Eleventh USA/Europe Air Traffic Management Research and Development Seminar (ATM2015)

Topological characteristics of air traffic situation

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***Abstract*—A method for description of structural characteristics of air traffic situation based on the theory of complex network was proposed. This method characterizes the air traffic situation from three dimensions, including single aircraft, local sector, and overall sector. This work provides a new clue for precise description of air traffic situation complexity. We selected the routinely-recorded flight data in an air traffic control sector within China's airspace in 2013. With the aircraft in the sector regarded as node, and with the between-aircraft proximity relations as edge, we constructed an undirected and unweighted aircraft network. The air traffic situation network under three thresholds were statistically analyzed using network topology indices including degree, edge, connection rate, clustering coefficient, and network structure entropy. The results show that network node degree can distinguish the key aircraft in the sector; the network connection rate reflects the proximity of aircraft; the clustering coefficient identifies the presence of high-density aircraft group; the network structure entropy reflects the homogeneity of aircraft node degrees.**

Keywords-air traffic management, air traffic situation, complex network, topological characteristic,airspace complexity

I. INTRODUCTION

The basic task of the air traffic management system is to guarantee the safety of air traffic. When two or more aircraft are approaching, the controller must observe the proximity between them, understand the danger degree of air traffic situation, and take corresponding solutions immediately. Thus, description of this between-aircraft proximity relation, quantitative analysis of air traffic situation, and description of the difficulty brought by different traffic situations to controllers are all very important. Currently, the concept of air traffic complexity is usually used to describe the air traffic situation.

In the existing air traffic control (ATC) systems, the airspace is divided into several sectors, and each controller is responsible for the flight safety in the sector. Thus, characterization of air traffic situation based on air traffic complexity should be founded on assessment of the controller's work load. The number of aircraft in a sector as the basic characteristic of air traffic is the basis for studying and assessment of the controller's work load, and is also the first accepted indicator that reflects air traffic complexity[1-3]. Besides the number of aircraft in a sector, many other indicators are correlated with a controller's work load, such as airspace structure and traffic flow characteristics[4]. The airspace structure covers the physical structure of airspace, including terrain structure, number of air routes, and number of intersections. Traffic flow characteristics include type mixing degree of aircraft, proportion of climbing aircraft, proportion of declining aircraft, and proportion of convergent aircraft. These spatial structure and traffic flow factors jointly interact to form the overall air traffic complexity[5-8]. The complexity of air traffic systems has been intensively studied from the perspective of complex systems. Based on aircraft tracking information (e.g. location and velocity), the basic intrinsic characteristics of air traffic situation (e.g. relative distance and relative velocity) can be computed. Then the mathematical description of between-aircraft influence relations is formed, and the complexity of single aircraft pair could be computed. Then indicators such as fractal dimension and Lyapunov exponent are used to describe the irregularity of between-aircraft influence relations, which serve as a measure of air traffic complexity[9,10]. Based on aircraft approaching effect and conflict effect, two algorithms for computation of sector complexity were proposed[11]. Regarding the impacts of abrupt disturbance on the between-aircraft relation in the original region, a complexity model based on traffic flow disturbance was proposed, which defined the complexity degree as a measurement reflecting the control activities needed by a controller in response to emergency[12-14]. Targeted at the characteristics of future ATC systems, the air traffic complexity based on flight path movement was analyzed[15-17]. Moreover, a dynamic model about the evolution of air traffic situations was built on basis of between-aircraft influence relations, and by describing the irregularity of traffic organization as topological entropy, a novel standard for measurement of air traffic complexity was built[18,19].

The above studies focus on the complexity of air traffic situations from different perspectives, but ignore the between-aircraft proximity from the perspective of structure. In fact, the structural characteristics of air traffic are the basic characteristics of air traffic situations, and can more delicately describe the proximity relations between two or more aircraft in a sector. Figure 1 illustrates three air traffic situations with different network structures, with 5 aircraft under each situation. Specifically, the between-aircraft distances in Figure 1(a) are large, without too close proximity relations; the between-aircraft distances in Figure (1b) are small, which will interfere with the allocation of beforehand conflicts by the controller. The between-aircraft distances in Figure (1c) are smaller with some ring-like structures, which further complicates the controller in formulation of appropriate solutions to conflicts. Thus, despite the same air traffic density in the three situations in Fig. 1, the actual control difficulties for the controller largely differ, but such structural differences cannot be well reflected by the existing air traffic complexity indicators.

