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Evolution of the international air transportation country network from 2002 to 2013

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ABSTRACT

In this research, we analyze the evolution of the international air transportation country network from 2002 to 2013 with two perspectives: The network's physical topology and the functional network with traffic information. Our analysis shows that the network is scale-free and has the small-world property. The evolution of triadic properties suggests that the network gears towards symmetric, transitive closure. We find that United States, Great Britain, and France are critical from both perspectives; Surprisingly, South Africa is particularly critical from topological point of view. Furthermore, topological and functional criticality are highly correlated to the GDP of a country.

1. Introduction

Air transportation is a complex socio-technical system and its function is to transfer passengers/cargos over long distances across countries or continents. With increased demand of air traffic, air transportation affects national or international economies significantly. Complex network theory can help us to understand the structure and dynamics of air transportation system. Previous studies on air transportation networks mainly focused on centrality measures of individual airports (Kotegawa et al., 2014; Zanin and Lillo, 2013), network robustness (Janic, 2015; Wei et al., 2014; Lordan et al., 2014), delay propagation (Baumgarten et al., 2014; Zhao et al., 2014; Zou and Hansen, 2014; Fleurquin et al., 2013), epidemic spreading (Gomes et al., 2014), route network similarity analysis (Sun and Wandelt, 2014), and temporal evolution (Jia et al., 2014; Sun et al., 2015; Azzam et al., 2013). Furthermore, Burghouwt and Redondi (2013) compare and classify different connectivity models for airport networks, for instance, shortest path length centrality (Malighetti et al., 2008), quickest path length centrality (Paleari et al., 2010), and weighted number of connections (Burghouwt, 2007).

Instead of looking at specific airports, as done in related work, we suggest to analyze air transportation at country level to identify the roles of whole countries in international air transportation and also to understand the network properties induced by the aggregation. While the idea of aggregating the airport network is not new, Guimera et al. (2005) and Bonnefoy (2008) aggregated the airport network to the city level, in order to identify the city's global roles, we are the first to look at the passenger air transportation at country level.

Country networks have been studied in other fields recently. Hawelka et al. (2014) constructed a country-to-country mobility network based on geo-located Twitter messages, with the countries as nodes and the number of Twitter users exchanging tweets between two countries as the link weight. The results showed that there is increased mobility in the

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developed countries and the Twitter mobility network is spatially connected and well aligned with common socio-geographical regions. Kaltenbrunner et al. (2014) built a social network for sister cities at country level; a link between two countries exists if a city of one country is twinned with a city of the other country. It is found that the impact of the geographical distance on the sister city country network is negligible and the cities with similar degree are preferentially connected. Moreover, Deguchi et al. (2014) analyzed the world trade network, where the nodes are countries; the links are exports and imports among the countries, weighted by the annual amounts of trade. Variants of the HITS (Hyperlink Induced Topic Search) algorithm were used to investigate the economic influences of the countries in the world trade network.

The structure and function of complex networks often interact with each other (Newman, 2003) and it has been shown that critical nodes in both networks are often different. Thus, the conclusions for structural networks cannot be directly extended to functional networks, and vice versa (Zhang and Sterbenz, 2014; Lehner, 2013). Hereby, we give a clear definition of what is topological criticality and what is functional criticality in air transportation networks:

Topological criticality is investigated from the properties of the physical network structure, independently from the actual passenger traffic on top of the network. From this topological view, connections with a small number of passengers are considered equally important as connections with a large number of passengers.

Functional criticality is identified from the properties of the network, when taking into account the actual passenger traffic on top of the network. From the functional point of view, connections with a large number of passengers are considered more important for the network, than connections with only few passengers.

Therefore, we refer to the physical network with passenger traffic data as a *functional network* (Newman, 2003), since one major function of air transportation systems is to deliver passengers from their origins to destinations. In this research, we investigate the temporal evolution of international air transportation country network from two perspectives separately: (1) the network's physical topology and (2) the functional network with passenger traffic data.

This paper is organized as follows. Section 2 discusses the state-of-art in the evolutionary analysis of air transportation networks. In Section 3, we build the international air transportation network at country level. Section 4 presents the evolution of the physical country network from 2002 to 2013, with focus on unweighted network properties and topologically critical nodes/links. Section 5 presents the evolution of the country network with passenger traffic data, focusing on traffic properties, weighted network properties, and functionally critical nodes/links. We discuss our results in Section 6 and conclude the paper with Section 7.

2. Related work

This section provides a literature review of the network evolution analysis in air transportation systems. Most research focused on airport networks, with airports as nodes and links exist if there is at least one direct flight connection between two airports. Azzam et al. (2013) studied the evolution of the worldwide airport network using Official Airline Guide (OAG) flight schedules data between 1979 and 2007. The authors found that the degree distribution is non-stationary and is subject to accelerated growth; the average degree increases while the average shortest path length decreases; the average clustering coefficient decreases for growing node degrees.

Several researchers investigated the evolution of the US airport network. Jia et al. (2014) examined the evolution of the US airport network from 1990 to 2010, based on a dataset provided by Bureau of Transportation Statistics (BTS). The results showed that the US airport network preserves the scale-free, small-world, and disassortative mixing properties; the evolution of stable cities and new cities has also been examined. Based on the same dataset, Lin and Ban (2014) studied the evolution of topological and spatial characteristics of the US airline network. They found that the dynamics of the US airline work is stable, distance becomes more significant with the passage of time, and the network efficiency decreases with the growth of the network. Kotegawa et al. (2014) presented a network restructuring algorithm in order to capture the evolutionary behavior of the US air transportation network. Gautreau et al. (2009) studied the evolution of the US airport network between 1990 and 2000 with the BTS data as well. The authors showed that although statistical distributions of most indicators are stationary, there exist several dynamics at the microscopic level, with many appearing/disappearing connections between airports. Neal (2013) presented the evolution of the business air travel network in the US from 1993 to 2011 and revealed that the business travel among US cities is becoming more symmetric and evenly dispersed. Bounova (2009) studied the evolution of the airline networks in US from 1990 to 2007 and showed that there are topology transitions; most airline networks have similar topology and historical patterns, with the exception of Southwest Airlines.

The evolution of European airport networks has also been widely studied. Burghouwt and Hakfoort (2001) analyzed the evolution of the European air traffic according to different airport groups, based on a weekly OAG data for the years 1990–1998. The authors showed that there is no clear trend of concentration of intra-European traffic on the primary hubs and a type of hub-and-spoke route structure has been developed. Jimenez et al. (2012) studied the evolution of the Portuguese airport network between 2001 and 2010. The analysis showed that the network is less concentrated and the low-cost carriers have a great impact on the evolution of the network. Papatheodorou and Arvanitis (2009) explored the evolution of the airport network in Greece over the period 1978–2006. The analysis showed that the spatial concentration and asymmetry remain high; Greece is short of traffic generated by the low-cost carriers. Guida and Maria (2007) analyzed the structure of the Italian airport network from the period 2005–2006, the data was derived from the OAG database. The authors found that the network is a scale-free, small-world network with a fractal structure.

The evolution of Chinese airport network has been investigated. Wang et al. (2014) analyzed the evolution process of the air transport network in China from 1930 to 2012, with the data from the Timetable of Air Carriers in China. The results showed that the network has improved its connectivity significantly; the six-stage structural changes were characterized by a spatial development model. Zhang et al. (2010) investigated the evolution of the Chinese airport network between 1950 and 2008, with the data provided by Civil Aviation Administration of China. The authors found that although the topology of the Chinese airport network is stationary, there exist network dynamics and the air traffic grows at an exponential rate with seasonal fluctuations.

The evolution of the Brazilian airport network between 1995 and 2006 was analyzed by Rocha (2009). He found that the number of airports decreased over this time span and the average shortest path length dropped slightly; the degree distribution decayed faster over time; and the network became increasingly sparse in spite of more than doubled number of passengers.

Furthermore, 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 to 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. Gillen and Morrison (2005) analyzed the link between airline business strategies and network structures. Burghouwt et al. (2009) argued that the analysis of network performance in hub-and-spoke systems should take into account the quantity and quality of both direct and indirect connections. Lehner et al. (2014) showed that the vast majority of all Intra-European passengers travel direct and the directness of the overall system increased from 2002 to 2012.

3. International air transportation at country level

In this research, we build the international air transportation network at country level, by aggregating all airports of a country into one node. For the physical network, discussed in this section, we assign the number of passengers traveling between two countries as link weight. Section 3.1 introduces the database used in this study. Section 3.2 presents the construction of the country network.

3.1. Database

We analyze the international air transportation between 2002 and 2013, based on the ticket data from the Sabre Airport Data Intelligence (ADI, http://www.airdi.net). The ticket data is stored by months and contains the following information: Origin/destination airports, up to three connecting airports, and the number of passengers who bought this ticket in one month. In total, we have the ticket data for 144 months (12 years, 2002–2013). Note that the origin/destination airports of the passengers are not necessarily the same as their home countries, since the demographics of the passengers are not available. Thus, the international passenger flows in our study show the mobility patterns among the countries, rather than the migration patterns (Manduca, 2014).

3.2. Construction of the country network

For each month, we transform the airport based ticket data into a country network. In total, we have 144 country networks in a monthly scale. We start with a collection of tickets on airports. We denote a ticket as a tuple $t = \langle [a_1, \ldots, a_m], p \rangle$, such that each a_i is one airport; a_1 is the origin of the ticket, a_m is the destination of the ticket, and p is the number of passengers who bought this ticket in a single month. The ticket database from ADI consists of n such tickets $T_1 = \{t_1, \ldots, t_n\}$. The tickets are grouped by the airports list $[a_1, \ldots, a_m]$ and the number of passengers is aggregated using summation. The result is denoted with T_2. For any $t_i = \langle A_i, p_i \rangle$ and $t_j = \langle A_j, p_j \rangle$ in T_2, we have the constraint: $i \neq j \rightarrow A_i \neq A_j$. The tickets in T_2 are converted to country-tickets as follows:

1. We map each airport to the country of the airport and obtain for each ticket $t \in T_2$ a country ticket $ct = \langle [c_1, \ldots, c_m], p \rangle$, where each c_i is a country.
2. We replace all consecutive occurrences of identical countries, since we are not interested in domestic flights, i.e., all occurrences of c, c are replaced with c.
3. We remove all country tickets with only one country (all tickets concerning domestic flights only).
4. We group all country tickets based on the country list, such that the number of passengers is aggregated (summation) over all country tickets with the identical country list. We obtain a set of country tickets $CT = \{ct_1, \ldots, ct_m\}$.
5. The physical network $\mathcal{N} = \langle N, L, w \rangle$ consists of a set of nodes N, a set of links $L \subseteq N \times N$, and a weight function w mapping links in L to real numbers. For weighted networks, we have that (n_1, n_2) is in the domain of w, if and only if $(n_1, n_2) \in L$. $\mathcal{N}$ is populated in the following way:

We set $N = C$ and iterate over all country tickets in CT. For each ticket $ct = \langle [c_1, \ldots, c_m], p \rangle$, and for each $1 \leqslant j < m$, we check whether $(c_j, c_{j+1}) \in L$. If $(c_j, c_{j+1}) \in L$, then we set $w(c_j, c_{j+1}) = w(c_j, c_{j+1}) + p$. If $(c_j, c_{j+1}) \notin L$, we add (c_j, c_{j+1}) to L and set $w(c_j, c_{j+1}) = p$.

Fig. 1 illustrates one example of the physical country network for the month August 2013, where each node is one country; a link between two countries exists when there is a direct flight connection between airports in these two countries; the node size is proportional to its weighted degree. We can observe that major European countries (such as Great Britain (GB), Germany (DE), and Spain (ES)) have the largest number of international traveled passengers; followed by United States (US) and China (CN). We provide some basic network statistics here. The country network for August 2013 consists of 222 nodes and 4620 links. It has an average degree of 21 and the density of the network is 0.094. An average clustering coefficient of 0.627 and an average shortest path length of 2.3 indicates that this network has a small-world property (Watts and Strogatz, 1998), i.e., most countries can be reached from each other country within few number of flight hops.

4. Topological evolution of the country network

This section presents the topological changes in the country network for the years 2002 to 2013. Throughout this section, links between countries are unweighted, unless mentioned otherwise. Therefore, our analysis reveals properties of the physical network structure, independently from the actual passenger traffic. We report on the temporal evolution of scale-free (Section 4.1.1) and small-world properties (Section 4.1.2), hubs and authorities (Section 4.1.3), and analysis of the triad census (Section 4.1.4) in the country network. Moreover, we identify the evolution of critical countries (Section 4.2) and critical flight connections (Section 4.3).

We begin our analysis with the investigation of two fundamental network metrics: Degree and density. Fig. 2 shows the evolution for the average degree (a) and density (b) in the 144 monthly-based country networks from 2002 to 2013 using STL (Seasonal and Trend decomposition using Loess) (Cleveland et al., 1990). STL is a filtering procedure for decomposing time series into (1) trend, (2) seasonal variation, and (3) remainder components, where the remainder component is the deviation of the actual data (signal) from the trend together with the seasonal components. The smaller the magnitude of remainder components compared to the original data, the more accurate is the decomposition into trend and seasonal patterns. We can observe from Fig. 2 that evolution of the average degree and density exhibit highly similar behavior: An overall increasing trend over the 12 years period indicates that the air traffic connections among the countries become denser. In average, countries increasingly attempt to serve direct connections to other countries. Accordingly, the density of the network is slightly increasing. This finding is consistent with the case of the worldwide airport network (Azzam et al., 2013): Both, the worldwide airport network and the country network become denser over time. Notably, there is an exception of a slight downturn in 2009. This can probably be explained by the global financial crisis in 2008/2009. The seasonal variation is analyzed in three different periods: The complete 12 years (2002–2013, denoted by the black line), the first 6 years (2002–2007, denoted by the red dashed line), and the other 6 years (2008–2013, denoted by the blue dashed line). In all three periods, we observe that the average degree and density show summer/winter seasonal variations: July and August are the peaks in summer; while February and November are the nadirs in winter. The minor deviations of the average degree and density for the three different periods show that the seasonal variations in the country network are rather stable during the 12 years period.

4.1. Network properties

4.1.1. Scale-free property

In a scale-free network, there are so called *hub* nodes which have more connections than other nodes and the degree exhibits a heavy-tailed (power law) distribution (Barabasi and Albert, 1999). The existence of a few hub nodes with high connectivity to other nodes, while the majority of nodes have very few connections, is the most notable characteristic for a scale-free network. The scale-free property is strongly correlated with the robustness of the network against failures. It has been shown that the scale-free network is highly robust to random failures, but rather fragile under targeted attacks (Holme et al., 2002). Another recent study also showed that some scale-free networks could be robust under targeted attacks, when taking into account the attack cost (Zheng et al., 2011).

