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Identification of Key Nodes in Aircraft State Network Based on Complex Network Theory

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ABSTRACT With the development of aviation, the air traffic density in the terminal area is high and the traffic situation is relatively complex, which brings challenges to the flight deployment. In order to fully understand the air flight situation and provide decision-making basis for controllers, this paper proposes a key conflict aircraft identification method based on complex network theory and node deletion method. First, an aircraft state network is constructed with an aircraft as nodes and airborne collision avoidance system (ACAS) communication relations as edges. Network efficiency, network robustness, connection density, and largest component were used as the indexes of network performance. The weight of each index is determined by using AHP-entropy weight method. A multi-attribute decision-making method was introduced to quantify network performance. Then we used a node deletion method to determine key conflict aircrafts. The simulation and experiment are respectively carried out on the artificial network and the aircraft state network of a certain day in the terminal area of Kunming Changshui Airport. The results show that the method proposed in this paper can identify the key conflict points in the aircraft state network. The deployment of selected nodes can not only effectively reduce the complexity of the flight state network, but also provide a reference for air traffic control services and reduce the control difficulty of the controller.

INDEX TERMS Aircraft state network, complex network, node deletion, air traffic control (ATC).

I. INTRODUCTION

In recent years, the civil aviation transportation industry has developed at a high speed, the air traffic flow (ATF) is increasing, and the airspace environment is becoming more complicated. These have brought tremendous deployment pressure to the controller. Accurate analysis of the current air flight situation can effectively reduce the control difficulty by providing assistant decision-making for controllers. This has also become a hot issue in the modeling and evaluation of current air traffic situation. In order to solve this problem, people use the controller workload, clustering algorithm, intrinsic attributes and other methods to describe the air traffic situation, to understand and master the basic laws of air traffic.

With the rapid development of complexity science, complex network theory has been widely applied in various fields. The research on air traffic using complex network theory has also become a hot topic. ZHANG made a detailed analysis of foreign methods and theoretical achievements on air traffic complexity [1]. In his research, he summarized the strengths and weaknesses, as well as the problems should be solved in the future. This has laid a foundation for the study of air traffic complexity. After that, WANG applied the complex network theory to the research of air traffic complexity [2], [3], and ATF complexity [4]. However, these researches mainly focus on the overall situation of airspace, and the relationship between agents behavior and the airspace situation is relatively few. In this study, a flight state network is established: aircraft are taken as nodes, ACAS communication is established between aircrafts as edges. Analyze the influence of each aircraft on the whole network.

In the study of complex networks, it is found that a few nodes play the role of "key nodes" [5], [6]. These nodes play an irreplaceable role in network performance and often determine the structure and function of the network. On the one hand, it can improve the survivability of the power grid [7], [8] and the Internet of Things (IoT) [9] by improving key nodes. On the other hand, it can also destroy some networks by deliberately attacking these nodes. For example,

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in preventing the spread of diseases [10] and subgraph robustness of complex networks under attacks [11]. Similarly, in the aircraft state network, the adjustment of a few aircraft will have a great impact on the current aircraft state structure. The deployment of these aircrafts will quickly relieve air traffic congestion and reduce air traffic complexity. How to find out these key nodes is the core problem to be solved in this paper.

At present, there are many researches on the identification of key nodes. The main method is to sort the nodes in the network according to some attributes of nodes, among which the first one is the key node. These attributes can be divided into two categories: node metrics and network metrics.

Some node metrics are introduced in [12], [13]. Reference [14] proposed the node contraction method to evaluate the node importance in complex networks. On this basis, Refs. [15], [16] comprehensively considered the influence of edge weights and proposed a node contraction method to improve the weighted network. This method was later applied to the road traffic network in [17]. Reference [18] adopts FCM algorithm to evaluate the key nodes of complex traffic network with node betweenness and node degree as indexes. Node metrics are simple but inefficient. Because it looks relatively simple, it ignores the overall characteristics of the network and cannot quantify the importance weight of nodes.

Typical network metrics mainly include degree centrality [19], closeness centrality [10], betweenness centrality [20], clustering coefficient [21] and so on. Each evaluation index evaluates the importance of nodes from a specific aspect and perform well in identifying key nodes. For example, Reference [22] use largest component and the clustering coefficient to find overlapping nodes in complex networks. Reference [23] proposes a method to determine the key nodes of complex networks by using the importance evaluation matrix. And then Reference [24] redefines the weighted network node importance contribution matrix and the node importance evaluation matrix. NAN applied the improved Page Rank algorithm to the protein interaction network to measure the importance of junctions [25]. Based on the network topology and the biological information characteristics of PPI (protein-protein Tnteraction) network, GUAN gives a key node search algorithm [26]. CAI proposed a node importance ranking algorithm based on improved kernel entropy theory [27]. On the basis of complex network theory and node deletion method, we proposed a ''No Return'' method to identify key nodes in the aviation network [28]. Then, the LS-SVM is used to speed up the algorithm [29]. Based on the entropy method theory REN identify the key points with great influence in the route [30].

The degree of damage caused when a node is removed from the network is equal to its importance. Node deletion method [31] is the most typical kind of system analysis, it avoids some problems resulted from unreasonable choice of attributes and indexes in network analysis by reverse thinking. The identification of key nodes of aircraft state network is precisely to guide the aircraft at this node to break away from the current network and reduce the complexity of air traffic. So it is of great practical significance to use node deletion method to sort the importance of nodes.

