To appear in *Transportmetrica B: Transport Dynamics*
Vol. 00, No. 00, Month 20XX, 1–15

Temporal Evolution Analysis of European Air Transportation System: Air Navigation Route Network and Airport Network

Xiaoqian Sun[a∗], Sebastian Wandelt[b], and Florian Linke[a]

[a]*Institute of Air Transportation Systems, German Aerospace Center, Blohmstrasse 18, 21079 Hamburg, Germany*; [b]*Department of Computer Science, Humboldt-University Berlin, Unter den Linden 6, 10099 Berlin, Germany*

(*Received 00 Month 20XX; final version received 00 Month 20XX*)

It is a challenging task to design an airspace with the required levels of safety, capacity, flexibility, responsiveness, and environmental performance. Airspace must be continuously analyzed and adapted in order to meet the increased demand of air traffic. The goal of this research is to study the temporal evolution of the European air transportation system. We analyze two network layers: the air navigation route network and the airport network. For each network layer, we analyze the temporal evolution of seven centrality measures: degree, weighted degree, clustering coefficient, betweenness centrality, closeness centrality, weighted betweenness centrality, and weighted closeness centrality. We quantify the seasonal and weekly variation patterns by the coefficient of variation. We find that the air navigation route network is dominated by the summer/winter seasonal variations; while the airport network shows both summer/winter seasonal variations and peak/off-peak weekly patterns. Furthermore, the air navigation points are more clustered and have shorter distance in summer than in winter; while the airports are more clustered and have shorter distance during the weekdays than the weekend. From the distributions of the metrics, we find that hub nodes existing in both network layers are potentially bottlenecks of the network. Our research helps the stakeholders in the air transportation systems to monitor the network performance over time and to better understand the network dynamics. According to the identified summer/winter seasonal variations and peak/off-peak weekly patterns, the airspace configurations could be adapted in time in order to meet the changed demands.

Keywords: temporal evolution analysis; air navigation route system; air transportation systems; complex network

1. Introduction

With continuously growing travel demand, it is much harder to achieve a strong sustainability in the transportation systems, taking into account the high costs of oil, carbon emissions reduction, and the additional requirement on gaining public acceptability (Banister 2007). The European air transportation system is directly facing new challenges regarding its competitiveness, performance, and sustainability (European Commission 2011). In order to understand the nature of traffic and transportation deeply, it is necessary to analyze and manage transportation systems as dynamic phenomena and processes (Lo and Sumalee 2013).

Complex network theory provides powerful tools to analyze the structure and dynamics of air transportation systems. Most research focused on airport networks, where each

∗Corresponding author. Email: xiaoqian.sun@dlr.de

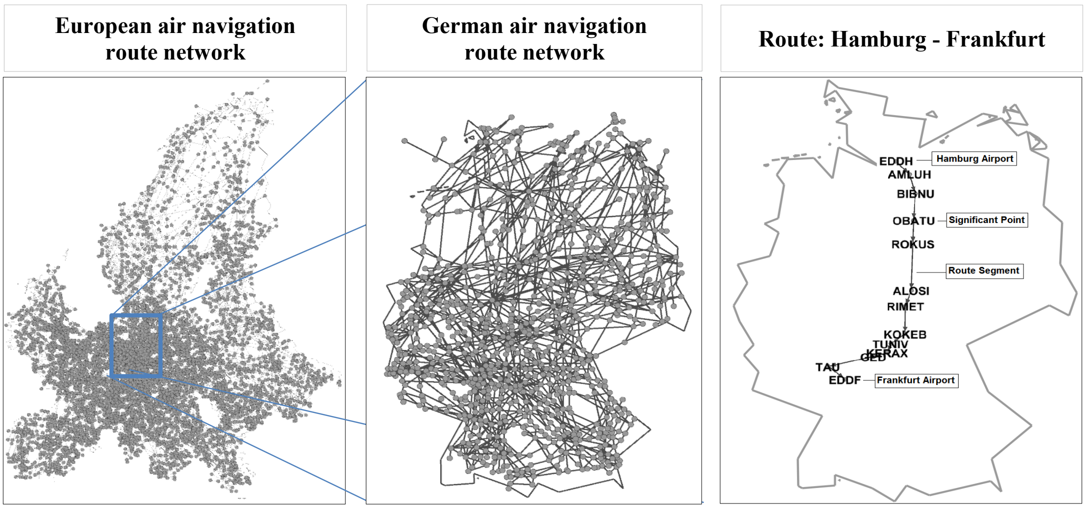


Figure 1.: An illustration of the air navigation route network

node represents one airport, and an edge exists if there is a flight between two airports (Holmes and Scott 2004; Newman 2004; Barrat et al. 2004; Kurant and Thiran 2006; Bonnefoy 2008; Reggiani, Nijkamp, and Cento 2010). Guimera et al. analyzed the worldwide air transportation network with nodes as cities and found that the most connected cities are not necessarily the most central ones (Guimera et al. 2005). DeLaurentis et al. examined the U.S. domestic air transportation network in terms of structural properties and scheduled/nonscheduled subnetworks (DeLaurentis, Han, and Kotegawa 2008). Yang proposed two models with different capacity constraints to determine the hub location and service network (Yang 2008). In his follow-up work, Yang proposed a two-stage stochastic model to address airline network design problems with stochastic demand, where the first-stage problem corresponds to hub location decision; and the second-stage corresponds to flight route determination and flow allocation (Yang 2010). Further, Zhang et al. proposed a dynamic fluctuation model for the airport networks (Zhang et al. 2014). Wei et al. formulated the flight routes addition/deletion problem to maximize the algebraic connectivity, with the airport network of Virgin America as a case study (Wei, Chen, and Sun 2014).

However, the airport network is only one perspective of the air transportation systems. Another perspective is to consider how aircraft actually fly through the airspace. Aircraft have to follow air routes, just like highways on the ground. Air routes are designed to channel the flow of air traffic in a predictable manner to ensure safety (Cordell 2006). A route is composed of several route segments, where one route segment consists of two consecutive significant points. Aircraft flying from the origin airport to the destination airport have to fly along the air route.

In the air navigation route network, a node is an air navigation point and an edge exists if there is a flight directly flying through two air navigation points. Figure 1 illustrates the air navigation route network: the left-hand side shows the European air navigation route network; the middle shows the air navigation route network in Germany; the right-hand side shows one example of an air route from Hamburg (EDDH) to Frankfurt (EDDF) in Germany. Aircraft from Hamburg to Frankfurt have to fly along the air route rather than a straight line.

