Airway Network Characteristics Based on Complex Network Model

WANG Hongyong[1*], *DENG Taotao*[1], *SONG Ziqi*[2], *WANG Fei*[1], *ZHAO Yifei*[1]

1. Tianjin Key Laboratory for Air Traffic Operation Planning and Safety Technology, College of Air Traffic Management, Civil Aviation University of China, Tianjin 300300, P. R. China;

2. Department of Civil and Environmental Engineering, Utah State University, Logan 84322, Utah, USA

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Abstract: Airway networks are the basic carriers of air traffic. Characterizing airway networks will significantly improve the operating efficiency of aviation. This study is targeted at the airway network composed of 1 479 waypoints in 2018 of China. Together with spatial structures, traffic flow characteristics, and the dominating traffic flow, four airway network models are constructed from the perspective of complex networks, including physical airway network, airway traffic network, directed airway traffic network, and dominance-based directed airway traffic network. Then the topological characteristics of different networks are statistically analyzed by using typical network measure indices, and the differences of these indices among different networks are investigated. Thereby, composite indices are proposed. Statistical results show that the airway network under the influence of traffic flows exhibits richer heterogeneity and asymmetrical between-node relationship, and the distributions of indices among different networks are significantly different. Comparative analysis of composite indices and traffic flows show that some waypoints yield great results in multiple composite indices and traffic volumes; some waypoints display large results in multiple composite indices but low traffic flows, and other waypoints only perform well in certain composite indices. The importance levels of waypoints are divided, by the K-means method based on degree composite index, betweenness composite index and closeness composite index, into three levels, and the reasonableness of clustering results is validated by the statistical results of traffic flows, airport number, and flight delay.

Key words: airway network; complex network; air traffic management

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0 Introduction

In air traffic management (ATM) systems, the airspace is organized in a predefined airways network. Given the rapid development of air transportation, the increasingly growing air traffic, the limited capacity of the ATM system have resulted in severe airspace congestion and flight delays[1]. For this reason, many efforts have been made to explore the structures and functions of ATM systems[2]. Air transportation systems are complex systems since there are large numbers of heterogeneous components with complex structures and interactions between groups of different components[3]. Thus, many researchers have tried to introduce the complex network theory into the analysis of air traffic systems. Their studies are mainly manifested in two aspects. Firstly, at the microscopic level, complex networks are utilized to build air traffic situation network models. In brief, the complexity, evolution, and control of air traffic are discussed with aircraft as nodes, and with between-aircraft potential conflict relations or closeness relations as edges[4-5]. Secondly, at the macroscopic level, complex networks are used in macroscopic networks (e.g., airport networks, airway networks), where nodes are individual airports or waypoints.

*Corresponding author, E-mail address: hy_wang@cauc.edu.cn.

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The airport network is a significant aviation network with nodes representing airports and edges representing flights during a fixed period, describing relationships between airports or cities. Burghouwt et al.[6] analysed the evolution of the European air traffic according to different airport groups based on weekly Official Airline Guide data for the years 1990—1998. Guimera et al.[7] analyzed the worldwide air transportation network with nodes as cities and found that the most connected cities are not necessarily the most central ones. Zhang et al.[8] investigated the evolution of the Chinese airport network between 1950 and 2008. They found that although the topology of the Chinese airport network is stationary, there exist network dynamics and the air traffic grows at an exponential rate with seasonal fluctuations. Du et al.[9] encapsulated the Chinese airline network into multi-layer infrastructures via the *k*-core decomposition method and found that it was not as redundant and robust as the Worldwide airline network under the high-degree targeted attack strategy.

The air route network or airway network intends to represent the route aircraft travel in the airspace, the nodes denote waypoints, and the links are the air route segments connecting waypoints. Wang et al.[10] constructed undirected unweighted networks and comparatively analyzed the topological characteristics between air route networks and airport networks by using the real data in China. Cai et al.[11] built undirected weighted Chinese air route networks with consideration into traffic volumes between waypoints and demonstrated that the flights' distribution was rather heterogeneous. Du et al.[12] systematically explored the robustness of the Chinese air route network on the basis of undirected network models, and identified the vital edges. Zhang et al.[13] discussed the network structure and flight conflict characteristics of undirected weighted air route networks. Sun et al.[14] built a graph for the network metrics, with each metric as a node, and analyzed the air navigation route system of fifteen different countries. Ren et al.[15] established undirected unweighted air route networks and compared the characteristics of air route networks among Beijing, Shanghai, and Guangzhou.

The above studies reflect that air route networks have attracted growing attention from researchers. This is because in real air traffic operation, airway network, which determines the routes of every flight traveling from one airport to another, is the backbone of ATM[12]. However, the existing research on airway network modeling is yet limited by the sole network type and the ignorance of direction or dominance of traffic flow between waypoints. Hence, with composite consideration into spatial structures, traffic flow characteristics, and traffic dominance degrees in this study, four network models, including physical airway network, airway traffic network, directed airway traffic network, and directed traffic network based on flow dominance, were established from the aspect of complex networks. Then the basic topological structural characteristics and some traditional network structure indices (degree, strength, betweenness, weighted betweenness, closeness, weighted closeness, clustering coefficient, weighted clustering coefficient) were compared among different networks. Furthermore, four composite indices (degree composite index, betweenness composite index, closeness composite index, clustering coefficient composite index) were proposed and characterized statistically under different scales of waypoints and flows. Finally, the importance levels of waypoints were classified from multiple aspects, and the waypoints were clustered by using the *K*-means method based on the degree composite index, betweenness composite index, and closeness composite index.

1 Data Description

From the airway data provided by the Air Traffic Management Bureau (ATMB) of China, the data in the airspace of Mainland China (excluding Hong Kong, Macao, Taiwan) in 2018 were extracted, including callsigns of waypoints, positions of waypoints, and airway segments. Totally there were 924 airways, 2 596 air route segments, and 1 479 waypoints, which all increased largely in numbers compared with 2015 (there were reportedly 1 499 airports and waypoints[13]). Undoubtedly, the increase of airway numbers brought certain changes to the structural characteristics of airway networks. Moreover, the airway networks were comprehensively analyzed from the aspect of traffic flows. Then the flight plans and dynamic information of 16 830 flights in 1 October, 2018 in mainland China were collected (Table 1), including callsign, departing airports (DEP), destination airports (ARR), the estimated time of departure (ETD), the estimated time of arrival (ETA), the actual time of departure (ATD), the actual time of arrival (ATA), and the planned waypoint list (PPL). Let the planned waypoint list of the ith flight f_i be PPL $(i)=\langle p_1,p_2,\cdots,p_m\rangle$, which indicates during its flying route, f_i successively passes m waypoints in the order of $p_1,p_2,\cdots,p_m$ (where p_i is the ith waypoint).

Table 1 Illustration of some flights

Callsign	Aircraft model	DEP	ARR	ETD	ETA	ATD	ATA	PPL
LKE9891	B738	ZPPP	ZHHH	10:05:00	12:03:00	11:00:00	12:41:00	KIBES LPS P417 BIPIP AGTIS MEMAG TAXOR EPGAL P281 NOMUK GUGAM
CES2739	A320	ZSWH	ZYDQ	10:30:00	12:26:00	11:00:00	12:51:00	WEH VIKOK SANKO CHI P388 NODAL TOSID ISKEM BIDIB NUBKI LEMOT HRB P111 SRT
CCA1260	B738	ZUGY	ZBTJ	10:30:00	13:08:00	11:00:00	13:41:00	UGUGU P447 HUY P281 P448 P61 P373 P53 SHX P24 P134 YCE BISAL P130 XIVEP UBLAT ISGOD AKLOL OC NIPES AVNIX IKENU NIRON CG
OTC7315	A320	ZPPP	ZBCZ	10:40:00	13:20:00	11:00:00	13:11:00	DADOL P334 ENTOV KAKMI FJC NSH PIKEM UGSUT SHX P24 P134 P355 P399 P279 SQ
CES2428	A320	ZBAA	ZLXN	10:25:00	12:39:00	11:01:00	13:08:00	SOSDI BEGRI ANOLO SELGO AKUKI EGANA DOTOS IRVAG P299 REPEP BAV P219 P203 JTA BUKPU PANRA
CES5178	A320	ZBAA	ZSNB	10:35:00	12:23:00	11:01:00	12:59:00	LADIX IDKUP P149 PANKI YQG DALIM ABTUB P86 P60 P58 OMUDI LAGAL ATVAD SUBKU NIXEM XUTGU PIMOL VMB SASAN EKIMU PK JTN DADAT AND BK
CQH8754	A320	ZLXY	ZGSZ	10:50:00	13:17:00	11:01:00	13:17:00	NSH P40 P322 P374 SULEP DS XOLAL UNRIX BONSA P440 P441 MEMAG LIDMA UBDID UGUGU LAGEX P168 SJG POU SAREX NLG KEVAR
CSN3876	B738	ZGSZ	ZSYW	10:55:00	12:30:00	11:01:00	12:39:00	GLN VIPAP P319 BEBEM IKATA TEBON AMURI ATSAB ENVEN AKAVO DAGMO OSPAM YEU

2 Model and Metrics

2.1 Airway network model

During air traffic, each aircraft is supposed to fly according to a filed flight plan path, which is a sequence of waypoints that will guide the aircraft from the origin to the destination. These waypoints and their air route segments connecting with adjacent waypoints jointly constitute an airway network, which is the air service infrastructure designed and planned by the airspace administration according to air service development, geographical environment, flight safety, and other restraints. The update cycle of an airway network is very long, so the waypoints maintain relatively constant topological relations with each other. Hence, the airway network can be considered as a static structure within a certain period. However, due to the dynamics and disequilibrium of air service, the traffic flows between waypoints may be largely different, generating relatively richer topological relations. To precisely describe such rich relations in the airway network, we built weighted air traffic airway network models from multiple aspects, including static topological structures and dynamic traffic flows. Let G be a weighted complex network model, $G=(V,E,w)$; $V=\{v_1,v_2,\cdots,v_n\}$ be a node set; $E=\{e_1,e_2,\cdots,e_m\}\subseteq V\times V$ be an edge set; $n=|V|$ be the number of nodes in a network, and $m=|E|$ be the number of edges. Moreover, $v_i\in V$ $(i=1,2,\cdots,n)$ is a node of the network, corresponding to a waypoint (excluding airports; nodes denote waypoints or airports in Ref.[13]) in the air route network; $(v_i,v_j)\in E$ means there is one edge between nodes v_i and v_j, corresponding to the topological relationship between waypoints; $w(v_i,v_j)$ is the weight between nodes v_i and v_j. In an undirected network, one has $w(v_i,v_j)=w(v_j,v_i)$, and in a directed network, one has $w(v_i,v_j)\neq w(v_j,v_i)$.

