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Navigating through and beyond the COVID-19 crisis: Evaluating the resilience of Chinese international air freighter networks

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ABSTRACT

The COVID-19 pandemic significantly affected the global air transport industry, but it also provided a business opportunity for the air freight sector. Many countries, including China, increased the use of all-cargo flights to compensate for the loss of belly capacity. This paper provides a deeper understanding of the Chinese international scheduled freighter network (CISFN) during and post-COVID-19. The results show that the CISFN adapted rapidly to the increasing air cargo volume and continued to expand. The focus of the network expansion has been on developing the hub-and-spoke (H&S) system, which is the most efficient model for accommodating the increase in dedicated cargo demand, rather than establishing point-to-point routes among existing communities. The densification of the H&S system provided more alternatives for the hub cities, and consequently the robustness of the system has improved. Government policies have played a crucial role in shaping China's dedicated air cargo networks. The introduction of some key policies has boosted cargo airline expansion and enhanced the resilience of this sector during the pandemic. However, the network remained vulnerable to disruptions, particularly at some key hubs.

1. Introduction

The COVID-19 pandemic represents an unparalleled worldwide health crisis, characterized by widespread lockdowns and travel limitations (Li et al., 2021; Warnock-Smith et al., 2021). Travel restrictions, which limit international passenger arrivals, were adopted by many countries as effective strategies to control the virus's spread (Li et al., 2021; Meng et al., 2021; Zhang et al., 2020a; Zhou et al., 2021). Some countries even implemented total or partial lockdowns (Han et al., 2020), leading to airport closures, flight rescheduling and route alterations. While these countries did not enforce policies specifically targeting cargo transit, akin to those implemented for passenger movement, COVID-19-related restrictions presented additional challenges to the availability of air freight capacity, which include ground handling staff shortages, flight cancellations, handling delays and empty return flights.

In China, the inter-province travel restrictions caused disruptions in logistics operations. Specifically, in early 2020, the vast majority of passenger flights were grounded as a possible measure to control the spread of COVID-19 (Zhang et al., 2020b; Tisdall et al., 2021). This resulted in a significant shrinkage of the overall cargo capacity initially because of the reliance on the carrying capacity of passenger flights (Deng et al., 2022). There is a significant overlap between passenger and cargo traffic in China, mostly due to Chinese airlines' reliance on belly space for cargo operations (Gong et al., 2018). Additionally, the restrictions imposed on truck drivers travelling through or originating from airport cities had a notable impact on inland trucking operations. The stringent quarantine protocols led to staff resignations, equipment shortages, and the implementation of crew quarantine rules, all of which affected the air freight sector. Consequently, during the COVID-19 pandemic, cargo handling time significantly increased, leading to operational challenges and a subsequent rise in freight rates. In some cases, these issues even resulted in airport closures. According to the International Air Transport Association (IATA), the predicted losses for Asia Pacific airline markets range from 47 billion to 57 billion USD During the pandemic period (Meng et al., 2021).

However, despite the disruptions and initial drop in air cargo volumes, the industry managed to bounce back rapidly (Bombelli, 2020; Li, 2020; Merkert, 2023). The prime obligation for worldwide supply chains to stay functional favoured the air cargo industry, as it offered a way to expedite the delivery of essential medical supplies and personal protective equipment, which the maritime transport industry could not

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deliver promptly. Also, the surge in online shopping further intensified the need for air cargo services (Bombelli, 2020; Merkert, 2023). Analysis of network development illustrates the importance of the high demand for dedicated cargo services during the pandemic (Deng et al., 2022). In fact, amidst the widespread suspension of international flights, the role of air cargo has become increasingly vital in maintaining the resilience and continuity of the supply chain during times of crisis.

As shown in Fig. 1, in 2019, China transported 2.42 million tons of cargo internationally by air. When Covid-19 first emerged in 2020, this volume declined to 2 million tons as travel restrictions took effect. However, dedicated air cargo capacities expanded to compensate, with freighter frequencies reaching 178,785 that year, up from 156,872 in 2019. As restrictions eased in 2021, international cargo volumes rebounded to 2.67 million tons. Freighters further increased to 260,464 frequencies to accommodate the rebound in demand. Continued recovery transpired in 2022, with volumes remaining stable at 2.64 million tons notwithstanding ongoing challenges. Freighter operations moreover grew to 308,165 frequencies, underscoring their significance.

These fluctuations in tonnage transported and dedicated cargo aircraft deployed demonstrate aviation's definitive role sustaining China's global supply lines. When passenger services suspended, all-cargo carriers provided indispensable connectivity. The crisis raised the importance of the network of dedicated cargo flights (Deng et al., 2022) and their capacity growth supported China's remarkable export-driven economic resilience throughout the crisis.

While most discussions tend to focus on both passenger and cargo routes, the emergence of the COVID-19 pandemic has underscored the significance of separately analysing dedicated cargo flight networks. This heightened importance is exemplified by the case of China, a nation that holds the distinction of being the world's largest exporter and the second-largest economy. Despite its economic prowess, China had yet to establish a robust and efficient dedicated air cargo flight network before COVID, a deficiency when compared to the well-developed systems in the United States and Europe. Compared to leading cargo carriers, Chinese carriers relied more on belly space carriage, and cargo space on return flights is more likely to be wasted. More importantly, leading cargo carriers such as FedEx, UPS and DHL have extensive global networks, which give them more flexibility in flight scheduling and planning (Gong et al., 2018). Notably absent in China is a major dedicated air cargo fleet and an integrated air logistics service provider of the calibre of industry giants such as FedEx, UPS, and DHL. Currently, leading global air cargo companies such as FedEx and UPS possess substantial fleets of dedicated cargo aircraft, with 684 aircraft as of May 2021 for FedEx and 576 aircraft as of August 2021 for UPS. Similarly, DHL operated over 280 aircraft as of April 2021, significantly surpassing the fleet size of air cargo companies in China. Furthermore, these companies have established global air cargo hubs and developed extensive cargo route networks, along with efficient air cargo handling capabilities.

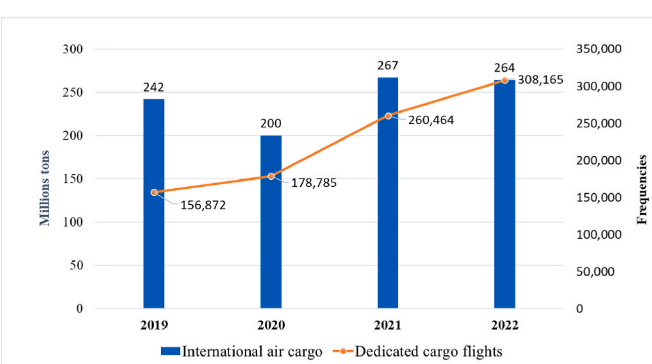


Fig. 1. Air cargo volume and number of dedicated cargo flights in China during 2019–2022 Source: Compiled by authors with data retrieved from Cirium database.

In response to the COVID-19 pandemic and the disruption it caused in global supply chains, several Chinese airlines took proactive measures to address the increased demand for cargo transportation. Airlines such as Air China, China Eastern Airlines, and China Southern Airlines converted some of their passenger aircraft into temporary cargo planes. By removing seats and utilizing the available cargo space, these airlines were able to quickly adapt their operations to meet the growing need for air freight services. Furthermore, the Chinese government has taken proactive measures to support this endeavour, offering subsidies to incentivise and sustain air cargo flights. In May 2022, the Ministry of Finance and the Civil Aviation Administration of China (CAAC) issued a notice to support the stability and improvement of international cargo transportation capabilities for civil aviation companies during the epidemic prevention and control period. The notice provided subsidies for airlines' expenses related to cabin-to-cargo conversion projects, with subsidies covering 80% of the conversion costs.

As discussed, the COVID-19 pandemic has had significant repercussions on the dedicated cargo flight network, with two distinct counteracting effects coming into play. Firstly, the pandemic has adversely affected various aspects of airport and hinterland logistics operations, leading to disruptions and challenges in the air cargo sector. The imposition of travel restrictions, lockdown measures, and health protocols has resulted in reduced workforce availability, limited operational capacities, and increased processing time at airports and logistics facilities. These factors have impeded the smooth flow of goods, caused congestion, and hindered the overall efficiency of air cargo operations.

Conversely, the pandemic has triggered a surge in air cargo demand driven by various factors. As passenger flights were suspended or significantly reduced due to travel restrictions and safety concerns, the available belly space in passenger aircraft, which is typically utilised for transporting cargo, diminished considerably. Consequently, airlines faced an urgent need to address the rising demand for air cargo transportation. To meet this challenge, airlines swiftly adapted by developing dedicated air freighter networks. By repurposing passenger aircraft or acquiring additional freighter planes, airlines sought to augment their cargo-carrying capacity and provide dedicated services exclusively for air cargo transportation. The overall impact of these opposing influences on the dedicated air freighter network is a complex matter that warrants a formal empirical analysis. A comprehensive examination of key indicators, including cargo volumes, flight routes, network connectivity, and operational efficiency, would enable researchers to assess the net effect of the pandemic on the dedicated cargo flight network.