The goal of this research is to study the temporal evolution of the European air transportation system. We analyze two network layers: the air navigation route network and the airport network. For each layer, we analyze seven network centrality measures: degree, weighted degree, clustering coefficient, betweenness centrality, closeness centrality, weighted betweenness centrality, and weighted closeness centrality. We use the coefficient of variation to quantitatively assess the seasonal and weekly variation patterns.

The main contributions of this paper are: 1) We find out that the air navigation route network is dominated by summer/winter seasonal variations; while the airport network shows both summer/winter seasonal variations and peak/off-peak weekly patterns. 2) The air navigation points are more clustered and have shorter distance in summer than in winter; while the airports are more clustered and have shorter distance during the weekdays than the weekend. 3) From the distributions of the metrics, we find that there are hub nodes existing in both network layers. These hub nodes are potentially bottlenecks and should be paid more attention in the network design of the air transportation systems in future.

This paper is organized as follows. Section 2 provides the literature review. Section 3 presents the Demand Data Repository (DDR) dataset. Section 4 presents the temporal evolution of the European air transportation system. Finally, the paper is concluded in Section 5.

2. Literature review

This section provides the literature review of the network evolution analysis and the air navigation route network in air transportation systems.

Most research on network evolution focused on airport network, with airports as nodes and edges exist if there are flight connections between two airports. Burghouwt and Hakfoort analyzed the evolution of the European air traffic according to different airport groups, based on a weekly Official Airline Guide (OAG) data for the years 1990-1998 (Burghouwt and Hakfoort 2001). 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. Da Rocha analyzed the evolution of the Brazilian airport network between 1995 and 2006 with the data by the Brazilian National Agency of Civil Aviation (da 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 Brazilian airport network became increasingly sparse in spite of more than doubled number of passengers. Gautreau et al. studied the evolution of the US airport network between 1990 and 2000 with the Bureau of Transportation Statistics data by the department of transportation (Gautreau, Barrat, and Barthlemy 2009). 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. Zhang et al. investigated the evolution of the Chinese airport network between 1950 and 2008, with the data provided by Civil Aviation Administration of China (Zhang et al. 2010). 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. Azzam et al. studied the evolution of the worldwide airport network using historical, worldwide Official Airline Guide (OAG) flight schedules data between 1979 and 2007 (Azzam, Klingauf, and Zock 2013). 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; and the average degree of nearest neighbors is constant over the time span 1979-2007. However, these works analyzed the evolution of the single layer airport network, the evolution of other network layers such as the air navigation route network has not been investigated.

Only a few researches have been conducted on the air navigation route network (see (Zanin and Lillo 2013) for a review). Cai et al. investigated the Chinese air navigation route network and compared its topological characteristics with the Chinese airline network (Cai et al. 2012). The authors found that the topological structure of the air navigation route network is more homogeneous than the airline network, while traffic flow on the air navigation route network is rather heterogeneous with exponential strength distribution. Vitali et al. analyzed the Italian air navigation route network and observed that the number of air navigation nodes in the planned trajectories is usually smaller than the number of those in the actual trajectories (Vitali et al. 2012).

Recently, there is a new trend of applying multi-layer networks in air transportation systems. Multi-layer networks are widely used in social networks (see (Kivel et al. 2013) for a review). Cardillo et al. analyzed the resilience of the European air transport network against flight cancellations from a multi-layer point of view, with each airline as an independent network layer (Cardillo et al. 2013). In total, the authors considered fifteen undirected layers of airline flight networks. The results indicated that the multi-layer structure strongly reduces the resilience of the system against perturbations. Gurtner et al. applied three community detection algorithms to European airspace (Gurtner et al. 2013). The results showed that unsupervised community detection algorithms can provide more meaningful partitions of the airspace than the existing expert partitioning of the airspace. Lehner investigated the structure-function networks of European air transport, with airline flight network representing the structure and passenger flow network characterizing the function (Lehner 2013). The airline flight network reflects how airlines operate aircraft between airports; while the passenger flow network reflects how passengers travel from their origin airports to destination airports.

In this research, we investigate the multi-layer structure-function from the airlines' perspectives (Newman 2003): The air navigation route network represents the structure and the airport network represents the function. The air navigation route network provides the structure for the airlines to operate the aircraft between airports; while the airport network offers the function for the airlines to transport passengers between their origin and destination airports. For each network layer, we analyze the temporal evolution of seven network centrality measures, as summarized in Table 1.

3. Database

We obtain the Demand Data Repository (DDR) dataset for 2011, 2012, and 2013, provided by EUROCONTROL[1]. The DDR is the central repository of air traffic demand for European Civil Aviation Conference (ECAC) airspace with flight intentions. There are two types of flight information in DDR: M1 (Model 1) is the last filed flight plan, and M3 (Model 3) is the actual flight plan updated with available radar tracks.

Each calendar year has thirteen AIRAC (Aeronautical Information Regulation And Control) cycles. An AIRAC cycle defines a series of common dates and an associated standard aeronautical information publication procedure. There are 28 days in each AIRAC cycle and the effective days are always on a Thursday. The AIRAC cycles for 2011, 2012, and 2013 are presented in Table 2.

In this research, we analyze the first week in the thirteen AIRAC cycles for 2011, 2012, and 2013, respectively[2]. In total, we have 217 days in our dataset: five first weeks of the

[1] http://www.eurocontrol.int/ddr
[2] Note that we only analyze the second half year of 2011, because the DDR dataset for the first half year of 2011 is not available.

Table 1.: Network centrality measures for the European air transportation system

Metrics	Equation	Interpretation
Degree	$k_i = \sum_j a_{ij}$	where a_{ij} is the connection between node i and node j: $a_{ij} = 1$ if there is a connection existing; $a_{ij} = 0$ otherwise. This metric refers to the number of connections with other nodes in the network.
Weighted degree	$k_i^w = \sum_j w_{ij}$	where w_{ij} is the weight between node i and node j. The weight could be the number of flights, the number of available seats, distance, and cost etc.
Clustering coefficient	$C_i = \frac{\sum_{j,k} a_{ij}a_{ik}a_{jk}}{k_i(k_i-1)}$	where a_{ik} is the connection between node i and node k, a_{jk} is the connection between node j and node k. This metric gives an overall indication of how nodes are embedded in their neighborhood.
Weighted betweenness centrality	$B_i^w = \sum_{s \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}$	where σ_{st} is the number of shortest paths going from node s to node t; $\sigma_{st}(i)$ is the number of shortest paths going from node s to node t and passing through node i. This metric is proposed by Freeman (Freeman 1978) and it indicates the number of shortest paths going through a node. The weight is defined the same as in the weighted degree. When the weight is one, this definition is equivalent with the betweenness centrality.
Weighted closeness centrality	$C_i^w = \frac{\sum_{j \in N, j \neq i} \sigma_{ij}}{(n-1)}$	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. This metric is the average distance from a given starting node to all other nodes in the network (Freeman 1978). The weight is defined the same as in the weighted degree. When the weight is one, this definition is equivalent with the closeness centrality.

