Evolution of domestic airport networks: A review and comparative analysis

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Previous studies on airport networks are strongly bounded time-wise or only conducted for single networks at distinct levels of abstraction and for distinct topological features. Here, we review and compare the evolution of domestic airport networks for Australia, Brazil, Canada, China, India, Russia, United States, and Europe during the period 2002–2013. This is the first study on a consistent global dataset and allows for direct comparisons of network features. The air passenger traffic is tremendously increasing in all eight networks, with the largest number of passengers in United States, followed by Europe and China. Degree distributions can often be best fitted with a truncated power law (e.g., Brazil and United States) or log-normal (e.g., Australia and Canada). While all eight networks clearly exhibit small-world properties, the average shortest path length is between 2.1 (China/Russia) and 4.0 (Canada). Our study sets a baseline for understanding the topology and evolution of domestic airport networks.

Keywords: Network evolution, domestic airport network, complex network

1. Introduction

One vital part of analyzing air transportation systems is to understand their complex structures and properties (Azzam et al. 2013), such as, scalability (Barabási et al. 1999), controllability (Jia et al. 2013), safety event patterns (Zanin 2014), resilience (Lordan et al. 2014) and communities (Palla et al. 2005). A multitude of complex networks has been analyzed, among them are social networks (Scott 2012), power grids (Pagani et al. 2013), biological networks (Bagler et al. 2005), and transportation systems (Wandelt et al. 2015b); see (Boccaletti et al. 2006) for an introduction. All these studies model a system as a set of nodes and links, where the actual semantic of a link is domain-dependent. The interactions between interdependent networks were studied in (Wang et al. 2013a,b); a comprehensive review on the structures and dynamics of such multilayer networks is provided in (Boccaletti et al. 2014).

Recent research analyzed domestic airport networks, with airports as nodes and direct flight connections as links. Examples include the US airport network (Jia et al. 2014; Lin et al. 2014; Neal 2013; Gautreau et al. 2009; Bounova 2009); the European airport networks for Portugal (Jimenez et al. 2012), Greece (Papatheodorou et al. 2009), and Italy (Guida et al. 2007); the Chinese airport network (Wang et al. 2014; Zhang et al. 2010; Zhang 2010); the Indian airport network (Bagler 2008) and the Brazilian airport network (da Rocha 2009).

It is interesting to investigate and compare different domestic airport networks regarding features and connectivity, since network structures are often directly affected by state policies and heterogeneous aviation laws developed inside geopolitical regions. However, since the experiments performed in related work are based on distinct databases, it is difficult to compare the results; in fact, the results are often contradicting, as, for instance, shown recently by Azzam et al. (2013). Moreover, as stated by Neal (2014),

air transportation networks come at conceptually and structurally distinct types: Existing research on networks often compares snapshots of different scale (e.g., airports, air routes, cities), species (e.g., passengers, cargo, flights), and seasons (yearly, monthly, winter/summer). Neal (2014) concludes that a comparison of such networks is not easy. Although their complex network properties can be very similar, they often have substantively structural differences. Thus, cross-country network comparison based on the results of different types of networks is at least onerous, but often intractable. Moreover, airport networks are not static, but evolve over time. This fact has been widely ignored by the research community and snapshots of networks at different points of time have often been analyzed (see Section 2 for an overview). As discussed by Barabási et al. (2002), most quantities used to characterize a network are time dependent and their values at a given time point tells little about the whole network. Therefore, it is difficult to perform a fair and consistent evaluation between domestic airport networks, based on comparing snapshots from different periods of time.

In this study, we investigate and report on the evolution of domestic airport networks for the top seven geographically largest countries (Australia, Brazil, Canada, China, India, Russia, United States) and Europe from 2002 to 2013. These eight domestic airport networks, for simplification we refer to the intra-European network as domestic as well, account for 54.2% of the worldwide airports, 68.5% of the airport connections, and 68.0% of all passengers in the year 2013. The aim of this paper is to compare the complex network-induced features and temporal evolution of these features for all eight domestic airport networks on a consistent dataset.

Among others, we investigate the seasonal variation of passenger traffic, scale-free and small-world properties, disassortative mixing, and self-similarities. According to the nested-type classification of (Neal 2014), this paper investigates all networks at a single scale (distinct airports), single species (all passengers), and variable season (temporal evolution over 12 years at a monthly resolution). The analysis on a common dataset and a common period of time is the key contribution of our work and complements the state-of-the-art in airport network analysis at a domestic level.

The remainder of this study is organized as follows. Section 2 discusses the literature on airport networks. Section 3 analyzes the temporal evolution of the eight domestic airport networks from 2002 to 2013. Finally, the results of our analysis are summarized in Section 4.

2.   Related work

During the past few years, complex network analysis has been used to study air transportation systems of different types and at different levels. We review the literature for individual domestic airport networks first. The results of studies are grouped by region, with the following order: US, Europe, China, Brazil, India, and others, comparative studies, and worldwide network. Our summary might seem repetitive or fragmented, but they reflect the state-of-the-art as published previously. In Table 1 we provide a concise and organized overview on related work.

Chi et al. (2003) found that the US airport network has small-world characteristics and degree distributions follow two-segment power-laws. Xu et al. (2008) analyzed the US domestic passenger air transportation network using weighted complex network methodologies. Cheung et al. (2012) showed the small-world properties and assortative mixing by degree. Jia et al. (2012) analyzed the structural properties of the US airport network and showed that it is a scale-free, small-world network, with disassortative mixture in both unweighted and weighted versions. Recently, temporal evolution of the US airport network at city level from 1990–2010 was analyzed by Jia et al. (2014) as well as by Lin et al. (2014), respectively. Both showed that the network preserves scale-free, small-world, and disassortative mixing properties over time. Furthermore, Jia et al. (2014) found that the dynamics of the network are stable, while some central cities become more crucial. Neal (2013) assessed the business travel US airport network for the period 1993–2011 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.

The evolution of the European airport network between 1990 and 1998 was analyzed by Burghouwt et al. (2001) and the authors did not find an indication of hub-nodes for intra-European traffic. The spatial configuration of airline networks in Europe was analyzed in (Burghouwt et al. 2003). Gurtner et al. (2014) analyzed the community structure in European air transportation. Several works analyzed the airport network in Italy (Guida et al. 2007; Quartieri et al. 2008a,b), Portugal (Jimenez et al. 2012), and France (Thompson 2002). 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 dataset was based on scheduled flights operating for October, 24th, 2007 and the data was provided by Innovata. 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. European air transport was investigated from its structure and function point of view (Lehner 2013). Lehner et al. (2014) also showed that the vast majority of all Intra-European passengers travel directly and the directness of the overall system increased from 2002 to 2012. The European air route network was analyzed by Sun et al. (2015). Recently, Zanin (2015) discussed the multi-layer representation of functional networks, with the European airport network as a test case.

