Worldwide Air Transportation Networks: A Matter of Scale and Fractality?

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\textbf{ABSTRACT}  
In this study, we take a new view on air transportation networks, inspired by the physical concept of fractality. While other studies analyze networks individually, we aim to provide a unified understanding of the transitions among network layers. As a case study, we investigate the worldwide air transportation networks for the year 2015. We derive aggregated network instances at six different levels: airports, cities, spatial distance 100 km, spatial distance 200 km, regional network, and country network. While few nodes are important at all levels of aggregation, others only become important for few aggregation levels. Fractality analysis highlights that, as one moves from finer granularity to more coarse aggregation level, the network becomes denser but with fluctuating assortativity patterns; and that the modularity and the number of communities both decrease slightly. Networks at higher aggregation levels are more robust than the fine-grained counterparts, airport and city networks.

\textbf{KEYWORDS}  
Air transportation networks; Fractality; Node importance; Network robustness

1. Introduction

With steadily increasing long-distance travel demand, air transportation networks become an essential part of transportation infrastructures in modern societies (Zanin and Lillo 2013; Cook et al. 2015; Balakrishnan et al. 2016). In order to better understand their structures and dynamics, a significant amount of research has been conducted, for instance, on topological properties of air navigation route networks (Sun and Wandelt 2014; Sun, Wandelt, and Linke 2017; Du et al. 2016b), evolution of airport networks (Azzam, Klingauf, and Zock 2013; Jia, Qin, and Shan 2014; Lin and Ban 2014; Sun, Wandelt, and Linke 2015; Wandelt and Sun 2015), network resilience against airport closures or flight cancellations (Cardillo et al. 2013; Lordan et al. 2014; Wei, Chen, and Sun 2014; Wandelt, Sun, and Cao 2015), as well as multiplex properties of airline networks (Cardillo and et. al. 2013; Gurtner et al. 2014; Zanin 2015). It is nevertheless by and large recognized that modeling the network around individual airports only
Figure 1.: Three different levels of aggregation for German airports. The airport level is visualized in the bottom. The layer in the center represents the airports aggregated within 100 km; and the top layer shows the airports aggregated with 200 km distance threshold.

provides a limited view on air transport in general (O’Connor and Fuellhart 2016). This is especially relevant in metropolitan areas, with increasing long-distance mobility demand being served by more than one airport. Therefore, the conceptual notion of Multi-Airport Region (MAR) is often used in air transport research, defined as a group of two or more major commercial airports in a metropolitan region (de Neufville 1986; Monteiro and Hansen 1996; Sarkis 2000; Bonnefoy, de Neufville, and Hansman 2010; O’Connor and Fuellhart 2016). For instance, intentional airport substitution inside a MAR is an efficient way to mitigate supply demand imbalances. The concept of MAR also facilitates the study of resilience of air transport systems: if an airport in a MAR was disabled, alternative airports could be identified as backups. Recently, the idea of airport aggregation has been further taken to the level of provincial and country networks (Wandelt and Sun 2015; Du et al. 2016a). The investigation and comparison of different aggregation levels of air transportation networks, regarding their topological features and connectivity, can reveal hidden network properties. Existing studies use distinct data sources, which makes it difficult to compare the corresponding results; in fact, results are often contradictory, as pointed out by Azzam, Klingauf, and Zock (2013).

In this study, we propose a new view on air transportation networks, taking different levels of aggregation into consideration, in a way consistent with the physical concept of fractality. In Figure 1, we visualize an example for the layers induced by different aggregation levels of the German airports. While other studies look at single such networks separately, we aim to provide a unified understanding of the transitions between airports/regions among network layers. As a case study, we investigate the worldwide air transportation network for the year 2015. Based on a consistent global dataset, we first build the traditional airport network, for then obtaining all other
aggregation levels through a contraction operation. In total, we derive aggregated network instances at six different levels: airports, cities, spatial distance of 100 km, spatial distance of 200 km, regional and country network. The aim of the analysis is to understand how the worldwide air transportation network evolves from fine-grained to coarse aggregation levels. Our results highlight some important facts, the main ones being that:

1. The network structure varies significantly among different aggregation levels, and specifically, aggregated networks have higher clustering coefficients and shorter average path length.
2. The importance of nodes gradually changes among aggregation levels, while few nodes are important in all of them. We also find that node degree and betweenness are weakly correlated at all aggregation levels.
3. Resilience analysis suggests that networks at higher aggregation levels are more robust than the fine-grained counterparts. Moreover, airports in Asia and Europe are often more important for the network robustness than other airports.
4. Most network communities follow geographical boundaries with few exceptions. The number of communities and their structures do not change significantly from fine-grained to coarse aggregation levels, which indicates that the community structure is a rather stable property of air transportation networks.
5. Further fractality analysis of the worldwide air transportation networks shows that the networks become denser but with fluctuating assortativity patterns.

