Asian Transport Studies 8 (2022) 100082

Contents lists available at ScienceDirect

Asian Transport Studies

journal homepage: www.sciencedirect.com/journal/asian-transport-studies

Network structure revelation and airport role evaluation under three different COVID-19 pandemic periods: Evidence from a Chinese airline

Haoyu Zhang [a,b], Weiwei Wu [b,*], Frank Witlox [a,b]

[a] Department of Geography, Ghent University, Krijgslaan 281/S8, B9000, Gent, Belgium
[b] College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, 210016, Nanjing, Jiangsu, China

ARTICLE INFO

Keywords:
Network structure
COVID-19
Airport role
Node importance
Network decomposition

ABSTRACT

The continuous spread of coronavirus disease 2019 (COVID-19) has had a substantial impact on China's domestic airline networks. It is important for airlines to identify key airports and airport roles in future network design. In this paper, a k-core algorithm is used to decompose the network layers during different periods of COVID-19 to investigate the network structure and the airport role change. By considering both airport degree and route traffic, network characteristics are analyzed, and the key airports are determined based on network evaluation. The results show that the airline network is robust due to its mixed hub-and-spoke network structure, which is basically dominated by direct flights between airports. However, different operation patterns should be implemented based on airport roles. It is not advisable for airlines to pursue network connectivity at the cost of a low passenger load factor.

1. Introduction

The spread of the coronavirus 2019 (COVID-19) has negatively impacted China's aviation industry since January 2020. Compared to 2019, the air passenger demand decreased by 36.7% in late 2020, even though air transportation began to recover gradually. It has been proven that the COVID-19 pandemic has long-term effects on passenger travel and network structure characteristics; therefore, the recovery of passenger demand is a slow process (Van Wee and Witlox, 2021).

During the pandemic period, some domestic airports have to reduce flights and routes due to the lack of demand, and some of them have even closed to avoid greater losses. Therefore, when more airports in the airline network cannot be reached, the connectivity of the network is reduced, and the network structure is affected. In the post-pandemic period, passenger demand began to increase gradually, and airport pairs were reconnected. However, the recovery situation of each airport and route varies in terms of route connectivity and flight frequency. This is because the recovery of passenger demand for each airline is less likely to be directly related to factors, such as airline size, airline type, and market but more likely to be related to airline network configuration, airline pattern, and airport role change. This may lead to different recovery patterns and efficiency among airlines. Many papers related to the pandemic's impact on airline networks have been published; however, they are still limited in terms of the way airline networks evolved step-by-step during the pandemic period and how to find key airports when airport roles changed. This information is important and will inspire airlines when redesigning their network in the future. Therefore, this paper focuses on the following issues:

1) The impact of the outbreak and the spread of the COVID-19 pandemic on the air network layers (including the impact of airport closures and reduced route traffic);
2) Changes in airline network characteristics due to COVID-19 (including the role of each airport, network efficiency, and airport importance); and
3) Different recovery patterns should be implemented according to network characteristics and airport role change to facilitate traffic demand and network connection recovery in various airports.

Aiming at this, the network in this paper is abstracted as an undirected weighted network where the network node refers to an airport and the route flight frequency is the weight of the network edge. To identify the airport role change, a k-core decomposition algorithm is used to decompose the airline network and cluster the airports into different layers. Complex network indices, such as node connectivity, clustering, and network efficiency are also used to evaluate the network

* Corresponding author.
E-mail address: nhwei@nuaa.edu.cn (W. Wu).

https://doi.org/10.1016/j.eastsj.2022.100082
Received 22 December 2021; Received in revised form 17 July 2022; Accepted 19 July 2022
Available online 1 August 2022

characteristics so that the key core airports and connecting airports can be determined. Accordingly, different recovery patterns for airports based on network connectivity and airport role change are suggested to accelerate passenger demand.

The remainder of this paper is organized as follows: Section 2 is a literature review. Section 3 introduces the methodology of k-core decomposition and network evaluation measures. Section 4 presents the data analysis and shows how the examination period is divided. Section 5 describes the evolution process of a network, which includes the change in network layers and network characteristics, and suggestions for airline flight scheduling are proposed. Section 6 provides an overview of the major findings and future research directions.

2. Literature review

2.1. Network decomposition

It has been proven that the pandemic may have different impacts on various kinds of network configurations (Yao et al., 2021; Scarpone et al., 2020); therefore, network characteristics and structures should be considered. Methods, such as community detection (Sun et al., 2016; Wu et al., 2019), k-core decomposition (Verma et al., 2014; Dai et al., 2018; Du et al., 2016), and complex network theory (Guimerà et al., 2005; Reggiani et al., 2010) are widely used to identify the role of each node in a network. K-core decomposition is effective in decomposing a multilayer structure of a complex network, such as an air transport network and in uncovering the relationship between node pairs in the same or different layers. Verma et al. (2014) decomposed the world airline network into three layers (core, bridge, and periphery) to examine the connectivity of airports in the world air transport network. Dai et al. (2018) utilized k-core decomposition to investigate the evolving structure of the Southeast Asian Air Transport Network from 1979 to 2012, as well as airport connections and passenger flows in different network layers. Du et al. (2016) divided the Chinese Airline Network into a multilayer structure using the k-core method and showed similarities between the Chinese airline network and the world airline network. In contrast from a centrality analysis (Gao et al., 2017) and community detection (Sun et al., 2016; Wu et al., 2019), k-core decomposition is able to identify and rank the important nodes while dividing the network. Therefore, we adopt the classification of Verma et al. (2014) to categorize airports into different distinct layers using k-core decomposition. This was done to determine whether the role of nodes in different layers would change after an outbreak. These changes can include the emergence of new nodes that become a connection or a bridge node or nodes that become obsolete.

2.2. Network characteristic analysis

In addition, the evaluation of node/edge importance is also important in examining the survivability and robustness of a network, and the vulnerability of a hub interconnection should be comprehensively examined (Zhou et al., 2021a). There are many other methods that focus on network structure analysis and network characteristic index, such as degree correlation (Wu et al., 2019; Sun et al., 2017), path length (Opsahla et al., 2020), clustering coefficient (Bona et al., 2021; Li et al., 2019), and network efficiency (Liu et al., 2016; Zhou et al., 2021b). Liu et al. (2016) proposed an effective ranking method based on the degree value and the importance of lines, which can identify the importance of bridge nodes. Wu et al. (2019) compared the dominant airports of American Airlines and Southwest Airline networks. Both route distance and passenger volumes are considered to distinguish their different network structures. Sun et al. (2017) determined the robustness of the worldwide air transportation network using different 'attacking' strategies. They found that degree and Bonacich-based attacks (i.e., the sum of all the links of a node and the impact of a node's neighbors) were the most harmful to the passenger weighted network. Li et al. (2021) studied the spatiotemporal evolution of the worldwide air transportation network. Connectivity-based metrics for the network analysis were considered, and it was concluded that the fluctuation of weighted connectivity (concerning airport degree, flight frequency, etc.) is more important than that of the unweighted one.

