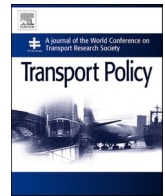




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Spatiotemporal variation of the worldwide air transportation network induced by COVID-19 pandemic in 2020

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ABSTRACT

This paper studies the spatiotemporal variation of the worldwide air transportation network (WATN) induced by the COVID-19 pandemic in 2020. The variations are captured from four perspectives: passenger throughput, network connectivity, airport centrality, and international connections. Further, this work also considers both global and local connectivity-based metrics for the network analysis. Supported by real-world data, we show that the performance of the WATN has experienced a dynamic pattern of decline and recovery in 2020. Interestingly, the network metrics undergo tremendous variations in a very short period after the World Health Organization declared COVID-19 as a pandemic, with the number of flights and connections dropping by more than 40% within only the first four weeks. Intuitively, the passenger throughput's changing rate is highly correlated to confirmed cases' growth rate during the early period of the COVID-19 outbreak. However, the air transport response to the pandemic condition is very diverse among different countries. The major airports in the WATN fluctuate gradually in different pandemic stages, which is further influenced by the domestic pandemic situation that restricts airport operations. Also, the restoration speed of local connectivity is faster than that of global connectivity because the recovery of international aviation is geographically dependent on different policies of travel restriction, conditional openings, and the number of COVID-19 cases. The analysis deepens our understanding to formulate bilateral policies for pandemic-induced ATN design and management.

1. Introduction

The COVID-19 outbreak has created worldwide disruptions to the economy, livelihood, business, and social functioning. Due to the surge in confirmed cases and the rapid spread of the virus, the World Health Organization (WHO) declared the COVID-19 outbreak as a pandemic on March 11, 2020. By the end of 2020, more than 82 million people were infected with COVID-19 globally, including over 1.8 million deaths (The World Health Organization, 2021). It is not exaggerated to say that the COVID-19 pandemic was the most destructive global black swan event in 2020.

In response to the COVID-19 pandemic, strict prevention measures and travel restrictions were implemented by many countries to avoid virus transmission. Therein, the global aviation demand for domestic and international travel plunged and brought the air transportation sector to a standstill (Hotle and Mumbower, 2021). According to the International Air Transport Association (2020), COVID-19 led to a 66%

decline in the worldwide revenue passenger kilometers (RPKs) during 2020, which is the largest shock to commercial air travel and aviation since World War II. This enormous variation in a very short period motivates us to analyze the spatiotemporal changes of the worldwide air transportation network in 2020.

Following previous literature studying the evolution of air transportation (Cheung et al., 2020; Dai et al., 2018; Wandelt and Sun, 2015; Wang et al., 2014), the network science method is used in this paper to investigate the spatiotemporal variation of the worldwide air transportation network (WATN) affected by COVID-19 throughout 2020. The WATN is regarded as an undirected network that comprises nodes and edges representing airports and their connections. On this basis, this paper seeks to answer the following questions: (1) How does the number of operating airports and flight connections fluctuate with the pandemic situation? (2) To what extent does the connectivity of the WATN collapse during the COVID-19 pandemic? (3) How do the major airports shift across different pandemic stages? (4) How does the number of

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international flights vary under travel restrictions?

This paper incrementally contributes to the literature on air transportation network (ATN) structure analysis. Specifically, the existing literature (Allroggen et al., 2015; Cheung et al., 2020; Dai et al., 2018; Lin and Ban, 2014; Siozos-Rousoulis et al., 2021; Wandelt and Sun, 2015; Wang et al., 2014) has investigated the long-term evolution of ATNs along with economic development. On the contrary, our study focuses on the dynamic short-term variation of the WATN induced by COVID-19, including decline and recovery. From the temporal point of view, a comprehensive analysis considering the COVID-19 pandemic situation is conducted to characterize the weekly variation of the WATN in 2020. Notably, the 52-week volatility of passenger throughput, network connectivity, airport centrality, and international connections in 2020 are evaluated with the corresponding metrics using real-world data. From the spatial point of view, the geographical migration of critical airports and countries affected by COVID-19 is explored. We also showcase the changes in the connectivity and centrality patterns of the WATN, respectively. Our major findings are summarized below.

- (1) The variation in throughput can be divided into three phases: gradual decline, sharp decline, and slow recovery, respectively corresponding to the pandemic outbreak in China, global outbreak, and new normalization. However, the decline in throughput has a time lag compared with the pandemic situation for most metrics.
- (2) The global and local connectivity of the WATN experienced a rapid decline pattern during the outbreak of COVID-19 but a significantly different pattern at the recovery stage due to the partial recovery of the WATN in local areas. Moreover, the fluctuation of weighted connectivity is more significant than that of unweighted one.
- (3) The centrality ranking of major airports is related to the local pandemic levels, but most critical airports at the pre-pandemic stage have come back to prominence in the new normalization period.
- (4) The changes in international aviation of different countries exhibit a mixed pattern, where some countries gradually recovered while the others maintain a low level of international flights. However, countries that used to have similar bilateral connectivity in the pre-COVID-19 era usually have similar trends in international aviation restoration.

The rest of this paper is organized as follows. Section 2 outlines the relevant literature. Section 3 introduces the data sources and elucidates the methodology framework used in this work. Section 4 to Section 7 present a thorough analysis of the variation of passenger throughput, network connectivity, airport centrality, and international connections in the WATN, respectively. Section 8 offers some managerial insights. Section 9 concludes the paper with future research directions.

2. Literature review

To highlight this study's positioning and contribution, we review the relevant literature around mutual influence between transportation and COVID-19 and the air transportation network (ATN) structure analysis.

2.1. Mutual influence between transportation and COVID-19

The COVID-19 pandemic has drawn considerable attention from researchers and decision-makers in the transportation field. For instance, Yilmazkuday (2020) developed a difference-in-difference model to investigate the impact of traveling across counties in the U.S. on county-level COVID-19 cases or deaths. Carteni et al. (2021) examined the correlation between positive COVID-19 cases and transport accessibility in Italy through a multiple linear regression model. The results show that transportation accessibility is the primary contagion

promoter and allows the spread of the virus among citizens. Mo et al. (2021) examined the spreading of COVID-19 through public transit systems. They proposed a time-varying weighted public transit encounter network and found that partial closure of bus routes helps to slow down but cannot fully control the epidemic's spread. Qian and Ukkusuri (2021) presented a Trans-SEIR model to study the coupling between the spreading dynamics of infectious diseases and the mobility dynamics through urban transportation systems. They analyzed the disease dynamics during the early COVID-19 outbreak in New York City. Hu et al. (2021) proposed a big-data-driven analytical framework to evaluate the human mobility trend during COVID-19 quantitatively. Gaskin et al. (2021) studied the associations between COVID-19 cases/deaths rates and proximity degree to airports, train stations, and public transportation employing negative binomial regressions and Cox regression models. Besides, the effects of policies and technological innovations attributed to COVID-19 on various transportation aspects are also attractive to researchers. For example, Pani et al. (2020) focused on a global spotlight on Autonomous delivery robot (ADR) technology for last-mile freight deliveries and analyzed the consumer preference and public acceptance of the technology. Bian et al. (2021) studied the time lag effects of COVID-19 policies on transportation systems in New York City and Seattle. Borkowski et al. (2021) discussed the impact of the COVID-19 pandemic on people's daily mobility and explored differences between various societal groups. Hu et al. (2021) employed a partial least square regression to study the impact of COVID-19 on transit ridership and find differences among various regions. Shakibaei et al. (2021) investigated the impacts of the COVID-19 pandemic on travel behavior evolution under residents' self-regulation and governmental measures in Istanbul. Moreover, there are also studies focusing on domestic transportation (Lee et al., 2020; Munawar et al., 2021; Zhang et al., 2020) and logistics (BASTUG and YERCAN, 2021; Illahi and Mir, 2021; Loske, 2020).

Similarly, relevant research on air transportation is also underway (Nakamura and Managi, 2020; Sun et al., 2021; Zhu et al., 2021; Zhou et al., 2021b). From the perspective of airlines, Amankwah-Amoah (2020) examined global airlines' responses to the COVID-19 pandemic and proposed a conceptual framework with strategic and tactical approaches. Pereira and Soares de Mello (2021) employed Multicriteria Data Envelopment Analysis (MCDEA) to assess the operational efficiency of Brazilian airlines considering the COVID-19 pandemic. From the perspective of passengers, Monmousseau et al. (2020) presented four metrics based on data generated by passengers and airlines to measure the impact of travel restrictions implemented during the COVID-19 pandemic on the U.S. air transportation system. Sokadjo and Atchadé (2020) studied the influence of passenger air traffic on the spread of COVID-19 with different statistical methods. From the global network perspective, Bombelli (2020) analyzed the worldwide network of freight forwarders such as FedEx, UPS, and DHL and provided insights into how the COVID-19 pandemic influenced the global capacity of freight forwarders and other cargo airlines. Tiwari et al. (2021) indicated the trends in the pandemic risk of the outbreak in the U.S. by evaluating the tendency of network density, flight frequency, and daily reported confirmed COVID-19 cases.

2.2. ATN structure analysis

The existing literature on ATN structure analysis can be divided into three categories: (1) network topology analysis, (2) network performance evaluation, and (3) network structure evolution. The topology analysis of ATNs involves measuring network properties with topological characterization and pattern recognition that can help to statistically assess connectivity, investigate critical airports, and detect communities. The performance evaluation of ATNs involves determining an air transportation system's ability to maintain its performance when facing disruptions. The studies on structure evolution illustrate the historical evolution of ATNs along with time and economic

Table 1
The network metrics and studied areas in the literature to analyze ATN structure.