The edges can be weighted by using similarity weight (which was adopted in this study) or dissimilarity weight. With comprehensive consideration into the static structures of airway networks and the characteristics of traffic flow, we establish physical airway network (PAN), airway traffic network (ATN), directed airway traffic network (DATN), dominance-based directed airway traffic network (DDATN) (Table 2), where PAN and ATN are undirected networks, while DATN and DDATN are directed networks. The PAN, which reflects the basic structure of air space systems, is a spatial network in which two waypoints are linked if there exist an air route segment between them, each link weight only characterizes the Euclidean distance between node pair[13], and the weight w_{ij} of waypoint p_i, p_j in PAN is computed as follows

$$w_{ij}=1/d_{ij} \tag{1}$$

where d_{ij} is the space distance between waypoints p_i and p_j. Clearly, a larger weight means the two nodes are closer in space. In PAN, the traffic flows on airways are not considered. In ATN, however, the information of flights between waypoints is considered. If there is at least one flight between two waypoints, then these two nodes are regarded as being connected (regardless of the direction of traffic flow), and the value of edge weight stands for the number of flights on the air route segment. Hence, the air route segment with a larger flow means that the corresponding weight of this edge is larger, and the relation between the two nodes is closer. The weight w_{ij} between waypoints p_i and p_j in ATN is calculated by

$$w_{ij}=\mathrm{FLOW}_{ij}+\mathrm{FLOW}_{ji} \tag{2}$$

where FLOW_{ij} stands for the traffic flow on the air route segment from waypoint p_i to p_j. Clearly, ATN, which is not considered the direction of traffic flow, cannot reflect the dissymmetry of air traffic flows in reality, i.e., FLOW_{ij} is not necessarily equal to FLOW_{ji}. For this reason, based on the directed traffic flows between waypoints, a directed weighting network DATN is built. And the weights w_{ij} of waypoints p_i, p_j in DATN are calculated as follows

$$w_{ij}=\mathrm{FLOW}_{ij} \tag{3}$$

Table 2 Different air route network models

Network	Node	Edge	Edge weight	Nature
Physical airway network(PAN)	Waypoints	$\langle p_i,p_j\rangle$ (p_i and p_j are on the same airway and directly adjacent)	Reciprocal of the distance from p_i to p_j	Undirected weighted
Airway traffic network (ATN)	Waypoints	$\langle p_i,p_j\rangle$ (one flight flying from p_i to p_j or from p_j to p_i)	Sum of number of flights from p_i to p_j and number of flights from p_j to p_i	Undirected weighted
Directed airway traffic network (DATN)	Waypoints	$\langle p_i,p_j\rangle$ (one flight flying from p_i to p_j)	Number of flights from p_i to p_j	Directed weighted
Dominance-based directed airway traffic network(DDATN)	Waypoints	$\langle p_i,p_j\rangle$ (one flight flying from p_i to p_j)	Ratio of number of flights from p_i to p_j to total number of flights entering p_j	Directed weighted

Moreover, owing to the heterogeneity of waypoints in a traffic network, the traffic flow starting from a certain waypoint, even with the same magnitude, will impose a smaller effect on busy waypoints than on free waypoints. It can be interpreted that the relation of dominating and being dominated is formed among waypoints due to traffic flows. Such dominance relation can be measured by the ratio of "flow from one waypoint to the target waypoint" to "total flow to the target waypoint". This dominance relation admittedly relates to the direction of traffic flow. For this reason, based on the directed traffic dominance relation between waypoints, a directed weighting network DDATN is built. And the weights w_{ij} of waypoints p_i, p_j in DDATN are calculated as follows

$$w_{ij}=\mathrm{FLOW}_{ij}\Big/\sum_{t=1}^{N}\mathrm{FLOW}_{tj} \tag{4}$$

At this moment, the corresponding weighted airway network models are built according to the airspace structures, traffic flows, and traffic dominance relations. As for each network model, the corresponding adjacency matrix (which describes the topology structure) and weighted matrix (which describes the link weights) are set up. If $w_{ij}=1$ constantly, it is an unweighted network.

2.2 Metrics

Topological analysis is usually one of the first steps in understanding the behavior of complex networks. Here, basic concepts from complex network theory are briefly introduced. They are relevant for the analysis of airway networks.

2.2.1 Degree

During air traffic operation, the airway intersection points and traffic flow convergent points all largely affect airspace safe operation, and these key waypoints can be rapidly identified by the degree index. In undirected networks, the degree k_i of a node i is the number of edge incident with the node and is defined as[16]

$$k_i=\sum_j a_{ij} \tag{5}$$

where a_{ij} is the connection between waypoint p_i and waypoint p_j, $a_{ij}=1$ when there is a connection existing; otherwise, $a_{ij}=0$. In PAN, for each pair (p_i, p_j) of waypoints connected by at least one air route segment the corresponding element a_{ij} equals 1, and otherwise, 0. In ATN, if there is at least one flight flying between waypoints p_i and p_j, then $a_{ij}=1$; otherwise, $a_{ij}=0$. As for a directed network, the degree k_i of node i is equal to the sum of its out-degree k_i^{out} and in-degree k_i^{in}. The out-degree k_i^{out} is the number of edges that start from node i. The in-degree k_i^{in} is the number of edges that end at node i. They are computed as

$$\begin{cases} k_i=k_i^{\text{out}}+k_i^{\text{in}} \\ k_i^{\text{out}}=\sum_{j=1}^{N}a_{ij} \\ k_i^{\text{in}}=\sum_{j=1}^{N}a_{ji} \end{cases} \tag{6}$$

where a_{ij} is an arc from waypoint p_i to p_j. In DATN, DDATN, if there is at least one flight flying from waypoint p_i to p_j, then $a_{ij}=1$; otherwise, $a_{ij}=0$.

2.2.2 Strength

Strength is an indicator of nodal importance. In an air route network, the strength of a waypoint is decided not only by the number of relevant waypoints, but also by the traffic volume passing this waypoint. The node degree is extended to the strength for a weighted airway network, which is the sum of the weights of all links attached to node i[17]. The strength of waypoint p_i in the undirected airway network is the total load on all its links

$$S_i=\sum_{j=1}^{N}a_{ij}w_{ij} \tag{7}$$

where N is the number of nodes in the network, and w_{ij} the edge weight connecting waypoints p_i and p_j. In PAN, the weight is the reciprocal of Euclidian distance between p_i and p_j; in ATN, the weight is the number of flights flying between p_i and p_j. In a directed network, the strength of a node is the sum of its in-strength S_i^{in} and out-strength S_i^{out}

$$\begin{cases} S_i=S_i^{\text{in}}+S_i^{\text{out}} \\ S_i^{\text{in}}=\sum_{j=1}^{N}a_{ji}w_{ji} \\ S_i^{\text{out}}=\sum_{j=1}^{N}a_{ij}w_{ij} \end{cases} \tag{8}$$

where w_{ij} is the weight of the arc from waypoint p_i to waypoint p_j. In DATN, the weight is the number flights from p_i to p_j; in DDATN, the weight is the ratio of the number of flights from p_i to p_j to the total number of flights entering p_j.

2.2.3 Network density

Networks with relatively low density are called sparse networks. As for airway networks, a higher density means the accessibility of network higher. Network density is ratio of the number of existing links to the number of possible links[18]

$$\rho=\begin{cases}\dfrac{2N_e}{N(N-1)} & \text{Undirected network}\\ \dfrac{N_e}{N(N-1)} & \text{Directed network}\end{cases}\qquad 0<\rho\leqslant 1 \tag{9}$$

where N_e is the number of edges in the network. An undirected network with N nodes has a maximum possible number of $N(N-1)/2$ edges, compared with $N(N-1)$ edges in a directed network.

2.2.4 Clustering coefficient

In an airway network, the clustering coefficient is a measure of local cohesiveness of neighbors of a waypoint that takes into account the intensity of the connections. If waypoint p_i is directly connected to k_i waypoints, then in an undirected network, the largest number of possible edges among these k_i nodes is $k_i(k_i-1)/2$. In a directed network, the largest number of possible edges among these k_i nodes is $k_i\cdot(k_i-1)$. Let the number of actual edges be E_i, then the clustering coefficient C_i of node i can be computed by[18]

$$C_i=\begin{cases}\dfrac{2E_i}{k_i(k_i-1)} & \text{Undirected network}\\ \dfrac{E_i}{k_i(k_i-1)} & \text{Directed network}\end{cases} \tag{10}$$

Furthermore, together with the weights of edges, the weighted clustering coefficient of node i is defined[17]

$$C^w{}_i=\frac{1}{s_i(k_i-1)}\sum_{j,h}\frac{w_{ij}+w_{ih}}{2}a_{ij}a_{ih}a_{jh} \tag{11}$$

where s_i is the strength of wayppoint p_i; k_i the number of connections from waypoint p_i; a_{ij} either 0 for the absence or 1 for the presence of a connection between p_i and p_j. In this way we consider the total relative weight of the closed triplets of any waypoint with respect to the strength of the waypoint.

