An overview of network structures and node importance in the global aviation system from the year 2011 to 2022

Massimiliano Zanin[1] and Sebastian Wandelt[2]

[1]*Instituto de Física Interdisciplinar y Sistemas Complejos IFISC (CSIC-UIB), Palma de Mallorca, Spain*
[2]*National Key Laboratory of CNS/ATM, School of Electronic and Information Engineering, Beihang University, 100191 Beijing, China*

Abstract: The aviation system is an essential constituent for human mobility in the 21st century. Accordingly, better understanding the underlying - possibly hidden - characteristics is one of the key challenges in air transport research. Network science has developed into a key domain for analyzing complex, inter-connected systems, with many studies having used network science techniques to dissect the universal patterns by the abstraction into a network-like structure. After more than two decades of aviation network analysis - the earliest influential papers date back to the early 2000s, providing a synopsis of the existing techniques and assessing the relevant characteristics on the global aviation system is judicious and helpful for the entire air transport community. In this study, we make three major contributions. First, we review the existing literature on complex network analysis of aviation system, having appeared in the past two decades, identifying key trends in the analysis and their results. Second, we provide a data-driven, network science-based analysis of the global aviation system and two of its variants for period from 2011 to 2022, leading to one of the most comprehensive studies in the literature. At the core of our analysis is the task of identifying node importance and answering the question how well complex network-based methods help to reveal the critical nodes in the system. Third, we derive a set of relevant research directions which we deem instrumental for advancing our understanding of global aviation and its subsystems through the lens of network science. We believe that our study provides a unique combination of biographical synopsis and data-driven analysis for the evolution of our global aviation system.
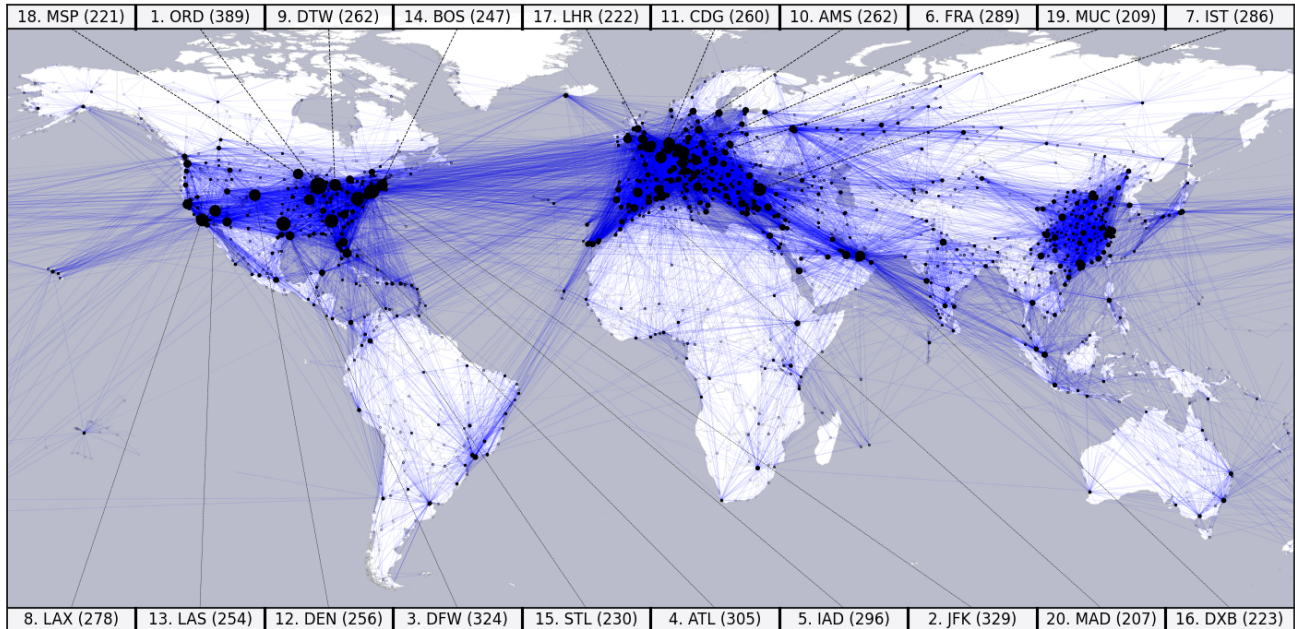**Keywords:** *Aviation;Complex networks;Data-driven analysis*

1. Introduction

Network science, an actively developed domain for more than two decades now, provides excellent tools for understanding the structures and dynamics of real-world systems (Barabasi 2013, Newman 2010, Zanin & Lillo 2013). A multitude of complex network abstractions have been analyzed, among which are social networks (Scott 2012), power grids (Pagani & Aiello 2013), biological networks (Bagler & Sinha 2005), and transportation systems (Wandelt et al. 2015); see Boccaletti et al. (2006) for an introduction. Air transportation is no exception here, with many studies having used techniques from the network science domain to identify the complexity and hidden dynamics of air transportation systems at various scales and spatial/temporal resolution (Sun, Wandelt & Zanin 2017). The most-frequently analyzed air transportation system abstraction are so-called airport networks, where nodes represent individual airports and a link exist between a pair of nodes, if and only if there exists at least one direct flight between these two airports in a given time interval. A central part of analyzing air transportation systems as a network addresses its complex properties (Azzam et al. 2013), such as, scalability (Barabási & Albert 1999), controllability (Jia & Barabási 2013), safety event patterns (Zanin 2014), resilience (Sun, Gollnick & Wandelt 2017), and communities (Palla et al. 2005). Existing research has mostly focused on the analysis of domestic / regional airport networks and relatively short periods of time, presumably due to the limited availability of data. It can be arduous to collect data at a global scale and for longer periods of time, e.g., multiple years. Examples for existing spatially / temporally-limited studies include research on the US airport network (Jia et al. 2014, Lin & Ban 2014, Neal 2013, Gautreau et al. 2009, Bounova 2009), the European airport networks (Paleari et al. 2010), some domestic subnetworks of Europe, such as Portugal (Jimenez et al. 2012), Greece (Papatheodorou & Arvanitis 2009), and Italy (Guida & Maria 2007); the Chinese airport network (Wang et al. 2014, Zhang 2010), the Indian airport network (Bagler 2008), and the Brazilian airport network (da Rocha 2009). Most studies in the literature analyze a single snapshot, e.g.,

using data for a single week or month. Cross-comparison of the results are often difficult, given the use of various data sources, discrepancies in data preparation, and differences in presentation / interpretation. This leads to situations in which results on aviation network analysis become seemingly contradicting, e.g., highlighted by Azzam et al. (2013), Neal (2014). Here, it should be particularly noted that airport networks are not static, but evolve over time. This fact is often neglected by the research community and snapshots of networks at different points of time have often been analyzed. As discussed by Barabâsi et al. (2002), most quantities used to characterize a network are time dependent and their values at a given time point alone could tell little about the whole network.

| 18. MSP (221) | 1. ORD (389) | 9. DTW (262) | 14. BOS (247) | 17. LHR (222) | 11. CDG (260) | 10. AMS (262) | 6. FRA (289) | 19. MUC (209) | 7. IST (286) |

| 8. LAX (278) | 13. LAS (254) | 12. DEN (256) | 3. DFW (324) | 15. STL (230) | 4. ATL (305) | 5. IAD (296) | 2. JFK (329) | 20. MAD (207) | 16. DXB (223) |

Figure 1: *The global airport network based on data for April - June 2022. Top 20 nodes with the highest number of connections are highlighted by their IATA code.*

In this study, we review the analysis of the global airport system through the usage of network science methodologies. Based on quarterly data for the years 2011 to 2022, we compute a set of widely used network characteristics / node centralities and report their evolution throughout the period under investigation. Figure 1 shows a visualization of the worldwide airport network for the second quarter (April - June) in the year 2022, i.e., during the so-far peak of the recovery from the COVID-19 pandemic. Here, nodes represent airports and a link exists between two nodes if there exists at least one direct flight between the two airports. The nodes are represented by circular markers whose size corresponds to the number of destinations which can be reached by a direct flight. The top 20 airports according to the number of directly reachable destinations are highlighted with their IATA code. We can clearly identify the three major powerhouses of aviation: North America, Europe, and China. In addition to investigating the airport network, we also cover two interesting contractions: city-networks and networks induced by multiple-airport regions. The nodes in these networks are aggregated from airports to cities and multiple-airport regions, respectively. Complex network techniques help to analyze a system, by identifying hidden, yet universal patterns. In this study, we report results for 48 quarterly snapshots of the three network layers. All results are accompanied by a comprehensive discussion of managerial implications, i.e., we do not only report the numerical results but also provide recommendations on how to interpret the results and what aviation stakeholders can take away from such an analysis. Based on our comprehensive analysis, we provide a set of suggestions for future research in the air transport domain. We are not aware of any other work in the literature covering the evolution of the global aviation system at such a depth and extensive temporal evolution. The most related work in the literature is Wandelt et al. (2019), who review and compare the evolution of domestic airport networks for Australia, Brazil, Canada, China, India, Russia, US and Europe during the period 2002–2013, being the first study performed on a consistent global dataset and allowing for direct comparisons of network features. Our analysis is complementary by investigating the recent evolution of the global airport system instead, notably covering the full COVID-19 pandemic cycle. In addition, our study is complementary to more review-like works, e.g. Zanin & Lillo (2013), Lin & Ban (2013), Rocha (2017), Sun & Wandelt (2021), by providing analysis and research guidelines through experiments on real-world data. We believe that our study contributes to the aviation community, by providing a comprehensive analysis of the global aviation system on a consistent dataset for a period of twelve years, accompanied by a thorough discussion of managerial insights and policy implications.

The remainder of this study is structured as follows. Section 2 provides a broad overview for studies on network-based analysis of air transportation subsystems. In addition, we highlight the relevance of the subject to the Air Transport Research

Society (ATRS)[1] by discussing related abstracts from the Air Transport Research Society World Conference series published in recent years. Section 3 lays the formal foundation of our study by introducing the definitions relevant to airport networks and their aggregations. In addition, we revisit the definition of various network characteristics and node centralities, in order to enable a well-defined, informed analysis of the global aviation system. Section 4 constitutes a major contribution of our study, the analysis of the system's development in the past twelve through the lens of complex networks. We report the evolution of a wide range of indicators, leading to - what we believe is - the most comprehensive study in the literature on the subject. Section 5 further contributes to the air transport research community by deriving a set of recommendations for future work, which will hopefully help other researchers do identify novel and relevant subjects for their future studies.

2. Literature review

In this section, we provide a broad overview on the existing literature covering network aspects of the aviation system. The domain of network science has emerged in the turn of the millennium, with several seminal papers on the analysis of real world systems as complex networks (Albert et al. 2000, Callaway et al. 2000, Cohen et al. 2000, Albert & Barabási 2002), see Barabasi (2013) for an excellent overview. The aviation system has been an exemplary case study in this area right from the beginning, given the tremendous importance of aviation for human mobility. Throughout the past 20 years, complex network analysis was used to study air transportation systems of various types, levels, and resolutions; we review the relevant literature on this subject below. Many previous studies have analyzed the degree distributions of the worldwide air transportation network and regional subnetworks, for instance, fitting distributions which obey double power-laws (Paleari et al. 2010, Guida & Maria 2007, Li & Cai 2004, Li et al. 2006, Chi et al. 2003), truncated power-law (Jia et al. 2014, Bagler 2008, Xu & Harriss 2008, Han et al. 2007, Guimera et al. 2005), or exponential (Wang et al. 2011, da Rocha 2009). Categorizing distributions into true power-laws and log-normal is often difficult, especially in presence of random multiplicative processes (Newman 2005, Clauset et al. 2009). This problem is discussed by Azzam et al. (2013) in the context of worldwide air transportation network, observing a non-stationary behavior of the distributions.