AIRAC cycles in 2011 (from I to M), thirteen first weeks of the AIRAC cycles in 2012 (from A to M), and thirteen first weeks of the AIRAC cycles in 2013 (from A to M).

We extract the flight trajectories for the passenger airlines flying within the ECAC airspace using the last filed flight plan (M1). The data we extracted include aircraft type, callsign, departing and destination airports, starting and ending dates and times of the flights, and route points used by the flights. We analyze two network layers for the European air transportation system: the air navigation route network and the airport network. We consider both layers as directed and weighted networks. In the air navigation route network we use the number of flights as weight; in the airport network, we use the number of available seats to weight the edge.

In the current research, we analyze the planned flight trajectories. However, several disturbances, such as adverse weather conditions (thunderstorm) or technical problems (conflict alert system, flight data processing system, and radio failure, etc.), might lead to the deviation of the flight trajectories or in the worst case the cancellation of the flights (Eurocontrol 2013). In future research, it would be interesting to investigate the robustness of the networks against these disturbances.

4. Temporal evolution of the European air transportation system

In this section, we analyze the temporal evolution for two network layers of the European air transportation system. Subsection 4.1 provides an overview of the temporal evolution of seven network centrality measures. These network centrality measures were summarized in Table 1. In subsection 4.2, we analyze the network centrality measures

Table 2.: The AIRAC cycles in 2011, 2012, and 2013 (Eurocontrol 03/12/2013)

Season	AIRAC cycle	2011	2012	2013
A	1	13-Jan	12-Jan	10-Jan
B	2	10-Feb	9-Feb	7-Feb
C	3	10-Mar	8-Mar	7-Mar
D	4	7-Apr	5-Apr	4-Apr
E	5	5-May	3-May	2-May
F	6	2-Jun	31-May	30-May
G	7	30-Jun	28-Jun	27-Jun
H	8	28-Jul	26-Jul	25-Jul
I	9	25-Aug	23-Aug	22-Aug
J	10	22-Sep	20-Sep	19-Sep
K	11	20-Oct	18-Oct	17-Oct
L	12	17-Nov	15-Nov	14-Nov
M	13	15-Dec	13-Dec	12-Dec

in two dimensions: per AIRAC season and per week. In subsection 4.3, we quantify the seasonal and weekly variation patterns using the coefficient of variation. We generate the distributions of the metrics in order to find out whether there exist any distributional properties in subsection 4.4.

4.1. *Temporal evolution overview*

As discussed in Section 3, we have 217 days in our dataset. We consider each of the 217 days as one network. For each day, we compute the seven network centrality measures. The results for the two network layers are shown in Figure 2 and Figure 3, where the horizontal coordinate represents the time interval under investigation: the first seven days for each AIRAC cycle, and the vertical coordinate shows the values for the seven network centrality measures. An AIRAC cycle always starts on Thursday, the first seven days are represented by Arabic numbers (1-Thursday, 2-Friday, 3-Saturday, 4-Sunday, 5-Monday, 6-Tuesday, and 7-Wednesday). The thirteen AIRAC cycles in each year are represented by Alphabetical letters, as summarized in Table 2 in Section 3. For example, the label *12A1* stands for the first day (1-Thursday) in the first AIRAC cycle (*A*) in 2012.

In the air navigation route network, the first three metrics (degree, degree weighted by the number of flights, and clustering coefficient) show strong summer peaks during the year. This indicates that air navigation nodes are more connected in summer than in winter. One reason is that in summer there are more passengers traveling for vacations, the airlines need to provide more capacity (either increase the number of flights or adjust the aircraft size) in order to meet the increased demand of passengers. When the airlines choosing to increase the number of flights, these flights need to follow the air routes in the airspace. Thus, there are more connections among the air navigation nodes in summer than in winter.

Note that the air navigation route network provides the infrastructure for airlines to operate their aircraft, it does not change significantly in different AIRAC cycles. When building the air navigation route network, we add an edge between two air navigation points if there is a flight directly flying through them. Therefore, it is these individual flights leading to the dynamics of the air navigation route network.

In the airport network, we find that the airports are also more connected in summer than in winter. We can explain the summer peak of the airports similarly as in the air navigation route network. On the other hand, the betweenness centrality and weighted betweenness centrality of the airports decrease in summer. One explanation could be that in summer there are more connections between the airports, the increased number