The Chinese airport network has been analyzed frequently in the past. Li et al. (2004) found that the Chinese airport network has small-world characteristics and that the in-degree and out-degree of each airport has significant linear correlations, suggesting a symmetric network. Zhang et al. (2010) showed that although the topology of Chinese airport network kept stable, the relative importance of airports and airlines has changed. Wang et al. (2011) examined the overall structure of the Chinese airport network and the centrality of individual cities. They found that the network is small-world, but not scale-free and its degree distribution is best fitted by an exponential function; the centrality measures of individual cities are highly correlated with their socio-economic indicators. Weekly flight patterns have been analyzed by Lin (2012) and a spatial hierarchical structure has been identified inside the Chinese airport network. Wang et al. (2014) analyzed the temporal evolution of the Chinese airport network from 1930 to 2012 and found that average path length is decreasing but clustering coefficient is increasing over time. They conclude that the Chinese airport network has evolved from scattered development to a complex network, with significantly improved connectivity.

Furthermore, da Rocha (2009) studied the temporal evolution of the Brazilian airport network between 1995 and 2006 at a yearly resolution. The network shrinks at the route level but grows in the number of passengers and amount of cargo. Given two fatal accidents in the Brazilian airport network in 2006–2007, Costa et al. (2010) analyzed the hub-and-spoke structure. The authors motivate more efforts to identify and monitor the concentration of flights in the Brazilian airport network. The airport network of India was evaluated by Bagler (2008). The network exhibits small-world properties, a truncated power-law degree distribution and a signature of hierarchy. This network is found to have disassortative mixing properties which are offset by the traffic dynamics. Donehue et al. (2012) provided an overview on the challenges faced by remote, rural, and regional airports in Australia.

The worldwide airport network, with airports aggregated by serving cities, is a scale-free and small-world network, and the most connected cities are not necessarily the most central ones (Guimera et al. 2005). An accelerating growth of the worldwide airport network was reported in (Azzam et al. 2013) and it was shown that the degree distribution of the network is non-stationary and subject to densification. Other studies investigate the properties of networks at levels of aggregation, where, for instance, each node represents a country, and links represent international passenger flows (Wandelt et al. 2015a).

Table 1.: Literature review for the analysis of individual airport networks, regarding region, time frame, number of nodes, number of links, Average Shortest Path Length (ASPL), clustering coefficient, and assortativity. All networks exhibit the small-world property (Watts et al. 1998). The symbol * indicates airport networks at city level, where multiple airports in one city are aggregated as one node in the network. The symbol ** indicates a mixed network of airports and cities. N/A represents Not/Available.

Region	Time frame	Nodes	Links	ASPL	Clustering	Assortativity
United States						
Chi et al. (2003)	Unknown	215	N/A	2.4	0.618	N/A
Xu et al. (2008)*	2002–2005	250–272	5,773–6,771	1.84–1.93	0.73–0.78	N/A
Paleari et al. (2010)	24th Oct. 2007	657	5,488	3.38	0.45	N/A
Cheung et al. (2012)	Jul. 2011	850	6,478	3.24	0.62	Close to 1
Jia et al. (2012)	8th–18th Aug. 2010	732	6,086	2.61	0.58	-0.3
Jia et al. (2014)*	1990–2010	300–1,150	12,000–26,000	2.18–3.02	0.52–0.7	-0.16– -0.28
Lin et al. (2014)*	1990–2010	304–893	12,626–18,273	2.4–3.0	0.6–0.7	N/A
China						
Li et al. (2004)**	One week (unknown)	128	1,165	2.067	0.733	N/A
Paleari et al. (2010)	24th Oct. 2007	144	1,329	2.34	0.49	N/A
Zhang et al. (2010)*	1950–2009	10–160	N/A	2.21–2.29	0.70–0.81	N/A
Wang et al. (2011)*	Oct. 2007–Mar. 2008	144	1,018	2.23	0.69	-0.429
Lin (2012)*	2008–2009	140	≈ 1,900	2.108	0.737	-0.41
Wang et al. (2014)*	1930–2012	24–170	23–1,129	2.29–5.61	0–0.62	N/A
Brazil						
da Rocha (2009)*	1995–2006	143–234	N/A	2.26–2.49	0.62–0.66	N/A
Europe						
Paleari et al. (2010)	24th Oct. 2007	467	5,544	2.8	0.38	N/A
India						
Bagler (2008)	12th Jan. 2004	79	442	2.2593	0.6574	-0.4
Italy						
Guida et al. (2007)	Jun. 2005–May 2006	50	310	1.98–2.14	0.07–0.1	N/A
Worldwide						
Azzam et al. (2013)	1979–2007	3,250–3,600	19,000–35,000	4.0–5.0	0.1–0.7	N/A
Guimera et al. (2005)*	Nov. 2000–Oct. 2001	3,883	27,051	4.4	0.62	N/A

We summarize the most related work in Table 1 and several observations can be obtained:

(1) The airport networks were constructed at different scales: Some evaluations were performed at airport level, others at city level; some research looked at directed networks, other at undirected networks. The use of different methodologies makes the results incomparable, since the networks do not describe the same system.

(2) The data sources for networks are often distinct with different time frames and in some work the time period or even the data source of the networks is not available.

(3) There are discrepant and fragmented results for individual domestic airport networks over time. For instance, the clustering coefficients for the US airport network vary from 0.45 to 0.78; the assortativity features are not always presented. The (fitted) degree distributions have a wide range of results alone for US and China (data not shown in Table 1, but discussed in Section 3.4). Another example are two recent papers on the US airport network (Jia et al. 2014; Lin et al. 2014): Albeit using the same data source, the same period of time, and looking at the same type of network, they report different number of nodes and links.

3. Evolution of domestic airport networks

In this section, we present the results of the comparative evolution for the eight Domestic Airport Networks (DANs) from 2002 to 2013. First, we describe how we extracted the data for all eight DANs in Section 3.1 and passenger traffic on top of the networks in Section 3.2. Then we analyze airport degree centrality (Section 3.3), scale-free property (Section 3.4), small-world property (Section 3.5), and assortativity mixing patterns (Section 3.6). We conclude with the analysis of node similarity (Section 3.7).