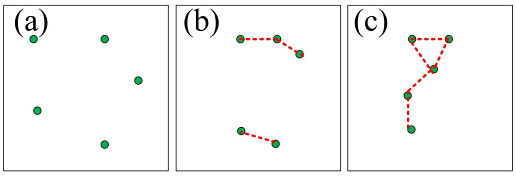

Figure 1 Air traffic situations with different network structures

Numerous complex systems in the nature can be described as networks. Complex networks are a method for abstraction and description of complex systems, and highlight the topological characteristics of system structures. Generally, any complex system containing abundant component units can be regarded as a complex network when the component units are abstracted into interrelated and abstract lines between nodes and units[20-22].

In this study, based on the theories and research methods of complex networks, the network models corresponding to air traffic situations at different time points were constructed. Abundant data were used as validation to investigate the structural properties of air traffic, aiming to probe into the characteristics of air traffic situations from a systematic perspective. Section 2 will introduce the air traffic network modeling methods and the data used in this study. Section 3 will analyze the structures of air traffic networks from multiple perspectives, including network degree, edge, clustering coefficient, and structure entropy, and will discuss the characteristics of air traffic situations reflected by these structural indicators. In this study, the theories and methods of complex networks were used to statistically analyze the air traffic situations. This study provides a new perspective for investigation into air traffic complexity, and helps to reveal the nature of air traffic situations.

II. METHODS AND DATA

Complex systems are widespread in the nature, society, organisms, engineering technology, and many other fields. The numerous complex systems in the real world can all be described as networks, such as traffic networks, communication networks, and cooperation networks. A complex network is an abstraction of abundant real complex systems, and thus can reflect the various interactions and relations inside the complex systems. The basis of complex networks is graph theory. A network can be defined as a graph G(V, E) composed of a node set V(G) and edge set E(G). Each edge e_i in E(G) corresponds to a pair of nodes(u, v). Each node in graph G represents an individual in the real network, and each edge represents the interaction between two individuals. The corresponding adjacent matrix in graph G is $A=[a_{i,j}]$. If node i and node j are connected, then $a_{i,j}=1$; otherwise $a_{i,j}=0$.

An air traffic system is essentially a complex system and thus can be abstracted and described from the perspective of complex networks[23]. In this study, with aircraft regarded as node, the spatial proximity relation between aircraft is expressed as undirected edge, and thereby, a corresponding air traffic situation network that represents the air traffic operation situation is constructed. If at time t, the horizontal distance between aircraft i and j is smaller than the preset threshold D, then it is considered that nodes i and j are connected via an edge, which is undirected and unweighted. As aircraft start to move, the between-aircraft distance relations also gradually change, and some aircraft will fly into or depart from the sector, indicating that the air traffic situation network is a dynamic relation network changing with time.

In this study, a sector controlled by an air traffic control station ZSAMAR02 from Civil Aviation Administration of China (CAAC) was selected. This is a medium- and low-altitude controlled sector, with altitude range of 5400-7800 km and horizontal separation minima of 10 km. The routinely-recorded radar data from 09:00 to 23:59 October 1, 2013 were collected, and the latitudes and longitudes of aircraft were computed. Then based on the information about the positions of aircraft, an air traffic network every 1 min was built, with a total of 900 networks. The number of nodes in a network is the total number of aircraft in the sector at that time. Under the limitation of the controller's work load, the scale of air traffic networks is not very large, and the numbers of nodes are generally smaller than 15. The change of traffic volume during specified time period is showed in Fig. 2. To characterize the structures of networks from different perspectives, we set three thresholds: 10, 30, and 60 km.

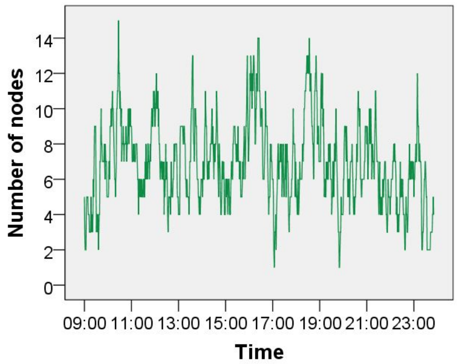

Figure 2. The change of traffic volume

III. NETWORK TOPOLOGICAL CHARACTERISTICS AND ANALYSIS

A. Degree

Degree is an important attribute for single nodes in a network. We set the total number of nodes in a network as N, and the degree of node i, marked as k(i), is defined as the number of edges connected to node i. In an air traffic network, degree represents the number of aircraft close to an aircraft and thus reflects the accessibility of this aircraft. A larger degree indicates a higher possibility that this aircraft may experience conflict, which should be paid high attention to. In the air traffic situation 1 in Fig. 3, the distances of aircraft P2 from aircraft P1/P3/P4 are all small. At the threshold D=60 km, k(P2)=3. On the contrary, the distances of aircraft P7 from other aircraft are all large, and then k(P7)=0.