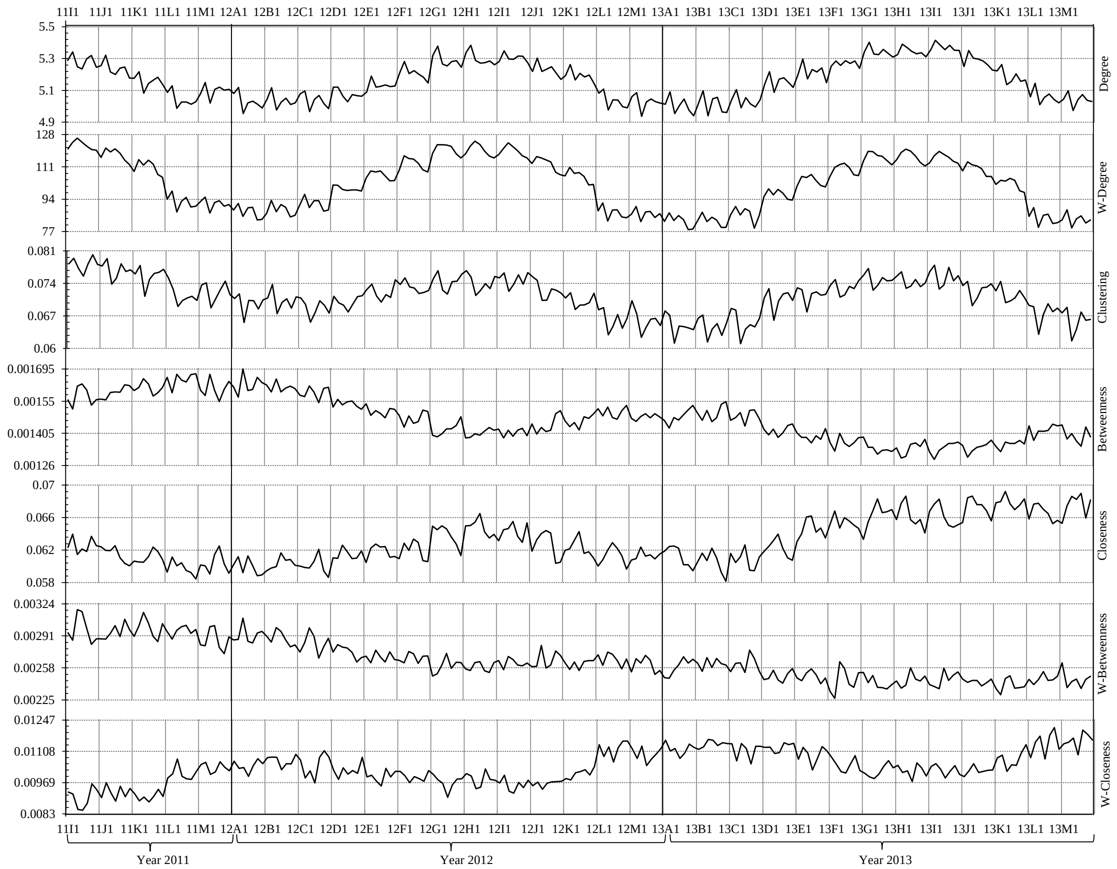


Figure 2.: Temporal evolution of the seven metrics in the air navigation route network

of connections provides more alternative paths in the network. Therefore, the probability that one airport is on the shortest paths between other airports is decreased in summer. Further, the clustering coefficient, closeness centrality, and weighted closeness centrality show strong weekly periodicity in the airport network.

Similar as the case of the air navigation route network, the airport network serves as the infrastructure for passengers to travel between their origin and destination airports. The decreased number of airports at weekends is because there are less passengers traveling at weekends than during the weekdays: Figure 4 shows the number of passengers traveled in the world during the first week of the 10th AIRAC cycle in 2013 (from 19 September to 25 September)[3].

Moreover, we summarize the mean and standard deviation (SD) of the seven network metrics in Table 4. We find that the air navigation route network is rather sparsely connected comparing to the airport network. The air navigation nodes are less clustered than the airport nodes. Our finding verifies the previous work on the comparison of the Chinese air navigation route network and the Chinese airport network on a large scale (Cai et al. 2012).

4.2. *Temporal evolution per AIRAC season and per week*

In this subsection, we analyze the network metrics in two dimensions: per AIRAC season (from A to M) and per week (from Thursday to next Wednesday). Table 3 takes the

[3]The data comes from the Sabre Aviation Data Intelligence (ADI): http://www.airdi.net

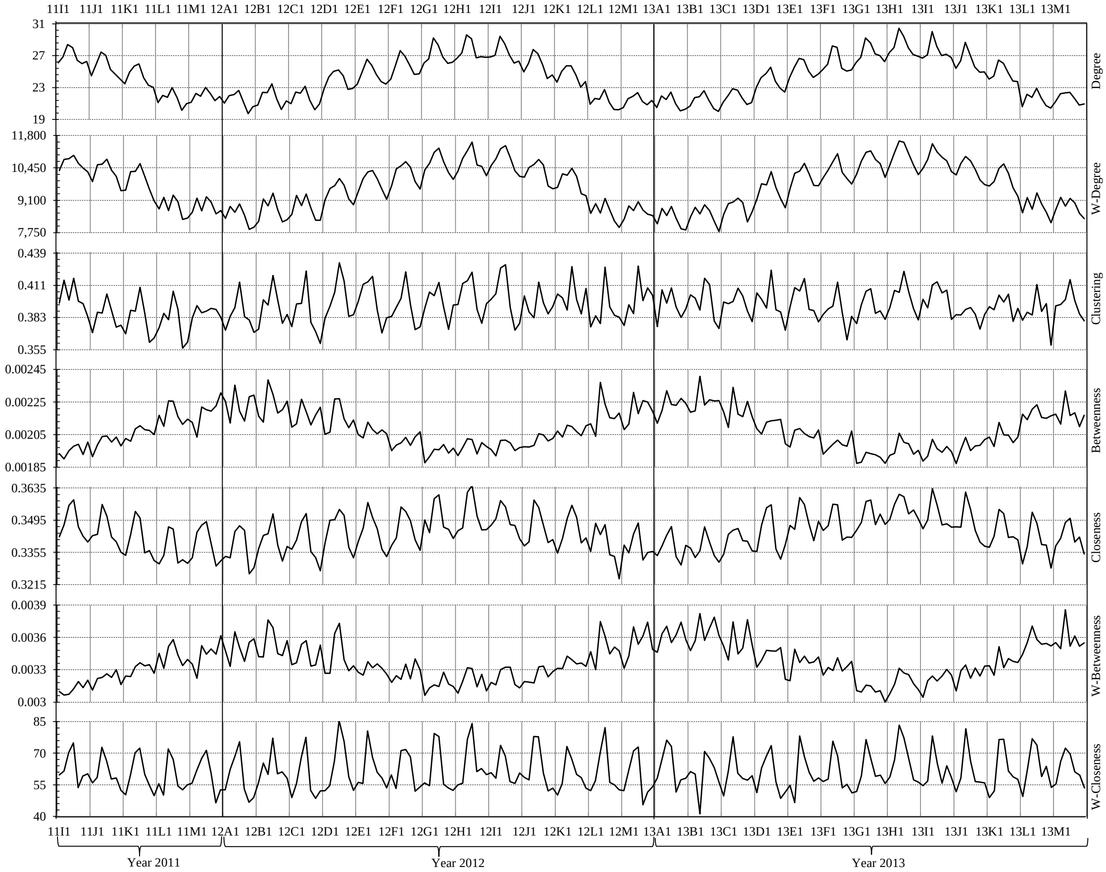


Figure 3.: Temporal evolution of the seven metrics in the airport network

weighted degree as an example to illustrate how to aggregate the network metrics per season and per week. In the first step, we compute the average weighted degree for season A in 2012 and 2013[4]. In this example, the average weighted degree for season A is 85. In the second step, we compute its relative change based on the mean value (102) in the thirteen AIRAC cycles: $\frac{(85-102)}{102} * 100\% = -16.67\%$. In a similar way, we compute the average weighted degree for all Thursdays in 2011, 2012, and 2013. Then we calculate its relative change based on the mean value in a week. The relative changes of the seven metrics for the two network layers are presented in Figure 5 and in Figure 6, respectively.

In the air navigation route network, the general trend is that seasonal variation is larger than weekly variation. The larger seasonal variation indicates that the air navigation route network is dominated by summer/winter seasonal dynamics. Especially, the weighted degree shows the strongest seasonal variation among the seven metrics. The increased number of flights in summer leads to the strongest seasonal variation of the weighted degree in the air navigation route network.