Category	Reference	Network metrics	Study areas
Topology	Guimerà et al. (2005)	Degree, betweenness, modularity	Worldwide
	Guida and Maria (2007)	Degree, betweenness, average path length	Italy
	Bagler (2008)	Degree, average path length, clustering coefficient	India
	Wang et al. (2011)	Degree, betweenness, closeness, average path length, clustering coefficient	China
	Du et al. (2016)	Degree, clustering coefficient, core, size of giant component	China
	Du et al. (2017)	Degree, clustering coefficient, average path length, diameter	China
	Gong et al. (2018)	Degree, clustering coefficient	China
	Wang et al. (2019)	Betweenness, network efficiency	India, U.S.
	Zhou et al. (2021a)	Degree, betweenness	The Belt and Road Initiative countries
	Lordan et al. (2014)	Clustering coefficient, average path length, network efficiency, average degree, size of giant component	Worldwide
Network performance evaluation	Pien et al. (2015)	Betweenness, relative area index	E.U.
	Zhou et al. (2019a)	Weighted network efficiency	Australia, Brazil, Canada, China, E.U., India, Russia, U.S.
	Chen et al. (2020)	Size of giant component, size of isolated clusters, network efficiency	China
	Wandelt et al. (2021)	Size of giant component	Worldwide
Network structure evolution	Lin and Ban (2014)	Degree, betweenness, average path length, clustering coefficient, network efficiency	U.S. (1990–2010)
	Wang et al. (2014)	Degree, betweenness, closeness, average path length, clustering coefficient, density, diameter	China (1930–2012)
	Wandelt and Sun (2015)	Degree, betweenness, average path length, clustering coefficient, density	The entire world at country level (2002–2013)
	Dai et al. (2018)	Degree, average path length, clustering coefficient, core	Southeast Asia (1979–2012)
	Wandelt et al. (2019)	Degree, average path length, clustering coefficient, assortativity	Australia, Brazil, Canada, China, India, Russia, U.S., E.U. (2002–2013)
	Cheung et al. (2020)	Degree, betweenness, closeness, eigenvector, regional importance	Worldwide (2006–2016)
	Sozos-Rousoulis et al. (2021)	Degree, betweenness, average path length, clustering coefficient, assortativity, network efficiency	U.S. (2001–2016)

development. To conduct the studies mentioned above on ATNs, researchers employ various network metrics, such as degree, betweenness, closeness, clustering coefficient, average path length, network efficiency, and size of giant component, among others. Relevant studies are summarized in Table 1 with the information on the corresponding metrics used and the studied areas.

Notice that from Table 1, we can find two characteristics of the ATN literature evolution. First, the ATN structure analyses expand from the unweighted network considering only physical properties (Guida and Maria, 2007; Guimerà et al., 2005) to the weighted network considering link capacity (Bagler, 2008; Zhou et al., 2019a). Second, these studies evolve from independent network metric evaluation (Dai et al., 2018; Du et al., 2016) to considering different network metrics as the proxies of different properties (Cheung et al., 2020; Wandelt et al., 2019).

2.3. Research gap

Based on the above-presented literature review, the following research gaps are identified. First, minimal research has been reported on the spatiotemporal changes of ATNs across different stages of the COVID-19 pandemic. Second, previous studies on ATNs' variation mainly focused on long-term evolution caused by economic development; however, it is different in the case of COVID-19, which has negatively impacted the WATN in a short period. In detail, long-term network evolution displays steady improvements accompanied by economic growth, with small fluctuations due to seasonal factors and some special events. However, COVID-19-related short-term variation of ATNs demonstrated steep declines and various recovery patterns. Besides, the change difference between metrics may be relatively large. Thus, the short-term variation of the WATN can help us evaluate the performance related to declining and restoration during emergencies and provide some insights on the planning and management of ATNs under the current COVID-19 pandemic. To the best of our knowledge, the performance decline in the WATN induced by COVID-19 and the associated recovery have not been systematically studied before. Therein, to support further research in this direction, we present a comprehensive study on the spatiotemporal variation of the WATN

affected by COVID-19 in 2020 (using 52 weeks scale).

3. Data and method

3.1. Data preparation

The flight data used in this paper were obtained from the global aviation data provider Official Airline Guide (OAG) (<https://analytics.oag.com/>). Each flight record contains information about the scheduled carrier, flight number, origin airport, destination airport, departure time, arrival time, elapsed time, distance, equipment, and time series. As the flight schedule is usually in a 7-day cycle, we divide the flight data from 2020 to 01-06 (Monday) to 2021-01-03 (Sunday) into 52 groups for our study. In addition, the flight data from 2019 to 01-07 (Monday) to 2020-01-05 (Sunday) are prepared in the same way for comparison.

The data relating to COVID-19 is obtained from WHO Coronavirus Disease (COVID-19) Dashboard (<https://covid19.who.int/>). The dashboard involves the number of confirmed cases and deaths worldwide, both newly and cumulatively. Following the temporal division of flights, we sorted the data in weeks.

3.2. Research method

3.2.1. Representation of the WATN

In this paper, the WATN (G) is assumed to be unweighted and undirected. The WATN in each week is represented by a $N \times N$ binary adjacency matrix A where N is the number of operating airports in this specific week. The element a_{ij} of A is equal to 1 if there are scheduled flights between airport i and airport j in the corresponding week, and 0 otherwise.

3.2.2. Review of network metrics used

The network metrics used in this paper are categorized into network connectivity metrics (network efficiency, average path length, and clustering coefficient) and airport centrality metrics (degree, betweenness, closeness, and eigenvector centrality). Their definitions in the WATN are as follows (Cheung et al., 2020; Dai et al., 2018; Wandelt

et al., 2019; Zhou et al., 2019b; Zhou and Wang, 2018).

(1) Network efficiency

Network efficiency (E) is defined as the average of the reciprocal of the shortest path length between two airports in the WATN:

$$E = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \frac{1}{d_{ij}}, \tag{1}$$

where d_{ij} is the shortest path length between airport i and airport j , and N is the number of operating airports in the WATN. It is noted that d_{ij} is equal to the number of connections in the corresponding shortest path. By this definition, we can see that the range of E is $[0, 1]$. If the network is a complete graph, $E = 1$; if all nodes in the network are isolated, $E = 0$.

(2) Average path length

Similar to network efficiency, average path length (L) is defined as the average of the shortest path length between two airports in the WATN:

$$L = \frac{1}{N(N-1)} \sum_{i \neq j \in G} d_{ij}. \tag{2}$$

It represents the minimum number of flights that passengers need to take from one airport to another on average in the WATN. Note that the shorter the average shortest path, the higher the network connectivity.

(3) Clustering coefficient

The clustering coefficient of an airport i (C_i) denotes the probability that two airports that are directly connected to a third airport are also directly connected. Therefore, the average clustering coefficient C of the WATN is the mean value of C_i :

$$C = \frac{1}{N} \sum_{i=1}^N C_i. \tag{3}$$

The above definition shows that the clustering level of a network is high when the clustering coefficient is close to 1. Note that the term “clustering coefficient” means the average clustering coefficient of the whole network in this paper.

(4) Degree

The degree of an airport i (k_i) is the number of airports directly connected to it in the WATN. Given the adjacency matrix A , it follows

$$k_i = \sum_{j=1}^N a_{ij}. \tag{4}$$

This metric is useful to judge the connection change of a node directly. The degree of a node will decrease if the number of nodes connecting to it declines. To make this quantification comparable between networks in different periods, we define the normalized degree (DC_i) as

$$DC_i = \frac{k_i}{N-1}, \tag{5}$$

where $N - 1$ means the maximum possible airports that airport i can connect.

(5) Betweenness

Betweenness centrality measures the frequency that an airport acts as a bridge along the shortest path between two other airports in the

WATN. Let σ_{st} be the number of shortest paths between airport s and airport t and σ_{st}^i be the number of those paths passing through airport i , so the betweenness of airport i (b_i) can be calculated as

$$b_i = \sum_{s < t \in G} \frac{\sigma_{st}^i}{\sigma_{st}}. \tag{6}$$

If one node is located in the shortest path of many node pairs, it will have a high betweenness centrality. For betweenness centrality, we give the normalized expression as well. Because the maximum number of possible airport pairs passing through airport i is equal to $(N-1)(N-2)/2$ (Freeman, 1979; Wang et al., 2019), the normalized betweenness (BC_i) can be written as

$$BC_i = \frac{2}{(N-1)(N-2)} \sum_{s < t \in G} \frac{\sigma_{st}^i}{\sigma_{st}}. \tag{7}$$

(6) Closeness

Closeness centrality describes how proximal an airport is to other airports in the WATN. Still relying on the concept of shortest path, the closeness of an airport i (CC_i) is defined as

$$CC_i = \frac{N-1}{\sum_{j \in G, j \neq i} d_{ij}}. \tag{8}$$

A higher closeness value represents that passengers from this airport can arrive at their destinations with fewer stopovers. Therefore, the closeness centrality will approach 1 if the distance between the corresponding node and all other nodes is very small.

(7) Eigenvector centrality

Eigenvector centrality is the eigenvector for the largest eigenvalue λ of the adjacency matrix A , and it portrays the airport’s importance on both its degree and the significance of its neighbor airports. The formula for the eigenvector centrality of an airport i (EC_i) is

$$EC_i = \frac{1}{\lambda} \sum_{j=1}^N a_{ij} EC_j. \tag{9}$$

Airports with high eigenvector centrality are generally connected to other airports which also have high eigenvector centrality. The eigenvector centrality of a node also varies between 0 and 1, with larger values indicating a higher centrality.

3.2.3. Outline of the spatiotemporal variation analysis

Our variation analysis of the WATN is conducted from four perspectives: (1) passenger throughput, (2) network connectivity, (3) airport centrality, and (4) international connections. In the first part, we provide the fluctuation of the number of nodes (operating airports) N , edges (airport connections) e , total flights f , and average flights per connection f/e both in 2019 and 2020. Then, we investigate the relationship between the ATN variation and the COVID-19 pandemic situation. In the second part, network connectivity is assessed from the global and local perspectives. Global connectivity is quantified by three metrics: network efficiency E , average path length L , and average betweenness $\frac{1}{N} \sum_{i=1}^N BC_i$, while local connectivity is quantified by clustering coefficient C , average degree $\frac{1}{N} \sum_{i=1}^N DC_i$, and average eigenvector

$\frac{1}{N} \sum_{i=1}^N EC_i$. Similarly, the evaluation of critical airports is implemented with global centrality (betweenness and closeness) and local centrality (degree and eigenvector) in the third part. Finally, the international connections are analyzed at the country level. For the sake of clarity of

exposition, we select the countries whose international flights ranked in the top five (based on network metrics) at least once in 2020 (during all 52 weeks) and investigate how they are connected in the same period.