We believe that our findings can be of interest to stakeholders like Air Navigation Service Providers (ANSP), e.g. Federal Aviation Administration (FAA), Eurocontrol or Civil Aviation Administration of China (CAAC), in that they allow to better understand the vulnerability of the system against the closure of one or more airports. They can also be of interest for airlines, especially for those operating in the airports belonging to a MAR, as they can be used to prepare better contingency plans in case of disruptions. Such a translation will require further research; but we strongly believe that the approach here presented will open new doors towards a more resilient and efficient air transport.

This paper is organized as follows. Section 2 provides a literature review on the state-of-the-art air transportation network analysis. Section 3 presents our methodology to construct multi-scale air transportation networks with different aggregation levels. In Section 4, we present the results of multi-scale worldwide air transportation networks for the year 2015. Finally, conclusions are drawn in Section 5.

2. Literature review

This section provides the literature review on the state-of-the-art analysis of air transportation networks at different aggregation levels. As previously introduced, most studies have been focused on single-airport networks and city networks, while only a few recent studies have investigated distance-based, regional and country networks. In what follows, we have organized this section according to the level (or dimension) of aggregation: from individual airports and cities, to MARs and countries.
2.1. **Airport/city level**

We group the studies of single-airport networks and city networks according to the regions that they covered.

The US domestic passenger air transportation network in a weighted version was analyzed by Xu and Harriss (2008), while a study of the structural properties of the US airport network was presented by Jia and Jiang (2012). Recently, the temporal evolution of the US airport network at the city level has been studied by Jia, Qin, and Shan (2014); Lin and Ban (2014); it was found that the dynamics of the network is stable, while some central cities become more crucial. The Chinese airport network has frequently been analyzed in the past. Zhang et al. (2010) found that the topology of Chinese airport network kept stable, while the relative importance of airports and airlines changed significantly between the years 1950 and 2010. The overall structure of the Chinese airport network and the centrality of individual cities were examined in (Wang et al. 2011). Lin (2012) analyzed the weekly flight patterns and identified a spatial hierarchical structure in the Chinese airport network. Temporal evolution of the Chinese airport network from 1930 to 2012 was analyzed in (Wang, Mo, and Wang 2014) with the conclusion that the Chinese airport network has evolved from scattered development to a complex network, with significantly improved connectivity.

With respect to other world regions, the temporal evolution of the Brazilian airport network between 1995 and 2006 at yearly resolution was studied in (da Rocha 2009) and it was shown that the network shrinks at the route level but grows in the number of passengers and amount of cargo. Bagler (2008) evaluated the airport network of India and this network has a truncated power-law degree distribution and disassortative mixing. Burghouwt and Hakfoort (2001) analyzed the evolution of the European airport network between 1990 and 1998 and the authors did not find an indication of hub nodes for intra-European traffic. Burghouwt, Hakfoort, and Ritsema van Eck (2003) studied the spatial configuration of airline networks in Europe. The structure and performance of the airport networks in US, Europe, and China were compared in (Paleari, Redondi, and Malighetti 2010). Zhang et al. (2014) evaluated on the airport networks for China, Brazil, and Europe with a dynamic fluctuation model. Recently, multi-layer representation of functional European airport networks was discussed in (Zanin 2015).

Gurtner et al. (2014) investigated the community structure of the European airspace at airport level, in addition to analyzing the route networks. In order to identify the global roles of cities in the air transportation system, Guimera et al. (2005) aggregated the airport network to the city level and it was shown that the most connected cities are not necessarily the most central ones. Azzam, Klingauf, and Zock (2013) found that the degree distribution of the worldwide airport network network is non-stationary and subject to densification.

With the Marketing Information Data Transfer data, Derudder, Devriendt, and Witlox (2010) analysed in detail the airport connectivity in four major multiple airport cities (London, New York, Los Angeles, and San Francisco). Functional divisions among airports, regarding their geographical scale and specific roles in the airline networks have been reported.

