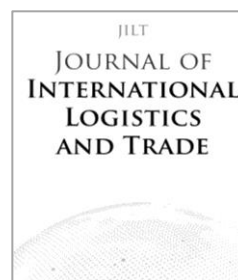

저자 (Authors)	Oh Kyoung Kwon, Soobi Lee, Hye Min Chung, Prem Chhetri, Ok Soon Han
출처 (Source)	Journal of International Logistics and Trade 17(4), 2019.12, 89–102 (14 pages)
발행처 (Publisher)	인하대학교 정석물류통상연구원 Jungseok Research Institute of International Logistics and Trade
URL	http://www.dbpia.co.kr/journal/articleDetail?nodeId=NODE09324602
APA Style	Oh Kyoung Kwon, Soobi Lee, Hye Min Chung, Prem Chhetri, Ok Soon Han (2019). Network Robustness of Major Asian Airlines and the Impact of Airports' Brokerage Roles. Journal of International Logistics and Trade, 17(4), 89–102.
이용정보 (Accessed)	이화여자대학교 203.255.***.68 2020/05/18 04:09 (KST)

저작권 안내

DBpia에서 제공되는 모든 저작물의 저작권은 원저작자에게 있으며, 누리미디어는 각 저작물의 내용을 보증하거나 책임을 지지 않습니다. 그리고 DBpia에서 제공되는 저작물은 DBpia와 구독 계약을 체결한 기관소속 이용자 혹은 해당 저작물의 개별 구매자가 비영리적으로만 이용할 수 있습니다. 그러므로 이에 위반하여 DBpia에서 제공되는 저작물을 복제, 전송 등의 방법으로 무단 이용하는 경우 관련 법령에 따라 민, 형사상의 책임을 질 수 있습니다.

Copyright Information

Copyright of all literary works provided by DBpia belongs to the copyright holder(s) and Nurimedia does not guarantee contents of the literary work or assume responsibility for the same. In addition, the literary works provided by DBpia may only be used by the users affiliated to the institutions which executed a subscription agreement with DBpia or the individual purchasers of the literary work(s) for non-commercial purposes. Therefore, any person who illegally uses the literary works provided by DBpia by means of reproduction or transmission shall assume civil and criminal responsibility according to applicable laws and regulations.



Journal of International Logistics and Trade

Network Robustness of Major Asian Airlines and the Impact of Airports' Brokerage Roles

Oh Kyoung Kwon^{a*}, Soobi Lee^a, Hye Min Chung^a, Prem Chhetri^b, Ok Soon Han^c

^a Graduate School of Logistics, Inha University, Incheon, South Korea

^b Business IT and Logistics, RMIT University, Melbourne, Australia

^c Incheon International Airport Corporation, Incheon, South Korea

ARTICLE INFO

Article history:

Received 30 September 2019

Revised 02 December 2019

Accepted 16 December 2019

Keywords:

Network robustness

Air transportation

Hub airport

Brokerage role

Asian airlines

Social network analysis

ABSTRACT

This study aims to evaluate the network robustness of major Asian airlines and to explore which airport types have the greatest impact on robustness. We also analyze airports' specific brokerage roles and their impacts on the robustness of the entire air route network. We select 10 major Asian full-service airlines that operate the main passenger terminals at the top-ranked hub airports in Asia. Data is collected from the Official Airline Guide passenger route dataset for 2017. The results of the network robustness analysis show that Air China and China Eastern Airlines have relatively high network robustness. In contrast, airlines with broader international coverage, such as Japan Airlines, Korean Air, and Singapore Airlines have higher network vulnerability. The measure of betweenness centrality has a greater impact on the robustness of air route networks than other centrality measures have. Furthermore, the brokerage role analysis shows that Chinese airports are more influential within China and Asia but are less influential globally when compared to other major hub airports in Asia. Incheon International Airport, Singapore Changi Airport, Hong Kong International Airport, and Narita International Airport play strong "liaison" roles. Among the brokerage roles, the liaison role has a greater impact on the robustness of air route networks.

© 2019 Jungseok Research Institute of International Logistics and Trade. All rights reserved.

1. Introduction

The Asia-Pacific region is one of the fastest growing aviation markets in the world. Airlines based in this region reported the fastest growth in international revenue passenger kilometers for the first time since 1994, as the growth rate increased from 8.8 percent in 2016 to 9.4 percent in 2017 (The International Air Transport Association, 2017). Furthermore, the Asia-Pacific aviation market has high growth potential driven by rapid economic growth, an increase in consumptive capacity, and growth in international travelers. Airlines in the region are making ongoing efforts to improve their operating capacity and service quality to increase their market share and revenue. In Asia, air transportation is playing an important role in the mobility of international passengers and valued goods. The development of a competitive airline network is highly important for improving the efficient flows of people and goods and achieving the sustainable development of the region.

The recent decades have seen the emergence of transport hubs, a centripetal form, as a common network structure for many types of transport services, notably for air transportation (Rodrigue et al., 2017). Unlike the point-to-point system,

* Corresponding author: Graduate School of Logistics, Inha University, Incheon, South Korea;
Email: scm@inha.ac.kr

in which each node has direct routes to other nodes, the hub-and-spoke system is organized as a large number of spokes connected via a small number of hubs. The hub-and-spoke concept has largely been adopted by global air carriers to design and operate their service networks to improve service connectivity and operational efficiency (Zhang, 1996; Dennis, 1994; Rodrigue et al., 2017). In a hub-and-spoke network, flight connectivity and passenger traffic are highly concentrated at major hub airports. In 2017, the world's 20 busiest airports represented 17% of global passenger traffic, with almost 1.5 billion passengers passing through their terminals. The air cargo handled by these airports reached 43% of global cargo volume (International Airports Council, 2018). Although hub-and-spoke networks often result in improved network efficiency, they have drawbacks linked to their vulnerability to disruptions and delays at hubs owing to the lack of direct connections (Rodrigue et al., 2017). Network robustness is a very important concern in many real-world network operations. In airline networks, failures at important airports (e.g., shutdowns due to extreme weather, large-scale accidents, or targeted attacks) can lead to major disruptions in service and huge economic losses.

An air transportation network can be modeled as a complex network in which nodes represent airports and two nodes are connected by a link if direct flight service is provided between them. Some previous studies using complex network approach explored the air transportation network on a country level such as China (Wang et al., 2011), India (Bagler, 2008), and Australia (Hossain et al., 2013). At a regional level, Malighetti et al. (2009) studied the positive relationship between the efficiency and centrality of European airports. Song and Yeo (2017) analyzed the aviation network of 1,060 airports in 173 countries and compared the individual networks of China and the US. Jiang et al. (2017), Lin and Ban (2014), and Sun et al. (2015) analyzed the temporal changes in the topological characteristics of air transportation network. Studies on air transportation networks that apply complex network theory largely focus on evaluating network performance in terms of connectivity and centrality. However, analyzing the robustness of air transportation networks has attracted the attention of researchers in recent years (Hossain et al., 2013; Lordan et al., 2014, 2015, 2016; Sun et al., 2017).

Given the above research gap and the growing importance of the aviation industry in Asia, this study mainly aims to evaluate the network robustness of major Asian airlines and to explore which airport types have the greatest impact on robustness. First, we examine whether Asian airlines' networks are characterized as hub-and-spoke networks with the scale-free property. Second, we perform a robustness analysis on the deterioration of the connectivity of airline networks as important nodes become more isolated. Third, we categorize the types of airports' intermediary roles and investigate their relationships with network robustness. We select 10 major Asian full service airlines that operate the main passenger terminals at the top-ranked hub airports in Asia for the analysis. Data is collected from the Official Airline Guide passenger route dataset for 2017.