2.2.5 Length of the shortest path

A path is an ordered sequence of nodes and edges, linking a source node and a target node. In this study, similar weights were used, so the distance between nodes is the reciprocal of weight, and a larger weight means the between-node relationship is closer. Consequently, the shortest path length is defined as the smallest sum of the inverse weights of the links throughout all possible paths from p_i to p_j, which is calculated as[18]

$$l_{ij}=\min_{r(i,j)\subset R(i,j)}\sum_{m,n\in r(i,j)}\frac{1}{w_{mn}} \tag{12}$$

where l_{ij} is the length of the shortest path between nodes i and j. In an undirected network. there is $l_{ij}=l_{ji}$, but $l_{ij}\neq l_{ji}$ in a directed network. $r(i,j)$ is a path from p_i to p_j; $R(i,j)$ the set of all possible paths from p_i to p_j; and m and n are the waypoints along with the path $r(i,j)$. When the weights in an airway network are not considered (namely $w_{mn}=1$), the shortest path is the route to connect two waypoints involved the least segments. For two nodes with the shortest path, the number of intermediate waypoints that must be passed to connect these two nodes is the smallest. In a weighted network, the shortest path largely differed along with the method to define weighting. In PAN, the weight is determined as the reciprocal of between-node spatial distance, so a larger between-node weight means the between-node spatial distance is shorter. Thus, in PAN, if the shortest path between two nodes is shorter, the spatial distance between them is shorter. In ATN and DATN, the flight flow between nodes is adopted as weight, so a larger between-node weight means the number of flights between two nodes is larger, and the relation distance between nodes is shorter. Thus, in ATN and DATN, if the shortest path between two nodes is shorter, there are more flights between them. In DDATN, the flow dominance degree between nodes is adopted as weight, so a larger between-node weight means the traffic dominance between two nodes is larger, and the relation distance between nodes is shorter. Thus, in DDATN, if the shortest path between two nodes is shorter, there is a stronger flow dominance relation between the two waypoints.

The average path length is defined as the average of the shortest path lengths between any two nodes of a network and calculated as follows

$$L=\begin{cases}\dfrac{2}{N(N-1)}\sum\limits_{i\geqslant j}l_{ij} & \text{Undirected network}\\ \dfrac{1}{N(N-1)}\sum\limits_{i\neq j}l_{ij} & \text{Directed network}\end{cases} \tag{13}$$

2.2.6 Betweenness

In a network, a node with a relatively smaller degree may be very important because it undertakes the key role of connecting with different parts. Thus, as an indicator of node intermediary ability, betweenness is used to measure the pivotability or centricity of nodes. In the context of the airway network, betweenness as a measure of the centrality of each waypoint. The metric indicates the number of shortest paths going through waypoint[18], and is defined as

$$b_i=\sum_{i\neq j}\frac{n_{jk}(i)}{n_{jk}} \tag{14}$$

where n_{jk} is the number of shortest paths connecting p_j and p_k (in directed networks, it goes from p_j to p_k), while $n_{jk}(i)$ the number of the shortest paths connecting p_j and p_k and passing through p_i(in directed networks, it goes from p_j to p_k, passing through p_i). After edge weights are considered, the shortest path between nodes may be changed and consequently, the number of the shortest paths between nodes will be adjusted. The weighted betweenness of nodes can be computed as follows

$$b^w{}_i=\sum_{i\neq j}\frac{n^w{}_{jk}(i)}{n^w{}_{jk}} \tag{15}$$

where $n^w{}_{jk}$ and $n^w{}_{jk}(i)$ are n_{jk} and $n_{jk}(i)$ with the consideration of weights, respectively.

2.2.7 Closeness

Closeness is based on the inverse distance of each node to every other node in the airway network and reflects the difficulty of a waypoint to get access to other waypoints in the network. For a node with larger closeness, it is more closely related to other nodes. In an equalized network, such nodes are usually located in the middle of the network. Contrarily, for a node with smaller closeness, its overall influence on the network is weaker. The closeness of a node was computed as follows[15]

$$C_c(i)=(N-1)\Big/\sum_{j=1,j\neq i}^{N}l_{ij} \tag{16}$$

where l_{ij} is the shortest path length between waypoints p_i and p_j. It is clear from the above definitions that closeness is closely related to the definition of the shortest path. When weights are ignored, the shortest path between two nodes is the path with the smallest number of hops between these two nodes. When weights are considered, the shortest path between two nodes is the path with the closest relational distance between these two nodes. To differentiate the closeness values computed from these two different ways, the closeness considering weights is named weighted closeness.

3 Results and Analyses

3.1 Basic network characteristics

Table 3 lists a simple comparison of the basic characteristics of the four airway networks. Since all network models involved the current waypoints in China as network nodes, all networks contained 1 479 nodes. In terms of network density, all air-

Table 3 Basic topological characteristics of airway networks

	PAN	ATN	DATN	DDATN
Number of nodes	1 479	1 479	1 479	1 479
Network density	0.002 3	0.091 9	0.059 9	0.059 9
Number of nodes with 0°	0	246	246	246
Maximum degree	13	583	873	873
Average degree	3	136	177	177
Average in-degree			89	89
Average out-degree			89	89
Clustering coefficient	0.100 6	0.453 0	0.322 8	0.322 8
Average path length	13.9	1.4	1.5	1.5

way networks were sparse, especially PAN, the density of which was only 0.002 3. In terms of node degrees, PAN contained no waypoint with a degree of 0, and the difference between the maximum degree (13) and the average degree (3) was small, or namely, the numbers of route segments connecting with waypoints were all small, and the differences between waypoints were small. However, such homogeneity of airway networks was largely changed under the action of traffic flows. In ATN, DATN, and DDATN, the largest degrees were all very large (which were 583, 873 and 873, respectively), and the average degrees all rose largely (which were 136, 177, and 177, respectively). Nevertheless, the degree was 0 in 246 waypoints (namely, the waypoints with no flights passing through), and their proportion was up to 16.6%, indicating the heterogeneity of traffic flows led to an abrupt decrease of homogeneity among airway networks, and hence, the structural characteristics of airway networks were richer. Moreover, a number of waypoints with the degree of 0 appeared, which implied to some extent that some resources in the airway networks were yet not fully utilized. Since DATN and DDATN were both directed networks, we further statistically analyzed the average out-degree and average in-degree of nodes in them (which were all 89). Results implied each waypoint in the traffic flow had 89 upstream waypoints and 89 downstream waypoints on average, which were smaller than the average degree of 136 in ATN. These results also validated that the traffic flows among waypoints were asymmetrical. The statistical analysis of the average shortest path length and clustering coefficient shows that the PAN is not a small-world network due to its low clustering coefficient (0.100 6), large average shortest path length (13.9), which are consistent with another study[11]. Nevertheless, ATN, DATN, and DDATN all had a short average shortest path and large clustering coefficient and thereby were all typical small world networks.

3.2 Degree and strength

Figs. 1(a)—(d) depict the degree distribution for the four networks in the semi-log scale. We can observe that most waypoints have only a few connections with other nodes. The degree distributions of all airway networks follow exponential functions $P(X \geqslant k) = e^{Ak}$, which is consistent with another study[11]. PAN, compared with the other three traffic networks, was more homogeneous (A in PAN, ATN, DATN, and DDATN was -0.28, -0.006, -0.008, -0.008, respectively). These results further imply that the airway networks under the influence of traffic flows were more heterogeneous.

Previous studies usually supposed that airway networks were fully symmetrical, and the in-degree and out-degree of each node were equal[14]. In this study, based on the latest data, the in-degrees and out-degrees of nodes in four networks were further compared, and the statistical results are shown in Figs. 1(e)—(h). As for PAN and ATN, owing to the ignorance of direction, the in-degree and out-degree were fully equal for all nodes. In DATN and DDATN, however, though the in-degree and out-degree were the same for the majority of nodes, there were some nodes with large in-degree and small out-degree (e. g., the waypoint NLG had flights to other 51 waypoints, but 413 waypoints had flight to this waypoint). There were also some nodes with small in-degree and large out-degree (e.g., YIN had flights to 383 waypoints, but only 117 waypoints had flights to YIN). These results suggest after traffic flows were considered, the values of traffic flows between waypoints were not symmetrical with dominance relation.

Then weights were further considered. The log-log coordinates in Figs. 2(a)—(d) showed the degree-strength correlation of different airway networks. The degree and strength in these networks all obeyed the power law relation $S(k) = \alpha k^{\beta}$, indicating the node strength was gradually enhanced with the rise of degree. Nevertheless, the enhancing rates differed among networks (it was reportedly different that the data in 2012 confirmed the degree and strength of an airway network were linearly related[11]). Nevertheless, our statistics with the latest data showed that in PAN and DDATN, the node

