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# Analysis of flight conflicts in the Chinese air route network

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ABSTRACT

The increase in economic exchange, brought about by globalization and leaps of progress in science and engineering, has led to a sharp increase in air traffic density. As a consequence, airspace has become increasingly crowded, and limitations in airspace capacity have become a major concern for the future development of air travel and transportation. In this paper, we adopt methods of network science to analyze flight conflicts in the Chinese air route network. We show that air conflicts are distributed heterogeneously along the waypoints of the Chinese air route network. In particular, the frequency of flight conflicts follows an exponential distribution. The time-space investigation of flight conflicts shows that they are concentrated at specific regions of the Chinese air route network and at specific time periods of the day. Our work offers fascinating insights into one of the world's largest and most busiest air route networks, and it helps us mitigate flight conflicts and improve air traffic safety.



## 1. Introduction

The increase of economic exchanges brought by globalization has led to a sharp increase in transportation activities. This development has been particularly relevant in China. Chinese air transportation has become the world's second largest in the world, and it is still growing: The number of passengers on average increased by 12.24% annually beginning in 2006 to almost 436.2 million in 2015, which is higher than worldwide growth (5.39%). The volume of aviation goods traffic in China was 6.29 million tons in 2015 after an annual increase of 7.76% beginning in 2006. The increment is almost three times worldwide growth (2.83%) [1-2]. Air traffic plays a vital role in today's world and has drawn continuous attention from many experts and scholars from different fields.

In the past decades, theory and application of complex networks has highlighted the analysis of airport networks, in which nodes represent airports and links are direct flights between node pairs. Guimerà et al. were the first to examine the worldwide airport network (WAN), finding that the WAN is a scale-free small-world network with a multi-community structure [3], shaped not only by geographical constraints but also by geopolitical considerations. Barrat et al. analyzed the WAN as a weighted network and found a strong correlation between edge weights and the topological properties in the WAN [4]. Other researchers have studied national airport networks, including the US [5-7], India [8], Brazil [9] and China [10-14]. For example, Li and Cai examined the Chinese airport for the first time, finding different relevant properties, such as a small-world and a two-regime power-law degree distribution [10]. Airport networks have also been studied from several other perspectives: multi-layered networks [15–16], network evolution [17–19], and network robustness [20–23], and so on.

The airport network is actually a significant aviation network, describing relationships between airports and cities. However, a new kind of aviation network structure has caught the attention of researchers in recent years: the air route network (ARN), the backbone of the air transportation network (ATN). This network intends to represent the way aircrafts travel in airspace: the nodes denote air route waypoints (ARWs), and the links are the air route segments (ARSs) connecting ARW pairs. We first investigated the Chinese air route network (CARN) and demonstrated that the topological structure of CARN and the flights distribution is rather heterogeneous [24]. The topological properties of ARN have also been studied for Italian and European networks [25–26].

The growth in air traffic demand has not been accompanied by a correlative increase in airspace capacity. Thus, analysis of

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the evolution in aircrafts in airspace is especially salient, as the probability of flight conflicts (coincidence of aircrafts in space and time) may increase significantly. Since ARN can reflect the flying mechanism of aircrafts, several papers study airspace safety issues based on ARN. Du et al. systematically explored the robustness of the Chinese air route network, and identified the vital edges which form the backbone of Chinese air transportation system [27]. Guan et al. planed traffic flow from a global view based on Memetic Algorithm (MA) to avoid flight conflicts [28]. Monechi et al. built efficient and globally optimized planned trajectories in European national airspace [29–30]. However, in China, there are many structural-specific factors that endanger airspace: (i) Only approximately 20% of airspace is available for civil aviation; (ii) traffic flow is geographically unbalanced; and (iii) airspace is fragmented into three areas: forbidden areas, restricted areas, and dangerous areas. To increase airspace safety, it is of great importance to examine how the network structure affects flight conflicts. Analysis of the statistical properties of flight conflicts based on ARN is quite a novelty in the literature. In this paper, we investigate the properties of flight conflicts based on CARN, mainly from the view of time-space characteristics. The results show that more flight conflicts would occur at ARWs that are located close to the geographic center of CARN and that the frequency of flight conflicts varies greatly depending on the time periods considered.