1.1 Robustness of air transportation networks

Robustness is an important aspect of a network because it improves networks' ability to resist failures or attacks (Liu et al., 2017). Robustness is defined as the ability of a network to maintain its total throughput under no or link removal (Manzano et al., 2014). Network robustness is a critical issue especially when a network has the scale-free property. The concept of scale-free networks was first introduced by Barabási and Albert (1999). A scale-free network can be defined as a network that contains hub nodes with a very high number of links and whose distribution of node linkages follows a power law (Barabási and Bonabeau, 2003). The most notable feature of a scale-free network is the existence of "hub" nodes with degrees that greatly exceed the average. This property strongly correlates with the network's vulnerability to failures, especially targeted attacks on hub nodes.

The current air transportation network has evolved as a hub-and-spoke network in which flight connections are highly concentrated on a small number of hub airports. Several studies adopt the complex network theory and show that the typology of air transportation networks has the scale-free property (Li and Cai, 2004; Guimerà et al., 2005; Wilkinson et al., 2012; Hossain and Alam, 2017; Sun et al., 2017). Beyond the network typology analyses, some studies analyze the economic implications of hub airports on airline networks (Borenstein, 1989; Zhang, 1996). One might think that robustness analysis is less important for the airline network than other networks with a more static structure such as electricity, road or rail network (Sun et al., 2017). Since establishing an airline route network is a long process that requires considerable efforts and investment, it is important to plan and build a robust network that can cope with potential failures where possible.

If a hub airport has failures or closures due to extreme weather, natural disasters, or targeted attacks, a major disruption in services or even a network collapse may result. Thus, securing robustness is a very important issue for the sustainable development of air transportation networks. However, few studies explore the robustness of air transportation networks. Hossain et al. (2013) analyze the resilience of the Australian domestic airport network using air traffic data for all domestic flights in Australia in 2011. The study considers different failure scenarios and shows that Australia's airport network is more sensitive to node failure under targeted failures (e.g., isolated airport shutdowns) than under random failures (e.g., airway unavailability due to bad weather). Lordan et al. (2014) analyze the robustness of the global air transport network to identify critical airports whose isolation would cause severe drops in network connectivity. They compare the impacts of several isolation criteria on network connectivity using a simulation. Lordan et al., (2015) analyze the robustness of the route networks of three major airline alliances (i.e., Star Alliance, Sky Team, and One World). They find that the Star

Alliance has the most robust network among three major alliances, followed by Sky Team and One World. A more recent study by Lordan et al. (2016) extends the analysis to analyze the topology and robustness of airlines' route networks for low cost carriers (LCCs) and full service carriers (FSCs). They find that FSC networks are more vulnerable than LCC networks are. Sun et al. (2017) investigate the resilience of global air transportation from a complex network perspective with a focus on attacking strategies in the airport network. They analyze the robustness of the worldwide airport network to random and targeted node failures under different attacking scenarios.

In air transportation studies, network robustness is commonly measured as the change in the size of the giant component when a fraction of nodes is isolated in the network, where the giant component is the largest connected sub-graph within the network (Wilkinson et al., 2012; Hossain et al., 2013; Lordan et al., 2014, 2015, 2016; Sun et al., 2017). The average shortest path distance between nodes (Wang et al., 2011; Lordan et al., 2014) and the efficiency, as the average of the reciprocals of the shortest path distances, are also often used to measure network robustness (Hossain et al., 2013; Lordan et al., 2014, 2015). Latora and Marchiori (2001) propose the efficiency metric to resolve the problem of calculating the average shortest path distance in a disconnected graph in which some nodes are unreachable from other nodes in the network.

1.2 Brokerage roles of hub airports

As reviewed in the previous section, several studies explore the typology and robustness of air transportation networks. Although some centrality measures (e.g., betweenness centrality) provide useful information on the degree of mediation in a network, it is hard to find studies that explore the specific intermediary roles of airports, especially hub airports, in air transportation networks. Although it is not a complex network analysis, Zhang (2003) analyzes the characteristics of air cargo in Hong Kong and categorizes it into three cargo types: local (domestic), gateway, and hub cargo. He concludes that Hong Kong's air-cargo activity is predominantly related to gateway business, with cargo either originating in or destined for Hong Kong's manufacturing hinterland in southern China. The data show that the gateway business accounted for 78% of total air-cargo trade in 2000.

In this study, we logically classify the types of brokerage roles of Asian airports in air passenger transportation networks and explore the impacts of the different brokerage roles on network robustness. The concept of brokerage roles was originally developed in the field of social network analysis. Gould and Fernandez (1989) provide the first definition of the brokerage role and identify five structurally distinct types of brokerage roles according to the way that each node mediates the other nodes within or outside its group (see Figure 1).

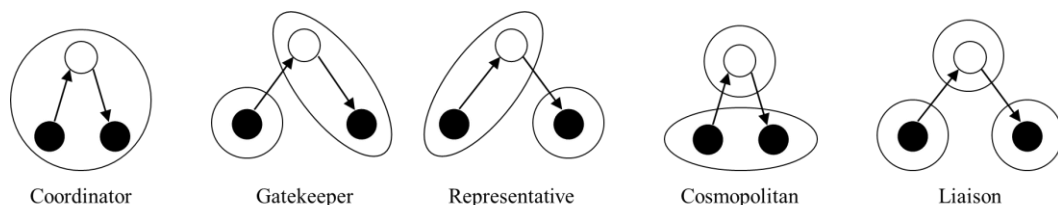


Figure 1. Brokerage role classification by Gould and Fernandez (1989), Source: Kirkels and Duysters (2010)

The coordinator role is a local broker who plays an intermediary role within a group. With this type of role, all three actors belong to the same group, and brokering happens within the group (Chaudhary and Warner, 2018). Thus, the range of influence of this broker node is relatively narrow. Gatekeeper and representative types mediate the nodes in their groups with nodes in other groups. With the gatekeeper type, the broker node controls incoming information and resources to its group and makes decisions about whether the unconnected actors in the group can access the information or resources (Gould and Fernandez, 1989; Fernandez and Gould, 1994; Chaudhary and Warner, 2018). The representative type plays a similar role to the gatekeeper type, but the information flows in the opposite direction.

The liaison role links three groups, including the broker's group, and mediates the flow between the other two groups. The liaison type is the only one of the five brokerage roles that mediates three groups. Thus, a liaison-type airport can be considered as a transfer hub in an air transportation network. In the case of the itinerant (cosmopolitan) and liaison types, broker nodes are called "outsiders" because they belong to different groups from the rest of the nodes, unlike the other brokerage roles Gould and Fernandez (1989). A node in a network can perform multiple roles. For example, it can serve as a gatekeeper for the group to which it belongs or as a liaison that passes along information to a cluster of nodes to which it does not belong (Kirkels and Duysters, 2010).

In this study, we exclude the itinerant (or cosmopolitan) role (e.g., stockbrokers in the banking industry or online retail companies in cross-border e-commerce) since it is not easy to find proper cases in the transportation industry. We consider four types of brokerage roles to show how an airport can serve as an intermediary actor among countries and continents and which airports are influential in Asia as either inter-country or inter-continental hubs.