3.1. Construction of domestic airport networks

We extract the global air traffic data from Sabre Airport Data Intelligence (ADI, http://www.airdi.net) to build the DANs from 2002 to 2013. The data is monthly-based with

Table 2.: Overview on the top seven geographically largest countries plus Europe (coded as EU). The largest value for each attribute is highlighted in bold. Geographical and population data was obtained from The World Factbook, CIA for July 2014. Passenger data was obtained from Sabre Airport Data Intelligence (http://www.airdi.net).

| Country	Code	Continent	Area (km)	Population	Pop. density	Total passengers
Australia	AU	Oceania	7,686,850	22,507,617	2.9	522,450,281
Brazil	BR	South America	8,511,965	202,656,788	23.8	695,318,907
Canada	CA	North America	9,984,670	34,834,841	3.5	340,832,848
China	CN	Asia	9,596,960	**1,355,692,576**	141.3	2,365,925,706
India	IN	Asia	3,287,590	1,236,344,631	**376.1**	444,945,278
Russia	RU	Europe	**17,100,000**	142,470,272	8.3	290,587,194
United States	US	North America	9,629,091	318,892,103	33.1	**7,026,376,484**
Europe	EU	Europe	4,849,804	518,976,130	107.0	3,658,361,004
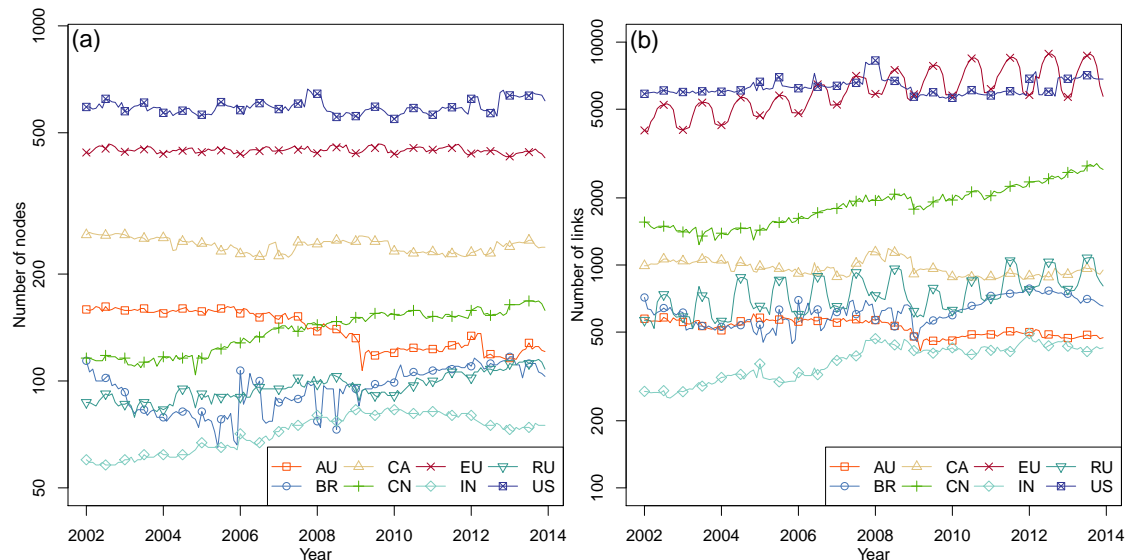
Figure 1.: Temporal evolution of the number of nodes (a) and links (b) for the eight DANs. United States (US) has the largest number of nodes (airports) and links (flight connections).

the following information for each flight ticket sold per month: Origin and destination airport of a trip, plus up to three connecting airports, and the total number of passengers using that type of ticket. In order to construct the domestic networks, we start with an empty network for each country. Next, we iterate all tickets in the ADI database. For each hop on a ticket, we check whether the two airports spanning up this hop are in the same country (the ADI dataset already provides the country name for each airport). If both airports are in the same country, we add this hop as a link to the corresponding domestic network, with the nodes being airports of the hop. If the link does not exist yet, we create a new link with the weight set as the number of passengers for the ticket. If the link exists already, we increase the weight of the link by the number of passengers on the ticket. After iterating all tickets, we have eight large domestic airport networks (for Australia, Brazil, Canada, China, India, Russia, United States, and Europe); other networks are not being considered in our study.

In the current study, we are interested in the comparative evolution of network structures for different regions in the world. We select the top seven countries based on the geographical area, plus Europe (consisting of the following 31 countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and United Kingdom).

Table 2 provides a geographical overview for the seven countries and Europe. For each country (for the sake of simplification, we refer to Europe as a country), we show six
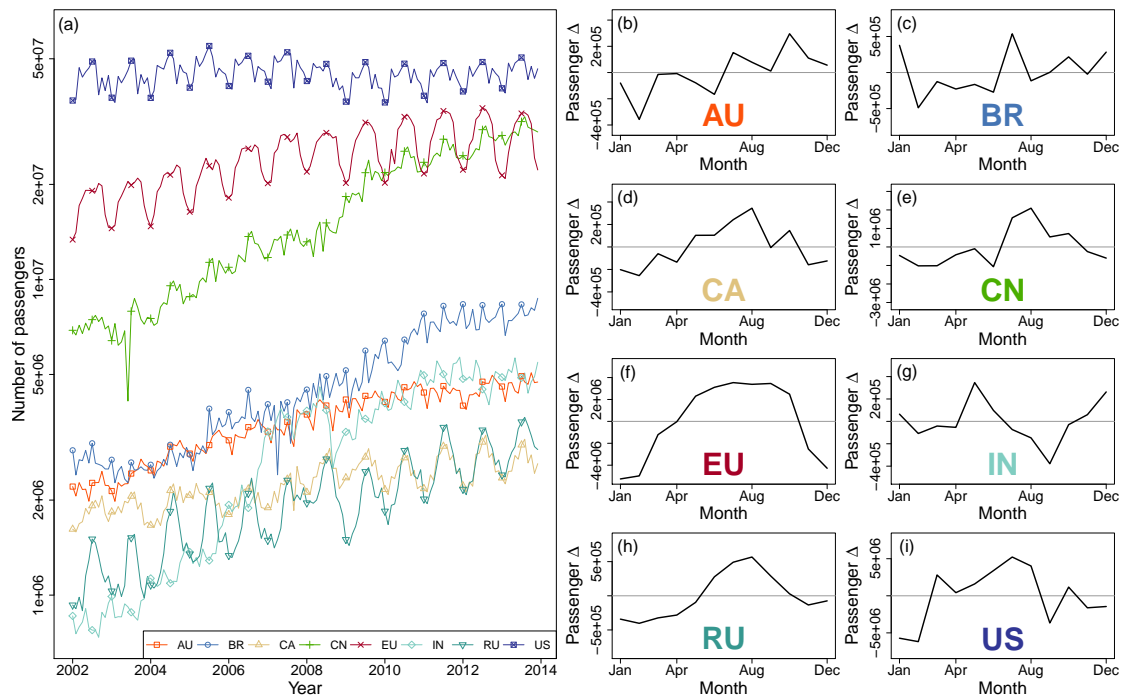
Figure 2.: Passenger traffic (a) and seasonal variations (b-i) for the eight DANs over the 12-year period. There is a strong increase of passenger traffic in China (CN), Brazil (BR), India (IN), and Russia (RU); United States (US) and Europe (EU) have the highest seasonal variations. The seasonal variations are computed with STL (Cleveland et al. 1990).

attributes: Country code using ISO-3166-ALPHA-2, continent, area (km^2), population, population density, and total number of domestic passengers from 2002 to 2013. The largest value for each attribute is highlighted in bold. The countries have different rankings according to the attributes. For instance, Russia has the largest geographical area; China has the largest population; India has the largest population density; US has the largest total number of domestic passengers over the years.