4. Throughput analysis

4.1. Variation of the WATN

The graphs of the WATN in three representative weeks in 2020 are presented in Fig. 1, namely week 1, week 16, and week 52, as the first week, the lowest-level week, and the last week, respectively. The red dots represent operating airports, and blue lines denote airport connections. The reason for choosing week 16 (April 20 to 26) is that the number of flight connections in this week is the lowest in 2020. We can see that the WATN changes remarkably, dropping from 24524 airport connections linking 3932 operating airports in week 1–11694 connections linking 3239 operating airports in week 16, and the decline in the southern hemisphere and island countries are more prominent. However, the airport connections in China and the U.S. maintain a high density. The primary reason for this difference is probably that the COVID-19 pandemic in China had been effectively controlled at that time, while the U.S. relies primarily on air transportation for medium- and long-distance travel compared to the ground transportation systems. It is also noted that there is a significant decrease in the number of airport connections in Russia. This is mainly owing to the concentrated outbreak of COVID-19 in April 2020. At the end of 2020, the number of operating airports and airport connections worldwide recovered to 3680 and 18019, respectively. Most of the restored connections are domestic connections, while the international connections have not resumed significantly. Moreover, some airports in peripheral islands were still not operational in week 52.

Fig. 2 shows the variation of the number of operating airports from

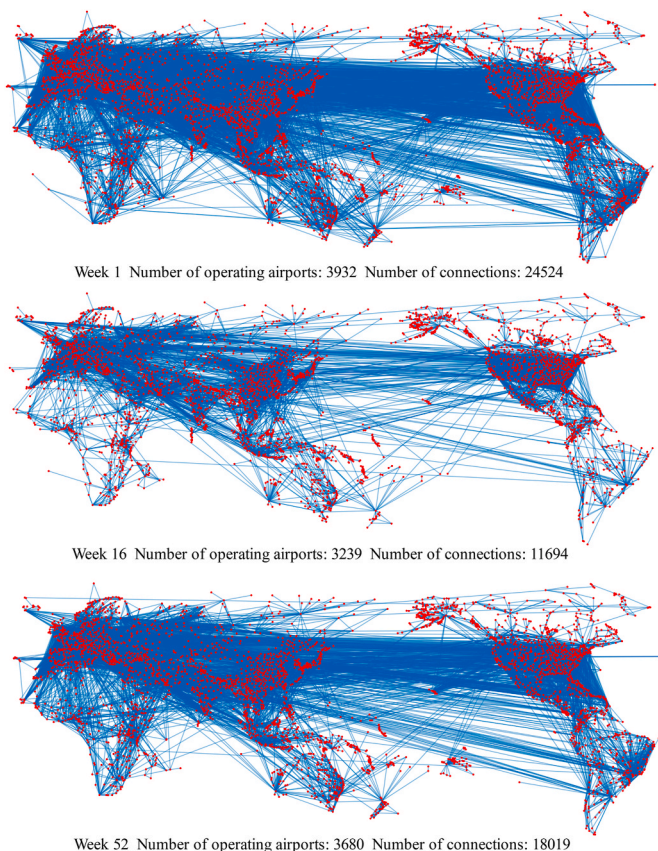


Fig. 1. The WATN in week 1, week 16 and week 52 of 2020.

week 1 to week 52 in both 2019 (dash grey line) and 2020 (solid black line). We observe that the trend in 2019 is very consistent with minimal differences. On the contrary, the fluctuation in the number of operating airports in 2020 is relatively high. The trend in the first few weeks of 2020 is similar to that in 2019, and it is not affected by the COVID-19 outbreak in China. The minor increase compared to the same period in 2019 is due to the opening of new airports in 2020. After the WHO declared COVID-19 as a pandemic in week 10, the number of operating airports starts to descend, but we can see that this decline has a time lag of 1–2 weeks. With the spread of the virus, travel restrictions have been adopted by an increasing number of countries. Correspondingly, the number of operating airports has also fallen sharply. By week 20, this number drops to 3201, which is the lowest value in 2020. Towards late June (week 24–26), it seems that there is a restart of an ascending trend. This is mainly due to the summer peak of air transportation in many countries. The trend tends to stabilize after week 35 because the COVID-19 pandemic became normal at that time and has a small peak in week 50 on account of the travel rush before Christmas.

The number of airport connections and total operating flights in 2019 and 2020 is illustrated in Fig. 3. The square denotes airport connection, and the triangle represents flight. The coordinates are subtly set so that the starting points of the four lines are close on the figure to compare the overall trends of 2019 and 2020. The average number of flights per connection is also calculated and shown using histograms at the bottom of Fig. 3. It can be observed that the number of flights and connections in 2019 shows seasonal variations, and their trends are very consistent. Thus, average flights per connection in one week appear to be very stable within the range from 28.2 to 30.2. On the contrary, influenced by the COVID-19 pandemic, the number of flights and connections decreases significantly in the first half of 2020. Unlike the changing trend of operating airports, the number of flights and connections first experienced slippage in weeks 5–7. This is mainly caused by the domestic mobility limitation in China and the entry restrictions implemented by other countries during the early COVID-19 outbreak. The concentrated reduction of connections and flights also results from the WHO's announcement of COVID-19 becoming a pandemic. As a result, the average number of flights per connection dropped a lot, down to 17.8 at most. The uptrend starting from week 25 is due to the arrival of the summer peak and the pandemic relief in some countries. After week 30, the variation trend of connections and flights tends to be constant, so average flights per connection remain stable. The changing trends of operating airports, airport connections, and total flights in 2020 are presented together for comparison in Appendix A. The throughput change is presented using three phases: gradual decline, sharp decline, and slow recovery. The gradual decline phase corresponds to the stage of the pandemic outbreak in China. In this phase, the number of airports does not remarkably change while airport connections and operating flights slightly drop. The sharp decline phase begins after the WHO's announcement of COVID-19 becoming a pandemic, and all three throughput metrics undergo huge decline. Especially from week 10 to week 14, the number of flights and connections decreases by more than 40% within only four weeks. After week 25, the aviation throughput begins to recover slowly, and it gradually stabilizes and reaches a new equilibrium at the end of 2020. It is shown that the restoration of airport connections is more resilient than that of operation flights in the recovery phase. This phenomenon occurs because most airlines largely control flights owing to declining demand during the COVID-19 pandemic, but they start to operate critical and valuable connections in the new normalization period.

Fig. 4 demonstrates the variation of domestic and international flights in the WATN. Again, the coordinates are subtly set to put the starting points of the two lines together. We can find that the COVID-19 pandemic has a greater impact on international flights than on domestic flights, whether during the outbreak period or normal period. This is mainly owing to the strict international travel restrictions and imported-cases prevention policies adopted by many countries. The only

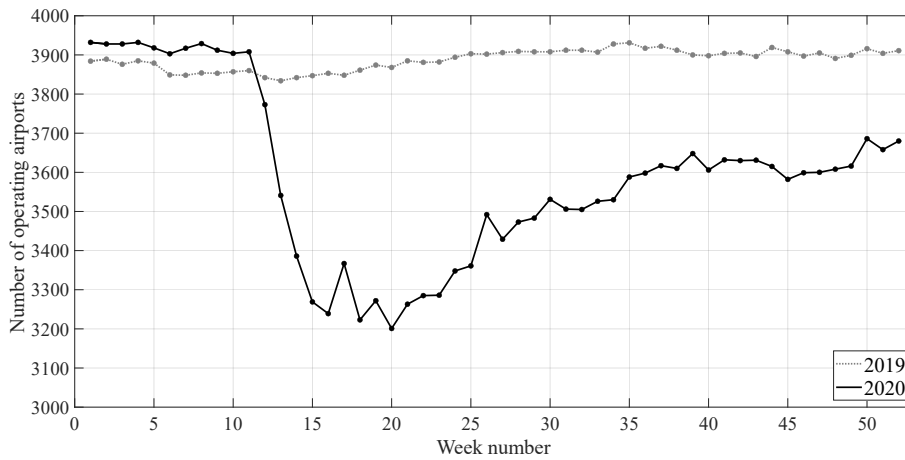


Fig. 2. The number of operating airports in 2019 and 2020.

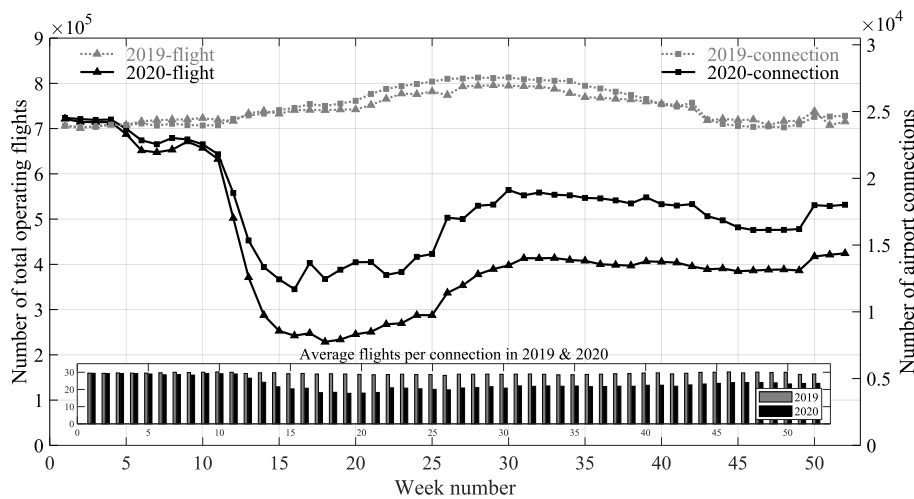


Fig. 3. The number of flights and connections in 2019 and 2020.

exception occurs in weeks 5–7 when many domestic flights in China are suspended.

4.2. Relationship between confirmed cases and flights

This section explores the relationship between the variation of total flights in the WATN and that of confirmed COVID-19 cases. Fig. 5 illustrates the number of weekly new COVID-19 cases in 2020. We can find that the confirmed cases are on the rise in most periods, reflecting the pandemic’s severity. Moreover, there are two ascending waves of confirmed cases, one is from week 10 to week 30, and the other is after week 40. Notice that the variation of the WATN (including airports, connections, and flights) after week 10 is quite obvious (declined with increasing COVID-19 cases). Interestingly, the situation after week 40 is noteworthy (gradually restoring, given the COVID-19 cases were still on the rise). This reflects that the factors affecting air transportation have gotten complicated after the COVID-19 pandemic became normal, and air transportation operations are no longer constrained by this event. Therefore, we investigate their relationship at the early period of the global COVID-19 outbreak.