The degree, clustering coefficient, and closeness centrality in the air navigation route network show slight peaks in summer. This indicates that air navigation nodes are more connected and have shorter distance in summer than in winter. One explanation is that in summer there are more flights passing through air navigation nodes.

Further, the betweenness centrality, weighted betweenness centrality, and weighted closeness centrality show slight minimums in summer. One explanation would be the

[4]Note that only the DDR dataset for the second half year of 2011 is available, e.g., from I to M. Thus, the season A in 2011 is not considered in the current study.

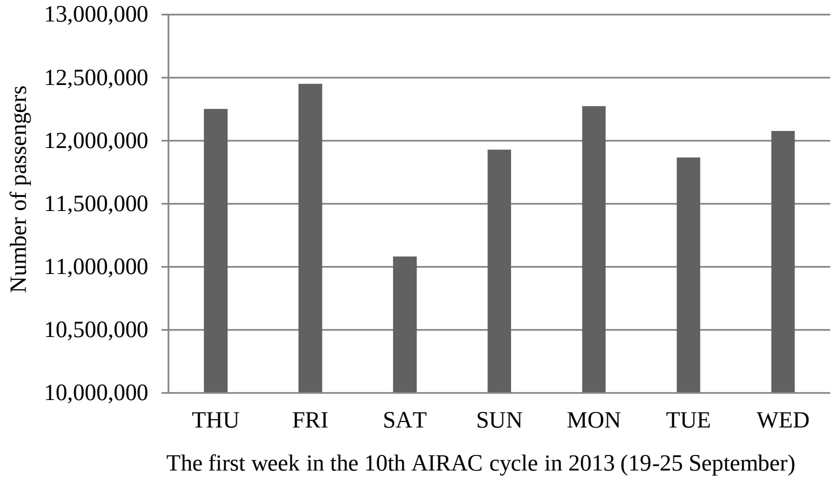


Figure 4.: Number of passengers traveled in the world during the first week of the 10th AIRAC cycle in 2013 (from 19 September to 25 September)

Table 3.: An example of the aggregation of the network metrics in two dimensions: per AIRAC season and per week

Season	W-Degree	Variation	Week	W-Degree	Variation
A	85	-16.67%	THU	101	-0.79%
B	85	-16.14%	FRI	105	3.43%
C	89	-12.93%	SAT	102	0.41%
D	98	-3.85%	SUN	104	2.05%
E	105	3.02%	MON	103	0.94%
F	111	8.90%	TUE	99	-2.94%
G	118	15.93%	WED	99	-3.10%
H	118	15.92%			
I	119	16.94%			
J	113	11.11%			
K	106	4.26%			
L	88	-13.84%			
M	87	-14.52%			

increased number of flights in summer provides more alternative paths between air navigation nodes in the network. The likelihood that an air navigation node is on the shortest paths between all other nodes is decreased in summer.

In the airport network, there exist both strong seasonal variation and weekly variation. In particular, the weighted closeness centrality shows the strongest peak at weekends; while the degree and weighted degree show the second strongest peaks in summer.

Note that we use the reciprocal of the number of available seats to weight the airport network, with the argumentation that larger number of available seats corresponds to a smaller *effective distance* between two nodes (Dall'Asta et al. 2006; Rozenblat et al. 2013). Since there are less passengers traveling at weekends, the values of the weighted closeness centrality are higher at weekends.

The strong summer peak of the degree can be explained by the increased number of flights in summer. The weighted degree is calculated by the sum of the available seats provided by one airport. In general, more flights could provide more capacity (more available seats). Thus, the weighted degree has a peak in summer.

The clustering coefficient and the betweenness centrality in the airport network keep stable during the season; while the betweenness centrality and the weighted betweenness centrality have slight minimums in summer. The reason is similar as the case in the

