–382 (2000)
16. L.C. Freeman, A set of measures of centrality based on betweenness. Sociometry **40**, 35–41 (1977)
17. G. Sabidussi, The centrality index of a graph. Psychometrika **31**, 581–603 (1966)
18. S.P. Borgatti, Centrality and network flow. Social Netw. **27**, 55–71 (2005)
19. M. Kitsak, L.K. Gallos, S. Havlin et al., Identification of influential spreaders in complex networks. Nat. Phys. **6**, 888–893 (2010)
20. Z. Eisler, I. Bartos, J. Kertesz, Fluctuation scaling in complex systems: Taylor's law and beyond. Adv. Phys. **57**, 89–142 (2008)
21. Z. Wang, X. Pei, Y. Wang et al., Ranking the key nodes with temporal degree deviation centrality on complex networks. In: 2017 29th Chinese Control And Decision Conference (CCDC), Chongqing, China, pp. 1484–1489 (2017)
22. J. Tang, M. Musolesi, C. Mascolo et al., Temporal distance metrics for social network analysis. In: 2nd ACM Workshop on Online Social Networks, Barcelona, Spain, pp. 31–36 (2009)
23. J. Tang, M. Musolesi, C. Mascolo et al., Analysing information flows and key mediators through temporal centrality metrics. In: 3rd Workshop on Social Network Systems, Paris, France, pp. 1–6 (2010)
24. H. Kim, R. Anderson, Temporal node centrality in complex networks. Phys. Rev. E **85**, 026107 (2012)
25. D. Taylor, S.A. Myers, A. Clauset et al., Eigenvector-based centrality measures for temporal networks. Multiscale Model. Simul. **15**, 537–574 (2015)
26. A. Garas, F. Schweitzer, S. Havlin, A k-shell decomposition method for weighted networks. New J. Phys. **14**, 083030 (2012)
27. M. Zhang, K. Luo, X. Wu et al., Temporal network and its application. J. Syst. Simul. [in Chinese] **31**, 679–686 (2019)

28. C. Yahnker, S. Bozzone, B. Newberry et al., Enhancements and performance of seaglider iridium communications system. In: 2012 Oceans, Hampton Roads, VA, USA (2012)
29. R. Diana, E. Lochin, L. Franck et al., Dtn routing for quasi-deterministic networks with application to leo constellations. Int. J. Satell. Commun. Netw. **35**, 91–108 (2017)
30. D.B. Chen, R. Xiao, A. Zeng et al., Path diversity improves the identification of influential spreaders. EPL **104**, 68006 (2013)
31. I. Vragović, E. Louis, A. Díaz-Guilera, Efficiency of informational transfer in regular and complex networks. Phys. Rev. E **71**, 036122 (2005)
32. V. Latora, M. Marchiori, A measure of centrality based on the network efficiency. New J. Phys. **9**, 188 (2007)
33. E.C. Fieller, H.O. Hartley, E.S. Pearson, Tests for rank correlation coefficients. Biometrika **44**, 470 (1957)
34. J. Yan, L. Xing, P. Wang et al., A scheduling strategy to inter-satellite links assignment in gnss. Adv. Space Res. **67**, 198–208 (2020)
35. L. Sun, Y. Wang, W. Huang et al., Inter-satellite communication and ranging link assignment for navigation satellite systems. GPS Solut. **22**, 38 (2018)

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Submit your manuscript to a SpringerOpen journal and benefit from:

- ► Convenient online submission
- ► Rigorous peer review
- ► Open access: articles freely available online
- ► High visibility within the field
- ► Retaining the copyright to your article

Submit your next manuscript at ► springeropen.com