We generate eight DANs, each of which has 144 instantiations: One for each month in the analyzed period (12 years with 12 months). Figure 1 shows the temporal evolution of the number of nodes (airports) and links (flight connections) for the eight DANs. The degree to which curves vary depends on how much a domestic network is influenced by seasonal variations. For instance, inside the EU, there is a strong summer/winter variations which is caused, among others, by people traveling to vacation destinations in the South. Inside China, on the other hand, the network is rather stable during a year (according to the number of links), this indicates that the travel behavior is not so fluctuating.

3.2. *Passenger traffic*

This section presents the passenger traffic in the eight DANs. Figure 2 (a) shows the total number of domestic passengers per month for each of the eight DANs over the years. We can observe that US has the largest number of passengers (approx. 50 million/month) and the passenger traffic is rather stable over the years, with summer/winter seasonal fluctuations; EU ranks the second place (approx. 20 million/month) and it has strong summer/winter seasonal variation; China has the third largest number of passengers (approx. 10 million/month), with a clear overall increasing trend. Notably, there is one sharp drop of passenger traffic in 2003, this was caused by the outbreak of the Severe Acute Respiratory Syndrome in China (Anderson et al. 2004). Overall, there are increasing trends of domestic passenger traffic in all countries, with the exception of US, whose domestic passenger traffic is rather stable. The strong passenger growth in China
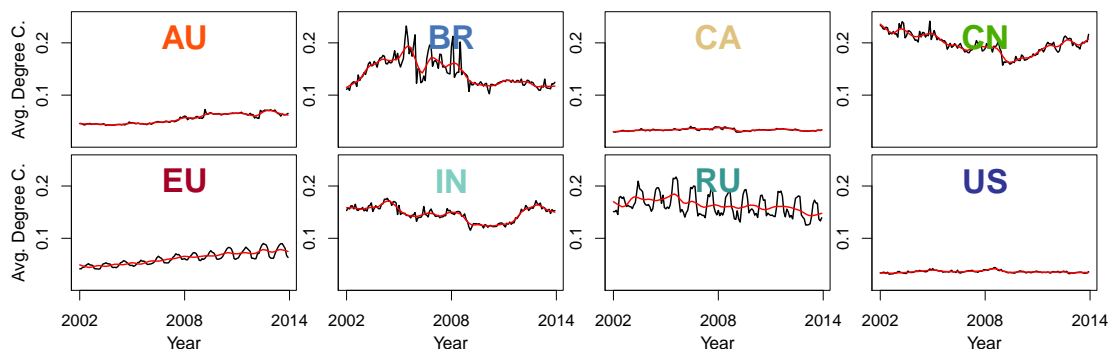
Figure 3.: An overview on the evolution of the average degree centrality in the eight DANs. The degree centrality of mature DANs (EU, US) is significantly lower than the degree centrality of emerging DANs (CN, IN, RU). For the Chinese DAN, each airport is, on average, connected to 20% of all other airports in the network, while for Canada an airport is on average connected to less than 5% of all other airports.

and Brazil is consistent with previous work on the evolution of the Chinese DAN (Zhang et al. 2010) and the Brazilian DAN (da Rocha 2009).

Figure 2 (b-i) present seasonal variations of domestic passenger traffic for the eight DANs over the 12-year period, based on STL (Seasonal and Trend decomposition using Loess) technique (Cleveland et al. 1990). STL splits a given time series into three components: Trend, seasonality and remainder. The algorithm consists of a sequence of applications of the loess smoother (Cleveland et al. 1988) and allows fast computation, even for very long time series. For further details, we refer the reader to (Cleveland et al. 1990). We can observe that US and EU have the highest seasonal variations of passenger traffic, with a magnitude in the order of millions. Particularly, EU exhibits a rather steady pattern of summer (peak)/winter (nadir) and the summer peak lasts around five months (from May to October). This is likely caused by three factors: 1) A large population, 2) a majority of people disposes of enough money for regular long-distance travel, and 3) historically developed, rather fixed holiday seasons between June and September. For instance, many European people prefer to travel on vacations inside Europe with their families. On the other hand, China only shows a short period of summer peak (around August). In China, people are often working during the year, with a longer holiday break in July/August. The only exception is the Chinese New Year festival, which is mainly visible as domestic (high-speed) railway traffic, not so much in air travel. Similar short periods of summer peak also hold for Canada, Russia (around August) and Brazil (around July). India shows a clear peak of passenger traffic in May, a nadir in September, and a sharp increase in December. The reason is the the Indian holiday season is earlier, compared to other countries: School holidays usually take place between the mid of May to the end of June. The passenger traffic in Australia exhibits a nadir in February and a peak in November. Again, this can be mostly attributed to the school holiday season (from the end of November to January), which allows Australian families to travel.

3.3.   *Evolution of airport degree centrality*

The degree of a node describes the local connectivity of an airport to its neighbors. When comparing DANs, one should keep in mind that there is not only a global trend regarding the change of degrees, but regions/communities inside the network show completely different behavior. In fact, researchers should refrain from comparing average degrees between DANs for assessing the overall state of development, as in (Lin 2012). If degrees need to be compared, then the degree centrality, i.e. the degree normalized by the number of nodes in the network, should be used, since the total number of nodes in the DANs are largely different, and thus also the maximum possible degree.