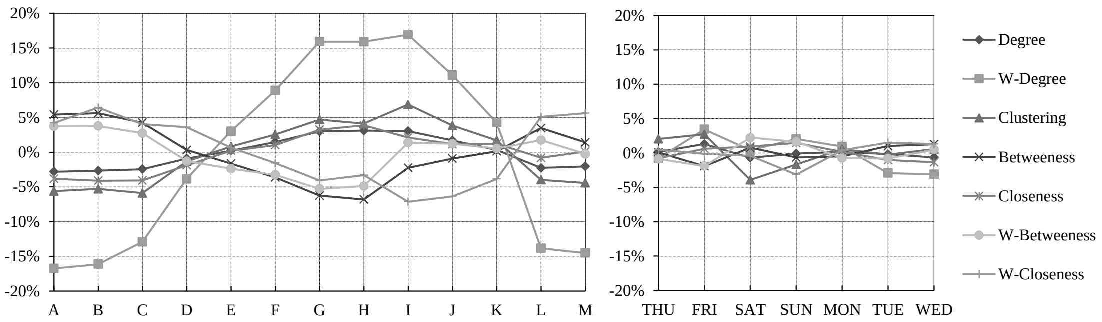


Figure 5.: Variations of the seven metrics in the air navigation route network

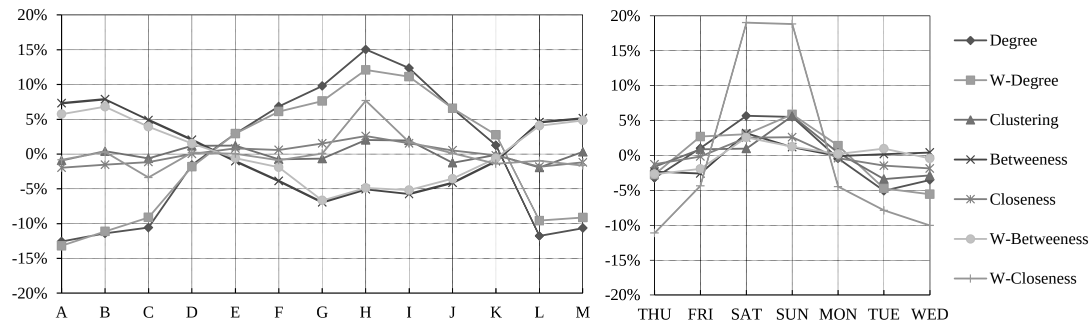


Figure 6.: Variations of the seven metrics in the airport network

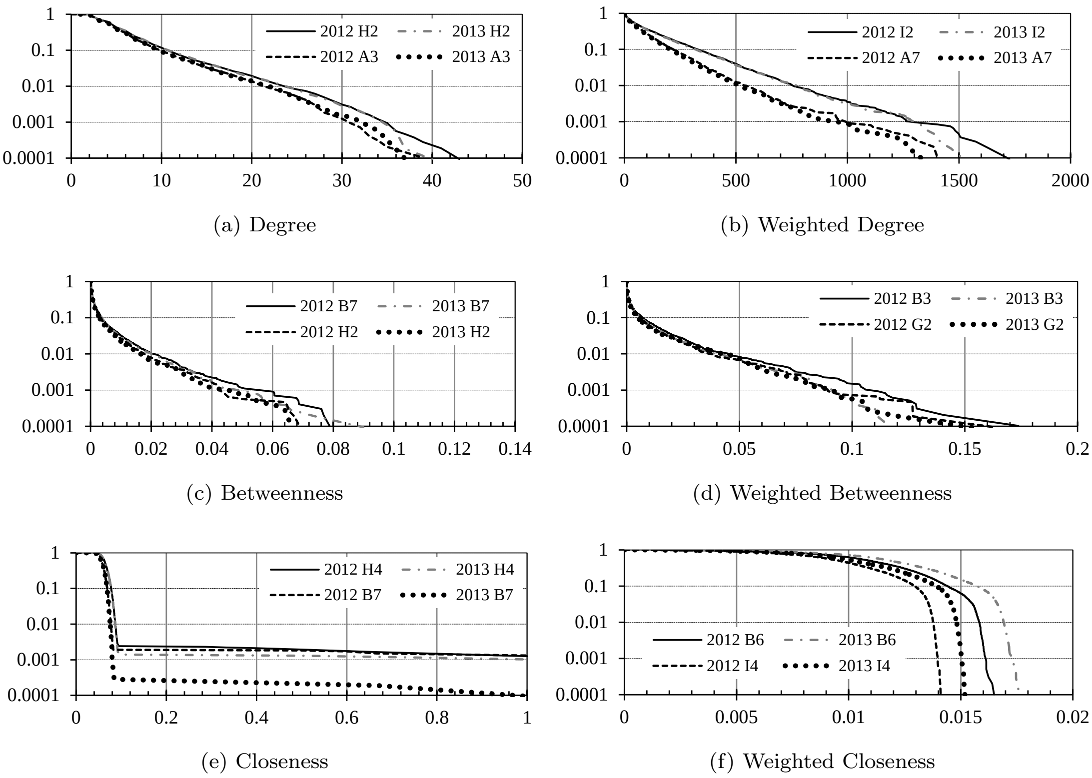
air navigation route network: There are more connections between airports in summer, the increased number of connections provides more alternative paths in the network. Thus, the probability that one airport is on the shortest paths between other airports is decreased in summer.

4.3. *Coefficient of variation per AIRAC season and per week*

In this subsection, we quantify the temporal evolution of seven metrics in the two network layers. Coefficient of Variation (CoV) is one widely used statistic for the comparison between different data series with different scales (Hallgrâimsson and Hall 2005). The CoV is defined as the ratio of the standard deviation to the mean. A higher CoV indicates a larger variation when comparing one data series to another.

We compute the seasonal CoV and weekly CoV for the two network layers and the results are presented in Table 4. For each network metric, the one with a higher CoV dominates the temporal evolution of the network. For example, in the air navigation route network, the seasonal CoV for weighted degree is 13.40%; while its weekly CoV is 2.45%. Here, 13.40% means that the standard deviation of the weighted degree is 13.40% of its mean. Higher value of seasonal CoV indicates that the air navigation route network is dominated by the summer/winter seasonal variations.

In the airport network, the weighted closeness centrality has the maximum weekly CoV (13.07%), while its seasonal CoV is 2.59%. Larger value of weekly CoV indicates that the airport network is dominated by the peak/off-peak weekly patterns. Furthermore, the degree has the second highest seasonal CoV (10.33%) and the weighted degree has the third highest seasonal CoV (9.28%). These two higher values of seasonal CoV indicate that the airport network also shows the summer/winter seasonal variations.



(a) Degree (b) Weighted Degree

(c) Betweenness (d) Weighted Betweenness

(e) Closeness (f) Weighted Closeness

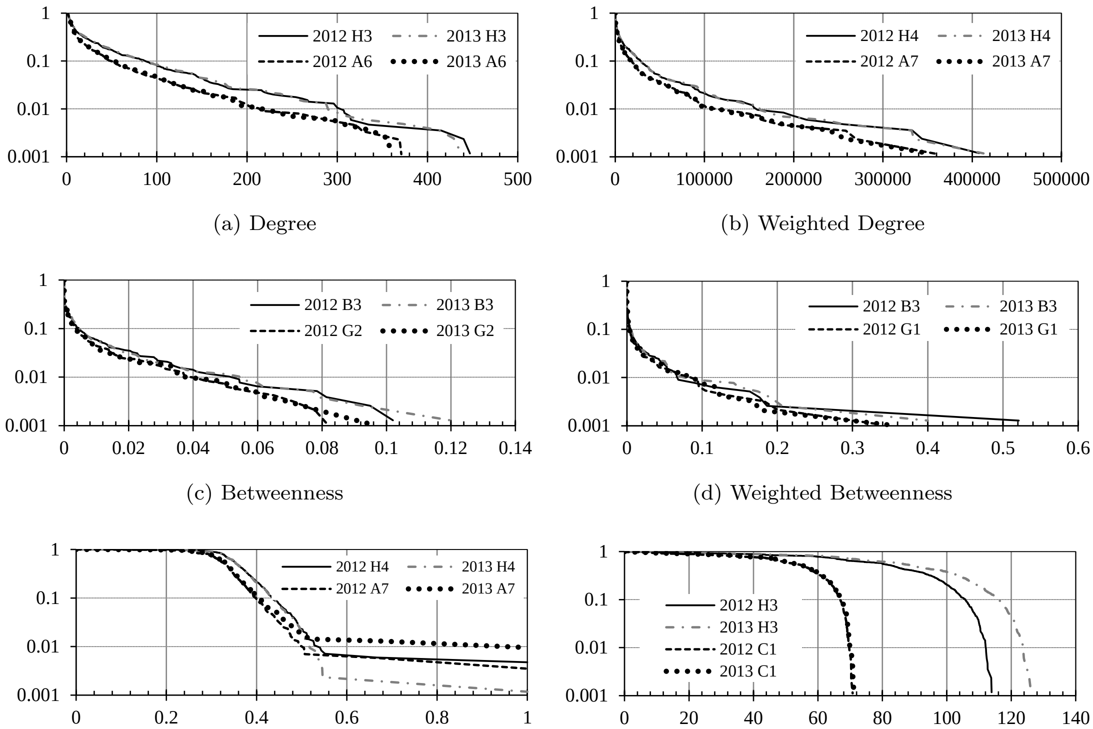
Figure 7.: Daily distributions of the metrics in the air navigation route network

4.4. *Distributional properties of the network metrics*

In order to find out whether there exist any distributional properties of the network metrics, the distributions of the metrics for the two network layers are generated as follows. At first, based on Figure 5 and in Figure 6, we select four extreme days for each metric: the maximum value per season with the maximum value per week and the minimum value per season with the minimum value per week for 2012 and 2013, respectively. For instance, in the air navigation route network (Figure 5), for the metric degree, season H has the maximum value (increased by 3.11% relative to the mean value 5.16) and season A has the minimum one (decreased by by 2.82% relative to the mean value 5.16); while Friday (indexed by 2) has maximum degree and Saturday (indexed by 3) has the minimum one during a week. Thus, we select the Friday in season H (labeled by *H2*) and the Saturday in season A (labeled by *A3*) for the year 2012 and the year 2013. We present the cumulative degree distributions for these four days (*2012 H2, 2013 H2, 2012 A3,* and *2013 A3*) in Figure 7 (a).