For node deletion method, the other fundamental problem is evaluating the network performance [32], [33] when a node isremoved. Most of these methods measure nodes importance by comparing network connectivity before and after removingnodes. Corley and Sha proposed ''shortest path'' [34]–[37], and measured the extent of the damage to network due to theremoval of node by comparing the change of the shortest path. Yong-Chen proposed ''spanning tree'' [38]–[41], measuredit by change of spanning trees' number. Since the characteristics of the aircraft state network, the density is an important index which cannot be neglected. On the basis of network robustness researches and aircraft state network reality, we propose four indexes: efficiency, robustness, connection density and largest component [42], [43] to calculate network overall performance. Evaluating node importance by comparing the change of network overall performance before and after deleting nodes.

The remainder of the paper is organized as follows. In Section 2, an aircraft state network is established. In Section 3, 4 indexes were chosen and the network performance was evaluated based on multi-attribute method. In section 4, the whole proposed method flow is introduced. In Section 5, the effectiveness of our method is verified by artificial network and actual network. Finally, this paper is concluded in Section 6.

II. AIRCRAFT STATE NETWORK MODEL

In complex network theory, the network $G = (V, E)$ refers to a collection of nodes and edges connecting nodes, $V = \{v_i | i = 1, 2, \ldots, n\}$ stands for the n nodes. $E = \left\{e_{ij}(v_i, v_j) \,|i \neq j \,, v_i, v_j \in V\right\}$ is the set of edges. The 'n' is the number of nodes in the network.

In the aircraft state network, as shown in Fig.1(a), nodes are aircraft, edges refers to the ACAS connection between aircraft. In other words, ACAS communication was established between aircraft to obtain flight information. And this model takes into account the relative distance between aircraft, and as a platform for conflict detection and resolution (CD&R) warning in the pre-tactical stage, aircraft with good interval are excluded, which can effectively reduce the frequency of CD&R.

According to ICAO document 8168 [44], ACAS interrogates other transponder-equipped aircraft within a nominal range of 26 km (14 nm). In the aircraft state network, $e_{ij} = e_{ji}$, that is, the network belongs to an undirected network. As a separate entity existing in the network, aircraft is also the meaning of the actual existence of the network.

The relationship between nodes in the network can be represented by adjacency matrix $A = \left(a_{ij}\right)_{n\times n}$.

$$a_{ij} = \begin{cases} 1 & \left(v_i, v_j\right) \in E \\ 0 & \left(v_i, v_j\right) \notin E \end{cases} \quad (1)$$

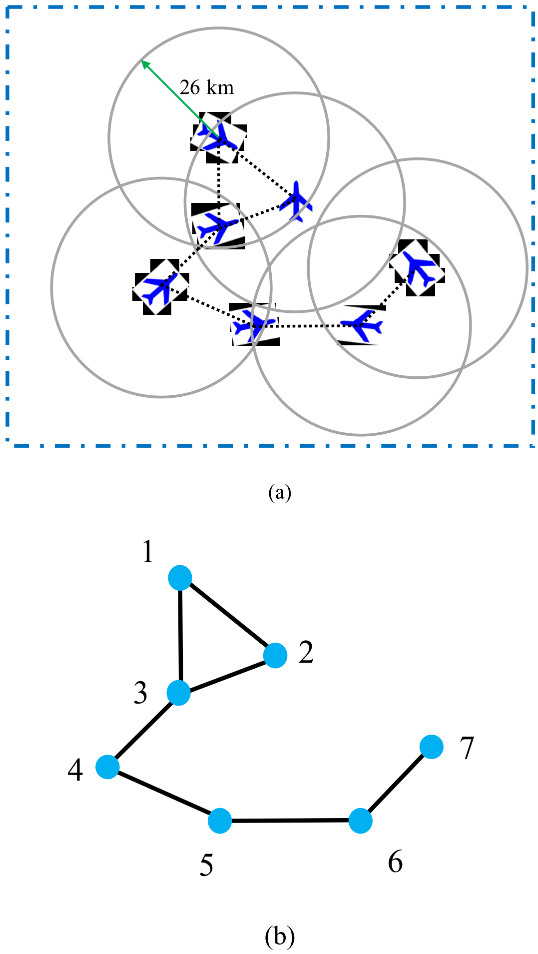

FIGURE 1. Model of aircraft state network. (a) Flight situation. (b) Topology structure.

As shown in Fig.1(b), the adjacency matrix of the network can be expressed as:

$$A = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \tag{2}$$

In the operation of air traffic control, aircraft that have a great impact on the network should be guided out as soon as possible to avoid the deterioration of the air traffic situation. According to the actual situation, we use the node deletion method to compare the node importance. After deleting a node, we calculate the network performance and compare it with the original network. The greater the change in network performance, the more important the node is.

To illustrate this method further, a flow chart was given as in Fig.2.

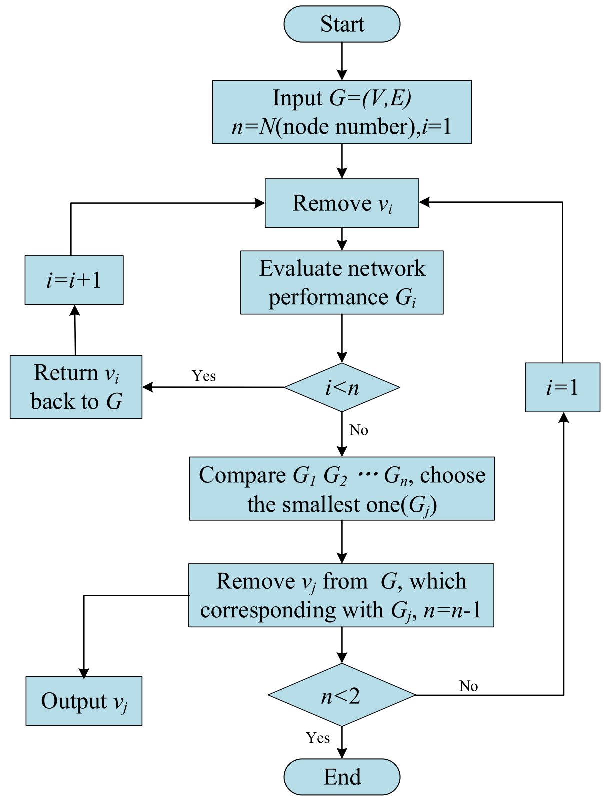

FIGURE 2. Node deletion method.