As traffic demand and connected routes of hub airports prove to have more positive and larger spillover effects on network structure and all other neighboring cities (Chen et al., 2021), route traffic and route connection are considered to be key indices that can affect network characteristics in this study. The node degree reflects the node connectivity, which represents the current connection state, i.e., connected or broken, and the edge weight can better reflect a future trend. For example, when route traffic decreases to a certain level, even if the current route is connected, at some point the airline will cancel the route due to factors, such as cost and low passenger load factor[1] (PLF). Then, the airports at both ends of the route would no longer be directly connected, thus affecting network efficiency and node properties. In this paper, since we also simulate the network performance by removing specific airports in the future network recovery process, denoting route traffic as the edge weight can reflect the network structure evolution trend driven by passenger demand (Baspinar and Koyuncu, 2016; Zhou et al., 2019).

3. Methodology

3.1. K-core decomposition

We explore the multilayer structure and the key connection airports of an airline network by drawing on the k-core decomposition method. During network evolution, it can be attacked by cancelled flights or closed airports (i.e., normal operations are no longer possible). Typically, if a connection between airports fails, then passengers are rerouted through another airport to their destination. This procedure is called a triangle (Verma et al., 2014). Any vertex of the triangle is a connection node of the other two vertices; thus, the node in a triangle is called the bridge node.

Inspired by the k-core method (Dorogovtsev et al., 2006) and according to the classification of Guimera et al. (2007), the core layer of a network is considered to be a set of remaining nodes that make up the most triangles after iteratively removing all isolated nodes. This indicates that even when a connection within this area is removed, there are still numerous alternative connections between the origin and destination. Nodes in the core layer of the air transportation network have higher degrees, and most of them are hub airports in the network. Therefore, removal of these airports may lead to a minor degradation in connectivity (the average path length increases and the network efficiency decreases), but the network remains connected (Gallos et al., 2005; Dorogovtsev et al., 2006). This paper focuses on the role of these nodes and their impact on other nodes, especially when some nodes in the network are under attack. Therefore, we mainly focus on the core and bridge nodes in the network.

3.2. Network evaluation measures

A set of fundamental network metrics to evaluate network structures, such as a degree-degree correlation, a clustering coefficient, and an average path length, were selected from Dai et al. (2018). Each of these measures is specified as follows in Equations (1)–(3).

Eq. (1) formulates the degree-degree correlation, which refers to the correlation between the k degree node and the average degree of their neighbors, where k_i represents the degree of node i, $K(i)$ is the average degree of the neighbors of node i, and $N(k)$ represents all nodes with

[1] Passenger load factor is defined as the actual number of passengers on an aircraft divided by the total number of seats provided by the aircraft.

degree k.

$$\overline{\mathrm{DC}(\mathrm{k})} = \frac{1}{\mathrm{N}(\mathrm{k})} \sum_{\mathrm{k_i}=\mathrm{k}} \mathrm{K}(\mathrm{i}) \tag{1}$$

Eq. (2) is the clustering coefficient, which measures the probability that two nodes are connected to each other when they both connect to node i. E_i indicates the number of connections that exist between the neighbors of i.

$$CC_i = \frac{2E_i}{k_i(k_i - 1)} \tag{2}$$

Eq. (3) measures the average distance between any node pairs in the network, where N represents the number of all nodes and d_{ij} is the distance for the shortest path between node pair $i - j$. Note that the distance in a complex network is measured by the number of edges between a node pair.

$$L = \frac{1}{N(N-1)} \sum_{i,\, j=1}^{N} d_{ij}\ (i \neq j) \tag{3}$$

In contrast to the above network measures that are mostly based on node degree, Verma et al. (2014) multiplied clustering coefficients and each route weight to define the degree of connectivity. Based on Verma et al. (2014), we modify the method proposed by Liu et al. (2016) to evaluate the importance of node and edge connectivity.

The ranking method used in Liu et al. (2016) is based on the idea of network damage caused by deleting a node. Node reduction is caused by the closure of the airport in the lockdown city (the removal of a node in the network) and the reduction of route traffic due to public awareness of the pandemic (e.g., cancelled travel plans), which leads to changes in airline flight frequency (the fluctuant weight of the edge). The former is represented by the node degree, and the latter relates to the edge weight.

As modified from Liu et al. (2016), the importance of an edge between nodes i and j is defined as follows:

$$I_{e_{ij}} = \frac{U}{\lambda} {*} w_{ij} \tag{4}$$

where $U = (k_i - p - 1){*}(k_j - p - 1)$ reflects the connectivity ability of edge e_{ij} and p is the number of triangles with one of its edges e_{ij}. $\lambda = \mathrm{p}/2 + 1$ is an alternative index of edge e_{ij}, and w_{ij} is the edge weight.

The importance of node i is defined as follows:

$$I_i = \left(k_i + \sum_{j \in \Gamma_i} W_{ij}\right) {*} S_i \tag{5}$$

where Γ_i is the set of neighbors of i and $W_{ij} = I_{e_{ij}} {*} \frac{k_i - 1}{k_i + k_j - 2}$ stands for the contribution that i makes to the importance of e_{ij}. $S_i = \sum_{j \in \Gamma_i} w_{ij}$ is the node strength of node i.

We also adopt the network efficiency formula defined in Liu et al. (2016) as follows:

$$\eta = \frac{1}{N(N-1)} \sum_{i \neq j} \eta_{ij} \tag{6}$$

where $\eta_{ij} = 1/d_{ij}$ is the efficiency between nodes i and j.

The reduction rate of the network efficiency is also defined to determine the importance of the removed node as follows:

$$\mu = 1 - \frac{\eta}{\eta_0} \tag{7}$$

where η is the efficiency of the destroyed network and η_0 is the efficiency of the initial network. The value of μ represents the connectivity of the entire network: the higher the value of μ, the more difficult it would be to access the airport due to node removals and the more important the deleted node becomes.

4. Data and examination period division

Daily data of all domestic flights in 2019 and 2020 of all Chinese airlines were collected for period division and passenger data of China Southern Airlines is collected for network decomposition (data obtained from the Official Airline Guide, http://analytics.oag.com/analyser-client/home). The data include date, airline name, flight numbers, domestic route, flight scheduling, and flight frequency. An overview of all domestic flight frequencies in 2019 and 2020 is compared, and the curve is shown by month in Fig. 1.

Affected by the COVID-19 pandemic, domestic traffic demand and flight frequency dropped sharply in February, which decreased by 85% and 72%, respectively, compared with those in 2019. This period is considered to be the peak of the impact and infection of the spread of COVID-19. With the resumption of work, people gradually returned to normal life, and domestic air travel began to recover slowly from March. Several key periods are of interest. First, January 1, 2020 was chosen as the starting point. The first important period began with the blockade of the city of Wuhan (from January 23, 2020), as well as the closure of all airports and the cancellation of all flights within the Hubei Province. It can be seen as the peak infection and the spreading period of pandemic propagation. The next important date is February 12, 2020, when the number of newly added patients in China began to drop from the peak, which indicated that the spread of COVID-19 was under control within China and led to a gradual recovery of the passenger travel plan.