Fig. 3(a) shows the box plot of the differences between indegree and outdegree (Delta = Indegree-Outdegree) for four months (February, May, August, and November) in three different years (2002, 2008, and 2013); while Fig. 3(b) presents the cumulative degree distributions for February and August in three different years (2002, 2008, and 2013). We select these four months because they are the four extrema in the seasonal variation of degree, among which February is the winter nadir and August is the summer peak, as shown in Fig. 2(a). In the box plot, the circles represent outliers and the color becomes darker with the frequency of these outlier values; the boxes contains 50% of the dataset for a month; the upper fence is the maximum value excluding outliers; and the lower fence is the minimum value excluding outliers. Among the 222 nodes in the country network, 50% of the countries have an absolute difference between indegree and outdegree of less than one. Previous studies on the evolution of the US airport network (Jia et al., 2014; Lin and Ban, 2014), the Chinese airport network (Zhang et al., 2010), and the Brazilian airport network (Rocha, 2009) showed that the in-degree and out-degree are perfectly linear correlated and thus indicates a high degree of symmetry of these airport networks in single countries. In fact, flight

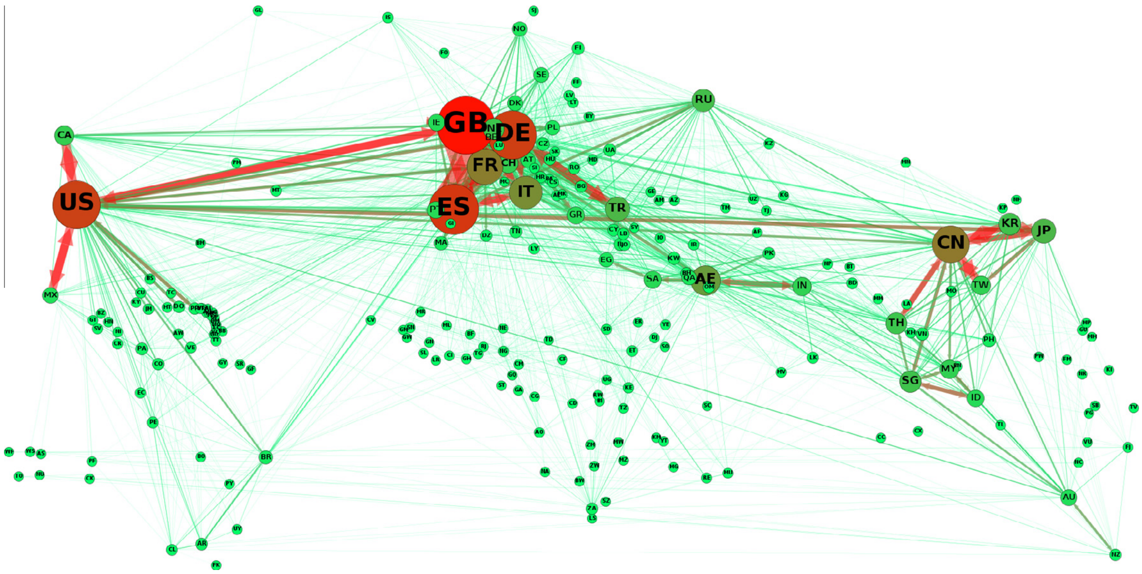
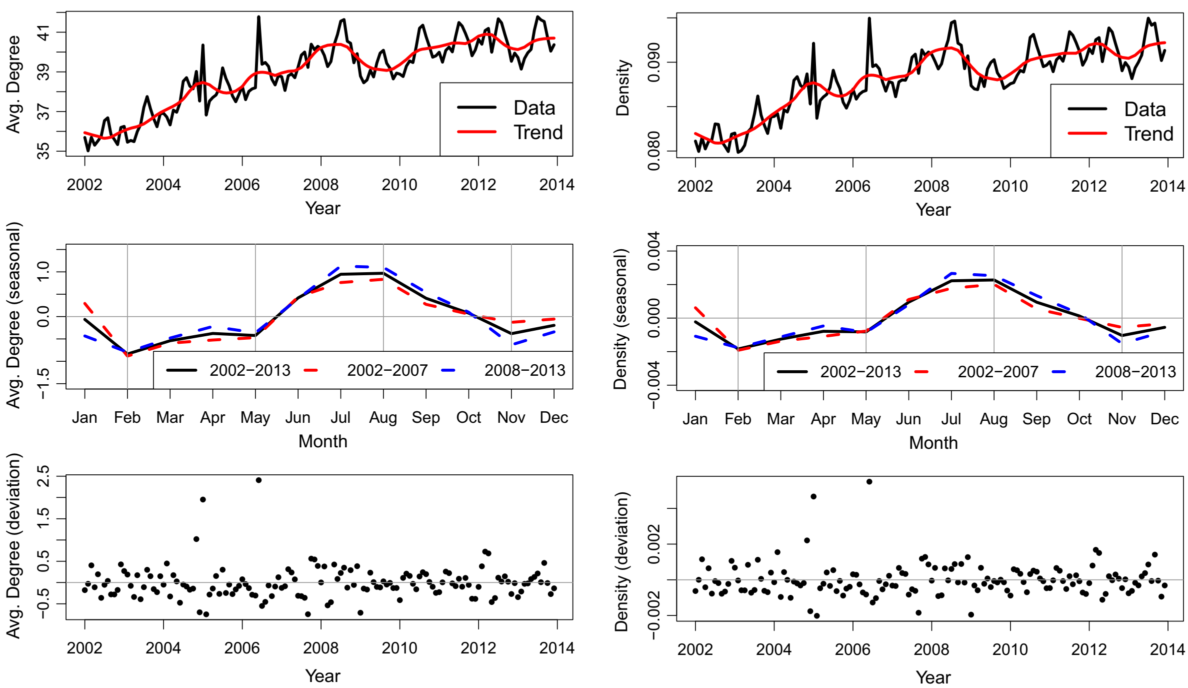


Fig. 1. An example of the physical country network for the month August 2013. Each node is one country; a link between two countries exists when there is a flight connection. The size of a node increases with its weighted degree. The color of nodes/links fades from green to red with increasing number of passengers. The countries are coded using ISO-3166-1 codes. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

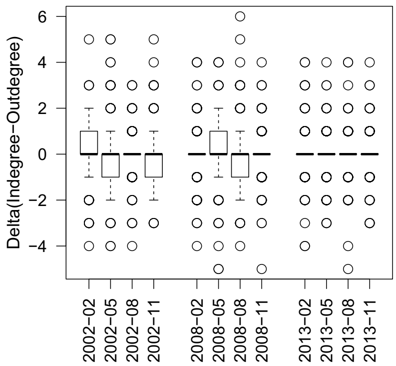


(a) The trend, seasonal variation, and deviation for the average degree

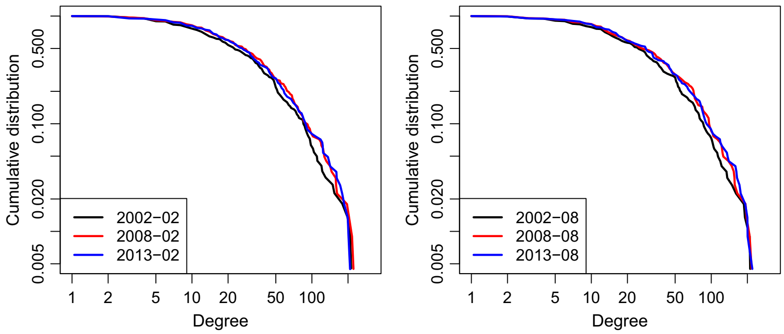
(b) The trend, seasonal variation, and deviation for the density

Fig. 2. Evolution of the average degree (a) and density (b) in the 144 monthly-based country networks from 2002 to 2013.

connections are often served in turns, where aircraft fly from their origin to the destination and then return to their origin. Our results indicate that not only many local airport networks are symmetric, but the international air transportation country network is symmetric as well. The degree distribution shown in Fig. 3(b) follows a heavy-tailed distribution and different time periods have rather similar degree distributions. We can also observe that the degree distribution is skewed slightly



(a) The box plot of the in/out-degree difference



(b) The cumulative degree distributions

Fig. 3. The box plot of the differences between indegree and outdegree for four months in three different years (a), with the circles representing outliers; the cumulative degree distributions for two months in three different years (b).

towards right over the 12 years period. This indicates the nodes are more connected over the years. This is consistent with our finding that the average degree of countries increased in the last 12 years (see discussion on Fig. 2).

While the degree of a node only considers the local connectivity of a network; the betweenness for a node also takes into account its global connectivity. The betweenness measure was proposed by Freeman (1978): $B_i = \sum_{s \neq t} \frac{\sigma(s,t|i)}{\sigma(s,t)}$, where $\sigma(s,t)$ is the number of shortest paths going from node s to node t; $\sigma(s,t|i)$ is the number of these paths passing through node i. In the following, we analyze the betweenness and its correlation to degree. While the calculation of the shortest paths in the unweighted network is based on the number of links (hops) connecting a given country node pair, another alternative is to use physical distance since it takes into account circuity of paths. It is interesting to compare hops-based betweenness with distance-based betweenness. In particular, we plot degree versus betweenness for both variants in Fig. 4(a).[1] The names of the outliers and high-degree countries are shown in red color. For both betweenness variants, the betweenness of a node increases with its degree. For instance, three major European countries (Germany, Great Britain, and France) show this phenomenon. We plot the correlation between hops-based and distance-based betweenness in Fig. 4(b). The correlation coefficient is stable around 0.7 for 2002–08 and 2013–08: A higher hops-based betweenness clearly correlates with a higher distance-based betweenness.

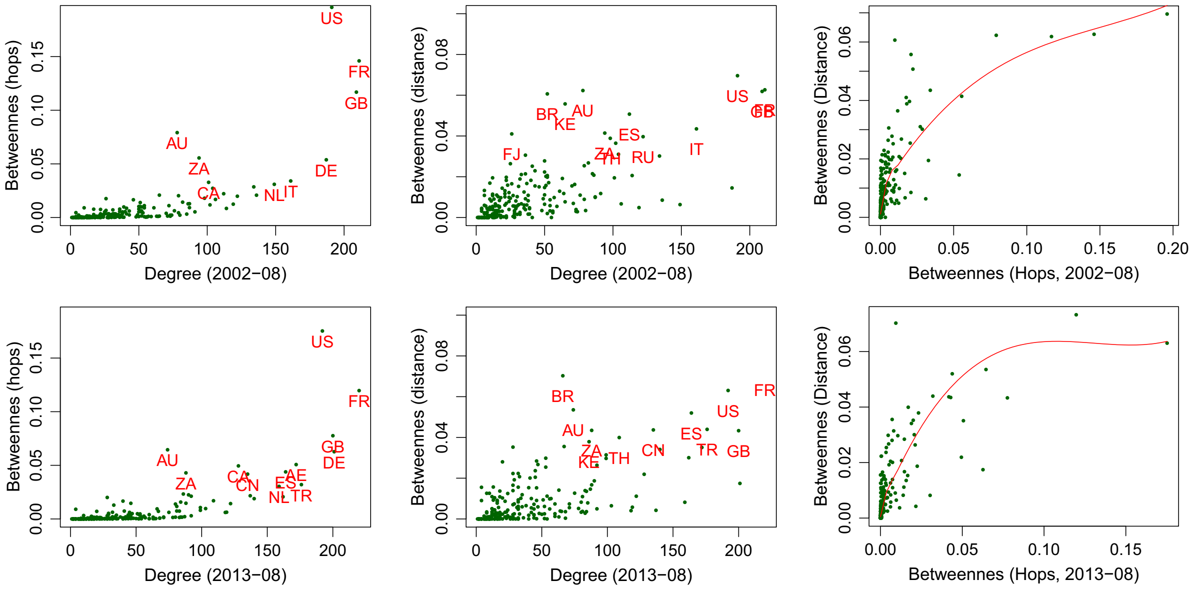
As shown by Guimera et al. (2005), correlation irregularities exist, because of geographical and political constraints: Most connected nodes (high degree) are not necessarily the most *central* ones (high betweenness), through which most shortest paths go. For instance, Australia (AU) and South Africa (ZA) show irregularities that although they are not the most connected nodes, they are on many shortest paths in the country network. The degree-betweenness irregularities can be explained by the geography of a country: Australia locates in the center of Oceania, many smaller countries in the Asia–Pacific regions go through Australia to connect to the rest of the world; while South Africa seems to be a kind of hub-country which enables the connections of the majority of African countries to the rest of the world. The high betweenness (both hops-based and distance-based variants) for Australia and South Africa indicates that these two countries have potentially large impacts on the flows going through the country network. The flow could be transferring international passengers, disease spreading (Gomes et al., 2014; Lemey et al., 2014), and delay propagation (Fleurquin et al., 2013). We think that Australia and South Africa should draw more attention in the analysis of international air transportation.

The above analysis is based on the computation of all-pairs-shortest-paths in the network. In practice, however, not for each pair of nodes there exists an actual travel request. We performed additional experiments to analyze, in how far taking into account real origin/destination information affects hops-based betweenness of nodes. We extracted the OD pairs from ticket data and applied an alternative definition of OD betweenness (Monechi et al., 2013), which is computed based on shortest paths between all OD pairs only. The correlation score of hops-based betweenness and OD betweenness is 0.96. Thus, the effect of taking into account real passenger OD information is rather small.

4.1.2. Small-world property

In a small-world network, there often exist *cliques*, a subset of nodes where every pair of nodes is connected by a link; and most nodes can be reached from other nodes within few number of steps. A small-world network can be identified by two structural features: Small average shortest path length, but higher clustering coefficient than its random counterpart network (Watts and Strogatz, 1998). The small-world property is closely related to the process dynamics on the networks, for instance, information and disease spreading (Newman, 2003).

[1] For interpretation of color in Figs. 4–6 and 8, the reader is referred to the web version of this article.



(a) Scatter plots of degree and betweenness (hops) as well as betweenness (distance) **(b)** Betweenness (hops) / betweenness (distance)

Fig. 4. Evolution of degree versus hops-based and distance-based betweenness for August 2002 and 2013.

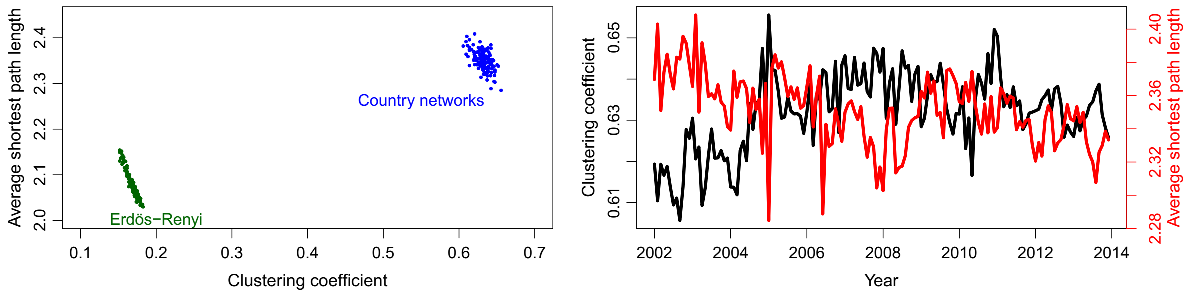


Fig. 5. Evolution of the small-world property in the 144 monthly-based country networks from 2002 to 2013.