III. EVALUATION OF NETWORK

A. INDEX DEFINITIONS

The network performance corresponding to the node is the performance of the network after the node is deleted. We need to evaluate the network performance when a node is removed from the network, so as to calculate how much destruction it caused. The evaluation of network overall performance need to be comprehensive and objective, according to the existing identification methods of key nodes in complex networks and the basic characteristics of aircraft state networks, this paper selects network efficiency, network robustness, connection density and largest component as the four typical overall performance indexes. The above indexes basically reflect all the information of static network performance and can objectively evaluate the key nodes of aircraft state network. The detailed introduction is as follows:

1) NETWORK EFFICIENT (NE)

Network efficiency is the average of the reciprocal sum of distances between all nodes.

$$NE = \frac{1}{n(n-1)} \sum_{i \neq j} 1/dij \tag{3}$$

where n is the total number of nodes in the network and dij is the shortest path distance between nodes v_i and v_j. The distance between two nodes in a graph is the number of edges in a shortest path (also called a graph geodesic) connecting them. This is also known as the geodesic distance. And it is calculated from the inverse of path distance between nodes, therefore avoiding the meaningless definition in non-connected graphs. Network efficiency can reflect the difficulty of network information transmission. The larger NE is, the closer the distance between nodes is, and the more likely flight conflicts will occur in the network.

2) NETWORK ROBUSTNESS (NR)

The network robustness [45] is used to measure the average influence of the ability to maintain connectivity between the nodes in the network. That is, the ratio of the actual number of connected edges in the network to the theoretical maximum number of connected edges in the network. The calculation formula of the network robustness NR is:

$$NR = \frac{1}{n\,(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} \tag{4}$$

where n represent that number of remain nodes, a_{ij} represents the connection relationship between nodes in the network.

3) CONNECTION DENSITY (CD)

In an unweighted network, connection density refers to the ratio of the existing connection edge to the possible connection edge in the network [46]. For aircraft state networks, this paper defines weighted connection density:

$$CD = \frac{\sum_{i}^{n} \sum_{j}^{n} a_{ij} w_{ij}}{n(n-1)} \tag{5}$$

$$w_{ij} = 1 \big/ l_{ij} \tag{6}$$

where n is the total number of current network nodes. l_{ij} is the distance between v_i and v_i. It can be seen that if CD is larger, the overall heterogeneity is higher, the network traffic is larger, and the network structure is more complex.

4) LARGEST COMPONENT (LC)

A sub-graph is a part of a network in which there is one or more paths between all node pairs. If the graph is non-connected, it can be divided into two or more subgraphs. Among these sub-graphs, the one with the most nodes is the largest component S:

$$LC = |S| \tag{7}$$

where $|S|$ is the size of the largest component. Generally speaking, the more nodes in the largest component, the higher the complexity of the aircraft state network.

B. AHP- ENTROPY WEIGHT METHOD

1) AHP METHOD

According to the contribution degree of the selected network topology index relative to the key nodes of aircraft state network, pairwise comparison is made. A represents the importance degree of index i compared with index j, and judgment matrix is constructed.

The value method of c_{ij} in the judgment matrix is shown in table 1:

TABLE 1. Fundemental Scales.

c_{ij}	The importance of index i compared with j
1	i is as important as j
3	i is slightly more important than j .
5	i is important than j
7	i is more important than j
9	i is extremely important compared with j

Note: 2, 4, 6 and 8 are the intermediate values of two adjacent judgments

TABLE 2. The RI value of the matrix order.

Matrix order	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

The inconsistency index is calculated by CI. The smaller CI is, the greater the consistency is. If $CI > 0.1$, the judgment matrix should be adjusted again until it passes the consistency test.

$$CI = \frac{[\lambda_{\max} - m]}{m-1} \tag{8}$$

$$CR = \frac{CI}{RI} \tag{9}$$

$\lambda_{\max}$ is the maximum eigenvalue of the break matrix, m is the number of evaluation index,RI is the average random consistency index. The value of RI is related to the order of judgment matrix, and Saaty has given RI values corresponding to partial matrix orders, as shown in table 3:

Then the weight of each evaluation index can be express as:

$$W_j = \frac{x(j,d)}{\sum_{i=1}^{m} x(j,d)}, \quad j = 1, 2, \cdots m \tag{10}$$

x is the eigenvector matrix of the judgment matrix, d is the column where the maximum eigenvalue is located and W_j is the weight corresponding to index j.

2) ENTROPY WEIGHT METHOD

In order to overcome the defects of subjectivity of AHP method and insufficient index identification ability [47], entropy weight method is introduced to correct the results.The entropy method [48] determines the index weight according to the variation degree of each index value, which is an objective weighting method and avoids the deviation caused by human factors. Therefore, the entropy weight method is used to revise the AHP method so as to make the evaluation result objective and accurate as far as possible. The algorithm steps are as follows:

① Establishing an original index data matrix

Let's say that the number of aircraft in the aircraft state network is n, the set of nodes is N, $N = (N_1, N_2, \ldots, N_n)$. The set of evaluation index is S, $S = \{S_1, S_2, \ldots, S_m\}$. The initial decision matrix formed by them is $G = (g_{ij})_{n\times m}$.

$$G = \begin{pmatrix} g_{11} & \cdots & g_{1m} \\ \vdots & \vdots & \vdots \\ g_{n1} & \cdots & g_{nm} \end{pmatrix} \tag{11}$$

where g_{ij} is the value of the j-th index of the i-th node.