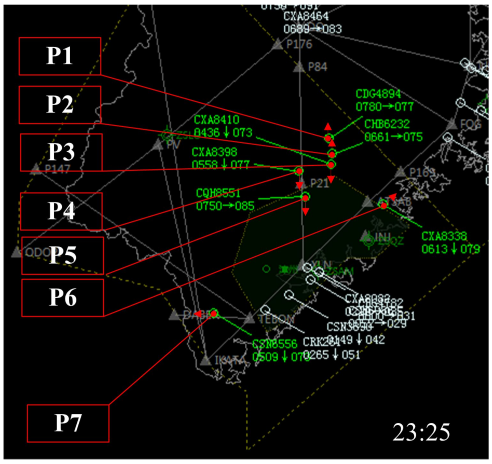

Figure 3. Air traffic situation 1

In most existing studies, the airspace congestion degree is defined as the number of aircraft in unit area or volume, and a larger such number indicates a higher congestion. This method is simple and applicable, but cannot differentiate the congestion degrees of different air traffic situations with the same number of aircraft. In this study, the congestion degree of air traffic situation at a time point was evaluated using the average degree, which is defined as the mean of degrees of all nodes in a network and reflects the average number of neighbors of nodes in the network. In air traffic, a larger number of neighbors indicates a smaller average distance between aircraft, and thus a larger airspace congestion degree. The curve of number of nodes corresponds to the average degree per hour was plotted and showed in Fig. 4. When the number of nodes is fixed, the hour-averaged means of degrees are not the same, which reflects the dynamic evolution of air traffic systems and indicates that the internal structures of air traffic situations with the same number of aircraft will be completely different. Moreover, at some periods, the network average degree with a small number of nodes is unexpectedly larger than that with a larger number of nodes. For instance, at 09:00, the mean of network average degrees with 6 nodes is 1.8, while the result with 7 nodes is 1.4. Similar situation occurred at 13:00, 14:00, 16:00 and 20:00. These results indicate that in some air traffic situations, a small number of aircraft unexpectedly results in a higher congestion degree than in the situation with a large number of aircraft. Thus, the network average degree can more finely describe the congestion degree of air traffic. As showed in Fig. 5, generally (though with some specific cases), the network average degree increases with the increasing number of nodes. Meanwhile, the network average degree is closely correlated with the preset threshold, since a too large threshold may induce more edges, which impacts the precision of determination, while with a too small threshold, some very important edges may be ignored. In practice, the threshold can be set as an appropriate multiple of the between-aircraft horizontal separation minima in that airspace.

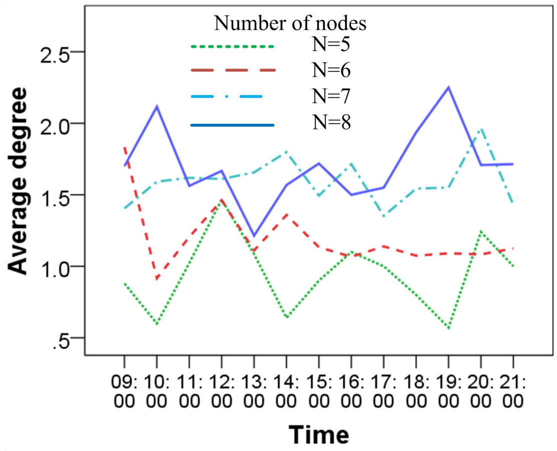

Figure 4. Curve of network average degree changing with time

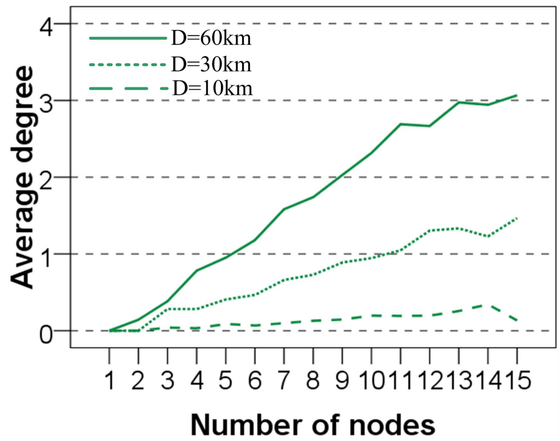

Figure 5 Growing curve of network average degree with the number of nodes

B. Edges, connection rate, and growth rate of edges

If the distance between two aircraft is smaller than the preset threshold, one edge exists between the nodes in the corresponding network. Thus, the number of edges in a network reflects the number of close aircraft pairs in the real air traffic. Connection rate also called network density is defined as the proportion of real edges accounting for the number of potential edges and thus describes the overall connectiveness of a network. Connection rate is computed as follows:

$$\rho = \frac{2 * E_l}{N * (N-1)} \tag{1}$$

where E_l is the number of edges in a network, and N is the number of nodes.