Fig. 5 shows that the country network (in blue color) exhibits a small-world property during the period 2002–2013. The country network has high clustering coefficients and low average shortest path lengths. We also computed 144 random Erdös-Rényi networks (the left panel of Fig. 5 in green color) with the same number of nodes and links. With roughly equivalent average shortest path length, the random Erdös-Rényi networks have much lower clustering coefficients than the country network. This indicates that the country network has the small-world property, i.e., it would take a random walker only a few number of flight hops when traveling around the whole world. The right panel of Fig. 5 shows the evolution of the clustering coefficient (in black color) and the average shortest path length (in red color) during the 12 years period. We can observe that although there are fluctuations, the clustering coefficient and the average shortest path length are rather stable during the evolution process of international air transportation. Only the clustering coefficient seems to change its behavior slightly in 2008/2009, from increasing to decreasing. However, we have no data for the years before 2002 and thus cannot prove/refute this observation further.

4.1.3. Hubs and authorities

In this section, we identify hubs and authorities in the country network. The notion of hubs and authorities was introduced to rate the importance of a node based on the HITS (Hyperlink Induced Topic Search) algorithm. This algorithm was originally developed to calculate the ranking of web pages used by search engines (Kleinberg, 1999). Authorities are web pages which are informative and are usually pointed to by many other hyperlinks; while hubs are web pages which point to a large number of authority pages (the situation is illustrated in Fig. 21 in Appendix). In general, authorities and hubs have a mutual reinforcement relationship.

The HITS algorithm proceeds as follows. First, HITS assigns two numbers to a node: An authority and a hub weight (both initially set to 1). Afterwards, a maximum number of iterations is performed, consisting of an authority update and hub update. An authority update recomputes each node's authority score to be the sum of the hub scores of each node that points to it. A hub update recomputes each node's hub score to be the sum of the authority scores of each node that it points to. The HITS algorithm terminates (a) after a maximum number of iterations or (b) when the results converge below a user-defined error threshold. We use NetworkX (Hagberg et al., 2008) to calculate hubs and authorities values in the country network. We set the default parameters for the HITS algorithm (Kleinberg, 1999) as follows: Maximum number iterations $max\_iter = 100$, error tolerance $tol = e^{-8}$, and $nstart = None$ (which implies equally distributed start weights).

Fig. 6(a) shows the scatter plots for hubs and authorities of the country network in four different time periods. We can observe a strong linear correlation between hubs and authorities in the country network. This indicates that a country with a high hub value often has a high authority value as well. Note that similar maximum hubs/authorities values are reported for the US airport network between 1990 and 2010 by Jia et al. (2014): A city with a high hub score tends to have a high authority score. Among the top-ranked countries with high hubs and authorities, Great Britain (GB) has one of the highest hub and authority values and it keeps being ranked in the top two over the time period 2002–2013. The hub and authority values for United States (US) descend with the years. On the contrary, Spain (ES) has increasing hub and authority values over the 12 years period. The rising role of Spain can probably be explained by its strong intra-European traffic connection with Great Britain. We will analyze the traffic properties of the country network further in Section 5.1. In order to further explore the falling role of United States and the rising role of Spain, Fig. 6(b) presents the evolution of hubs and authorities for United States (in red color) and Spain (in blue color). Furthermore, the hub and authority values for Spain show a rather strong summer/winter seasonal variations.

4.1.4. Triads

The triad census (Davis and Leinhardt, 1967; Batagelj and Mrvar, 2001) is computed by counting the number of occurrences of each unique 3-node substructure in the network. In a directed network, in general, there are sixteen possible triads. These sixteen triads are labeled with *abcZ*, where *a* is the number of reciprocated ties, *b* is the number of unreciprocated ties, and *c* is the number of null ties. The *Z* letter (U, C, D, or T) is used to differentiate between different triads in which these numbers are the same. The triads in a network often strongly correlate with nodal and dyadic properties (Faust, 2006). In large and sparse networks, most triads are of type 003 (Faust, 2010).

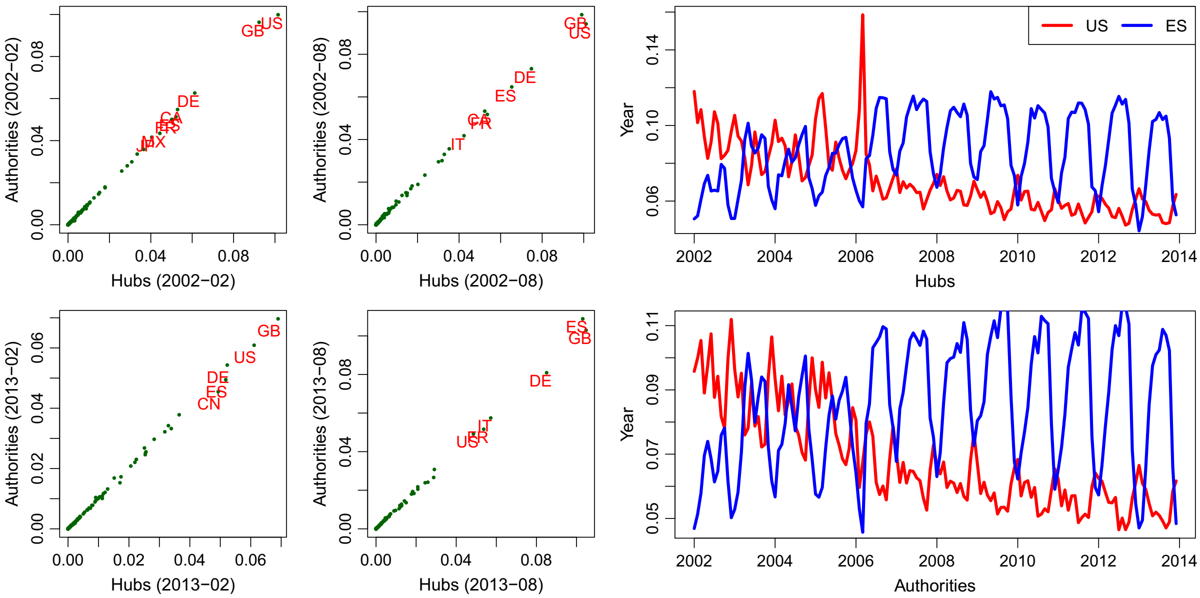
Fig. 7 shows the evolution of triad census for the country network in the time frame 2002–2013. The monthly-based data is shown with black points; the trend line is extracted with STL and shown in red color. The triads are ordered by the average number of occurrences over the whole 12-year time period. The most frequent type of triad is 003 (sets of three countries with no links among them), which shows that the overall network is rather sparse. The least frequent type of triad is 030C. Three types of triads are steadily increasing: 102, 201, and, 210. This shows that the country network gears towards symmetric, transitive closure. This observation is supported by the decreasing number of triads of types 012 and 210. However, one should note that the number of these triads is 1–2 orders of magnitude smaller than the dominating number of 003-triads.

4.2. Topologically critical nodes in the country network

In this section, we present the evolution of the topologically critical nodes in the country network from 2002 to 2013, based on Minimum Dominating Set (MDS). The MDS was proposed by Nacher and Akutsu (2014) and is an optimization procedure to identify which nodes play important roles for the control of a network. The controllability of a network is defined as if it can be driven from any initial state to any desired final state in finite time (Liu et al., 2011). For instance, in protein–protein networks nodes in the MDS affect the network resilience significantly (Wuchty, 2014).

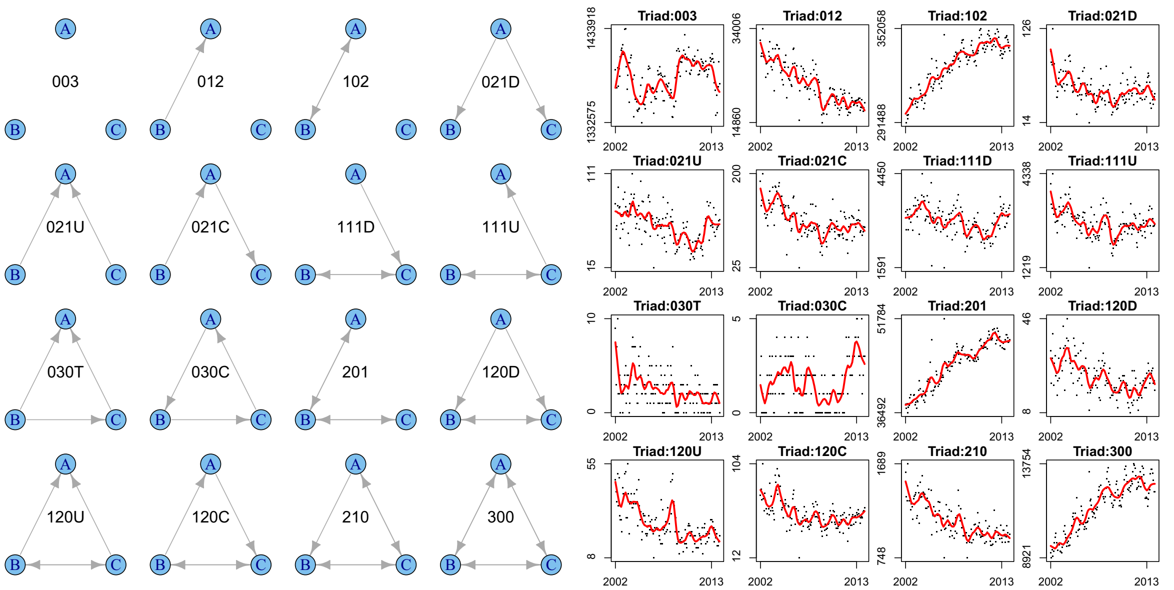
For a network with the set of nodes N, a dominating set is a set of nodes S with $S \subseteq N$, such that for each $n \in N$, we have $n \in S$ or n is a neighbor of at least one $s \in S$. The MDS is the dominating set with the smallest size (Nacher and Akutsu, 2014). A small example of a dominating set is shown in Fig. 22 in Appendix. Because there exists no unique MDS, there are several configurations with the same number of drivers that can control the whole network. Therefore, all nodes can be classified depending on the whether a node is part of all (=critical), some but not all (=intermittent), or does not participate in any possible MDS (=redundant) (Nacher and Akutsu, 2014). Scale-free networks with small power-law exponents values require few nodes to be controlled (lower or around 20%). For each of the 144 monthly-based country networks, we apply the MDS to identify which countries are topologically critical. Thus, we obtain 144 sets of critical countries, one for each month.

The top ten frequently rated critical countries are highlighted in Fig. 8(a), where the number associated with each country represents how many times this country is rated as critical in the 144 monthly-based country networks. The evolution of the critical roles over the 12 years period is presented in Fig. 8(b), where the green dot represents the status of a country of being critical or non-critical and the red line is the moving average over 12 months. Among the top ten topologically critical countries, there are three countries from Europe (France (FR), Portugal (PT), and Great Britain (GB)), two from North/South America (United States (US) and Antigua and Barbuda (AG)), two from Oceania (Australia (AU) and Fiji (FJ)), two from Africa (South Africa (ZA) and Kenya (KE)), and one from Asia (China (CN)). As expected, several large countries are identified as critical, such as United States, China, and three European countries; it is quite interesting to note that some smaller countries, such as Fiji and Antigua and Barbuda, are identified as critical countries as well. The strong connections of Fiji in the Melanesia region and to other small island countries in the South Pacific Ocean make Fiji critical. The critical role of Antigua



(a) The scatter plots for hubs and authorities **(b)** Hubs and authorities for United States (US) and Spain (ES)

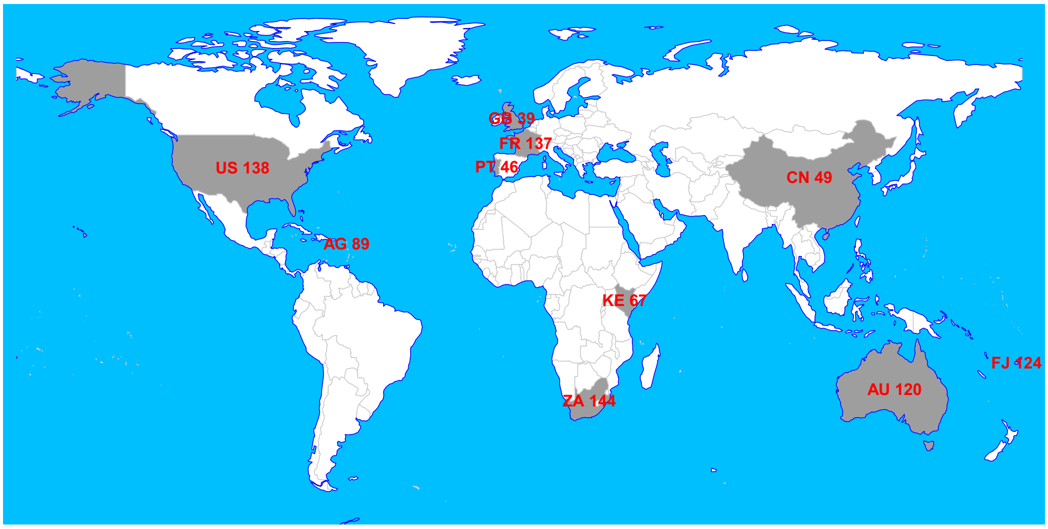
Fig. 6. Evolution of hubs and authorities in the 144 monthly-based country networks from 2002 to 2013.



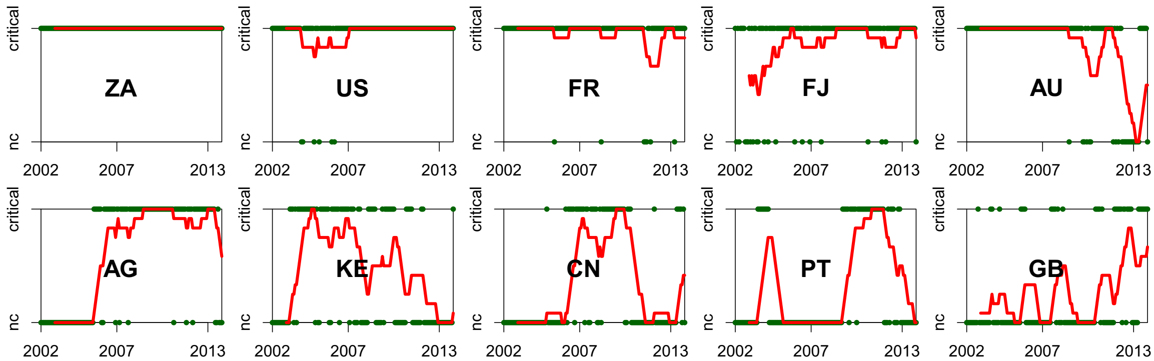
(a) Types of triads in a network (Batagelj and Mrvar, 2001) **(b)** Monthly data is shown as black points, the trend line is extracted with STL (Cleveland et al., 1990) and shown in red.

Fig. 7. Evolution of triad census for the country network (a) and frequency of triads by month (b).

and Barbuda is explained similarly. It is important to note that these countries are important from its topology point of view. In how far these countries are critical when taking into account passenger traffic data, is analyzed in Section 5.3. Among the 222 nodes in the country network, South Africa (ZA) is rated as topologically critical in each month over the 12 years period. The stable critical role of South Africa can be explained by its important role in the air traffic connections inside the continental region of Africa. Except for the top three topologically critical nodes (South Africa, United States, and France), the critical roles of the other seven countries fluctuate strongly in the 12 years period.