The pandemic condition is measured by the growth rate of confirmed COVID-19 cases weekly, and it is given by:

$$r_k^p = \frac{\text{the confirmed cases in week } k}{\text{the cumulative cases until week } k} \tag{10}$$

Simultaneously, the variation of the number of global flights is expressed by the changing rate:

$$r_k^f = \frac{f_k - f_{k-1}}{f_{k-1}}, \tag{11}$$

where f_k is the number of global flights in week k . We choose week 13 to week 30 in 2020 as the study period, where week 13 is the first time when the number of flights dropped below 400000 due to COVID-19 and week 30 was when this number returned to over 400000. Fig. 6 shows the result of the correlation analysis between r^p and r^f , where the size of the dot is proportional to the number of flights in the corresponding week. We can see that the changing rate of global flights has a strongly negative relationship with the growth rate of confirmed cases. Quantitatively, the absolute value of the correlation coefficient is up to 0.8992. It is also shown that the number of global flights is more uncondusive to recover with the more rapid increase of confirmed cases during the studied period.

Furthermore, we chose four countries with the maximum number of domestic flights at the pre-pandemic stage, namely the U.S., China, India, and Indonesia, to investigate how different waves of COVID-19 confirmed cases within a country affect the corresponding domestic flight network. Fig. 7 shows the variation of weekly new COVID-19 cases and domestic flights operating in the above four countries. Interestingly, the air transport responses to the pandemic condition are quite different among these four countries. For instance, in the U.S., there are three

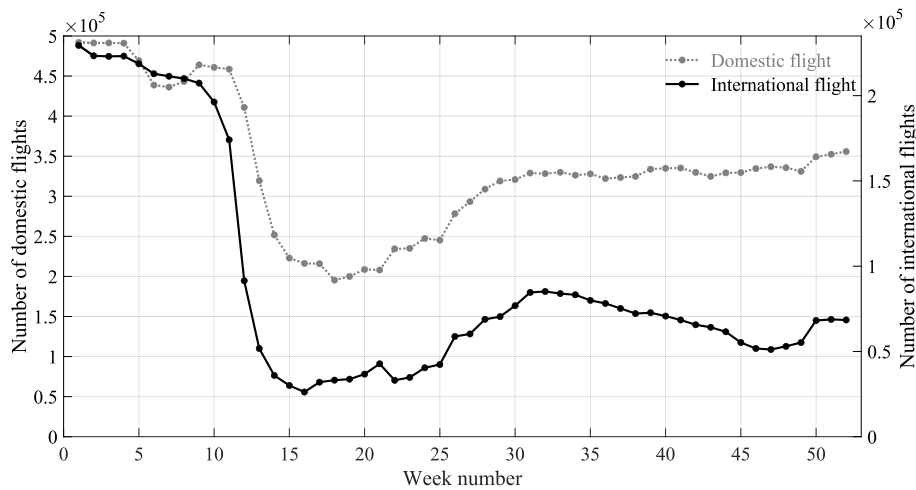


Fig. 4. The number of domestic and international flights in 2020.

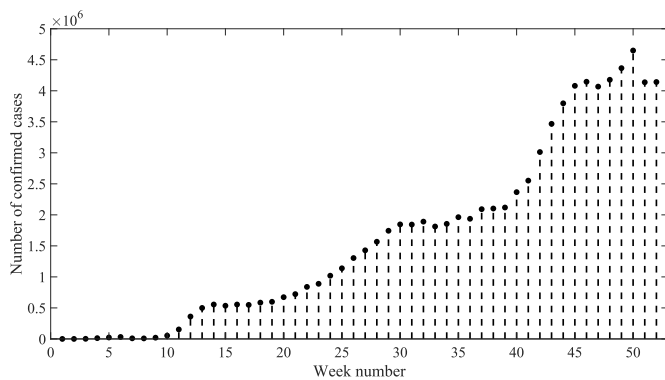


Fig. 5. The number of confirmed cases of COVID-19 in 2020.

apparent waves of weekly new COVID-19 cases in 2020, but only the first wave has seriously affected the number of operating flights. We can also see that the decline of operating flights has a 2–3 week time lag with the first wave of confirmed cases. In the new normalization period, flight recovery has not been severely restricted due to the rise in confirmed cases. However, only the large-scale increase in confirmed cases reduces the number of operating flights to a certain extent. The variation in China is relatively simple. Only a huge wave of confirmed cases at the beginning of 2020 corresponds to the fast decrease in domestic flights. It is worth mentioning that the domestic throughput of China has recovered to the pre-pandemic level from the middle of 2020. The number of

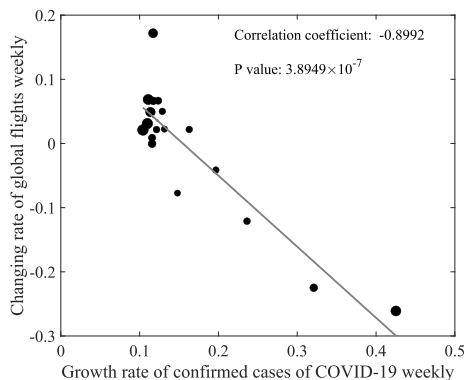


Fig. 6. The relationship between confirmed cases and flights from week 13 to week 30.

domestic flights in India also experiences a large decline after the pandemic outbreak, and then it fluctuates up and down. It can be found that the flight volume is extremely low when the number of weekly confirmed cases increases significantly from week 30 to week 36. By contrast, the flight variation in Indonesia is atypical. The number of domestic flights has no significant relationship with the waves of confirmed cases.

5. Network connectivity analysis

This section presents the connectivity variation of the WATN across the 52 weeks in 2020. The network connectivity in our study consists of (1) global connectivity and (2) local connectivity. Global connectivity characterizes the entire accessibility of the WATN based on the distribution of shortest paths between airport pairs, while local connectivity focuses on the connection of airports with their neighboring airports.

5.1. Global connectivity

As shown in Fig. 8, there are three metrics to describe the global connectivity variation, namely, network efficiency, average path length, and average betweenness. We can find that the efficiency of the WATN begins to decline from week 10 rapidly, and it drops to the lowest level in week 16, which is the same time when the number of airport connections is the lowest. The COVID-19 pandemic is so destructive that there is a 20.9% decline in network efficiency from week 1 to week 16. Because of the restoration of operating airports and airport connections during the summer peak, the efficiency of the WATN also gradually improves. After week 30, it flattens out with slight fluctuation but is still much lower than the pre-pandemic level. On the contrary, the average path length of the WATN generally displays the opposite trend, which rises first and then declines. It climbs from 4.03 in week 1 to 4.56 in week 15, which means that passengers have to take additional transits to their destinations compared to pre-pandemic situations. Moreover, it is interesting to find that the average path length in week 51 is the smallest in 2020. The variation of average betweenness exhibits a highly similar trend with that of average path length. The reason is that the increase (decrease) of average path length represents the more (less) number of airports on shortest paths, and then the betweenness of some airports will become larger (smaller). Thus, high average betweenness is also a sign of low connectivity. This indirectly reflects that the centrality of some airports increases due to the suspension of other airports and the interruption of some connections. In all, the global connectivity of the WATN experienced deterioration first and then slowly recovered to a stable level in 2020.

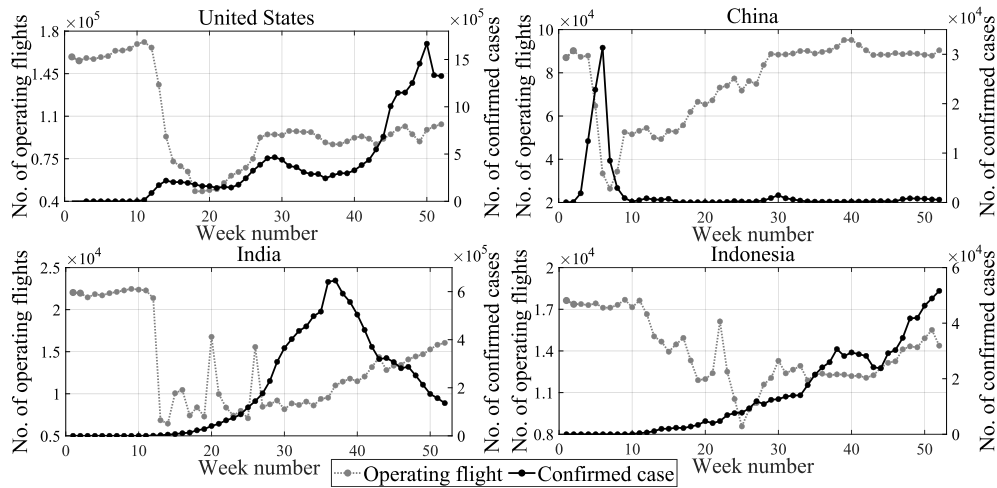


Fig. 7. The waves of COVID-19 confirmed cases and domestic flights in four countries in 2020.

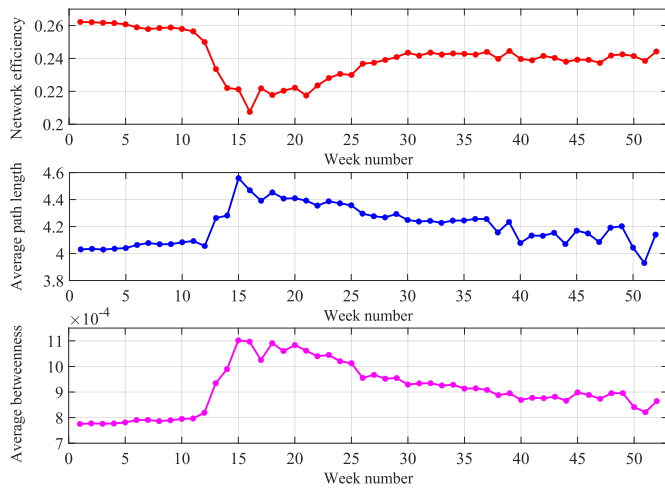


Fig. 8. The variation of global connectivity metrics in 2020.