2.2. **Multi-airport regions**

Since the introduction of the Multi-Airport Regions (MARs) concept, MARs have been frequently studied, with a special focus on the US system. Hansen and Weidner (1995) defined a MAR with two criteria: 1) A spatial threshold of 50 km; 2) the Herfindahl
concentration index for the airport is less than 0.95, i.e. the degree to which the passenger activity is concentrated at a single airport within a region is no more than 0.95. Monteiro and Hansen (1996) analyzed the effects of improvements to airport ground access by non-automobile modes in a MAR; an extension of a Bay Area Rapid Transit rail link into the San Francisco International Airport was used as a case study. Also with the San Francisco Bay Area as a case study, Hansen and Du (1993) proposed a traffic allocation model in a MAR. Based on the empirical study on the operational efficiency of 44 major US airports, Sarkis (2000) showed that the characteristics of MARs may not strongly affect airport operational efficiency. Wu and Caves (2002) developed a simulation model for aircraft turnaround operation and aircraft enroute in a multi-airport environment, which also accounts for delays due to operational disruptions and schedule uncertainties. With the case of Des Moines International Airport, a medium airport in central Iowa in US, Suzuki, Crum, and Audino (2004) showed that airlines often under-estimate the tendencies of airport leakage in single-airport regions and the revenues could be increased by reducing airfares. Pels, Njegovan, and Behrens (2009) studied the competition between full-service airlines and low-cost airlines serving adjacent airports in the Greater London Area, based on a nested logit model. Noruzoliaee, Zou, and Zhang (2015) studied the capacity and pricing choice of two congestible airports in a MAR; analytical models with three privatization scenarios have been developed: public–private duopoly, private–private duopoly, and private monopoly. With the London MAR as a case study, Sidiropoulos et al. (2015) proposed a prioritization framework for the arrival and departure routes in the terminal maneuvering areas. An in-depth multiple-case study analysis of 59 MARs in the world was performed in (Bonnefoy, de Neufville, and Hansman 2010) and a feedback model to capture the evolution dynamics of MARs was developed as well. Based on the US Census Bureau primary statistical areas, Wittman (2014) found that most US regions lost access to air service between 2007 and 2012.

2.3. Country level

Recently, few research has been done on the air transportation networks at a country level. Wandelt and Sun (2015) analyzed the evolution of the international air transportation network from 2002 to 2013. Two perspectives have been considered: the topological properties of the network as well as the functional properties with passenger traffic data. Moreover, country networks have also been identified as instructive abstractions in other fields, focusing rather on communication network (Hawelka et al. 2014; Kaltenbrunner et al. 2014) and trade network (Deguchi et al. 2014).

2.4. Others

Finally, it is worth discussing a few works that have indirectly tackled the problem of the aggregation level, but considering a different point of view. Cardillo and et. al. (2013) analyzed the structural properties of the European multiplex airline networks, where each commercial airline defines a network layer. Results showed that topology of the aggregated network is generally not present in the single layers and thus highlighted the importance of considering the multi-level aggregation of most real networked systems. Lastly, Belkoura et al. (2016) studied how topological metrics of air transport networks depend on the way the network is built, i.e. the rules for sampling nodes and connections. In all the three previous cases, the aggregation is performed.
Algorithm 1 Creating MARs based on Haversine distance

<table>
<thead>
<tr>
<th>Input:</th>
<th>Number of passengers per airport in 2015 ( \text{pass} ), distance threshold ( \delta ) in km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output:</td>
<td>Multi-airport regions mapping ( m )</td>
</tr>
</tbody>
</table>

1. Let \( \text{airports} \) be the airports in \( \text{pass} \) sorted descendingly by the number of passengers
2. Let \( m = \emptyset \)
3. Let \( \text{seen} = \emptyset \)
4. for \( a_1 \in \text{airports} \) do
5.   Add \( a_1 \) to \( \text{seen} \)
6.   for \( a_2 \in \text{airports} \) do
7.     Let \( d \) be the Haversine distance between \( a_1 \) and \( a_2 \)
8.     if \( a_2 \notin m \) and \( a_2 \notin \text{seen} \) and \( d \leq \delta \) then
9.       \( m(a_2) = a_1 \)
10. end if
11. end for
12. end for
13. return \( m \)

across dimensions different from the spatial one: respectively airlines, temporal and data-driven ones. Yet, they all highlight the importance of the aggregation process, and of the information in it hidden.

Based on the Airline Origin and Destination Survey, Neal (2010) constructed air traffic networks among 115 US metropolitan areas in 2006, distinguishing between hub/spoke and origin/destination networks, as well as networks of business-oriented and leisure-oriented passengers. The evolution of the business air travel network in the US from 1993 to 2011 has been studied as well (Neal 2013). Wandelt, Sun, and Zhang (2017) provide a comprehensive comparison of eight (domestic) air transportation subnetworks and their evolution, based on complex network properties.