(a) Top ten topologically critical nodes identified by the minimum dominating set. The number associated with each country represents the frequency of being rated as critical in the 144 monthly-based country networks.



(b) Evolution of the top ten topologically critical nodes over the 12 years period, where nc stands for non-critical. The green dot represents the status of a country of being critical or non-critical for the 144 monthly-based country networks. The red line is the moving average over 12 months.

Fig. 8. The top ten topologically critical nodes (a) and the evolution of critical roles over the 12 years period (b).

4.3. Topologically critical links in the country network

In this section, we identify topologically critical links based on *dispersion*, a novel network measure which has been recently proposed for estimating tie strength in the social network (Backstrom and Kleinberg, 2014). The dispersion is based on the idea that when the mutual neighbors of nodes u and v are not well connected to each other, u and v act jointly as the only intermediaries between these different parts of the network. The dispersion is formally defined as: $disp(u,v) = \sum_{s,t \in C_{uv}} d_v(s,t)$, where C_{uv} denotes the common neighbors of nodes u and v; d_v is a distance function on the nodes of C_{uv}. The set of common neighbors C_{uv} contains all nodes which are connected to both u and v. Formally, we have that $C_{uv} = \{x|((x,u) \in L \vee (u,x) \in L) \wedge ((x,v) \in L \vee (v,x) \in L)\} \cup \{u,v\}$, where L are the links of the graph. In Backstrom and Kleinberg (2014), the authors discuss several distance functions d_v. They argue, that the following definition yields the best results: $dv(s,t) = 1$ when s and t are not directly linked and also have no common neighbors in G_u other than u and v; otherwise $dv(s,t) = 0$, where G_u represents the graph induced on u and all neighbors of u. This induced graph is a sub-graph, whose nodes are composed of u (itself) and the nodes which are linked with u (its neighbors). Formally, the induced graph $G_u = \langle N_u, L_u \rangle$ is defined such that $N_u = \{x|((x,u) \in L \vee (u,x) \in L)\} \cup \{u\}$ and $L_u = \{(x,y)|x \in N_u \wedge y \in N_u\}$.

A high dispersion value for a link between two nodes indicates their mutual neighbors are not well connected to one another. In the context of the country network, the dispersion reflects how important a link between two countries is for connecting their common neighbor countries, when their common neighbor countries are not themselves well connected, i.e., when there is demand among the common neighborhoods, passengers have to go through this unique link and thus this link becomes critical. We use NetworkX (Hagberg et al., 2008) to calculate dispersion values for links in the country network. We explain the parameters in the dispersion algorithm as follows (Backstrom and Kleinberg, 2014).

- $u = None$: The source for the dispersion score is not specified, since we want to compute dispersion on all node pairs.
- $v = None$: The target of the dispersion score is not specified, since we want to compute dispersion on all node pairs.
- $normalized = True$: The dispersion score is normalized by the embeddedness of the nodes u and v, where the embeddedness (Marsden and Campbell, 1984) is the number of common neighbors two nodes (u and v) share and it is denoted by $emb(u, v)$.
- $alpha = 1.0, b = 0.0$, and $c = 0.0$: The function form $(disp(u, v) + b)^{\alpha}/(emb(u, v) + c)$ is one strengthening of the normalized dispersion that leads to increased performance (Backstrom and Kleinberg, 2014). Since the performance of dispersion is highest for functions with monotonically increasing $disp(u, v)$ but monotonically decreasing $emb(u, v)$ (Backstrom and Kleinberg, 2014), we select this setting of $alpha = 1.0, b = 0.0$, and $c = 0.0$, so that the function form $(disp(u, v) + b)^{\alpha}/(emb(u, v) + c)$ becomes: $disp(u, v)/emb(u, v)$. In this case, the absolute dispersion value is normalized by the embeddedness.

Fig. 9(a) shows the top ten topologically critical links between distinct country pairs. The links are selected based on the mean value of dispersion over all 144 monthly-based country networks. Remarkably, intra-continental connections within North America, inter-continental connections between North America and Europe are all critical. Furthermore, inter-continental connections between Europe (particularly France) and Africa (Ethiopia, Libya, South Africa, and Sudan) are identified as critical as well. The same holds for the intra-continental connections within Oceania and within Africa. In summary, North America and Europe have dominating roles in terms of critical connections in international air transportation from the topology point of view. Fig. 9(b) shows the evolution of the roles for the topologically critical links. We observe that the connection between United States and Great Britain is losing its importance since 2008, indicating that their neighbors themselves become more connected. This is consistent with the fact that the air traffic connections among the countries are denser, as evidenced by the increasing trends of the network's degree and density shown in Fig. 2. Among the four critical links between France and Africa, only the connection to Ethiopia gains importance since 2007. This suggests that their mutual neighborhoods (France and Ethiopia) become less connected, and thus this link becomes more important for the connections among these neighborhoods. In how far these links are critical when taking into account the passenger traffic data, is analyzed in Section 5.4.

5. Functional evolution of the country network with traffic data

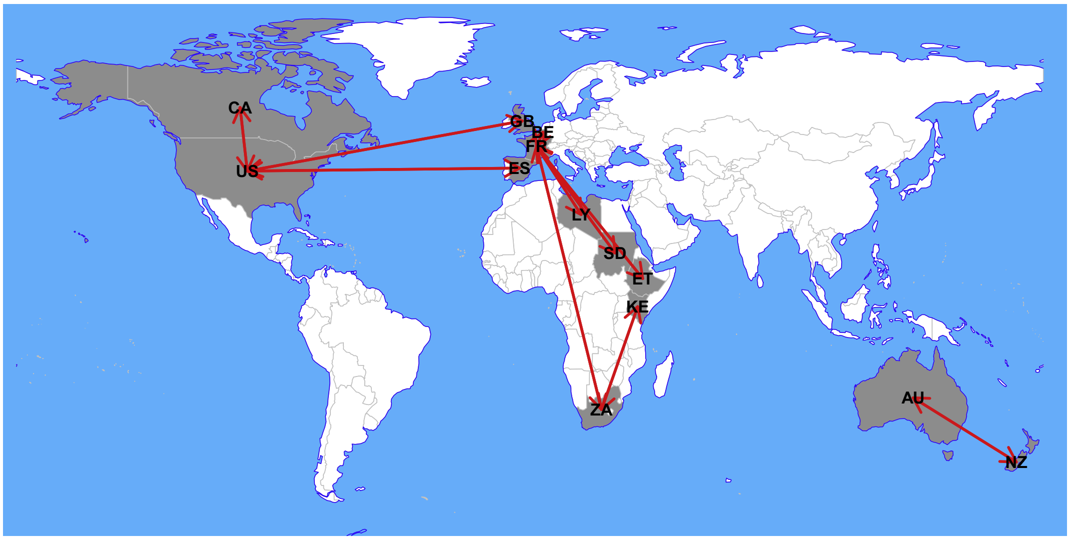
This section presents the changes in the country network from 2002 to 2013 including passenger traffic data. Therefore our analysis reveals interesting properties of the functional network (Newman, 2003). First, we analyze the international passenger traffic in Section 5.1 and network-theoretic properties in Section 5.2. Functionally critical nodes/links with traffic data are identified in Sections 5.3 and 5.4, respectively.

Before reporting the results, we would like to point out that the links in the network are weighted in a different way throughout this section. In Section 5.1, links between countries are weighted with the number of passengers using that connection within a month. This follows the intuition that links with higher weights are more important than links with only a few passengers. In Section 5.2 and below, link weights are set to the reciprocal of the number of passengers traveling between two countries. This modification of link weights is necessary to obtain meaningful results for betweenness/closeness variants, which are based on computation of shortest paths. The intuition is that a large fraction of traffic is effectively equivalent to a short distance between nodes (Brockmann and Helbing, 2013).

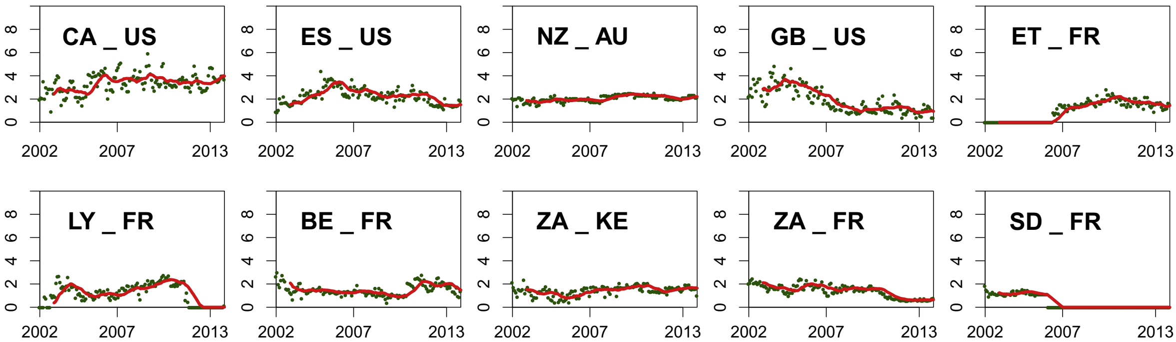
5.1. Traffic properties

The evolution of the traffic patterns for the international passenger flows is discussed at three different levels: (1) The global air transportation level, (2) the top 5 countries at the nodal level, and (3) the connections among the top 5 countries at the link level. Fig. 10(a) shows the evolution of the international passenger flows from 2002 to 2013 using STL. We observe an increasing trend for the number of international passengers over the 12 years period. In all three periods, we observe that the number of international passengers clearly shows summer (peak)/winter (nadir) seasonal variations. The deviation for the monthly-based number of international passengers does not show common patterns, instead, the feature of the deviation is similar with white noise: Uncorrelated random variables with zero mean and finite variance (Diebold, 1998). Notably, the overall increase in the number of international passengers follows a linear trend, as opposed to an exponential domestic passenger growth in the Chinese airport network (Zhang et al., 2010).

The average number of country hops is shown in Fig. 10(b): For each country ticket, we have counted the distinct number of countries in that ticket minus one and computed the mean value over all tickets. This measure represents how many international borders passengers cross for their travel to the destination (note that our evaluation does not include intra-country tickets). For instance, if we have one ticket from India (IN) to United States (US) via Unites Arab Emirates (AE) denoted by (IN, AE, US), then the number of country hops is 2; if we have another ticket from Australia (AU) via Singapore (SG) and Unites Arab Emirates (AE) to Great Britain (GB) denoted by (AU, SG, AE, US), then the number of country hops is 3. Thus, the average number of country hops for these two country tickets is 2.5. We can observe from Fig. 10(b) that the average



(a) Top ten topologically critical links, based on the mean value of dispersion over all 144 monthly-based country networks.

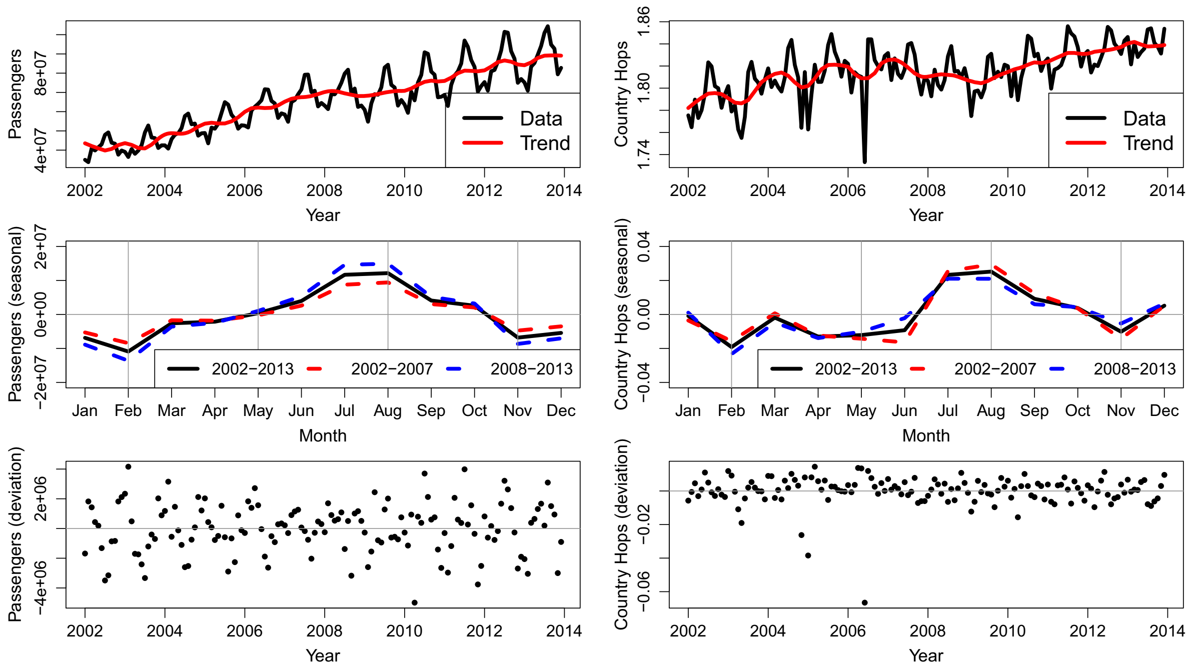


(b) Evolution of the dispersion for the top ten topologically critical links over the 12 years period. The green dot represents the dispersion value for each of the 144 monthly-based country networks; the red line is the moving average over 12 months.

Fig. 9. The top ten topologically critical links ranked by dispersion (a) and evolution of dispersion over the 12 years period (b).

number of country hops is slightly increasing, which means that passengers are actually increasingly using other countries as hubs to go to their destinations. This seems to contradict our observation that the degree of countries is increasing in average and that the average shortest path length is slightly decreasing (from the network topology point of view). We think the increase in country hops is caused by more exotic travel destinations of passengers over the years. Passengers want to explore more non-standard countries recently, for which there are often no direct flights yet, or where it does not pay off for airlines to have regularly scheduled connections. Note that although Low-Cost Carriers (LCC) are emerging and becoming more popular, they typically connect already well-established countries, with reduced complexity and a very low price.

Fig. 11 presents the evolution of the number of international passengers from 2002 to 2013 for the top 5 countries at the nodal level: Great Britain (GB), United States (US), Germany (DE), Spain (ES), and France (FR). The countries are selected based on the weighted degree. All the top 5 countries show clearly summer (peak)/winter (nadir) seasonal variations. Remarkably, the number of international passengers traveled from/to three European countries (Great Britain, Germany, and Spain) increased significantly from 2006 and the magnitudes of summer/winter seasonal variations are quite large (approximately 7 million). The number of international passengers traveled from/to United States is rather stable since 2002. The magnitudes of summer/winter seasonal variations for United States and France are approximately 2 million. It is worth noting that in August 2012, the number of international passengers traveled to/from Great Britain reached the peak over the 12 years period. This was mainly caused by the London 2012 Summer Olympics, which took place from July, 25th to August, 12th. Fig. 12 shows the evolution of the international passenger flows in the peak travel month (August) from 2002 to 2013 among the connections for the top 5 countries at the link level. The connection with the largest number of international passengers is between Great Britain (GB) and Spain (ES). This dominating position in the passenger traffic maintains stable during the 12 years period. The major reason for the dominance of this connection is probably the financial crisis in Spain and young Spanish people moving to Great Britain. Great Britain has been the biggest destination for emigrating



(a) The trend, seasonal variation, and deviation for the passengers (b) The trend, seasonal variation, and deviation for the country hops

Fig. 10. Evolution of the international passenger flows (a) and the average number of country hops (b) in the 144 monthly-based country networks from 2002 to 2013.