Similar to the network average degrees, the number of edges per unit time and connection rate can also be used as indicators for determination of between-aircraft proximity. A larger connection rate indicates higher interconnection degree between nodes. In real air traffic, a larger connection rate also indicates that a larger proportion of aircraft are distributed in small distances. At this moment, the possibility of potential conflicts is also high, and thus the controller should undertake more work load.

Fig. 6 shows the curve between the number of edges and the number of nodes in a network. Clearly, the number of edges increases with the increased number of nodes, which conforms to the real situation. Fig. 7 shows the distribution of connection rate. At D=60 km, the connection rate obeys a normal distribution with mean about 0.12. Under most situations, the connection rate is < 0.19, which is far smaller than that in the tree-like networks (about 0.3). Thus, under normal conditions, the number of connections in a network is within a specific range, and the minima and maxima account for a very small proportion. Moreover, a smaller threshold D means a smaller number of edges and a smaller connection rate (Fig. 6 and Fig. 7).

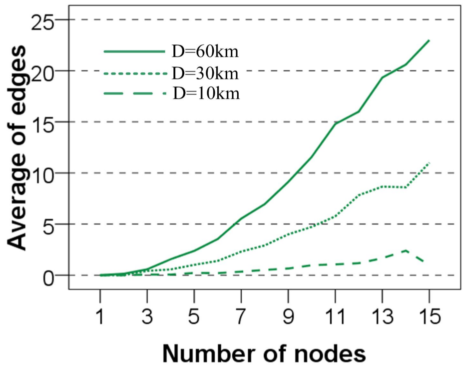

Figure 6. Relation between number of edges and number of nodes

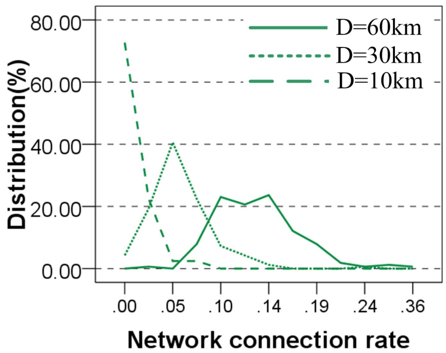

Figure 7 Distribution of connection rate

As reported, the key indicators reflecting the air traffic complexity include the level of convergence and divergence of many aircraft [10-12]. To reflect the between-aircraft convergent effect from the perspective of air traffic network structures, we propose an indicator of "growth rate of edges" in this study. This indicator means the increasing number of edges per unit time, which can be computed as follows:

$$\rho_g = \frac{E_l(t) - E_l(t-1)}{E_l(t-1)} \qquad (2)$$

Fig. 8 and Fig. 9 show two air traffic situations, and the aircraft with green marks were observed, where the red arrowhead indicates the moving direction of aircraft. Then the number of corresponding edges and the growth rate of edges in different situations were computed, and the results are showed in Table I. Situation 2a contains 6 edges: (P1,P2), (P1,P3), (P2,P3), (P2,P4), (P3,P4), and (P4,P5). After 1 min, as the aircraft start to move, the distances of P1/P3, P2/P3, and P2/P4 all exceed the preset threshold D, only leaving 3 edges (P1,P2), (P3,P4), and (P4,P5). Then the growth rate of edges in scene 2b was computed to be -0.5. Situation 3a contains 2 edges: (P1,P2), and (P4,P6). After 1 min, as the aircraft start to move, the distances of P1/P3, P2/P3 and P4/P5 are all smaller than the preset threshold D, increasing the number of edges to 5. Then the growth rate of edges in situation 3b was computed to be 1.7. During the transitions from situation 2a to situation 2b, and from situation 3a to situation 3b, the growth rate of edges macroscopically reflects the level of convergence of an aircraft in the sector. A positive increasing rate indicates that the number of convergent aircraft in the sector is increasing; otherwise, the number of diverging aircraft is increasing.