We show the evolution of the degree centrality for the eight DANs in Figure 3. Each data point shows the average value for a DAN per month. The black line connects
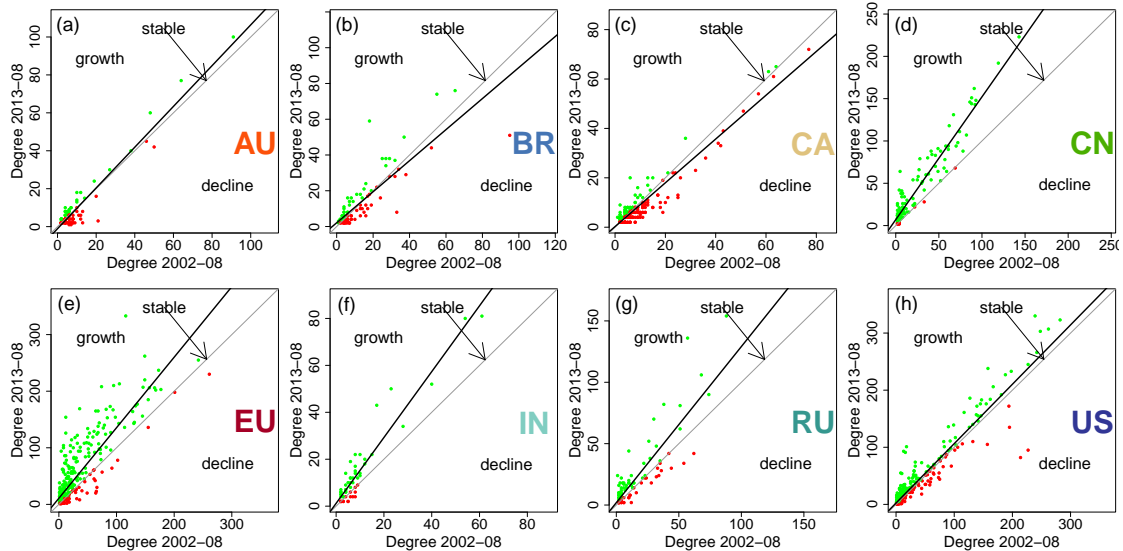
Figure 4.: Comparison of the degree growth for the eight DANs in two time periods: 2002-08 and 2013-08. The green dots indicate growing degree; red dots indicate decreasing degree; the black bold line is the linear regression. The diagonal line is labeled as stable in the sense that there is neither growth nor decline in the two time periods.

monthly-based data points, while the red line shows the trend derived with STL technique (Cleveland et al. 1990). In general, we can conclude that the majority of DANs is rather sparse, with an average degree centrality below or around 20%. The highest average degree centrality can be observed for China, India, Russia, and, partially, Brazil. For these countries, each node is, in average, directly connected to 20% of all other nodes. This type of network structure, compared to sparser networks, is typical for emerging countries in air transportation. Similarly, during the last decade, low-cost carries, such as Ryanair, create networks with high density. The advantage of such networks is a higher connectivity for passengers, while being more demanding on the operator. Other mature networks, on the other hand, such as Canada and United States have a rather low and almost constant degree centrality of 0.03. The degree centrality of the European DAN is slightly increasing over time. This is an interesting observation, and can be attributed to the increased successful competition of Ryanair and other low-cost carriers in Europe. In summary, these differences in degree centrality, and therefore in network structure and efficiency, should be taken into account in future work, when comparing results for different DANs: The degree of completion of a DAN has large impacts on network features, such as resilience and delay propagation.

It is interesting to find out how the degrees of actual airports changed over the period in our study. Figure 4 presents the degree growth for the eight DANs comparing two time periods: August 2002 is plotted against August 2013. Each dot represents one airport in a DAN; we only show airports that have been present in both time periods, 2002-08 and 2013-08, respectively. The green dots exhibit growing degree; red dots indicate decreasing degree; the black bold line is the linear regression trend. All the airports on the gray diagonal line have the same degree in 2013-08 as they had in 2002-08. The diagonal line is labeled as *stable* in the sense that there is neither growth nor decline. Note that although a stable airport has the same degree value, the actual flight connections could be still different at these snapshots. Our analysis supports the findings of the previously discussed degree centrality (see Figure 3). The emerging networks of China, India, and Russia show a strong increasing average degree of airports. Similarly, the DAN of Europe becomes increasingly connected. The other four DANs have a stable airport degree or even a decreasing degree. The decreasing degree of the Brazilian DAN can be explained with tremendous consolidation and privatization efforts in the Brazilian air transport business, started in 2010. Overall, a trend of increasing connectivity can be observed for many DANs. We see two major reasons: First, low-cost carriers gradually
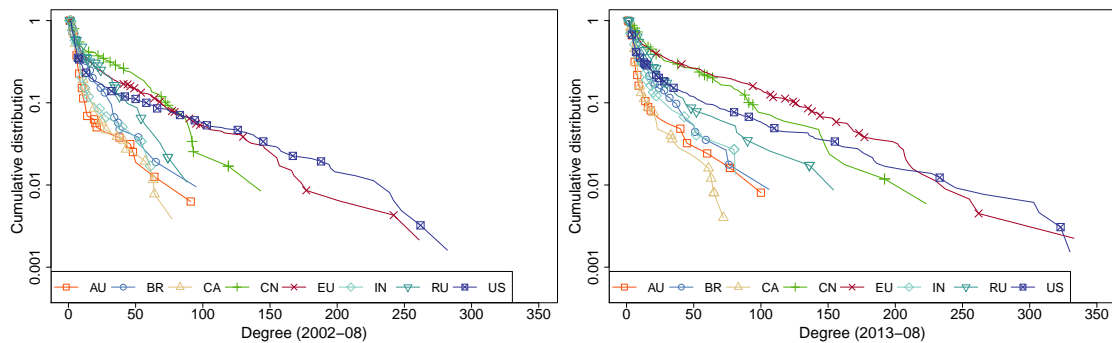
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Figure 5.: Cumulative degree distributions for the eight DANs in 2002-08 (a) and 2013-08 (b) at semi-log scale. US and EU show rather flat decaying behaviors; while the remaining six DANs decay relatively fast. The degree distributions are evolved slightly towards right in 2013 compared to 2002.

extend their networks. Second, ongoing goals to improve the door-to-door connectivity inside Europe and other regions can only be achieved by avoiding flights with layovers as much as possible. Please note that in Figure 4 we do not claim to have identified a linear correlation between both periods; the line is rather a means of visualizing the trend from smaller to larger airports.

3.4.   Degree distributions and best fits

Previous studies have often 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 et al. 2007; Zhang et al. 2010; Li et al. 2004, 2006; Chi et al. 2003), truncated power-law (Jia et al. 2014; Bagler 2008; Xu et al. 2008; Han et al. 2007; Guimera et al. 2005), or exponential (Wang et al. 2011; da Rocha 2009). One use of degree distributions is to identify scale-free networks, where hub nodes exist with high connectivity to other nodes and most nodes have few connections. A network is scale-free, if its degree distribution follows a heavy-tailed (power-law) distribution (Barabási et al. 1999).

A considerable number of networks has been categorized as scale-free, while statistical techniques were used to refute many of these claims and seriously questioned others (Clauset et al. 2009). As already discussed by Newman (2005), categorizing such distributions into true power-laws and log-normal is often difficult, especially in presence of random multiplicative processes. This problem is discussed by Azzam et al. (2013) in the context of worldwide air transportation. While Azzam et al. (2013) do not decide, whether their degree distributions for the worldwide airport network follow power-law or log-normal, they observe non-stationary behavior of the distributions. The slope of the degree distributions is decreasing, indicating that the topology of the network is subject to densification and a shrinking diameter.