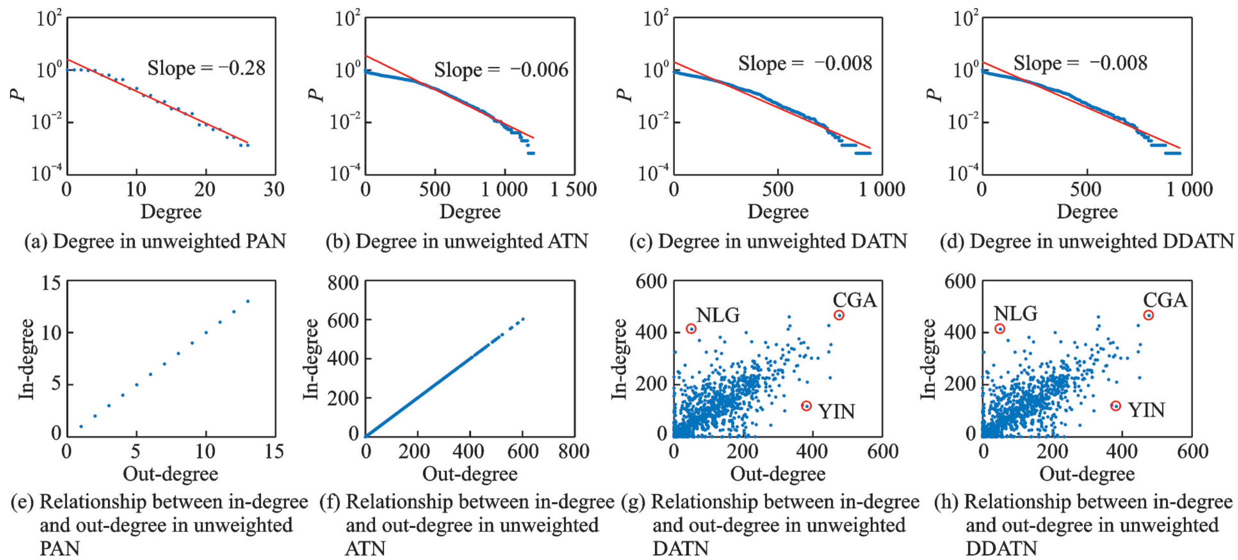


Fig.1 Distribution of degree and relationship between in-degree and out-degree

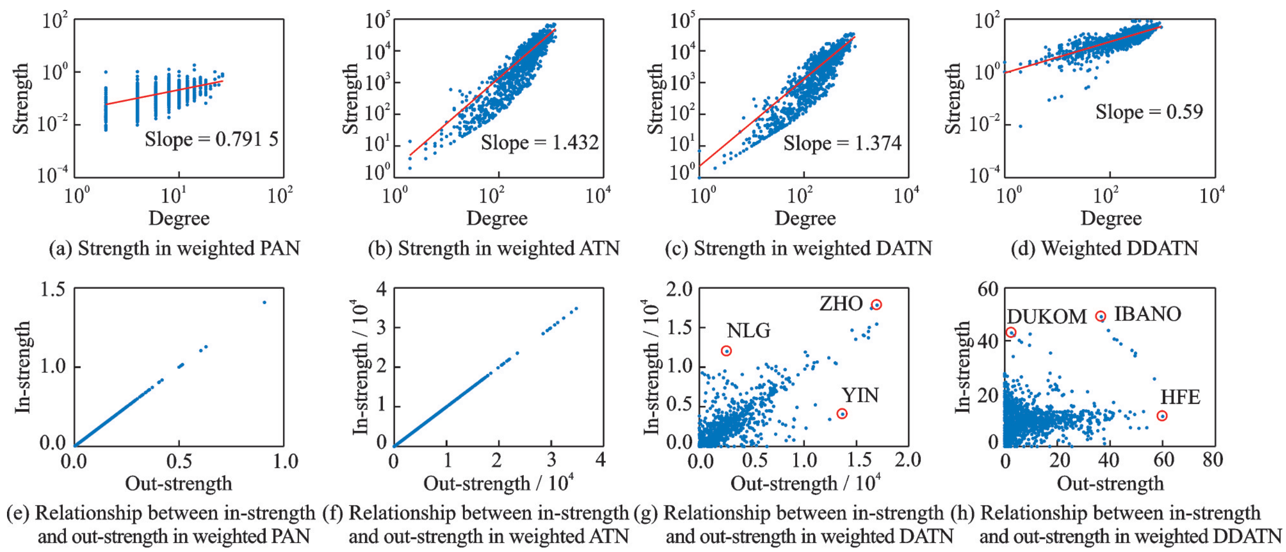


Fig. 2 Distribution of strength and relationship between in-strength and out-strength

degree and strength were sub-linearly related: With the increase of node degree, the strength was enhanced at a slower rate. This was because when a new airway was opened, the larger-degree waypoints were more likely to connect with distant waypoints, but avoided to be connected with close waypoints. In ATN and DATN, however, the node degree and strength were super-linearly related: The increasing rates of strength were faster compared with node degrees, indicating the flows of waypoints rose at faster rates than the number of route segments. Statistical results of in-strength and out-strength were similar compared with unweighted networks. In PAN and ATN, the in-strength and out-strength were the same for all nodes, but in DATN and DDATN, unmatching between in-strength and out-strength was very common. For instance, in DATN, YIN had flights to 383 waypoints, with nine flights on average, and received flights from 117 waypoints, with three flights on average. However, NLG had flights to 51 waypoints, with two flights on average, and had flights from 413 waypoints, with eight flights on average. ZHO had flights to 446 waypoints, with 11 flights on average, and had flights from 326 waypoints, with 12 flights on average. In DDATN, HFE had flights to 446 waypoints, but the flow from HFE to each waypoint accounted for a large proportion (with a mean of 13.5%) of total in-flow of each waypoint, and was up to 50% in 27 waypoints, suggesting HFE relative to these waypoints played a role of "super-importer" and was absolutely dominant in the traffic flows of these waypoints. Though 427 waypoints had flights to HFE, the flows from these waypoints to HFE only accounted for 2% of the total in-flow of HFE on average. This is because HFE had very large flows and other waypoints can hardly play the role of "super importer" on HFE. DUKOM was located near the west border of China. The traffic flows passing through DUKOM were all from east to west, and the flights can even fly to DUKOM from the 250 waypoints in the east of DUKOM. Moreover, the traffic flow of each waypoint to DUKOM accounted for 2.9% of the total flow of DUKOM on average. However, only 12 waypoints in China were located at the west of DUKOM, so this waypoint relative to other waypoints was the dominant role in traffic flows.

The importance levels of waypoints in different networks were classified according to degree and strength (Table 4). In PAN, since 13 waypoints directly connected with YQG and LLC, they ranked top in the unweighted PAN, but CEH ranked the first in the weighted PAN. Among the waypoints connecting with CEH, though only seven waypoints directly connected with it, there were waypoints that were very close to CEH (e.g., the distances of P69, NUKSU, and P82 from CEH were only 3 km, 4 km, and 4 km, respectively). After traffic flows were considered, SHX had flights to 332 waypoints and accepted flights from 460 waypoints, but when the direction was not considered (some repeated waypoints should be deleted), SHX had flights to or from 583 waypoints, so it ranked the first in the unweighted ATN. HFE had flights to 446 waypoints and received flights from 427 waypoints. Namely, when the direction was considered, 873 waypoints were related with HFE, ranking the first (when the direction was not considered, it was related with 580 waypoints, ranking the second only after SHX). Furthermore, when flows on route segments were considered in weighted networks, ZHO ranked the first in both ATN and DATN, but HFE dropped from the first place and ranked the second. Fig. 3 shows the airspace structures of multiple waypoints as well as the peak-hour radar tracks. Comparative analysis displayed that though ZHO had a simpler airway structure than HFE, it was located on the busiest airway A461, and thus its traffic flow was more concentrated. Though the number of ZHO-related waypoints was smaller compared with HFE, the traffic flows on ZHO-related route segments were generally large, so ZHO ranked before HFE in the flow-based weighted networks. In the DDATN based on traffic flow dominance relation and strength weighting, URC ranked the first, which was because URC was a regional hub located near ZWWW in northwest China, and the traffic flows of its neighboring waypoints mostly passed through URC, and these waypoints were absolutely dominated by URC, or namely, URC was a "super importer" in this region.

To comprehensively consider the characteristics of different networks, we proposed the degree composite index and defined it as the geometric av-

Table 4 Top ten waypoints ranked by degree and strength in different networks

No. of node	Unweighted PAN	Unweighted ATN	Unweighted DATN	Unweighted DDATN	Weighted PAN	Weighted ATN	Weighted DATN	Weighted DDATN
1	YQG	SHX	HFE	HFE	CEH	ZHO	ZHO	URC
2	LLC	HFE	WXI	WXI	UPLEL	HFE	HFE	HFE
3	TYN	ZHO	SHX	SHX	OLRIS	LKO	LKO	ZHO
4	CG	POLHO	ZHO	ZHO	SNQ	PAVTU	PAVTU	PAVTU
5	DBL	WXI	TYN	TYN	IJ	ESDOS	ESDOS	YIN
6	PU	VYK	NUBKI	NUBKI	PU	WXI	WXI	LKO
7	POU	TYN	CHG	CHG	ARGUK	OBLIK	OBLIK	IPMUN
8	DO	LADIX	LJB	LJB	LLC	P192	P192	LADIX
9	XKC	P450	POLHO	POLHO	OBLAP	P450	P450	SHX
10	TMR	CGA	CGA	CGA	LUPVI	HOK	HOK	WXI

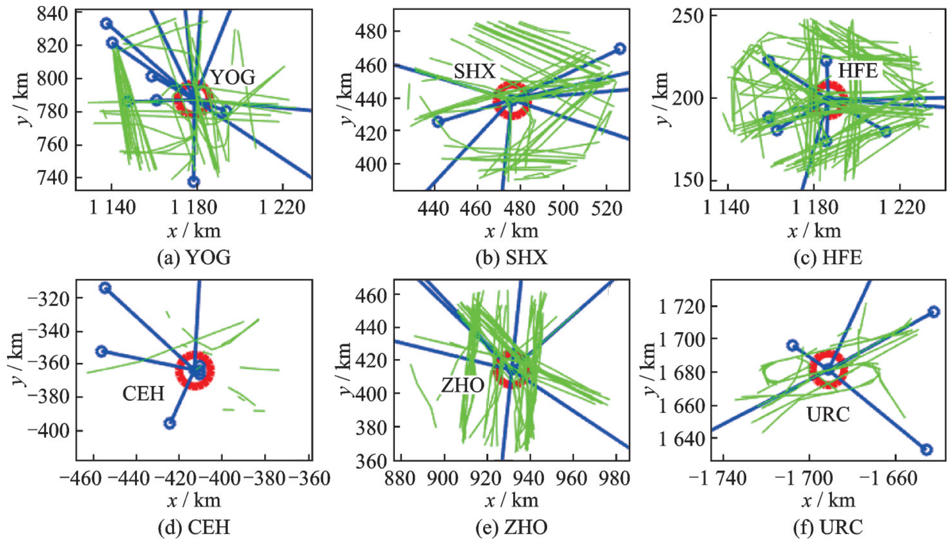


Fig.3 Waypoints with the largest degree and strength in different networks

erage value of degree and strength from different networks. Since the scales of degrees and strengths are not the same among different networks and in order to eliminate such impact from scale differences, we adopted Min-Max normalization to normalize the degree and strength indices in different networks. Moreover, to avoid the impact of some extreme values from a part of indices, we used geometric average method that is insensitive to extreme values. The relation between the degree composite index and traffic flow was illustrated in Fig.4(a). Clearly, the degree composite index generally was positively correlated with waypoint flow and was linearly increased with the rise of waypoint flow. According to mean values of flows and degree composite index, the waypoints were classified into four types. In the first type (56%), the flows and degree composite index of the waypoints were smaller than the mean values, and in the second type (32%), the flows and degree composite index were larger than the mean values. Moreover, the degree composite index and flows of HFE, WXI and ZHO all ranked top five, indicating these waypoints played key pivotal roles in topological structures and traffic flows. Fig.4(b) showed the geographical locations of the top ten waypoints ranked by the degree composite index.