② Standardize the original index data matrix

Due to the difference of magnitude of each data, the index are standardized by min-max:

$$b_{ij} = \frac{g_{ij} - g_{j\min}}{g_{j\max} - g_{j\min}} \tag{12}$$

$$c_{ij} = \frac{b_{ij}}{\sum\limits_{i=1}^{n} b_{ij}} \tag{13}$$

The decision matrix $C = \left(c_{ij}\right)_{n\times m}$ is obtained by standardize each element of the original index data matrix according to the above equation.

③ Calculate information entropy e

$$e_j = -k \sum_{i=1}^{n} C_{ij} \ln C_{ij} \tag{14}$$

$$k = 1\big/\ln m \tag{15}$$

④ Calculate the difference coefficient d (information utility value)

$$d'_j = 1 - e_j \tag{16}$$

Using entropy method, the difference coefficient d'_j of the j-th index can be calculated from equation (14). The larger the difference coefficient, the more important the index is and the greater the impact on the evaluation results.

In order to avoid the interference of other external factors,this paper is used to revise the aircraft state network in 10 same airspace, different dates and different times, and the obtained 10 groups of difference coefficients are averaged to obtain the final difference coefficients d_j.

⑤ Revise the AHP evaluation index weight and normalize it to obtain the final index weight:

$$H'_j = W_j \times d_j, \quad j = 1, 2, \cdots m. \tag{17}$$

$$H_j = \frac{H'_j}{\sum\limits_{i=1}^{m} H'_j} \tag{18}$$

C. EVALUATION BASED ON MULTI-ATTRIBUTE DECISION-MAKING METHOD

The change of network comprehensive performance is obtain by multi-attribute decision-making method [49]. Since our research is the network changes after different nodes are deleted, we regard deleting different nodes as a solution, then the evaluation indexes of network can be regarded as attributes of each solution, thus the evaluation of the network performance can be transformed into a multi-attribute decision problem, and the evaluation of the comprehensive performance of each solution is a decision criterion.

For comparison, the standard decision matrix $C = \left(c_{ij}\right)_{n\times m}$ obtained by equation (12) is adopted. As can be seen from equation (16), the weight of the j-th index is $H_j (j = 1, 2, \cdots m)$, $\sum H_j = 1$, based on standardized decision matrix C, weighted standardized matrix is formed:

$$Y = \left(y_{ij}\right)_{n\times m} = \left(H_j c_{ij}\right)_{n\times m} = \begin{pmatrix} H_1 c_{11} & \cdots & H_m c_{1m} \\ \vdots & \ddots & \vdots \\ H_1 c_{n1} & \cdots & H_m c_{nm} \end{pmatrix} \tag{19}$$

Based on TOPSIS method [50], positive ideal scheme A is decided according to matrix Y. The element in A are the maximum of each column of the matrix Y. Among all the schemes, A has the smallest reduction in comprehensive performance value after deleting:

$$\begin{aligned} A &= \left\{ \max_{i=1,2,\cdots,n} (y_{i1}\ y_{i2}\ \cdots\ y_{im}) \right\} \\ &= \{y_{1\max}\ y_{2\max}\ \cdots\ y_{m\max}\} \end{aligned} \tag{20}$$

Then, calculate the distance from each scheme A_i to the positive ideal scheme A:

$$D_i = \sqrt{\left[\sum_{j=1}^{m} \left(y_{ij} - y_{j\max}\right)^2\right]} \tag{21}$$

The greater the distance between scheme A_i and positive ideal scheme A, the greater the change in the comprehensive performance of the network after deleting node v_i, that is, the more important the node is.

IV. ALGORITHM PROCESS

A flight state network modeling method proposed in this paper identifies the aircraft with key conflict nodes, the method steps are shown in Fig.3:

In the key conflict node identification method based on the complex network theory, the weight of each index is preliminarily determined through AHP analysis, and the final weight [51], [52] is obtained after the entropy weight method is revised. The comprehensive performance of the network is determined through multi-attribute decision-making, and the key conflict node is determined by comparing the changes after node deletion. There are mainly the following five steps:

- *Step 1:* A weighted network of flight states is constructed. With aircrafts as nodes, the aircrafts in ACAS communication range from connected edges, and the reciprocal of the distance between aircrafts is the edge weight.
- *Step 2:* Calculate topological index. Select a complex network topology index that can fully reflect the network performance and evaluate the network.

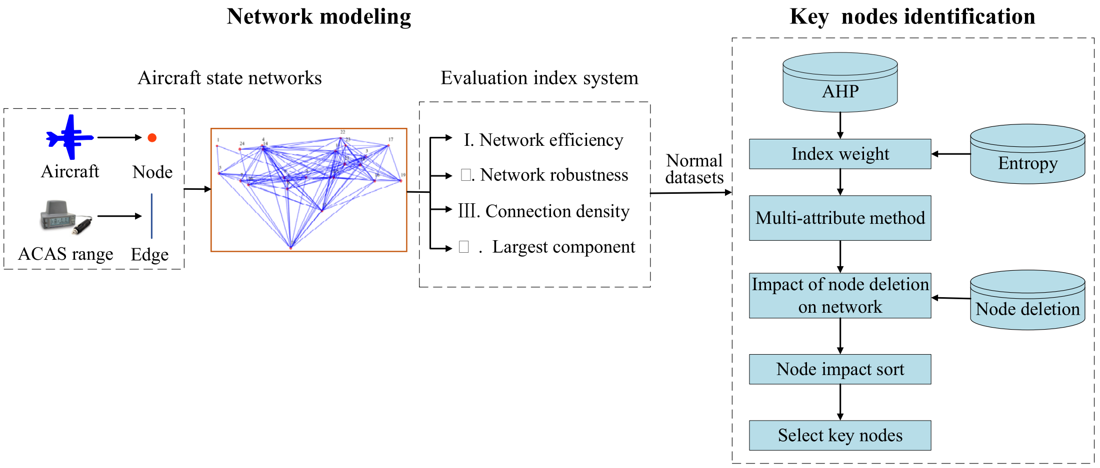

FIGURE 3. Algorithm process.