Thus, this paper aims to provide a comprehensive understanding of these disruptions and their impact on the Chinese international scheduled freighter network[1] (CISFN) through a graphical analysis and the utilization of complex network metrics. The COVID-19 pandemic profoundly disrupted global air transportation networks. While some studies have explored impacts on passenger markets, limited research has examined the resilience and evolution of dedicated cargo networks that played a vital role in supply chain continuity. As a major global trade partner, China significantly increased reliance on cargo flights during the pandemic to transport medical and consumer goods. However, no known study to date has leveraged complex network analysis to provide quantitative insights into both the structural changes and resilience demonstrated by China's international scheduled freighter network (CISFN).

This research addresses this gap through a comprehensive

[1] A scheduled freighter network (SFN) refers to a system of dedicated cargo flights that operate on a fixed, regular schedule across a network of airports. These flights are typically operated by freight-only airlines or cargo divisions of passenger airlines. The SFN, as a counterpart to the passenger scheduled flights network, is a core component of the Air Transport Network (ATN), providing more affordable, regular, reliable cargo transportation that supports global trade and logistics (Derigs and Friederichs, 2013).

examination of the CISFN's topological adaptations and robustness from 2019 to 2023. Key findings show the network expanded rapidly in scale and connectivity while navigating pandemic disruptions. Notably, the study identifies Shanghai, Guangzhou and Beijing as central hubs through influence rankings. Further, simulation modelling reveals the network's vulnerability to disruptions at major cargo airports. The rigorous analysis employing network graphs, metrics and modelling contributes novel perspectives on adaptive behaviours within specialised logistics networks during crises. Crucially, the findings offer policymakers valuable considerations for strengthening critical dedicated cargo systems' resilience against future global supply chain threats.

This paper is organised as follows: Section 2 reviews the existing literature on the impact of significant global events, including COVID-19, and the measurements of robustness in the air transport network. The data collection and methodology are presented in Section 3. In Section 4 a graphical analysis of the CISFN, further topological measures, and the robustness of the network are conducted. Also, the structural changes observed in the CISFN are discussed in Section 4. Section 5 concludes the paper, summarising the findings and their implications.

2. Literature review

2.1. Impact of significant global events on the ATN

The Air Transport Network (ATN) is integral to global transport connectivity, acting as the backbone for international trade and people flow. Its resilience and adaptability have been focal points for scholars, especially considering the potential threats and disruptions it faces, such as terrorism and financial crises (Lordan et al., 2014a; Woolley-Meza et al., 2011).

Research has extensively looked into the dynamics of the ATN in the face of external disruptions. Siozos-Rousoulis et al. (2021) investigated the US domestic ATN's robustness, focusing on the post-9/11 restructuring, showing significant network modifications that enhanced efficiency and security. Similarly, Chi and Baek (2013) explored the consequences of major events on air passenger and freight services in the US, pointing out the profound influence of these events on the airline sector.

The financial crisis of 2008 had a deep impact, causing a significant reduction in freight volume and dedicated cargo operations (Boonekamp and Burghouwt, 2017). However, the ATN has demonstrated its ability to recover, with 2015 seeing a resurgence in freighter operations. The eruption of Iceland's Eyjafjallajökull volcano in 2010 and other weather-related events have further demonstrated the fragility of global trade and transport systems, underscoring the need for adaptability in global cargo traffic (Woolley-Meza et al., 2011).

Malighetti et al. (2019) highlighted transformative changes in Asian air networks in 2019, driven primarily by the rapid growth of Chinese e-commerce and the establishment of global carrier hubs. These developments underscore the significant impact of economic and commercial trends on the evolution of air transport networks.

2.2. Impact of the COVID-19 pandemic on the ATN

The COVID-19 pandemic brought unprecedented disruptions to the ATN, leading to a surge in academic investigations into its varied effects on the aviation sector. For instance, studies by Warnock-Smith et al. (2021) and Mueller (2022) focused on the Chinese and the European markets respectively, exploring the pandemic's impact on airlines and airports and addressing how major network reductions impact European air transport connectivity and user convenience.

Bao et al. (2021) and Li et al. (2021) investigated the pandemic's effects on global air transport networks, analyzing changes in centralities among airports worldwide and the impact of international flight entry restrictions, respectively. In cargo transportation, research by Li (2020) and Deng et al. (2022) highlighted the potential growth in China's air cargo industry and enhancements in domestic freighter networks due to increased demand and strategic importance. Park et al. (2023) observed improvements in cold chain networks post-COVID-19 and underlined the increased importance of major air cargo airports during the pandemic.

Limited research has focused into resilience metrics during pandemics. Zhou et al. (2021) explored how network topology influenced a country's resilience during pandemics and proposed new metrics to evaluate connectivity and the ability to maintain international connections. Janić (2022) assessed the resilience, robustness, and vulnerability of major airports during the prolonged disruption of the COVID-19 pandemic, revealing low resilience and robustness but high vulnerability in studied cases.

An extensive body of literature has investigated various impacts of the COVID-19 pandemic on air transportation networks. As highlighted earlier, existing studies primarily examined consequences for passenger demand and route structures across major markets like China, Europe and the United States. Additionally, research on air cargo perspectives has grown, with some exploring domestic freight network enhancements in China and the strategic importance of key airports during the pandemic. However, there remains a notable lack of in-depth analyses dedicated solely to specialised logistics networks.

Reasons for the dearth of dedicated research may relate to data availability challenges. Schedules for all-cargo operations are not readily accessible when compared to combined passenger-freight itineraries. Additionally, rapidly evolving restrictions complicated longitudinal analyses. Overall, while the existing literature offers foundations, further refinement is warranted to advance understanding of specialised logistics networks' resilience and evolution when faced with severe disruptions like the ongoing pandemic. This study aims to address this need.

2.3. Measurements of robustness in the ATN

The Air Transport Network (ATN) plays a crucial role in global connectivity and trade. Its resilience and adaptability are tested during significant global events, from financial crises to natural disasters and pandemics. Robustness generally refers to the ability of a network to continue functioning under adverse conditions, such as when certain nodes or connections are removed. It focuses on the network's inherent strength and capacity to maintain performance despite disruptions (Zhou et al., 2021). Understanding and enhancing the robustness of the ATN is vital for ensuring smooth global operations and trade in an increasingly interconnected world.

Complex network theory has been widely used to assess the robustness of ATN, with numerous studies exploring the effects of diverse network topologies on transport network resilience and the intrinsic relationship between resilience and network structure under extreme disruptive events (Lordan et al., 2014a). Reggiani (2013) introduced a framework combining network resilience and transport security, highlighting the role of transport security in governmental policies and the significance of structural properties of a network in understanding its organization. Chen et al. (2020) emphasized the importance of robustness analysis for policymakers, offering recommendations to enhance ATN security and providing strategies to reduce losses and enhance transport efficiency during airport or route failures.

Zhou et al. (2019) introduced a weighted efficiency metric to assess the robustness of ATNs by considering the number of flights or seats available between airports, focusing on how critical airports affect network resilience under random closures and targeted attacks. Pien et al. (2015) proposed the Relative Area Index (RAI), which measures the operational capacity and network flow reduction due to local disruptions. Wandelt et al. (2015) provided a computationally efficient attack design framework to simulate targeted disruptions, offering insights into resilience under various scenarios. These studies, while diverse in their methodologies, share a common goal of understanding the impact of disruptions on ATNs and provide complementary approaches to evaluating robustness.

Studies by Wilkinson et al. (2012) and Lordan et al. (2014b) have focused on the global ATN, exploring the impact of significant events like the 2010 eruption of the Icelandic volcano Eyjafjallajökull and developing methods to identify critical airports in the global ATN whose exclusion would severely impact network connectivity. Wandelt et al. (2015) evaluate the global ATNs, with a particular emphasis on understanding how targeted disruptions affect networks in different regions. Siozos-Rousoulis et al. (2021) and Chen et al. (2020) conducted research at a national level, assessing the resilience of the U.S. and China's air transport networks and exploring their response to disruptions from both topological and spatiotemporal perspectives. Zhou et al. examines eight domestic air transport networks (ATNs) from different countries, offering a broad global perspective that includes the US, China, and India. Pien et al. focus specifically on the European ATN, addressing operational challenges unique to the region.