3.3 Betweenness and weighted betweenness

Fig.5 depicts the betweenness and weighted betweenness distributions of the different airway networks. The cumulative distribution of betweenness and weighted betweenness can be fitted by an exponential function: $P(X \geqslant b) = e^{Ab}$, which is consistent with previous research[11,14]. However, the A values differed largely among different networks, and $|A|$ was larger, so the proportion of waypoints with low betweenness or low weighted betweenness

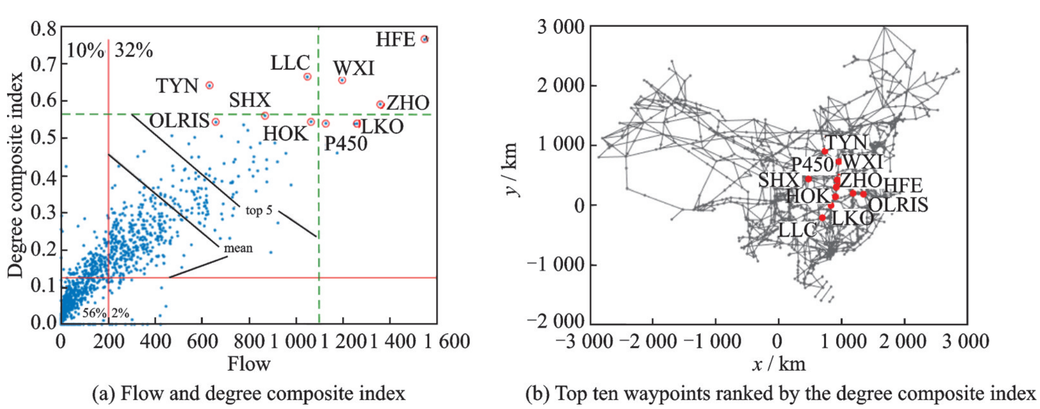


Fig.4 Flow and degree composite index and top ten waypoints ranked by the degree composite index

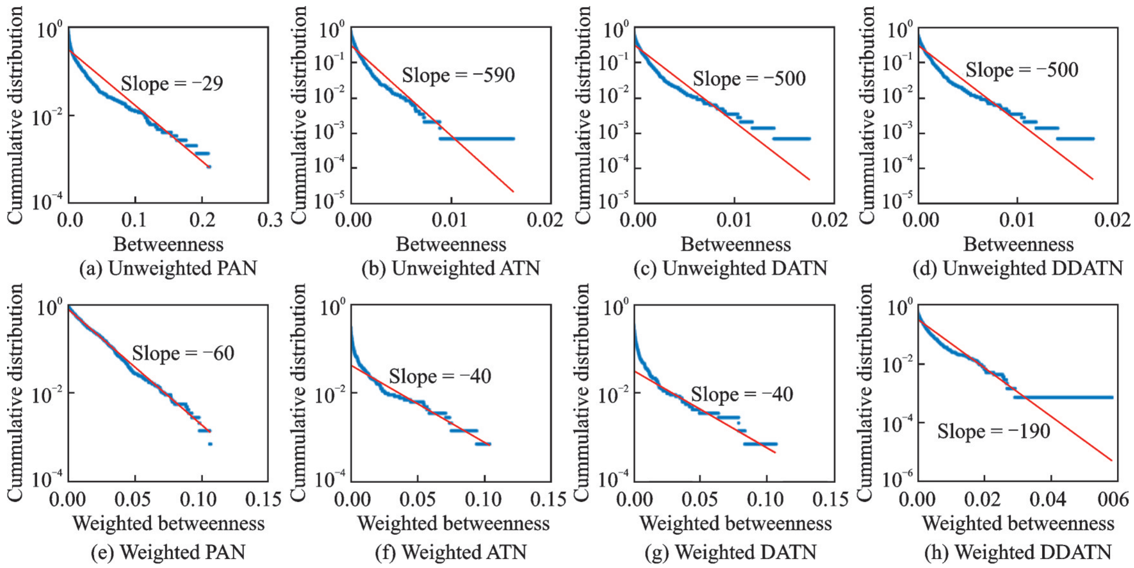


Fig.5 Betweenness and weighted betweenness cumulative distributions

was higher and the proportion of waypoints with high betweenness or high weighted betweenness was lower. Comprehensively, when weights were not considered, the proportion of waypoints with high betweenness in PAN was larger, but after weights were considered, the proportion of waypoints with high weighted betweenness in DDATN was the lowest. Moreover, a comparison of betweenness distribution and degree distribution showed that the number of waypoints with high betweenness in the airway network was far less than that of waypoints with a large degree.

Figs.6 (a) — (d) show the relation between node degree and betweenness when weights were not taken into account. Generally, the degree-betweenness correlation obeyed the power law $b(k)=\alpha k^{\beta}$ in all networks. In other words, as the degree rose, the node betweenness gradually increased, but the increasing rates differed among different networks (which were different from another study that reported a linear relationship between degree and betweenness[11]). Our statistics of the latest data showed the node degree and betweenness were super-linearly related in all four networks: The increase rate of node betweenness was faster than that of node degree. The relation between strength and weighted betweenness with consideration into weights in each network is illustrated in Figs.6(e)—

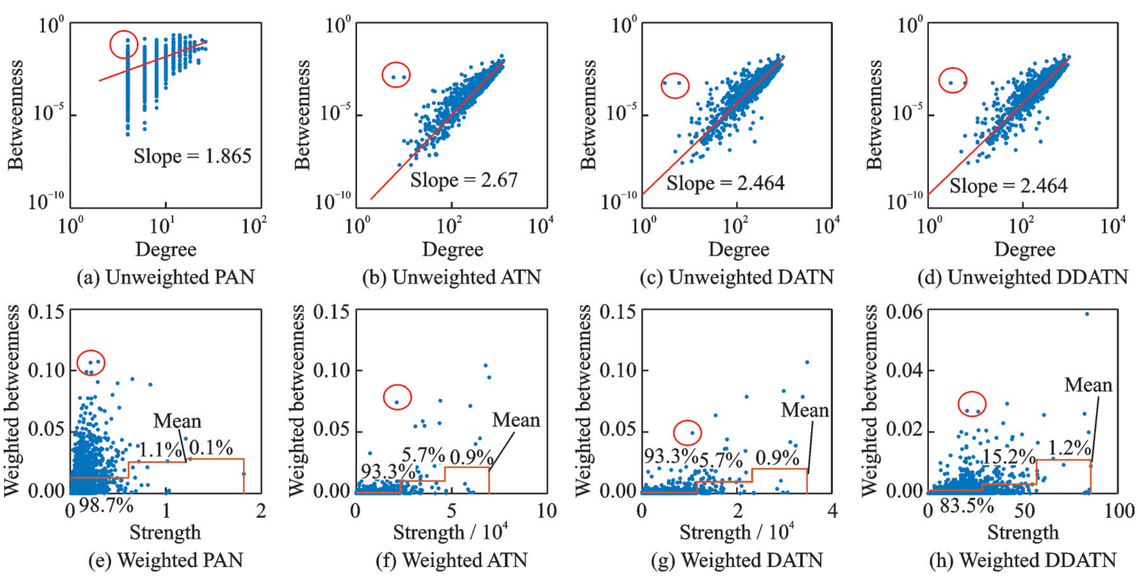


Fig.6 Degree-betweenness and strength-weighted betweenness correlation

(h). The average strength was divided into 3 segments, and the mean weighted betweenness of each segment was marked by red ladder lines, and the proportion of waypoints in each segment was labeled. Among the four networks, though the relation between weighted betweenness and strength was not obviously a power law, the weighted betweenness generally rose with the increment of node strength and the majority of waypoints possessed low strength and low weighted betweenness (the proportions of such waypoints in PAN, ATN, DATN, and DDATN were 98.7%, 93.3%, 93.3%, and 83.5%, respectively), indicating the most waypoints did not fall in the shortest path of each network, and the strength was also low. Furthermore, some low-degree or low-strength nodes were found in each network, but the betweenness or weighted betweenness was very high (marked by circles in Fig.6), suggesting the importance of these nodes was not reflected by the connectivity within local areas, but by the connectivity between local areas.