We discuss region-specific studies, which analyze a subset (often domestic or continental) of the global aviation system. Many studies have been conducted on the United States domestic network, mainly due to the availability of data and the size of the network. Chi et al. (2003), Cheung & Gunes (2012), Jia & Jiang (2012) have revealed small-world characteristics of the network, scale-freeness, and disassortative mixing properties. The temporal evolution of the United States airport network at city level from 1990–2010 was analyzed by Jia et al. (2014) as well as by Lin & Ban (2014), respectively. Both showed that the network preserves scale-free, small-world, and disassortative mixing properties over time. Neal (2013) reviewed the business travel aviation network in the United States from 1993 to 2011 at node level, dyadic level, and system level. The system-wide analysis revealed that business travel among US cities is increasingly symmetric and evenly dispersed. Various studies have analyzed the complex network properties of the European aviation system as a complex network (Burghouwt & Hakfoort 2001, Burghouwt et al. 2003, Sun et al. 2015, Zanin 2015), including its community structure (Gurtner et al. 2014) and individual subnetworks, such as Italy (Guida & Maria 2007, Quartieri et al. 2008a,b), Portugal (Jimenez et al. 2012), and France (Thompson 2002). The third region of high interest is the Chinese airport network, see Li & Cai (2004), Wang et al. (2014). A few studies in the literature perform comparisons of subnetworks. Paleari et al. (2010) compared the structure and performance of the airport networks in US, Europe, and China in order to find out which network is most beneficial for the passengers. The results showed that the Chinese airport network provides the quickest travels for passengers; the US airport network is the most coordinated; while the European airport network provides the most homogeneous level of service. A dynamic fluctuation model is proposed by Zhang et al. (2014) and evaluated on the airport networks for China, Brazil, and Europe. Wandelt et al. (2019) provided a comprehensive comparison of domestic aviation network evolution for the years 2002 to 2013.

Given the wide application of tools for network science and the importance of designing resilient air transportation systems, a rich body of studies has emerged in recent years. It is beyond the scope of our study to review all existing papers on this subject. Instead, we report a few seminal papers. For a recent, broad overview on complex network-based robustness / resilience analysis, please refer to Wandelt et al. (2018) and Sun & Wandelt (2021).

Much of the literature on complex network robustness is concerned with the identification of important nodes. While defining a measure for computing the optimal ranking of nodes is straightforward (given a clear concept of dependency of the network on a specific node), these definitions are usually computationally intractable. Accordingly, many researchers have proposed different methods for node importance rankings, usually a) adapted from traditional node centrality using in network science or b) based on tailor-made, yet scalable definitions. We review studies which have appeared in the past twelve years below, based on the recent survey of Sun & Wandelt (2021).

Wilkinson et al. (2012) investigate the vulnerability of the European airport network to spatial hazards, arguing that spatially coherent phenomena are much more damaging than uniformly random ones. Conti et al. (2013) investigates disruptions to the airport network of the United States based on centralities, including PageRank, Hubs/Authorities, closeness, and betweenness. Kim & Anderson (2013) explore the robustness of network under dynamic attacker and defender interactions, with a use case on the United Staes airport network. Marzuoli et al. (2014) study the resilience

---

of the United States airport network under different attack strategies, including degree, distance strength, and outreach. The authors discuss the inherent vulnerability of the air transportation system. Wandelt et al. (2015) propose a novel node attack computation strategy for air transportation networks based on Monte-Carlo tree search, which scales up well to continental-sized airport networks. Requião da Cunha et al. (2015) design a so-called module-based attack method, based on topological communities, which is evaluated on the United States airport network. Clusella et al. (2016) report on the explosive percolation process, based on a subset of the global airline network. Cong et al. (2016) use spectral clustering to identify the critical airports in the Chinese airport network, leading to six distinct categories of criticality. Sun, Gollnick & Wandelt (2017) examine the resilience of the worldwide airport network under a wide range of targeted attacks, using difference attacking strategies and distinct resilience measures. Clark et al. (2018) compare a set of node properties on the United States air transportation network and dissect the nodes' central roles for robustness and recovery. Wen et al. (2018) propose a node importance ranking based on so-called no-return nodes. Results on the Chinese airport network and the United States airport network are reported. Wong et al. (2020) use data-driven methods to analyze the resilience of individual US airline networks; it is shown that simultaneously considering multiple approaches leads to more comprehensive understanding of the robustness. Sun et al. (2020b) identify the critical nodes in the air transportation city network, where nodes are aggregated from airports to cities, and links represent flights between cities. Chen et al. (2020) investigate the network robustness evolution of the Chinese air transportation city network from 1975 to 2017. Qian & Zhang (2022) take into account weights when analyzing the robustness of the Yangtze River Delta airport network. Ersoz et al. (2022) discusses the opening up of Turkey's aviation system under the perspective of resilience against COVID-19 from the perspective of complex networks.

In order to highlight the importance of complex network analysis to the Air Transport Research Society, we review related abstracts / presentations from the ATRS World Conference within the last six years, in historical order. Takada (2017) investigates historical changes of Japanese air transportation network. Various node / network properties were computed, including clustering coefficient, inter-vertex distance and the analysis of degree distribution changes in the network. Sallan (2017) develops a cascading failure model for air transportation, which is evaluated on the Oceanic air transport network for data in the year 2014. The effectiveness of various node attacking strategies is compared, including node degree, strength, betweenness, and random selection. Klophaus (2017) performs a complex network analysis for three major airline alliances: Star Alliance, Oneworld and Skyteam. The authors clarify differences between connectivity and vulnerability. Airlines are being ranked based on the order of importance regarding the network dismantling problem. It is found that the passengers of an airline are only loosely related to the importance within the airline alliance network. Kim (2019) surveys the robustness of the Northeast Asian air transport network using network science techniques. Properties such as the characteristic path length and clustering coefficient are reported; and a spatially-driven analysis of node importance is conducted. Li (2021) investigates the so-called morphological structure of China's civil aviation freight transport network using data for the years 2015 to 2019. The authors try to explore the nexus between the attributes of network and the influence factor. Liao (2021) analyzes the evolution of Chinese low-cost carriers in response to the COVID-19 pandemic, with a focus on Spring Airlines. Results concerning network connectivity and topological characteristics are discussed. Toledo (2021) presents an analysis of the Brazilian multiplex air transportation network where each layer corresponds to an individual airline. Results regarding degree distribution, efficiency, centrality, and node importance are discussed. Deng (2021) investigates the temporal evolution of the Chinese scheduled freighter networks for the years 2019 to 2021. The authors highlight small-world and scale-free properties and identify a set of critical nodes in the network. Jimenez (2022) analyzes the airline network of China using data for the years 2009 to 2019. While the authors present the overall structure and topological characteristics of the network, they propose a multi-layer realization of the system using three layers (i.e., core layer, bridge layer, periphery layer) based on k-core values. In addition, the value and node rankings based on various centrality metrics are reported. He (2022) categorizes market and network characteristics of Chinese international cargo charter services network in the year 2020 using network science techniques, among others. It is found that route diversity and density have quickly recovered from the impact of COVID-19. Sampaio (2022) analyzes the resilience of the Brazilian air traffic management system using complex network theory. The authors report that the network behaves similarly to a scale-free network, i.e., it is resistant to random failures, but vulnerable to targeted attacks.

3. Preliminaries

This section provides an overview on the network types in our study as well as the fundamental complex network characteristics and node centralities. For an in-depth review of complex networks and their applications, the readers are referred to Albert & Barabási (2002), Boccaletti et al. (2006), Costa et al. (2007, 2011), Barabasi (2013), Cimini et al. (2019). We start by revising the commonly-used definition of a complex network and then proceed to discuss three instances related to air transportation. The data used in this study was obtained from Sabre Market Intelligence [2].

Definition 1 (Complex network). *A complex network CN consists of a set of nodes, denoted with $nodes(CN)$ and a set of unweighted links between nodes, denoted with $links(CN)$. Each link is represented as a tuple (u, v), where u is the source*

---

[2]https://www.sabre.com/products/market-intelligence/

of the link and v is the target of the link. A link (u, v) is called outgoing *for node u and* incoming *for node v. The length of a path (a sequence of nodes $[u_1, ..., u_n]$) is defined as the sum of the weights, in an unweighted network this is the number of links on the path. A shortest path in a complex network between two nodes u and v is a sequence of nodes with the minimum path length. The number of shortest paths between nodes u and v is denoted with $\sigma_{u,v}$. Two nodes u and v are* connected, *if there exits at least one path from u to v.*

The most frequently used application of complex network to air transportation is presumably the so-called airport network, given the rather natural interpretation of nodes and links:

Definition 2 (Airport network). *An airport network APT is a complex network such that $nodes(APT)$ is a set of airports and $links(APT)$ contains all pairs of airports which have at least one direct flight in a specific period of study.*

While the airport network is undeniably of importance, it neglects one essential element of the aviation system: Airports are not evenly distributed across the land surface on earth. Instead, they tend to cluster together around populated areas, maybe with the most notable exception of the Arctic and polar areas. Generally, there are various metropolitan regions which are served by multiple airports. For instance, New York is served by seven airports and London is served by six airports[3]. Keeping this in mind, it is very natural to aggregate all airports serving a city into a single node, obtaining a city network:

Definition 3 (City network). *An airport network CIT is a complex network such that $nodes(CIT)$ is a set of cities and $links(CIT)$ contains all pairs of cities which have at least one direct flight in a specific period of study. The presence of a direct flight between two cities is evaluated based on a predefined mapping of airports to cities. In our study, the mapping comes directly from Sabre Market Intelligence.*

The third type of network in this study is a combination of airport networks and city networks, based on the notion of multiple-airport regions. Airports are the constituting elements for the nodes:

Definition 4 (Multiple-airport region network). *An multiple-airport region network MAR is a complex network such that $nodes(MAR)$ is a set of airports (representing specific airport regions) and $links(MAR)$ contains all pairs of regions which have at least one direct flight in a specific period of study.*

We have constructed the multiple-airport regions following the methodology of Sun, Wandelt, Hansen & Li (2017), briefly explained below. Using the Open Source Routing Machine (OSRM) (Luxen & Vetter 2011), the car driving times between all pairs of airports have been estimated. Then, we iterate over all airports in our study in the descending order of passengers (with the year 2019 as reference) and evaluate the driving distance to all other airports. Once the distance to the larger airport is below a threshold, we assign that airport as belonging to the MARs of the larger airport. In addition, we mark the airport as being assigned and do not try to reassign it in the future. The threshold for temporal distance is set to 2.5 hours in this study, which means, that if two airports are reachable within 2.5 hours by ground transportation, they are potentially merged.

Figure 2 provides an example of the three different network aggregations based on a small example for Great Britain and Ireland. Figure 2(left) shows the locations of 60 regularly served airports for these two countries. Figure 2(center) shows the locations of cities after aggregation from airport-level to city-level. The number of cities is slightly smaller than the number of airports in this example[4]. The reduction in our example is mainly due to the number of airports serving the Greater London region. In the city network aggregation, these airports are all represented by a single node. Figure 2(right) further aggregates the network by multiple-airport regions. It can be seen that the number of nodes is reduced significantly, compared to the two other aggregation levels, 22 airports (in MAR) versus 57 airports (in APT) and 53 cities (in CIT). The reason is that now airports are merged based on their ground accessibility, irrespective of the cities they are associated with. Two properties of the MAR aggregation should be noted. First, the airports are rather regularly distributed for most part of the two countries which is due to the contraction based on driving times. Second, the airports on islands are not aggregated. The rationale is that the islands have no driving connection and, accordingly, do not have a convenient ground alternative. While one could argue that these islands could be connected by ferry or similar services, we do not have global data for ferry connections, let alone their frequency.

A common problem in complex network analysis is the identification of node importance. Naturally, the definition of how important a node is in the network, depends on the dynamics one wants to consider. Table 1 revisits the definition of three frequently used node centralities. While the degree and clustering coefficient are local node centralities, since they only consider the neighborhood of a node when computing the centrality value, betweenness centrality requires global knowledge about the network. We briefly interpret the three metrics in context of aviation as follows. The degree of a node counts the number of nodes which can be reached by a direct flight; in case of the CIT / MAR network, this includes

---

[3]Determining the exact number of *serving* airports is non-trivial depends on the ground infrastructure, passenger choice models, and the selection of appropriate thresholds.