Figure 5 presents the cumulative degree distributions for the eight DANs for August 2002 and August 2013, respectively. We can observe that US and EU show rather flat decaying behaviors; while the other six DANs decay relatively fast. In general, the degree distributions for the same month are evolved slightly towards right in 2013 compared to 2002, particularly for US and EU. Moreover, for the same year, the degree distributions in August (summer) are slightly skewed towards right compared to February (winter) (data not shown). In summer there are higher traffic demands and thus airlines provide more flight connections. Instead of building super-hubs which have connections to every other airport inside a country, the development of several medium-hubs contributes to the trade-offs between the efficiency and the robustness of the network. These medium-hubs are nodes which have smaller degrees than traditional hubs, yet larger degrees than the average degree of the network. Having several such hubs in the network, the susceptibility for node-failures is significantly reduced, since it is unlikely that the majority of medium
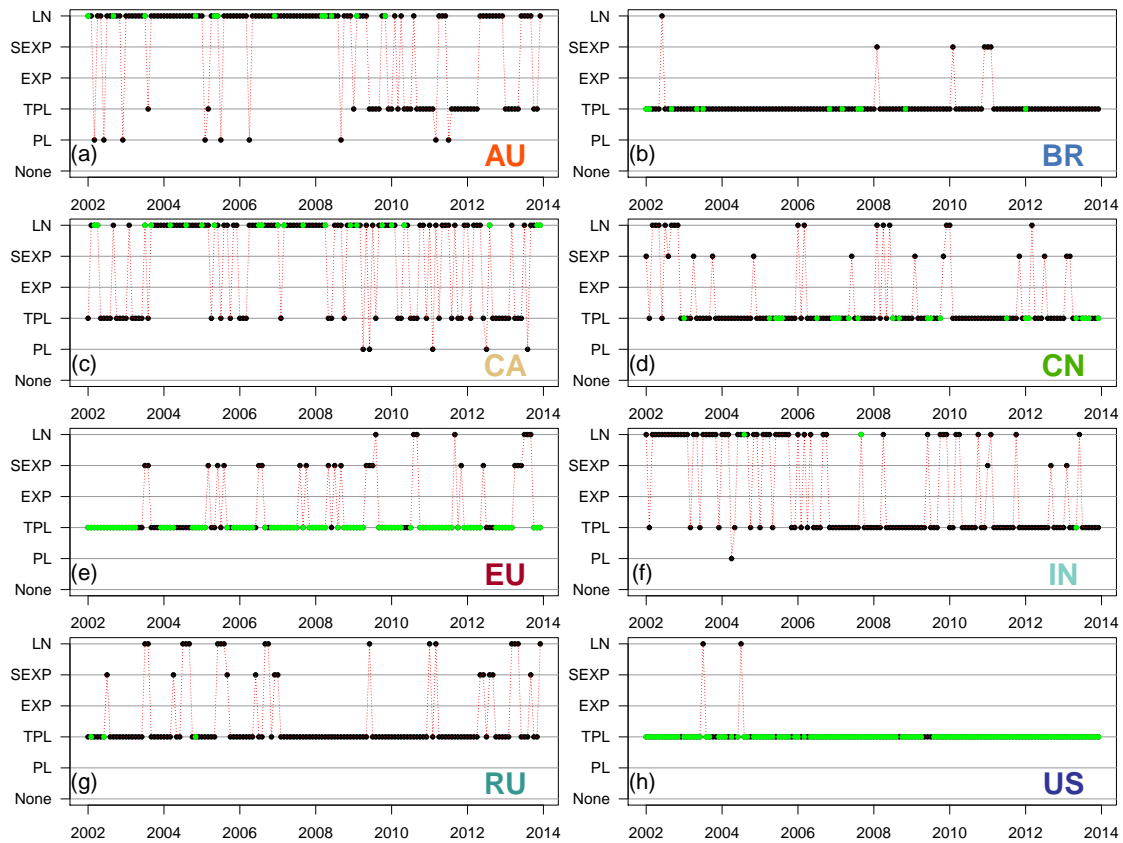
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Figure 6.: Best fitted function types of degree distributions for the 144 monthly-based DANs in the eight regions: Log-Normal (LN), Stretched Exponential (SEXP), Exponential (EXP), Truncated Power-Law (TPL), and Power-Law (PL).

hubs fails at the same time. Intuitively, networks build on medium-hubs are a compromise between high robustness (peer-to-peer structures) and low network costs (hub structures). Ultimately, these medium-hubs scale up with air transportation systems and emerge as multi-airport systems (Bonnefoy 2008). While we are not aware of any formal definition for these medium hubs, the key message here is that the strategy of only growing a few (very large, dominant) hubs has apparently be replaced by aiming towards more hubs, with slightly less connectivity, yielding intended redundancy in the network.

In the following, we discuss the best fits for the degree distributions of the eight DANs over time. For each of the 144 snapshots, we have computed the best fit regarding five function types:

- Power-law: $f(x) \propto x^{-\alpha}$
- Truncated power-law: $f(x) \propto x^{-\alpha}e^{-\lambda x}$
- Exponential: $f(x) \propto e^{-\lambda x}$
- Stretched exponential: $f(x) \propto x^{\beta-1}e^{-\lambda x^{\beta}}$
- Log-normal: $f(x) \propto \frac{1}{x}exp^{-\frac{(\ln x - \mu)^2}{2\sigma^2}}$