Based on the propagation of the COVID-19 pandemic and the substantial demarcation point of air demand and flight frequency in February, the impact of the COVID-19 propagation process on civil air transportation can be divided into two main periods: the 'pandemic impact period' and the 'recovery period.' Table 1 shows the specific network and its corresponding period, as well as a 'normal' comparison period calculated based on the data from 2019. Total Flight frequency is calculated based on the actual flight transportation of the entire duration in each examined period, and the corresponding network in each period is represented as N0, N1, and N2.

In addition, according to the air transportation data of 2019, the 10 million-sized[2] airports (39 airports) and non-10 million-sized airports (198 airports) are classified to compare the changes in capacity (i.e., total flight frequency), passenger demand (i.e., total traffic volume) and network connectivity (i.e., total degree of airport) between the two airport categories. The relationship between passenger demand, capacity and network connectivity of different types of airports is also analyzed. Changes in indices can be seen clearly from Fig. 2 below, where f_h and f_{nh} refer to the total flight frequency (million) in 10 million-sized airports and non-10 million-sized airports, respectively; p_h and p_{nh} refer to the total traffic volume (billion) in 10 million-sized airports and non 10 million-sized airports (billion), respectively; and c_h and c_{nh} refer to the total airport degree (ten thousand) in 10 million-sized airports and non-10 million-sized airports, respectively.

The relationship between supply and demand in different types of airports can be found. In the period of recovery (N2), the index of passenger demand, flight frequency and airport network connectivity in different airports all increase; however, the growth rate varies by different types of airports. From Fig. 2, the increment of traffic volume in 10 million-sized airports is the highest, reaching 418.2%, nearly twice that of non 10 million-sized airports, but there is still a big gap compared with that in N0 period. This also confirmed that the impact of the pandemic has dispersed the passenger demand that often concentrated in the hub airport to the whole network. However, the increase in flight frequency and airport degree is not as fast as that of non-10 million-sized airports. The flight frequency in large airports shows a relatively slow

[2] 10 million-sized airport is the airport with more than 10 million passenger volume a year, classified by Civil Aviation Administration of China (CAAC, http://www.caac.gov.cn).

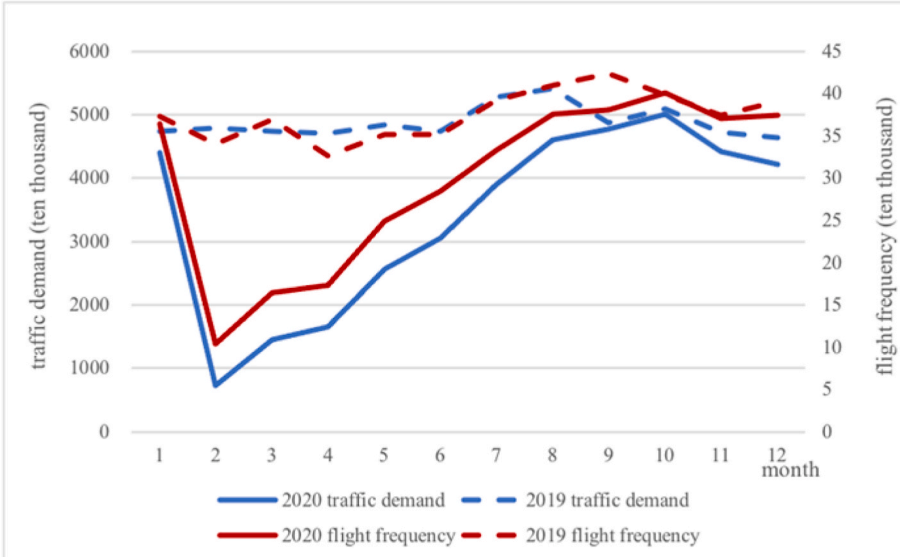


Fig. 1. Domestic traffic demand and flight frequency in 2020.

Table 1
COVID-19 pandemic periods in China.

Network code	Period name	Time period	Airport numbers	Total Flight frequency (ten thousand)
N0	Normal period	Jan 01, 2019–Dec 31, 2019	237	533
N1	Pandemic period	Jan 01, 2020–Feb 28, 2020	228	58
N2	Recovery period	Mar 01, 2020–31 Dec 2020	238	298

recovery that is mainly because of the regional repeated pandemic, larger number of COVID-19 cases, incomplete recovery of network connectivity and flow control.

Although the frequency of flights and the airport degree in non-10 million-sized airports respectively increased more than 8 times and 5 times, while passenger demand increased only 4 times. In other words, the low PLF caused by excess capacity is a common phenomenon throughout the year and is more likely to occur in small and medium airports, especially in the middle and late stages of N2 when the repeated pandemic occurred in some regions; the airlines did not adjust their flight capacity in time, which led to seat redundancy also having adverse effects on airlines.

It can be concluded that in the N2 period, the network overemphasized the recovery of the original route connection, resulting in insufficient demand for small and medium-sized airports, and the capacity of 10 million-sized airports can still be continuously increased. As a result, it would be necessary to optimize the flight scheduling and the network according to the route passenger demand to avoid seat redundancy, which may lead to cost increases, as well as satisfy passenger demand.

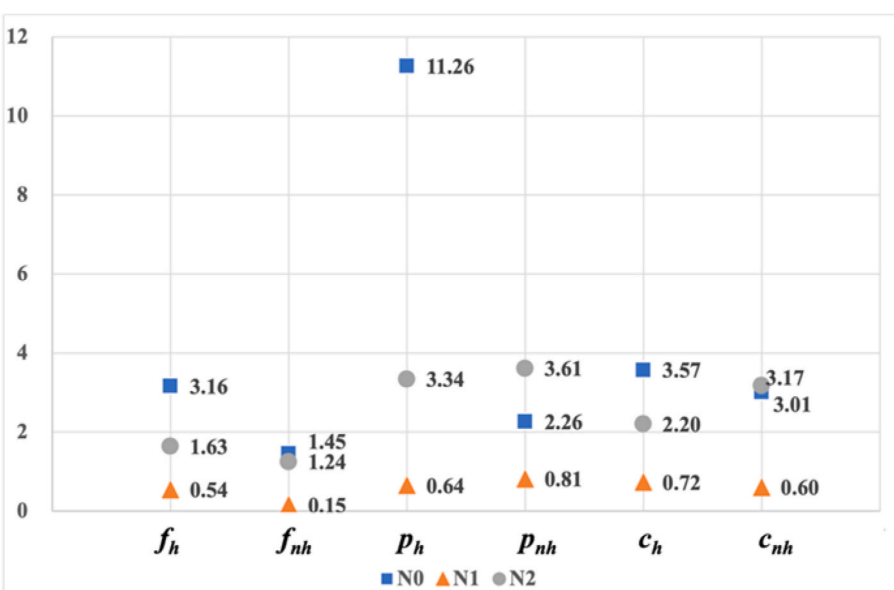


Fig. 2. Capacity, passenger demand and network connectivity comparison.