[4]The cities are determined by Sabre Market Intelligence.
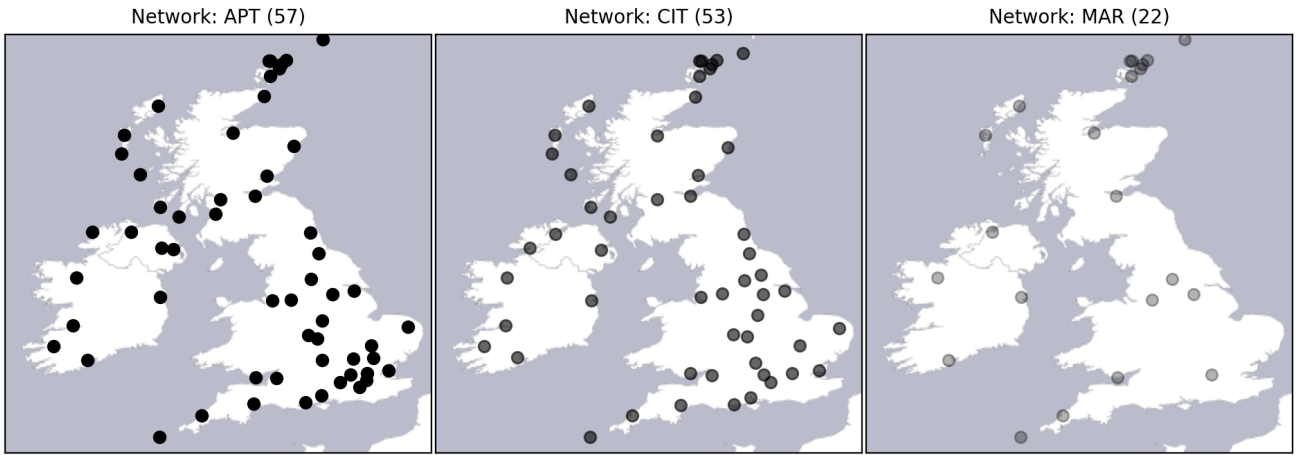
Figure 2: *Aggregation example for Great Britain and Ireland (only nodes are shown).*

additional ground-based transportation at the origin or destination. Sometimes normalized values are reported instead, where the degree is divided by the total number of nodes. The betweenness centrality of a node indicates how frequently this node lies on shortest paths in a network. This centrality is maybe the most mis-interpreted centrality in aviation research: The computation of this value assumes that there exist uniform demands between all pairs of nodes in the network; an assumption which is clearly invalid in reality. The demand across airports (and cities) is highly skewed and depends on population size, distance, economic indicators, and various other properties. Accordingly, one needs to be very careful, when taking the betweenness of a node as representative for its importance in the aviation system, while taking into account the true managerial implications. We will report on the extent of this effect in our analysis below (Section 4). The clustering coefficient - from a managerial perspective - asks how much connectivity does an airport / city provide to its connected airports, i.e., whether it is likely that these neighbored nodes are well-connected by themselves or not.

Table 1: *Commonly-used node centrality measures for the analysis of air transportation systems*

Metrics	Equation	Interpretation
Degree (centrality)	$k_i = \sum_j a_{ij}$	where a_{ij} is the connection between node i and node j: $a_{ij} = 1$ if there is a connection existing; $a_{ij} = 0$ otherwise. This metric refers to the number of connections with other nodes in the network.
Betweenness centrality	$B_i^w = \sum_{s \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}$	where σ_{st} is the number of shortest paths going from node s to node t; $\sigma_{st}(i)$ is the number of shortest paths going from node s to node t and passing through node i. This metric is proposed by Freeman (Freeman 1978) and it indicates the number of shortest paths going through a node.
Clustering coefficient	$C_i = \frac{\sum_{j,k} a_{ij} a_{ik} a_{jk}}{k_i(k_i-1)}$	where a_{ik} is the connection between node i and node k, a_{jk} is the connection between node j and node k. This metric gives an overall indication of how nodes are embedded in their neighborhood.

In addition to the node centralities introduced above, we review a set of network characteristics below. One interesting measure for complex networks is the so-called all-pairs shortest path average length. In an airport network, this indicator represents how many hops a passenger needs to make on average to travel from an origin to a destination, assuming a uniform demand across all node pairs in the network. If the network was fully connected, i.e., there is a flight between every airport pair, then the all-pairs shortest path average length would be one. Such a solution, however, is infeasible from a practical point of view, given the limited number of aircraft and the airlines' desire to be profitable. Accordingly, with a decreasing extent of being fully-connected, the average length increases. A related measure is the global efficiency of a network. The definition of network efficiency is based on the rationale that the efficiency is inversely proportional to the distance of node pairs in the network. The average efficiency is then defined as $E = \frac{1}{N*(N-1)} * \sum_{i \neq j \in nodes} \frac{1}{d_{i,j}}$, where N is the number of nodes and $d_{i,j}$ is the distance between Node i and Node j.

4. Analysis

This section reports our experimental results on the three network instances (APT, CIT, and MAR) over the period of twelve years. Section 4.1 investigates the evolution of network-level characteristics, including the number of nodes, the number of links, diameter, the global efficiency and the community structure of the network. Section 4.2 sheds light on

the importance of individual nodes and their centrality values, by reporting on the evolution of degree, betweenness, and clustering coefficient.

4.1. Evolution of network characteristics

The most fundamental aspects of a network are the number of its core entities: the number of nodes and the number of links. Figure 3 and Figure 4 reports the evolution of both indicators for the three network instances (APT: left, CIT: center, and MAR: right), respectively. The number of nodes and the number of links is continuously increasing from the year 2011 until the onset of the COVID-19 pandemic early in the year 2020. The increase in the number of nodes can be explained by a set of potential factors: the operation of new airports, increasing traffic which leads to exceeding the cut-off threshold for constructing the networks, as well as an increased coverage of Sabre Market Intelligence. Particularly the latter is hard to quantify from our side. Given the rather strong seasonality of these time series, we conjecture that the two former factors are much more significant in contribution than the latter. In fact, it is noteworthy how the growth and seasonality is clearly visible in all three network types. COVID-19 had a severe impact on all networks and both indicators, an effect which we will not discuss in detail here, since it has been covered extensively in the existing literature, see, e.g. Sun et al. (2020a). The most notable insight from the two figures is the year 2022, in which we can observe a recovery which not only outperforms pre-pandemic values but even closely reaches the pre-pandemic trends obtained by visually extrapolation of quarterly data from the year 2011 to 2019. This observation is striking, and it highlights that the aviation industry is back on the growth track. The moving average lags behind so far and the future will show whether this recovery is permanent or was more of a no-travel-restrictions release event in Q2/Q3 2022. Naturally, this recovery observation based on the number of nodes and links does not mean that the recovered aviation system is identical to the pre-pandemic one. Our analysis below will shed further light on the observable differences.
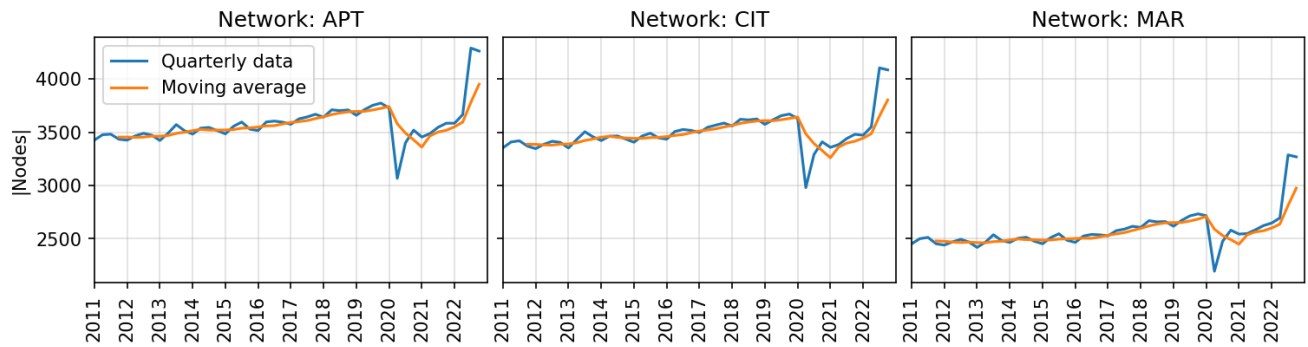

Figure 3: *Evolution of the number of nodes in the global aviation system at the three different layers.*
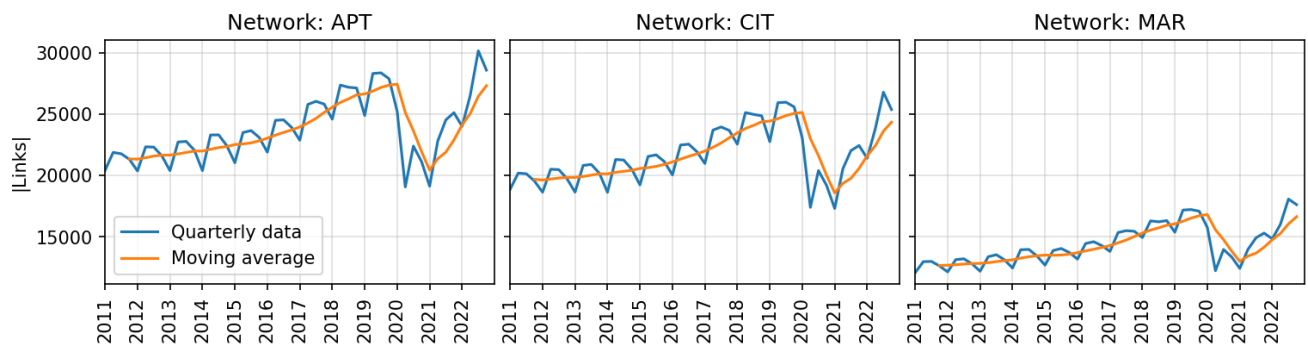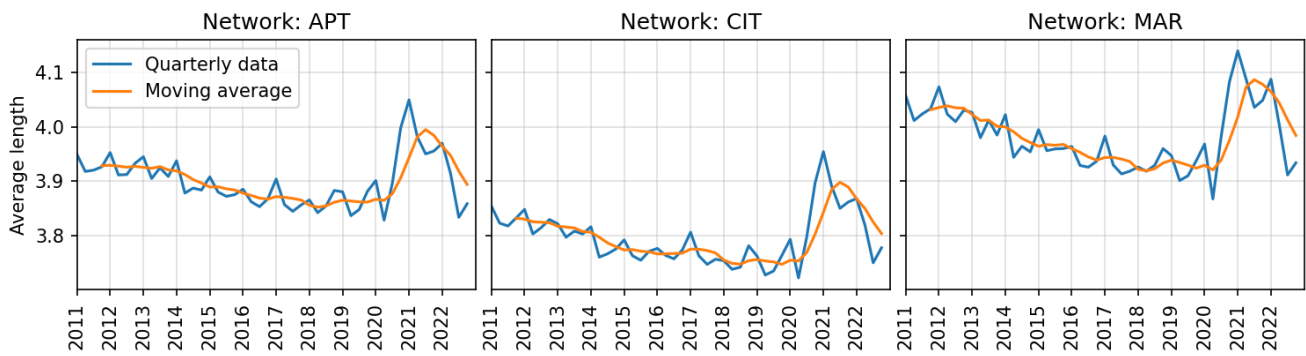

Figure 4: *Evolution of the number of links in the global aviation system at the three different layers.*

Figure 5 reports the evolution of the average path length on the three network types. The average number of hops is around 3.9 – 4.0. Before the onset of the COVID-19 pandemic, we can observe a slightly decreasing trend in the length, from 3.95 to 3.85 (for airports). During the pandemic, this indicator increased significantly, but has returned to near pre-pandemic levels in the year 2022.