2. Data and methods

2.1 Data resources

The sample for this study is a set of full-service airlines based on the top-ranked Asian airports from OAG Megahubs International Index (2017). These airlines include Air China, China Eastern Airlines, Korean Air, Japan Airlines, Singapore Airlines, Cathay Pacific, Thai Airways, Air India, Malaysia Airlines, and Garuda Indonesia Airlines.

Table 1. Megahub airports (OAG, 2017) and airlines included in this study

Airport code	City (Country)	Airline
PEK	Beijing (China)	Air China
PVG	Shanghai (China)	China Eastern Airlines
ICN	Incheon (South Korea)	Korean Air
HND	Tokyo (Japan)	Japan Airlines
SIN	Singapore (Singapore)	Singapore Airlines
HKG	Hong Kong (China)	Cathay Pacific
BKK	Bangkok (Thailand)	Thai Airways
DEL	Delhi (India)	Air India
KUL	Kuala Lumpur (Malaysia)	Malaysia Airlines
CGK	Jakarta (Indonesia)	Indonesia-Garuda Airlines

Passenger route data for these airlines were extracted from OAG's Traffic Analyser based on ticket reservation information for each airline gathered from the Market Information Data Tapes system.

The study period is from January to October 2017, and the analysis includes 2,149 airports in total, including 164 in Africa, 666 in Asia, 462 in Europe, 240 in Latin America, 59 in the Middle East, 398 in North America, and 160 in Oceania.

The networks of each airline are constructed to analyze the network robustness of major Asian airlines, where the nodes are airports and two airports are connected if at least one non-stop passenger airline route between them exists (see Table 2). The robustness analysis is performed for individual airlines. Air India, Malaysia Airlines, and Garuda Indonesia Airlines are not included because of their relatively small network sizes, but they are included in the brokerage role analysis.

Table 2. Network sizes of the airlines in the study

Airline	Number of nodes	Number of links
Entire network	2,149	136,416
Air China	1,384	37,768
China Eastern Airlines	1,192	35,075
Cathay Pacific Airways	1,435	33,359
Singapore Airlines	1,533	29,863
Korean Air	1,496	25,773
Thai Airways	1,171	18,816
Japan Airlines	1,305	18,579
Air India	977	15,436
Malaysia Airlines	846	12,244
Indonesia- Garuda Airlines	671	6,584

2.2 Methods

2.2.1 Methods

As described in the previous section, network robustness is a critical issue, especially if a network has the scale-free property. A scale-free network is a network whose degree distribution follows a power law and is defined as in (Barabási and Albert, 1999).

$$p(k) \sim k^{-\gamma} \quad (1)$$

where $p(k)$ is the probability that each node is connected to k vertices, k is a degree, and γ is an exponent. Previous studies, including that of Barabási and Albert (1999), find real-world examples of scale-free networks and show that the exponent γ lies between two and three. Even when γ is out of this range, if the degree follows a power-law distribution, the network can still be broadly defined as a scale-free network.

The cumulative degree distribution ($p_{cum}(k)$) is defined as follows (Boccaletti et al., 2006).

$$p_{cum}(k) = \sum_{k'=k}^{\infty} p(k') \quad (2)$$

$\gamma = \gamma_{cum} + 1$ where γ_{cum} is a scaling exponent.

A network typically represents a hierarchical node-link structure in which sub-groups are embedded within components, where a component is a subgroup of nodes that are connected to one another. A node belonging to one component is therefore not connected to nodes belonging to other components. The component with the greatest number of nodes is referred to as the giant component.

According to Barabási (2016), the removal of nodes cause little damage to the whole network if the fraction of removed nodes f is small. However, increasing f can isolate chunks of nodes from the giant component. Finally, for sufficiently large f , the giant component breaks into tiny, disconnected components.

In this study, we use the size of the giant component and efficiency as network structure metrics to assess the robustness of air transportation network. The giant component size is the number of nodes in the largest connected component. A network that maintains higher giant component size can be considered as more robust in terms of connectivity. The efficiency proposed by Latora and Marchiori (2001) is a network structure metric to measure the distances between node pairs in the network. Decreasing efficiency means increasing the average shortest path distance between node pairs. The efficiency of the network is expressed as in equation (3).

$$E = \frac{1}{(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \quad (3)$$

where d_{ij} is the shortest path distance between nodes i and j and N is the number of nodes in the network G . The Floyd-Warshall algorithm is used to solve all-pairs shortest path problem.

We perform a simulation to measure the size of the giant component and efficiency when the fraction of node isolation increases. In the simulation, the fraction of node isolation increases from 1% to 10% when moving from the nodes with the highest centrality scores to the nodes with the lowest scores.

We use degree centrality, betweenness centrality, and closeness centrality as the node centrality measures as the criteria of node importance. The degree is defined as the number of direct connections that each node has with other nodes in the network.

Degree centrality of node i is expressed as in equation (4).

$$DC(i) = \frac{\sum_{j=1}^N x_{ij}}{N-1} \quad (4)$$

where x_{ij} equals one when nodes i and j are connected and zero otherwise. Degree centrality is defined as the number of links incident upon a node. For degree centrality, higher value means the node has higher connectivity with other nodes in the network.

Betweenness centrality of node i is expressed as in equation (5).

$$BC(i) = \frac{\sum_{j \neq k} g_{jk}(i) / g_{jk}}{(N-1)(N-2) / 2} \quad (5)$$

where g_{jk} is the number of the shortest path between nodes j and k , and $g_{jk}(i)$ is the number of the shortest path between nodes j and k that passes through node i . Betweenness centrality is defined as the number of times that a node falls on the shortest path between two other nodes (Freeman et al., 1979) and is a measure of “control.” Specifically, it indicates the extent to which a node controls flows in the network based on its role as an intermediary between other nodes (Liebowitz, 2008). The betweenness centrality of an airport refers to the degree of its mediation role in the air transportation network. Airports with high betweenness centralities are likely to act as hub airports in an aviation network.

Closeness centrality of node i is expressed as in equation (6).

$$CC(i) = \frac{N-1}{\sum_{j=1}^N d_{ij}} \quad (6)$$

where d_{ij} is the shortest path distance between nodes i and j . The closeness centrality of a node is determined by taking the reciprocal of the sum of the distances between that node and the other nodes. Closeness centrality is calculated based on the distances between all nodes directly and indirectly connected to that node and, thus, the higher a node’s closeness

centrality is, the closer it is to the other nodes (Freeman et al., 1979). Closeness centrality measures the number of steps an individual must take on average to reach everyone else in the network. Individuals with high closeness centrality measures can most efficiently contact others in the network (Freeman et al., 1979; Costenbader and Valente, 2003).

2.2.2 Brokerage role analysis

We conduct a brokerage role analysis to understand the specific brokering types of airports. An important part of brokerage role analysis is grouping the nodes. We set the grouping criteria (i.e., partition value) at the “national information” and “continental information” levels (see Figure 2). We assume that an airport performs a different brokerage role when the group criteria are different.

The brokerage role analysis is performed for the entire network of 10. We count the number of times that each node plays each of the four brokerage roles by examining every triad in the network under each grouping criterion.