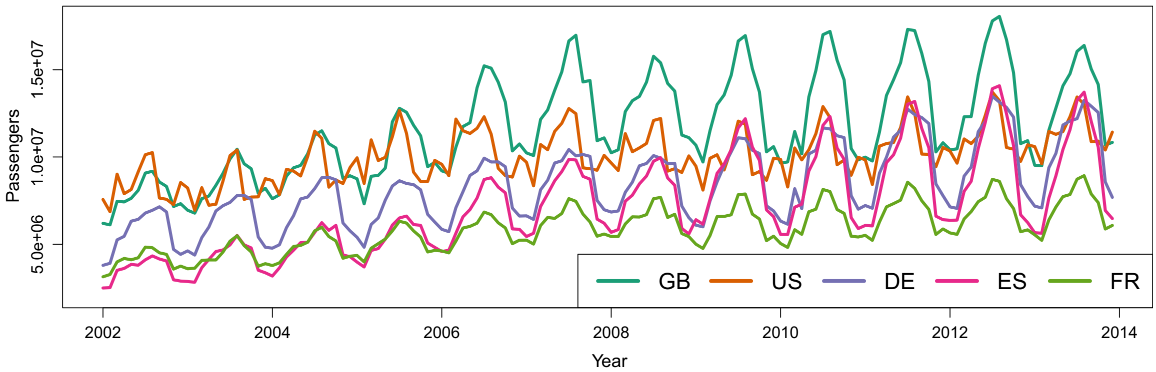


Fig. 11. Evolution of the international passenger flows from 2002 to 2013 for the top 5 countries: Great Britain (GB), United States (US), Germany (DE), Spain (ES), and France (FR). The 5 countries are selected based on the weighted degree. All the top 5 countries show clearly summer (peak)/winter (minimum) seasonal variations.

Spaniards for eight of the past ten years (Bloomberg, 2013), according to the University of Oxford's Determinants of International Migration project.

5.2. Weighted network properties

The comparison of two variants of betweenness, hops-based betweenness and distance-based betweenness, was presented in Fig. 4 in Section 4.1.1. In this section, it is interesting to compare another variant of betweenness with traffic data: Passenger-based betweenness. The link weights are set to the reciprocal of the number of passengers traveling between two countries, based on the idea that a large fraction of traffic is effectively equivalent to a short distance (Brockmann and Helbing, 2013).

Fig. 13(a) shows the scatter plots between the degree and passenger-based betweenness for August (summer peak) in 2002 and 2013. The countries with high passenger-based betweenness are shown in red color. Compared with the unweighted version shown in Fig. 4(a), irregularities do not exist in the weighted country network, i.e., countries with high

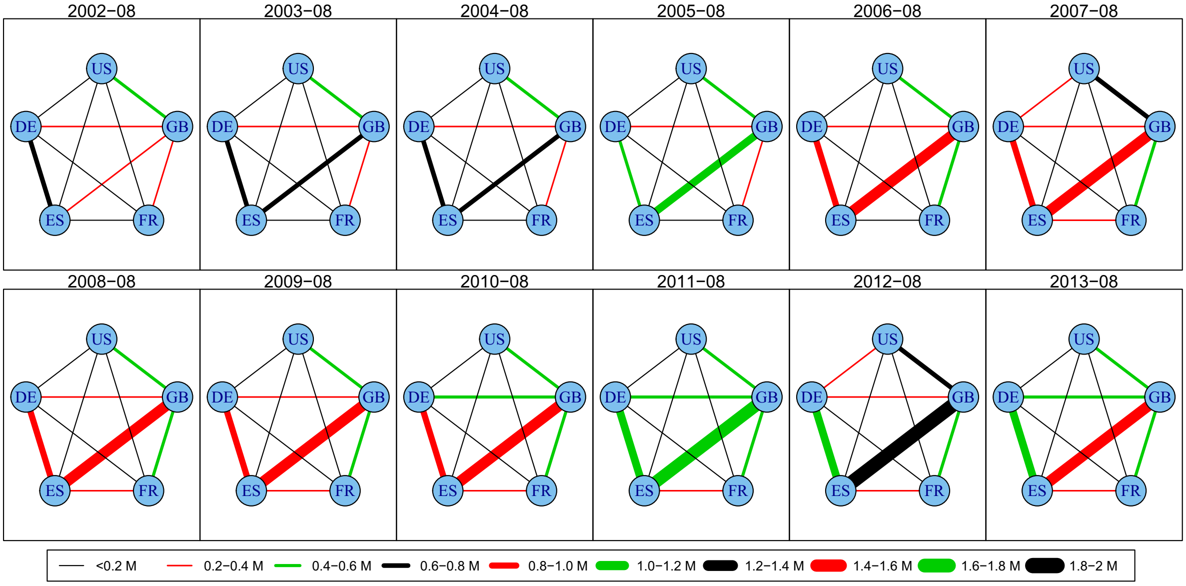
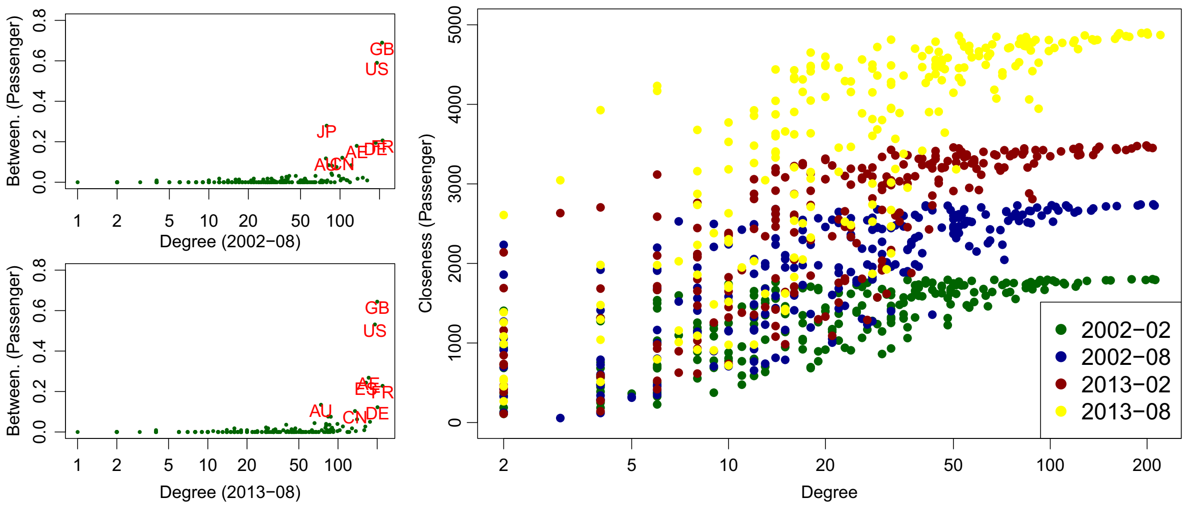


Fig. 12. Evolution of international passenger flows in the peak travel month (August) from 2002 to 2013 among the connections for the top 5 countries. The connection with the largest number of passengers is between Great Britain (GB) and Spain (ES).



(a) Degree versus passenger-based betweenness

(b) Degree versus weighted closeness

Fig. 13. Evolution of the correlation between degree against passenger-based betweenness (a) and weighted closeness (b).

degree also have high passenger-based betweenness, when taking into account the traffic (passenger flows) on the country network. Furthermore, top-ranked countries, for instance, Great Britain (GB) and United States (US), are rather stable during the 12 years period. Notably, the rising position of United Arab Emirates (AE) deserves more attention in the evolution process of international air transportation. With increasing strong economic cooperation between Asia and Europe as well as Asia and Africa, United Arab Emirates act as an important *bridge* for the air traffic connections for these economic partners.

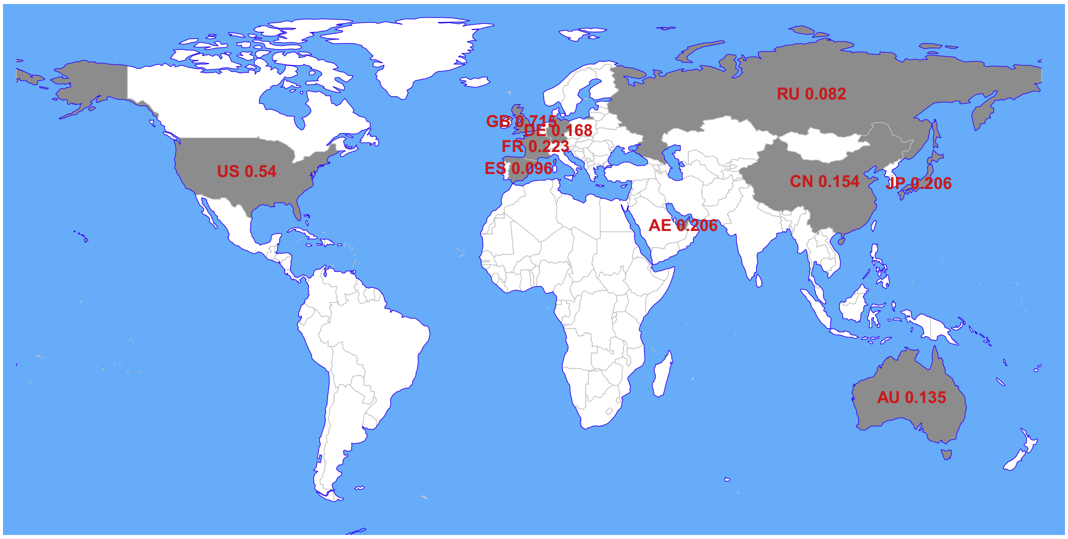
While betweenness centrality of a node counts the number of shortest paths in the network passing through this node; closeness centrality of a node measures how long it would take to spread information from one node to all other nodes. Closeness centrality of a node is defined as the reciprocal of the sum of its distances to all other nodes (Freeman, 1978): $c_i = \frac{\sum_{j \in N, j \neq i} \sigma_{ij}}{(n-1)}$, where N is the set of all nodes in the network, n is the number of nodes, σ_{ij} is the shortest path between node i and node j. In the context of air transportation country network, a country with higher closeness value is more central and has shorter total distance to all other countries in the network.

Fig. 13(b) shows the scatter plots between degree and passenger-based closeness (link weights are set to the reciprocal of the number of passengers traveling between two countries) for February and August for 2002 and 2013. We can observe a strong correlation between these two metrics. Over the 12 years, the distances to all other nodes in the country network become smaller, particularly for these countries with strong international passengers mobility. For a certain year, the weighted closeness exhibits summer/winter seasonal variations: The nodes in summer (August) have shorter distances to all other nodes; while in winter (February) shows the opposite behavior. We think this is because in summer there are more international passengers traveling.

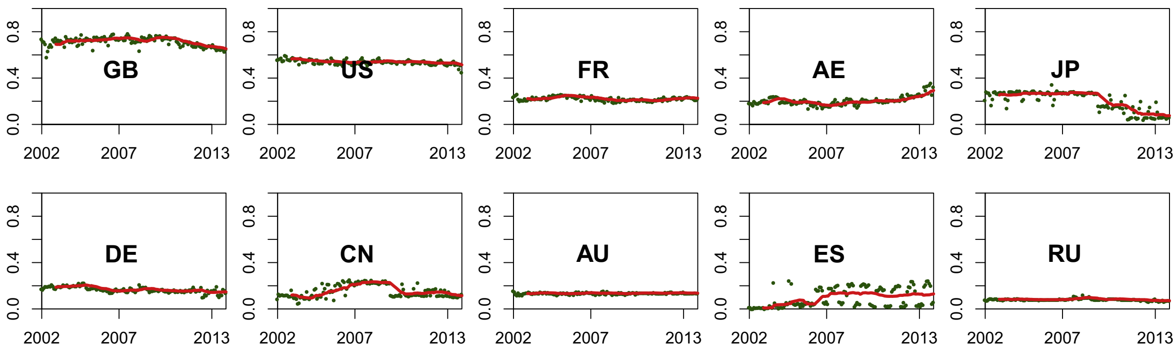
5.3. Functionally critical nodes in the country network with traffic data

The betweenness of a node can be interpreted as the extent to which a node has control over pair-wise connections between other nodes, based on the assumption that the importance of connections is equally divided among all shortest paths for each pair and that item transfers follow shortest paths (Brandes, 2008). In this section, we identify functionally critical nodes in the country network, using passenger-based node betweenness.

Fig. 14(a) presents the top ten functionally critical nodes with traffic data. The nodes are selected based on the mean value of passenger-based node betweenness over all 144 monthly-based country networks. It is not surprising to find that large countries, including United States (US), Russia (RU), Australia (AU), four major European countries (Great Britain (GB), France (FR), Germany (DE), and Spain (ES)), as well as two major Asian countries (China (CN) and Japan (JP)), are critical for the international air transportation, i.e., these countries have great responsibilities in transferring international passengers from their origins to destinations, simply due to the size of their populations.

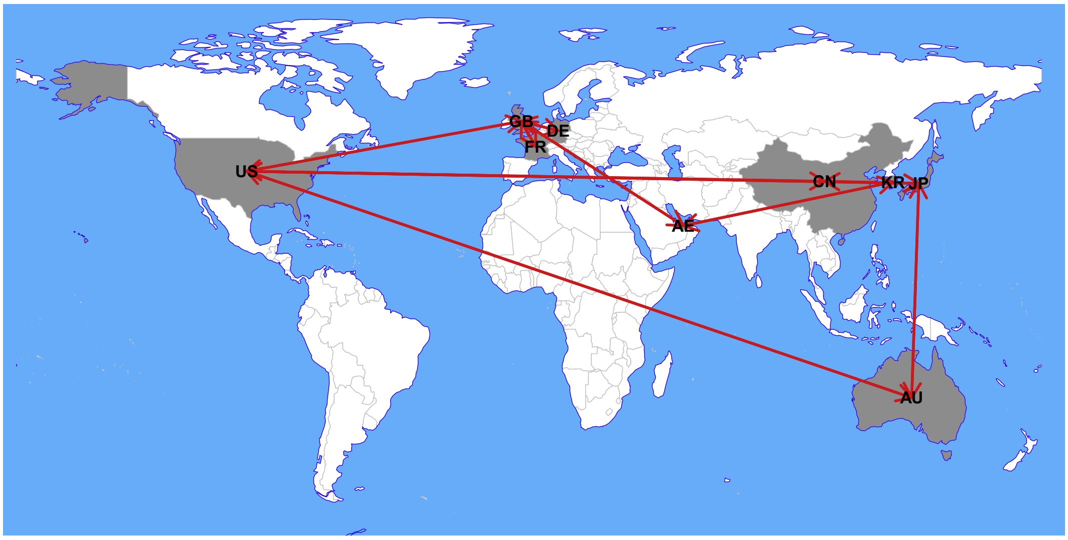


(a) Top ten functionally critical nodes, based on the mean value of passenger-based node betweenness over all country networks.