The next complex network indicator in our analysis is global efficiency (Latora & Marchiori 2001). Intuitively, the definition of efficiency can be best understood in terms of communication systems: The underlying assumption is that efficiency is inversely proportional to distance. In terms of a network, the communication between nodes with a longer distance, is less efficient. In terms of aviation, one could describe such an inefficiency maybe best as inconvenience to the passenger, requiring more hops for reaching the destination. The global efficiency of a network is the sum over all reciprocal

Figure 5: *Evolution of the average all-pair shortest path length in the global aviation system at the three different layers.*

node pair distance divided by the maximum number of possible links for normalization. Figure 6 reports the evolution of global efficiency for the years 2011 – 2022. The overall magnitude of the indicator is rather stable over time ranging between 0.265 and 0.29 for all three network layers. There is a slightly increasing trend pre-pandemic. The impact of COVID-19 is apparent. In general, the global efficiency is believed to be more reliable than path-based measures (Bullmore & Sporns 2009). Accordingly, this indicates that the aviation community needs to work towards ensuring a fully-efficient recovery of the aviation system post-pandemic.
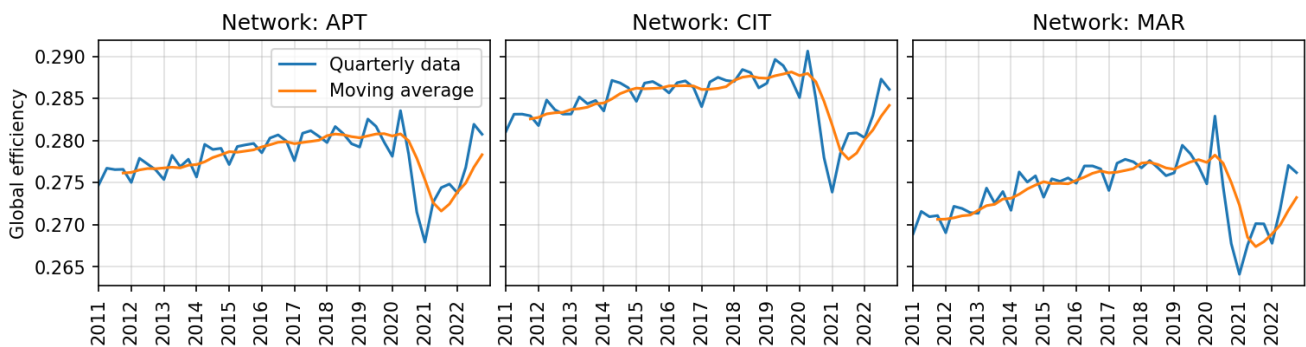
Figure 6: *Evolution of the global efficiency in the global aviation system at the three different layers.*

We analyze the community structure of the global airport network for the third quarter of the year 2022 in Figure 7. The communities were computed based on the Louvain method for community detection (Blondel et al. 2008). Intuitively, the method aims to optimize the density of links inside communities compared to links between communities, iteratively defining new community assignments until no further refinements are possible or a predefined minimum improvement step is not achieved. In total, we obtain eight larger communities for the airport network. The largest community - in terms of the number of nodes - is constituted by airports in North America (except from Canada and parts of Alaska). This shows that the United States are much better integrated with their Southern neighbors (e.g., Mexico, Bahamas, and various Caribbean holiday destinations), compared to their Northern neighbor Canada. The second largest community surprisingly consists of Africa, Oceania, and South-Asia (notably without China). The next communities are covering Europe, South America, and China, respectively. The case of China is very interesting, as China was well integrated into its neighborhood before the onset of the COVID-19 pandemic, but isolated itself for a period of almost three years. This isolation presumably had an impact on the entire South-East Asian aviation market. It will be interesting to see the future development in this area, given that China has just released all aviation policy restrictions in early 2023.

4.2. Evolution of nodal centralities

In the following part of our evaluation, we will investigate the evolution of three node centralities. We begin with the degree, which measures the number (or fraction in case of centrality) of destinations which are reachable by a direct flight. Figure 8 reports the evolution of the average degree, aggregated over all nodes in the network. The average degree varies between 9.5 and 15 for all three network layers. Between the years 2011 and 2019, this value increased by roughly 2.5, which means that airports (or cities) were increasingly connected to two or three more other entities at the end of the period. During the recovery from COVID-19, in the year 2022, we are back to 2017/2018 levels concerning all three network instances. The degree in MAR is slight lower (two nodes) than in APT / CIT networks, but the overall evolution trend is highly similar.

Figure 9 visualizes the evolution of the top degree nodes in the aviation system. For each network, we have selected the top 12 nodes with the highest average degree over the entire period in our study. These nodes are reported with their IATA
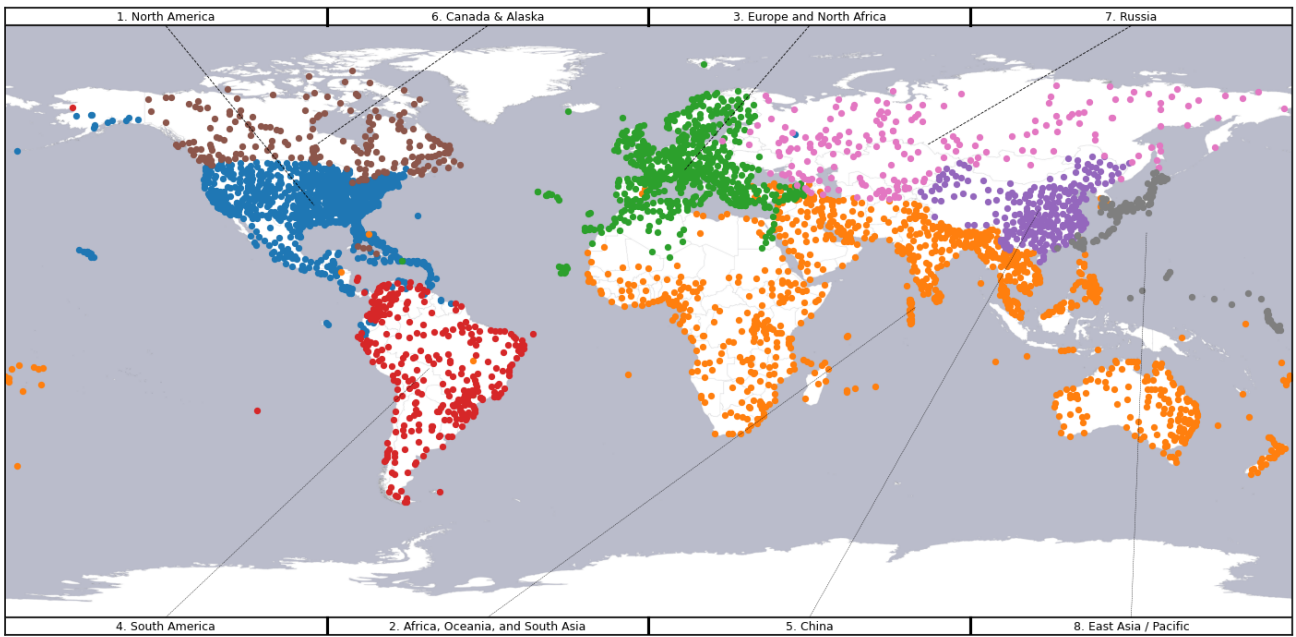
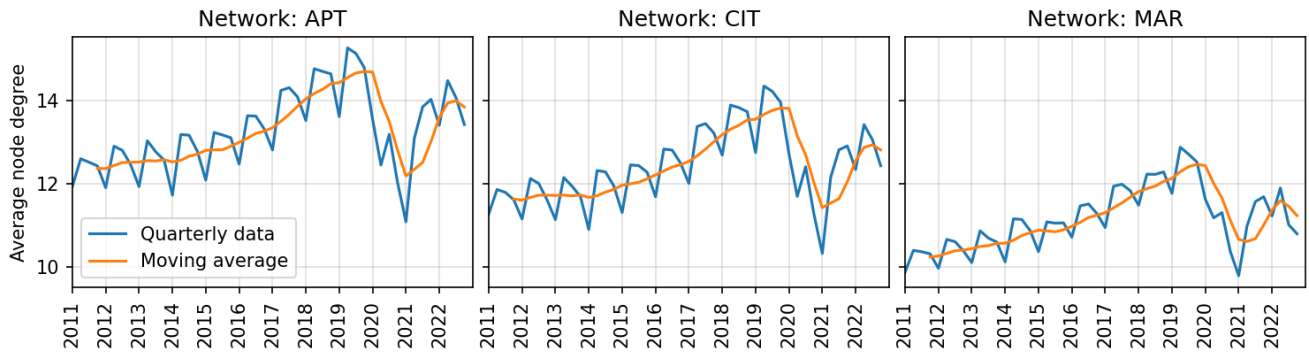**Figure 7:** *Communities in the global airport network.*

Figure 8: *Evolution of the average degree in the global aviation system at the three different layers.*

codes (for airports) and city codes (for cities). Before the onset of the COVID-19 pandemic, the ranking of top nodes was considerably stable, FRA being the highest ranked airport (in APT and MAR) and LON (London) being the highest ranked city. During the pandemic and also in the recovery, the rankings of nodes are largely shuffled, indicating a structurally changed aviation system, where the important roles have undergone unprecedented changes.

Given the trend of growing average degrees in the system, Figure 10 further investigates which nodes are growing most. We have computed the changes in degree for each quarter with respect to the previous year's quarter and color coded the fraction of airports which have grown in degree (from red indicating 0% to blue indicating 100%). We have grouped airports along the y-axis according the log of degree in the year. The airports with the lowest degrees (bottom row in Figure 10) are most coherently growing, indicating by the blue color. The higher the degree an airport (moving up along the y-axis), the fewer airports have increased their degrees further, with a notable exception around the years 2017 and 2018: In both years we find that almost all airports with the highest degree have succeeded in increasing the degree. Furthermore, we can see the obvious impact of the COVID-19 pandemic, in which all airports have lost their connectivity (indicated by the red color). The extent of degree reductions coherence inside a class correlated with the airport size. This indicates that some smaller airports indeed went better through the pandemic, by maintaining their degrees between 2020 and 2021, i.e, during the peak pandemic impact on aviation. The listed observations are consistent for all three network layers under investigation.