In both network layers, the distributions of the degree and the weighted degree for the four selected extreme days almost coincide with each other. This is because most nodes have only a few connections with other nodes and a few hub nodes have large number of connections. For instance, in the air navigation route network, 90% of the nodes have a degree less than 10 (Figure 7 (a)) in these four selected extreme days. The difference between the distributions of these four days becomes slightly obvious when using the number of flights to as the edge weight. This finding confirms the results of the daily distributions for the degree and the weighted degree within a week for the Chinese airport network (Li and Cai 2004).

The distributions of the betweenness centrality and the weighted betweenness centrality for the four selected extreme days also coincide with each other. This is also because



(a) Degree

(b) Weighted Degree

(c) Betweenness

(d) Weighted Betweenness

(e) Closeness

(f) Weighted Closeness

Figure 8.: Daily distributions of the metrics in the airport network

in both network layers, most nodes have rather small betweenness centralities. Small betweenness centrality indicates that most nodes are not part of the shortest paths within the network. Any removal of these nodes would not easily collapse the whole network.

The distributions of the closeness centrality and the weighted closeness centrality for the four selected extreme days still coincide with each other regarding most nodes with small values, but they are distinguishable from each other regarding a few nodes with high values. The difference between the distributions of these four days becomes more obvious when taking into account the traffic in the network.

In summary, from the distributions of the metrics for the four selected extreme days, we discover that there exist hub nodes in both network layers. These hub nodes have large number of connections with other nodes, they are on many shortest paths within the network, and they have ease of assess to all other nodes in the network. These hub nodes are potentially bottlenecks in the air transportation systems. For instance, a node with high degree or betweenness centrality is most likely to be congested (Cook et al. 2012). It is crucial to validate this proposition with empirical data in further research.

5. Conclusions

The goal of this research was to study the temporal evolution of the European air transportation system. We analyzed two network layers between 2011 and 2013: the air navigation route network and the airport network. For each network layer, we investigated the temporal evolution in two dimensions: per season and per week. We quantified the seasonal and weekly variation patterns by the coefficient of variation. Our main findings are summarized in Table 4.

We found out that the air navigation route network is the dominated by summer/winter

Table 4.: Summary for the temporal evolution of the European air transportation system

Metrics	**Mean**	**SD**	**Seasonal CoV**	**Weekly CoV**	**Variation pattern**
Air navigation route network					
Degree	5.16	0.12	2.32%	0.67%	Seasonal (peak in summer)
Weighted degree	102	14	13.40%	2.45%	Seasonal (peak in summer)
Clustering coefficient	0.0713	0.0040	4.49%	2.26%	Seasonal (peak in summer)
Betweenness centrality	0.0015	0.0001	4.09%	1.12%	Seasonal (peak in winter)
Closeness centrality	0.0630	0.0027	2.68%	1.07%	Seasonal (peak in summer)
Weighted betweenness centrality	0.0027	0.0002	3.06%	1.49%	Seasonal (peak in winter)
Weighted closeness centrality	0.0104	0.0007	4.84%	1.56%	Seasonal (peak in winter)
Airport network					
Degree	24.21	2.61	10.33%	4.11%	Seasonal (peak in summer)
Weighted degree	9,648	944	9.28%	4.09%	Seasonal (peak in summer)
Clustering coefficient	0.3931	0.0149	1.22%	2.95%	Weekly (peak at weekends)
Betweenness centrality	0.0021	0.0001	5.30%	1.99%	Seasonal (peak in winter)
Closeness centrality	0.3440	0.0083	1.47%	1.84%	Weekly (peak at weekends)
Weighted betweenness centrality	0.0034	0.0002	4.57%	1.79%	Seasonal (peak in winter)
Weighted closeness centrality	61	9	2.59%	13.07%	Weekly (peak at weekends)

seasonal variations; while the airport network shows both summer/winter seasonal variations and peak/off-peak weekly patterns. Furthermore, the air navigation points are more clustered and have shorter distance in summer than in winter; while the airports are more clustered and have shorter distance during the weekdays than the weekend. From the distributions of the metrics, we found that there are hub nodes existing in both network layers. These hub nodes are potentially bottlenecks of the air transportation systems and should draw more attention in the network design in the future.

The temporal evolution analysis can help the stakeholders in the air transportation systems to monitor the network performance over time and to better understand the network dynamics. Based on the detected summer/winter seasonal variations and peak/off-peak weekly patterns, the airspace configurations could be adapted in time in order to meet the changed demands.

Future research could focus on the interdependence among the multi-layer structure-function networks in the air transportation systems: passenger flow network, airport network, and air navigation route network. Especially, the robustness of the interdependent networks against cascading failures: How the failure of the nodes or edges in one network leads to the failure of dependent nodes in the other networks (Buldyrev et al. 2010).

Acknowledgment

The authors would like to thank EUROCONTROL for providing the data in this study.

References

Azzam, Mark, Uwe Klingauf, and Alexander Zock. 2013. "The accelerated growth of the worldwide air transportation network." *The European Physical Journal Special Topics* 212: 35–48.

Banister, David. 2007. "Sustainable transport: Challenges and opportunities." *Transportmetrica* 3 (2): 91–106. `http://www.tandfonline.com/doi/abs/10.1080/18128600708685668`.

Barrat, A., M. Barthlemy, R. Pastor-Satorras, and A. Vespignani. 2004. "The architecture of complex weighted networks." *PNAS* 101 (11): 3747–3752.

Bonnefoy, Philippe. 2008. "Scalability of the air transportation system and development of multiairport systems: A worldwide perspective." Ph.D. thesis. Massachusetts Institute of Technology.

Buldyrev, Sergey V., Roni Parshani, Gerald Paul, H. Eugene Stanley, and Shlomo Havlin. 2010. "Catastrophic cascade of failures in interdependent networks." *Nature* 464: 1025–1028.