The paper is organized as follows. In the next section, we describe the model of flight conflicts on the Chinese air route network and the correlation between flight conflicts and network properties in detail. In Section 3, we present the network property results and correspondent analysis of time-space characteristics. Research results are summarized in Section 4.

## 2. Data description

In this work, we use real data from a CARN and flight plans from a week in June 2015 provided by the Civil Aviation Administration of China (CAAC) and Aviation Data Communication Corporation (ADCC). In the CARN, nodes denote ARWs or airports (number of nodes is $N = 1499$), and links are ARSs (number of links is $M = 2242$). Each aircraft is supposed to fly according to a certain flight plan, which is a sequence of ARWs {*n1, n2,…np*} that will guide the aircraft from origin to destination. The plan path of the aircrafts is from the flight plan message. The data of the ARN allows us to obtain occurrences of flight conflicts, that is, coincidences of aircrafts in time and space. The steps of flight conflict detection are:

- First, the representation of an aircraft route as a series of scheduled ARWs from origin to destination allows us to calculate the total flight distance ($L_{total}$) for each aircraft. Total flight duration ($t_{total}$) can also be obtained as the difference in the departure and arrival times.
- A typical flight process is separated into three phases [29] (Fig. 1a): (i) departure phase, (ii) en-route phase, (iii) approach phase. Existing research recognizes the disposed method due to the limitation of data and assumes that the aircraft flies at a constant speed [30, 31]. In this paper, $v_1$ is in the en-route phase:

$$v_1 = \frac{L_{enr}}{t_{enr}} = \frac{L_{total} - L_{arr} - L_{dep}}{t_{total} - t_{arr} - t_{dep}} = \frac{L_{total} - L_{arr} - L_{dep}}{t_{total} - L_{arr}/v_2 - L_{dep}/v_2},$$

where $L_{dep} = L_{arr} = 30$ km represents the range of the departure phase and approach phase. Each aircraft is assumed to fly at an average horizontal speed $v_2 = 100$ km/h in the departure and approach phase.

Then, we can get the time each aircraft crosses each ARW. A flight conflict occurs when the difference in the times in which a pair of aircrafts cross the same ARW is less than $\delta = 60$ s. (In ref. [28–30,32], the minimum safe separation is 5 NM (9.26 km); thus, the minimum safe time interval is 60 s.)

Fig. 1(b) illustrates a flight conflict occurring between two aircrafts, as they cross the red ARW at the same time. In this paper, we only consider flight conflicts occurring near the ARWs to better analyze how the ARN structure affects flight conflicts. Fig. 2 represents the frequency of flight conflicts $N_C$ for a given day. The color and size of nodes represent the value of frequency of flight conflicts on the ARW, and the edge width represents the flow of aircrafts on the ARSs in the same day. The majority of flight conflicts are clustered at the trunk ARSs; therefore, crossing of the trunk ARSs increases the probability of flight conflicts ($N_C$) significantly. The top 3 ARWs with the most frequent flight conflicts, namely, HEF, ZHO, and XLN, are emphasized in Fig. 2. It is found that eastern China has a larger flight flow, and the majority of ARWs with most frequent flight conflicts are located in eastern China. The majority of flight conflicts (more than 500) in western China occur around URC (Urumchi), the transportation hub in western China.

## 3. Results and discussion

### 3.1. Topological properties

Most previous studies focus on conflict avoidance by changing the location of ARWs or strategically planning traffic flow. Few examine the causes of flight conflicts and what the flight conflicts are related to. The topological properties of complex networks can reflect the network structure effectively. It is natural to investigate the correlation between flight conflicts and the topological properties of CARN.

First, we examine the structural heterogeneity of CARN. Fig. 3(a) shows the cumulative degree distribution of CARN. Degree distribution $p(k)$ is the probability distribution of the node degree in the network, and the accumulated degree distribution $P(k)$ is $P(k) = \sum_{k'=k}^{\infty} p(k')$. One can see that the function follows an exponential distribution, illustrating the heterogeneous topological structure of the CARN. Fig. 3(b) shows the cumulative distribution $P(N_C)$ of flight conflicts $N_C$ at ARWs. Flight conflict frequency also exhibits an exponential distribution, being heterogeneous also. Betweenness centrality is an important parameter that is defined as the number of shortest paths between nodes that pass through a node $i$: $BC_i = \sum_{s \neq i \neq t} \frac{n_{st}^i}{g_{st}}$, where $g_{st}$ is the number of shortest paths from $s$ to $t$ and $n_{st}^i$ is the number of shortest paths in $g_{st}$ paths through node $i$. As shown in Fig. 3(c), most ARWs have low values of betweenness and frequency of flight conflict. Two red nodes are highlighted: ENH (high betweenness and low conflict) and HFE (low betweenness and high conflict). ENH, located in the HuBei Province, sustains low traffic. HFE, located in the geographical center of eastern China, is the intersection of east-west and north-south flights.