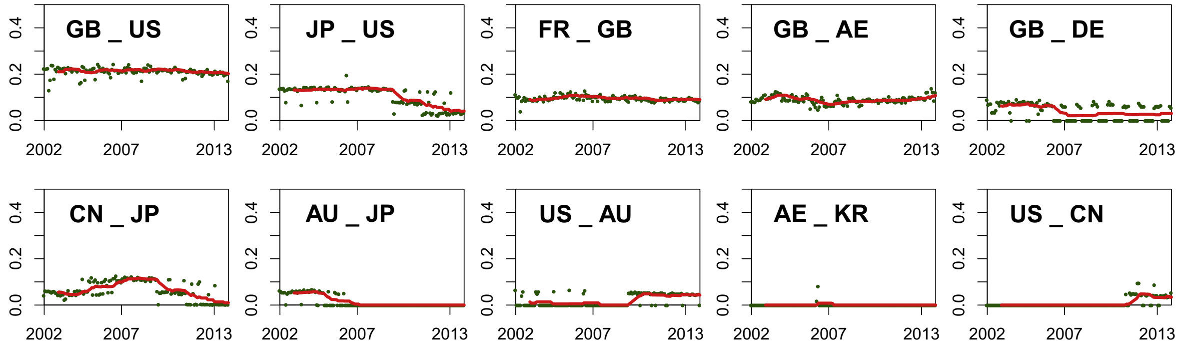


(b) Evolution of passenger-based node betweenness for the top ten functionally critical nodes over the 12 years period. The green dot represents the value for each of the 144 monthly-based country networks; the red line is the moving average over 12 months.

Fig. 14. The top ten functionally critical nodes with traffic data in the country network (a) and the evolution of critical roles (b).



(a) Top ten functionally critical links, based on the mean value of passenger-based link betweenness over all country networks.



(b) Evolution of passenger-based link betweenness for the top ten functionally critical links over the 12 years period. The green dot represents the value for each of the 144 monthly-based country networks; the red line is the moving average over 12 months.

Fig. 15. The top ten functionally critical links with traffic data in the country network (a) and the evolution of critical roles (b).

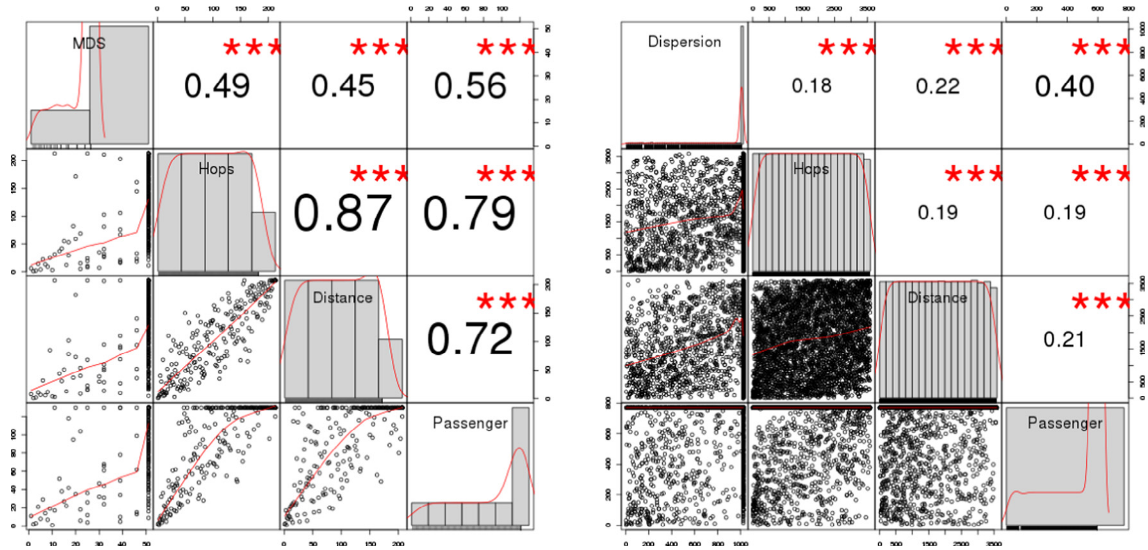
Compared with the top ten topologically critical nodes shown in Fig. 8 in Section 4.2, five countries maintain the critical roles and five countries are replaced by new ones. Among the five countries with double critical roles, the ranking positions for United States and France keep stable: They are ranked the second and third places regarding both critical roles in the country network. Among the other five countries only with single critical role, two small island countries (Fiji (FJ) and Antigua and Barbuda (AG)), two African countries (South Africa (ZA) and Kenya (KE)), as well as Portugal (PT) disappear from the list of critical nodes with traffic data; instead, United Arab Emirates (AE), Japan (JP), Germany (DE), Spain (ES), and Russia (RU) show up on the list. The disappearance of the two small island countries and two African countries is reasonable since they do not carry large share of the passenger traffic in international air transportation. The critical role of Portugal is taken over by another two major European countries (Germany and Spain). This can be explained by the large amount of passenger traffic in these two countries (Germany ranks third and Spain ranks fourth in terms of the number of international passengers, as shown in Fig. 11 in Section 5.1). Remarkably, the rising role of United Arab Emirates in international air transportation is mainly caused by the increasingly strong economic cooperation between Asia and Europe/Africa, as discussed in Fig. 13(a).

Fig. 14(b) shows the evolution of the functionally critical nodes. We observe that the criticality is rather stable over the 12 years period. Japan, China, and Spain have minor fluctuations during the evolution process of international air transportation. Notably, Japan clearly lost importance starting from 2008. This is very likely related to the financial crisis in 2008/2009, which hit Japan harder than most other countries (Kawai and Takagi, 2009).

5.4. Functionally critical links in the country network with traffic data

Similar with the node betweenness (Freeman, 1978), the betweenness for a link l is defined as the sum of the fraction all pairs of shortest paths that pass through this link: $B_l = \sum_{s,t \in V} \frac{\sigma(s,t|l)}{\sigma_(s,t)}$, where $\sigma_{s,t}$ is the number of shortest paths going from node s to node t; $\sigma(s,t|l)$ is the number of those paths passing through link l (Brandes, 2008). We identify functionally critical links, based on passenger-based link betweenness.

Fig. 15(a) presents the top ten functionally critical links with traffic data. The links are selected according to the mean value of passenger-based link betweenness over all 144 monthly-based country networks. We observe that the connections between North America and Europe/Asia/Oceania are identified as critical. Intra-continental connections within Europe and within Asia are also identified as critical. We believe that the *bridging* role of United Arab Emirates (AE) between Europe and Asia deserves more attention in future work. Compared with the top ten topologically critical links shown in Fig. 9 in Section 4.3, the dominating critical roles of North America (particularly United States) and Europe keep the same. The topologically critical links inside Africa are not critical anymore when taking into account traffic data, since they do not carry large share of international passenger traffic in the world. Instead, the roles of functionally critical links are shifted towards Asia. This suggests that the rising role of Asia regarding transferring passengers in international air transportation.



(a) Node rank correlation **(b)** Link rank correlation

Fig. 16. Pairwise node and link rank correlation among the four metrics: MDS/Dispersion, hops-based betweenness, distance-based betweenness, and passenger-based betweenness. For the nodes, MDS is least correlated with other three metrics; while hops-based betweenness is mostly correlated with distance-based betweenness. For the links, the four metrics are uncorrelated.

Node	MDS	Hops	Distance	Passenger
US	2	1	1	2
FR	3	2	2	3
GB	10	3	4	1
AU	5	4	7	8
ZA	1	6	8	11
CN	8	9	12	7
KE	7	13	6	14
FJ	4	14	11	21
AE	25	8	15	4
BR	11	31	3	17
TH	22	15	9	18
DE	22	5	40	6
ES	51	11	5	9
RU	39	17	10	10
JP	39	16	27	5
AG	6	22	32	29
CA	30	7	30	32
PT	9	25	85	19
NL	25	10	68	36

(a) Top ten critical nodes

Link	Dispersion	Hops	Distance	Passenger
MH_US	121	5	242	74
FJ_US	28	1	19	771
KI_US	165	6	138	771
GB_SH	1025	4	39	59
EG_PS	1025	10	54	95
FR_GB	207	471	675	3
GB_US	4	159	1248	1
JP_US	108	456	988	2
AU_NZ	3	1423	199	12
CA_US	1	1166	649	32
SB_US	1025	2	196	771
PR_SN	1025	393	2	771
ES_GP	1025	464	7	771
AN_ES	1025	531	6	771
AN_PT	1025	775	5	771
FR_LY	8	1131	984	529
GB_ZA	205	222	2242	8
BR_TG	1025	941	10	771
ES_US	2	685	1386	771
GM_PR	1025	1076	1	771

Link	Dispersion	Hops	Distance	Passenger
PG_SB	1025	1458	9	442
FR_ZA	9	224	1932	771
GY_SN	1025	1181	4	771
CV_PR	1025	1328	3	771
BR_SN	1025	1502	8	771
DE_GB	11	1964	1322	9
ES_GB	51	1123	2401	6
KE_ZA	7	1493	1496	640
ET_FR	5	877	2013	771
AU_FR	544	3	2406	771
ET_KE	10	2748	393	641
CN_JP	322	2429	1208	5
BE_FR	6	1280	2030	650
AU_GB	547	7	2655	771
AE_GB	124	1145	2884	4
FR_NC	1025	8	2506	771
US_ZA	866	9	2928	771
DE_RU	481	2065	2716	7
DE_ES	632	1642	3021	10

(b) Top ten critical links

Fig. 17. Ranks of the top ten critical nodes/links identified by at least one of the four metrics.

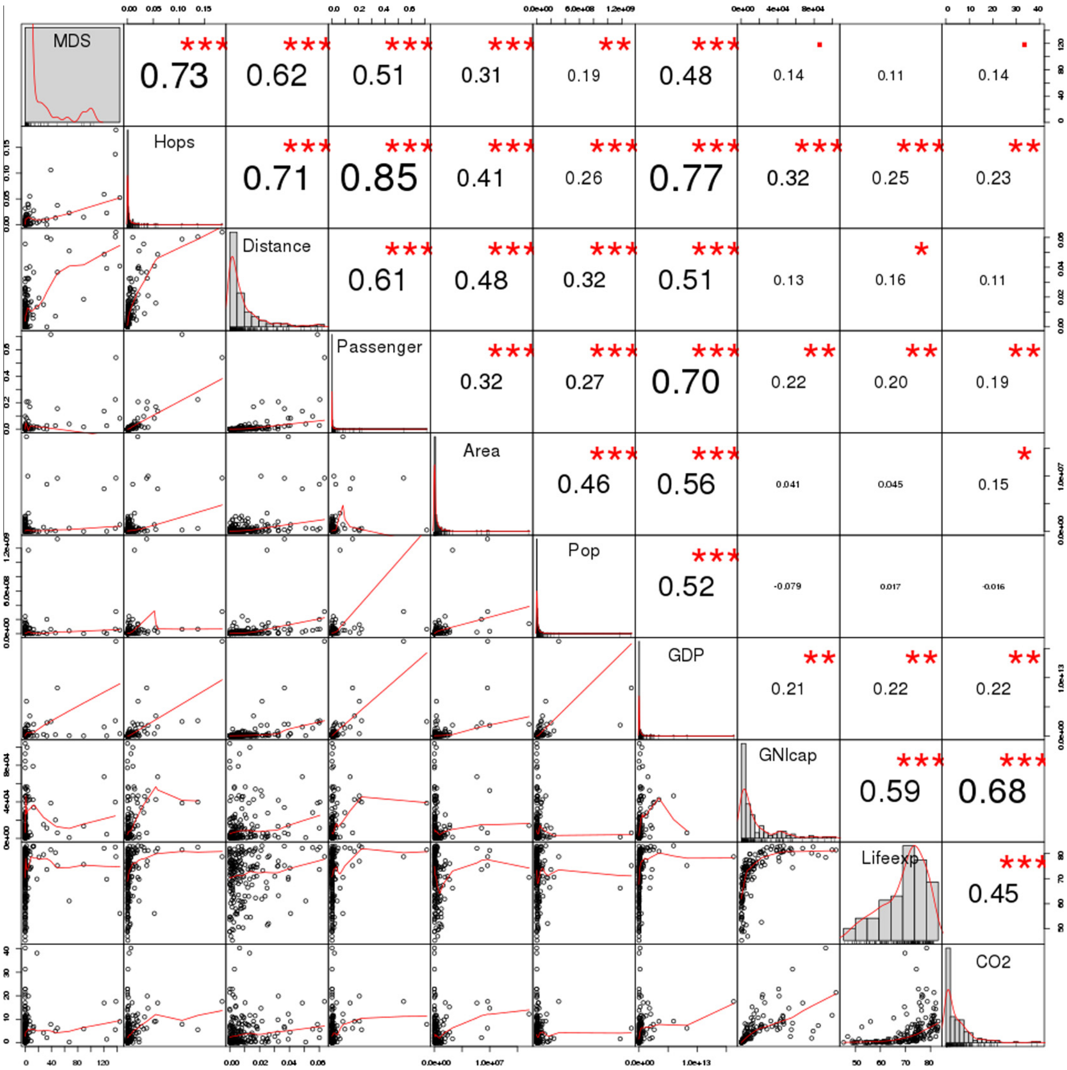


Fig. 18. Pairwise correlation between the raw data of critical nodes and six explanatory variables: Area, population, GDP, GNI per capita, life expectation, and CO_2 emission. Hops-based betweenness is highly correlated with passenger-based betweenness and GDP. Among the six explanatory variables, GDP shows relatively close correlation with node criticality.

Fig. 15(b) shows the evolution of the roles for the functionally critical links with traffic data. We observe that the general trend of the critical roles is rather stable over the 12 years period. Note that all three functionally critical links for Japan (with United States, China, and Australia) are losing the importance since 2007/2008. We think this is also mainly because Japan was severely affected in the global financial crisis in 2008/2009 (Kawai and Takagi, 2009), as with the case of the functionally critical nodes shown in Fig. 14(b). On the other hand, two functionally critical links for United States with Asia/Oceania (China and Australia) gain importance since 2009. This might be related to the fact that United States is actually trying to strengthen their partnerships with Asian/Oceania-countries.

6. Discussion

In the following we further discuss the criticality of nodes and links, based on the results reported in the previous section. In Section 6.1, we discuss the dependencies between topological and functional criticality. Section 6.2 analyzes the correlation and regression between criticality and explanatory variables about countries, e.g. population and GDP.