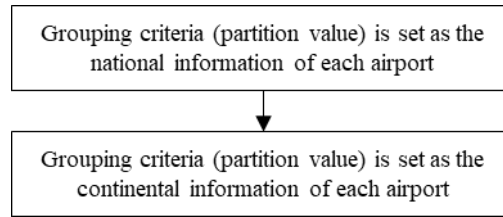


Figure 2. Process for the brokerage role analysis

3. Analysis results

3.1 Scale-free property of Asian airline networks

Figure 3 shows the cumulative degree distribution ($p_{cum}(k)$) on a log-log scale for the combined air transportation network of 10 major Asian airlines. The exponent γ for the air transportation network of these airlines is estimated to be 2.24 for the in-degree distribution and 2.28 for the out-degree distribution. Overall, the entire network of the 10 Asian airlines is a scale-free network.

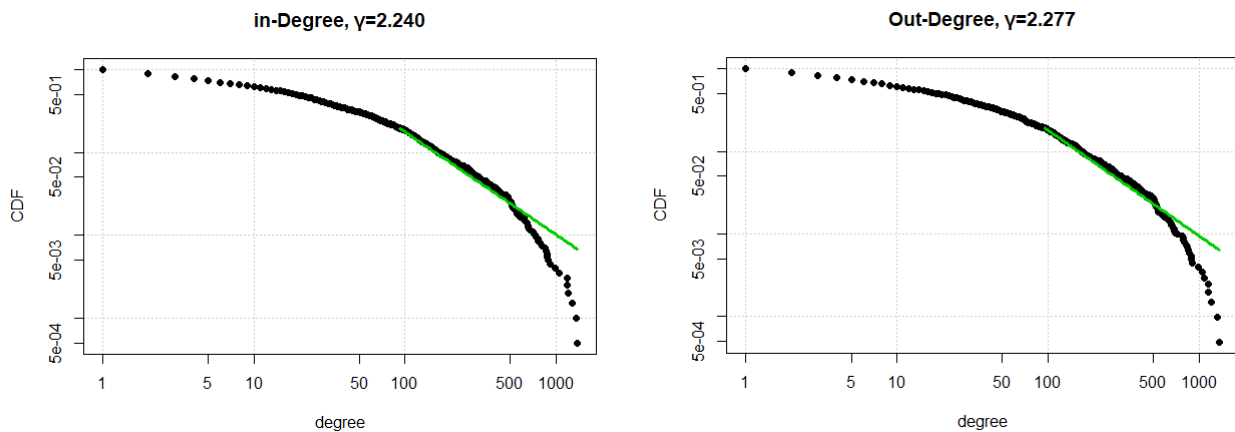


Figure 3. Cumulative degree distributions for 10 Asian airlines (in-degree and out-degree)

Figure 4 shows the cumulative degree distributions of the individual Asian airlines. The air transportation networks of all the major Asian airlines except for that of Air China have the scale-free property, in which their degree distributions follow a power law, at least asymptotically. Air China's network ($\gamma = 6,248$) does not have the scale-free property, which may indicate that its hub-and-spoke network has not fully matured.

3.2. Robustness of Asian airline networks

We analyze the network robustness of major Asian airlines' networks by measuring the size of the giant component and the efficiency when the fraction f of node isolation increases from the nodes with the highest centrality scores to the nodes with the lowest scores. In the simulation, the fraction f of node isolation increases from 1% to 10%. Three centrality measures - degree, betweenness, and closeness centrality - are used as the criteria for node isolation in the robustness analysis.