### 3.2. Spatial characteristics

The territorial imbalances in economic development in China are shown in its air transport network. As a result, the majority of Chinese air traffic occurs in the east. Additionally, East China airspace is highly fragmented, as there are many airspace areas that are forbidden, restricted or dangerous. Chinese air transportation is an example of how airport network development is influence by geographical constraints [3]. As a result, the frequency of flight conflicts is influenced by the location of ARWs [27]. The geographical environment heavily affects air transportation, so it is natural to take geographical factors into account. Based on the gravity model [33], we propose a node index, the geographical centrality $O_i$, described as follows:

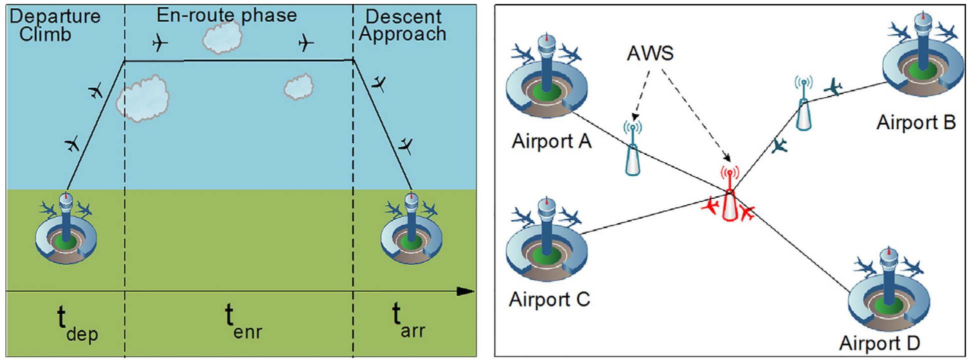


**Fig. 1.** (a) An illustration of the phases of a flight from origin to destination: (i) departure phase, (ii) en-route phase, (iii) approach phase; (b) An illustration of a flight conflict: the red aircrafts represent a conflict.

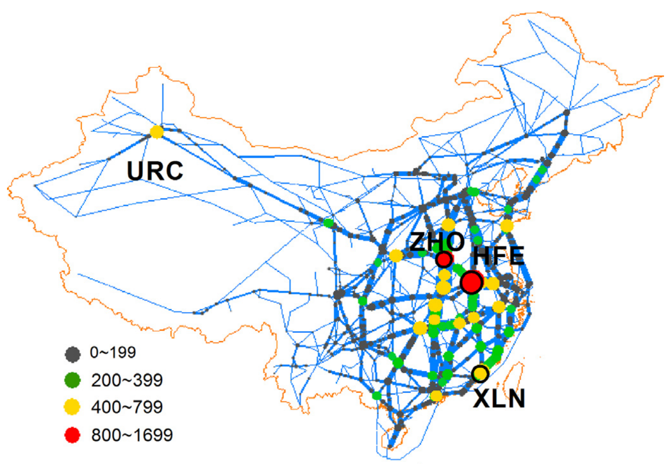


**Fig. 2.** The Chinese air route network (CARN) containing 1499 ARWs and 2242 ARSs. The color and size of the node signify the total number of conflicts on the ARWs in one day, namely, $N_C$. Edge width represents the flow of aircrafts on the ARSs in one day. The 3 ARWs with the most flight conflicts, namely, HEF, ZHO, and XLN, are emphasized.