5. Results

5.1. Airline network decomposition

From the perspective of node influence, nodes with the same k-core value also have similar characteristics (Wagner et al., 2007). The hierarchical distribution of nodes based on the k-core value means that the nodes are distributed from the inner layer to the outer layer in descending order of the k-core value. The larger the k-core value of the nodes, the more likely they will be clustered and affected by each other. That is, the distribution of a network will be more centralized where there are higher k-core value layers.

In general, airports in the core layer play an important role in transit, while airports in the periphery layer are mainly decentralized and less responsible. The bridge layer route is responsible for part of the transfer function and serves the function of collecting and distributing to connect the trunk route and the branch route. According to the k-core algorithm, in the three stages of network change, airports in the core layer and in the bridge layer, as well as their connectivity and node importance, are normalized. Table 2 shows airports in the core layer during network configuration changes. The connection of each airport reflects its connectivity, and I_i refers to its importance in the whole network in each period. Table 3 shows airports in the bridge layer during network configuration changes.

The core layer of the network consists of three international hubs (PEK, PVG and CAN) and some regional hubs, and the bridge layer consists of regional airports. In addition to the five hub airports (i.e., three international hubs, SZX and CTU) that have been consistently in the core layer, other core airports all have the entrance or exit experience. During the pandemic period (N1), some regional airports cancelled passenger flights because passenger travel demand decreased dramatically as a result of local areas going into lockdown. The main role of regional hub airports is to gather traffic flow in their respective regions for trans-provincial transfer. When passengers arrive at the destination province, they usually change to ground transportation. Compared with N0, the number of airports in the core layer was reduced to 5, but the internal connection between these airports increased with a 5% increase in internal flight frequency. The average node importance increased to 0.74, reaching its highest value in the three periods. The core layer is particularly important for the connectivity of the whole network transportation in this time. During the recovery period (N2), the number of routes and passenger demand in the network increase substantially compared with those in the N1 period. Some airports returned to the core layer, increasing the number of airports to 9. However, the increase in the network routes makes the passenger transportation more dispersed, and the importance of the airport nodes in the core layer has declined, but it is still higher than that in the N0 period. In addition, according to the ranking of I_i, the importance of the airports has also changed in different periods. Before the outbreak (N0), PEK, PVG and CAN had absolute advantages, while after the pandemic occurred, it was difficult for PEK and PVG to recover; however, CAN, CGQ, SZX and other airports located in regions that were affected little by the pandemic recovered rapidly and increased their importance to the network.

The change in passenger demand and route number also has a great influence on the bridge layer. In the N1 period, due to the stagnation of inner air transportation in many regions, the main function of the bridge layer was to transport passengers to the core layer. The number of bridge airports was increased to 15, airports exiting from the core layer were all subsumed into the bridge layer, and two airports from the bridge layer degenerated to the periphery layer (TSN and HRB). At this time, the average number of routes in the connection layer is 90, among which 5.6% of the routes are connected with the core airport, and the flight frequency accounts for 20.7% of the total network frequency. In the N2 period, the main routes were connected more closely with larger traffic flows, and the branch routes in the bridge layer were connected with the core layer. A few airports entered the core layer, which made the bridge airports decline to 11, with 5 airports moving out and one airport (WUH) moving in. The average routes recovered to 96, with one route more than that in N0, but the importance of the nodes reached the lowest value of 0.24 in N2, which indicated that the demand had not completely recovered in some large and regional airports.

Changes in the airline network configuration from N0 to N2 are shown in Fig. 3.

The airports with role changes from the N0 period to the N2 period are summarized in Table 4. Most airports remained in their initial layer as the network changed. However, the role of some airports changed due to traffic demand and airport domination in their region. Note that WUH was removed from the network in N1.

Overall, the number of airports in the core layer and the bridge layer did not change considerably, which stabilized the network connectivity in the core layer. However, the role of some airports changed due to the differences in the markets and policies of various regions. WUH airport was the most seriously affected by the pandemic. As the city of the first announced COVID-19 case, Wuhan has suffered from the lockdown and the suspension of passenger flights, which had a severe impact on traffic flow. Before COVID-19 (i.e., N0), Wuhan was an important ground hub connecting 9 provinces and played a key role in collecting and distributing traffic flow. Therefore, WUH was closely connected with both trunk and branch roads and was a key connecting airport. After the outbreak (N1), passenger flights decreased dramatically until the route was cancelled, and WUH no longer belonged to the bridge layer until the city of Wuhan began to recover and then belonged to the bridge layer again in the N2 period. However, the node importance ranking dropped sharply, and neither the airport connectivity nor the passenger flow recovered to the N0 period. CSX, as a regional hub airport in the neighboring province of Wuhan, was severely affected by the pandemic situation in the Hubei Province. When the passenger flights of WUH were suspended, CSX once retrogressed to the periphery layer airport during N1, but in the recovery period (N2), due to the later recovery of

Table 2
Airports in the core layer[a].

N0			N1			N2		
Airport	Connection	I_i	Airport	Connection	I_i	Airport	Connection	I_i
PEK	142	1	PEK	127	0.69	CAN	150	1
PVG	138	0.69	PVG	127	0.56	CTU	159	0.84
CAN	144	0.73	CAN	130	0.79	SZX	135	0.76
SZX	131	0.64	SZX	122	0.64	PEK	120	0.66
KMG	122	0.57	CTU	147	1	SHA	93	0.38
URC	86	0.42				CKG	132	0.63
CTU	154	0.67				KMG	131	0.54
CKG	128	0.61				XIY	158	0.61
SHA	89	0.43				PVG	153	0.54
XIY	147	0.62						
Average	126	0.64	Average	131	0.74	Average	137	0.66

[a] The airport full name and their IATA code is presented in Appendix A.

Table 3
Airports in the bridge layer.

N0			N1			N2		
Airport	Connection	I_i	Airport	Connection	I_i	Airport	Connection	I_i
NKG	95	0.34	SHA	72	0.33	CGO	96	0.25
CSX	91	0.24	HAK	93	0.49	NKG	102	0.27
WUH	81	0.20	KMG	112	0.45	CSX	102	0.26
CGO	95	0.31	CGO	81	0.29	HGH	119	0.45
XMN	93	0.33	URC	76	0.38	HAK	101	0.24
TAO	94	0.21	CSX	81	0.44	SHE	88	0.16
TSN	113	0.36	NKG	79	0.36	SYX	79	0.17
HGH	115	0.41	XMN	87	0.39	KWE	101	0.23
HRB	97	0.25	XIY	135	0.26	WUH	82	0.17
KWE	99	0.27	HGH	100	0.43	URC	85	0.16
SHE	83	0.25	TAO	83	0.48			
HAK	102	0.41	KWE	89	0.45			
SYX	73	0.18	SHE	79	0.26			
			SYX	64	0.21			
			CKG	116	0.47			
Average	**95**	**0.29**	**Average**	**90**	**0.38**	**Average**	**96**	**0.24**

the Wuhan airport relative to all domestic airports, the connection between CSX and the airports inside and outside the province is closer than that before COVID-19, and the importance ranking in the bridge layer rises. This phenomenon continues until the end of the year.