Figure 11 performs a comparison of node degree against a more realistic measure of node importance: the ticket-based OD centrality, for data of Q3 2022 in the global airport network. This centrality measures the fraction of tickets a node appears in as an intermediate stopover. More specifically, we have iterated all passenger tickets available from Sabre Market Intelligence which involved more than one hop and then counted how often each airport (or city) appeared on the ticket. This number is normalized by dividing through the total number of tickets. We visualize the result as a scatter plot where degree is shown along the x-axis and OD centrality on the y-axis. If both metrics were perfectly correlated, then all markers
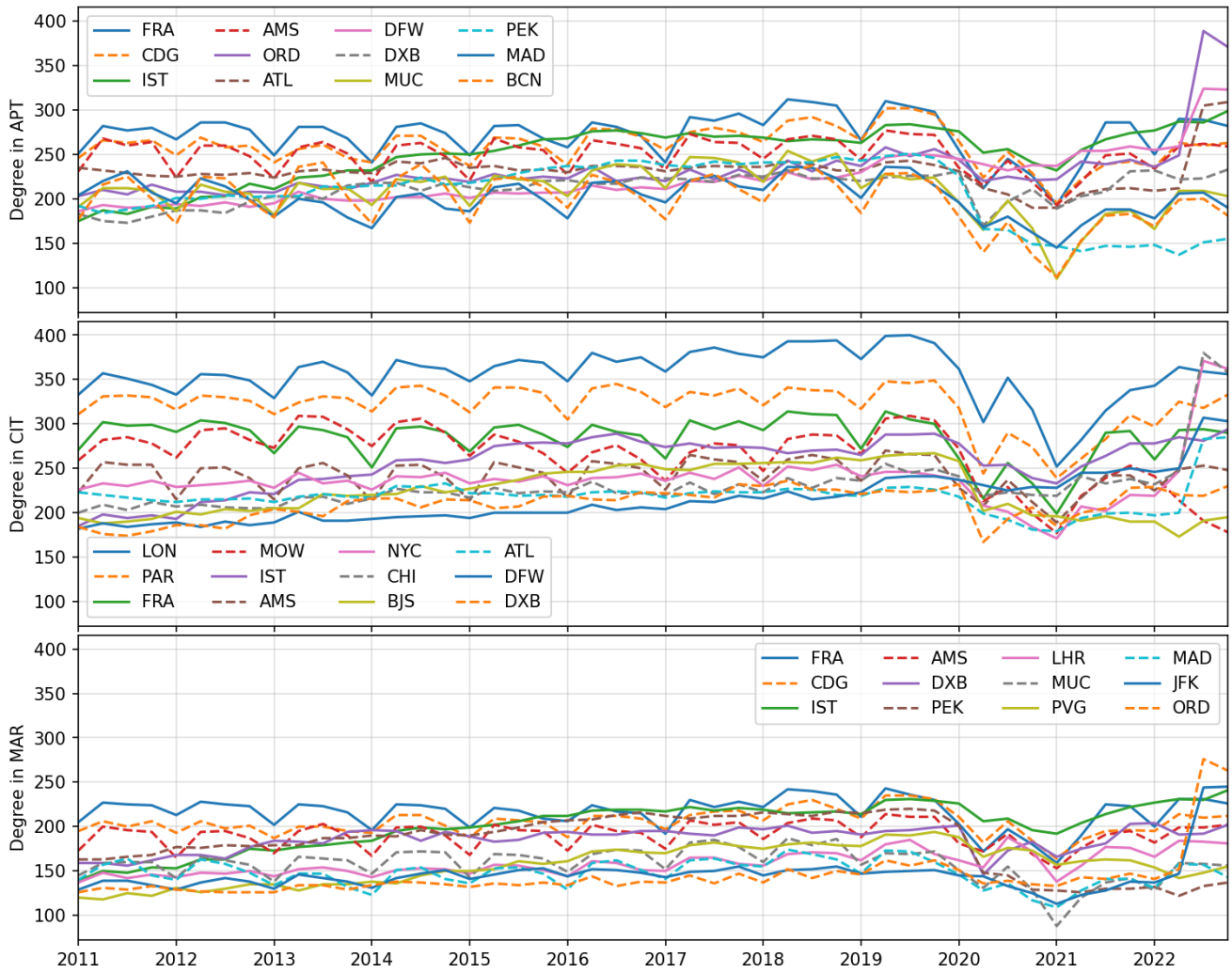
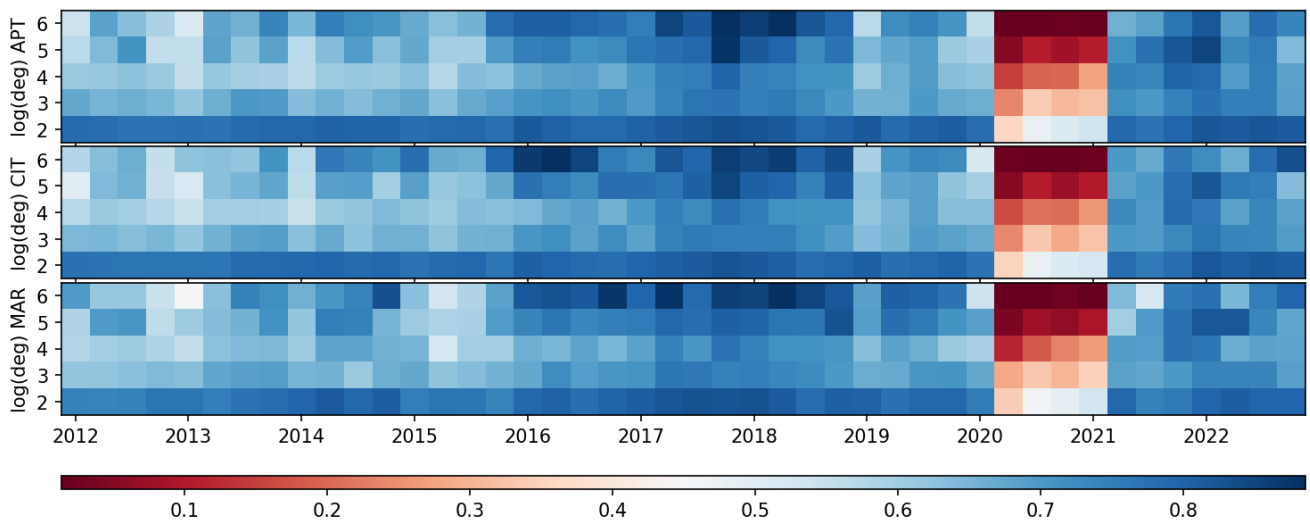**Figure 9:** *Evolution of top 12 degree nodes.*

Figure 10: *Changes of degree in the global aviation system.*

would be located along the dashed diagonal. We find that there exists a positive correlation between both indicators (the Pearson correlation coefficient is 0.71 at a p-value of 0.0). Nevertheless, there exist airports with high OD centrality and low degree centrality (e.g., Hamad International Airport, DOH) and vice versa (e.g., Boston Logan International Airport, BOS and Harry Reid International Airport, LAS). The latter airports do provide an efficient service for their local population, by

providing connections to many destinations, but do not play a significant role as a hub - presumably due to their location inside the United States and post-COVID-19 ramifications. This highlights that using the degree for measuring the extent of being a (true) hub in the aviation system should be done with care, as the potential connectivity does not necessarily imply that a node is indeed used as a hub.
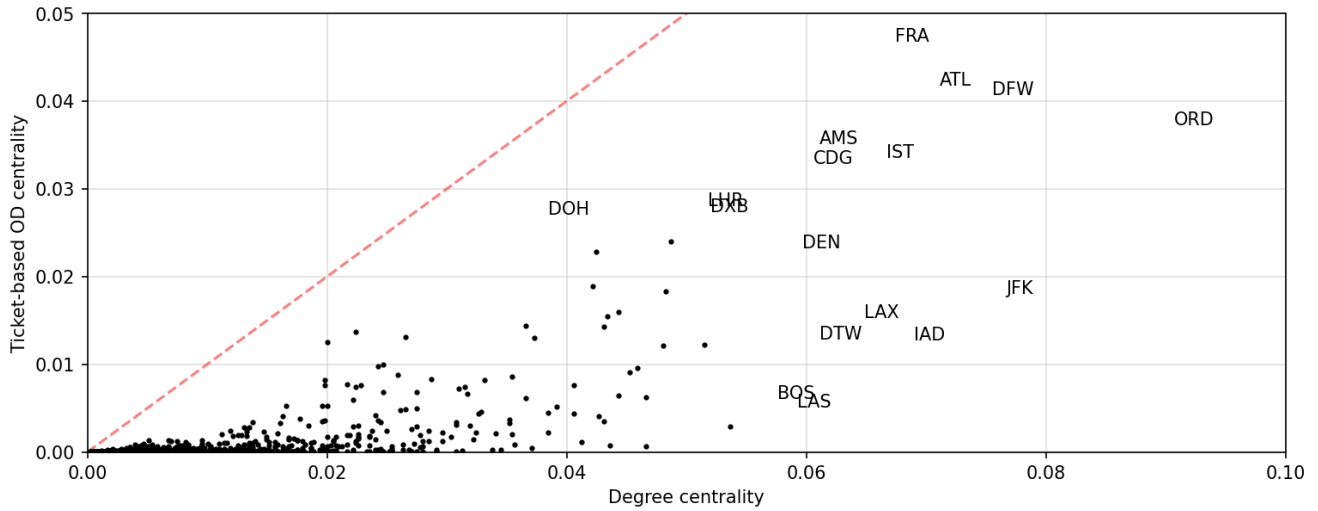

Figure 11: *Comparison of degree centrality and ticket-based OD centrality for Q3 2022 in APT.*

In the next experiments, we investigate the betweenness of nodes. Figure 12 visualizes the evolution of system-average betweenness centrality values. Overall, we can observe a slightly decreasing trend of the metric pre-COVID-19, which indicates that the role of individual roles as network hubs is slightly decreasing. The betweenness saw a spike during the COVID-19 pandemic. Yet, during the year 2022, the value has essentially returned to its pre-pandemic trend. Figure 13 compares the values of betweenness centrality against ticket-based OD centrality for Q3 2022 in the global airport network. The extent of correlation with betweenness is larger than degree (the Pearson correlation coefficient is 0.80 at a p-value of 0.0). We can, again, airports with high OD centrality and low betweenness centrality (e.g., Charlotte Douglas International Airport, CLT and Munich International Airport, MUC) and vice versa (e.g., Ted Stevens Anchorage International Airport, ANC and Los Angeles International Airport, LAX). Especially the case of Ted Stevens Anchorage International Airport has become infamous in the network science literature, as an outstanding example for an airport with a large mismatch between degree and betweenness, given its central role in accessing other airports in and around Alaska.
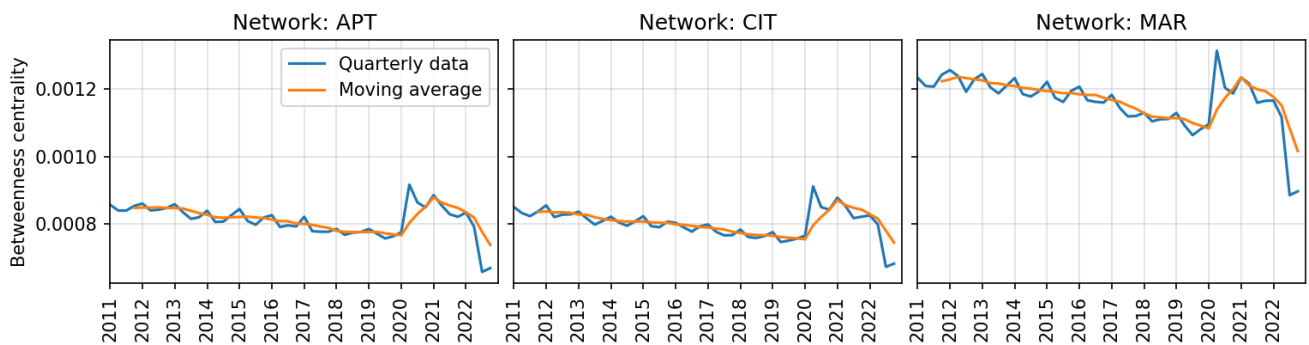

Figure 12: *Evolution of the average betweenness centrality in the global aviation system.*

Next, we investigate the clustering coefficient of nodes. Figure 14 visualizes the evolution of system-average clustering coefficient values. For APT and CIT, this metric is rather stable, only interrupted by the impact of the COVID-19 pandemic in 2020 and 2021. For MAR, however, we can observe and increasing trend from 0.5 to 0.52. This increase shows that at the MAR level, the neighbors of nodes get increasingly connected, which indicates a potential reduction in hubbing effects in the global aviation system. This trend seems to be manifested even during the recovery process. Figure 15 complements our analysis by reporting the scatter plot between OD centrality and clustering coefficient. Contrary to degree and betweenness, we can observe that the OD critical nodes have lower values of clustering coefficient. This observation is intuitive, given that hubs should connect preferably disconnected nodes. The correlation between the two measures is relatively weak (the Pearson correlation coefficient is -0.21 at a p-value of 0.0). The presence of some nodes with high OD centrality and large clustering coefficient are interesting, managerial wise. For instance, the position of Munich International Airport
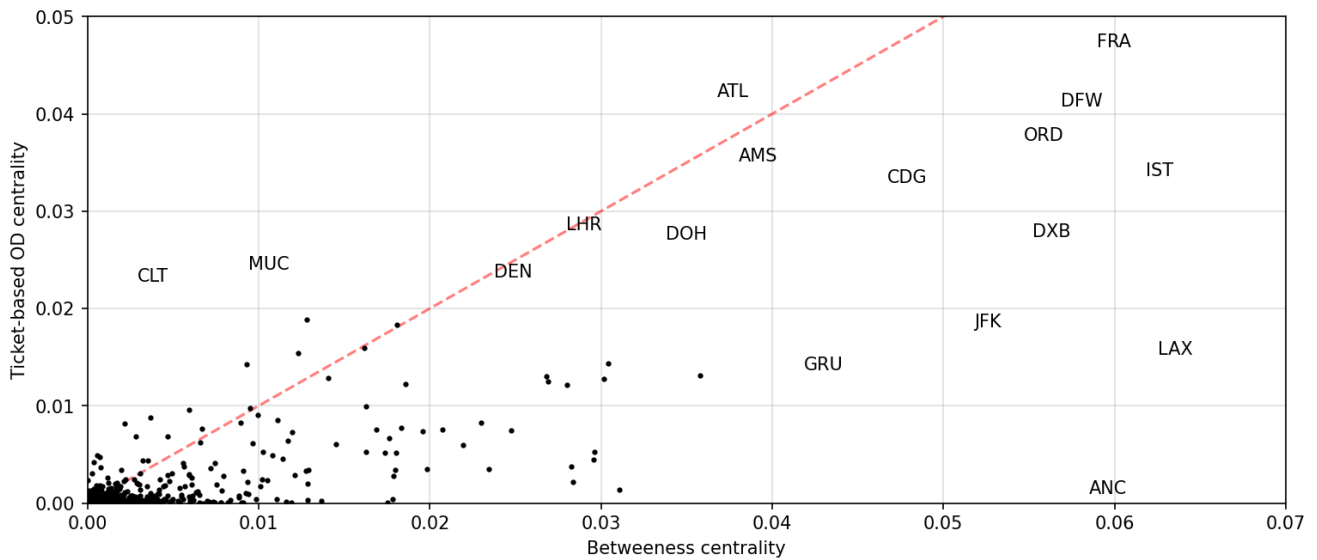
Figure 13: Comparison of betweenness centrality and ticket-based OD centrality for Q3 2022 in APT.