We determine the best fit for a network snapshot by comparing the loglikelihood ratio for each pair of function types. If the loglikelihood ratio is larger than 0 for one type T against all other types, which indicates that the former type is preferred, we conclude that T is the best fit. In addition, we perform a stricter experiment: The statistical significance of the loglikelihood ratio has to be smaller than 0.05 for all function types. We used the best fit power-law comparison method *distribution_compare* implemented in (Alstott et al. 2014), which returns the loglikelihood ratio and statistical significance for a pair of function types. Figure 6 presents the best fitted function types of degree distributions for the 144 monthly-based DANs in the eight regions. Black dots indicate a best fit
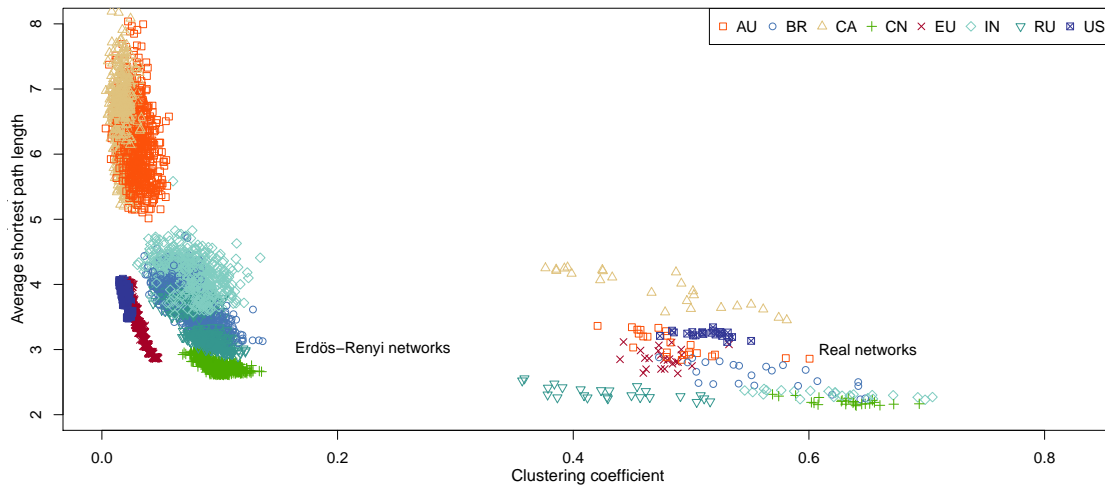
Figure 7.: The small world property for the eight DANs. The real DANs are shown on the right hand side; while their counterpart random Erdös-Rényi networks are shown in the left hand side, with the same data shape and color. With comparable average shortest path lengths, much higher values of clustering coefficients indicate that the real DANs have the small-world property.

for a function type without considering statistical significance; green dots represent the outcome of the stricter experiments with statistical significance less than 0.05.

Most of the DAN snapshots are best fitted by truncated power-law or log-normal. Interestingly, only very few snapshots are best fitted by pure power-law or stretched exponential. One reason might be that pure power-law or stretched exponential have only one parameter to serve as a degree of freedom for fitting; while truncated power-law and stretched exponential have two parameters, which enables a fitting advantage (Alstott et al. 2014). With very few exceptions for Canada and Australia, there exists always one best fit. When taking into account statistical significance (indicated by green dots), the results are not as certain as before, yet for EU and US, the dominant function type is still truncated power-law. In general, our results show that claims about the best fit of a DAN's degree distribution should be made cautiously, since the best fit varies within the 12 years of our evaluation. There are no clear seasonal variations, but the DANs seem to rather go through longer periods of stable degree distribution fits (for instance, Brazil and United States).

3.5.   *Small-world property*

Watts et al. (1998) found that networks can be categorized according to two structural features: Average shortest path length and clustering coefficient. Random networks, which are built using the Erdös-Rényi (ER) model (Erdős et al. 1959), often have small average shortest path lengths and low clustering coefficients. Many real-world networks, however, have small average shortest path lengths, but their clustering coefficients are significantly higher than one would expect. In such a small-world network, most node pairs are not direct neighbors, but many nodes can be reached from every other node by using only a small number of hops. In opposite to scale-freeness, which is highly related to the robustness of a network (Holme et al. 2002), small-worldness correlates strongly with the process dynamics on the network, such as information spreading (Newman 2003b).

Figure 7 presents the average shortest path length and clustering coefficient for the eight DANs. For each DAN and each year (2002-2013), we select two monthly-based networks: February (winter nadir) and August (summer peak). Thus, we have 24 real-world subnetworks, as shown on the right hand side of Figure 7. Each data point represents one of these 24 network snapshots. Similarly, for each of the 24 monthly-based subnetworks, we generate 30 random ER networks with the same number of nodes and links. In total, we have 720 random ER networks for each of the eight DANs, as shown in the left hand
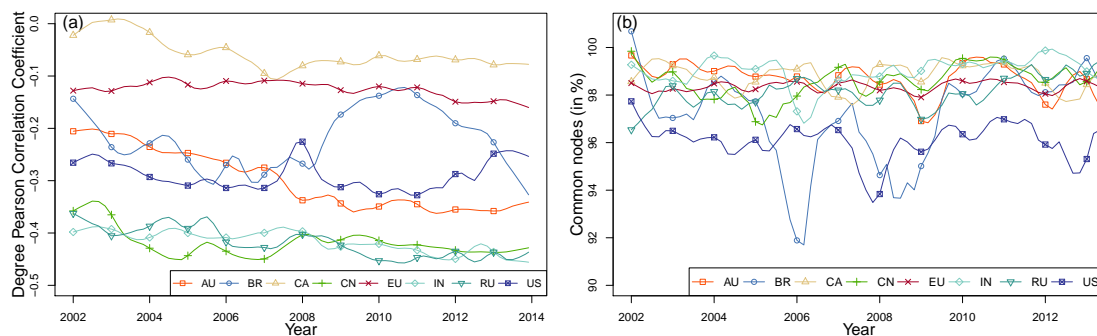
Figure 8.: a) Temporal evolution of the Degree Pearson Correlation Coefficient (DPCC) for the eight DANs. Most DANs have the DPCC values around -0.3, indicating that the DANs are disassortative. Remarkably, India and China have the lowest DPCC values. b) The node similarity of consecutive months for the eight DANs. For each month, we show the percentage of common nodes between current month and previous month.

side of Figure 7. The data shapes and colors of the random ER networks are the same as their counterpart real-world DANs, and thus, the two network features, average shortest path length and clustering coefficient, can be compared directly.

The observations are twofold. First, the average shortest path length between DANs and ER counterparts are rather similar for all DANs, with the exception of Canada and Australia, both of which have a heavily skewed network structure, caused by geographical reasons. Second, the clustering coefficient is considerably smaller for ER networks. These observations suggest that all DANs exhibit the small-world property, i.e., it takes only a few hops for passengers to travel inside each region. Moreover, it can be seen that the average shortest path length for Canada and Australia in random networks is significantly higher than for the other regions. Both countries, Canada and Australia, have higher average shortest path lengths because they have the lowest density (ratio between the number of existing links and the number of possible links). For instance, the density of Canada and Australia is significantly lower than the density of China and Europe. The less dense a random network is, the more steps are needed to reach all nodes in the network.

3.6. *Network assortativity*

Assortative mixing refers to the preference for nodes to attach with highly similar nodes, where similarity is often measured by the degree of the nodes (Newman 2003a). Several types of real-world networks exhibit correlations between nodes of similar degree, for instance, highly connected users tend to be connected with other well-connected users on Facebook and other social networks (Newman et al. 2003), a phenomenon often coined homophily in that context. On the other hand, several technological and biological networks show disassortative mixing: High-degree nodes tend to be connected to low-degree nodes (Newman 2002).