TABLE 3. The comparative results of the Index.

C	*NE*	*NR*	*CD*	*LC*
NE	1	1/5	1/4	1/3
NR	5	1	3	3
CD	4	1/3	1	2
LC	3	1/3	1/2	1

- *Step 3:* Determination of index weight. Based on AHP method, the weight of each index is preliminarily analyzed and determined, and the entropy weight method is used for correction.
- *Step 4:* Multi-attribute decision-making. Based on TOPSIS multi-attribute decision making, the comprehensive performance of flight state network is determined.
- *step 5:* Identification of key nodes. The comprehensive performance changes of the network after different nodes are deleted are compared to determine the key nodes.

V. SIMULATION AND ANALYSIS

A. SOLVING INDEX WEIGHT

According to the analysis results of each index in section 3, the original judgment matrix is established, as shown in Tab.3:

So the judgment matrix is:

$$C = \begin{pmatrix} 1 & 1/5 & 1/4 & 1/3 \\ 5 & 1 & 3 & 3 \\ 4 & 1/3 & 1 & 2 \\ 3 & 1/3 & 1/2 & 1 \end{pmatrix} \tag{22}$$

Weight vector is obtained from AHP: $w_i = (0.0708, 0.5141, 0.2514, 0.1637)$. Then, the final weight vector is obtained through the entropy weight method: $v_i = (0.140, \ 0.420, \ 0.268, \ 0.172)$.

TABLE 4. Weight distribution of evaluation index.

Index	*NE*	*NR*	*CD*	*LC*
Weight	0.140	0.420	0.268	0.172

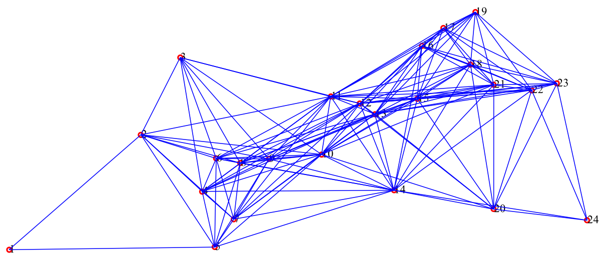

FIGURE 4. Aircraft state network topology.

According to Eqs.(13), $CR = 0.0333 < 0.1$, which satisfies the consistency check. So the weight values of each index are shown in Tab.4.

B. IDENTIFICATION IN ARTIFICIAL NETWORK

In order to verify the effectiveness of the method, a simulated flight state network with 24 nodes is generated by Matlab 2016a, as shown in Fig.4, and tested.

In the same way, the node deletion method is adopted. First, the importance value of all nodes is calculated, and the maximum value is selected as the key node. Then, the node is deleted and the importance value of each node is recalculated. By analogy, the importance ranking of all nodes is given. The ranking results are shown in Tab.5. In this paper, we also give the node importance ranking results obtained by: the closeness, degree centrality, and the [53] method. Unlike the proposed method, the reference [53] adopts a 'return' node deletion approach: the deleted node is put back after calculating the node importance.

When nodes are removed from the network according to the node importance ranking of the node deletion method and the normal method, the change trends of the four evaluation

TABLE 5. Node importance ranking.

Method	Node importance ranking
Closeness	12>11>10>13>14>15>6>2>5>1>4>9>7>3>8>22>23>18>21>16>17>19>20>24
Degree centrality	11>12>13>10>14>15>2>5>22>23>18>21>4>6>8>17>9>16>20>1>3>7>19>24
Ref. [53] method	10>12>15>14>16>13>11>3>4>18>7>17>21>2>22>5>20>6>23>24>19>1>9>8
Node deletion	10>14>12>15>16>13>3>11>23>17>4>1>7>18>19>24>2>5>9>6>8>20>21>22

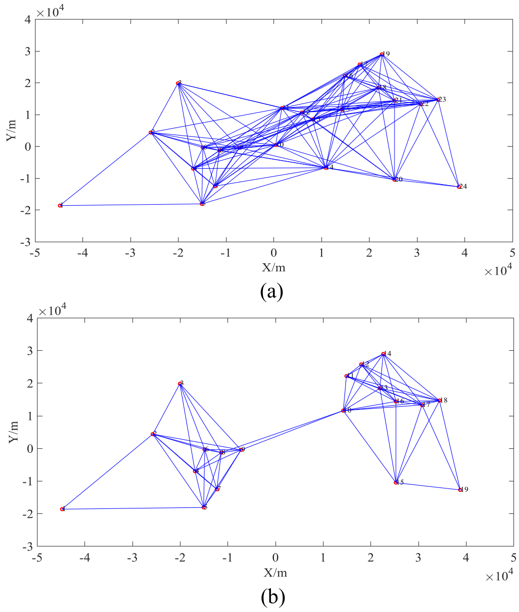

FIGURE 5. Comparison of network structure before and after key node deletion. (a) Original network structure. (b) The network structure after key nodes are deleted.

indexes are shown in Fig.6(a) to 6(d). As can be seen from the figure, as nodes are removed from the network one by one, the robustness, efficiency, maximum connectivity subgraph and connection density of the simulated flight state network continue to decline. Obviously, most curves of the node deletion method are located below the normal method, that is, when the same number of nodes is deleted, the node deletion method has a greater impact on the network.