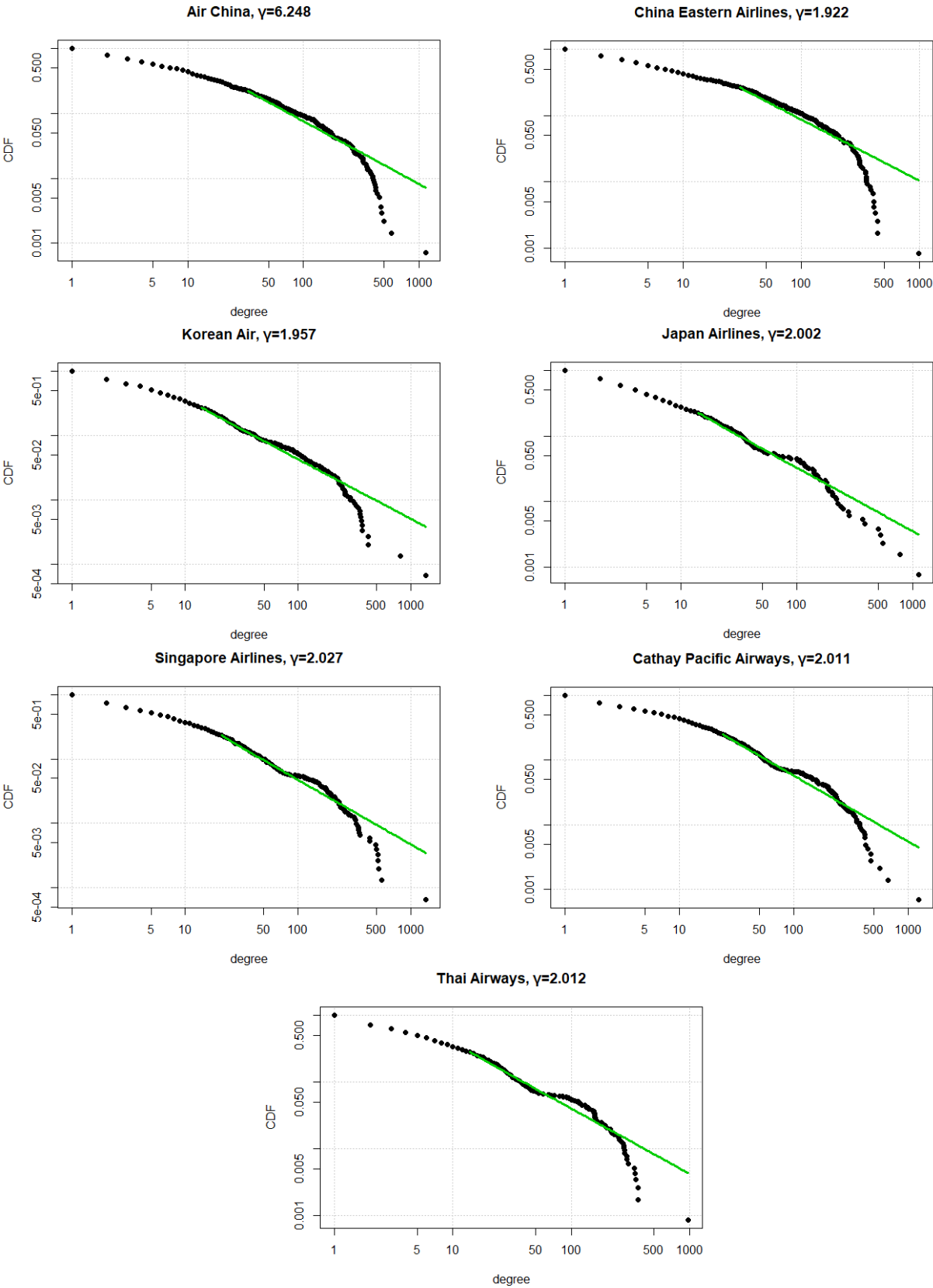


Figure 4. Cumulative degree frequency distributions of major Asian airlines

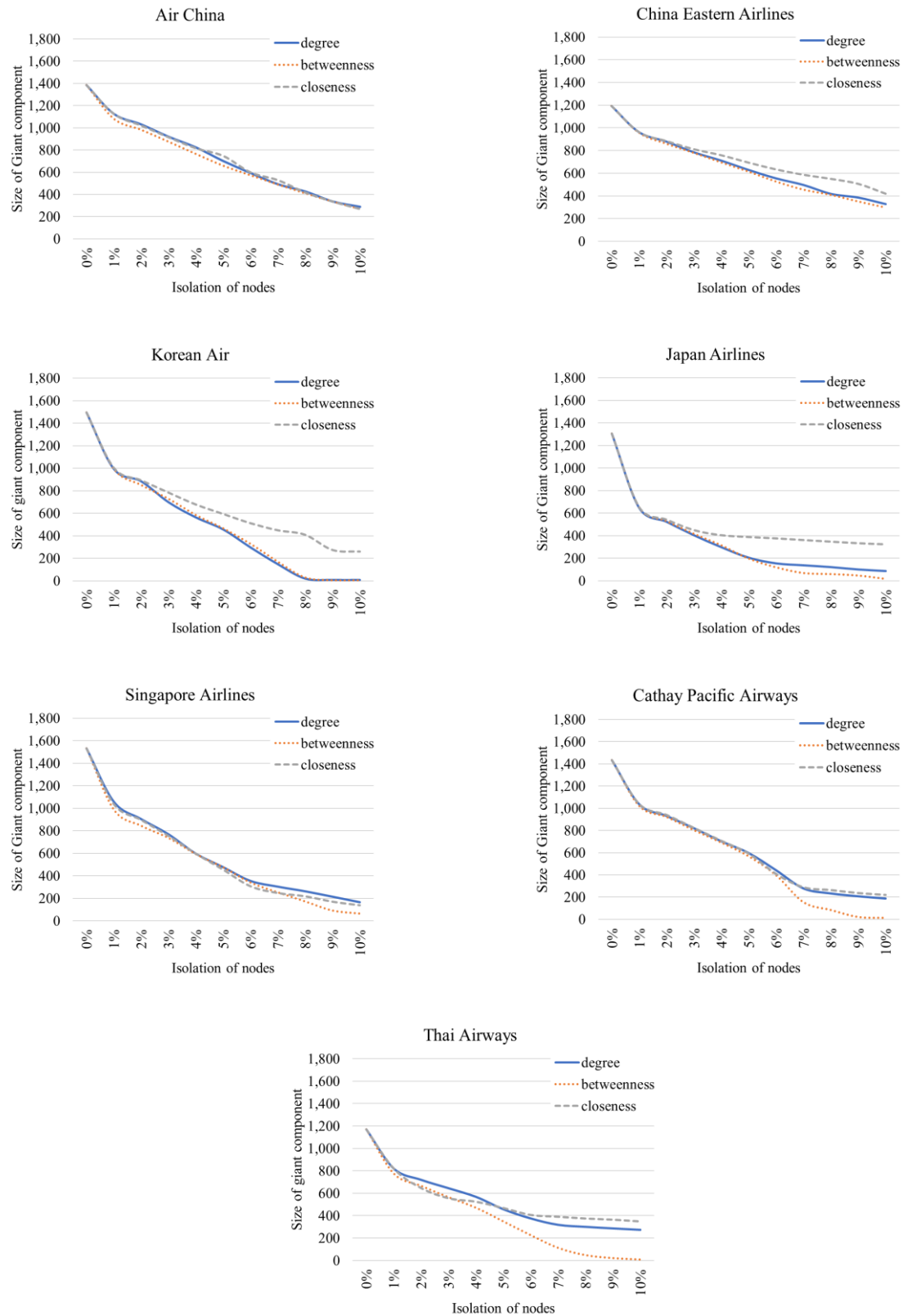


Figure 5. Robustness analysis results: Giant component size

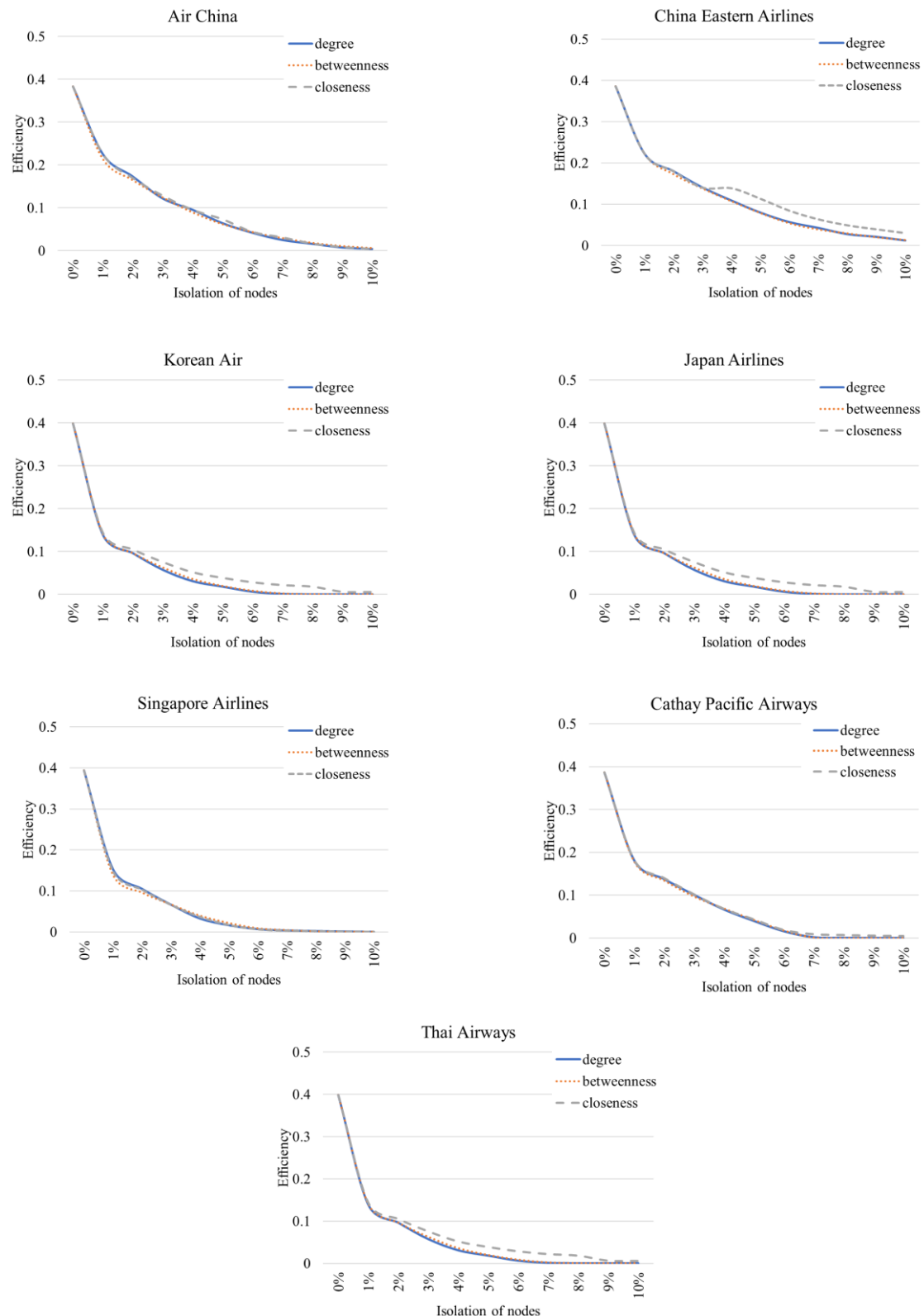


Figure 6. Robustness analysis results: Efficiency

Firstly, we examined the size of giant component for each Asian airline's network (see Figure 5). In the first iteration, the size of the giant component is measured when 1% of the highly connected nodes are isolated. In the case of Air China, the size of the giant component decreases by 18.7%, 21.9%, and 18.7% for degree, betweenness, and closeness centrality, respectively. We find similar results for China Eastern Airlines (19.3%, 19.7%, and 19.3%, respectively). In contrast, Japan Airline is the most sensitive to the isolation of important nodes, with a decrease in the giant component size of

about 50%. The other Asian airlines' giant components decrease in size by 27.6%-35.6%.