We measure the assortativity of a network using the Degree Pearson Correlation Coefficient (DPCC). The DPCC was proposed to distinguish network types (Newman 2002): Positive values indicate a correlation between nodes with similar degree; while negative values indicate relationships between nodes with different degree.

Figure 8 a) shows the evolution of DPCC for the eight DANs in the time frame 2002-2013. We can observe that the connectivity patterns are quite stable over the years. Most DANs have DPCC values around -0.3, indicating that the DANs are rather disassortative and highly connected airports (hub airports) tend to connect to airports with few connections. This can be explained by the classical hub-and-spoke (Bryan et al. 1999) network structures for DANs in most countries. India and China have the lowest DPCC values, thus their DANs are most disassortative among the eight DANs. Bagler (2008) evaluated the airport network of India for a single day (January 12th, 2004) and re-

ported the Indian DAN to be disassortative with a DPCC of -0.4. We confirm that the Indian DAN, according to our data, is disassortative to a degree of -0.44 (January, 2004). Overall, Brazil is the only country whose DAN has faced larger evolutionary changes in assortativity, while the other countries' assortativity is rather stable.

3.7. *Network similarity by number of common nodes*

We have shown that all DANs undergo significant changes during the period in this study, often with seasonal variations. However, the number of nodes per month does not allow to draw conclusions on the similarities of airport networks over time: Even if the number of nodes is similar, the actual instantiation of nodes can be completely different. Therefore, we analyze the similarity of node instantiations between consecutive months next. In order to quantify the network similarity of two consecutive months, we compute the number of nodes which occur in both months and divide the result by the number of nodes which occur in at least one of the months. Formally, let n_1 and n_2 be the set of nodes for both months, the network self-similarity is defined as $\frac{|n_1 \cap n_2|}{|n_1 \cup n_2|}$.

The network self-similarity of consecutive months is shown in Figure 8 b). All networks exhibit a large similarity: Often, more than 95% of the airports are carried over from one month to the next month. It can be observed that India has the highest average node similarity and thus it is the most stable network. The Brazilian network undergoes several large changes in the period of our study. This is explained as follows: Around 2006/2007, a big blackout occurred in the Brazilian DAN, which was due to series of operational slowdowns by air traffic controllers. The implications of this event carried on until 2010, which could be attributed to carriers attempting to reorganize their networks from a crisis management perspective. The carriers actually accomplished such management by reducing flight frequencies at major airports (Oliveira et al. 2015).

In general, node similarity can be inversely correlated with the amount of seasonal variation (see Figure 2), if not only the number of people changes significantly over a year, but also their destinations; for instance, by typical holiday-like locations as Majorca and Fuerteventura. In the case of US, we can see that the node similarity is relatively low between consecutive months, which means that destinations change during a year. Yet, we can also observe seasonal variations for US and other DANs. This analysis confirms our hypothesis, that the analysis of a single DAN snapshot, for instance only one day or one month, should not be considered as representative for the whole DAN over time, similarly to observations in other networks (Barabási et al. 2002). We believe that it is required to report the results for at least a whole year, in order to obtain meaningful insights. There are too many studies which only look at very short periods of time, such as a single day or a single week. In our experiments, we have shown that properties can vary significantly within even a few months; for example, the best fit function types for degree distributions. By using at least a whole year of data, it becomes clear whether one is analyzing outliers or more regular network properties.

4. Conclusions

The analysis of domestic airport networks is of utmost importance, in order to meet increasing demands on air traffic in the future. The understanding of complex structures in the networks, however, is limited, because previous studies are strongly bounded time-wise or only conducted for single domestic airport networks at different levels of abstraction (airports/cities, directed/undirected) and for different network features. In this study, we analyzed the comparative evolution of domestic airport networks for the top seven geographically largest countries together with Europe for the period 2002-2013, based on a consistent global air traffic dataset. The contributions of the paper to the literature are:

(1) The passenger traffic in all domestic airport networks is steadily increasing during

Table 3.: Summary of the comparative evolution of the eight DANs for the time frame 2002-2013, in terms of number of nodes, number of links, degree centrality, average shortest path length (ASPL), clustering coefficient, assortativity, and the best fitted function type for the degree distribution. Average values for these network metrics are shown. LN represents log-normal and TPL represents truncated power-law.

Networks	Nodes	Links	Degree centr.	ASPL	Clustering	Assortativity	Degree dist.
Australia	141	524	0.05	3.08	0.48	-0.29	LN/TPL
Brazil	95	622	0.13	2.60	0.56	-0.22	TPL
Canada	241	969	0.03	3.92	0.47	-0.05	LN/TPL
China	139	1,893	0.20	2.19	0.63	-0.41	TPL
India	72	375	0.14	2.31	0.62	-0.41	TPL
Russia	96	753	0.16	2.33	0.43	-0.41	TPL
United States	591	6,284	0.03	3.14	0.49	-0.29	TPL
Europe	447	6,159	0.05	2.86	0.47	-0.12	TPL

our time period; most networks exhibit clear seasonal variations. We conclude that domestic airport networks should not be compared based on snapshots taken at different time periods. In particular, seasonal variations are sometimes higher than the growth (US and Europe). The airport network of India has a seasonal peak in winter, while all other networks exhibit a seasonal peak in summer. In 2013, China is already on par with Europe, according to the number of domestic passengers.

(2) The number of nodes/links is rather stationary for most domestic networks, in particular for US. In India and China, while the number of nodes slightly increases, the number of links is growing considerably.

(3) The degree distributions of most domestic airport networks are best fitted by truncated power-law, rather than pure power-law or pure exponential. The best fitted function types vary within the 12 years, without clear seasonal variations. It seems that domestic airport networks undergo longer periods of stable degree distributions and shorter periods of unstable transitions.

(4) The network similarity of two consecutive monthly network snapshots is often above 95%. Our evaluation shows that India has the highest average network similarity and thus is the most stable network during the time period, while Brazil ans US are most fluctuating.

In this work, topological properties of domestic airport networks for the eight largest regions have been analyzed. The numerical results of our analysis are summarized in Table 3.

While we analyzed Europe as a whole, future work could analyze European countries in order to compare commonalities/differences. Moreover, our study only covers temporal evolution over 12 years at a monthly resolution, it would be interesting to analyze even longer time period in order to analyze the long-term development of networks. Besides, it would be also interesting to analyze networks at different scales, such as at city or metropolitan area level, where airports are grouped together. Furthermore, an important challenge remains to achieve a comprehensive understanding of socio-technical dynamics associated with airport networks. Our results also lay the foundation for discussing the scale of evolution between different airport networks and can contribute to identify representative networks (Sun et al. 2014), instead of only analyzing the largest US airport network, which is prevalent in the literature so far.

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