6.1. Correlation and regression between criticality metrics

First, we analyze the dependency between topologically critical nodes and functionally critical nodes. Since MDS and betweenness are conceptually different approaches, it is difficult to compare the results for topological criticality and functional criticality. Therefore, we add two new betweenness-based node criticality measures. In total, we use the following four metrics: **Minimum Dominating Set** (link weights are 1), **hops-based node betweenness** (link weights are 1), **distance-based node betweenness** (link weights are assigned according to the distance between the center of two countries), and **passenger-based node betweenness** (link weights are set to the reciprocal of the number of passengers traveling between two countries). Fig. 16(a) presents the node rank correlation among the four metrics, where the diagonal line shows histograms (bars) and kernel density (lines) for each method. The lower triangle of the matrix shows data points; while the upper triangle shows absolute correlation scores together with significance asterisks (0.05, 0.01, 0.001). We can observe that

Table 1
Regression between each of the four node criticality metrics and the six explanatory variables.

Metric	Explanatory variable	Coefficient	Standard error	R^2	p-Value
MDS	Area	3.75E−06	7.66E−07	0.0972	0
MDS	Pop	3.30E−08	1.16E−08	0.0351	0.0048
MDS	GDP	7.76E−12	1.03E−12	0.2320	0
MDS	GNIcap	1.36E−04	7.71E−05	0.0200	0.0788
MDS	Lifeexp	2.76E−01	1.88E−01	0.0116	0.1440
MDS	CO_2	5.02E−01	2.60E−01	0.0194	0.0554
Hops	Area	4.24E−09	6.37E−10	0.1650	0
Hops	Pop	3.88E−11	9.86E−12	0.0651	0.0001
Hops	GDP	1.07E−14	6.48E−16	0.5910	0
Hops	GNIcap	2.52E−07	5.94E−08	0.1060	0
Hops	Lifeexp	5.46E−04	1.59E−04	0.0603	0.0007
Hops	CO_2	7.11E−04	2.22E−04	0.0518	0.0016
Distance	Area	3.30E−09	4.09E−10	0.2260	0
Distance	Pop	3.29E−11	6.43E−12	0.1050	0
Distance	GDP	4.66E−15	5.64E−16	0.2650	0
Distance	GNIcap	7.80E−08	4.86E−08	0.0165	0.1110
Distance	Lifeexp	2.34E−04	1.05E−04	0.0263	0.0269
Distance	CO_2	2.29E−04	1.47E−04	0.0127	0.1210
Passenger	Area	1.19E−08	2.36E−09	0.1020	0
Passenger	Pop	1.45E−10	3.51E−11	0.0709	0.0001
Passenger	GDP	3.50E−14	2.58E−15	0.4930	0
Passenger	GNIcap	6.83E−07	2.50E−07	0.0464	0.0071
Passenger	Lifeexp	1.56E−03	5.77E−04	0.0383	0.0074
Passenger	CO_2	2.10E−03	8.03E−04	0.0352	0.0095

Table 2
Regression between each of the four link criticality metrics and the six explanatory variables, where the prefix 'D' represents the absolute difference between values of linked nodes.

Metric	Explanatory variable	Coefficient	Standard error	R^2	p-Value
Dispersion	DArea	4.19E−09	8.54E−10	0.0067	0
Dispersion	DPop	5.42E−12	1.23E−11	0.0001	0.6600
Dispersion	DGDP	1.03E−14	9.48E−16	0.0318	0
Dispersion	DGNIcap	−5.45E−07	1.42E−07	0.0041	0.0001
Dispersion	DLifeexp	1.90E−04	1.43E−04	0.0005	0.1820
Dispersion	DCO2	−1.11E−04	4.33E−04	0.0000	0.7980
Hops	DArea	4.78E−11	3.32E−12	0.0548	0
Hops	DPop	3.06E−13	4.88E−14	0.0109	0
Hops	DGDP	1.03E−16	3.42E−18	0.2030	0
Hops	DGNIcap	2.63E−09	5.66E−10	0.0060	0
Hops	DLifeexp	7.53E−06	5.54E−07	0.0490	0
Hops	DCO2	1.20E−05	1.71E−06	0.0134	0
Distance	DArea	1.64E−13	6.87E−12	0.0000	0.9810
Distance	DPop	−7.00E−14	9.90E−14	0.0001	0.4790
Distance	DGDP	−1.36E−17	7.72E−18	0.0009	0.0789
Distance	DGNIcap	−9.26E−09	1.13E−09	0.0183	0
Distance	DLifeexp	9.56E−06	1.13E−06	0.0194	0
Distance	DCO2	−1.79E−05	3.46E−06	0.0074	0
Passenger	DArea	1.04E−10	2.39E−11	0.0052	0
Passenger	DPop	1.09E−12	3.44E−13	0.0028	0.0016
Passenger	DGDP	1.90E−16	2.67E−17	0.0140	0
Passenger	DGNIcap	3.01E−09	3.98E−09	0.0002	0.4500
Passenger	DLifeexp	−1.05E−06	3.98E−06	0.0000	0.7930
Passenger	DCO2	7.99E−06	1.21E−05	0.0001	0.5090

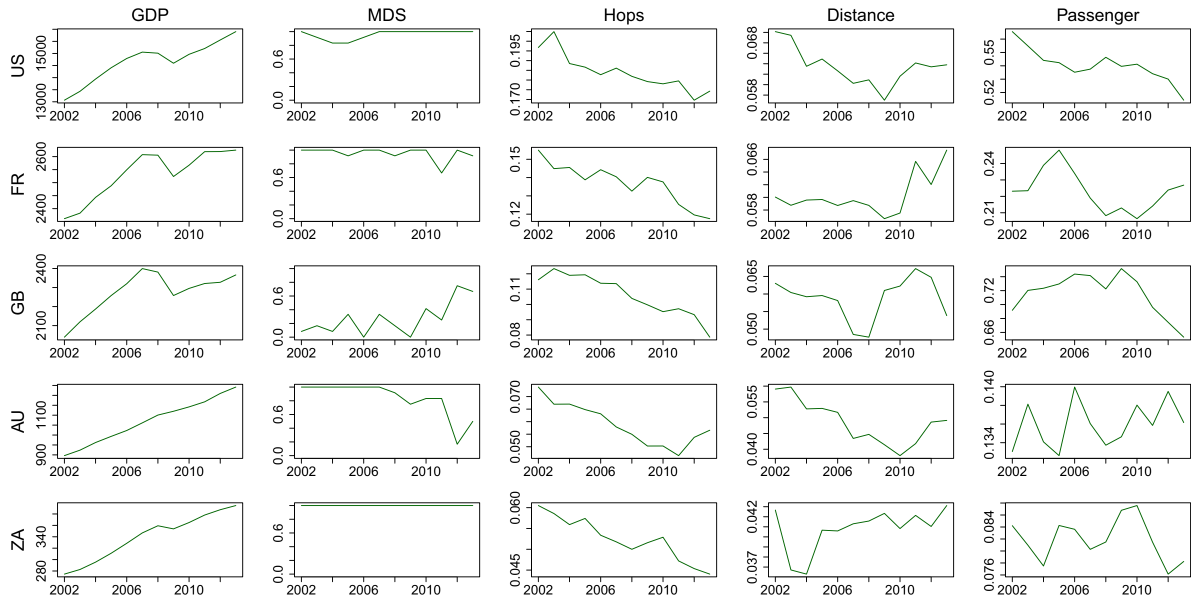


Fig. 19. Evolution of the correlation between GDP and node criticality for the top five countries in the time frame 2002–2013. No obvious correlation between the temporal evolution of GDP and criticality can be observed.

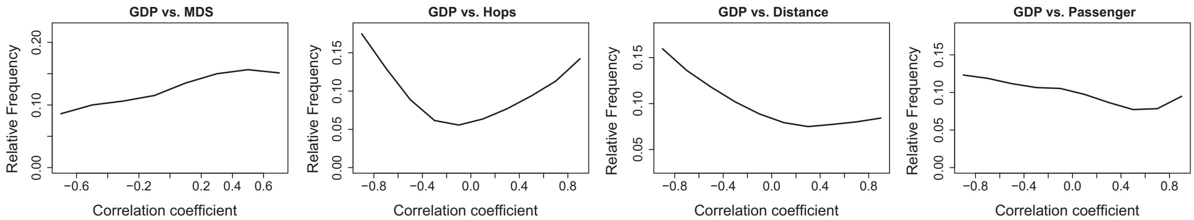


Fig. 20. Evolution of the correlation coefficient between GDP and the four metrics for node criticality. None of the four curves shows a clear trend for correlation.

MDS is least correlated with other three metrics; while hops-based betweenness is mostly correlated with distance-based betweenness. Fig. 17(a) shows top ten critical nodes identified by at least one of the four metrics, where the nodes are presented in the order of their average rank. It is very interesting to see the high correlation between hops-based node betweenness (topological roles) and passenger-based node betweenness (functional roles).

We further analyzed the dependency between topologically critical links and functionally critical links. As with the case of node criticality, it is difficult to compare the results for topological and functional link criticality, since dispersion and betweenness are conceptually different approaches. Thus, we add two new betweenness-based link criticality measures. In total, we use the following four metrics: **Dispersion** (link weights are 1), **hops-based link betweenness** (link weights are 1), **distance-based link betweenness** (link weights are assigned according to the distance between the center of two countries), and **passenger-based link betweenness** (link weights are set to the reciprocal of the number of passengers traveling between two countries). Fig. 16(b) presents the link rank correlation among the four metrics. It can be seen that there is no high correlation between any of the four metrics. Fig. 17(b) shows top ten critical links identified by at least one of the four metrics, where the links are presented in the order of their average rank. No correlation between topologically and functionally critical links can be observed.

6.2. Correlation and regression between node/link criticality and explanatory variables

We compare the data values for critical countries (MDS, hops/distance/passenger-based betweenness) against the following six explanatory variables obtained from CIA World Factbook: **Area** (in m^2), **population** (Pop), **GDP** (in international dollars), **GNI per capita** (GNIcap, in international dollars), **life expectancy at birth** (Lifeexp, in years), and **total amount of dioxide emissions** (CO_2, in metric tons). First, the values for each explanatory variable were averaged over the period from 2002 to 2013, in order to identify correlations between criticality and magnitude of variables. Fig. 18 presents pairwise correlation between critical nodes and the six explanatory variables. Please note that in this figure raw data values are shown

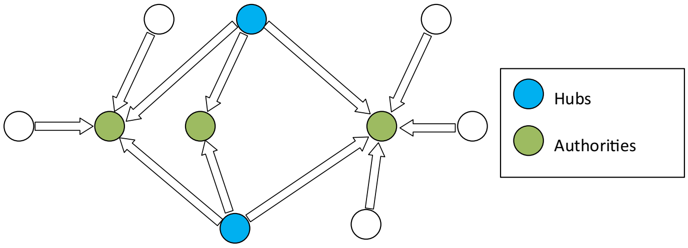


Fig. 21. An illustration of Authority and Hub in HITS: Authorities are filled with green color and hubs are filled with blue color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

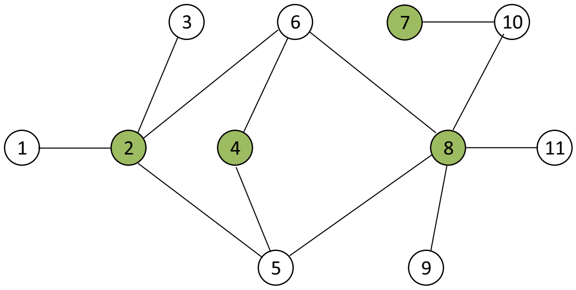


Fig. 22. An illustration of a small network example and its dominating set.

for criticality (opposed to ranks, as in Fig. 16). It can be seen that GDP has always the highest correlation with the four criticality metrics; the highest correlation is to hops-based node betweenness. This shows that countries with high GDP are also the most influential from the topological and the functional point of view. Notably, other variables about the size of a country, e.g. area and population, are always less correlated to criticality than GDP.

We also perform regression analysis between node/link criticality and the above six explanatory variables, the results for linear regression are shown in Tables 1 and 2 (both in Appendix). We can observe that GDP has a slightly high contribution to the node criticality, especially when using hop-based node betweenness metric ($R^2 = 0.5910$); while none of the six explanatory variables contributes to the link criticality using any of the four metrics (The highest $R^2 = 0.203$ is between hop-based link betweenness metric and DGDP, where the DGDP represents the absolute GDP difference between values of linked nodes). We have performed additional experiments for non-linear regression models, using Eureqa (Schmidt and Lipson, 2009), but the results did not improve significantly.

While the above experiments show that absolute GDP and criticality of countries are correlated, it is interesting to analyze the actual dependency in the temporal evolution process. For instance, if the GDP of a country is decreased in a recession, does this also have an effect on the criticality of a country? We show an example for the temporal evolution of GDP and country criticality for the top five countries in Fig. 19. There is no obvious correlation between the temporal evolution of GDP and criticality. For instance, while the GDP of US and AU are increasing from 2002 to 2013, passenger-based node betweenness for US is decreasing but for AU it is stable (with some fluctuations).

Since no conclusions can be drawn from the sample of five countries, we perform additional experiments to identify the overall correlation between GDP and criticality for all countries. We compute correlation coefficients for all countries between GDP and each of the four node criticality metrics. Fig. 20 presents the frequency distribution of the correlation coefficients. None of the four curves shows a clear trend for correlation. GDP and MDS are, on average, slightly positive correlated, while GDP and distance/passenger-based betweenness are rather negatively correlated. GDP and hops-based betweenness is often negative or positive correlated, but rarely uncorrelated. Given these results, we believe that the magnitude of the GDP of a country is much more important for criticality, than the temporal evolution, which is often orders of magnitude lower than the original values.

7. Conclusions

In this research, we investigated the evolution of international air transportation country network from 2002 to 2013 with two perspectives: The network's physical topology as well as the functional network with traffic information. From the methodological point of view, the construction of the country network can provide insights on the roles of countries in international air transportation and travel patterns of international passenger flows. The contributions of our paper to the literature based on empirical analysis are:

1. The international air transportation country network is scale-free/small-world. While there have been plenty of papers showing scale-freeness/small-worldness for the worldwide airport networks and subnetworks, we are the first to report that the aggregated network at country level is a scale-free/small-world network; and that these properties are stable over the period of our study. The average shortest path length is approximately 2.3. This value is much lower than for the worldwide airport network (4.0–5.0), reported in (Azzam et al., 2013; Guimera et al., 2005). Further analysis of ticket data revealed that the actual average number of hops is even lower, between 1.74 and 1.86, slightly increasing from 2002 to 2013.
2. The country network gears towards a symmetric, transitive closure. While analyses on airport network evolution show that the average degree in the worldwide airport network increases (Azzam et al., 2013), we are the first to report that countries are indeed increasingly connected to each other.
3. Top five critical countries are US, France, Great Britain, Australia, and South Africa. We assess the criticality of countries from a topological and functional point of view, using four distinct metrics. South Africa is ranked in the top ten critical countries by three out of four metrics. According to the minimum dominating set, it is even ranked first. Inter-continental connections for North America with Europe and Europe with Africa, as well as intra-continental connections within North America and within Oceania are identified as the most critical links, based on dispersion. Similarly, we find that the small country United Arab Emirates plays a rising role in international air transportation.
4. Topological and functional criticality of countries are highly correlated. Analysis of four different metrics (Minimum dominating set, three variants of betweenness) exhibits the existence of high ranking correlations. Our experiments show that topological relevance implies functional relevance with passenger traffic, and vice versa. The criticality of links, on the other hand, is almost uncorrelated for all four metrics used in this study.
5. Criticality of a country is correlated to the GDP. We show that in the international air transportation country network, node criticality is highly correlated to the GDP of a country. Other soft criteria, such as country size or population, are much less correlated than GDP. Furthermore, we show that link criticality is almost uncorrelated to any of the six explanatory variables used in our study: Only the absolute difference in GDP between two countries is slightly correlated with the hops-based link betweenness.