Bombelli et al. (2020) focused on the air cargo perspective of the ATN, examining whether airports deemed critical uphold similar or distinct roles in maintaining the connectivity of the global Air Cargo Transport Network (ACTN). However, a notable gap exists in studies related to the structure and resilience of dedicated cargo networks, contrasting with the progress made in studies of passenger airline networks. This study seeks to address this deficiency by examining the challenges encountered by air cargo operators and assessing the resilience of the networks during the COVID-19 pandemic period, considering the sector's vital role in the international supply chain for electronics, fresh food, and medical supplies.

3. Data and methods

3.1. The data

The data were pre-flight schedules released by the CAAC. Typically, the schedule is updated and issued in late October and late March annually. The pre-flight plan distinguishes between passengers and dedicated freight flights. There is the northern summer timetable in March and the northern winter timetable in October. We manually collected the data from 2020 to 2023 via the official website (https://pre-flight.cn/WebHome/Index). The network analysis conducted in this paper focuses on international scheduled all-cargo flights that originate from or have destinations in mainland China (excluding Hong Kong, Macao and Taiwan), in timetables covering the period from October 2019 to October 2023. The timeframe considered spans from before the pandemic outbreak[2] to after the cessation[3] of China's dynamic zero-COVID-19 strategy.

In this research, a node denotes a city instead of an airport. The majority of cities in the dataset have only one airport. However, Beijing, Tokyo and London have multiple airports and so the data from these cities were merged. The data specifically focuses on regular all-cargo flights and does not include passenger or charter flights. The term 'Chinese international scheduled freighter network' refers to the network that consists of incoming and outgoing flights to or from China.

3.2. Measurements

Prior to conducting the exploratory analysis, this study established various measurements to characterise the properties of the CISFN. All the variables and indices utilised for network analysis are presented in Table 1. The study employs these structural measures, including average degree, reciprocity, efficiency, density, average shortest path length and clustering coefficient, to analyse the networks and gain insights into their characteristics.

Centrality measures, including degree, betweenness, closeness and eigenvector, are introduced as metrics to evaluate the importance of nodes in the network. The aim is to assess the significance of hub-and-spoke (H&S) cities within the network. In Section 4 these indices are used to rank the influence of nodes, providing insights into their relative importance.

4. Analysis

4.1. Adaption of the CISFN through the COVID-19 pandemic

The CISFN is represented as a connected series of vertically directed lines on a graph: $G = (V, E)$, where $V = vi$: $i = 1, 2, \ldots, n$; $n = |V|$ is the number of nodes (navigable cities) and $E = ei$: $i = 1, 2, \ldots, m$, $m = |E|$ the number of edges (routes). The network can be characterised as a symmetric matrix $A_{n\times n}$ that represents the connectivity or adjacency between its elements. When a flight route exists between node i and j, an element $aij = 1$,otherwise $aij = 0$. These connected two nodes are considered as neighbours. Different metrics and indicators are utilised to evaluate the structure of the network. These measures help quantify the configuration and organisation of the network, providing insights into its connectivity and overall layout.

Table 2 presents the main topological characteristics of the CISFN during the different timetable periods. The analysis covers the timeframe from the 2019 winter timetable, issued prior to the outbreak of the

Table 1
Network indices.

Index	Description
k_i	the degree of node i
$\langle k \rangle$	the average degree of the network
$k_{in}(i)$	the in-dgree of node i
$k_{out}(i)$	the out-dgree of node i
Reciprocity	the ratio between the number of node pairs connected in both directions and the number of node pairs connected in at least one direction
Efficiency	the inverse of average shortest path length among all pairs of nodes.
γ	density, the ratio of actual links to the maximal number of air routes
d_{ij}	the shortest distance between nodes i to j
D	the diameter of a network; the longest shortest path in the graph
L	the average shortest path length or characteristic path length
C_i	the clustering coefficient of node i
C	the clustering coefficient of the network
$C_d(i)$	the degree centrality of node i
$C_b(i)$	the betweenness centrality of node i
$C_c(i)$	the closeness centrality of node i
$C_e(i)$	the eigenvector centrality

[2] The World Health Organization (WHO) officially designated COVID-19 as a Public Emergency of International Concern on 30 January 2020. Then, on 11 March 2020, Dr. Ghebreyesus, the Director of WHO, declared the COVID-19 outbreak as a global pandemic (Zhang et al., 2020a).

[3] Following the emergence of COVID-19 in late 2019, China implemented a proactive, community-focused approach known as the zero-COVID-19 policy. On 7 December 2022, China announced its decision to ease restrictions and implement enhanced prevention and control measures for managing the outbreak of SARS-CoV-2 (The State Council The People's Republic of China, 2022). On 8 January 2023, China announced the conclusion of its dynamic zero-COVID-19 policy. The updated protocol no longer requires the quarantine of positive cases at designated venues (The State Council of the People's Republic of China, 2023).

[4] The degree of a node in a directed graph, which counts all connections to and from the node. It is the sum of the nodes' indegree and outdegree. The average degree of a graph is the sum of the degrees of all the nodes in the graph divided by the total number of nodes.

Table 2
Topological properties.

Schedule	Nodes	Edges	Average[4] Degree <K>	Reciprocity	Efficiency	Density (γ)	Clustering Coefficient (C)	Average shortest path (L)	Diameter (D)
2019^{Winter}	95	371	7.811	0.695	0.360	0.042	0.253	2.781	6
2020^{Summer}	92	352	7.652	0.705	0.379	0.042	0.245	2.636	6
2020^{Winter}	130	708	10.892	0.856	0.364	0.042	0.155	2.746	6
2021^{Summer}	141	797	11.305	0.856	0.376	0.040	0.190	2.661	7
2021^{Winter}	132	790	11.97	0.871	0.380	0.046	0.160	2.633	6
2022^{Summer}	140	810	11.571	0.884	0.376	0.042	0.147	2.659	6
2022^{Winter}	137	781	11.401	0.891	0.377	0.042	0.074	2.650	5
2023^{Summer}	120	655	10.917	0.840	0.387	0.046	0.144	2.583	6

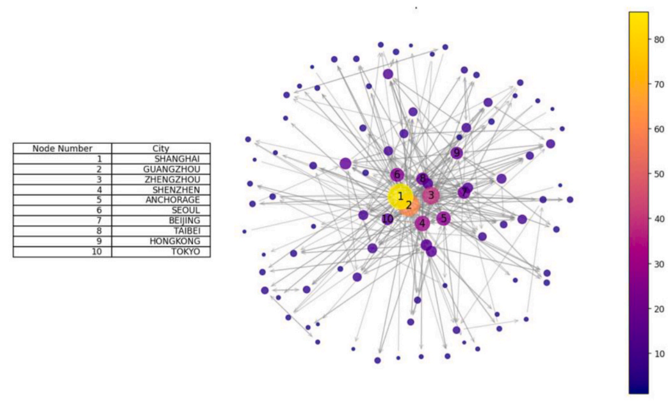
COVID-19 pandemic, to the 2023 summer timetable, following the cessation of zero-COVID-19 measures. Notably, the CISFN has experienced significant growth in terms of network size, with the number of nodes increasing from 95 to 120 and the number of edges expanding from 371 to 655. This development is reflected in the observed increase in the average degree, which has risen from 7.811 to 10.917.

The change in the degree of nodes across different time periods was analyzed using a repeated measures ANOVA. Table A1 in the appendix suggest that the corresponding p-value ($p < 0.001$) indicates that this result is statistically significant. There is a very strong likelihood that the observed differences in degree are not due to chance but are instead due to the policy intervention over time. Figure A in the appendix shows the overall trend of average values across all cities over time. There is a clear upward trend in the earlier periods, particularly from the 2020 Winter to the 2021 Summer, followed by a slight decline or stabilization in the later periods. In August 2020, prior to the October launch of the 2020 Winter Schedule, the National Development and Reform Commission and the CAAC issued a memorandum providing recommendations for the development of China's air cargo transport infrastructure. The memorandum emphasized the need for cargo airlines to expand their fleets and invest in dedicated aircraft for freight transport (Deng et al., 2022).

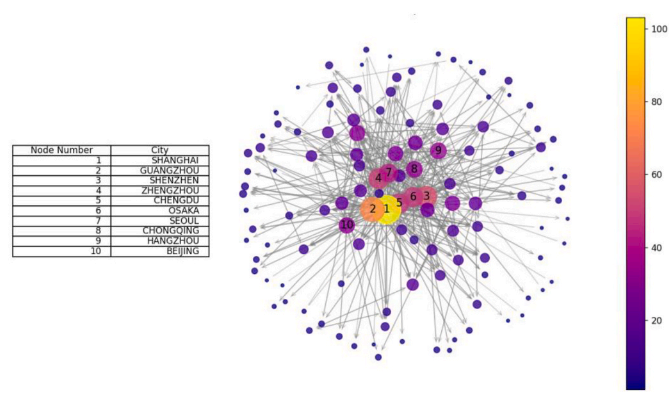
Furthermore, there have been noteworthy changes in other network indicators. The reciprocity, which measures the extent of mutual connections between nodes, has dramatically increased from 0.695 to 0.84. Efficiency refers to the network's enhanced capability to handle and transport air cargo efficiently, which has improved from 0.36 to 0.387. Additionally, the density of connections has displayed a noticeable 10% increase, rising from 0.042 to 0.046. However, it is important to note that there has been a decrease in the cluster coefficient, dropping from 0.253 to 0.144.