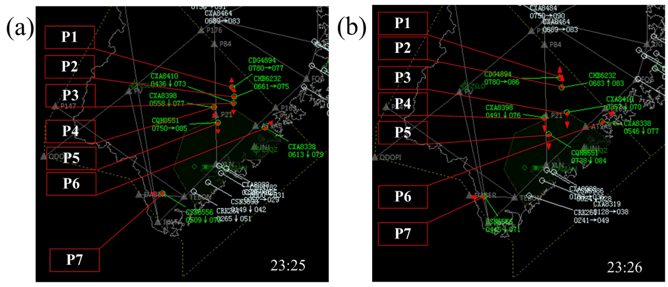

Figure 8. Two traffic situations with 7 aircraft (a): situation 2a , (b): situation 2b

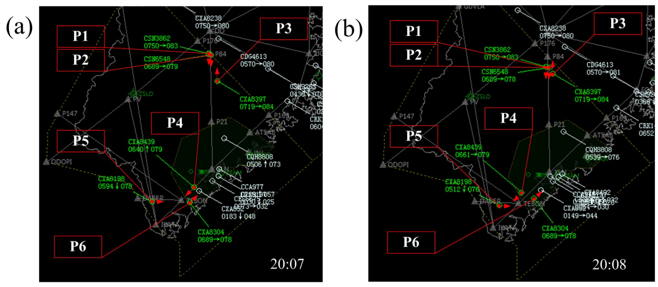

Figure 9. Two traffic situations with 6 aircraft (a): situation 3a, (b): situation 3b

TABLE I. GROWTH RATE OF EDGES IN DIFFERENT SITUATIONS

Situation No	Time	Number of nodes	Number of edges (D=60 km)	Growth rate of edges (D=60 km)
Situation 2a	23:25:00	7	6	/
Situation 2b	23:26:00	7	3	-0.5
Situation 3a	20:07:00	6	2	/
Situation 3b	20:08:00	6	5	1.7

C. Clustering coefficient

Some aircraft groups will appear in real air traffic, when the distances among several aircraft are small. In situation 4 showed in Fig. 10, the distances among nodes P1/P2/P3 are all small, forming a high-density aircraft group. Then control of any aircraft in the group may interfere with other aircraft, which is unfavorable for the controller to resolve the multi-aircraft conflict. In this study, a concept of clustering coefficient was introduced to analyze the between-aircraft clustering from the perspective of aircraft network structures.

Clustering coefficient describes the clustering of nodes in a network, or namely the proximity in the network. A larger clustering coefficient indicates that the nodes are closer. In an air traffic network, the clustering coefficient of an aircraft represents the proximity of this aircraft from other nearby aircraft. A larger clustering coefficient indicates a high-density aircraft group with this aircraft as the center. A smaller clustering coefficient indicates a small number of aircraft around this aircraft. Thus, clustering coefficient macroscopically reflects the high proximity between aircraft.

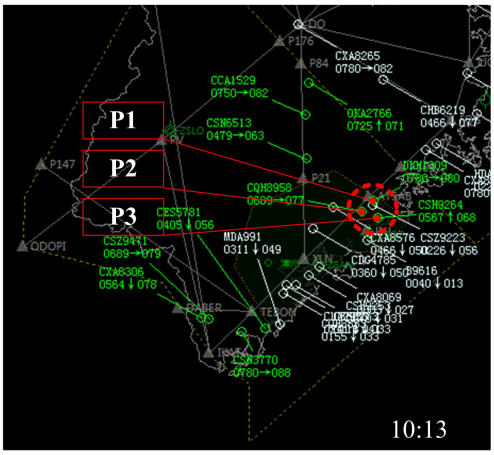

Figure 10. The example of clustering coefficient: air traffic situation 4

Clustering coefficient is computed as follows: if node i is connected via k_i edges to other k_i nodes, there are probably up to $k_i(k_i-1)/2$ edges formed by these k_i nodes, and the ratio of "the real number of edges", E_i, to $k_i(k_i-1)/2$ is called the clustering coefficient C_i of node i:

$$C_i = \frac{2 * E_i}{k_i(k_i - 1)} \tag{3}$$

The clustering coefficient C of the whole network is the means of C_i from all nodes:

$$C = \sum_{i=1}^{N} C_i / N \tag{4}$$

The clustering coefficients of air traffic networks under 3 thresholds were computed. The results show that the clustering coefficients were 0.339, 0.09 and 0.01 respectively, which were all small and indicated no proximity relations between aircraft in this sector. The probability distribution of clustering coefficient is showed in Fig. 11. This distribution conforms to the real situation, since in real life, the controllers always try to avoid the occurrence of high-density aircraft groups and keep the controlling and commanding difficulty within specific ranges.