(MUC) can be explained by the prominent role of Lufthansa at this airport. Accordingly, a significant number of tickets have MUC as an intermediate stop, while other airlines might actually connect their origin and destination by direct flights. Accordingly, we believe that the clustering coefficient deserves more attention by researchers in the future.
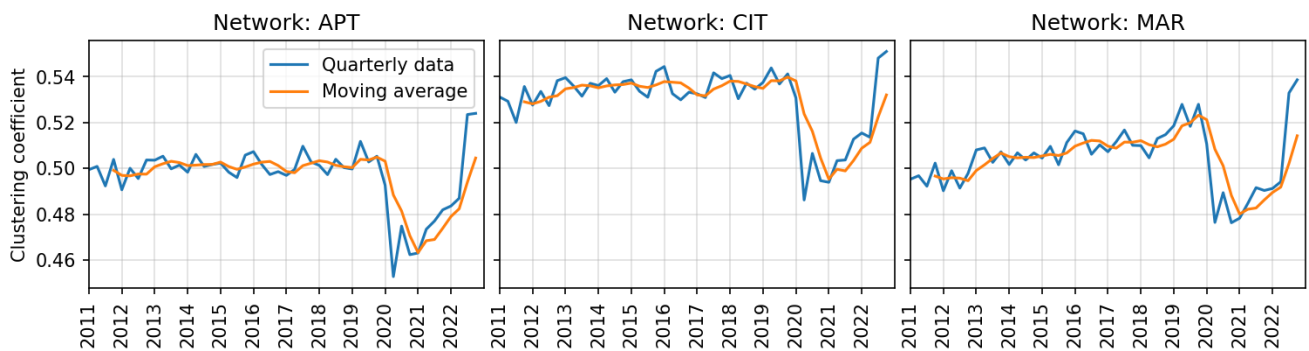

Figure 14: Evolution of the clustering coefficient in the global aviation system.

5. Discussion

We review the major findings of our study in this section and provide a set of recommendations for future work. These major findings and their recommendations are discussed in individual subsections, respectively.

5.1. Explaining the mismatch between global city and MAR network

In our analysis we have found that the CIT and MAR network reveal distinct characteristics. MAR had a lower average degree and a higher average betweenness compared to CIT. In addition, we found the MAR network to be relatively less efficient than the CIT network. While some of these results could change depending on the availability of data at city level and the resolution, the difference is striking, given that both of these networks aim to measure the same phenomenon: How do groups of airports interact in the global aviation system? Accordingly, we believe that there is room for future work on this subject, especially concerning the development of a realistic and representative measure for aggregation. Many studies in the literature still use hard-coded line-by-sight distance threshold, despite the availability of more realistic criteria such as the ground-based driving distance, applied in this study.

5.2. A more realistic node importance measure

We have used a ticket-based OD centrality measure as reference for node importance in our study. Our findings show that neither of the complex network measures adequately represent the node importance. While betweenness centrality reaches a rather high extent of correlation, there are significant differences especially for nodes with high betweenness values. Accordingly, betweenness centrality could be used to filter out unimportant nodes, but not for obtaining a clear ranking of
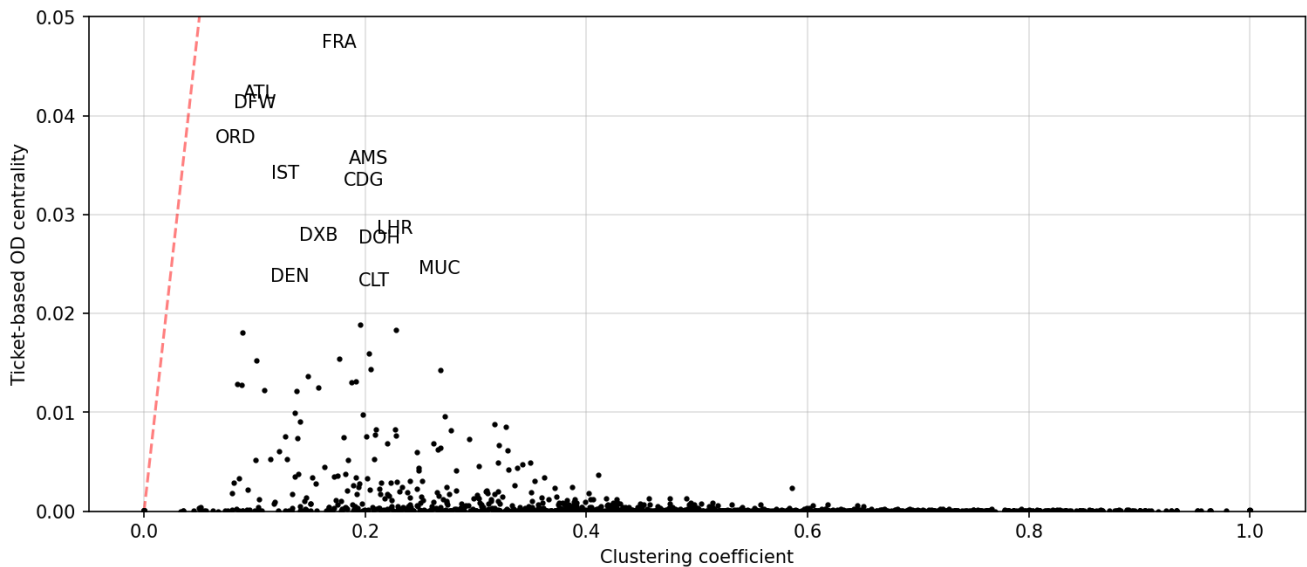
Figure 15: Comparison of clustering coefficient and ticket-based OD centrality for Q3 2022 in APT.

the top nodes. This fact should be considered carefully in future studies. Especially when constructing econometric models, degree and betweenness of a network are often used as proxies for importance. There is a need for research which develops better estimation techniques and takes into account universal patterns present in the global aviation system. In this light, we would like to explicitly mention the need for models which considers actual aircraft operations for the identification of true node importance.

5.3. Other network types

While we have analyzed three network types which are most prevalent in aviation research, there are other networks which could be further investigated using network science techniques. Particularly, we see two major areas here. First, we believe that the analysis of time-space networks - as they are inherent to aircraft as assignment and routing algorithms, could lead to interesting results, not only regarding empirical analysis but also as a potential driver for guiding optimization algorithms / heuristics. Second, there is a need for better understanding multi-modal interactions, most importantly with respect to high-speed railway. The analysis of multi-modal networks, especially at larger scale, could lead to the identification of universal insights and improvements of our transportation system.

5.4. Reproducible data / network models for aviation research

We presume that few studies in the literature analyze the global aviation system due to the limited availability of the data. While some of the data can be obtained commercially, like we did from Sabre Market Intelligence, such acquisitions come with significant costs and also non-disclosure agreements. Accordingly, we would like to motivate the research community to develop better models for generating system-representations alike to our global aviation system. The fundamental gravity model of trade - still used in studies to date - is nearly 70 years old (Isard 1954). Given the emergence of data science and increasing availability of big data, it should be possible to derive methodologically-novel models which describe the complex patterns in aviation to a better extent than simple gravity models do. Here, we would like to highlight particularly the promising usage of grid-based datasets covering, e.g., population density, census information, and possibly transportation-related data. Using such grid-based data will likely lead to novel insights beyond the traditional view of cities as atomic spatial entities.

Acknowledgement

References

Albert, R. & Barabási, A.-L. (2002), 'Statistical mechanics of complex networks', *Reviews of modern physics* **74**(1), 47.

Albert, R., Jeong, H. & Barabasi, A.-L. (2000), 'Error and attack tolerance of complex networks', *Nature* **406**, 378–382.

Azzam, M., Klingauf, U. & Zock, A. (2013), 'The accelerated growth of the worldwide air transportation network', *The European Physical Journal Special Topics* **212**, 35–48.

Bagler, G. (2008), 'Analysis of the airport network of India as a complex weighted network', *Physica A: Statistical Mechanics and its Applications* **387**(12), 2972–2980.

Bagler, G. & Sinha, S. (2005), 'Network properties of protein structures', *Physica A: Statistical Mechanics and its Applications* **346**(12), 27 – 33.
  URL: *http://www.sciencedirect.com/science/article/pii/S0378437104011586*

Barabasi, A.-L. (2013), 'Network science', *Philosophical Transactions of the Royal Society A: Mathematical,Physical and Engineering Sciences* **371**(1987).
  URL: *http://rsta.royalsocietypublishing.org/content/371/1987/20120375.abstract*

Barabási, A.-L. & Albert, R. (1999), 'Emergence of scaling in random networks', *Science* **286**(5439), 509–512.
  URL: *http://www.sciencemag.org/cgi/content/abstract/286/5439/509*

Barabâsi, A.-L., Jeong, H., Néda, Z., Ravasz, E., Schubert, A. & Vicsek, T. (2002), 'Evolution of the social network of scientific collaborations', *Physica A: Statistical mechanics and its applications* **311**(3-4), 590–614.

Blondel, V. D., Guillaume, J.-L., Lambiotte, R. & Lefebvre, E. (2008), 'Fast unfolding of communities in large networks', *Journal of statistical mechanics: theory and experiment* **2008**(10), P10008.

Boccaletti, S., Latora, V., Moreno, Y., Chavez, M. & Hwang, D.-U. (2006), 'Complex networks: Structure and dynamics', *Physics reports* **424**(4), 175–308.

Bounova, G. A. (2009), Topological evolution of networks: case studies in the US airlines and language Wikipedias, PhD thesis, Department of Aeronautics and Astronautics, Massachusetts Institute of Technology.

Bullmore, E. & Sporns, O. (2009), 'Complex brain networks: graph theoretical analysis of structural and functional systems', *Nature reviews neuroscience* **10**(3), 186–198.

Burghouwt, G. & Hakfoort, J. (2001), 'The evolution of the European aviation network', *Journal of Air Transport Management* **7**(5), 311–318. Developments in the Deregulated Air Transport Market.

Burghouwt, G., Hakfoort, J. & Ritsema van Eck, J. (2003), 'The spatial configuration of airline networks in Europe', *Journal of Air Transport Management* **9**(5), 309–323.

Callaway, D. S., Newman, M. E., Strogatz, S. H. & Watts, D. J. (2000), 'Network robustness and fragility: Percolation on random graphs', *Physical review letters* **85**(25), 5468.