Our research helps to understand how the network's topology and function in air transportation systems interact with each other and to identify the roles of countries in international air transportation. Future work could focus on the impacts of big events on global air transportation to find out how these big events change the structure of air transportation networks, i.e., how the operators react to these temporary sharp increase of traffic demand? Not only large-scale disasters, such as the outbreak of Ebola disease (Gomes et al., 2014), volcanic eruption (Wilkinson et al., 2012), and the September 11th terrorist attacks (Woolley-Meza et al., 2013); but also big sport (social) events, such as 2014 Brazil football world cup, 2012 London Olympics, 2008 Beijing Olympics, and 2006 football world cup in Germany.

Another line of future research is the construction of an open database for historical flight data at different scales and with different aggregation functions; following recent advances in efficient storage of (possibly compressed) data in main memory databases (Plattner, 2014; Wandelt and Sun, 2015; Eldawy et al., 2014).

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Appendix A

A.1. HITS (Hyperlink Induced Topic Search)

This algorithm was originally developed to calculate the ranking of web pages used by search engines (Kleinberg, 1999). Authorities are web pages which are informative and are usually pointed to by many other hyperlinks; while hubs are web pages which point to a large number of authority pages. This situation is illustrated in Fig. 21.

A.2. MDS (Minimum Dominating Set)

For a network with the set of nodes N, a dominating set is a set of nodes S with $S \subseteq N$, such that for each $n \in N$, we have $n \in S$ or n is a neighbor of at least one $s \in S$. The Minimum Dominating Set (MDS) is the dominating set with the smallest size (Nacher and Akutsu, 2014). A small example of a dominating set is shown in Fig. 22. The nodes $S = \{2, 4, 7, 8\}$ comprise the MDS, i.e., there is no set with less than four nodes, such that for all nodes n we have $n \in S$ or n is a neighbor of at least one $s \in S$. For instance, node 4 dominates node 5 and node 6.

References

Azzam, M., Klingauf, U., Zock, A., 2013. The accelerated growth of the worldwide air transportation network. Eur. Phys. J. Special Topics 212, 35–48.

Backstrom, L., Kleinberg, J., 2014. Romantic partnerships and the dispersion of social ties: a network analysis of relationship status on facebook. In: Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work 38; Social Computing. ACM, New York, NY, USA, pp. 831–841.

Barabasi, A.L., Albert, R., 1999. Emergence of scaling in random networks. Science 286, 509–512.

Batagelj, V., Mrvar, A., 2001. A subquadratic triad census algorithm for large sparse networks with small maximum degree. Social Networks 23, 237–243.

Baumgarten, P., Malina, R., Lange, A., 2014. The impact of hubbing concentration on flight delays within airline networks: an empirical analysis of the US domestic market. Transp. Res. Part E: Logis. Transp. Rev. 66, 103–114.

Bloomberg, 2013. <http://tinyurl.com/BloombergSpain>.

Bonnefoy, P., 2008. Scalability of the Air Transportation System and Development of Multi-Airport Systems: A Worldwide Perspective. Ph.D. Thesis. Massachusetts Institute of Technology.

Bounova, G.A., 2009. Topological Evolution of Networks: Case Studies in the US Airlines and Language Wikipedias. Ph.D. Thesis. Department of Aeronautics and Astronautics, Massachusetts Institute of Technology.

Brandes, U., 2008. On variants of shortest-path betweenness centrality and their generic computation. Social Networks 30, 136–145.

Brockmann, D., Helbing, D., 2013. The hidden geometry of complex, network-driven contagion phenomena. Science 342, 1337.

Burghouwt, G., 2007. Airline Network Development in Europe and Its Implications for Airport Planning. Ashgate Studies in Aviation Economics and Management, Ashgate.

Burghouwt, G., Hakfoort, J., 2001. The evolution of the European aviation network. J. Air Transp. Manage. 7, 311–318 (Developments in the Deregulated Air Transport Market).

Burghouwt, G., Redondi, R., 2013. Connectivity in air transport networks: an assessment of models and applications. J. Transp. Econ. Policy (JTEP) 47, 35–53.

Burghouwt, G., de Wit, J., Veldhuis, J., Matsumoto, H., 2009. Air network performance and hub competitive position: evaluation of primary airports in East and South-East Asia. J. Airport Manage. 3, 384–400.

Cleveland, R.B., Cleveland, W.S., McRae, J., Terpenning, I., 1990. A seasonal-trend decomposition procedure based on loess. J. Official Statist. 6, 3–73.

Davis, J., Leinhardt, S., 1967. The Structure of Positive Interpersonal Relations in Small Groups. Darthmouth College.

Deguchi, T., Takahashi, K., Takayasu, H., Takayasu, M., 2014. Hubs and authorities in the world trade network using a weighted HITS algorithm. PLoS ONE 9, e100338.

Diebold, F., 1998. Elements of Forecasting. HG – Cycles and Forecasting Series. South-Western College Pub.

Eldawy, A., Levandoski, J., Larson, P.A., 2014. Trekking through siberia: managing cold data in a memory-optimized database. Proc. VLDB Endow. 7, 931–942.

Faust, K., 2006. Comparing social networks: size, density and local structure. Metodološki zvezki 3, 185–216.

Faust, K., 2010. A puzzle concerning triads in social networks: graph constraints and the triad census. Social Networks 32, 221–233.

Fleurquin, P., Ramasco, J.J., Eguiluz, V.M., 2013. Systemic delay propagation in the US airport network. Sci. Rep. 3.

Freeman, L.C., 1978. Centrality in social networks conceptual clarification. Social Networks 1, 215–239.

Gautreau, A., Barrat, A., Barthlemy, M., 2009. Microdynamics in stationary complex networks. Proc. Nat. Acad. Sci. 106, 8847–8852.

Gillen, D., Morrison, W.G., 2005. Regulation, competition and network evolution in aviation. J. Air Transp. Manage. 11, pp. 161–174. (Eighth Annual Air Transport Society Conference, Toulouse, July 2003).

Gomes, M.F.C., Pastore, Rossi, L., Chao, D., Longini, I., Halloran, M.E., Vespignani, A., 2014. Assessing the International Spreading Risk Associated with the 2014 West African Ebola Outbreak. PLoS Currents.

Guida, M., Maria, F., 2007. Topology of the Italian airport network: a scale-free small-world network with a fractal structure? Chaos Solitons Fract. 31, 527–536.

Guimera, R., Mossa, S., Turtschi, A., Amaral, L.A.N., 2005. The worldwide air transportation network: anomalous centrality, community structure, and cities global roles. PNAS 102, 7794–7799.

Hagberg, A.A., Schult, D.A., Swart, P.J., 2008. Exploring network structure, dynamics, and function using NetworkX. In: Proceedings of the 7th Python in Science Conference (SciPy2008), Pasadena, CA USA. pp. 11–15.

Hawelka, B., Sitko, I., Beinat, E., Sobolevsky, S., Kazakopoulos, P., Ratti, C., 2014. Geo-located twitter as proxy for global mobility patterns. Cartogr. Geogr. Inf. Sci. 41, 260–271.

Holme, P., Kim, B.J., Yoon, C.N., Han, S.K., 2002. Attack vulnerability of complex networks. Phys. Rev. E 65, 056109.

Janic, M., 2015. Modelling the resilience, friability and costs of an air transport network affected by a large-scale disruptive event. Transp. Res. Part A: Policy Practice 71, 1–16.

Jia, T., Qin, K., Shan, J., 2014. An exploratory analysis on the evolution of the US airport network. Physica A 413, 266–279.

Jimenez, E., Claro, J., de Sousa, J.P., 2012. Spatial and commercial evolution of aviation networks: a case study in mainland Portugal. J. Transp. Geogr. 24, 383–395 [Special Section on Theoretical Perspectives on Climate Change Mitigation in Transport].

Kaltenbrunner, A., Aragon, P., Laniado, D., Volkovich, Y., 2014. Not all paths lead to Rome: analysing the network of sister cities. In: Elmenreich, W., Dressler, F., Loreto, V. (Eds.), Self-Organizing Systems, Lecture Notes in Computer Science, vol. 8221. Springer, Berlin, Heidelberg, pp. 151–156.

Kawai, M., Takagi, S., 2009. Why was Japan hit so hard by the global financial crisis? ADBI Working Paper. Tokyo: Asian Development Bank Institute, vol. 153, pp. 1–19.

Kleinberg, J., 1999. Authoritative sources in a hyperlinked environment. J. ACM 46, 604–632.

Kotegawa, T., Fry, D., DeLaurentis, D., Puchaty, E., 2014. Impact of service network topology on air transportation efficiency. Transp. Res. Part C: Emerging Technol. 40, 231–250.

Lehner, S., 2013. Separate yet interdependent networks: the structure and function of European air transport. Complex Networks IV, vol. 476. Springer, pp. 109–120.

Lehner, S., Koelker, K., Luetjens, K., 2014. Evaluating temporal integration of european air transport. In: 29th Congress of the International Council of the Aeronautical Sciences (ICAS), St. Petersburg, Russia, 7–12 September.

Lemey, P., Rambaut, A., Bedford, T., Faria, N., Bielejec, F., Baele, G., Russell, C.A., Smith, D.J., Pybus, O.G., Brockmann, D., Suchard, M.A., 2014. Unifying viral genetics and human transportation data to predict the global transmission dynamics of human influenza H3N2. PLoS Pathog 10, e1003932.

Lin, J., Ban, Y., 2014. The evolving network structure of US airline system during 1990–2010. Physica A 410, 302–312.

Liu, Y.Y., Slotine, J.J., Barabási, A.L., 2011. Controllability of complex networks. Nature 473, 167–173.

Lordan, O., Sallan, J.M., Simo, P., Gonzalez-Prieto, D., 2014. Robustness of the air transport network. Transp. Res. Part E: Logis. Transp. Rev. 68, 155–163.

Malighetti, P., Paleari, S., Redondi, R., 2008. Connectivity of the European airport network: self-help hubbing and business implications. J. Air Transp. Manage. 14, 53–65.

Manduca, R., 2014. Domestic Migration Networks in the United States. Master's Thesis. Department of Urban Studies and Planning, MIT.

Marsden, P.V., Campbell, K.E., 1984. Measuring tie strength. Soc. Forces 63, 482–501.

Monechi, B., Ducci, M., Cipolla, M., Vitali, S., Micciché, S., Mantegna, R., Gurtner, G., Lillo, F., Valori, L., Pozzi, S., 2013. Exploratory analysis of safety data and their interrelation with flight trajectories and network metrics. In: Air Transportation System Conferences – Interdisciplinary Science for Innovative Air Traffic Management.

Nacher, J.C., Akutsu, T., 2014. Analysis of critical and redundant nodes in controlling directed and undirected complex networks using dominating sets. J. Complex Networks, cnu029.

Neal, Z., 2013. Evolution of the business air travel network in the US from 1993 to 2011: a descriptive analysis using airnet. Res. Transp. Business Manage. 9, 5–11, International Business Travel.

Newman, M.E., 2003. The structure and function of complex networks. SIAM Rev. 45, 167–256.
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? Transp. Res. Part E: Logis. Transp. Rev. 46, 198–210 (Selected Papers from the 12th {ATRS} Conference).
Papatheodorou, A., Arvanitis, P., 2009. Spatial evolution of airport traffic and air transport liberalisation: the case of Greece. J. Transp. Geogr. 17, 402–412.
Plattner, H., 2014. The impact of columnar in-memory databases on enterprise systems: implications of eliminating transaction-maintained aggregates. Proc. VLDB Endow. 7, 1722–1729.
da Rocha, L.E., 2009. Structural evolution of the Brazilian airport network. J. Stat. Mech.: Theory Exp. 2009, P04020.
Schmidt, M., Lipson, H., 2009. Distilling free-form natural laws from experimental data. Science 324, 81–85.
Sun, X., Wandelt, S., 2014. Network similarity analysis of air navigation route systems. Transp. Res. Part E: Logis. Transp. Rev. 70, 416–434.
Sun, X., Wandelt, S., Linke, F., 2015. Temporal evolution analysis of the European air transportation system: air navigation route network and airport network. Transp. B: Transp. Dyn. 3, 153–168.
Wandelt, S., Sun, X., 2015. Efficient compression of 4D-trajectory data in air traffic management. IEEE Trans. Intell. Transp. Syst. 16, 844–853.
Wang, J., Mo, H., Wang, F., 2014. Evolution of air transport network of China 1930–2012. J. Transp. Geography, 1–14.
Watts, D., Strogatz, S., 1998. Collective dynamics of 'small-world' networks. Nature, 440–442.
Wei, P., Chen, L., Sun, D., 2014. Algebraic connectivity maximization of an air transportation network: the flight routes addition/deletion problem. Transp. Res. Part E: Logis. Transp. Rev. 61, 13–27.
Wilkinson, S., Dunn, S., Ma, S., 2012. The vulnerability of the European air traffic network to spatial hazards. Nat. Hazards 60, 1027–1036.
Woolley-Meza, O., Grady, D., Thiemann, C., Bagrow, J.P., Brockmann, D., 2013. Eyjafjallajkull and 9/11: the impact of large-scale disasters on worldwide mobility. PLoS ONE 8, e69829.
Wuchty, S., 2014. Controllability in protein interaction networks. Proc. Nat. Acad. Sci. 111, 7156–7160.
Zanin, M., Lillo, F., 2013. Modelling the air transport with complex networks: a short review. Eur. Phys. J. Special Topics 215, 5–21.
Zhang, D., Sterbenz, J., 2014. Modelling critical node attacks in manets. In: Elmenreich, W., Dressler, F., Loreto, V. (Eds.), Self-Organizing Systems, Lecture Notes in Computer Science, vol. 8221. Springer, Berlin Heidelberg, pp. 127–138.
Zhang, J., Cao, X.B., Du, W.B., Cai, K.Q., 2010. Evolution of Chinese airport network. Physica A 389, 3922–3931.
Zhao, C., Fu, B., Wang, T., 2014. Braess paradox and robustness of traffic networks under stochastic user equilibrium. Transp. Res. Part E: Logis. Transp. Rev. 61, 135–141.
Zheng, B., Huang, D., Li, D., Chen, G., Lan, W., 2011. Some scale-free networks could be robust under selective node attacks. Europhys. Lett. 94, 28010, 6pp.
Zou, B., Hansen, M., 2014. Flight delay impact on airfare and flight frequency: a comprehensive assessment. Transp. Res. Part E: Logis. Transp. Rev. 69, 54–74.