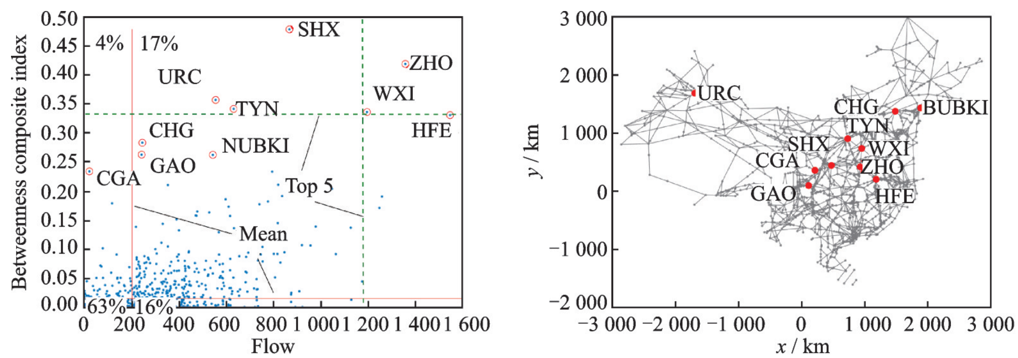
The importance levels of waypoints in different networks were classified according to betweenness and weighted betweenness (Table 5), which showed the ranking of betweenness differed among networks. In PAN, the betweenness was high in JND and ZHO (which were located slightly in the east of middle China), because these two waypoints fell within the junction among three regional routes, including North China, East China, and Central South China, and played very important bridging roles in airway structures. In the PAN with consideration into weights, the waypoints with large weighted betweenness became ZS and P450, which were close to the middle of China. Traffic flow networks were largely affected by the flows in route segments related with HFE and ZHO, so these route segments showed closer relations when the spatial distance was the same (relation distance in the networks was shorter), so that the number of shortest paths between these two waypoints was large and that the weighted betweenness ranked in the top in ATN and DATN. In DDATN which was based on traffic flow dominated strength weighting, since URC was located in the bridge from inland routes to Xinjiang, its weighted betweenness ranked 1st.

By referring to the computational method of degree composite index, we proposed the conception and computational method of betweenness composite index to comprehensively consider the characteristics of different networks. And betweenness composite index was defined as the geometric average value of betweenness and weighted betweenness from different networks. The relation between the betweenness composite index and traffic flow is illustrated in Fig.7 (a). Clearly, the betweenness composite index was positively correlated with waypoint flow, and the betweenness composite index rose with the increment of waypoint flow, but the increasing amplitude was smaller than that of the degree composite index. According to the mean value of flows and the betweenness composite index, the waypoints were classified into four types. In most of the waypoints (63%), the flows and betweenness

Table 5 Top ten waypoints ranked by betweenness and weighted betweenness in different networks

No. of node	Unweighted PAN	Unweighted ATN	Unweighted DATN	Unweighted DDATN	Weighted PAN	Weighted ATN	Weighted DATN	Weighted DDATN
1	JND	POLHO	POLHO	POLHO	ZS	HFE	ZHO	URC
2	ZHO	CHG	CGA	CGA	P450	ZHO	WXI	PIKAS
3	OMBON	CGA	CHG	CHG	SHX	SHX	SHX	YCE
4	GAO	IKELA	IKELA	IKELA	HOK	SHZ	HFE	P16
5	WTM	SHX	NUBKI	NUBKI	TYN	WXI	URC	ANDIM
6	ENH	NUBKI	SHX	SHX	WXI	NUBKI	SHZ	YIN
7	XSH	DOTOS	LJB	LJB	HFE	ANDIM	TYN	LMN
8	MEPEP	ANDIM	DOTOS	DOTOS	LLC	TYN	PAVTU	ZYG
9	DUMIN	LJB	HRB	HRB	ENH	URC	LKO	LXA
10	PANKI	HRB	URC	URC	P192	LKO	YIN	VIBOS

composite index were smaller than the mean values, and in the second type (17%), the flows and betweenness composite index were larger than the mean values. Different from the statistical results of the degree composite index, the proportion of waypoints with traffic flow above the mean value and betweenness composite index below the mean value was larger (16%). Specifically, the betweenness composite index and flows of ZHO and WXI both ranked top five, indicating these waypoints not only had large flows, but also played important intermediary roles in the networks. Fig.7(b) shows the geographical locations of the top ten waypoints ranked by the betweenness composite index.

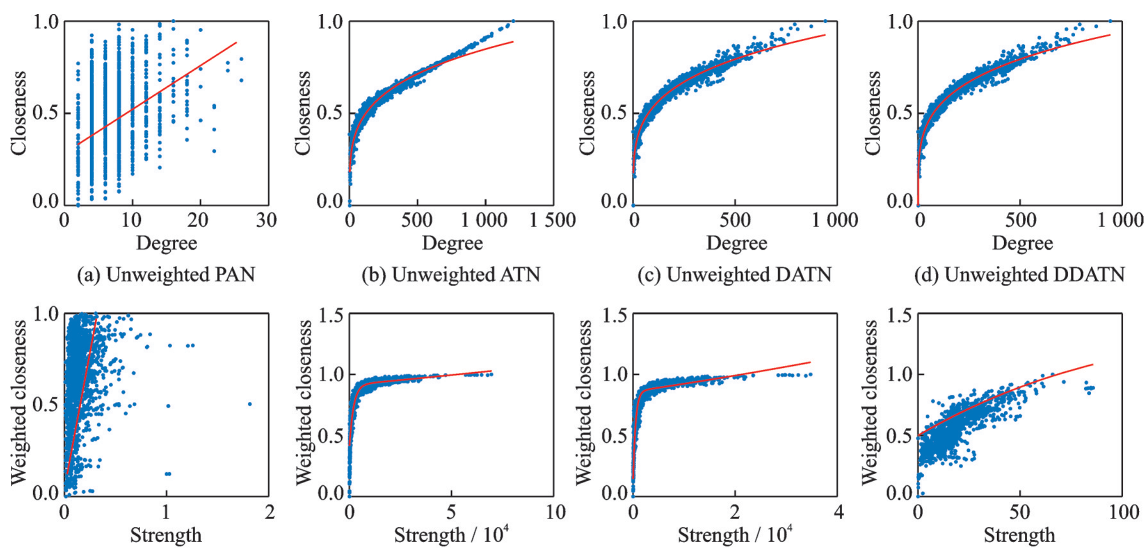


(a) Flow and betweenness composite index (b) Top ten waypoints ranked by the betweenness composite index

Fig.7 Flow and betweenness composite index and top ten waypoints ranked by the betweenness composite index

3.4 Closeness and weighted closeness

Figs.8(a)—(h) show the relation between degree-closeness and strength-weighted closeness in different networks. Generally, the closeness and weighted closeness in each network rised with the increment of degree and strength, but the increasing trends differed among different networks. In PAN, the mean betweenness corresponding to specific degree increased basically in a linear way with the increment of degree, but the closeness at the same degree varied in a large range, and there were abundant nodes with a low degree and high closeness. With consideration of weights, the weighted closeness increased in a steeper linear way compared with strength. Interestingly, the statistical results with consideration of weights significantly differed among ATN, DATN, and DDATN. When weights were ignored, the relationship between closeness and degree was an evident power law. When weights were considered, the relation be-



(a) Unweighted PAN (b) Unweighted ATN (c) Unweighted DATN (d) Unweighted DDATN

(e) Weighted PAN (f) Weighted ATN (g) Weighted DATN (h) Weighted DDATN

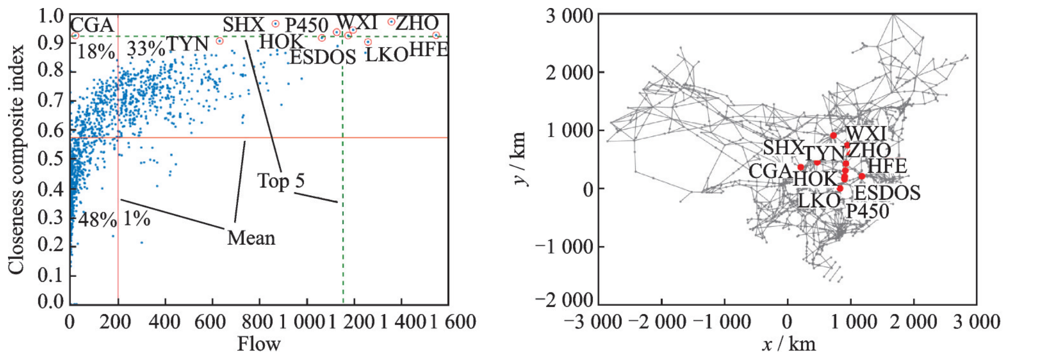
Fig.8 Degree-closeness and strength-weighted closeness correlation tween weighted closeness and strength was a two-segment exponential function. In other words, whether weights were considered or not, the increasing rates of closeness and weighted closeness following the increment of degree or strength were fast at an early stage and slower at a late one, but the increasing rate of weighted closeness with strength at an early stage was faster than that of closeness with the degree and slower at a late stage. In DDATN, the weighted closeness increased more gently with the rising strength, compared with the uptrend of closeness with the degree.

The ranking of waypoint importance, according to closeness and weighted closeness in different networks, is listed in Table 6. In PAN, closeness reflected the spatial distance between a certain waypoint and other waypoints, and when the closeness was higher, the average shortest distance from this waypoint to other waypoints was also shorter. The shorter average shortest distance meant the network operation was faster, and the number of midway nodes passes during flights was smaller. In PAN, ENH showed the highest closeness and ML had the highest weighted closeness, and these two nodes were geographically located in middle China. In ATN and DATN, closeness reflected the magnitude of flows between a certain waypoint and all other waypoints in a network. In DDATN, closeness stood for the dominance degree of a waypoint over the traffic flows of other waypoints. In ATN, DATN, and DDATN, the node with the highest closeness centricity was always CGA, which was located in middle China, and the numbers of airports and waypoints linked to CGA were both very large. In ATN, DATN, DDATN, the node with the highest centricity of weighted closeness was always ZHO, which was located not as much in middle China as CGA and the number of air routes linked to this node (1 118) is slightly smaller, compared with CGA, SHX and HFE (1 204, 1 166, 1 160, respectively). Nevertheless, its flights were concentrated on certain route segments, which maximized its weighted closeness. Hence, it largely dominated the traffic flows of other waypoints.