Chen, Y., Wang, J. & Jin, F. (2020), 'Robustness of china's air transport network from 1975 to 2017', *Physica A: Statistical Mechanics and its Applications* **539**, 122876.
  URL: *https://www.sciencedirect.com/science/article/pii/S0378437119316334*

Cheung, D. P. & Gunes, M. H. (2012), A Complex Network Analysis of the United States Air Transportation, *in* 'Advances in Social Networks Analysis and Mining (ASONAM), 2012 IEEE/ACM International Conference on', pp. 699–701.

Chi, L.-P., Wang, R., Su, H., Xu, X.-P., Zhao, J.-S., Li, W. & Cai, X. (2003), 'Structural Properties of US Flight Network', *Chinese Physics Letters* **20**(8), 1393.
  URL: *http://stacks.iop.org/0256-307X/20/i=8/a=362*

Cimini, G., Squartini, T., Saracco, F., Garlaschelli, D., Gabrielli, A. & Caldarelli, G. (2019), 'The statistical physics of real-world networks', *Nature Reviews Physics* **1**(1), 58–71.

Clark, K. L., Bhatia, U., Kodra, E. A. & Ganguly, A. R. (2018), 'Resilience of the us national airspace system airport network', *IEEE Transactions on Intelligent Transportation Systems* **19**(12), 3785–3794.
  URL: *https://ieeexplore.ieee.org/document/8306449*

Clauset, A., Shalizi, C. R. & Newman, M. E. J. (2009), 'Power-law distributions in empirical data', *SIAM Review* **51**(4), 661–703.

Clusella, P., Grassberger, P., Pérez-Reche, F. J. & Politi, A. (2016), 'Immunization and targeted destruction of networks using explosive percolation', *Phys. Rev. Lett.* **117**, 208301.
  URL: *https://link.aps.org/doi/10.1103/PhysRevLett.117.208301*

Cohen, R., Erez, K., Ben-Avraham, D. & Havlin, S. (2000), 'Resilience of the internet to random breakdowns', *Physical review letters* **85**(21), 4626.

Cong, W., Hu, M., Dong, B., Wang, Y. & Feng, C. (2016), 'Empirical analysis of airport network and critical airports', *Chinese Journal of Aeronautics* **29**(2), 512 – 519.
  URL: *http://www.sciencedirect.com/science/article/pii/S1000936116000376*

Conti, E., Cao, S. & Thomas, A. (2013), 'Disruptions in the us airport network', *arXiv preprint arXiv:1301.2223* .
  URL: *https://arxiv.org/abs/1301.2223*

Costa, L. d. F., Oliveira Jr, O. N., Travieso, G., Rodrigues, F. A., Villas Boas, P. R., Antiqueira, L., Viana, M. P. & Correa Rocha, L. E. (2011), 'Analyzing and modeling real-world phenomena with complex networks: a survey of applications', *Advances in Physics* **60**(3), 329–412.

Costa, L. d. F., Rodrigues, F. A., Travieso, G. & Villas Boas, P. R. (2007), 'Characterization of complex networks: A survey of measurements', *Advances in physics* **56**(1), 167–242.

da Rocha, L. E. (2009), 'Structural evolution of the Brazilian airport network', *Journal of Statistical Mechanics: Theory and Experiment* **2009**(04), P04020.
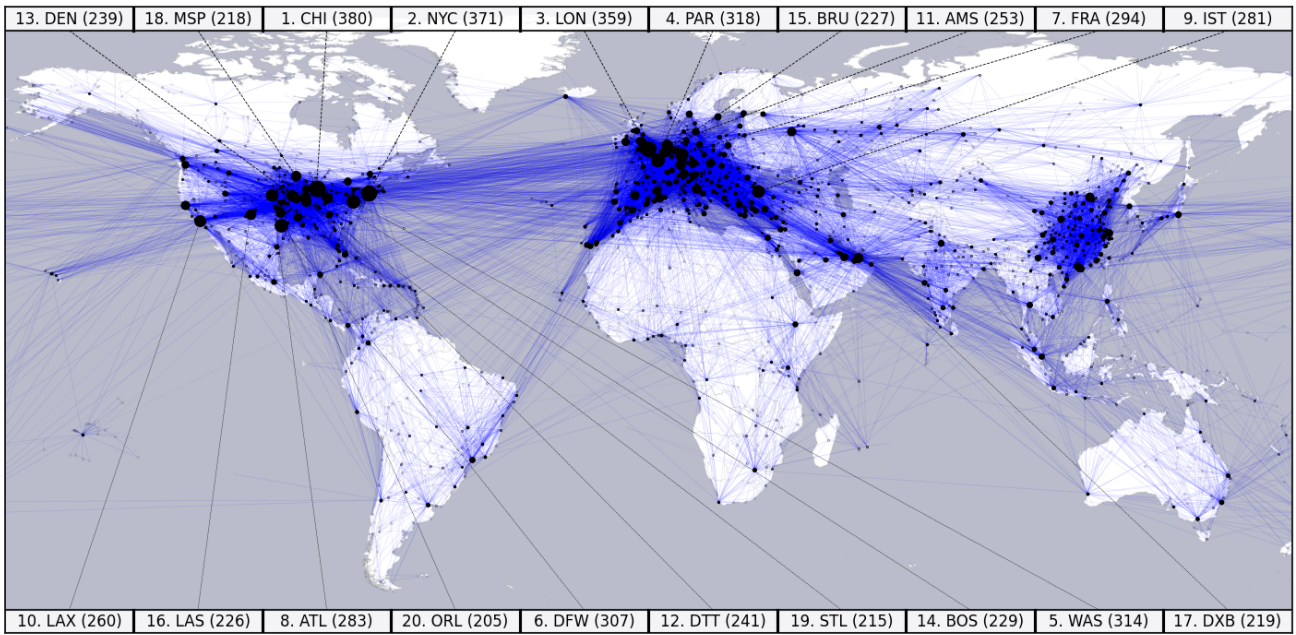
Deng, Y. (2021), Scheduled freighter network analysis of chinese cargo airlines in the course of covid-19 pandemic, *in* 'Proceedings of the Air Transport Research Society (ATRS) 24th Annual World Conference'.

Ersoz, C., Kilic, S. & Aldemir, H. O. (2022), 'Analysis of turkey's airport network structure and centrality in the opening-out period after the first wave of covid-19: A complex network approach', *Case Studies on Transport Policy* **10**(4), 2506–2518.

Freeman, L. C. (1978), 'Centrality in social networks conceptual clarification', *Social Networks* **1**(3), 215 – 239.
URL: *http://www.sciencedirect.com/science/article/pii/0378873378900217*

Gautreau, A., Barrat, A. & Barthélemy, M. (2009), 'Microdynamics in stationary complex networks', *Proceedings of the national academy of sciences* **106**(22), 8847–8852.

Guida, M. & Maria, F. (2007), 'Topology of the Italian airport network: A scale-free small-world network with a fractal structure?', *Chaos, Solitons & Fractals* **31**(3), 527 – 536.
URL: *http://www.sciencedirect.com/science/article/pii/S0960077906001792*

Guimera, R., Mossa, S., Turtschi, 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* **102**(22), 7794–7799.

Gurtner, G., Vitali, S., Cipolla, M., Lillo, F., Mantegna, R. N., Micciche, S. & Pozzi, S. (2014), 'Multi-scale analysis of the european airspace using network community detection', *PloS one* **9**(5), e94414.

Han, D.-D., Qian, J.-H. & Liu, J.-G. (2007), 'Network Topology of the Austrian Airline Flights', *arXiv:physics/0703193* .

He, Y. (2022), Evolution of international cargo charter flights under covid-19 pandemic impacted environment in china, *in* 'Proceedings of the Air Transport Research Society (ATRS) 25th Annual World Conference'.

Isard, W. (1954), 'Location theory and trade theory: short-run analysis', *The Quarterly Journal of Economics* **68**(2), 305–320.

Jia, T. & Barabási, A.-L. (2013), 'Control capacity and a random sampling method in exploring controllability of complex networks', *Scientific Reports* **3**, 2354.

Jia, T. & Jiang, B. (2012), 'Building and analyzing the US airport network based on en-route location information', *Physica A: Statistical Mechanics and its Applications* **391**(15), 4031 – 4042.
URL: *http://www.sciencedirect.com/science/article/pii/S0378437112002257*

Jia, T., Qin, K. & Shan, J. (2014), 'An exploratory analysis on the evolution of the US airport network', *Physica A: Statistical Mechanics and its Applications* **413**(0), 266 – 279.
URL: *http://www.sciencedirect.com/science/article/pii/S0378437114005482*

Jimenez, E. (2022), An in-depth analysis of multi-layer interactions in the domestic air transport network of china: 2009-2019, *in* 'Proceedings of the Air Transport Research Society (ATRS) 25th Annual World Conference'.

Jimenez, E., Claro, J. & de Sousa, J. P. (2012), 'Spatial and commercial evolution of aviation networks: a case study in mainland portugal', *Journal of transport geography* **24**, 383–395.

Kim, H. & Anderson, R. (2013), 'An experimental evaluation of robustness of networks', *IEEE Systems Journal* **7**(2), 179–188.
URL: *https://ieeexplore.ieee.org/abstract/document/6414589*

Kim, S. (2019), Robustness analysis of the northeast asian air transport network as a complex network, *in* 'Proceedings of the Air Transport Research Society (ATRS) 23th Annual World Conference'.

Klophaus, R. (2017), Network vulnerability analysis of star alliance, oneworld and skyteam, *in* 'Proceedings of the Air Transport Research Society (ATRS) 21th Annual World Conference'.

Latora, V. & Marchiori, M. (2001), 'Efficient behavior of small-world networks', *Physical review letters* **87**(19), 198701.

Li, J. (2021), The morphological structure and influence factors analysis of china's civil aviation freight transport network, *in* 'Proceedings of the Air Transport Research Society (ATRS) 24th Annual World Conference'.

Li, W. & Cai, X. (2004), 'Statistical analysis of airport network of China', *Physical Review E* **69**, 046106.

Li, W., Wang, Q. A., Nivanen, L. & Le Mehaute, A. (2006), 'How to fit the degree distribution of the air network?', *Physica A: Statistical Mechanics and its Applications* **368**(1), 262 – 272.
URL: *http://www.sciencedirect.com/science/article/pii/S0378437106001051*

Liao, M. (2021), Network change of low-cost carriers during the post covid-19 era, *in* 'Proceedings of the Air Transport Research Society (ATRS) 24th Annual World Conference'.

Lin, J. & Ban, Y. (2013), 'Complex network topology of transportation systems', *Transport reviews* **33**(6), 658–685.

Lin, J. & Ban, Y. (2014), 'The evolving network structure of US airline system during 1990–2010', *Physica A: Statistical Mechanics and its Applications* **410**(0), 302 – 312.
URL: *http://www.sciencedirect.com/science/article/pii/S037843711400421X*

Luxen, D. & Vetter, C. (2011), Real-time routing with openstreetmap data, *in* 'Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems', GIS '11, Association for Computing Machinery, New York, NY, USA, p. 513–516.
URL: *https://doi.org/10.1145/2093973.2094062*

Marzuoli, A., Feron, E. & Boidot, E. (2014), 'Resilience of the national airspace system structure: A data-driven network approach', *AIAA/IEEE Digital Avionics Systems Conference - Proceedings* pp. 1D21–1D213.

Neal, Z. (2013), 'Evolution of the business air travel network in the US from 1993 to 2011: A descriptive analysis using AIRNET', *Research in Transportation Business & Management* 9(0), 5–11. International Business Travel.
  URL: *http://www.sciencedirect.com/science/article/pii/S2210539513000382*

Neal, Z. (2014), 'The devil is in the details: Differences in air traffic networks by scale, species, and season', *Social networks* **38**, 63–73.

Newman, M. E. (2010), *Networks-An Introduction*, Oxford University Press.

Newman, M. E. J. (2005), 'Power laws, Pareto distributions and Zipf's law', *Contemporary Physics* **46**, 323–351.
  URL: *http://arxiv.org/abs/cond-mat/0412004*

Pagani, G. A. & Aiello, M. (2013), 'The power grid as a complex network: a survey', *Physica A: Statistical Mechanics and its Applications* **392**(11), 2688–2700.