Tourist destinations, such as KMG were also seriously affected. Kunming, located in the Yunnan Province, is a famous tourist city that attracts tourists from all over the country. The airports in the Yunnan Province are densely distributed, and the transportation between cities mainly depends on flights. Therefore, KMG was a core airport in N0. As COVID-19 became more widespread, people avoided unnecessary travel plans, and tourist travel declined. The proportion of trunk traffic flow increased substantially, and KMG gradually became a passenger transfer center, entering the bridge layer in the N1 period. In the N2 period, since the Yunan Province is located in the most southwestern part of China, which is relatively remote with underdeveloped ground transportation, KMG returned to the core layer again because it has irreplaceable centrality. Similar to KMG, URC is also located in the province of Xinjiang, which formed a relatively independent provincial airport system due to its close connection with airports inside the province and relatively weak links outside the region. URC plays the role of core airport in traffic transferring inside and outside Xinjiang Province. During the pandemic period, traffic inside the province was almost suspended, and the URC was only opened as a channel to connect with a small number of airports outside the province. In addition, seriously and repeatedly affected by the pandemic, the URC continued to be an important bridge airport for traffic distribution in the province until the N2 period.

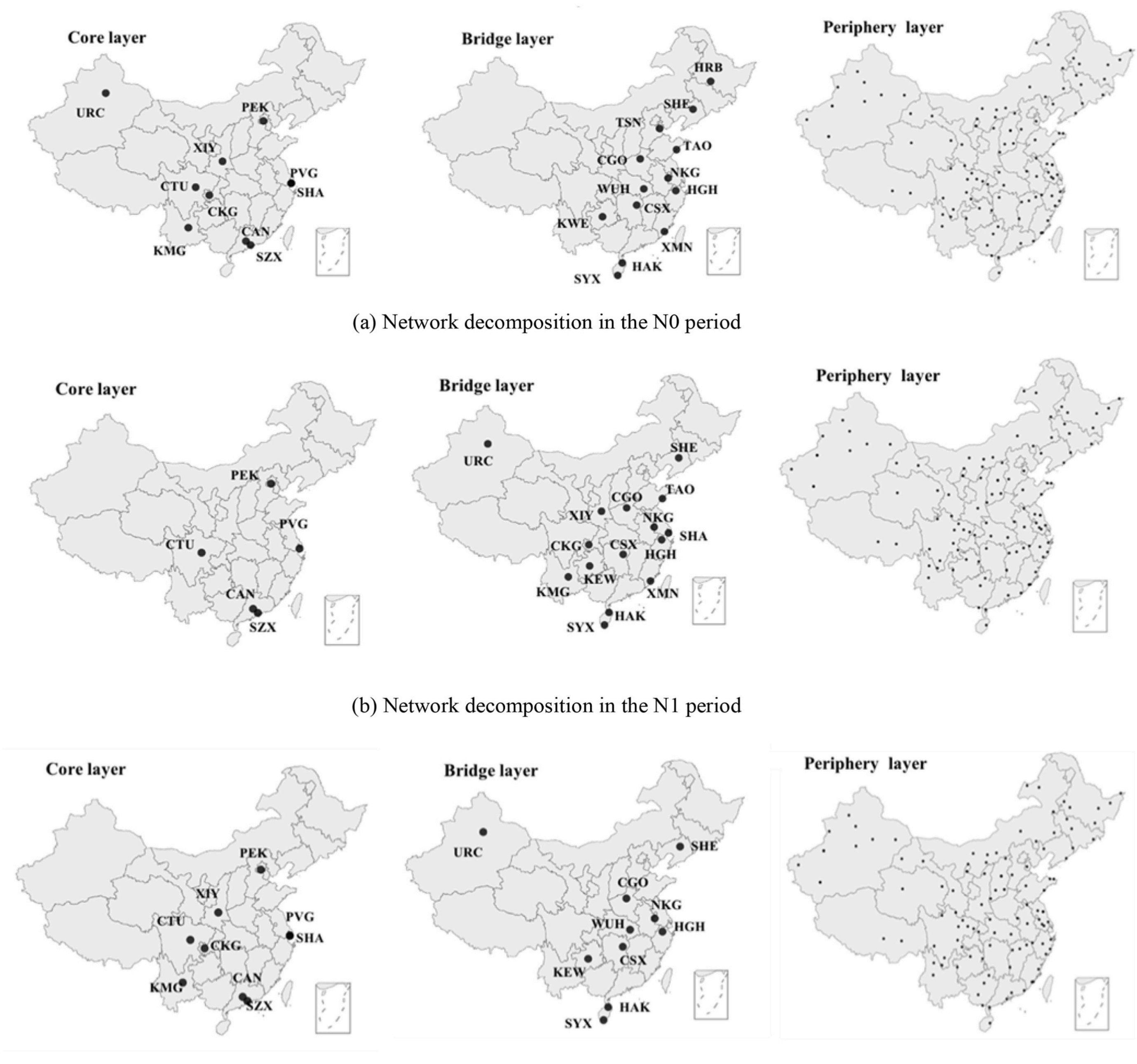
Some regional hub airports, such as XIY and SHA, are core airports and are dominated in the region during the N0 period. In N1, XIY was an important gateway hub in northwest China, but its airport roles were slightly different from those of CTU, the hub in southwest China. XIY operated less flight frequency but had approximately 15% more routes than CTU, which makes the traffic flow of XIY more dispersed. In fact, most traffic flows from neighboring provinces were connected to XIY, forming a subsystem covering the Shaanxi, Ningxia, and Qinghai Provinces. In the N1 period, the main role of XIY was to transport passengers within the system to the core hubs. Due to the larger coverage of provinces in the recovery period, XIY again entered into the core layer. As a supplementary airport for PVG in Shanghai, the passenger destination of SHA tends to be domestic airports. In the N1 period, due to the reduction in passenger demand, PVG occupied most of the passenger flow, leading to SHA retreating to the bridge layer. In the flight recovery period, passenger demand increased, and SHA again became the core airport.

TSN and HRB are the regional hub airports. TSN is one of the cooperative airports in the airport group system of the Beijing-Tianjin-Hebei Province, and adjacent to Beijing, it has always served as the connecting airport to share the traffic demand of PEK. Therefore, TSN played a role in passenger collection and distribution and was more closely related to hub core airports where 97.4% of the flights were trunk flights and became the bridge airport in the N1 period. However, when the passenger flow decreases, this kind of airport group network with a denser distribution of airports and a higher homogeneity of routes was not conducive to the increase in passenger demand. Therefore, the route and flight frequency in the TSN are reduced, making it a peripheral airport, which forms a close connection between the airports in the region and the airport function is clearer and more accurate. Similarly, the HRB, located in northeast China, delivered passenger demand to SHE, the main hub in the region, and was less affected by the pandemic in the N1 and N2 periods. HRB remained in the periphery layer due to the unrecovered demand in northeast China. As an emerging international hub in Beijing, as PEK was seriously affected by repeated outbreaks in the first half of the year and was limited by traffic, PKX airport temporarily appeared in the bridge layer in the N2 period and was predicted to return to the periphery layer after that.