3. Methodology

In the following, we describe the methodology underlying our study. First, we describe how we derived different aggregation levels of air transportation networks, based on the fine-grained information of airport-level connections. Second, we introduce the methods required for understanding the fractality of the networks from a complex network point of view, and also lay the foundation for robustness analysis of the networks.
3.1. Airport network as a baseline

We extract the global air traffic data from Sabre Airport Data Intelligence (ADI, \url{http://www.airdi.net}) to build the aggregated worldwide air transportation network for year 2015. The data set contains information on a yearly basis for all commercial direct flights, including: origin/destination airports, number of passengers, revenue, average fare, and traffic type (scheduled or charter). This data is used to reconstruct the traditional airport network as follows: an airport is a node if it is either an origin or destination of any flight; and a link is created between two nodes if there is at least one direct flight between the corresponding airports. The obtained network is unweighted for the remainder of our study, since we aim at analysing the topological properties and topology-induced robustness of the worldwide network and its aggregations. Given this step, we have a network with nodes \( N \) and links \( L \). This airport network is the most fine-grained air transportation network in our study and it serves as the input for coarser aggregation levels.

3.2. Computation of network aggregations

In general, all other aggregation levels are obtained by a contraction operation on the original airport network. Given the airport network with nodes \( N \) and links \( L \), we define a mapping \( m \), such that the domain of \( m \) is \( N \) and the range of \( m \) is the set of transformed nodes \( N_t \). The links \( L_t \) are obtained by applying the mapping to the nodes of each link in the original network, \( i.e. \) if \((a,b) \in L\), then we have \((m(a), m(b)) \in L_t\). Below we describe how we derive the mapping \( m \) for all aggregation levels.

- **Airport network:** The mapping \( m_{airport} \) is simply an identity mapping, \( i.e. \) all airports in the network are preserved.
- **City network:** The mapping \( m_{city} \) maps each airport to the city it belongs to. The information about the cities of the airports comes from the Sabre dataset.
- **Distance-based network of 100 km:** The mapping \( m_{havd100} \), as inspired by previous research works on MARs (Bonnefoy 2008; Bonnefoy, de Neufville, and Hansman 2010; Wittman 2014; O’Connor and Fuellhart 2016), is created as follows. First, we sort the airports according to the total number of passengers in the year 2015, including both inbound and outbound passengers. Next, we iterate over all airports in the descending order of passengers and compute the Haversine distance to all other airports. Once the distance to the larger airport is below a threshold \( \delta \), we assign that airport as belonging to the MARs of the larger airport. Finally, we mark the airport as being assigned to avoid reassigning it in the future. The algorithm is formalized in Algorithm 1. Here the distance threshold is set to \( \delta = 100 \text{km} \).
- **Distance-based network of 200 km:** The mapping \( m_{havd200} \) is created similarly to \( m_{havd100} \), with a threshold of \( \delta = 200 \text{km} \).
- **Regional network:** The mapping \( m_{region} \) is based on \( m_{city} \), and maps each city to its ISO 3166-2 code. ISO 3166-2 is a short, unique alphanumeric code representing sub-national administrative territories of all countries in the world. In practice, the cooperating/competing regions can improve the overall system performance (Zhang et al. 2011b). Each code consists of two sub-codes: a first ISO 3166-1 alpha-2 code of the country, and the second part containing up to three alphanumeric characters. For instance, the code US-AK stands for United States-Alaska.
• **Country network:** The mapping \( m_{\text{country}} \) maps each airport to the country it belongs to, based on the region as codified by the ISO 3166-1 alpha-2 code. Following the previous example, the code US stands for United States.

### 3.3. Complex network properties

In order to analyze the transition of properties along the aggregation-induced fractality, we investigate a set of standard network properties, which have been introduced in the literature. We revisit the definition of these properties below, for convenience. For an introduction into the science of complex networks, we refer the reader to several excellent survey/textbooks (Newman 2003; Costa et al. 2007; Barabási 2016). In our study, we treat the network as undirected, unweighted network.

1. **Assortativity:** The assortativity coefficient of a network is the Pearson correlation coefficient of degree between pairs of linked nodes. A positive value indicates a correlation between nodes of similar degree, while negative values indicate relationships between nodes of different degree.

2. **Average Shortest Path Length:** The average shortest path length of a network is the sum of the lengths of all shortest paths divided by the number of node pairs. This number represents the average number of steps it takes to get from one node to another.

3. **Betweenness:** The betweenness of a node \( n \) is defined as \( \sum_{u \neq n \neq v} \frac{\sigma_{uv}(n)}{\sigma_{uv}} \), i.e., the fraction of shortest paths the node is contained in, where \( \sigma_{uv} \) the number of shortest paths between \( u \) and \( v \) and \( \sigma_{uv}(n) \) is the number of these paths going through node \( n \).