The graphical representation in Fig. 2 depicts the connected components of the CISFN, highlighting the network's expansion and showcasing the top ten cities based on the degree of nodes. The nodes are visually represented using a gradient colour scheme that corresponds to their respective degree values. The colour map utilises plasma, ranging from dark blue to bright yellow, signifying lower and higher values, respectively. The node degrees are directly mapped to the colour map range, resulting in nodes with higher degrees appearing closer to the yellow end of the colour spectrum. Additionally, specific nodes within the top 10 ranks of degrees are labelled numerically, beginning with 1 assigned to the node with the highest degree. To facilitate interpretation, a table is provided alongside the graph, offering a mapping of these numerical labels to their corresponding city names.

When analysing the indegree and outdegree of individual cities (Fig. 3), it becomes apparent that the establishment of routes within the CISFN was not concentrated in a limited number of hub cities but rather spread across the entire network. The colour map employed in conjunction with the scatter plot utilises a sequential scheme, transitioning smoothly from a vibrant yellow colour to various shades of orange, culminating in a deep red hue. In the scatter plot itself, the colour assigned to each data point corresponds to a specific year, with the colour intensity denoting the progression of time from 2019, represented by a luminous yellow shade, to 2023, depicted as a vivid red



(a) 2019 winter timetable.



(b) 2023 summer timetable.

Fig. 2. Connected components of the graph.

tone. This visual representation effectively conveys the temporal evolution of the network, facilitating a comprehensive understanding of the route development within the CISFN.

Upon examining the structural properties of the CISFN during the COVID-19 pandemic (Fig. 4), significant developments on a larger scale emerged. Following a relatively mild impact of the pandemic in the first half of 2020, the number of edges doubled, reaching 708. Despite the implementation of COVID-19 restrictions, the number of navigable cities remained consistent, ranging from 130 to 140. The network's maximum size expanded to approximately 140 nodes and 800 edges, indicating substantial growth and expansion.

In Fig. 5, during this period, the reciprocity of the network reached almost 90%, indicating that only 10% of the routes were one-way flights. The efficiency of the network remained stable, with a consistent value of around 0.38, denoting its effectiveness in facilitating the transportation of air cargo. However, it is important to note that the cluster coefficient, which measures the degree of interconnectedness between nodes, reached its lowest point in the 2022 winter period, recorded at 0.074.

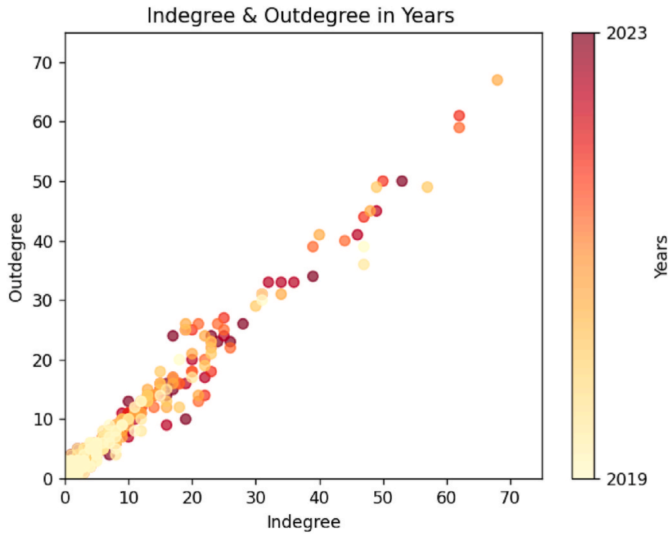


Fig. 3. Indegree and outdegree in years.

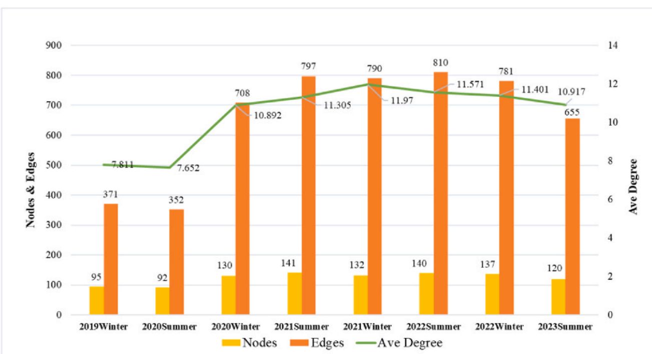


Fig. 4. Topological characteristics cross the pandemic period (1).

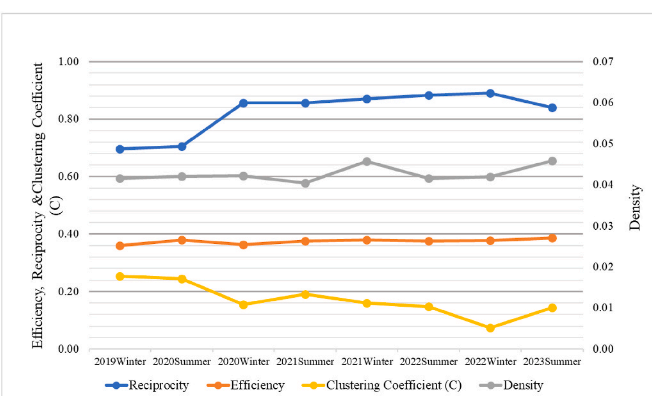


Fig. 5. Topological characteristics cross the pandemic period (2).

These findings highlight several noteworthy aspects. The higher reciprocity during the COVID-19 period suggests that the reduction in international passenger flights led to an increased demand for all cargo flights to compensate for the gap left by passenger flight restrictions. Consequently, this alteration in the network's structure deviates from the typical H&S configuration, necessitating more arcs to connect the same number of cities. Generally speaking, this change may impact overall efficiency. Additionally, the decline in the clustering coefficient does not necessarily indicate a decrease in the network's effectiveness or efficiency. Instead, it could indicate a shift towards a more distributed or decentralised structure, dependent on the network's context and nature. Furthermore, the addition of nodes or edges to the network without forming new clusters can contribute to a decrease in the overall clustering coefficient as these additions dilute the network's overall clustering.

Considering the suggestion by Malighetti et al. (2019) that the most efficient configuration is the single-hub H&S system, which caters to destinations requiring the minimum number of routes and aircraft, it becomes apparent that as the CISFN expands, the focus of development is primarily on enriching the overall structure within the H&S system rather than establishing point-to-point routes among existing local communities. This observation aligns with the drop in the clustering coefficient, suggesting that new hub cities have been incorporated into the network with new routes added to connect peripheral cities. More detailed evidence and analysis of these aspects will be provided in subsequent sections of the network analysis.

4.2. Identifying nodes influence

Numerous approaches have been proposed to identify critical nodes within complex networks, including degree centrality (DC), betweenness centrality (BC), closeness centrality (CC) and eigenvector centrality (EC). Lei and Cheong (2022) provide a comprehensive overview of these measures, emphasising that closeness centrality and betweenness centrality are global indices that require significant computational resources. Eigenvector centrality, however, faces challenges when applied to asymmetrical, extensive and diverse networks. In contrast, degree centrality is a straightforward and fundamental measure that solely considers the number of neighbouring nodes. It is common practice to employ these measures collectively when identifying influential nodes.

Technically speaking, the degree centrality is a measure that captures the extent of interconnectivity among nodes in a network, thus serving as an indicator of a node's significance within the network. Likewise, the closeness centrality quantifies the reciprocal of the average shortest distance between a given node (i) and all other nodes in the network, reflecting the node's proximity and ease of reaching other nodes. Higher values of i indicate enhanced connectivity to the network as a whole (Wang et al., 2011). Conversely, the betweenness centrality is employed to assess the impact of a specific city on the transit traffic between other cities, with higher values indicating nodes that act as bridges (Jia et al., 2014). Moreover, the eigenvector centrality evaluates the importance of a node by taking into account both the quantity and quality of its neighbouring nodes (Lei and Cheong, 2022).