First, we search for the geographical center in the weighted CARN, weighted by node strength S.

$$x_c = \frac{1}{S}\sum_{i=1}^{n} x_i S_i$$

$$y_c = \frac{1}{S}\sum_{i=1}^{n} y_i S_i$$

where $x_i$ and $y_i$ are the longitude and latitude of node $i$ and $x_c$ and $y_c$ are the longitude and latitude of the geographical center. $S_i$ is the strength of node $i$ and $n$ is the total number of nodes. $S$ is defined as $S = \sum_{i=1}^{n} S_i$. Then, it is found that HFE, the zone with a higher frequency of flight conflicts, is the ARW closest to the center. Then, the geographical centrality $O_i'$ of node $i$ is defined as the reciprocal of the distance from node $i$ to the center.

$$O_i' = \frac{1}{\sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}}$$

For a clearer description, we normalize the geographical centrality $O_i$ as:

$$O_i = \frac{O_i - O_{min}}{O_{max} - O_{min}}$$

where $O_{min}$ is the node with lowest geographical centrality and $O_{max}$ is the node with the highest geographical centrality. $O_i$ is the normalized geographical centrality, which is shown on the CARN (Fig. 4(a)). The white star denotes HFE, the geographical center of CARN.

Then, we study the frequency of flight conflicts $N_C$ as a function of geographical centrality O, as shown in Fig. 4(b). When the geographical centrality O is less than 0.5, the ARWs seldom have conflicts, reflecting the fact that there are not many conflicts at remote ARWs, except URC. URC is located in Urumchi and is the transportation hub in western China; it therefore lies on a significant number of northwest ARW paths. URC is also the only way to eastern China for some northwest ARWs. So, although the flights of western China are spare, URC has a high frequency of flight conflicts as the majority of routes pass through it. XLN, ZHO and HFE are the most prominent ARWs whose normalized geographical centrality is all higher than 0.5. ZHO, as the traffic hub of China, is a hinge point between east-west and south-north airlines. HFE is also a hinge point and more eastern than ZHO; therefore, it is closer to the coastal area of economic prosperity. As the geographical center of CARN, HFE produces even more flight conflicts. XLN is located in Xiamen city, next to ZSAM (Xiamen Gaoqi International Airport). To study the relationship between geographical centrality and the number of conflicts, flight conflicts ($N_C$) of similar geographical centrality O are averaged as $\overline{N_C}$ in the insert illustration. (Fig. 4(b)). The flight conflicts $N_C$ remain low when the geographical centrality O is smaller than 0.5 (except when O is 0.2, where $N_C$ is affected by URC). Then, flight conflicts $N_C$ grow linearly with

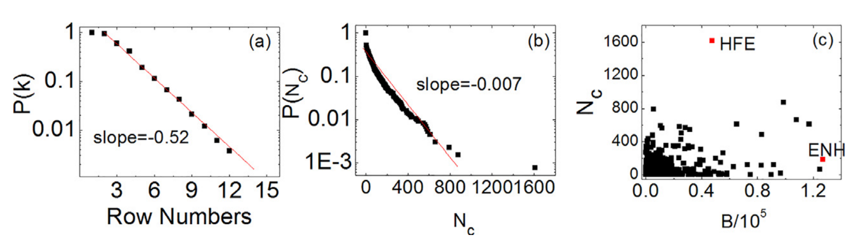


**Fig. 3.** (a) Cumulative degree distribution of CARN; (b) Cumulative frequency distribution of flight conflict of CARN; (c) Betweenness-frequency of flight conflict correlation of CARN.

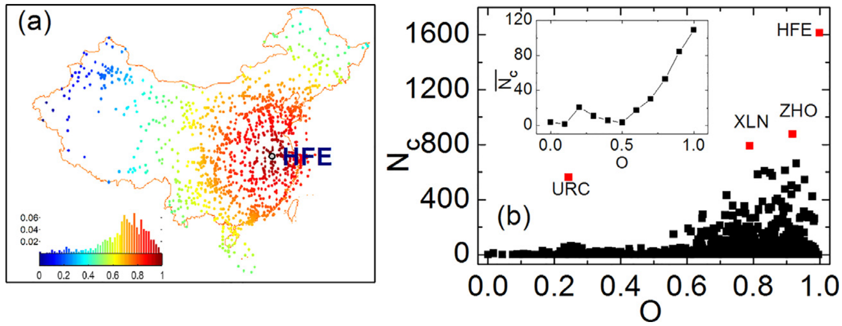


**Fig. 4.** (a) The geographical centrality of the ARWs on the Chinese air route network (CARN). Node color represents the geographical centrality of each ARW. The white star denotes HFE, the center of CARN; (b) the flight conflicts $N_C$ as a function of geographical centrality O. The small graph is the flight conflicts averaged by geographical centrality ($\overline{N_C}$) as a function of geographical centrality O.