Paleari, S., Redondi, R. & Malighetti, P. (2010), 'A comparative study of airport connectivity in China, Europe and US: Which network provides the best service to passengers?', *Transportation Research Part E: Logistics and Transportation Review* **46**(2), 198 – 210.
  URL: *http://www.sciencedirect.com/science/article/pii/S1366554509001094*

Palla, G., Derényi, I., Farkas, I. & Vicsek, T. (2005), 'Uncovering the overlapping community structure of complex networks in nature and society', *Nature* **435**(7043), 814–818.

Papatheodorou, A. & Arvanitis, P. (2009), 'Spatial evolution of airport traffic and air transport liberalisation: the case of Greece', *Journal of Transport Geography* **17**(5), 402 – 412.
  URL: *http://www.sciencedirect.com/science/article/pii/S0966692308000872*

Qian, B. & Zhang, N. (2022), 'Topology and robustness of weighted air transport networks in multi-airport region', *Sustainability* **14**(11), 6832.

Quartieri, J., Guida, M., Guarnaccia, C., D'Ambrosio, S. & Guadagnuolo, D. (2008a), Complex network applications to the infrastructure systems: the Italian airport network case, *in* 'Proc. Of the Int. Conf. on Urban Planning and Transportation, Heraklion, Crete Island, Greece'.

Quartieri, J., Guida, M., Guarnaccia, C., D'Ambrosio, S. & Guadagnuolo, D. (2008b), 'Topological properties of the Italian airport network studied via multiple addendials and graph theory', *International Journal of Mathematical Models and Methods in Applied Sciences* **2**, 312–316.

Requião da Cunha, B., González-Avella, J. C. & Gonçalves, S. (2015), 'Fast fragmentation of networks using module-based attacks', *PLOS ONE* **10**(11), 1–15.
  URL: *https://doi.org/10.1371/journal.pone.0142824*

Rocha, L. E. (2017), 'Dynamics of air transport networks: A review from a complex systems perspective', *Chinese Journal of Aeronautics* **30**(2), 469–478.

Sallan, J. M. (2017), Cascading failures in air transport networks, *in* 'Proceedings of the Air Transport Research Society (ATRS) 21th Annual World Conference'.

Sampaio, F. C. (2022), Resilience analysis of air traffic systems based on complex networks, *in* 'Proceedings of the Air Transport Research Society (ATRS) 25th Annual World Conference'.

Scott, J. (2012), *Social network analysis*, Sage.

Sun, X., Gollnick, V. & Wandelt, S. (2017), 'Robustness analysis metrics for worldwide airport network: A comprehensive study', *Chinese Journal of Aeronautics* **30**(2), 500–512.
  URL: *https://www.sciencedirect.com/science/article/pii/S1000936117300390*

Sun, X. & Wandelt, S. (2021), 'Robustness of air transportation as complex networks: Systematic review of 15 years of research and outlook into the future', *Sustainability* **13**(11), 6446.

Sun, X., Wandelt, S., Hansen, M. & Li, A. (2017), 'Multiple airport regions based on inter-airport temporal distances', *Transportation Research Part E: Logistics and Transportation Review* **101**, 84–98.

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**(2), 153–168.

Sun, X., Wandelt, S. & Zanin, M. (2017), 'Worldwide air transportation networks: a matter of scale and fractality?', *Transportmetrica A: Transport Science* **13**(7), 607–630.
  URL: *https://doi.org/10.1080/23249935.2017.1312632*

Sun, X., Wandelt, S. & Zhang, A. (2020a), 'How did COVID-19 impact air transportation? A first peek through the lens of complex networks', *Journal of Air Transport Management* **89**, 101928.
  URL: *http://www.sciencedirect.com/science/article/pii/S0969699720305111*

Sun, X., Wandelt, S. & Zhang, A. (2020b), 'Resilience of cities towards airport disruptions at global scale', *Research in Transportation Business & Management* **34**, 100452. Data analytics for international transportation management.
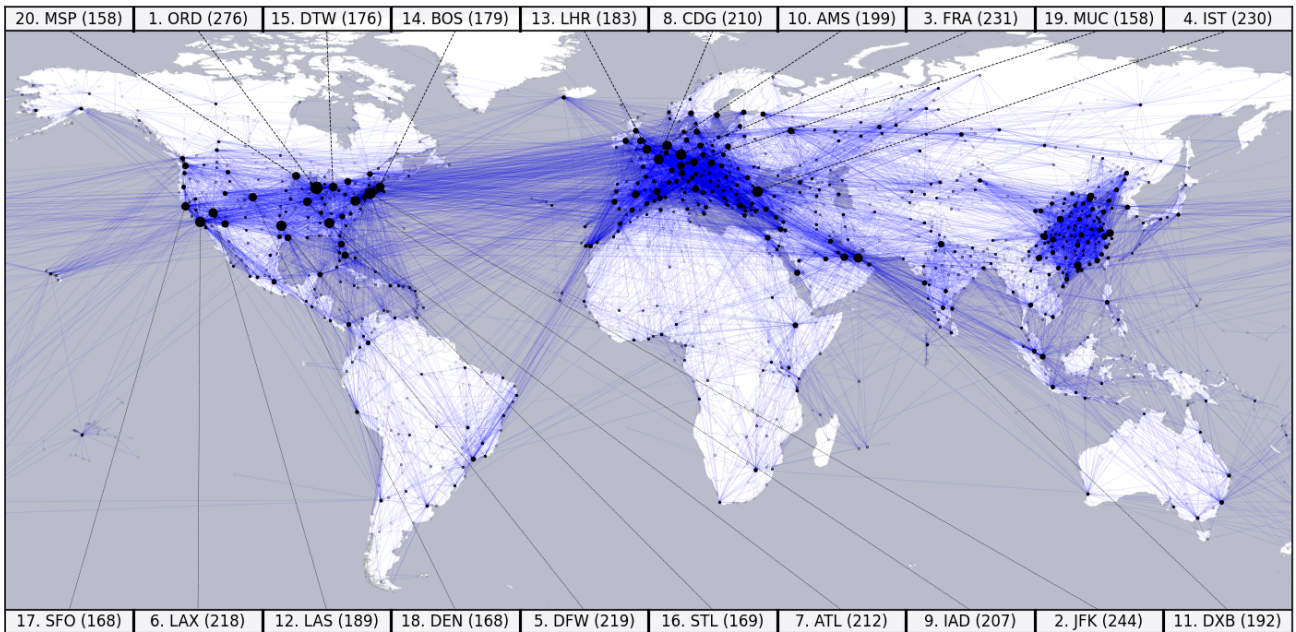 **URL:** *http://www.sciencedirect.com/science/article/pii/S2210539519301658*

Takada, K. (2017), Reasearch on the transition of aviation network structure in japan, *in* 'Proceedings of the Air Transport Research Society (ATRS) 21th Annual World Conference'.

Thompson, I. B. (2002), 'Air transport liberalisation and the development of third level airports in France', *Journal of Transport Geography* **10**(4), 273 – 285.
  URL: *http://www.sciencedirect.com/science/article/pii/S0966692302000431*

Toledo, F. (2021), Towards on multiplex networks and applications, *in* 'Proceedings of the Air Transport Research Society (ATRS) 24th Annual World Conference'.

Wandelt, S., Sun, X. & Cao, X. (2015), 'Computationally efficient attack design for robustness analysis of air transportation networks', *Transportmetrica A: Transport Science* **11**(10), 939–966.
  URL: *https://www.tandfonline.com/doi/full/10.1080/23249935.2015.1089953*

Wandelt, S., Sun, X., Feng, D., Zanin, M. & Havlin, S. (2018), 'A comparative analysis of approaches to network-dismantling', *Scientific reports* **8**(1), 1–15.

Wandelt, S., Sun, X. & Zhang, J. (2019), 'Evolution of domestic airport networks: a review and comparative analysis', *Transportmetrica B: Transport Dynamics* **7**(1), 1–17.
  URL: *https://www.tandfonline.com/doi/full/10.1080/21680566.2017.1301274*

Wang, J., Mo, H. & Wang, F. (2014), 'Evolution of air transport network of china 1930–2012', *Journal of Transport Geography* **40**(0), 145 – 158.
  URL: *http://www.sciencedirect.com/science/article/pii/S096669231400026X*

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**(4), 712–721.

Wen, X., Tu, C. & Wu, M. (2018), 'Node importance evaluation in aviation network based on "no return" node deletion method', *Physica A: Statistical Mechanics and its Applications* **503**, 546–559.
  URL: *https://www.sciencedirect.com/science/article/pii/S0378437118301997*

Wilkinson, S. M., Dunn, S. & Ma, S. (2012), 'The vulnerability of the european air traffic network to spatial hazards', *Natural hazards* **60**(3), 1027–1036.
  URL: *https://link.springer.com/article/10.1007/s11069-011-9885-6*

Wong, A., Tan, S., Chandramouleeswaran, K. R. & Tran, H. T. (2020), 'Data-driven analysis of resilience in airline networks', *Transportation Research Part E: Logistics and Transportation Review* **143**, 102068.
  URL: *https://www.sciencedirect.com/science/article/pii/S1366554520307195*

Xu, Z. & Harriss, R. (2008), 'Exploring the structure of the U.S. intercity passenger air transportation network: a weighted complex network approach', *GeoJournal* **73**(2), 87–102.
  URL: *http://dx.doi.org/10.1007/s10708-008-9173-5*

Zanin, M. (2014), 'Network analysis reveals patterns behind air safety events', *Physica A: Statistical Mechanics and its Applications* **401**(0), 201 – 206.
  URL: *http://www.sciencedirect.com/science/article/pii/S0378437114000430*

Zanin, M. (2015), 'Can we neglect the multi-layer structure of functional networks?', *Physica A: Statistical Mechanics and its Applications* **430**, 184 – 192.
  URL: *http://www.sciencedirect.com/science/article/pii/S0378437115002289*

Zanin, M. & Lillo, F. (2013), 'Modelling the air transport with complex networks: A short review', *The European Physical Journal Special Topics* **215**(1), 5–21.
  URL: *http://dx.doi.org/10.1140/epjst/e2013-01711-9*

Zhang, H.-T., Yu, T., Sang, J.-P. & Zou, X.-W. (2014), 'Dynamic fluctuation model of complex networks with weight scaling behavior and its application to airport networks', *Physica A: Statistical Mechanics and its Applications* **393**(0), 590 – 599.
  URL: *http://www.sciencedirect.com/science/article/pii/S0378437113008352*

Zhang, Y. (2010), 'Network structure and capacity requirement: The case of China', *Transportation Research Part E: Logistics and Transportation Review* **46**(2), 189 – 197.
  URL: *http://www.sciencedirect.com/science/article/pii/S1366554509001082*

Appendix

| 13. DEN (239) | 18. MSP (218) | 1. CHI (380) | 2. NYC (371) | 3. LON (359) | 4. PAR (318) | 15. BRU (227) | 11. AMS (253) | 7. FRA (294) | 9. IST (281) |

| 10. LAX (260) | 16. LAS (226) | 8. ATL (283) | 20. ORL (205) | 6. DFW (307) | 12. DTT (241) | 19. STL (215) | 14. BOS (229) | 5. WAS (314) | 17. DXB (219) |

Figure 16: *Network visualization of cities (CIT) based on data for April - June 2022. Top 20 nodes with the highest number of connections are highlighted by their IATA code.*

| 20. MSP (158) | 1. ORD (276) | 15. DTW (176) | 14. BOS (179) | 13. LHR (183) | 8. CDG (210) | 10. AMS (199) | 3. FRA (231) | 19. MUC (158) | 4. IST (230) |

| 17. SFO (168) | 6. LAX (218) | 12. LAS (189) | 18. DEN (168) | 5. DFW (219) | 16. STL (169) | 7. ATL (212) | 9. IAD (207) | 2. JFK (244) | 11. DXB (192) |

Figure 17: *Network visualization of multiple-airport regions (MAR) based on data for April - June 2022. Top 20 nodes with the highest number of connections are highlighted by their IATA code.*