The airline networks of Korean Air and Japan Airlines collapse when 8-9% of the highly connected nodes are isolated. By contrast, Air China and China Eastern Airlines have relatively high network robustness.

Secondly, we examine the efficiency for each airline's network (see Figure 6). The results showed that the node isolation has a greater impact on the efficiency (distances between nodes) than the size of giant component. In case of Air China, the efficiency decreases by 41.2%, 44.2%, and 41.2% for degree, betweenness, and closeness centrality, when 1% of the highly connected nodes are isolated. As the size of giant component, Japan Airline is the most sensitive to the node isolation, with a decrease in the efficiency about 80%. After Japan Airline, Korean Air and Singapore Airlines showed the highest decrease in efficiency, with a decrease in the efficiency by 61.3-65.2%.

The relatively high robustness of the Chinese airlines may stems from China's high-density domestic traffic. In contrast, the airlines relying heavily on international traffic, such as Singapore Airlines, Cathay Pacific Airways, and Korean Air, have less robust networks. Recent statistics on international and domestic passengers by airline partly support the above result (see Table 3). The domestic passenger shares of the two Chinese airlines reached 78-80% in 2018.

Table 3. Domestic vs. international passenger traffic of selected airlines (2018)

Country	Carrier	Total Pax.	International Pax. (%)	Domestic Pax. (%)
China	China Eastern Airlines	68,831,824	19.7%	80.3%
	Air China	51,646,872	22.3%	77.7%
Hong Kong China	Cathay Pacific Airways	16,134,298	99.8%	0.2%
Japan	Japan Airlines	27,454,864	26.8%	73.2%
Korea	Korean Air	20,340,376	74.1%	25.9%
Singapore	Singapore Airlines	12,755,157	100.0%	0.0%
Thailand	Thai Airways	13,113,076	90.0%	10.0%

Source: Official Aviation Guide.

Table 4. Sensitivity of robustness metrics for different centrality measures

Indicator	Decrease in giant component (%)	
	1% isolation of nodes	10% isolation of nodes
Degree centrality	18.7-50.4	72.3-99.5
Betweenness centrality	19.7-50.2	74.8-99.7
Closeness centrality	18.7-50	64.8-91

Indicator	Decrease in efficiency (%)	
	1% isolation of nodes	10% isolation of nodes
Degree centrality	41.2-80.5	96.9-100
Betweenness centrality	42.3-80.1	96.5-100
Closeness centrality	41.2-80	92.1-99.8

We further examined which centrality measures have greater impacts on network robustness. The analysis shows that the robustness of air route network is influenced in the order of betweenness, degree, and closeness centralities (see Table 4).

It implies that the isolation of an airport that intermediates between other airports has a greater influence on the robustness of airline networks. Thus, an airport with a high betweenness centrality in an airline network has a strong influence over the connections among other airports and is a powerful intermediary in the overall network. On the contrary, closeness centrality has the least influence on the three measures. For major Asian airlines' networks, we can assume that an airport a short distance from the network has less importance than an airport that plays an intermediary role in the network.

3.3. Brokerage roles of airports

In the previous section, we found that the hub nodes with higher betweenness centralities have greater impacts on airline network robustness. In the next sections, we further explore the impacts of hub nodes on network robustness based on their brokerage roles.

Tables 5 and 6 shows the airport rankings for each type of brokerage role under different grouping criteria. When the grouping criteria are set at the national level, Chinese airports dominate as coordinators (Coord.), gatekeepers (GateKp.), and representatives (Rep.) (see Table 5). Beijing Capital International Airport (PEK), Xian Airport (XIY), and Shanghai Pudong International Airport (PVG) are the top-ranked coordinator airports. These airports play intermediary roles by mediating domestic airports.

PEK, Hong Kong International Airport (HKG), and PVG are the top-ranked gatekeeper and representative airports. These airports play intermediary roles as gateways from Chinese airports to neighboring countries and vice versa.

Finally, Singapore Changi Airport (SIN), Incheon International Airport (ICN), Narita International Airport (NRT), Bangkok Suvarnabhumi Airport (BKK), and HKG are the top-ranked liaison airports. These well-known hub airports play intermediary roles by mediating among airports in three countries. PEK and PVG, however, are ranked seventh and eighth in the liaison role.

Table 5. Brokerage role analysis results with partitioning into national groups

Rank	Coord.	Group	GateKp.	Group	Rep.	Group	Liaison	Group
1	PEK	China	PEK	China	PEK	China	SIN	Singapore
2	XIY	China	HKG	China	HKG	China	ICN	Korea
3	PVG	China	PVG	China	PVG	China	NRT	Japan
4	CTU	China	TPE	Chinese Taipei	TPE	Chinese Taipei	BKK	Thailand
5	SHA	China	CAN	China	CAN	China	HKG	China
6	HKG	China	CTU	China	CTU	China	MNL	Philippines
7	HGH	China	CGK	Indonesia	TAO	China	PEK	China
8	KMG	China	DEL	India	CGK	Indonesia	PVG	China
9	CAN	China	TAO	China	DEL	India	KIX	Japan
10	NKG	China	XIY	China	XIY	China	KUL	Malaysia
11	TAO	China	KMG	China	DLC	China	HND	Japan
12	DLC	China	HGH	China	NKG	China	SYD	Australia
13	WUH	China	WUH	China	SHA	China	PUS	Korea
14	SZX	China	NKG	China	KMG	China	DEL	India
15	TPE	China	BOM	India	HGH	China	CGK	Indonesia
16	CKG	China	SHA	China	XMN	China	SGN	Viet Nam
17	TSN	China	HND	Japan	BOM	India	MEL	Australia
18	TYN	China	DLC	China	WUH	China	NGO	Japan
19	NGB	China	SZX	China	CKG	China	TPE	Chinese Taipei
20	URC	China	CKG	China	HND	Japan	PER	Australia

Table 6. Brokerage role analysis result with partitioning into continental groups

Rank	Coord.	Group	GateKp.	Group	Rep.	Group	Liaison	Group
1	SIN	Asia	SIN	Asia	SIN	Asia	ICN	Asia
2	HKG	Asia	ICN	Asia	ICN	Asia	SIN	Asia
3	BKK	Asia	HKG	Asia	HKG	Asia	HKG	Asia
4	PEK	Asia	BKK	Asia	BKK	Asia	NRT	Asia
5	ICN	Asia	PEK	Asia	NRT	Asia	BKK	Asia
6	PVG	Asia	NRT	Asia	PEK	Asia	SYD	Oceania
7	KUL	Asia	PVG	Asia	PVG	Asia	PEK	Asia
8	HND	Asia	MNL	Asia	MNL	Asia	MEL	Oceania
9	NRT	Asia	HND	Asia	KIX	Asia	MNL	Asia
10	KIX	Asia	KUL	Asia	KUL	Asia	PVG	Asia
11	CGK	Asia	KIX	Asia	HND	Asia	PER	Oceania
12	DEL	Asia	CGK	Asia	CGK	Asia	BNE	Oceania
13	MNL	Asia	DEL	Asia	DEL	Asia	DEL	Asia
14	TPE	Asia	PUS	Asia	PUS	Asia	HND	Asia
15	NGO	Asia	SGN	Asia	SGN	Asia	KIX	Asia
16	BOM	Asia	TPE	Asia	TPE	Asia	AKL	Oceania
17	CAN	Asia	NGO	Asia	NGO	Asia	CGK	Asia
18	PUS	Asia	BOM	Asia	BOM	Asia	PUS	Asia
19	SGN	Asia	CAN	Asia	CAN	Asia	KUL	Asia
20	CTU	Asia	DPS	Asia	DPS	Asia	SGN	Asia