5.2. Local connectivity

Fig. 9 illustrates the variation of local connectivity in terms of clustering coefficient, average degree, and average eigenvector centrality. It is shown that all three metrics show a significant decline after the WHO declared COVID-19 as a pandemic, and the average eigenvector centrality seems to have a two-week lag. The changing trend of clustering coefficient is similar to that of network efficiency, showing a first descending trend and then ascending. The bounce in week 17 is mainly caused by the increase in airport connections at that time. For average degree and average eigenvector centrality, we can see the first wave of decline around week 5. The primary reason is that the degree of Chinese airports dropped a lot during the outbreak of COVID-19 in China. As of week 16, the average degree of the WATN has dropped by 29.7% compared to week 1, which indicates that each airport shuts down 30% of its pre-pandemic connections on average. However, it is interesting to find that the average degree returns to the pre-pandemic level in July and August, which is different from many other network metrics. The restoration of the average eigenvector is more complicated, where the bounce appears in the summer peak and the fourth quarter. One possible conjecture is that the recovery of connections in the WATN always emerges in hub-to-hub links after the COVID-19 pandemic became normal; thus, some adjacent airports of hub airports are also critical. As a whole, the local connectivity of the WATN also displays a trend of decline first and then rise, but its recovery speed is faster than that of

the pre-pandemic level and last for many weeks.

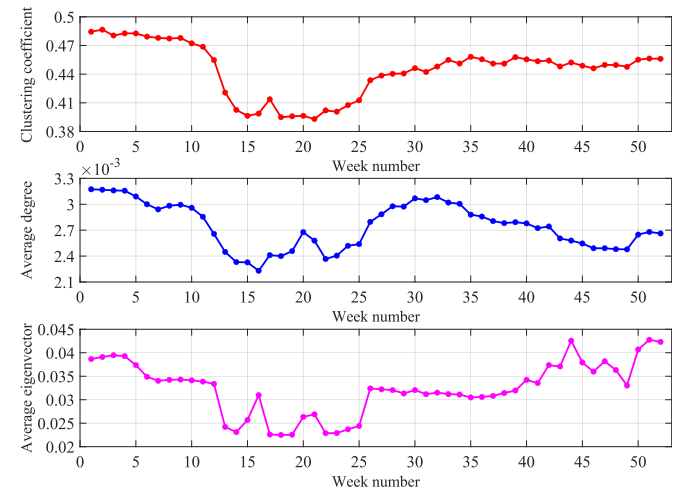


Fig. 9. The variation of local connectivity metrics in 2020.

global connectivity. Interestingly, some metrics reach the pre-pandemic level and last for many weeks.

To better demonstrate the decline caused by COVID-19 in WATN's global and local connectivity, the connectivity change of the WATN from 2009 to 2019 was calculated for comparison¹. The flight data of 2009-01-01 to 2019-01-01 was processed in the same way to acquire the value of the associated metrics. We define the changing rate from 2009 to 2019 as

$$r_1 = \frac{Metric_{2019} - Metric_{2009}}{Metric_{2009}} \tag{12}$$

Also, the connectivity decline from week 1 to the worst week (of these six metrics) in 2020 were calculated, and the corresponding changing rate is defined as

$$r_2 = \frac{Metric_{worst} - Metric_{week\ 1}}{Metric_{week\ 1}} \tag{13}$$

The results of r_1 and r_2 are shown in Table 2. We can observe that the connectivity of the WATN improves significantly from 2009 to 2019, but

¹ Due to data limitations, only the flight data of January 1st in 2009 and 2019 were used.

Table 2
The comparison of connectivity change in two periods.

Category	Network metric	r_1 (2009–2019)	r_2 (2020)
Global connectivity	Network efficiency	4.74%	–20.86%
	Average path length	–9.81%	13.10%
	Average betweenness	–19.94%	42.12%
Local connectivity	Clustering coefficient	4.79%	–18.87%
	Average degree	18.00%	–29.73%
	Average eigenvector	39.53%	–41.80%

Table 3
Top 1 airports of four centrality metrics in 52 weeks.

Global centrality								Local centrality							
Betweenness				Closeness				Degree				Eigenvector			
Week	Airport	Week	Airport	Week	Airport	Week	Airport	Week	Airport	Week	Airport	Week	Airport	Week	Airport
1	ANC	27	CDG	1	DXB	27	CDG	1	IST	27	DFW	1	FRA	27	AMS
2	ANC	28	AMS	2	DXB	28	AMS	2	IST	28	DFW	2	FRA	28	AMS
3	ANC	29	CDG	3	DXB	29	AMS	3	IST	29	DFW	3	FRA	29	AMS
4	ANC	30	ANC	4	DXB	30	AMS	4	IST	30	CDG	4	FRA	30	AMS
5	ANC	31	AMS	5	DXB	31	AMS	5	IST	31	AMS	5	FRA	31	AMS
6	ANC	32	ANC	6	DXB	32	AMS	6	IST	32	AMS	6	AMS	32	AMS
7	ANC	33	ANC	7	DXB	33	AMS	7	IST	33	AMS	7	AMS	33	AMS
8	ANC	34	ANC	8	DXB	34	AMS	8	IST	34	AMS	8	AMS	34	AMS
9	ANC	35	ANC	9	DXB	35	AMS	9	IST	35	AMS	9	AMS	35	AMS
10	ANC	36	ANC	10	DXB	36	AMS	10	IST	36	AMS	10	AMS	36	AMS
11	ANC	37	ANC	11	CDG	37	AMS	11	IST	37	AMS	11	AMS	37	AMS
12	ANC	38	ANC	12	CDG	38	AMS	12	DFW	38	CDG	12	ORD	38	AMS
13	DOH	39	DXB	13	LHR	39	AMS	13	DFW	39	CDG	13	ORD	39	FRA
14	DOH	40	ANC	14	LHR	40	AMS	14	DFW	40	DFW	14	DFW	40	FRA
15	SEA	41	SEA	15	LHR	41	AMS	15	DFW	41	DFW	15	DFW	41	FRA
16	SEA	42	AMS	16	AMS	42	AMS	16	DFW	42	DFW	16	DFW	42	AMS
17	SEA	43	AMS	17	ICN	43	AMS	17	DFW	43	IST	17	CTU	43	AMS
18	ANC	44	AMS	18	LHR	44	AMS	18	DFW	44	DFW	18	CTU	44	FRA
19	ANC	45	AMS	19	LHR	45	AMS	19	DFW	45	DFW	19	CTU	45	PVG
20	CDG	46	LAX	20	CDG	46	AMS	20	DFW	46	DFW	20	CAN	46	PVG
21	CDG	47	LAX	21	CDG	47	AMS	21	DFW	47	DFW	21	CTU	47	CAN
22	DOH	48	LAX	22	DOH	48	AMS	22	DFW	48	DFW	22	CTU	48	CAN
23	DOH	49	LAX	23	DOH	49	FRA	23	DFW	49	DFW	23	CTU	49	CAN
24	DOH	50	ANC	24	DOH	50	AMS	24	DFW	50	DFW	24	CTU	50	AMS
25	DOH	51	LAX	25	DOH	51	AMS	25	DFW	51	DFW	25	CTU	51	AMS
26	DOH	52	LAX	26	DOH	52	FRA	26	DFW	52	DFW	26	FRA	52	AMS

it experienced a sharp decline in 2020 because of the COVID-19 pandemic. Note that for average path length and average betweenness, their value decreased with the historical growth of the WATN, and increased during the COVID-19 pandemic. While for the other four metrics, the opposite is true. The numbers in Table 2 indicate that the largest decline of network connectivity of the WATN caused by COVID-19 in 2020 is larger than its historical growth in the past ten years before 2019.

In order to observe the variation of the WATN more comprehensively, two weighted metrics are evaluated in Appendix B.

6. Centrality and critical airports

This section investigates the spatiotemporal variation of the WATN’s central airports in 2020 from the global (betweenness centrality and closeness centrality) and local (degree centrality and eigenvector centrality) perspective.

Table 3 lists the airports ranked top 1 in terms of any of the four centrality metrics in the 52 weeks. Their ranks on corresponding metrics across the 52 weeks are shown in Fig. 10. The detailed information of the airports represented by IATA codes can be found in Appendix C. Following observations can be drawn from the comparison analysis:

- (1) There are a total of 7 airports having ranked first place at least once on betweenness centrality across the 52 weeks. ANC (Ted Stevens Anchorage International Airport), the major hub in

Alaska, stands first most time in the ranking of betweenness, which means that it lies most frequently in the path of indirect connections. The reason is that ANC acts as the bridge connecting the airports in Alaska and the rest airports of the world. We can see the COVID-19 pandemic has not changed the role of ANC as an important hub as its rank is always in the top five. Note that LAX (Los Angeles International Airport) takes first place six times in 2020, and its rank is in the top fifteen at other times, no matter how severe the pandemic is. An important reason is that LAX is the gateway to the U.S. for many countries in Oceania and East Asia, so it must lay in the shortest paths between many airport pairs. In contrast, the fluctuation of DXB’s (Dubai International Airport) rank is quite variable after week 12. The surge in the number of confirmed cases of COVID-19 has primarily affected the betweenness ranking, and DXB loses its position as a global hub until the pandemic becoming normal in the United Arab Emirates.² Comparing LAX and DXB, we can find that LAX operates plenty of flights not only domestic but also international, and it serves as a hub for many airlines. However, DXB mainly carries international flights and acts as a base for only a few airlines; thus, many indirect connections will choose other hubs

² The number of weekly confirmed cases in the United Arab Emirates rose from 51 in the week 11–1037 in week 13. <https://covid19.who.int/> (accessed 22 January 2021).