In order to show the advantages of this method over other methods, nodes are removed according to the node importance ranking of node deletion method, normal method, closeness method and degree centrality method, and the overall performance curve changes of four different methods are compared as shown in Fig.7. As the number of deleted nodes increases, the overall network performance of each method steadily decreases. However, when nodes are removed according to the node deletion method, the overall performance decreases significantly faster.

The aircraft impact the overall air traffic situation in different degrees. This also reflects the different importance degrees among nodes, which is called a nonhomogeneous network. Thus network structure entropy is introduced to measure whether the influence degrees of aircraft on the whole traffic situation are homogeneous. The network structure entropy is a macro-index measuring the topological nature of a network and describes the homogeneity or not of node degrees.

$$E_s = -\sum_{i=1}^{n} I_i \ln I_i \tag{23}$$

$$I_i = k_i \Big/ \sum_{j=1}^{N} k_j \tag{24}$$

where E_s is the structure entropy of an aircraft state network; n is the number of aircraft; and I_i is the ratio of the node degree(k_i) of aircraft i to the sum of all node degrees.

The larger the structure entropy, the higher homogeneity of node degrees. Fig.8 shows the structure entropy change of after node removal when node importance are sorted according in different methods.

As can be seen from the figure, when the first 10 nodes are deleted, the network structure has little difference. Starting from the 11th node deletion, the node deletion method proposed in this paper shows its advantages, and the network structure entropy decreases rapidly.

C. IDENTIFICATION IN ACTUAL NETWORKS

In the actual work of air traffic control, all flight situations in the airspace under its jurisdiction are displayed on the radar control screen, as shown in Fig. 9:

Using radar data to model the flight state network can restore the current radar screen information. In order to further verify the effectiveness and practicability of the aircraft identification method for key conflict nodes in this paper, we took the radar data of the terminal area of Kunming Changshui airport as the sample for analysis. Radar data in a random time period were selected and the flight state network was modeled every 5 minutes. Key conflict aircraft identification in each scenario is shown in Fig. 10 (a)-(f):

The bigger red dot in the figure is the key conflict aircraft. Most of the five nodes are distributed on the approach routes near the center of the sector. These nodes are located in the center of the network and have many neighbor nodes, which have strong ability to affect the network performance. In Fig.9(a), even five nodes are distributed in the center. In addition, although a small number of nodes are not located closest to the center, they have a common characteristic: they are separated from the adjacent aircrafts by a small distance, i.e. the edge weights of the connected edges are very large.

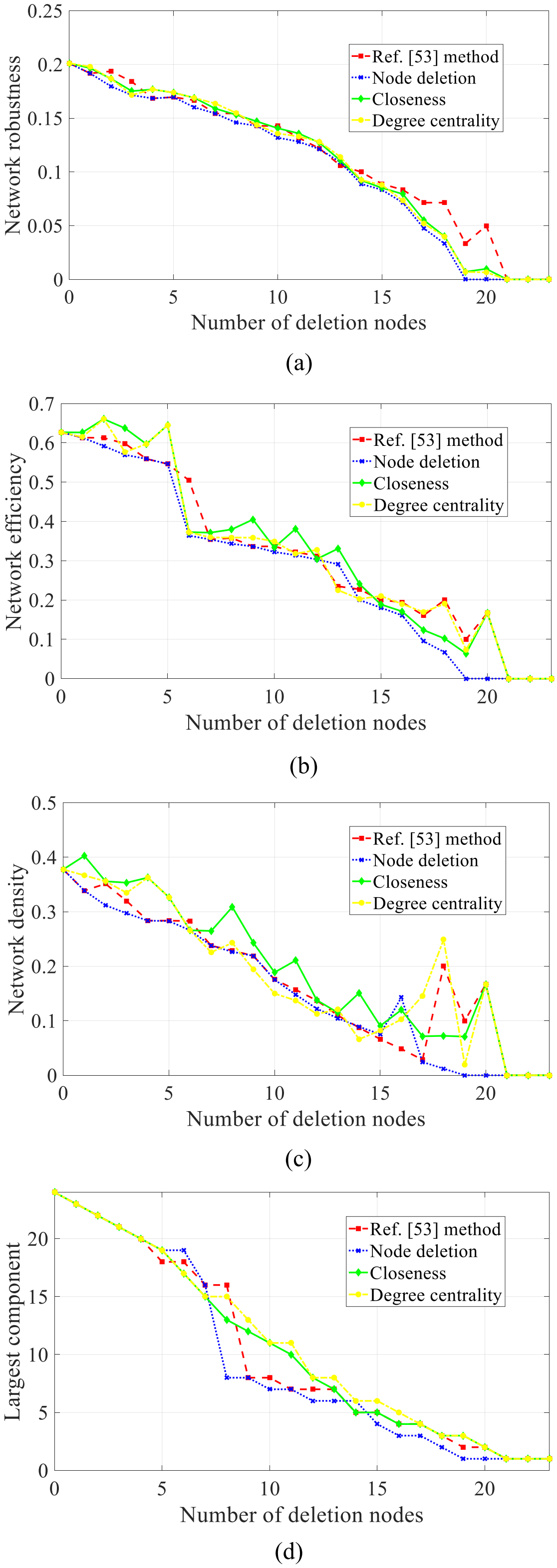

FIGURE 6. Changes in network indexes. (a) Robustness analysis. (b) Efficiency analysis. (c) Network density analysis. (d) Largest component analysis.