When the grouping criteria are set at the continental level, the results are significantly different (see Table 6). These results substantially differ from the rankings at the national level, for which most of the top 20 airports are Chinese airports, except in the case of the liaison role. XIY, which ranked second for the coordinator role at the national level, is ranked 30th at the continental level. Chengdu Shuangliu International Airport (CTU) and Shanghai Hongqiao International Airport (SHA), which ranked fourth and fifth in the coordinator role at the national level, ranked only 20th and 26th, respectively, at the continental level.

In the rankings for coordinator, gatekeeper, and representative at the continental level, SIN ranked first, reflecting its pivotal intermediary role within its group and also in linking its group to airports in other continents. ICN ranked first in the liaison role and is significant in that it intermediates more than three continents, including Asia. Following ICN, SIN, HKG, NRT, and BKK also act as international transfer hub airports. HKG plays a high-ranked brokerage role at both the national and continental level.

PEK and PVG rank fourth and sixth as coordinators, fifth and seventh as gatekeepers, and seventh and ninth as liaisons,

respectively. This result indicates that these two airports have much room to improve to develop into more competitive international transfer hub airports.

3.4. Robustness analysis based on brokerage roles

Lastly, we apply the brokerage roles of each airport to the robustness analysis. For each type of brokerage role, we apply a node removal simulation to the combined air transportation network. The fraction of node isolation increases from 1% to 20%. By measuring the change in the size of the giant component, we try to examine which types of brokerage roles (among coordinator, gatekeeper, representative, and liaison) have the greatest impact on network robustness.

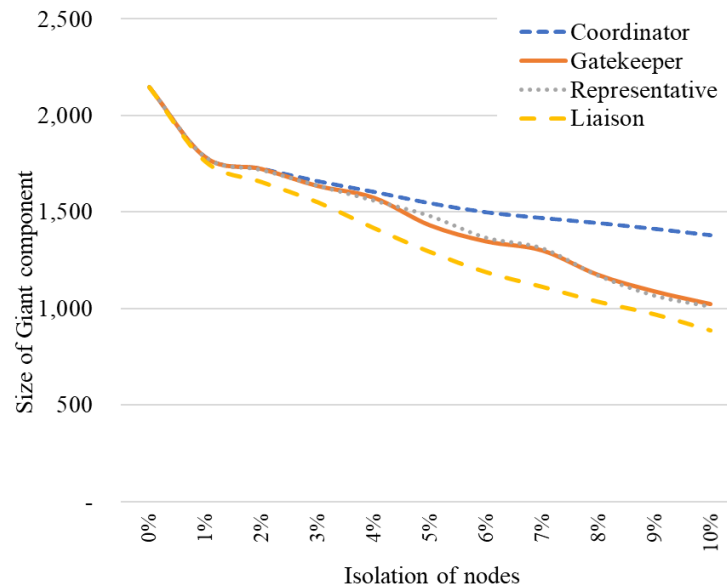


Figure 7. Robustness analysis based on brokerage roles

As shown in Figure 7, the broker type that has the greatest impact on the robustness of the air transportation network is the liaison role, followed by the gatekeeper and representative roles.

In the first stage, in which 1% of high-value nodes are isolated based on each brokering type, similar results are obtained for each type, as the size of the giant component is maintained at around 81% to 83% on average. However, in the fifth stage, in which 5% of the nodes are isolated, the size of the giant component is still maintained at 64% for the coordinator role but drops to 41% when nodes are isolated based on the liaison role. In the last stage, in which 20% of nodes are isolated in the network, the giant component size is maintained at 38% for the coordinator role, 19% for the gatekeeper role, 21% for the representative role, and 14% for the liaison role.

The findings indicate that the liaison role is the most influential for air transportation network robustness. Thus, airports that act as inter-continental transfer hubs are more important for air transportation network robustness than those that act as intermediaries within their own groups are.

4. Conclusion

This study reveals several useful insights on the robustness of Asian air transportation networks.

The robustness analysis shows that Chinese airlines, such as Air China and China Eastern Airlines, exhibit a higher degree of network robustness owing to China's highly dense domestic air route network. The stronger connectedness of Chinese airports within China through domestic air routes has a profound effect on the robustness of airlines' networks. On the contrary, airlines relying heavily on international connections, such as Korean Air, Japan Airlines, and Cathay Pacific, have less robust networks. As Chinese airlines are expanding their international routes and developing more international hub airports, they will be exposed to vulnerability issues.

The robustness analysis also shows that the size of the giant component and the efficiency decrease faster when nodes with high betweenness centralities are isolated.

The brokerage role analysis also contributes useful insights on the robustness of Asian air transportation networks. Using national-level grouping criteria, we find that Chinese airports exert greater influence on the network. They not only act as strong coordinators through their intermediary roles within China but also rank highly as gatekeepers and representatives. SIN is ranked first in terms of the liaison role, followed by ICN, NRT, BKK, and HKG.

At the continental level, non-Chinese airports are ranked highly for all brokerage roles. SIN is ranked the highest for the coordinator, gatekeeper, and representative roles, reflecting its pivotal intermediary role within its group and also in linking its group to airports in other continents. ICN is ranked first in the liaison role and is significant in that it intermediates more than three continents, including Asia. Following ICN, SIN, HKG, NRT, and BKK also act as international transfer hub airports.

We concluded that the influence of Chinese airports, such as PEK, PVG, and XIY, is growing but is restricted to China. Their impacts are not as wide as those of SIN and ICN, implying that SIN and ICN have greater global impacts as intercontinental transfer hub airports. HKG appears to be influential in China as well as in connectivity between countries and continents. Lastly, the airports that play the most important roles in the robustness of air transportation networks in the Asia-Pacific region are those that serve as liaisons or gatekeepers. Thus, if an airport links two or three groups, it may be an intermediate airport, and, thus, it plays a critical role in the air transportation network. In summary, airports with high betweenness centralities and airports that play liaison-type mediation roles have the greatest impact on the robustness of air transportation networks.

In summary, this study expands the existing literature in two ways. First, we evaluated network robustness for major Asian airlines. Second, we further explored which airport types have the greatest impact on robustness. For the first time, we categorized the brokerage roles of Asian airports and examined their impacts on the robustness of air route networks.

The approaches and methods applied in this study have some limitations. In this study, domestic and international passenger data were combined and analyzed together. To compare and analyze airlines with large proportions of domestic passengers and airlines with large proportions of international passengers, it would be useful to analyze the data separately. Additionally, we used cross-sectional passenger route data from 2017. To better reflect the rapid, dynamic changes in the Asian aviation market, it may be more useful to analyze data over several years rather than cross-sectional data. Furthermore, most aviation network analysis using complex network analysis considers the air route networks as binary networks. A weighted network approach should be applied to better reflect realistic link properties (i.e., capacity, frequency, or volume) of air transportation networks in future research.