Burghouwt, Guillaume, and Jacco Hakfoort. 2001. "The evolution of the European aviation network." *Journal of Air Transport Management* 7 (5): 311–318. Developments in the Deregulated Air Transport Market.

Cai, Kai-Quan, Jun Zhang, Wen-Bo Du, and Xian-Bin Cao. 2012. "Analysis of the Chinese air route network as a complex network." *Chinese Physics B* 21 (2): 1–7.

Cardillo, Alessio, Jesus Gomez-Gardenes, Massimiliano Zanin, Miguel Romance, David Papo, Francisco del Pozo, and Stefano Boccaletti. 2013. "Emergence of network features from multiplexity." *Scientific Reports* 3 (1344): 1–6.

Cook, A., G. Tanner, S. Cristbal, and M. Zanin. 2012. "Passenger-oriented enhanced metrics." In *Second SESAR Innovation Days,* .

Cordell, Barb. 2006. "EnRoute routes." `http://www.aixm.aero/gallery/content/public/design_review`.

da Rocha, Luis EC. 2009. "Structural evolution of the Brazilian airport network." *Journal of Statistical Mechanics: Theory and Experiment* 2009 (04): P04020.

Dall'Asta, Luca, Alain Barrat, Marc Barthlemy, and Alessandro Vespignani. 2006. "Vulnerability of weighted networks." *Journal of Statistical Mechanics: Theory and Experiment* P04006.

DeLaurentis, Daniel, En-Pei Han, and Tatsuya Kotegawa. 2008. "Network-theoretic approach for analyzing connectivity in air transportation networks." *Journal of Aircraft* 45 (5): 1669–1679.

Eurocontrol. 03/12/2013. "DDR2 Reference Manual 1.0.1 Version." `https://www.eurocontrol.int/services/ddr2`.

Eurocontrol. 2013. "Network Operations Report." `http://www.eurocontrol.int/publications/network-operations-report-may-2013`.

European Commission. 2011. "Flightpath 2050 Europe's vision for aviation." .

Freeman, L. C. 1978. "Centrality in social networks: Conceptual clarification." *Social Networks* 1: 215–239.

Gautreau, Aurelien, Alain Barrat, and Marc Barthlemy. 2009. "Microdynamics in stationary complex networks." *Proceedings of the National Academy of Sciences* 106 (22): 8847–8852.

Guimera, R., S. Mossa, A. Turtschi, and L. A. N. Amaral. 2005. "The worldwide air transportation network: Anomalous centrality, community structure, and cities global roles." *PNAS* 102 (22): 7794–7799.

Gurtner, G., Stefania Vitali, Marco Cipolla, Fabrizio Lillo, Rosario Nunzio Mantegna, Salvatore Micciche, and Simone Pozzi. 2013. "Multi-scale analysis of the European airspace using network community detection." *arXiv:1306.3769v1* 1–22.

Hallgrâimsson, B., and B.K. Hall. 2005. *Variation: A Central Concept in Biology.* Elsevier.

Holmes, Bruce, and John Scott. 2004. *Transportation network topologies.* Technical report. NASA Langley Research Center.

Kivel, Mikko, Alexandre Arenas, Marc Barthelemy, James P. Gleeson, Yamir Moreno, and Mason A. Porter. 2013. "Multilayer Networks." *physics arXiv:1309.7233* 1: 1–37.

Kurant, Maciej, and Patrick Thiran. 2006. "Extraction and analysis of traffic and topologies of transportation networks." *Physical Review E* 74 (3): 036114.

Lehner, Stephan. 2013. "Separate Yet Interdependent Networks: The Structure and Function of European Air Transport." In *Complex Networks IV,* Vol. 476109–120. Springer.

Li, W., and X. Cai. 2004. "Statistical analysis of airport network of China." *Physical Review E* 69: 046106.

Lo, Hong K., and Agachai Sumalee. 2013. "Transport dynamics: its time has come!." *Transportmetrica B: Transport Dynamics* 1 (1): 1–2. `http://www.tandfonline.com/doi/abs/10.1080/21680566.2013.787659`.

Newman, Mark EJ. 2003. "The structure and function of complex networks." *SIAM review* 45 (2): 167–256.

Newman, M. E. J. 2004. "Analysis of weighted networks." *Physical Review E* 70 (5): 056131.

Reggiani, Aura, Peter Nijkamp, and Alessandro Cento. 2010. "Connectivity and concentration in airline networks: A complexity analysis of Lufthansa's network." *European Journal of Infor-*

mation Systems 19 (4): 449–461.

Rozenblat, Céline, Guy Melançon, Romain Bourqui, and David Auber. 2013. "Comparing Multilevel Clustering Methods on Weighted Graphs: The Case of Worldwide Air Passenger Traffic 2000–2004." In *Methods for Multilevel Analysis and Visualisation of Geographical Networks,* 141–154. Springer.

Vitali, S., M. Cipolla, G. Gurtner, F. Lillo, V. Beato, and S. Pozzi. 2012. "Statistical regularities in ATM: Network properties, trajectory deviations and delays." In *Second SESAR Innovation Days,* .

Wei, P., L. Chen, and D. Sun. 2014. "Algebraic connectivity maximization of an air transportation network: The flight routes addition/deletion problem." *Transportation Research Part E: Logistics and Transportation Review* 61 (0): 13–27. `http://www.sciencedirect.com/science/article/pii/S1366554513001750`.

Yang, Ta-Hui. 2008. "Airline network design problem with different airport capacity constraints." *Transportmetrica* 4 (1): 33–49. `http://www.tandfonline.com/doi/abs/10.1080/18128600808685680`.

Yang, Ta-Hui. 2010. "A two-stage stochastic model for airline network design with uncertain demand." *Transportmetrica* 6 (3): 187–213. `http://www.tandfonline.com/doi/abs/10.1080/18128600902906755`.

Zanin, Massimiliano, and Fabrizio Lillo. 2013. "Modelling the air transport with complex networks: A short review." *European Physical Journal Special Topics* 215: 5–21.

Zhang, Hai-Tian, Tao Yu, Jian-Ping Sang, and Xian-Wu Zou. 2014. "Dynamic fluctuation model of complex networks with weight scaling behavior and its application to airport networks." *Physica A: Statistical Mechanics and its Applications* 393 (0): 590–599. `http://www.sciencedirect.com/science/article/pii/S0378437113008352`.

Zhang, Jun, Xian-Bin Cao, Wen-Bo Du, and Kai-Quan Cai. 2010. "Evolution of Chinese airport network." *Physica A: Statistical Mechanics and its Applications* 389 (18): 3922–3931.