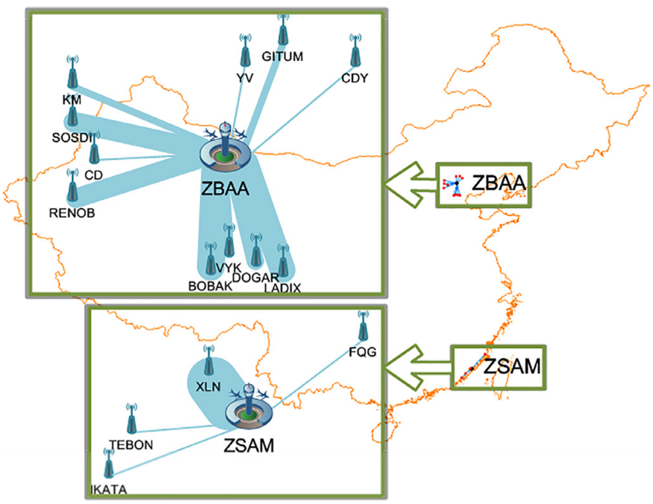


**Fig. 5.** Traffic flow between the airports (ZBAA or ZSAM) and connecting ARWs. The position of ARWs in the figure is the relative position to the airport, and the width of lines connecting ARWs and the airports denotes the relative amount of traffic flow.

geographical centrality O, indicating the fact that the closer to the center HFE is, the more conflicts the ARWs generate.

It is very interesting that so many flight conflicts occur in XLN, which is next to ZSAM despite the relatively low geographical centrality (0.789) of XLN. To explore further, we investigate the frequency of flight conflicts at the ARWs next to ZBAA (Beijing Capital International Airport). The geographical centrality of ZBAA is 0.846, larger than that of ZSAM (0.789). Additionally, ZBAA sustains more than 13% of China's air traffic flow, which is almost 3 times that of ZSAM. Considering these facts, there should be frequent flight conflicts at ARWs near ZBAA, but it is puzzling that the number is few; i.e., the ARW that has the heaviest traffic flow is LADIX, which only experiences 250 per day, less than XLN (497). Then we examined the air traffic flow of ZSAM, as shown in Fig. 5. The position of the ARWs in the figure is the relative position to the airport, and the width of lines connecting ARWs and the airports denotes the relative amount of traffic flow. It can be seen that almost all the traffic of ZSAM flows to XLN, while the traffic of ZBAA flows to 11 ARWs. This indicates that effective measures are adopted to separate air traffic flow in ZBAA, reducing the conflicts. It appears that separating the flow of hub ARWs is an effective measure to reduce flight conflicts. Similar measures can be adopted in other ARWs, such as XLN, HEF, and ZHO.

To further examine the effect of geographical centrality O, we consider the flight conflicts from the flight perspective. Fig. 6(a) depicts the correlation of $N_{cx}$, $N_{arw}$ and $O_x$. $N_{arw}$ denotes the number of ARWs a flight crosses from origin to destination. $N_{Cx}$ is the number of flight conflicts experienced by each flight. $O_x$ is the average geographical centrality of all ARWs that an aircraft crosses from origin to the destination. It can be seen that $N_{Cx}$ could not reach 2.4 times the $N_{arw}$. In Fig. 6(b), we consider the flights with $N_{arw}$=20 as an example. Here, $O_x = \sum_{j=0}^{m}\sum_{i=1}^{20} O_{ij}/(20 * \mathrm{m})$ and $N_{Cx} = \sum_{j=0}^{m}\sum_{i=1}^{20} C_{ij}$ The results show that $N_{Cx}$ increases with $O_x$ as linear growth. The bigger the $O_x$, the bigger $N_{Cx}$ is. That is, when the flight is flying through the center of CARN, it generates many flight conflicts. Thus, the flight conflicts are greatly affected by geographical factors.