Table 6 Top ten waypoints ranked by closeness and weighted closeness in different networks

No. of node	Unweighted PAN	Unweighted ATN	Unweighted DATN	Unweighted DDATN	Weighted PAN	Weighted ATN	Weighted DATN	Weighted DDATN
1	ENH	CGA	CGA	CGA	ML	ZHO	ZHO	ZHO
2	WTM	SHX	SHX	SHX	SHX	WXI	WXI	YIN
3	SNJ	HFE	HFE	HFE	P320	LKO	ESDOS	WXI
4	YIH	ZHO	ZHO	ZHO	P175	ESDOS	OBLIK	HFE
5	SHX	WXI	POLHO	POLHO	P450	OBLIK	P192	ESDOS
6	P373	POLHO	WXI	WXI	UGSUT	P192	LKO	ANDIM
7	P53	VYK	VYK	VYK	ZHO	P450	P450	OBLIK
8	ZS	TYN	TYN	TYN	P192	HOK	HOK	P192
9	XSH	LADIX	LADIX	LADIX	P402	PAVTU	AKOMA	LKO
10	OKTUV	P450	P450	P450	DXM	HFE	IDULA	P450

To comprehensively consider the characteristics of different networks, the conception and computational method of closeness was proposed composite index and it was defined as the geometric average value of closeness and weighted closeness from different networks by referring to the computational method of degree composite index. The relation between the closeness comprehensive index and traffic flow is illustrated in Fig.9(a). Generally, the closeness composite index was positively correlated with waypoint flows, and the increasing rate was super-linear, but the increasing rate surpassed that of the degree comprehensive index. According to mean values of flows and closeness composite index, the waypoints were classified into four types. In most of the waypoints (48%), the traffic flows and closeness composite index were smaller than the mean values, and in the second type (33%), the traffic flows and closeness composite index were larger than the mean values. The proportion of waypoints with traffic flow below the mean value and closeness composite index above the mean value was large (18%), which was different from the statistical results of degree composite index and opposite from the results of the betweenness composite index. It is indicated that even some small-flow waypoints show high closeness in airway networks. Among all waypoints, the closeness composite index and flows of ZHO, WXI and HFE all ranked top five, indicating that these waypoints were busy and largely affected other waypoints in the whole networks. Fig.9 shows the top ten waypoints ranked by the closeness composite index in the airway network. Clearly, the waypoints with low flows but top-ranking closeness composite index were mainly located in middle China, such as CGA and TYN.

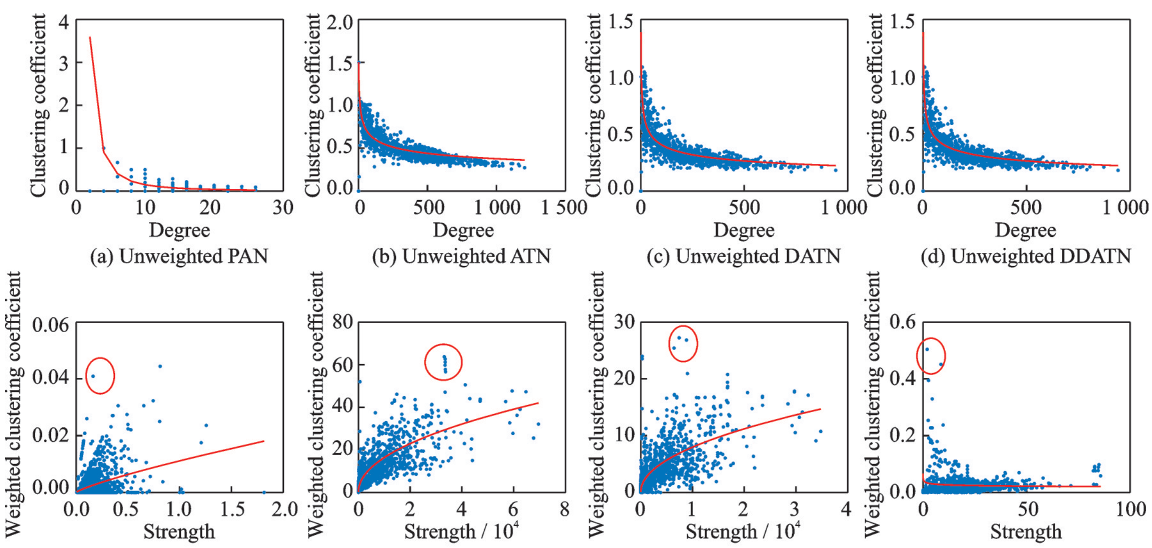


(a) Flow and closeness composite index (b) Top ten waypoints ranked by the closeness composite index

Fig.9 Flow and closeness composite index and top ten waypoints ranked by the closeness composite index

3.5 Clustering coefficient and weighted clustering coefficient

The relation of degree-clustering coefficient and strength-weighted clustering coefficient differed among different networks (Figs.10 (a) — (h)). When weights were ignored, the relation between clustering coefficient and degree generally obeyed a power law: The clustering coefficient gradually decreased with the increasing degree, and the downtrend of the clustering coefficient was more evident when the degree was smaller. It was indicated the smaller-degree nodes probably had a larger clustering coefficient. After weights were considered, though the weighted clustering coefficient slightly increased with the improvement of strength, there were still some waypoints with low strength and high weighted clustering coefficient (circled in Fig.10).



(a) Unweighted PAN (b) Unweighted ATN (c) Unweighted DATN (d) Unweighted DDATN

(e) Weighted PAN (f) Weighted ATN (g) Weighted DATN (h) Weighted DDATN

Fig.10 Degree-clustering coefficient and strength-weighted clustering coefficient correlation

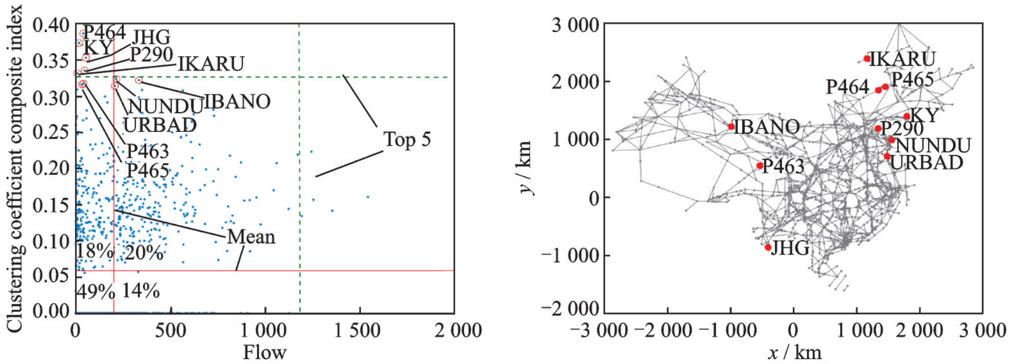
The importance levels of waypoints in different networks were classified according to the clustering coefficient and weighted clustering coefficient (Table 7). Since only two waypoints (MUDAL and DONVO) were adjacent to AGAVO and there was an airway connecting these two waypoints, the clustering coefficient of AGAVO was 1 (despite its low degree of 2), ranking the first in PAN. For other large-degree nodes, since they had many adjacent waypoints, the adjacent waypoints were unlikely to form a triangle, so the clustering coefficient was usually very small. After weights were considered, some waypoints located at higher local waypoint density can acquire a larger clustering coefficient. For instance, OBLAP had four adjacent waypoints, but the spatial distance of OBLAP from OLRIS or LUPVI was too short (7 km and 5 km, respectively), so the weighted clustering coefficient of OBLAP was the largest. Among ATN, DATN, and DDATN, when weights were ignored, only two flights passed P177, so very few waypoints were linked to P177 (only four). And since these waypoints were mostly related with each other (at least one regular flight), finally the clustering coefficients of P177 in UFARN, UFDARN, and UEARN were all very large. After the traffic flow and traffic flow dominance relations on air route segments were considered, the top one waypoint previously ranked by the weighted clustering coefficient also changed with traffic flow and became NIXUK, P391, and P164, respectively.

Table 7 Top ten waypoints ranked by clustering coefficient and weighted clustering coefficient in different networks

No. of node	Unweighted PAN	Unweighted ATN	Unweighted DATN	Unweighted DDATN	Weighted PAN	Weighted ATN	Weighted DATN	Weighted DDATN
1	AGAVO	P177	P177	P177	OBLAP	NIXUK	P391	P164
2	BUNTA	P387	P387	P387	RUPID	NOGEX	P346	P80
3	ESPEG	SARUL	SARUL	SARUL	P204	P407	RENOB	P245
4	KAMUD	GUSEV	IKARU	IKARU	P324	LAXEV	NOBOB	P136
5	P109	IKARU	P96	P96	SAPIN	TODOD	GUSEV	FYJ
6	P167	NOBOB	AKBEP	AKBEP	BEMTA	P434	LARAD	IKARU
7	RUPID	DBC	P394	P394	DODSA	OMGUP	LAXEV	SQH
8	VISIN	IGRID	NONIM	NONIM	TEDIB	GUSEV	NOGEX	P222
9	ALS	XODAS	P04	P04	ESPEG	NOBOB	P434	P177
10	BMS	‘JR’	P164	P164	LUPVI	AKUBA	P407	P387

To comprehensively consider the characteristics of different networks, the conception and computational method of clustering coefficient composite index was proposed and it was defined as the geometric average value of clustering coefficient and weighted clustering coefficient from different networks. The relation between the clustering coefficient composite index and traffic flow is illustrated in Fig.11(a). Clearly, the clustering coefficient composite index did not significantly increase or decline with the rise of waypoint flow. Instead, for the majority of busy waypoints, their clustering coefficients were mostly at medium levels. According to mean values of flows and clustering coefficient composite index, the waypoints were classified into four types. In most of the waypoints (49%). The traffic flows and clustering coefficient composite index were smaller than the mean values. And in the second type (20%), the flows and coefficient composite index were larger than the mean values. The clustering coefficient composite index was low for the majority of waypoints and is 0 in up to 62.6% of waypoints. In other words, the interconnection of waypoints with adjacent points is weak, so local community structures with high relative density can be hardly formed in the airway networks. Moreover, no waypoint ranked top five in both the clustering coefficient composite index and flow. The top ten waypoints ranked by the clustering coefficient composite index are shown in Fig. 11. It is found these waypoints were not located in busy airspace. The clustering coefficient had implications on local robustness.