5.2. Airline network performance

From the overall operation effectiveness of the network, changes in the role of the nodes had minimal impact on the core layer. The connection between airports inside the core layer and between external airports maintained an operation level comparable to before COVID-19. The average route distance remained at approximately 1, indicating that the intralayer accessibility was still dominated by direct flights. The importance of the airports and routes in the core layer is always the highest in the process of network change, and the removal of core layer nodes has the greatest impact on the whole network. The network was able to maintain strong connectivity during the outbreak period and the recovery period largely due to the priority placed on the core layer airport operation. Table 5 shows the network performance measures of each layer during the different periods examined. $\overline{\mathrm{DC(k)}}$, $\overline{CC_i}$, $\overline{L}$ and $\overline{I_{e_{ij}}}$ refers to the average degree-degree correlation, clustering coefficient, distance and edge importance of all nodes and edges in each layer. $\overline{I_{e_{ij}}}$ is the normalized result.

The value of the average degree-degree correlation $\overline{\mathrm{DC(k)}}$ in the core layer first increased and then decreased. This value for the periphery layer first decreased and then increased, while the value for the bridge layer increased over the three periods. During the N1 period, the core layer airports and bridge layer airports were more connected with the high-degree airports, and the internal connection and the correlation between these two layers was greater. The number of periphery layer airports in the network decreased at this time. In the recovery period,



(a) Network decomposition in the N0 period

(b) Network decomposition in the N1 period

(c) Network decomposition in the N2 period

Fig. 3. Changes in airline network configuration.

the number of regional airports in the network increased, and some of the periphery layer airports were directly connected with the hub again.

The clustering coefficient $\overline{CC_i}$ and the path length $\overline{L}$ remained stable in each layer during the different periods, indicating that accessibility and connectivity were maintained. $\overline{L}$ was the largest and increased in the periphery layer due to a network scale that covered a larger area. The average edge importance $\overline{I_{e_{ij}}}$ of the core layer reached its highest value during the N1 period and decreased substantially in the N2 period. This occurred because traffic gathered in hub airports during the peak outbreak period. Similarly, the connecting airports in the bridge layer were busy transferring passengers from local areas to hub airports. This situation continued even after the N1 period, as more airports were connected to the network and people resumed travel.

Network efficiency was calculated based on data from 2019 to determine the difference between the COVID-19 period and a ‘normal’ period. Table 6 shows the initial network efficiency and the decline rate of network efficiency. η_0 was calculated from Eq. (6), which refers to the network efficiency before the removal of airports in the network. μ is the decline rate of the network efficiency calculated from Eq. (7); the higher the value of μ, the lower efficiency of the destroyed network due to node removals and the more important the deleted node will become.

As seen in Table 6, network efficiency does not decline much during N1 and N2 (0.86 and 0.80, respectively) compared to the normal network efficiency (0.91 in N0), which indicates that the airline network is robust. In contrast to the hub-and-spoke network structure in the domestic air transportation network in America and Europe (25,23Dobruszkes and Wang, 2019; Qian et al., 2013), the airline network in domestic China is a mixed hub-and-spoke network dominated by direct flights and a limited number of hub airports. High-degree

Table 4
Changes in airport roles.

role \ period / airport	N0	N1	N2
WUH	Bridge	/	Bridge
CSX	Bridge	Periphery	Bridge
KMG	Core	Bridge	Core
URC	Core	Bridge	Bridge
XIY	Core	Bridge	Core
SHA	Core	Bridge	Core
TSN	Bridge	Periphery	Periphery
HRB	Bridge	Periphery	Periphery
PKX	Periphery	Periphery	Bridge

Table 5
Network performance measures of each layer during different periods.

Type	Core layer			Bridge layer			Periphery layer		
	N0	N1	N2	N0	N1	N2	N0	N1	N2
$\overline{DC(k)}$	45.8	47.7	42.5	31.5	35.3	37.2	4.4	2.1	3.2
$\overline{CC_i}$	0.36	0.34	0.36	0.27	0.26	0.27	0.07	0.05	0.05
$\overline{L}$	1.91	2.04	2.23	1.27	1.12	1.26	3.42	3.04	3.95
$\overline{I_{e_{ij}}}$	0.87	1	0.49	0.79	1	1.1	1	0.52	0.55

Table 6
Initial network efficiency and decline rate of the network efficiency.

time period / removal μ / airport	N0 (η_0= 0.91)	N1 (η_0= 0.86)	N2 (η_0= 0.80)
PEK	0.56	0.77	0.73
KMG	0.25	0.37	0.43
URC	0.23	0.37	0.36
XIY	0.34	0.44	0.39
CSX	0.15	0.41	0.47
WUH	0.17	0.22	0.26

international hubs are connected with low-degree local airports as their neighbors. Hub airports in the core layer not only have the passenger transit function but also take part of the collection and distribution role. While this network configuration may not have the highest efficiency, it has an advantage when under 'attack.' With the preservation of international hubs and regional hubs, network connectivity can be maintained and preferred by airlines (Wang and Wang, 2019).

During the different periods, deleting the same node would lead to different network operation efficiencies. As shown in Table 6, in general, the decline rate of network efficiency μ in N0 is between N1 and N2, which indicates that the network efficiency now (recovery period) is not as high as before. However, the overall efficiency of the initial network was the highest in the N0 period rather than in the N2 period. After the COVID-19 outbreak, passenger flow tended to cluster among hub airports due to the cancellation of some branch routes. Therefore, the network was more like a typical hub-and-spoke network. Furthermore, changes in the role of different airports also helped to maintain network connectivity and efficiency. The core layer undertook more transfer functions during the outbreak period, and the positioning of each node at the network level was clearer. In the recovery period, due to the gradual recovery of the routes (especially the increase in routes in the periphery layer), some subnetwork configurations changed to point-to-point networks. As a result, network efficiency decreased.

When the core hub airport (such as PEK and XIY) was removed, the network efficiency was dramatically reduced. Especially during the outbreak period (N1), as an important connection and distribution hub, PEK played a key role in ensuring the overall operation of the whole network. In the network recovery period, although the traffic flow was shared by surrounding airports so that the importance of the node was slightly reduced, it was still the core of the whole network. Focusing on the recovery of the core airport traffic flow will help the network's overall recovery.

When bridge airports, such as WUH and CTU, were removed in N1, as there were more alternative routes in the network at this time, the decline rate μ remained stable, showing that the network was robust. However, in N2, due to changes in the role of airports caused by the outbreak, these airports became particularly important. When the airports were removed, the network efficiency was considerably reduced.