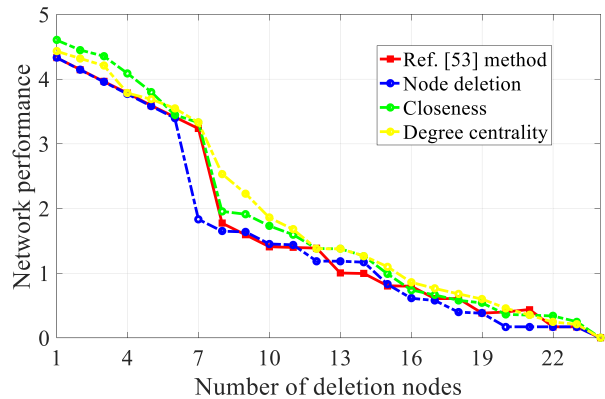

FIGURE 7. Change of network comprehensive performance.

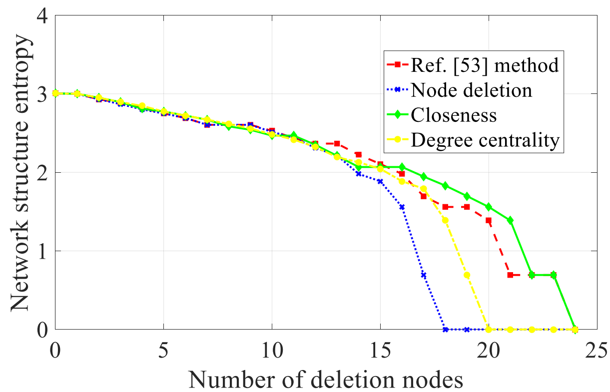

FIGURE 8. Network structure entropy analysis.

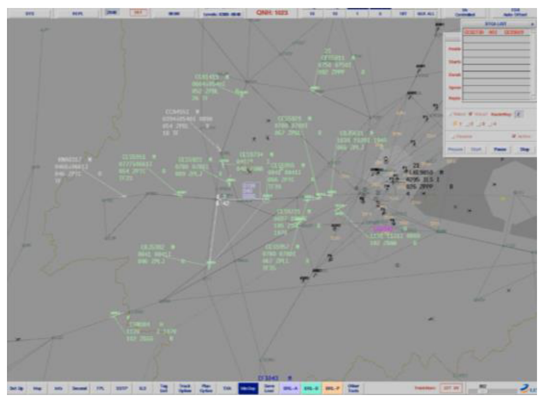

FIGURE 9. Real-time scene of radar control.

The characteristics of these nodes are well captured by the network topology index, which reflects that the key conflict node identification method in this paper considers the macro-scale and individual micro-scale of the network comprehensively and verifies the effectiveness of this method.

Table 6 shows the comprehensive network performance values after removing the first five key nodes after sorting the nodes by various methods. Obviously, in each scenario, the network performance obtained by the node deletion method is the smallest.

Fig.10 shows the identification result of the key conflict aircraft at 17 min 30 s, i.e. Fig.9(c). From Table 8, we can get the scores of each evaluation index of the five key aircrafts. The node degree of each aircraft exceeds 10, and the weighted