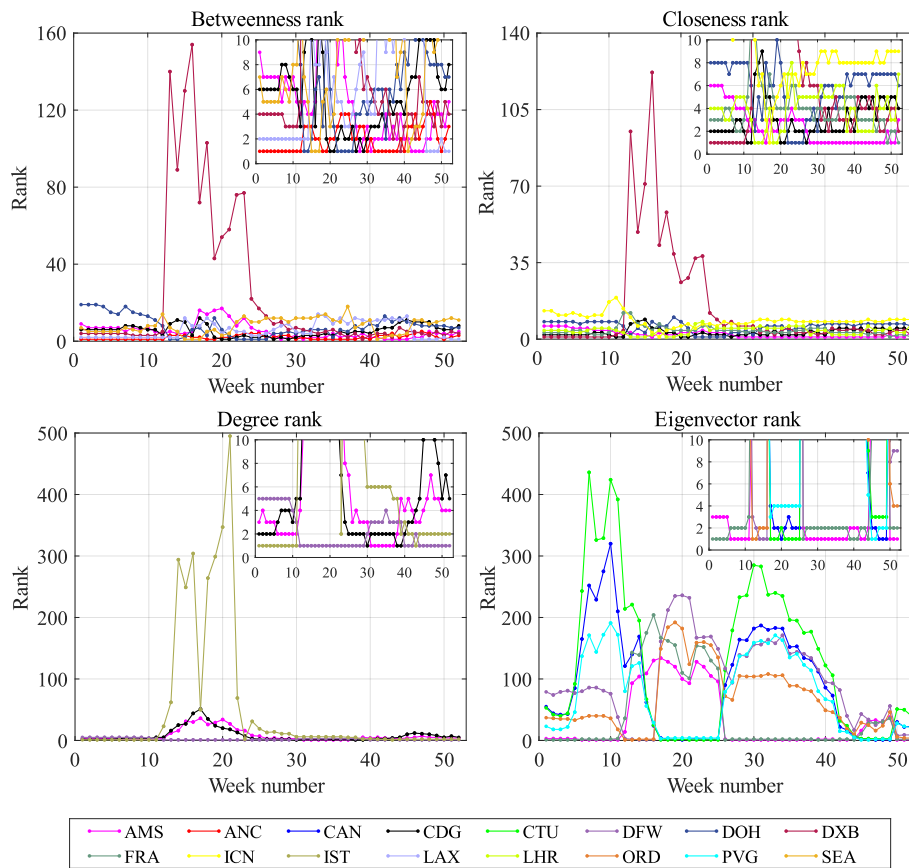


Fig. 10. Ranking fluctuation of airports having been ranked top 1 at least once in the 52 weeks of 2020.

for transferring when the pandemic situation in the United Arab Emirates got worse in COVID-19.

- (2) The ranking of closeness and degree is very similar to that of betweenness, where most airports maintain a relatively high rank while a few airports wave up and down. It is found that the COVID-19 pandemic also makes the closeness rank of DXB drop significantly, and it never returns to No. 1 after week 10. Likewise, IST (Istanbul Airport) experiences a tremendous drop in degree after the large-scale outbreak of pandemic in Turkey.³ In the second half of 2020, AMS (Amsterdam Airport Schiphol) and DFW (Dallas Fort Worth International Airport) occupy first place for most time in terms of closeness and degree. We can see that most central airports at the pre-pandemic stage still hold a core position in terms of betweenness, closeness, and degree centrality. This is probably because airport connections are mostly reduced on spoke-to-spoke links but rarely on the connections involving critical hubs. However, the spread of COVID-19 and the strict entry restrictions implemented by some countries largely reduced the centrality of some hub airports (like DXB and IST) and resulted in the dynamic shift of central airports in the WATN.
- (3) Differently, the top 1 airports on eigenvector centrality across the 52 weeks are distributed in many regions, which is the most variable in these four centrality measures. It is noted that there are two waves of up and down in Chinese airports, which are just opposite to the trend of most other airports. During the COVID-19 outbreak in China, the eigenvector centrality ranking of airports in China has quickly declined because the importance of their

adjacent airports decreases a lot in this time period. For example, the rank of PVG (Shanghai Pudong International Airport) decreases from No.18 in week 2 to No.191 in week 10. As the virus spreads around the world, other airports' ranks started to decline while Chinese airports' ranks rose rapidly. However, after the pandemic became normal, Chinese airports' rank dropped because AMS and FRA (Frankfurt am Main Airport) returned to the top again. In the second half of 2020, most international flights of China have not recovered (see Section 7 for details), and there were only a small number of connections to many critical foreign airports. On the contrary, some other airports such as AMS and FRA may have restored many connections to other hub airports in the world, so their rank rose significantly. The rise of Chinese airports' rank after week 44 is probably due to the serious outbreak of the pandemic in Europe.⁴

From the above analysis, we can identify some characteristics of airports that led to different shifts across different pandemic stages. At the stage of pandemic outbreak, the loss of connections determines the airport centrality variation to a certain extent. Specifically, airports that lose more connections with other airports tend to drop significantly in their centrality rankings. For instance, the betweenness rank of DXB and CDG (Charles de Gaulle International Airport) is very close at the pre-pandemic stage (4th and 6th in week 1 individually) but varies significantly after the pandemic outbreak (140th and 9th in week 13 individually). The reason is that CDG still maintains 45.7% connections in

³ The number of weekly confirmed cases in Turkey rose from 6 in the week 10–6455 in week 12. <https://covid19.who.int/> (accessed 22 January 2021).

⁴ European countries with spiraling Covid-19 outbreaks are shutting back down. <https://www.vox.com/21514530/europe-covid-second-wave-update> (accessed 4 March 2021).

week 13 while this value of DXB is only 19.9%. In the period of aviation restoration, the importance of neighboring airports influences the shifts of airport centrality ranking. Generally, the airport with connections to more regional airports is prone to have a higher betweenness rank, whereas the airport with connections to more hub airports is inclined to have a higher eigenvector rank.

Fig. 11 illustrates the geographical location and times being ranked top 1 of the airports that appeared in Fig. 10. The red nodes represented all the 4200 airports having operated in 2020. The different colored bars represent the times that an airport ranked top 1 in terms of different centrality metrics in the 52 weeks. We can see that airports in the U.S. often take the first place on betweenness and degree due to their special locations. The top-ranked airports on closeness in the 52 weeks are all situated in Europe and West Asia. Apart from the fact that they are important hubs, another reason is that the airports in these two regions are very dense. Chinese airports ranked No. 1 on eigenvector for some time because of the recovery of domestic air transportation. Taken together, AMS is the most central airport. Specifically, from week 26 to week 44, AMS ranked top 10 on all the four-centrality metrics, indicating that AMS is very central in the WATN after the COVID-19 pandemic becomes normal.

7. International connections

The enormous variation of international flights in the WATN analyzed in Section 4 motivates us to explore the worldwide international connections in depth. In this section, the international connections are evaluated on two aspects: (1) the change of international flights of major countries; (2) the aviation interconnections among these major countries.

The number of international flights of countries ranked top 5 at least once worldwide in 2020 is illustrated in Fig. 12. The number of their international flights has typically dropped during the COVID-19 pandemic. We can see China was the first to shut down its international connections, and the number of international flights of China decreased from week 5, which is caused by the strict travel restrictions implemented by many countries during the COVID-19 outbreak in China (Li et al., 2021). Additionally, the international flights in South Korea also dwindled during the same period. This is because many flights between China and South Korea were suspended at that time. Besides, from week 13 to week 29, the international flights of all countries worldwide are less than 10000, although flights of some European countries have increased around week 20. It can be seen that COVID-19 has brought the international aviation industry to a standstill. The recovery of international flights of different countries displayed a mixed pattern. For European countries, the international flights climbed up in the summer peak and went down in November due to the second wave of the pandemic in Europe. For countries like China, South Korea, and Canada, their international flights maintained a relatively low level to control the imported COVID-19 cases. On the contrary, international flights in the U.S. show an upward trend after the pandemic's normalization. This is probably owing to the ascending global travel demand in the U.S.

To better compare the changing trend of the number of international flights in different countries, the ratio of weekly international flights in 2020 to week 1 is calculated and shown in Fig. 13. Several findings are observed from these trends. In the descent phase, China's international flights' changing trend shows a cliff-like decline in week 5 and week 6. Similar trends can be observed in South Korea's case because of the nearby (China) spread of COVID-19. In Italy's case, the decline from week 10 to week 11 is observed due to the national lockdown beginning

at week 10.⁵ In the ascent phase, Qatar, an important international transit hub, is the first to resume international flights. This is also in accordance with that DOH (Hamad International Airport) took first place on betweenness and closeness centrality from week 22 to week 26 in the WATN (see Table 3). Countries in Europe reached their highest level after the pandemic outbreak during the summer peak, but it is still far from their pre-pandemic level. The number of international flights of Mexico exhibits an upward trend in the second half of 2020, mainly because the number of flights with its neighboring countries increased.

Next, the interconnections among these major countries are studied. The variation of international flights of countries in North America, Asia, and Europe is illustrated in Fig. 14, Fig. 15, and Fig. 16. It is found that the countries in the same region tend to have a similar changing trend in the number of international flights. In general, the number of flights with surrounding countries is much greater than that with other countries regardless of the pre-pandemic or in-pandemic stage. The general trend of the number of flights is like that in Fig. 13. Most countries first shut down international flights with China and further reduce their connections with other countries when COVID-19 spread across the world. After the pandemic became normal, different countries implemented different recovery strategies and exhibited a distinct trend in the number of international flights. We can see that China's international flights' recovery is very cautious due to the policy "Both imported cases and spread within the city should be prevented"⁶. In contrast, the international flights between some countries return to the pre-epidemic level in some periods. This is mainly attributed to the launch of the air travel bubble between many countries. The air travel bubble allows citizens of the cooperative countries to travel freely between each other without quarantine and strict travel restrictions. Furthermore, we can speculate that the recovery of these flights has promoted the climb in the local connectivity of the WATN as mentioned in Section 5.

8. Managerial insights

From our study on the spatiotemporal variation of the WATN induced by COVID-19 as compared to the evolution of ATNs caused by time and economic development, many characteristic differences can be summarized as follows. From the temporal point of view, the performance change of the WATN presents the trend of rapid decline and slow recovery. At the beginning of the global outbreak, the passenger throughput and network connectivity underwent tremendous changes in a very short period. Specifically, many associated metrics (as mentioned in previous sections) dropped from normal to the lowest within 5–10 weeks. From the spatial point of view, network performance's geographical difference is huge due to the pandemic situation and prevention policies of different countries. Naturally, the centric airports of the WATN have migrated to a certain extent. Based on our analysis, some constructive insights on the planning and operation of ATNs under the current COVID-19 pandemic are proposed for aviation regulators, industry managers, and policymakers.

8.1. Recovering and expanding regional ATNs

The regional ATN comprises short-distance connections between small and medium cities. Expanding the regional ATN could supplement improving the WATN structure. The results of our work suggest that the recovery of connections in the WATN is always concentrated on critical hub airports, and most spoke-to-spoke links have not been restored yet.

⁵ Italy expands COVID-19 lockdown to whole country. <https://www.cidrap.umn.edu/news-perspective/2020/03/italy-expands-covid-19-lockdown-whole-country> (accessed 19 March 2021).

⁶ Fighting COVID-19: China in Action. <http://www.scio.gov.cn/zfbps/32832/Document/1681809/1681809.htm> (accessed 19 March 2021).