### 3.3. Temporal characteristics

Li and Cai examined the daily evolution of the topology of a Chinese airport network within a week and found that the Sunday airport network slightly differs from Monday to Saturday [10]. The variation in flight flow within 24 hours exhibits an obvious tide phenomenon [12]. In addition to the spatial characteristics of flight conflicts, time is another significant factor. In Fig. 7, we examined the variation in flight conflicts within 24 h in a week. The results show the flight conflicts $N_{Ct}$ for all ARWs in each hour. First, there is almost no difference in $N_{Ct}$ on weekdays. $N_{Ct}$ exhibits an interesting phenomenon: It is high in daytime and low late at night. In particular, the frequency of flight conflicts greatly increases from 6:00 to 8:00, reaching a morning peak from 8:00 to 8:59. The frequency of fight conflicts remains relatively stable from 9:00 to 16:00, reaching a night peak from 17:00 to 17:59. The frequency of flight conflicts slightly decreases from 18:00 to 21:00 and then descends abruptly from 21:00 to 23:00.

To better demonstrate the dynamics of flight conflicts, we show the flight conflicts on the ARWs on a Chinese air route network (CARN) for six time periods (three hours apart) in Fig. 8: 01:00–01:59, 05:00–05:59, 09:00–09:59, 13:00–13:59, 17:00–17:59 and 21:00–21:59. In Fig. 8(a)-(b), air traffic is low. ARSs do not have many flights, and there are very few conflicts. Usage of ARSs during 01:00–01:59 is slightly higher than in 05:00–05:59. In Fig. 8(c)-(f), although the total flight conflicts represented are similar, there are some differences in the geographical distribution of the flight conflicts on ARWs. The ARWs with more flight conflicts are located almost in the middle and eastern part of China, and the ARWs of most flight conflicts are always HFE, the center of air traffic flow. This fact makes HFE a unique geographical location, where east-west and north-south air traffic flows converge. There are differences in the locations of ARWs with most flight conflicts in Fig. 8(c)-(f). In Fig. 8(c), the ARWs with most flight conflicts are HFE, ZHO and LLC. Note that the trunk ARSs in this time period are the routes from HFE to ZHO, and from ZHO to LLC. However, from 13:00 to 13:59, the trunk ARSs are from ZHO to LLC and from HFE

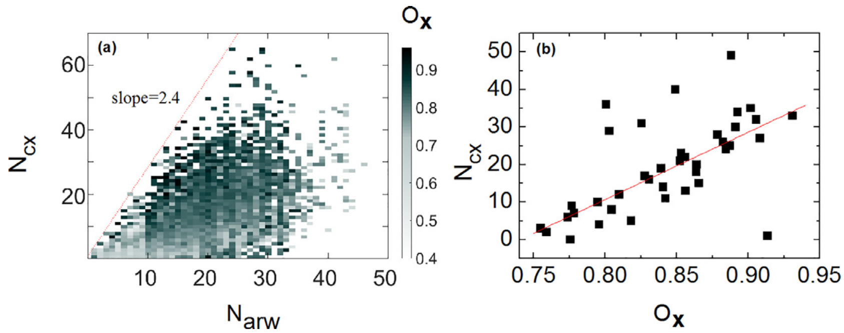


**Fig. 6.** (a) Correlation of $N_{arw}$, $N_{cx}$ and $O_x$. $N_{arw}$ denotes the number of ARWs a flight crosses from origin to destination. $N_{cx}$ is the number of flight conflicts of each aircraft in one flight. $O_x$ is the average geographical centrality of all ARWs that the aircraft crosses from origin to destination; (b) Correlation of $N_{cx}$ and $O_x$ when $N_{arw} = 20$, $N_{Cx} = \sum_{j=0}^{m}\sum_{i=1}^{20} C_{ij}$ and $O_x = \sum_{j=0}^{m}\sum_{i=1}^{20} O_{ij}/(20 * \mathrm{m})$, where $O_{ij}$ is the geographical centrality of the $i$th ARW of $j$th flight that crosses 20 ARWs and $m$ is the total number of flights that have $N_{arw} = 20$.

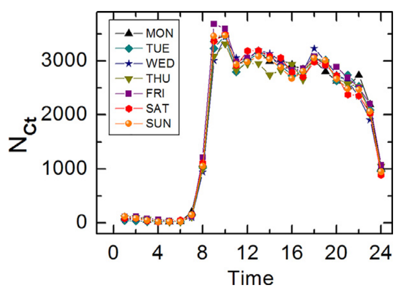


**Fig. 7.** Variation in flight conflicts $N_{Ct}$ by day of week.

and SHX (Fig. 8(d)). In Fig. 8(e), the ARWs with most flight conflicts are located at different trunk ARSs, and HFE, ZHO and WXI are the top 3 ARWs. In 21:00–21:59, the frequency of flight conflicts on CARN is relatively low and HFE, URC and HOK are the top 3 ARWs. It is noted that some ARW conflicts are highly time varying, as in the case of SHX, WXI and HOK. Thus, the frequency of flight conflicts in these ARWs would be significantly reduced by modifying the flight schedules and adjusting the routes of flights. However, the flight conflicts on ARWs HFE, ZHO are relatively high in most time periods. These conflicts can only be reduced by adjusting the structure of the CARN, which would be accomplished only by a sacrifice of efficiency and at huge cost.