In contrast, some important regional hub airports (e.g., URC and KMG) are important gateways to connect the region with the outside world. When these nodes were removed, some subnetworks were isolated from the main network, resulting in a substantial increase in and worse network efficiency. Compared to airports with larger traffic flow but that can be replaced in their located regions, the flight frequency of these airports should be appropriately increased during the recovery period to ensure network connectivity and network efficiency.

6. Conclusion

This paper examines the impact of COVID-19 on an airline network. Changes in airport roles, network configuration and efficiency, and network recovery are analyzed. The purpose is to determine the key core airports, key bridge airports, and route traffic distribution during the spread of COVID-19 to provide guidance for airline flight scheduling recovery.

After comparing the transportation indices, such as traffic demand and flight frequency, around the pandemic spread, three examined periods are determined in chronological order, namely, the normal period, the pandemic period and the recovery period. The network is divided into the core layer, bridge layer and periphery layer using the k-core method. Therefore, changes in the network structure and network efficiency are investigated. A modified node ranking method based on degree and edge weight is used to identify the importance of the nodes. Therefore, the key airports during the recovery period could be determined.

In terms of network configuration, the network is robust due to having a mixed hub-and-spoke network configuration. Regional hub airports are responsible for connecting, collecting and distributing functions. Therefore, when some airports are removed, there are still alternative routes and network connectivity can be maintained. However, in the network recovery period, airlines will ensure network connectivity at the cost of reducing the PLF. In fact, different flight recovery strategies should be implemented due to different airports roles. Some airports need to accelerate the recovery of the original route connection and the flight frequency, while others need to adjust the network in time to increase passenger demand:

1. The reduction in flight frequency in some key airports will lead to a considerable decline in network efficiency, especially for some regional hub airports, such as URC and XIY, that are responsible for the connecting function. The network configuration also shows weakness in terms of a limited number of hub airports in these regional areas. If flights from these airports cannot be guaranteed, then the regional subnetwork will be separated from the main network. As a result, network efficiency will be substantially reduced. Even though these airports do not have the highest traffic volume, they are the most important and irreplaceable connecting airports. During the recovery period, apart from maintaining the hub airport, properly increasing the flight frequency of these connecting airports can promote rapid recovery in the network.
2. There are also some airports with network design defects, such as TSN, which is located in the airport group system of Beijing-Tianjin-Hebei Province, and the route homogeneity is high. When the network is attacked and the structure changes, the operation airport ability degenerates massively, and its passenger demand is difficult to recover. Therefore, in the network design, we should not only consider the benefits of homogeneous routes sharing passenger demand in the normal period but also optimize the network in time when the traffic is generally declining to avoid airport group system routes with too high of a homogeneity.

Declarations

All authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Financial support from the National Natural Science Foundation of China (U1933118, U2033205) and National Key Research and Development Project (2018YFB1601200) are gratefully acknowledged.

Appendix A

Airport code	Airport full name
CAN	Guangzhou Baiyun International Airport
CGO	Zhengzhou Xinzheng International Airport
CGQ	Changchun Longjia International Airport
CKG	Chongqing Jiangbei International Airport
CSX	Changsha Huanghua International Airport
CTU	Chengdu Shuangliu International Airport
DLC	Dalian Zhoushuizi International Airport
HAK	Haikou Meilan International Airport
HGH	Hangzhou Xiaoshan International Airport
HRB	Harbin Taiping International Airport
KMG	Kunming Changshui International Airport
KWE	Guiyang Longdongbao International Airport
NKG	Nanjing Lukou International Airport
NNG	Nanning Wuxu International Airport
PEK	Beijing Capital International Airport
PKX	Beijing Daxing International Airport
PVG	Shanghai Pudong International Airport
SHA	Shanghai Hongqiao International Airport
SHE	Shenyang Taoxian International Airport
SYX	Sanya Phoenix International Airport
SZX	Shenzhen Bao'an International Airport

(*continued on next page*)

(continued)

Airport code	Airport full name
TSN	Tianjin Binhai International Airport
URC	Urumchi Diwopu International Airport
WUH	Wuhan Tianhe International Airport
XIY	Xi'an Xianyang International Airport
ZUH	Zhuhai Jinwan International Airport

References

Bona, A.D., Marcelo, D., Fonseca, K.O., Luders, R., 2021. A reduced model for complex network analysis of public transportation systems. Phys A: Statist Mech Appl. 567 (1), 125715 https://doi.org/10.1016/j.physa.2020.125715.

Baspinar, B., Koyuncu, E., 2016. A data-driven air transportation delay propagation model using epidemic process models. Int. J. Aerospace Eng. 7, 1–11. https://doi.org/10.1155/2016/4836260.

CAAC. Statistical bulletin on the development of civil aviation industry in 2020. In: Civil Aviation Administration of China Website. http://www.caac.gov.cn/XXGK/XXGK/TJSJ/index_1215.html.

Chen, X., Xuan, C., Qiu, R., 2021. Understanding spatial spillover effects of airports on economic development: new evidence from China's hub airports. Transport. Res. Pol. Pract. 143, 48–60. https://doi.org/10.1016/j.tra.2020.11.013.

Dai, L., Derudder, B., Liu, X., 2018. The evolving structure of the Southeast Asian air transport network through the lens of complex networks, 1979–2012. J. Transport Geogr. 68, 67–77. https://doi.org/10.1016/j.jtrangeo.2018.02.010.

Dobruszkes, F., Wang, J., 2019. Developing a low-cost airline in a semi-protected regime: comparing China to Europe and the US. J. Transport Geogr. 77 (5), 48–58.

Dorogovtsev, S., Goltse, A.V., Mendes, J.F.F., 2006. K-core organization of complex networks. Phys. Rev. Lett. 96, 040601 https://doi.org/10.1103/PhysRevLett.96.040601.

Du, W.B., Zhou, X.L., Lordan, O., Wang, Z., Zhao, C., Zhu, Y.B., 2016. Analysis of the Chinese airline network as multi-layer networks. Transp. Res. Part E: Logist. Transp. Rev. 89, 108–116. https://doi.org/10.1016/j.tre.2016.03.009.

Gallos, L.K., Cohen, R., Argyrakis, P., Bunde, A., Havlin, S., 2005. Stability and topology of scale-free networks under attack and defense strategies. Phys. Rev. Lett. 94, 188701 https://doi.org/10.1103/PhysRevLett.94.188701.

Gao, X., Dang, Y., Chen, G., Gu, J., Wang, Y., 2017. Topology and survivability analysis for flight flow networks: case studies of three China airline companies, IMCOM'17. In: Proceeding of the 11th International Conference on Ubiquitous Information Management and Communication, pp. 1–8. https://doi.org/10.1145/3022227.3022273. Article No 47.

Guimerà, R., Mossa, S., Turtschi, A., Amaral, L.A.N., 2005. The world-wide air transportation network: anomalous centrality, community structure, and cities' global roles. Proc. Natl. Acad. Sci. USA 102 (22), 7794–7799. https://doi.org/10.1073/pnas.0407994102.

Guimera, R., Sales-Pardo, M., Amaral, L.A., 2007. Classes of complex networks defined by role-to-role connectivity profiles. Nat. Phys. 3, 63–69. https://doi.org/10.1038/nphys489.