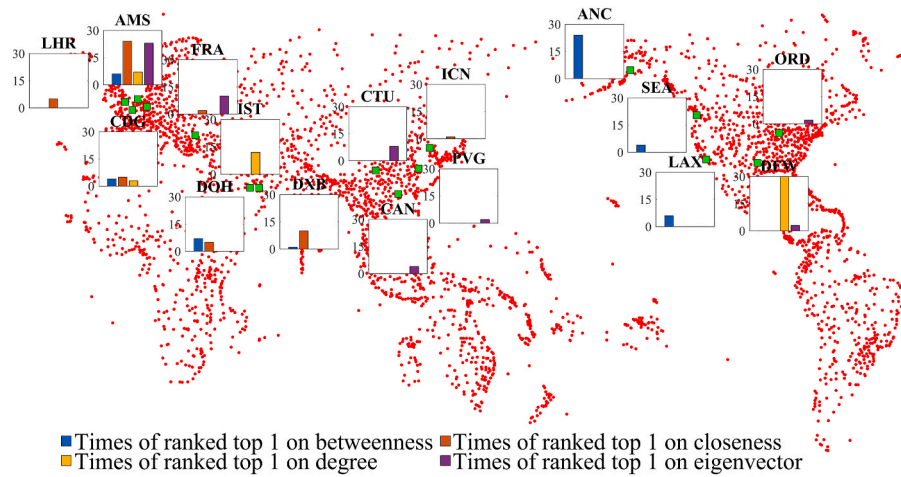


Fig. 11. Geography and frequency display of central airports.

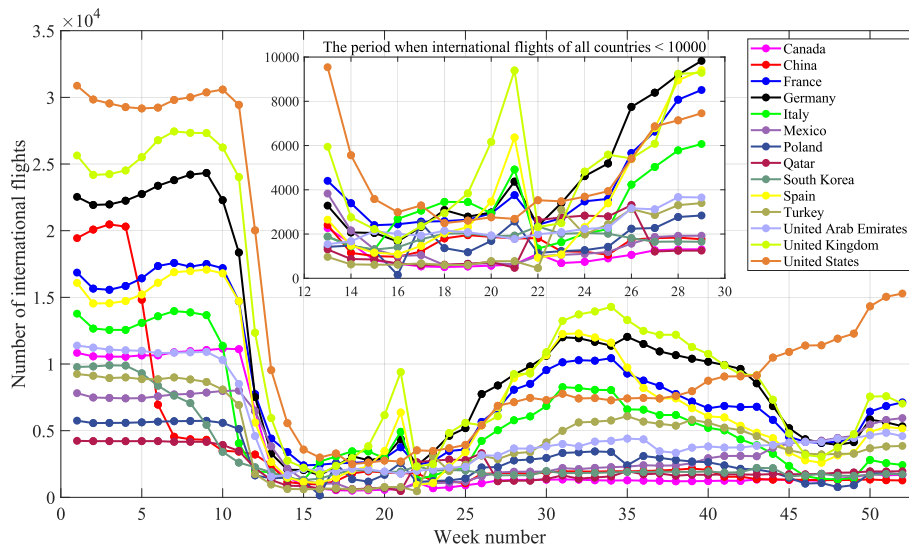


Fig. 12. The number of international flights of countries having ranked top 5 at least once in the 52 weeks of 2020.

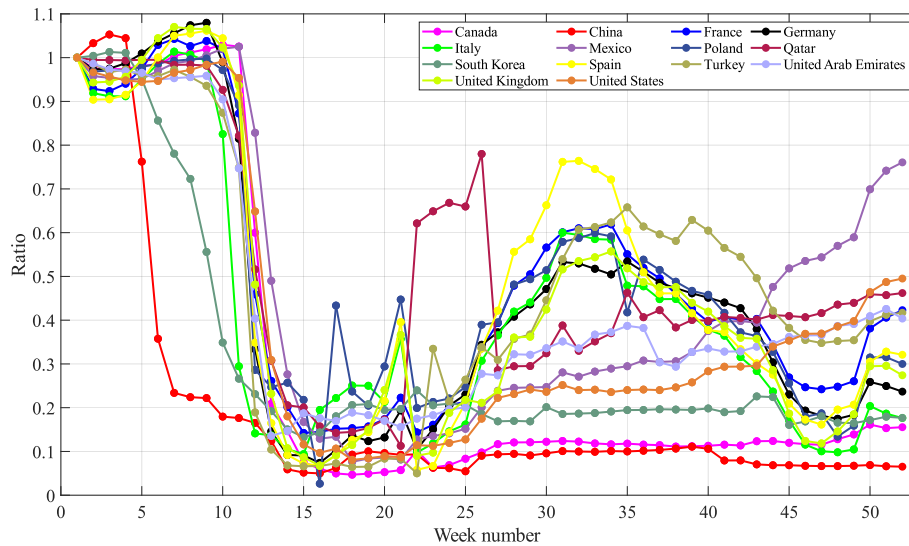


Fig. 13. Trends in the number of international flights of countries having ranked top 5 at least once in the 52 weeks of 2020.

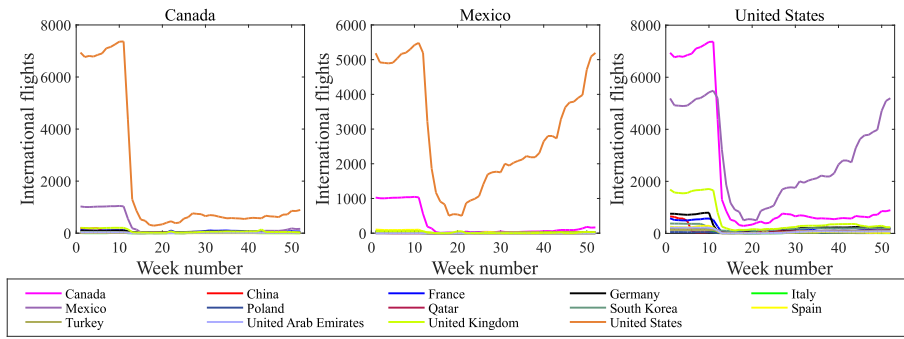


Fig. 14. The number of international flights with other major countries (North America).

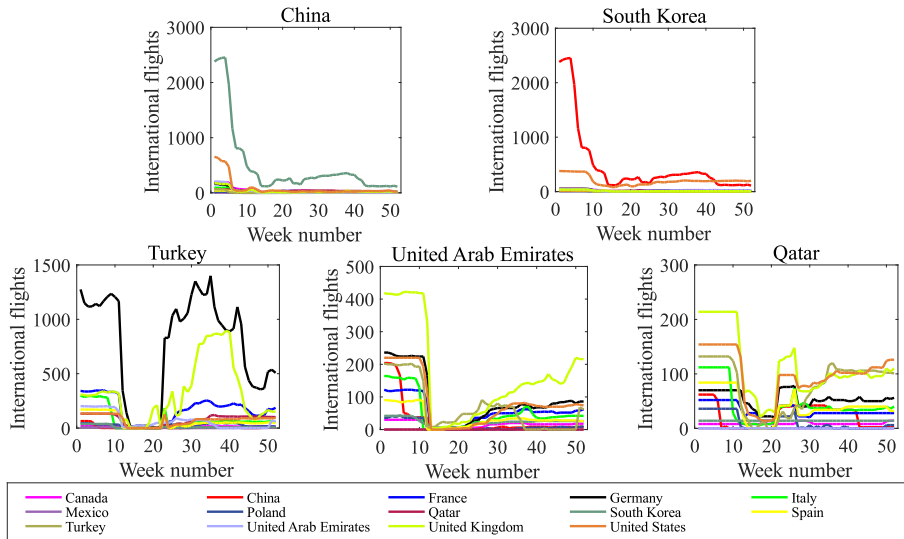


Fig. 15. The number of international flights with other major countries (Asia).

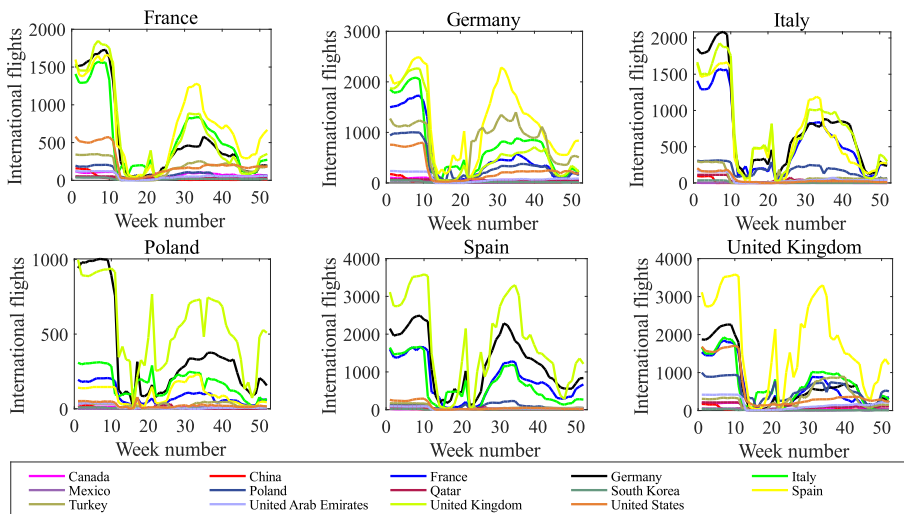


Fig. 16. The number of international flights with other major countries (Europe).

Regional ATNs can enlarge the range of critical hub airports and improve the connectivity of the integrated ATN. Through circular flights between regional airports, the passenger flows are accumulated at a core airport of the regional ATN, which can then be connected to the critical hub airport in the WATN. Regional ATNs are beneficial for assembling the passenger traffic and constituting a valuable interaction with

WATNs to form economies of scale. Moreover, regional ATNs can enhance the emergency response capability of air transportation. The restoration of regional ATNs guarantees the rapid and frequent delivery of COVID packages (like testing kits and vaccines) to remote areas. Besides, it enables the labor force and products to quickly return to their jobs and markets in major cities after the pandemic becomes normal.