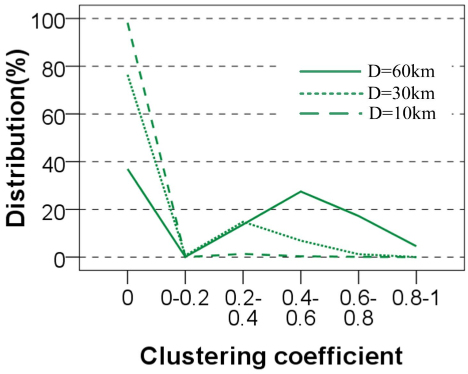

Figure 11. Probability distribution of clustering coefficient

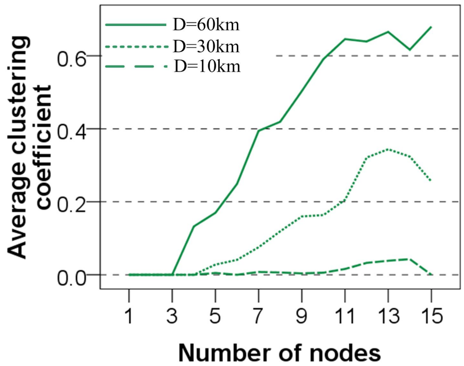

Figure 12. Curve of clustering coefficient with the number of nodes

Fig. 12 shows the changes of clustering coefficient with the number of nodes. When the number of nodes is fixed, a larger threshold D is more likely to generate proximity between aircraft, and thus, the corresponding clustering coefficient is larger. Moreover, the clustering coefficient increases with the increasing network scale, and stabilizes when the number of nodes exceeds 12. Coincidentally, the maximum number of airplanes controlled by controllers in the medium- and low-altitude air traffic control sector is 12, provided by CAAC. In other words, network clustering coefficient is an indicator measuring the airspace service ability. Compared with the number of aircraft describing quantify the congestion in an air sector, the clustering coefficient also reflects the occurrence of high-density aircraft group.

D. Network structure entropy

During airborne traffic operation, some aircraft are at high-density space, and thus, slight adjustment to the aircraft will induce a new flight conflict. On the contrary, some aircraft are at low-density space and very far from other aircraft, the possibility of inducing conflict is very small within short time. In other words, the aircraft will impact the overall air traffic situation to different degrees. From the perspective of networks, this fact also reflects the different importance degrees among nodes, which is called a non-homogeneous network.

In an air traffic network, the importance degree of a node can be computed as follows:

$$I_i = k_i / \sum_{j=1}^{N} k_j \tag{5}$$

where I_i is the importance degree of aircraft i; N is the number of aircraft; k_i is the number of aircraft adjacent to aircraft i.

Then 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-indicator measuring the topological nature of a network and describes the homogeneity or not of node degrees:

$$E_r = -\sum_{i=1}^{N} I_i \ln I_i \tag{6}$$

where E_r is the structure entropy of an air traffic network; N is the number of aircraft; I_i is the importance degree of aircraft i.

A larger structure entropy indicates higher homogeneity of node degrees. For a regular network with fixed node degrees, the structure entropy is assigned with the maximum ln$N$. Fig. 13 shows two air traffic situations, where the green marked aircraft belong to the sector ZSAMAR02 studied here. This sector under two situations both involved 6 aircraft. In situation 5, however, the between-aircraft distances are very homogeneous, and the between-node differences are very small. In situation 6, the distances of P1/P2/P5/P6 are very large, and only the distance of P3/P4 is small. Thus, the structure entropy in situation 5 is larger than that in situation 6, and the results of structure entropy in the two situations are showed in Table II.