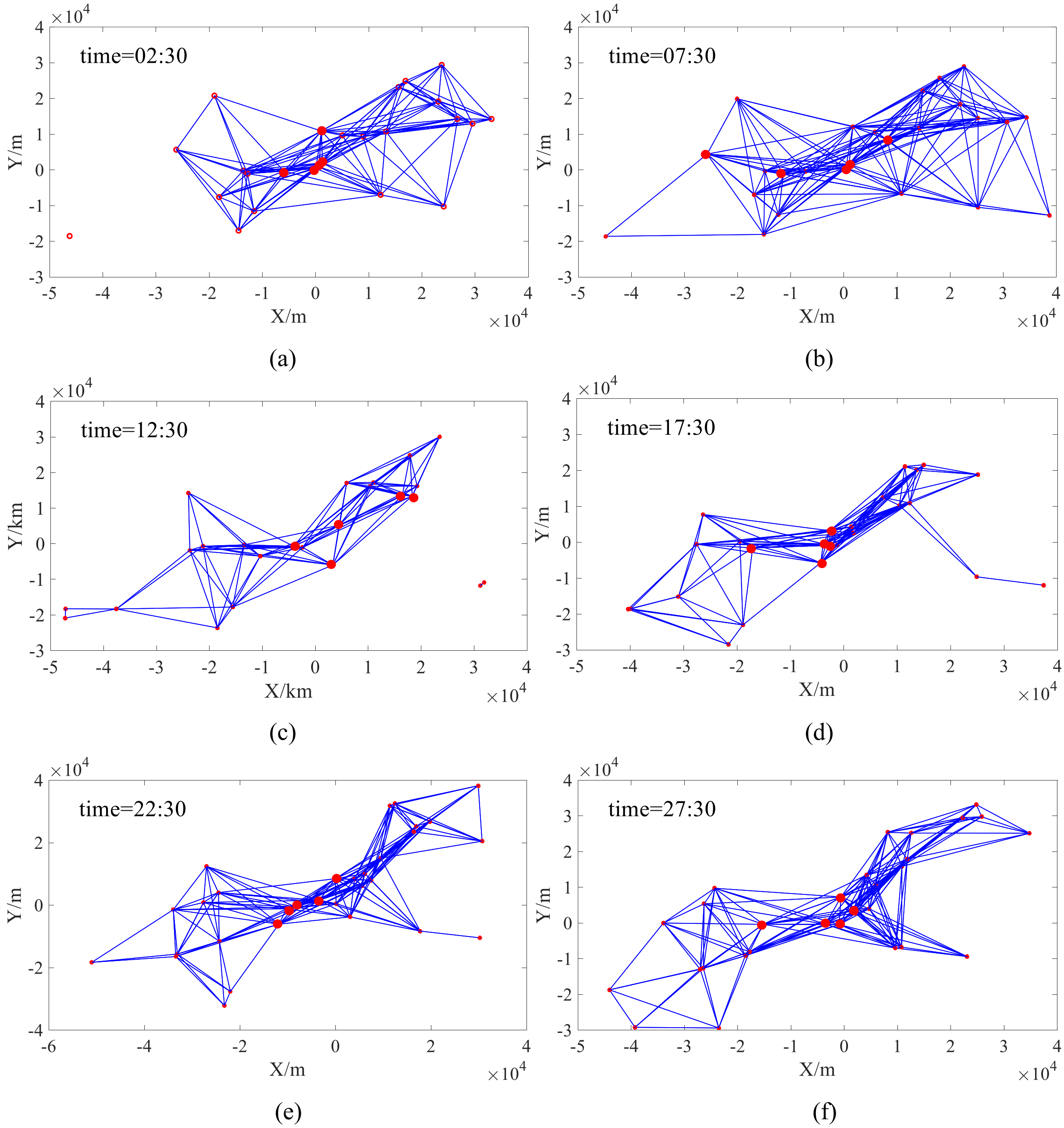

FIGURE 10. Aircraft state networks at different times. (a) time 02 min 30 s. (b) time 07 min 30 s. (c) time 12 min 30 s. (d) time 17 min 30 s. (e) time22 min 30 s. (f) time27 min 30 s.

TABLE 6. Comparison of network complexity before and after removal the key nodes.

Time	Original complexity	Complexity after removing the first five key nodes			
		Closssness	Degree centrality	Ref. [53] method	Node deletion
02 min 30 s	4.5	3.76	3.56	3.36	3.32
07 min 30 s	4.8	4.01	3.92	3.79	3.76
12 min 30 s	4.3	3.62	3.34	3.44	3.23
17 min 30 s	4.4	3.90	3.73	3.62	3.44
22 min 30 s	4.6	3.86	3.65	3.61	3.56
27 min 30 s	4.7	3.84	3.96	3.82	3.73

clustering coefficient is 0.66 at the minimum and even 0.93 at the maximum. It can be seen that the flight environment around these five aircrafts is very complex, and the number of aircrafts around the key conflict aircrafts is large and the distance is very close. From the table, it can be seen that the node degree of the aircraft ranked 3rd is less than that

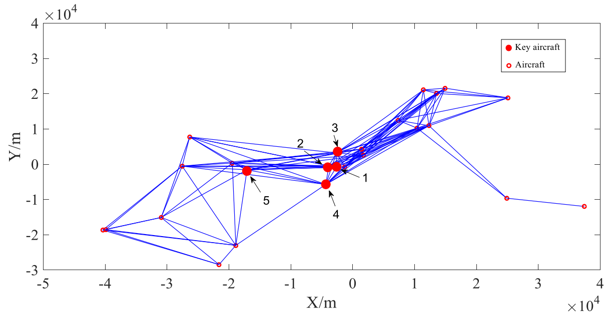

FIGURE 11. Identify the key aircraft nodes.

TABLE 7. Node index score.

Ranking	Node degree	Node weight	Weighted clustering coefficient	Node betweenness
1	18	2.7421	0.7124	0.0298
2	18	2.4347	0.7124	0.0114
3	16	1.8429	0.8000	0.0265
4	17	1.2230	0.6618	0.0200
5	13	0.4616	0.9286	0.0132

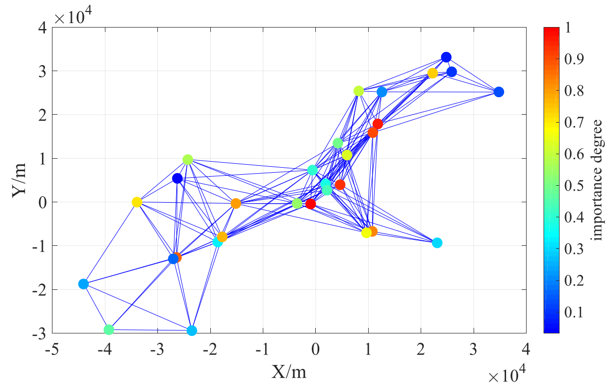

FIGURE 12. Aircraft state network situation.

of the aircraft ranked 4th, but the node weight, weighted clustering coefficient and node betweenness are larger. Therefore, the aircraft is of higher importance. If we do not pay attention to the monitoring and deployment of these key aircrafts, it is easy to cause conflicts with other aircrafts around.

The current airspace flight situation at 27 min 30 s is given according to the node importance, as shown in Fig.11. Red indicates nodes with more complicated flight situations. If the aircraft is not guided correctly, flight conflicts will easily occur and the safety situation of the entire airspace will be destroyed. From the figure, the controller can easily obtain the current airspace situation information, each point represents an aircraft, and different colors represent the importance of nodes.

VI. CONCLUSION

In this paper, an aircraft state network model is established based on complex networks, and a node deletion method is proposed to identify key conflicting nodes in the network. In order to verify the recognition effect of the proposed method on key nodes, we compare the recognition effect with other methods. The results show that the method has better recognition effect on key conflict nodes. Identifying the key aircraft that make up the aircraft state network can not only help the air traffic management department to determine the focus of Air Traffic Control (ATC) in its daily operation. In addition, in emergency management, the controller can be helped to finish the allocation of emergency resources in a focused and targeted manner, so that the air traffic management work can be carried out in an orderly manner.

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