Fig. 6 provides a comprehensive overview of the rankings of major cities during the pandemic period, highlighting their significance within the network in comparison with other navigable nodes. The timetables in the figure are organised chronologically, ranging from the earliest period (2019 winter) on the left to the most recent period (2023 summer) on the right. Each timetable section is divided into four columns representing degree centrality (C_d), betweenness centrality (C_b), closeness centrality (C_c) and eigenvector centrality (C_e). The cities are listed in descending order based on their rankings, with the highest-ranked cities positioned at the top. To further emphasise the importance of certain cities, colour-coded markers are used and explained in the legend. By examining Fig. 6, it is possible to perceive the evolving trends in the influence rankings of these significant cities throughout the observed period.

Shanghai and Guangzhou consistently secure the top two positions throughout the period from 2019 to 2023, with Shanghai consistently maintaining degree centrality approximately 40% higher than that of Guangzhou. However, during the summer and winter of 2020, this gap narrowed to 23% and 8%, respectively. At that time, Guangzhou served as an alternative choice for cargo flights when Shanghai was affected by stringent restriction measures. Throughout the examined period, Shanghai and Guangzhou consistently emerged as the central hubs for

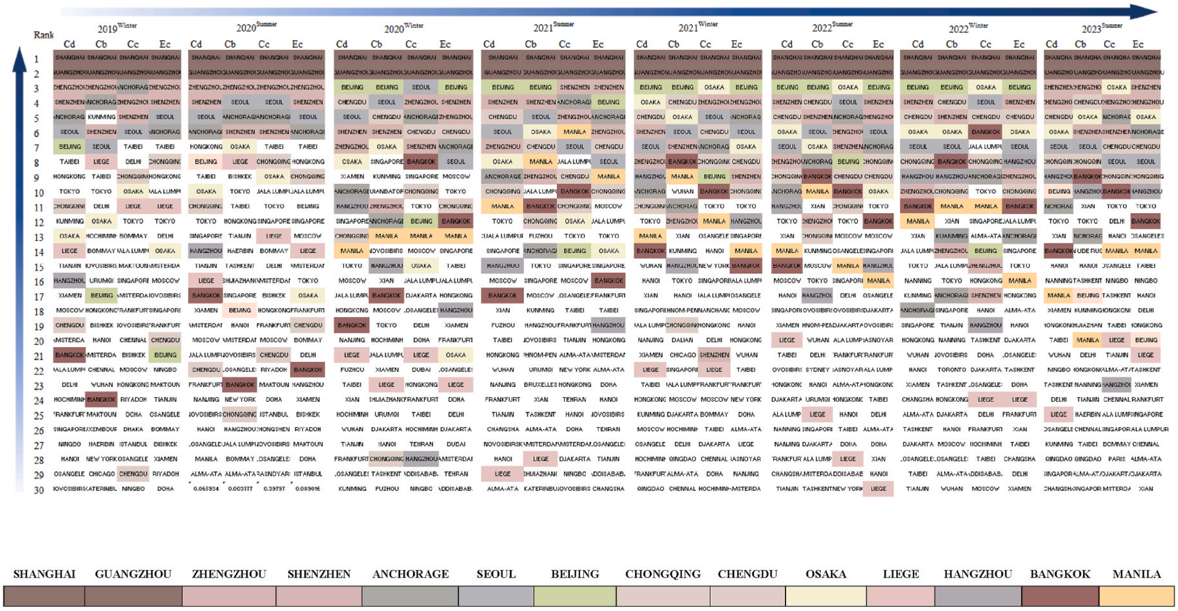


Fig. 6. Temporal evolution of city influence rankings in the pandemic-era network.

China's international cargo flights, occupying dominant positions across all four centrality indices. This warrants further examination. One plausible explanation lies in their status as major Asia-Pacific cargo hubs for FedEx and UPS respectively.

FedEx and UPS are industry giants with extensive experience and resources in air freight operations worldwide. Their presence in East Asia since the 1990s endowed Shanghai and Guangzhou with mature infrastructure and capabilities for cargo handling, storage and ground transportation. Such integrated logistics networks were integral to maintaining regional and global supply chain connectivity during the pandemic. When international passenger flights sharply decreased, FedEx and UPS leveraged their Asia hubs to rapidly deploy dedicated freighter services. By capitalising on existing hub operations and coordinating global fleets, they addressed the urgent need for reliable air cargo capacity. This likely conferred comparative advantages to Shanghai and Guangzhou over other Chinese cities still developing dedicated operations.

Another contributing factor was the fleets of China's major state-owned carriers. As two of China's "Big Three" airlines, China Eastern and China Southern possessed sizable wide-body fleets prioritizing domestic and international routes. This afforded them substantial flexibility to reroute passenger aircraft as temporary freighters. Leveraging home-bases in Shanghai and Guangzhou enhanced efficiency of cabin conversions. It also facilitated cargo scheduling through their established networks. Overall, the multi-pronged effects of international experience, mature infrastructure paired with fleet dynamism reinforced Shanghai and Guangzhou's dominance of CISFN air cargo flows.

During the epidemic, the degree centrality of Beijing exhibited a significant increase, positioning its importance in proximity to that of Guangzhou. The degree centrality of Beijing as an air cargo hub experienced a noticeable decline following the peak of the pandemic. During the early stages of the pandemic in 2020, Beijing rapidly expanded its freighter network to include more international destinations to fill the gap from passenger flight suspension. However, as passenger flights gradually resumed from late 2021, bellyhold capacity on returning passenger aircraft began substituting some dedicated freighter routes. Additionally, periodic domestic outbreaks in China disrupted inland distribution networks. This compromised the sustainability of long-haul freighter routes initiated during the strictest pandemic control measures. With passenger capacity and domestic disruptions impacting dedicated freighters, some capacity feeding destinations with restored passenger service was substituted or rerouted to other hubs like Shanghai that were less affected. Consequently, Beijing's degree centrality declined from its elevated level during the pandemic's initial waves. In 2019 Beijing maintained connections with only eight cities in the network, with Frankfurt being the farthest destination. However, in 2020 winter the number of connected cities skyrocketed to 29, as Beijing expanded its network to encompass Southeast Asian and Middle Eastern destinations, reaching as far as Helsinki in Northern Europe and spanning across the Pacific Ocean to Dallas in the US. Although most cargo flights to these cities ceased by 2023, Beijing still maintains connectivity with 14 nodes, including the significant international cities of Tokyo, London, Paris, New York and San Francisco. Throughout the pandemic period, Beijing ranked third in terms of degree centrality, betweenness centrality and eigenvector centrality, showcasing its strength in fostering connectivity and serving as a bridge airport for inter-community transportation.

In the analysis of network evolution, Jia et al. (2014) introduce the concept of 'stable cities' to characterise certain cities' role within the network. According to their definition, stable cities are those that have consistently maintained interconnections throughout the entire period under investigation, forming the fundamental framework of the network. These cities exhibit a persistent presence and demonstrate structural regularity over time, reflecting their enduring significance and stability within the network. Apart from Shanghai and Guangzhou, cities such as Shenzhen, Zhengzhou, Seoul and Anchorage also serve as prominent stable cities within the context of the CISFN.

Shenzhen and Zhengzhou are recognised as second tier hub nodes within the CISFN. Prior to the pandemic, Hong Kong served as a key air cargo gateway between China and global markets. However, strict pandemic border controls at the Hong Kong-China border likely prompted some cargo flows to shift to Shenzhen instead to avoid challenges involving cross-border operations. For Henan, as early as 2014, Henan Aviation Investment acquired a 35% stake in Luxembourg Cargo. This stake position helped develop air cargo services between China and Europe over subsequent years by leveraging Luxair's extensive cargo flight network and experience. Although these two cities experienced some fluctuations in all four centrality indices during the COVID-19 period, by 2023 they have regained their third and fourth positions in most influential indices' rankings in the network. Anchorage, however, witnessed a modest increase in its degree centrality, rising from 25 to 29 between 2019 and 2023. But while other cities observed a significant growth in direct cargo flights, Anchorage's degree centrality and betweenness centrality rankings declined, causing it to drop out of the top 10 positions in these two indices by 2023. Nonetheless, Anchorage maintained favourable values in closeness centrality and eigenvector centrality, signifying its continued accessibility and connections with significant neighbouring cities. Within the CISFN, Seoul, Tokyo and the rising city of Osaka stand as highly important cities in China's neighbouring countries in East Asia. This increased prominence can likely be attributed to the launch of the 5th freedom cargo operations between Osaka, Beijing, and Anchorage in 2021. This liberalization directly improved connectivity for Osaka by facilitating new freight flows via the Beijing and Anchorage hubs. It possibly also contributed to Anchorage partially maintaining its rankings, despite declines in other indices. More broadly, China's increasing openness to such liberalised air freedoms has strengthened the CISFN's resilience by fostering alternatives and diversifying routes.