8.2. Adjusting the role of large airports flexibly

Our analysis shows that many large airports' centrality varies with different countries' operation measures of ATNs to the COVID-19 pandemic. Indeed, airports' commercial role has been fading during this pandemic, and airports have been increasingly being operated as public utility services. The financial pressure of airports and the recovering demand for air travel urges operators and managers to adjust the role of airports according to the pandemic situation. For countries with a gradual relaxation of travel restrictions, the large airports should enhance their international competitiveness and strengthen the hub status. This can be realized by building the strategic channel for international transfers with airlines' cooperation and coordinating with other countries' aviation resources through code sharing and transit passes. Of course, the airport's necessary prevention measures are indispensable, such as health screening and automatic check-in (Lee and Yu, 2018). Operators and managers can also control the passenger density through flexible flight schedules and passenger movement at airports. On the contrary, for countries with continuous strict travel restrictions, the large airports can effectively utilize idle resources by replacing passenger transportation with freight transportation. This strategy can also meet the growing demand for medical supplies and general cargo in the global market. It is also a good choice to maintain stable domestic flights and short-haul international flights to ensure a certain amount of passenger flow.

8.3. Configuring dynamic change of international flights

The findings in Section 7 illustrate that the restoration of international flights between some countries is evident after the normalization of the pandemic. However, the convenient international accessibility increases the risk of virus transmission and raises the possibility of imported cases. Therefore, the first essence is how to dynamically layout the restored international flights in line with the pandemic situation. Aviation regulators and policymakers should optimize the allocation of international flights and operating airports by considering the infective risk (for example, the number of newly confirmed cases and the basic reproduction number) in cities having international airports of the corresponding countries. The dynamic flight change should also precisely satisfy the international travel demand while maximizing passengers' travel safety.

9. Conclusions

This paper explored the spatiotemporal variation of the WATN induced by COVID-19 in 2020. The whole year is divided into 52 weeks, and the flight data of each week is separately used to construct the real-time WATN. Integrating various network metrics, the analysis is conducted from four perspectives, namely passenger throughput, network connectivity, airport centrality, and international connections. The conclusions of this research are highlighted as follows.

First, the number of operating airports, connections, and flights in the WATN has experienced a remarkable decrease during the pandemic outbreak. The number of flights and connections was first slightly influenced by the COVID-19 outbreak in China, while the number of operating airports responded with a delay of 1–2 weeks when the WHO announced COVID-19 as a pandemic. The aviation throughput is very

sensitive to the pandemic situation during the initial period of the global COVID-19 outbreak, while the changing rate of global flights is closely related to the growth rate of confirmed cases.

Second, both global connectivity and local connectivity exhibit an initial decrease trend followed by a subsequent increase. The decline in the efficiency of the WATN is up to 21%. At the same time, each airport, on average, lost 30% of its destination. The unusual decrease in network connectivity even exceeds the growth brought by the 10-year evolution of the WATN. The aviation restoration in partial areas and the recovery of some hub-to-hub connections made the local connectivity improve fast after the pandemic's normalization.

Third, the centrality rankings of most critical airports have not altered significantly during the COVID-19 pandemic, which implies that the fundamental structure of the WATN has not been crucially transformed. The decline in ranking of some airports is probably because of the national policies on pandemic prevention and control during the local outbreak.

Fourth, the impact of COVID-19 on international flights' variation is more significant than that on domestic flights. From a national point of view, the international flights in East Asian countries were rapidly reduced at first, and then other countries followed up after the global outbreak of COVID-19. In addition, the flight interconnection between major countries varied a lot. The speed of flight recovery among some countries is prompt due to the policies like the travel bubble, while some other countries still do not enhance international flights on a large scale for the sake of the prevention of imported cases.

To conclude, there are limitations and various future research directions as suggested. The first one is that the throughput analysis does not consider the actual passenger flows. The second one is that the link capacity, measured by flight frequencies on links, is not considered when assessing the connectivity and centrality of the WATN. For instance, the betweenness centrality used in our approach is based on the unweighted network without considering the traffic intensity. This is the reason why ANC (Ted Stevens Anchorage International Airport) in Alaska takes first place on betweenness for most of the time. Therefore, future work will focus on the following directions: (1) to apply more detailed data, such as passenger flows and the frequency of flights, in studying the variation of the weighted WATN; (2) to observe the in-depth changes of the WATN from the perspective of community and regional importance; and (3) to investigate the variation of airline networks and domestic aviation networks influenced by COVID-19.

CRediT authorship contribution statement

Siping Li: Methodology, Software, Validation, Writing – original draft. **Yaoming Zhou:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Tanmoy Kundu:** Supervision, Writing – review & editing. **Jiuh-Biing Sheu:** Supervision, Writing – review & editing.

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Appendix A. Comparison of the trend in three throughput metrics

As shown in Fig. A1, a lag appears in the variation of operating airports at the early stage of the global COVID-19 outbreak.

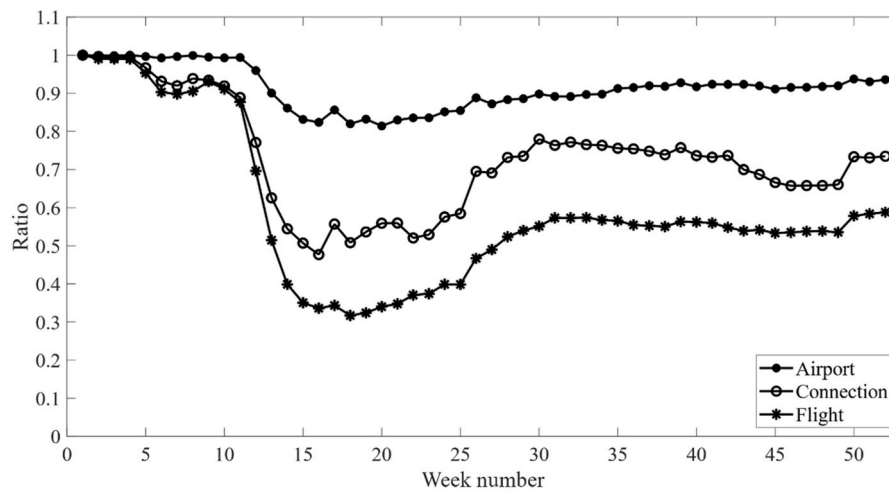


Fig. A1. Trends in the number of operating airports, airport connections and total flights in 2020⁷.

Appendix B. Weighted network metrics

As all the network metrics are unweighted in our paper, some important phenomena in the WATN cannot be captured. Therefore, here we select two weighted network metrics to investigate the global and local property of the WATN, respectively. The global one is the weighted efficiency proposed by Zhou et al. (2019a), and the local one is the average weighted degree which is common and widely used. The variation of two weighted metrics in 2020 is shown in Fig. A2. It is noted that there are two differences between the variation of weighted and unweighted metrics. The first is that the weighted metrics decline more rapidly at the early stage of the pandemic than their corresponding unweighted metrics. For example, from week 1 to week 11, the weighted efficiency drops by 8.06%, while the unweighted one only decreases by 2.20%. It is mainly because the air travel demands decrease faster than the airport connections in this time period. The second is that at the recovery stage in the second half of 2020, the rebound of weighted metrics is not as obvious as the unweighted ones. This is primarily due to the fact that the restoration in the new normalization period is always concerned with airport connections rather than flight capacity at first.

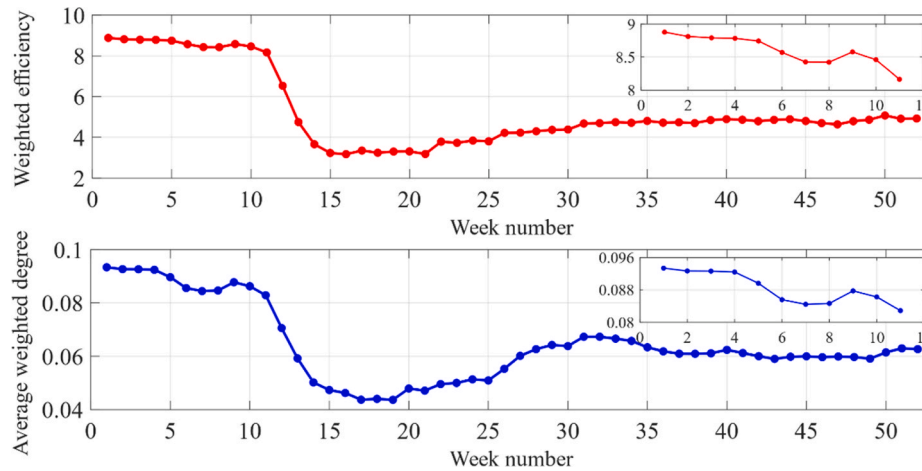


Fig. A2. The variation of weighted network metrics in 2020.

Appendix C. Airport information

IATA code	Airport Name	Longitude	Latitude	City	Country	Continent
AMS	Amsterdam Airport Schiphol	4.76	52.31	Amsterdam	Netherlands	Europe
ANC	Ted Stevens Anchorage International Airport	-150.00	61.17	Anchorage	United States	North America
CAN	Guangzhou Baiyun International Airport	113.30	23.39	Guangzhou	China	Asia
CDG	Charles de Gaulle International Airport	2.55	49.01	Paris	France	Europe
CTU	Chengdu Shuangliu International Airport	103.95	30.58	Chengdu	China	Asia
DFW	Dallas Fort Worth International Airport	-97.04	32.90	Dallas	United States	North America

(continued on next page)

⁷ The ratio in Fig. A1 is equal to the value in the corresponding week to that in week 1, so the starting points of three throughput metrics are identical.

(continued)

IATA code	Airport Name	Longitude	Latitude	City	Country	Continent
DOH	Hamad International Airport	51.61	25.27	Doha	Qatar	Asia
DXB	Dubai International Airport	55.36	25.25	Dubai	United Arab Emirates	Asia
FRA	Frankfurt am Main Airport	8.57	50.03	Frankfurt	Germany	Europe
ICN	Incheon International Airport	126.45	37.47	Seoul	South Korea	Asia
IST	Istanbul Airport	28.75	41.28	Istanbul	Turkey	Asia
LAX	Los Angeles International Airport	-118.41	33.94	Los Angeles	United States	North America
LHR	London Heathrow Airport	-0.46	51.47	London	United Kingdom	Europe
ORD	Chicago O'Hare International Airport	-87.90	41.98	Chicago	United States	North America
PVG	Shanghai Pudong International Airport	121.81	31.14	Shanghai	China	Asia
SEA	Seattle Tacoma International Airport	-122.31	47.45	Seattle	United States	North America

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