A higher clustering coefficient indicated greater robustness because alternate connection paths may exist when a neighboring node failed. These results indicated the robustness of Chinese airway networks was not strong, especially in some busy waypoints. Namely, when waypoints were overly congested or fail, few waypoints or airway resources were available for selection, and the affected flights only had to delay on the airport or circle in the air, which decreased the air traffic efficiency to some extent.



(a) Flow and clustering coefficient composite index (b) Top ten waypoints ranked by the closeness composite index

Fig.11 Flow and clustering coefficient composite index and top ten waypoints ranked by the clustering coefficient composite index

3.6 Level of importance

The above statistical analysis implies that owing to the influence of geographical locations, airspace structures, and traffic flow characteristics, the importance levels of the same waypoint may differ depending on the statistical index. For instance, the importance level of HFE ranks the first in terms of degree and is above ZHO, but ranks below ZHO in terms of both betweenness and closeness. Also, HFE and ZHO have a large degree and betweenness, and their clustering coefficients do not rank top ten. Thus, different network topology indices only reflect certain characteristics of waypoints. Furthermore, statistical results suggest that clustering coefficient focuses more on local factors, since it is affected by some extremely low connection degrees, extremely low traffic flows and other extreme conditions, but ignors some key nodes that are very important in the whole networks. Therefore, we think the clustering coefficient and the weighted clustering coefficient cannot be regarded as measures of node criticality. To comprehensively analyze the importance levels of waypoints from multiple aspects, the K-means method based on the degree composite index, betweenness composite index, and closeness composite index was introduced, and the waypoints in China were divided into three levels (Table 8 and Fig.12). Specifically, the indices at the first level were all large, so the waypoints at this level (21.8% of waypoints) were comprehensively more important than those on the other two levels. The waypoints at the third level accounted for the largest proportion and were comprehensively least important.

Table 8 Level classification of waypoints

Level	Mean of degree composite index	Mean of betweenness composite index	Mean of closeness composite index	Proportion/%	Mean of F_1	Mean of F_2	Mean of F_3	Mean of F_4	Mean of F_5	Mean of F_6	Mean of F_7
1	0.31	0.05	0.77	21.8	456	59	191	55	55	20	34
2	0.15	0.01	0.66	32.3	181	24	70	28	27	9	16
3	0.02	0	0.42	45.9	22	2	5	5	5	2	3

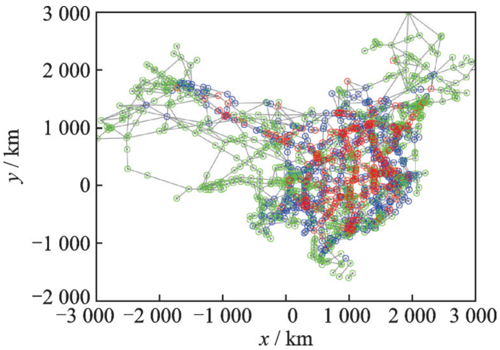


Fig.12 Classification of waypoints in China (Red: level 1; blue: level 2; green: level 3)

To validate the classification results, the typical functional indices reflected by the airway system were statistically analyzed further according to the idea of "structure decides functions". These indices mainly included traffic volume passing a waypoint (F_1), traffic volume passing the waypoint and with departure delay (F_2), traffic volume passing the waypoint and with arrval delay (F_3), number of departure airports of all flights passing the waypoint (F_4), number of destination airports of all flights passing the waypoint (F_5), number of departure airports of all flights passing the waypoint and with departure delay (F_6), and number of destination airports of all flights passing the waypoint and with arrival delay (F_7). These statistical results suggested that the traffic flows of waypoints at the first level were all large, two and a half times compared with the waypoints at the second level, and all were busy with the aspect of traffic volume. Moreover, a number of departure and destination airports were involved with the waypoints at the first level, indicating that the traffic flows related to the level of waypoints were involved in broader areas. From the perspective of a flight delay, these waypoints related to a number of delayed flights and delay airports, indicating that flight delay mainly occurred in the traffic flows related to these waypoints and that these waypoints most obviously affected the flight delay at the state level in China. In terms of geographical distributions, the waypoints at the first level concentrated in middle China, but the waypoints at the third level largely distributed in Northeast China, and Northwest China, which were consistent with the unbalanced air traffics in these regions.

Fig. 13 shows the waypoints near HFE. HFE was a critical waypoint in the Chinese airway network and connected the main north-south airports and east-west airports in China. HFE had a complicated airway structure and very heavy traffic flow and was classified as level 1 waypoint in this study. However, even this critical level 1 waypoint had many neighboring waypoints in level 2 and even in level 3, of which some were less accessible in the network and some had low traffic loading. In other words, while HFE and other level 1 waypoints gradually became the bottlenecks of the air traffic system, a number of level 3 waypoints were limited by low resource utilization rates. The reasons mainly attributed to the airway network design at the strategic aspect and to the traffic assignment at the tactical aspect. Strategically, if the airspace administration can set new airways at these level 3 waypoints, especially those near a level 1 waypoint, the connectivity of level three waypoints can be raised and thereby the airway networks can be more scientifically optimized. Tactically, the air traffic management administration, while examining and approving the airways for flying plans, did not fully consider the airspace structures and traffic flow complexity among waypoints, so that a number of level 1 waypoints became system bottlenecks. Hence, from the aspect of traffic assignment, if a part of flights can be reroute from some level 1 waypoints to some level 3 or level 2 waypoints at the stage of flight planning, this will relieve the traffic pressures of level 1 waypoints and thereby balance the whole air traffic

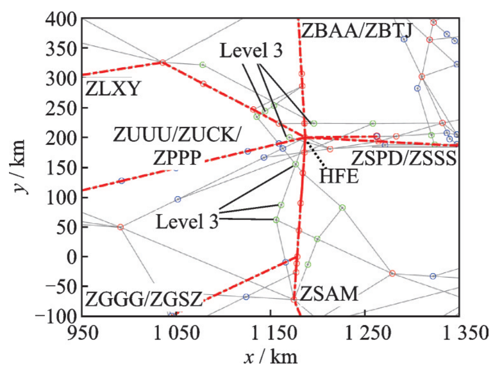


Fig.13 Waypoints near HFE (Red: level 1; blue: level 2; green: level 3)

management system.

4 Conclusions

The topological structures of China's airway networks are characterized by using the complex network theory. Firstly, two undirected networks and two directed networks are built according to airspace static structures and traffic flow characteristics, and by using the Euclidean distance, traffic flows, and traffic flow dominance as weights. After the basic topological characteristics of the four networks are statistically analyzed, the distributive characteristics of degree, strength, betweenness, closeness, and clustering coefficient are further statistically analyzed. Since the same index of the same waypoint differs among different networks, the degree composite index, betweenness composite index, closeness composite index and clustering coefficient composite index is further proposed, and probed into the different roles undertaken by waypoints by analyzing the relations of these composite indices with traffic flows. Statistical results show that some waypoints yield large results in multiple composite indices and traffic flows (e.g., HFE, WXI, ZHO), some waypoints display large results in multiple composite indices but low traffic flows (e.g., TYN, CGA), and other waypoints only perform well in certain composite indices (e.g., P464). Based on the degree composite index, betweenness composite index and closeness composite index, the importance of waypoints is classified into three levels, and the reasonableness of waypoint importance levels is validated by the statistical results of traffic volume, flight delay, and related airports. In addition to the perfect airway network modeling and the analytical theory frame, the findings in this paper will help to more comprehensively understand the operational characteristics of waypoints in practical applications and will significantly contribute to strategy-level airspace planning, state-level flight planning, and tactics-level flight reroute management.

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Author Dr. **WANG Hongyong** received the Ph.D. degree from Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 2017. He is currently an associate professor with Civil Aviation University of China. His research interests include air traffic flow management, trajectory prediction and complex network.

Author contributions Dr. **WANG Hongyong** designed the study, complied the models, conducted the analysis, interpreted the results, and wrote the manuscript. Mr. **DENG Taotao** performed the data analyses. Dr. **SONG Ziqi** contributed to analysis and manuscript preparation. Dr. **WANG Fei** helped perform the analysis with constructive discussions. Prof. **ZHAO Yifei** contributed to the discussion and background of the duty. All authors commented on the manuscript draft and approved the submission.

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基于复杂网络模型的航路网络特性分析

王红勇[1], 邓涛涛[1], SONG Ziqi[2], 王　飞[1], 赵巍飞[1]

(1.中国民航大学空管学院天津市空管运行规划与安全技术重点实验室, 天津 300300, 中国;
2.犹他州立大学土木与环境工程系, 犹他州, 84322, 美国)

摘要: 航路网络是航空运输的基本载体,挖掘其特征对航空运行效率的提高有显著意义。以2018年中国大陆1 479个航路点组成的航路网络为研究对象,结合空域结构、交通流特征以及交通流支配关系等,从复杂网络视角构建了物理航路网络、无向航路交通网络、有向航路交通网络,以及基于交通流支配关系的有向航路交通网络等4个网络模型。基于典型网络测度指标统计了不同网络的拓扑特征,并分析了典型测度指标在不同网络中所展现的差异特征,进而提出了测度指标的综合指数概念。统计结果表明,航路网络在交通流的影响下展现了更丰富的异质性,节点间的关系并不对称,不同网络中的指标分布特征有明显差异。测度指标综合指数和交通量水平的对比分析表明,某些航路点不但在多个测度指标的综合指数中有较大值且交通量繁忙;某些航路点虽然在多个测度指标的综合指数中有较大的值,但交通量不繁忙;还有一些航路点只在某一特定指标的综合指数中比较突出。为反映航路点的综合重要程度,采用K-means方法基于度综合指数、介数综合指数、接近度综合指数将航路点的重要性划分为3个级别,交通量、机场数量、航班延误等的统计结果验证了分级结果的合理性。

关键词: 航路网络;复杂网络;空中交通管理