(a) (b)

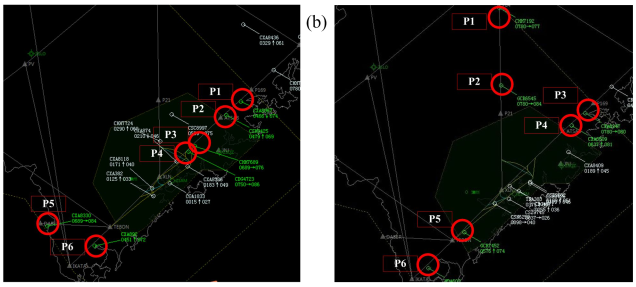

Figure 13 Two traffic situations with 6 aircrafts (a): situation 5, (b): situation 6

TABLE II. NETWORK STRUCTURE ENTROPY UNDER TWO SITUATIONS

Situation No	Number of nodes	Network structure entropy		
		D=60 km	**D=30 km**	**D=10 km**
Situation 5	6	1.91	1.79	1.79
Situation 6	6	1.56	0.69	0

The relations between structure entropy and number of nodes with different thresholds are illustrated in Fig. 14. Clearly, network structure entropy is enhanced along with the increased number of nodes, indicating that with a larger number of aircraft, the influence degrees of aircraft on the overall traffic situation will be homogeneous. Considering the effects of thresholds on structure entropy, with the same number of nodes, a larger threshold corresponds to a larger structure entropy (Fig. 14), indicating that the effect of aircraft on the overall situation is smaller. Moreover, the evolution of a network can also be reflected by the increasing rate of network structure entropy, which is defined as the variation of structure entropy with a same increased number of nodes. As showed in Fig. 14, at D=60 km, the increasing rate of structure entropy is clearly divided into two stages: Stage 1 corresponds to the period when the number of nodes is < 7, or namely in the sector, the number of aircraft instantaneously is < 7. This is the non-peak traffic stage, and the air traffic density is low and heterogeneous, with unstable network structures and large variation of structure entropy. When the number of nodes increases from 1 to 7, the structure entropy is improved by 30% from 0 to 1.8. Stage 2 corresponds to the period when the number of nodes is > 7. This is the peak stage of air traffic, when the air traffic density is very large and homogeneous. As the network scale is enhanced, the network is gradually mature, the network structure is also stabilized, and the increasing rate of network structure entropy is decreasing. When the number of nodes increases from 7 to 15, the structure entropy is improved by 10% from 1.8 to 2.6. When the number of nodes is 14, the increasing rate of structure entropy stabilizes to 0.

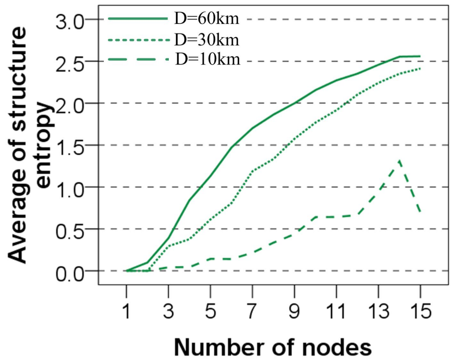

Figure 14. Relation between network structure entropy and number of nodes

IV. CONCLUSION

Air traffic situation can be mapped into a network structure, whose structural characteristics are significant for describing the air traffic complexity in a sector. We selected the routinely-recorded radar data in an air traffic control area within China's airspace in 2013. With the aircraft in the sector as node, and with the between-aircraft distance closeness as edge, we constructed an undirected and unweighted aircraft network. The thresholds would differently affect the network structures, and in this study, the thresholds were set at 60, 30 and 10 km. The air traffic situation networks under dissimilarity distance thresholds were statistically analyzed using network topology indices including more degree, number of edge, connection rate, clustering coefficient, and network structure entropy. The results show that node degree and node clustering coefficient reflect whether or not a single aircraft is within a high-density aircraft group, and the key aircraft from the sector can be identified from the perspective of airspace congestion. Network average degree, number of edge, connection rate, and network clustering coefficient reflect the proximity of aircraft within the sector from different perspectives. The clustering coefficient also indicates whether or not a high-density aircraft group exists in the sector. The growth rate of edges reflects the evolution of proximity of air traffic, or namely the convergence or divergence of traffic situation in the sector. Network structure entropy macroscopically reflects the homogeneity of aircraft congestion degree in a sector, and can identify whether some aircraft are at very high-density or very low-density airspace. Thus, the analysis of topological structural characteristics of air traffic situation networks shows that though air traffic systems are very complex systems, there are internal development laws and characteristics. However, we only statistically analyzed the data of a sector from only one day. In the future, data from more sectors and covering longer periods will be collected and applied into analysis of relations between network structural characteristics and air traffic situations.

ACKNOWLEDGMENT

The author would like to thank to Zhang Zhanbo, Huang Junxiang from Xiamen Air Traffic Management Station of Civil Aviation of China for providing air traffic operational data. This work is supported by National Nature Science Foundation of China under Grant No. U1333108. And it is also supported by Tianjin Research Program of Application Foundation and Advanced Technology under Grant No. 14JCQNJC04500

REFERENCES

[1] B. Hilburn, Cognitive complexity in air traffic control: A literature review, Eurocontrol, Brussels, Belgium, Tech. Rep. 04/04, 2004.