Li, S.P., Zhou, Y.M., Kundu, T., Sheu, J.B., 2021. Spatiotemporal variation of the worldwide air transportation network induced by COVID-19 pandemic in 2020, 2021 Transport Pol. 111, 168–184. https://doi.org/10.1016/j.tranpol.2021.08.001.

Li, T., Yu, X., Jing, B.Y., 2019. Measuring the clustering strength of a network via the normalized clustering coefficient. Comput. Sci. 8 (1), 1–10. https://doi.org/10.48550/arXiv.1908.00523.

Liu, J., Xiong, Q.Y., Shi, W.R., Shi, X., Wang, K., 2016. Evaluating the importance of nodes in complex networks. Phys. A: Statist. Mech. Appl. 452, 209–219. https://doi.org/10.1016/j.physa.2016.02.049.

Opsahla, T., Agneessensb, F., Skvoretzc, J., 2020. Node centrality in weighted networks: generali-zing degree and shortest paths. Soc. Netw. 32 (3), 245–251. https://doi.org/10.1016/j.socnet.2010.03.006.

Qian, Y.E., Wu, D.T., Dai, T.Q., 2013. A comparative analysis of hierarchy and regional system of domestic air passenger transport network between China and USA. Geogr. Res. 32 (6), 1084–1094. https://doi.org/10.11821/yj2013060012.

Reggiani, A., Nijkamp, P., Cento, A., 2010. Connectivity and concentration in airline networks: a complexity analysis of Lufthansa's network. Eur. J. Inf. Syst. 19 (4), 449–461. https://doi.org/10.1057/ejis.2010.11.

Scarpone, C., Brinkmann, S.T., Groe, T., Sonnenwald, D., Fuchs, M., Walker, B.B., 2020. A multimethod approach for county-scale geospatial analysis of emerging infectious diseases: a cross-sectional case study of COVID-19 incidence in Germany. Int. J. Health Geogr. 19, 32. https://doi.org/10.1186/s12942-020-00225-1.

Sun, X.Q., Gollnock, V., Wandelt, S., 2017. Robustness analysis metrics for worldwide airport network: a comprehensive study. Chin. J. Aeronaut. 30 (2), 500–512. https://doi.org/10.1016/j.cja.2017.01.010.

Sun, Y.R., Mburua, L., Wang, S.H., 2016. Analysis of community properties and node properties to understand the structure of the bus transport network. Phys. A: Statist. Mech. Appl. 450, 523–530. https://doi.org/10.1016/j.physa.2015.12.150.

Van Wee, B., Witlox, F., 2021. COVID-19 and its long-term effects on activity participation and travel behaviour: a multiperspective view. J. Transport Geogr. 95, 103144 https://doi.org/10.1016/j.jtrangeo.2021.103144.

Verma, T., Araujo, N.A.M., Herrmann, H.J., 2014. Revealing the structure of the world airline network. Sci. Rep. 4 (5638), 1–6. https://doi.org/10.1038/srep05638.

Wagner, I., Bertacco, V., Austin, T., 2007. Microprocessor verification via feedback-adjusted markov models. IEEE. T. Comput. AID. D. 26 (6), 1126–1138. https://doi.org/10.1109/TCAD.2006.884494.

Wang, C., Wang, X.Y., 2019. Why do airlines prefer multi-hub networks. Transp. Res. Part E: Logist. Transp. Rev. 124, 56–74, 2019. https://10.1016/j.tre.2019.02.009.

Wu, W.W., Zhang, H.Y., Zhang, S.R., Witlox, F., 2019. Community detection in airline networks. An empirical analysis of American vs. Southwest Airlines. J. Adv. Transport. 8, 1–11. https://doi.org/10.1155/2019/3032015.

Yao, Y., Shi, W., Zhang, A., 2021. Examining the diffusion of coronavirus disease 2019 cases in a metropolis: a space syntax approach. Luo S Int. J. Health Geogr. 20, 17. https://doi.org/10.1186/s12942-021-00270-4.

Zhou, Y.M., Kundu, T., Wei, Q., Goh, M., Sheu, J.B., 2021a. Vulnerability of the worldwide air transportation network to global catastrophes such as COVID-19. Transp. Res. Part E: Logist. Transp. Rev. 154, 102469 https://doi.org/10.1016/j.tre.2021.102469, 2021.

Zhou, Y.M., Li, S.P., Kundu, T., Bai, X.W., 2021b. The impact of network topology on air transportation robustness to pandemics. IEEE Trans. Netw. Sci. Eng. 99, 1. https://doi.org/10.1109/TNSE.2021.3085818, 1.

Zhou, Y., Wang, J., Huang, G.Q., 2019. Efficiency and robustness of weighted air transport networks. Transport. Res. Part E: Logist Transp Rev. 122, 14–26. https://doi.org/10.1016/j.tre.2018.11.008.

HAOYU ZHANG is currently pursuing the Ph.D. degree in science with the Geography Department, Ghent University (UGent), Belgium. She Participates with the Natural Science Foundation of China Project and has published nine publications on these topics, four of them are on SCI indexed and three are EI indexed. Her research interests include transportation planning and management, transportation network optimization, complex network theory and flight delay propagation and controlling.

Address: Department of Geography, Ghent University, Krijgslaan 281/S8, 9000 Gent, Belgium **Email:** 1123851665@qq.com

WEIWEI WU received the Ph.D. degree in management science and engineering from the Nanjing University of Aeronautics and Astronautics (NUAA), China. She is currently the Associate Dean and a supervisor of graduate student with the Civil Aviation Department, NUAA. She heads the Natural Science Foundation of China Project and has published around 50 publications on these topics, five of them are on SCI indexed and ten are EI indexed. Her research interests include transportation planning and management, transportation system optimization, economic analysis of transportation and flight delay propagation and controlling.

Address: College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, 210016 Nanjing, Jiangsu, China **Email:** nhwei@nuaa.edu.cn

FRANK WITLOX received the master's degree in applied economics and the master's degree in maritime sciences from the University of Antwerp, Belgium, and the Ph.D. degree in urban planning from Eindhoven University of Technology, The Netherlands. He is currently the head of the Department and a Senior Full Professor of economic geography with the Department of Geography, Ghent University (UGent). He is a Visiting Professor with the Department of Geography, Faculty of Science and Technology, University of Tartu, Estonia, and the International Head of the Mobility Laboratory. In April 2017, he is also an appointed Visiting Professor/High-end Foreign Expert with the College of Civil Aviation, Nanjing University of Aeronautics and Astronautics (NUAA), China. Since September 2018, he has been a 100 Talents Program Laureate of Jiangsu Province. In December 2018, he received the Degree of Doctor (honoris causa) in geography from the University of Tartu (Estonia). In February 2020, he was awarded a similar degree from the Odessa National Polytechnic University, Ukraine.

Address: Department of Geography, Ghent University, Krijgslaan 281/S8, 9000 Gent, Belgium **Email:** Frank.Witlox@UGent.be