Making air route networks more robust and resilient is always a top priority for all airline and aviation policy authorities. The current airline alliances can be an effective way to mitigate vulnerabilities in aviation networks. Alliances can allow participating airlines to quickly identify and respond to network risks by sharing relevant information. Collaborating with LCCs may also be an alternative way to alleviate vulnerability in aviation networks. Compared with the FSCs, LCCs tend to offer more direct services between airports, and their reliance on hub airports is relatively low. Lordan et al. (2016) compare the robustness of airlines' route networks for LCCs and FSCs and find that LCC networks are more robust than FSC networks. A hybrid use of FSC and LCC route networks could be a way to provide passengers with alternative travel routes in the event of a serious problem at a hub airport.

More intuitively, configuring and operating multiple hubs can be an effective strategy for improving network robustness. Airlines adopt multi-hub network strategies to improve spatial coverage, reduce hub airport congestion, or provide more itinerary options to customers. In addition to improving efficiency and customer service, a multi-hub strategy can be an effective measure for improving robustness. These subjects need to be explored through further research.

Acknowledgments

This work was supported by Global Research Network program through the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2017S1A2A2041812).

References

- Bagler, G. 2008. Analysis of the airport network of India as a complex weighted network. *Physica A: Statistical Mechanics and its Applications* 387, 2972-2980.
- Barabási, A.L. 2016. *Network Science*. Cambridge university press, Cambridge.
- Barabási, A.L., Albert, R., 1999. Emergence of scaling in random networks. *Science* 286, 509-512.
- Barabási, A.L., Bonabeau, E., 2003. Scale-free networks. *Scientific American* 288, 60-69.
- Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., Hwang, D.U., 2006. Complex networks: Structure and dynamics. *Physics Reports* 424, 175-308.
- Borenstein, S., 1989. Hubs and high fares: Dominance and market power in the U.S. airline industry. *The RAND Journal of Economics* 20, 344-365.
- Chaudhary, A.K., Warner, L.A., 2018. *Introduction to Social Network Research: Brokerage Typology*. University of Florida, Available at: <https://edis.ifas.ufl.edu/wc197>.
- Costenbader, E., Valente, T.W., 2003. The stability of centrality measures when networks are sampled. *Social Networks* 25, 283-307.
- Dennis, N., 1994. Airline hub operations in Europe. *Journal of Transport Geography* 2, 219-233.
- Fernandez, R.M., Gould, R.V., 1994. A dilemma of state power: Brokerage and influence in the national health policy domain. *American Journal of Sociology* 99, 1455-1491.
- Freeman, L.C., Roeder, D., Mulholland, R.R., 1979. Centrality in social networks: ii. experimental results. *Social Networks* 2, 119-

141.

- Gould, R.V., Fernandez, R.M., 1989. Structures of mediation: A formal approach to brokerage in transaction networks. *Sociological Methodology* 89-126.
- Guimerà, R., Mossa, S., Turttschi, A., Amaral, L.N., 2005. The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles. *Proceedings of the National Academy of Sciences of the United States of America* 102, 7794-7799.
- Hossain, M., Alam, S., 2017. A complex network approach towards modeling and analysis of the Australian airport network. *Journal of Air Transport Management* 60, 1-9.
- Hossain, M., Alam, S., Rees, T., Abbass, H., 2013. Australian airport network robustness analysis: A complex network approach. *Proceedings of Australasian Transport Research Forum (ATRF)*, 36th. Brisbane, Queensland, Australia.
- International Airports Council, 2018. ACI World publishes annual World Airport Traffic Report. Montreal, Quebec.
- Jiang, Y., Yao, B., Wang, L., Feng, T., Kong, L., 2017. Evolution trends of the network structure of Spring Airlines in China: A temporal and spatial analysis. *Journal of Air Transport Management* 60, 18-30.
- Kirkels, Y., Duysters, G., 2010. Brokerage in SME networks. *Research Policy* 39, 375-385.
- Latora, V., Marchiori, M., 2001. Efficient behavior of small-world networks. *Physical Review Letters* 87, 198701 1-4.
- Li, W., Cai, X., 2004. Statistical analysis of airport network of China. *Physical Review E* 69, 046106 1-6.
- Liebowitz, J. 2008. *Knowledge Retention: Strategies and Solutions*. Auerbach Publications, Florida.
- Lin, J., Ban, Y., 2014. The evolving network structure of US airline system during 1990-2010. *Physica A: Statistical Mechanics and its Applications* 410, 302-312.
- Liu, J., Zhou, M., Wang, S., Liu, P., 2017. A comparative study of network robustness measures. *Frontiers of Computer Science* 11, 568-584.
- Lordan, O., Sallan, J.M., Escorihuela, N., Gonzalez-Prieto, D., 2016. Robustness of airline route networks. *Physica A: Statistical Mechanics and its Applications*, 445 18-26.
- Lordan, O., Sallan, J.M., Simo, P., Gonzalez-Prieto, D., 2014. Robustness of the air transport network. *Transportation Research Part E: Logistics and Transportation Review* 68, 155-163.
- Lordan, O., Sallan, J.M., Simo, P., Gonzalez-Prieto, D., 2015. Robustness of airline alliance route networks. *Communications in Nonlinear Science and Numerical Simulation* 22, 587-595.
- Manzano, M., Sahneh, F., Scoglio, C., Calle, E., Marzo, J. L., 2014. Robustness surfaces of complex networks. *Scientific Reports* 4, 6133 1-6.
- OAG, 2017. *Megahubs International Index 2017*. Luton, Bedfordshire.
- Rodrigue, J.P., Comtois, C., Slack, B., 2017. *The Geography of Transport Systems*. 4th Ed. Routledge, New York.
- Song, M.G., Yeo, G.T., 2017. Analysis of the air transport network characteristics of major airports. *The Asian Journal of Shipping and Logistics* 33, 117-125.
- Sun, X., Gollnick, V., Wandelt, S., 2017. Robustness analysis metrics for worldwide airport network: A comprehensive study. *Chinese Journal of Aeronautics* 30, 500-512.
- Sun, X., Wandelt, S., Linke, F., 2015. Temporal evolution analysis of the European air transportation system: Air navigation route network and airport network. *Transportmetrica B: Transport Dynamics* 3, 153-168.
- The International Air Transport Association., 2017. *Air passenger market analysis - December 2017*. Montreal, Quebec.
- Wang, J., Mo, H., Wang, F., Jin, F., 2011. Exploring the network structure and nodal centrality of China's air transport network: A complex network approach. *Journal of Transport Geography* 19, 712-721.
- Wilkinson, S.M., Dunn, S., Ma, S., 2012. The vulnerability of the European air traffic network to spatial hazards. *Natural Hazards* 60, 1027-1036.
- Zhang, A., 1996. An analysis of fortress hubs in airline networks. *Journal of Transport Economics and Policy* 30, 293-307.
- Zhang, A., 2003. Analysis of an international air-cargo hub: The case of Hong Kong. *Journal of Air Transport Management* 9, 123-138.
- Zhou, Y., Wang, J., Huang, G.Q., 2019. Efficiency and robustness of weighted air transport networks. *Transportation Research Part E: Logistics and Transportation Review* 122, 14-26.