[2] B. Sridhar, K. Sheth, and S. Grabbe, Airspace complexity and its application in air traffic management, in Proc. 2nd USA/Eur. Air Traffic Manag. R&D Semin., Orlando, FL, Dec. 1998.

[3] A. Masalonis, M. Callaham, and C. Wanke, Dynamic density and complexity metrics for real-time traffic flow management, in Proc. 5th USA/Eur. Air Traffic Manag. Semin., Budapest, Hungary, 2003.

[4] R. Mogford, J. Guttman, S. Morrow, and P. Kopardekar, The complexity construct in air traffic control: A review and synthesis of the literature, Fed. Aviation Admin., Atlantic City, NJ, Tech. Rep. DOT/FAA/-CT TN95/22, 1995.

[5] S. Athénes, P. Averty, S. Puechmorel, D. Delahaye, and C. Collet, Complexity and controller workload: Trying to bridge the gap, in Proc. Int.Conf. HCI-Aero, Cambridge, MA, 2002.

[6] E. Buckley, B. DeBaryshe, N. Hitchner, and P. Kohn, Methods and measurements in real-time air traffic control system simulation, Fed. Aviation Admin., Atlantic City, NJ, Tech. Rep. DOT/FAA/CT83/26, 1983

[7] B. Kriwan, R. Scaife, and R. Kennedy, Investigating complexity factors in U.K. air traffic management, Human Factors Aerosp. Safety, vol. 1,no. 2, pp. 125-144, 2001.

[8] S. Mondoloni and D. Liang, Airspace fractal dimension and applications, in Proc. 4th USA/Eur. Air Traffic Manag. R&D Semin., Santa Fe, NM, 2001.

[9] Puechmorel S. Air traffic complexity: towards intrinsic metrics. The 3rd USA/Europe Air Traffic Management R&D Seminar, 2000.

[10] Delahaye D， Puechmorel S， Hansman R J, et al． Air traffic complexity map based on non linear dynamical systems． Air traffic control quarterly，2004，12(4):367-388

[11] Wang Hongyong,Zhao Yifei,Wang Fei,Wen Ruiying, Evaluation of Air Traffic Control Sector Complexity. Journal of Transportation Systems Engineering and Information Technology, 2013,13(6):147-153.

[12] Lee K, Feron E, Peitchett A. Air traffic complexity. 44th Annual Allerton Conference, 2006.

[13] Lee K, Feron E, Peitchett A. Air traffic complexity: an input-output approach.The 7th USA/Europe Air Traffic Management R&D Seminar, 2007.

[14] Lee K, Feron E, Peitchett A. Describing airspace complexity: airspace response to disturbances. Journal of guidance, control and dynamics, 2009. 32(1): 210-222

[15] Maria Prandini, Luigi Piroddi, Stephane Puechmorel, S L Brázdilová, Toward air traffic complexity assessment in new generation air traffic management systems. IEEE transactions on intelligent transportation systems,2011, 12(3): 809-818

[16] S L Brázdilová, P Cásek, and J Kubalcík, Air traffic complexity for a distributed air traffic management system. The institution of mechanical engineers, Part G: Journal of aerospace engineering, 2011, 225: 665-674

[17] Rhonda Lyons.Complexity analysis of the Next Gen Air Traffic Management System: trajectory based operations. WORK, 2012, 41:4514-4522

[18] Delahaye D, Paimblanc P, Puechmorel S, Histon J, and Hansman R, A new air traffic complexity metric based on dynamical system modelization. The 21st Dig.Avionics Syst. Conference, 2002:1-12.

[19] Delahaye D, Puechmorel S, Hansman R, Histon J. Air traffic complexity based on nonlinear dynamical systems. The 5th USA/Eur. Air Traffic Management. R&D, 2003.

[20] Barabasi A L,Albert R. Emergence of scaling in random network.Science,1999,286(5439):509-512,

[21] Barabasi A L Scale-free networks: a decade and beyond. Science, 2009,325(5939):412-413

[22] Boccaletti S, Latora V, Moreno Y, et al. Complex networks:structure and dynamics.Physics Reports, 2006,424(4):175-308

[23] Daniel DeLaurentis, En-Pei Han, Tatsuya Kotegawa. Network-theoretic approach for analyzing connectivity in air transportation networks. Journal of aircraft,2008,45(5): 1669-1679

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