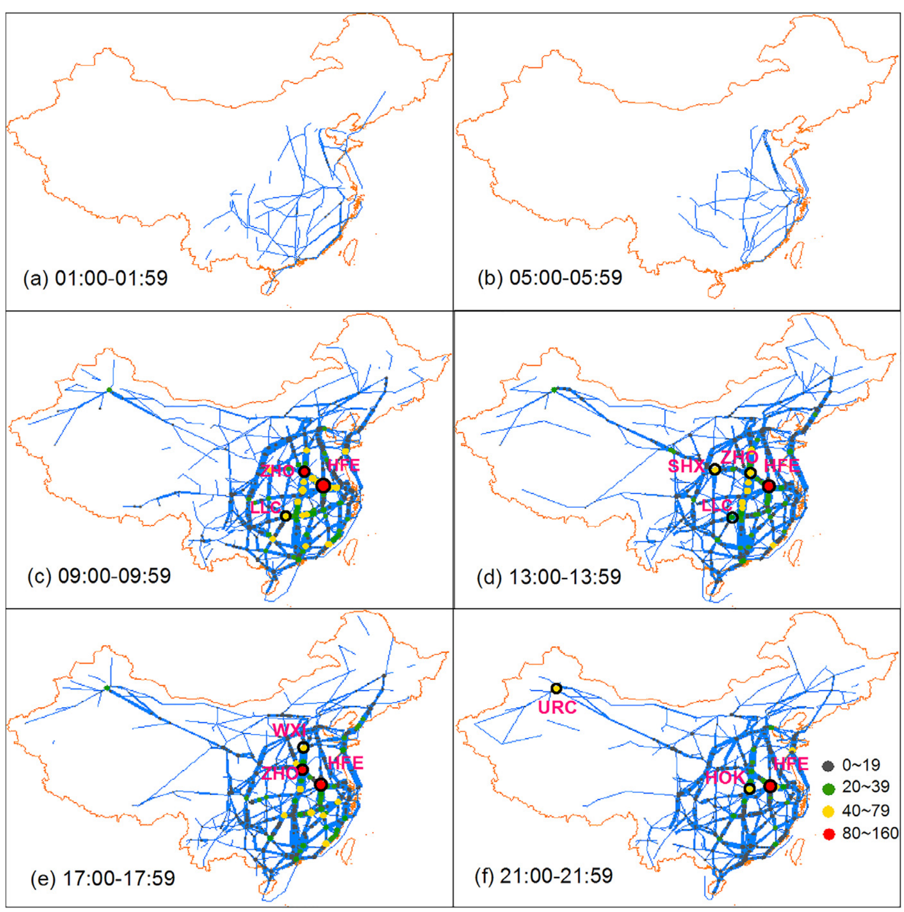


**Fig. 8.** Flight conflicts on the CARN at different time periods. The color and size of nodes represent the total number of conflicts on the ARWs for one day. The line width represents the flight flow of the ARSs for one day (unused ARSs are not shown). The top 3 ARWs with the most flight conflicts are emphasized.

## 4. Conclusion

In summary, we have analyzed the flight conflicts on the CARN within the framework of complex network theory. Distribution of frequency of flight conflicts on CARN nodes is heterogeneous with exponential distribution, and flight conflicts are more frequent in ARWs to a high degree. Flight conflicts are related to the geographical centrality of the ARWs, and distributing the flow of hub ARWs evenly through close ARWs would help to reduce the frequency of flight conflicts. The distribution of flight conflicts varies for different time periods. Therefore, designing different routes for the same origin and destination for different times of the day can help to reduce flight conflicts. Our work will offer a novel approach for understanding the causes of flight conflicts and help to redesign the air route network to improve the safety of air traffic service.

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