In addition to Osaka, two other emerging cities in the CISFN are Bangkok and Chengdu. Over the course of five years, the number of connections between Bangkok and Chinese cities increased significantly, rising from 10 to 34. Meanwhile, the degree centrality of Chengdu experienced a remarkable surge, escalating from 11 to 65. In 2019 Chengdu had connections with Seoul, Anchorage and Osaka. However, by 2023 its flight network had expanded globally to include destinations such as Jakarta, Delhi, Mumbai, Maldives, Iqbal, Astana, Moscow, Helsinki, Paris, Los Angeles, Vancouver and Amsterdam. Notably, Hangzhou and Chongqing also demonstrated noticeable development in their influential indices.

Throughout the pandemic period these cities consistently maintained top positions in the network rankings, underscoring their crucial role as central hubs for China's international cargo flights. Their presence contributed to network stability and structural regularity. Moreover, the network exhibited substantial growth during the epidemic, establishing connections with influential global cities and expanding its reach. The emergence of cities like Bangkok and Chengdu as prominent nodes further highlights their growing significance and global impact.

4.3. Robustness of the network

Bombelli et al. (2020) conducted a study where they simulated attacks that involved the removal of airports from the network. The simulation accounted for complete shutdowns or severe disruptions of airports, which could arise from factors like natural hazards or national strikes. To assess the impact of such disruptions, if the airports are being shut down due to the restriction measures, we adopted a similar approach to that which they employed.

In our analysis, we focused on identifying the airport with the highest value of the index under investigation and iteratively removed it from the network. The size of the giant component in the updated network served as a robustness measure. To ensure clarity in our analyses, we plotted the normalized size of the giant component against the ratio of removed airports, denoted as S(q). This ratio was obtained by dividing the size of the actual giant component by $|V|$, representing the initial size of the giant component calculated before any nodes were removed.

Our model considered different types of attacks based on various indices, including degree (k), unweighted betweenness centrality (Cb), closeness centrality (Cc), eigenvector centrality (Ce), clustering coefficient (Ci) and weighted[4] betweenness centrality (C_b^w). These indices played a crucial role in evaluating the network's robustness and understanding the effects of different types of attacks on its structure.

Bombelli et al. (2020) emphasise that analysing the network topology alone cannot provide a comprehensive understanding of the relative impact of disruptions on highly ranked airports based on different indices. Therefore, the objective of applying this model is to investigate whether airports identified as crucial according to different indices play similar or distinct roles in the overall connectivity of the network. By employing the model, we can assess the impact of various attack strategies on both the 2019 winter and 2023 summer timetables. This analysis allows us not only to determine the significance of these indices but also to examine how the network's robustness evolves during the COVID-19 pandemic.[5]

Figs. 7 and 8 depict the relationship between the size of the giant component S(q) and the ratio q of removed nodes for the six different removal strategies. The horizontal axis represents the proportion of top nodes removed, while the vertical axis represents the maximum connected component ratio in the network after node removal. A lower percentage of removed nodes indicates more severe damage to the network structure and a higher accuracy in identifying the significant nodes. Additionally, Fig. 6 presents the ranking of the top 30 airports based on the indices (C_d,[6] C_b, C_c and C_e) which were successively removed first in the model.

The analysis of the clustering coefficient reveals a relatively mild disruptive effect, as it follows a linear relationship with a slope of -1 until approximately 40% of nodes are removed. This relationship can be approximated by the expression $S(q) = -q + 1$, which suggests that the removal ratio corresponds to the loss suffered by the giant component due to the removal of a node. Additional insights provided in Fig. 9 show a negative correlation between the clustering coefficient and the degree indices. Consequently, nodes with higher clustering coefficient values are more likely to represent peripheral cities, highlighting the limited effectiveness of this attack strategy.[6]

In contrast, the remaining five strategies exhibit more significant effects. Regardless of the specific index-based strategy employed, the removal of the top 10% identified nodes results in approximately 50% of the nodes remaining in the giant component. Notably, strategies targeting the degree indices demonstrate the most pronounced disruptive effect, characterised by a sharp and steep decline. This indicates that the removal of hub nodes significantly impacts on the core structure of the network, leading to the fragmentation of the network into smaller local or inter-communities with connected nodes. Steeper declines in these strategies signify greater fragility among inter-communities and the transformation of a single peripheral city into isolated entities. Moreover, the presence of flat segments in the decline indicates the existence of nodes with similar index values, which act as hubs within several small communities that have an equal number of connected nodes. This pattern of alternation between flat and steep segments contributes to a distinct stepped downward trend observed in the network's disruption.[7]

The study by Bombelli et al. (2020) highlights that attacks targeting the degree centrality (k) primarily impact the connectivity within different H&S communities by removing the hubs. However, attacks focused on betweenness centrality (Cb) tend to destroy bridges between communities, resulting in a significant impact on inter-community connectivity. This suggests that attacks based on degree centrality disrupt the connections within communities, while attacks based on betweenness centrality affect the connectivity between communities. Understanding these distinct effects is crucial for comprehending the overall resilience and robustness of the network under different attack scenarios.

The simulation results consistently demonstrate that attacks targeting the degree centrality result in a more significant decrease in the size of the giant component. This is due to the removal of hub airports, which

[5] Edges are weighted based on the number of weekly cargo flights before betweenness centrality for C_b^w.

[6] C_d is the normalized form of the degree centrality.

[7] The high infection rate and frequent outbreaks of the Omicron variant pose significant challenges in epidemic prevention and control in China. Although symptoms are milder, its high infectivity can lead to increased mortality, especially among the unvaccinated elderly. Maintaining strict mobility policies and educating the public are crucial in preventing virus spread (Yuan et al., 2022).

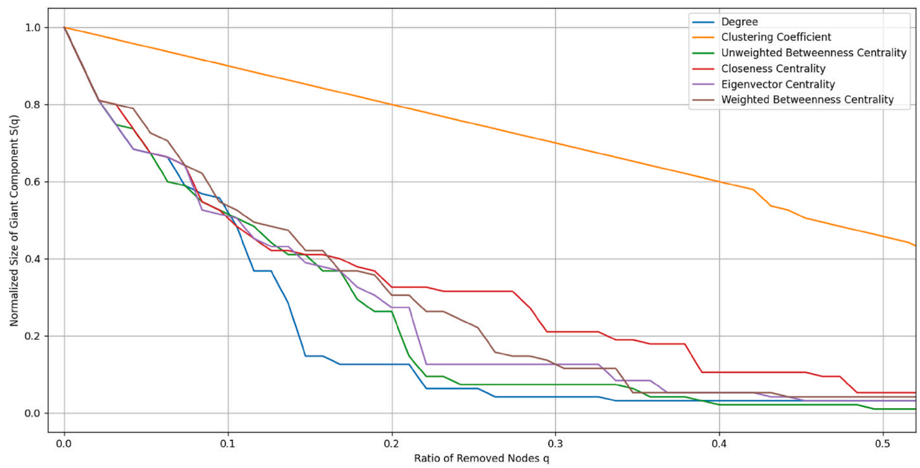


Fig. 7. The 2019 winter timetable under simulation of different attack strategies.

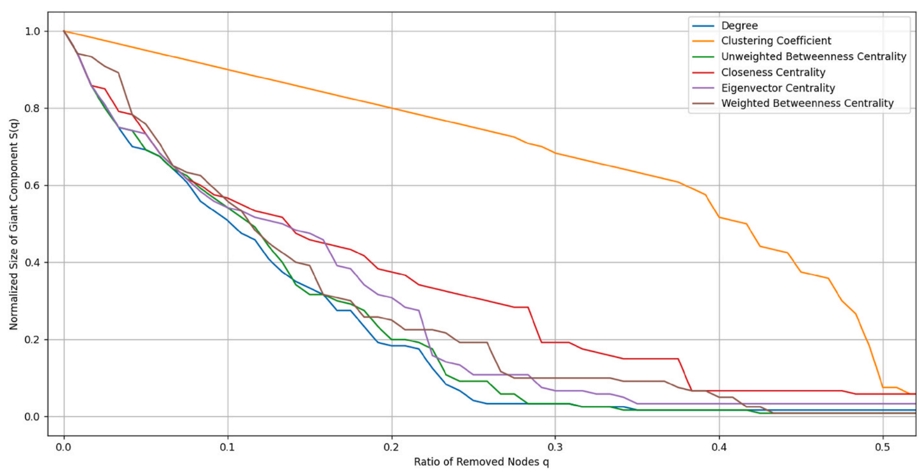


Fig. 8. The 2023 summer timetable under simulation of different attack strategies.

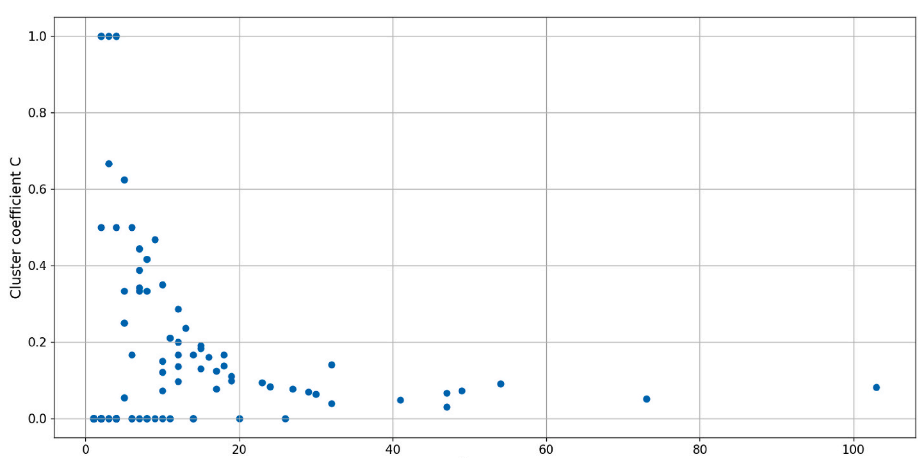


Fig. 9. A comparison between the degree and the local clustering coefficient for the CISFN in 2023.

act as the backbone of the network and play a crucial role in connecting local and global nodes. The fragmentation of the network into smaller communities leads to a pronounced loss in connectivity. In contrast, attacks focused on weighted or unweighted betweenness centrality do not have as strong an impact on connectivity. It reflects that the network density is not relatively high and point-to-point routes are insufficient, thus the disruption of airports that frequently appear in the shortest paths is not powerful enough to isolate the network into communities.

In the CISFN, the network follows a spring radial pattern layout (Fig. 2). The network's structure is characterised by the prominence of cities within China or in close neighbouring countries, particularly those in first and second-tier hubs. These cities serve as important nodes in the network. Nodes representing inter-community, cross-regional or cross-country connections may not exhibit sufficient density.

The model's findings highlight the network's vulnerability to targeted attacks and underscore the potential impact of disruptions at major air cargo hubs on the overall network. To enhance the network's robustness, several strategies can be implemented. First, establishing multi-hubs at different levels of tiered hubs can improve the network's resilience. Additionally, increasing the density of connections between hubs, inter-community links and direct flights to higher-level hubs can enhance the network's overall robustness and flexibility. These measures aim to strengthen the network's connectivity and reduce its vulnerability to disruptions.

In Fig. 10 we present a comparison of the network's resilience to node removal attacks based on degree strategies from 2019 to 2023. The analysis reveals that the network in 2019 and 2020, characterised by a lower density of 0.042 (Table 2), exhibits relatively lower robustness. However, in the removal ratio range of 0.15–0.19, the network in 2020 demonstrates it is more resilient. In contrast, the network in 2023 and 2021, with a higher density of 0.046, shows greater resilience. Notably, the network in 2022 winter appears to be the most vulnerable, particularly during the winter timetable, when the Omicron variant[7] significantly affect China. During this period, there is a dramatic reduction of around 25% in the number of edges at main hub nodes like Shanghai and Beijing compared with the 2022 summer timetable. Indeed, as density decreases, with fewer point-to-point connections, the network tends to adhere to the typical multi-hub configuration, resulting in less flexibility and robustness.

According to Bombelli (2020), based on the data from a similar period (November 2019 to June 2020), FedEx and UPS' networks are highly dependent on their primary hubs. When some hubs are removed based on degree and betweenness centrality (weighted or unweighted), the connectivity of both networks deteriorates rapidly due to the critical role these nodes play in linking different regions within their hub-and-spoke structures. Notably, both networks exhibit a steeper decline in robustness metrics before the removal of the top 10% of nodes compared to the CISFN network. The removal of the top 10% of identified nodes results in approximately 30% of the nodes remaining in the giant component of the integrators' networks, compared to approximately 50% for the CISFN. This comparison highlights that the CISFN network relies less on critical hubs and demonstrates greater resilience in such scenarios.

4.4. Discussion of structural change

The expansion of the CISFN in terms of nodes and edges has been significant, as discussed in Section 4. In the 2023 timetable 38 new entry cities have been added to the network since 2019. These additions are expected to bring about changes in the network structure in two ways: by forming new clusters within the network or by densifying the graph under the existing H&S system. To examine the impact of these new cities and their routes on the evolution of the network's structural changes, we adopt the approach proposed by Jia et al. (2014). This approach involves investigating the structural changes that would occur if one city were to be removed from the network.

To assess the evolution of structural changes resulting from the removal of a city, we utilise the network betweenness B(N), which represents the average value of betweenness centrality (C_b) across all cities and reflects the network's transit capability. The structural change caused by the removal of a city can then be quantified as $\tau(i) = (B(N) - B_i(N))/B(N)$, where B(N) is the network betweenness value and $B_i(N)$ is the betweenness value of the network without city i. The $\tau(i)$ value is employed to evaluate the impact of removing a city, and it can be either positive or negative. Cities with the highest τ values are considered the most influential in terms of structural changes within the network during the year. The magnitude of the gap between the highest and lowest τ values indicates the intensity of the structural changes observed.

The distribution of τ values, representing the impact of removing a city on the network's structural changes, can be approximated as a uniform distribution regardless of the year. To characterise this uniform distribution, we analyse the minimum, maximum and average values of τ and plot them over time in Fig. 11. Prior to the COVID-19 pandemic in 2019, τ exhibits the largest range, with a maximum value of 15.54% and a minimum value of -2.08%. Following the outbreak, the network responded swiftly, resulting in significant changes to the 2020 winter timetable. From 2020 to 2022, during the rest of the pandemic period,

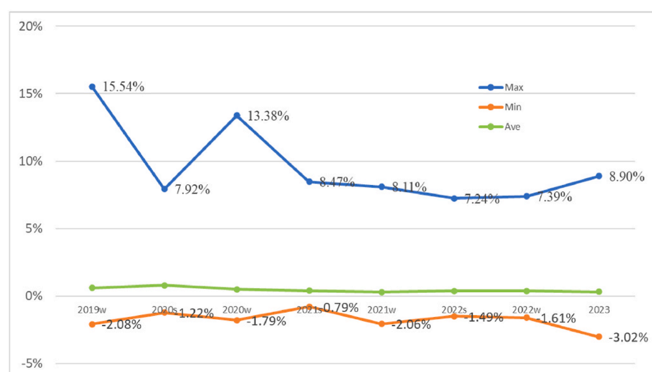


Fig. 11. Structural change value (τ).

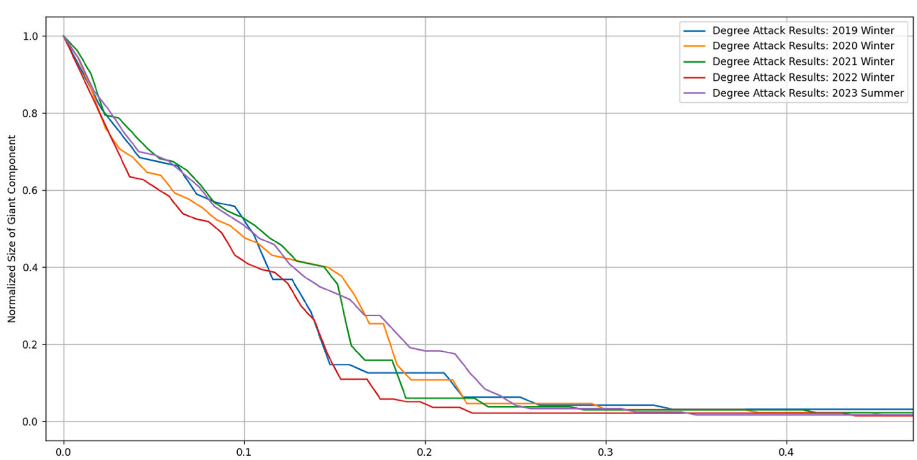


Fig. 10. Simulating attacks results by year based on the degree removal strategy.

the range of τ values remains relatively small, with a maximum value around 8% and a minimum value of -1%. These findings provide insight into the extent of structural changes resulting from the introduction of new cities and routes during the pandemic period, both before and after the outbreak.

In the recent decade, Chinese aviation policy, influenced by the 'One Belt One Road Initiative' has aimed to enhance transportation connectivity between China and other regions. This includes opening up airspace and establishing more direct air routes, leading to increased air freight capacity and potential impact on air cargo strategies (Malighetti et al., 2019). In 2019 it was observed that specific new cities emerged as highly influential within the network, indicating significant pre-pandemic growth. Significantly, Kunming exhibited a high τ value and established itself as a sub-hub for countries in the South Asian region. This highlights the network's efforts to expand and strengthen connectivity with South Asian countries during that period.

The outbreak of the pandemic in 2019 prompted significant changes in the network structure to accommodate the surge in demand. Notably, Beijing and Guangzhou, although not new cities, experienced a substantial increase of nearly 50% in routes within the second half of the year, resulting in high τ values in 2020. However, after the 2020 winter, the development of new cities and routes played a less crucial role, as the focus shifted towards adding or removing routes connected to the main hubs. This stability can be attributed to the densification process described by Jia et al. (2014). The network entered a phase of densification during the remaining period under restrictive measures.

After the release of pandemic measures, the structural changes in the network became more active, leading to an increased gap between the highest and lowest τ values. Hubs such as Zhengzhou and Chengdu, with high τ values, have gained influence in the network, indicating further evolution in the post-pandemic period. During the pandemic, network development focused on global coverage, while in the post-epidemic phase, there is an expected shift towards aligning network development with trade growth and prioritizing the construction of regional networks.

Additionally, the implementation of the Regional Comprehensive Economic Partnership (RCEP) Agreement between Australia, China, Japan, New Zealand and ASEAN Member States, starting from January 1, 2022, highlights the commitment of these nations to foster a fair and inclusive multilateral trading system. The RCEP Agreement is expected to play a vital role in stimulating economic recovery efforts following the pandemic. The influence of cities such as Bangkok, Kuala Lumpur, Osaka and Manila within this region has been observed to be on the rise in Section 4.

5. Conclusion

Concluding insights

This paper applies the complex network theory approach to analyse the international cargo network with all-cargo flights plans from 2019 to 2023. First, the paper evaluated the CISFN's topological properties and explored the changes during the pandemic. From 2019 to 2023 the CISFN witnessed significant growth, with nodes increasing from 95 to 120 and edges from 371 to 655. Reciprocity grew from 0.695 to 0.84, efficiency from 0.36 to 0.387 and connection density rose by 10%. However, the cluster coefficient decreased from 0.253 to 0.144. These observations highlight the notable growth and resilience of the CISFN throughout the pandemic, maintaining stable efficiency and a balanced flow of air cargo.

The average values across all cities show a clear upward trend, particularly from Winter (2020) to Summer 2021. In August 2020, before the Winter Schedule launch, the National Development and Reform Commission and CAAC issued a memorandum urging cargo airline expansion and investment in dedicated freight aircraft (Deng et al., 2022). Government policies have always been crucial in shaping China's air cargo sector (Jiang et al., 2003; Li, 2020). Similarly, a 2014 CAAC memorandum on low-cost carriers led some full-service airlines to adopt the LCC model (Wu et al., 2020). It's believed the government took effective measures not only to boost dedicated cargo development but also to enhance resilience during crises, meeting e-commerce demands and responding promptly to public health emergencies.

The analysis highlight the key roles of cities like Shanghai and Guangzhou, consistently top-ranked as central hubs for China's international cargo flights. Beijing exhibited remarkable growth during the pandemic, expanding its network and connections with influential global cities. Stable cities such as Shenzhen, Zhengzhou, Seoul and Anchorage played pivotal roles, ensuring network stability. Moreover, the rise of Bangkok and Chengdu as prominent nodes underscores their growing influence. Overall, the analysis reveals the dynamic nature of the network and the significance of specific cities in driving connectivity and influence.

Furthermore, the robustness analysis results revealed that strategies targeting degree indices had the most pronounced disruptive effect, indicating that the removal of hub nodes significantly impacts the network structure. The study found the network to be particularly vulnerable to targeted attacks at major air cargo hubs. To enhance robustness, the study suggests establishing multi-hubs at different levels and increasing the density of connections between hubs and direct flights to higher-level hubs. A comparison of the network's resilience from 2019 to 2023 showed that 2023 and 2021 exhibited greater resilience, characterized by a higher density of connections and more robust network structures. In contrast, the network was most vulnerable in the winter of 2022, with a significant reduction in the number of edges at key hubs including Shanghai and Beijing, largely due to the "dynamic zero" policy implemented to contain the Omicron variant (Yuan et al., 2022).

Finally, the CISFN saw a significant expansion with the addition of 38 new cities in 2023, causing changes in the network structure. Post-pandemic, the structural changes became more active with hubs such as Zhengzhou and Chengdu gaining influence. The network focus shifted from global coverage during the pandemic to aligning with trade growth and regional network construction post-pandemic. The implementation of the RCEP Agreement is anticipated to stimulate economic recovery post-COVID-19. Cities like Bangkok, Osaka and Manila within this region have seen increasing influence.

To sum up, during the pandemic period the network adapted quickly to the increasing cargo volume. Despite restrictions, the network continued to expand. Meanwhile, a decrease in the clustering coefficient does not necessarily indicate reduced network effectiveness but could signify a shift towards a more distributed structure. As the CISFN expands, the development focus is enriching the H&S system, rather than establishing point-to-point routes among existing communities. The main focus on developing the H&S system is the most efficient way to fulfil the blowout in dedicated cargo volume. The densification that happened in the H&S system provides more alternatives for hub cities and, consequently, the robustness has been improved since the outbreak of the pandemic.

Limitation and future direction

Although the paper provides a holistic understanding of the CISFN's resilience and adaptability during and after the COVID-19 pandemic, offering insights into both the immediate impact of the pandemic and the strategic changes that contributed to the network's robustness, several research limitations are noteworthy and should be considered in future studies.

First, the paper presented an attack scenario based on weighted complex network metrics, where the edges were weighted by the number of weekly cargo flights before calculating betweenness centrality. Future studies should propose complementary methods to evaluate robustness, for instance, measures could be developed to evaluate the impact of local capacity reductions on the overall network, integrating both topological and operational aspects using a flow maximization approach (Pien et al., 2015). Additionally, targeted disruptions could be simulated under more dynamic scenarios, rather than static ones, in which metrics are typically computed once at the start. For a more comprehensive analysis, scenarios like interactive attacks, where the network metric is recalculated after each node removal, should be considered (Wandelt et al., 2015). Furthermore, this study focuses on regular all-cargo flights and does not include passenger or charter flights, which may moderate the accuracy of the network structure. Finally, the evolution of the CISFN during and after the COVID pandemic was also influenced and shaped by policies from other countries, which was not considered in this research. For example, Kim and Sohn (2022) highlight South Korea's proactive policy response during the COVID period, which supported the expansion of freight operations by Korean Air including cargo services into the China market. Korean Air's cargo revenue amounted to 80% of its total revenue during the pandemic while before 2020, this figure was about 40–50%. Similar to Korean Air, several other Asian airlines such as China Airlines also reported profits in the pandemic period thanks to the strong growth in cargo revue. There is no doubt that the neighbouring countries' air cargo policies and cargo carriers' network have also had an impact on the growth of the CISFN. In addition, the expansion of the CISFN was also constrained by regulatory barriers and airlines' existing fleet. All these factors should be considered in future research.

CRediT authorship contribution statement

Yu Deng: Writing – original draft, Methodology, Formal analysis. **Yahua Zhang:** Writing – review & editing, Supervision, Conceptualization. **Kun Wang:** Writing – review & editing. **Yulu He:** Writing – review & editing.

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Appendix A

Table A1
Analysis of the repeated-measurements ANOVA

Source	df	Mean Square	F Value	P Value
Period	7	1155.756	29.962	<0.0001

Table A2
Descriptive statistics

	No of Nodes	Minimum	Maximum	Mean	Std. Deviation
2019 winter	95	1	86	7.811	11.878
2020 Summer	92	1	83	7.652	11.858
2020 Winter	130	1	106	10.89	15.633
2021 Summer	139	1	135	11.45	17.686
2021 Winter	132	1	121	11.97	16.824
2022 Summer	140	1	123	11.57	17.705
2022 Winter	137	1	94	11.4	16.121
2023 Summer	120	1	103	10.92	14.925

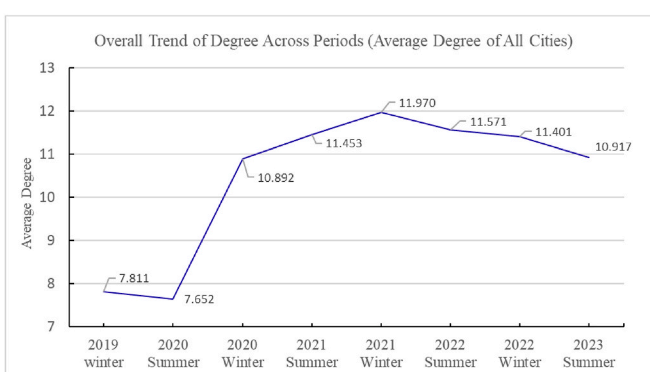

Figure A: Overall trend of degree across periods (average degree of all cities).

Data availability

Data will be made available on request.

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