4. **Clustering Coefficient:** The clustering coefficient of a node is the ratio of existing links connecting a node’s neighbors to each other to the maximum possible number of such links.

5. **Degree:** The degree of a node is the number of its direct neighbors.

6. **Density:** The density of a network is defined as \( \frac{2L}{N(N-1)} \), i.e., the ratio of the number of links \( L \) to the number of possible links in the network.

7. **Diameter:** The diameter of a network is the length of the longest of all the shortest paths in a network.

8. **Modularity:** The modularity of a network is the fraction of the edges that fall within the given groups minus the expected fraction if edges were distributed at random.

### 3.4. Network robustness

The robustness of a network mirrors the response of the network to the removal of nodes. Complex networks are often resilient to random failures, where all nodes are disrupted with the same probability. Under targeted attacks, however, many networks break down fast. In the literature, attack strategies for evaluating the robustness of a network are often based on node importance measures and node centralities. Particularly, the degree and the betweenness of a node have been frequently used in the past to guide attacks. The degree attacks so-called hubs first, i.e., nodes with a high degree, and the betweenness favors nodes on many shortest paths. The effect of an attack on the topology of the network is usually measured as the relative size of the giant component. The curve obtained from simulating attacks can be used to estimate
how quickly a network breaks down under failures/attacks.

### 4. Results

We report the results of our experimental evaluation, following the methodology outlined in Section 3. We provide an overview on standard topological properties of the network at different scales in Section 4.1. Section 4.2 discusses how the importance of nodes gradually changes from fine-grained aggregations to coarser levels. In Section 4.3, we analyze the resilience of the networks against random failures and targeted attacks. The community structure of all networks is compared in Section 4.4. Finally, an analysis of the whole system’s fractality is presented in Section 4.5.

#### 4.1. Network overview

First, we discuss and compare several relevant topological properties for the six network aggregation levels. The results are summarized in Table 1. As one may expect, the airport and city networks have the largest number of nodes; and, with further aggregation, the network’s size and link density respectively decreases and increases. The country network, the most coarse aggregation, has 231 nodes and a 20 times higher density than the original network. Accordingly, the average node degree is increasing from around 30 to almost 50. Radius, diameter, and average shortest path length of

<table>
<thead>
<tr>
<th>Network metrics</th>
<th>airport</th>
<th>city</th>
<th>haved100</th>
<th>haved200</th>
<th>region</th>
<th>country</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of links</td>
<td>60694</td>
<td>45701</td>
<td>38199</td>
<td>26948</td>
<td>20959</td>
<td>5676</td>
</tr>
<tr>
<td>Network density</td>
<td>0.01064</td>
<td>0.00934</td>
<td>0.0154</td>
<td>0.02861</td>
<td>0.02845</td>
<td>0.21868</td>
</tr>
<tr>
<td>Average node degree</td>
<td>92.7</td>
<td>60.1</td>
<td>34.4</td>
<td>29.3</td>
<td>41.0</td>
<td>49.1</td>
</tr>
<tr>
<td>Network diameter</td>
<td>8</td>
<td>6</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Average shortest path length</td>
<td>2.84897</td>
<td>2.83462</td>
<td>2.79962</td>
<td>2.56819</td>
<td>2.49641</td>
<td>1.82564</td>
</tr>
<tr>
<td>Assortativity</td>
<td>-0.17593</td>
<td>-0.18976</td>
<td>-0.20950</td>
<td>-0.21746</td>
<td>-0.25624</td>
<td>-0.23746</td>
</tr>
<tr>
<td>Modularity</td>
<td>0.67800</td>
<td>0.67753</td>
<td>0.67700</td>
<td>0.67906</td>
<td>0.67800</td>
<td>0.67753</td>
</tr>
</tbody>
</table>

Table 1: Topological properties of the worldwide air transportation networks at six different aggregation levels.

<table>
<thead>
<tr>
<th>city-level</th>
<th>haved100-level</th>
<th>haved200-level</th>
<th>region-level</th>
<th>country-level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank Node</td>
<td>Airports</td>
<td>Rank Node</td>
<td>Airports</td>
<td>Rank Node</td>
</tr>
<tr>
<td>1</td>
<td>London</td>
<td>5</td>
<td>1</td>
<td>BET</td>
</tr>
<tr>
<td>2</td>
<td>New York</td>
<td>4</td>
<td>2</td>
<td>LHR</td>
</tr>
<tr>
<td>3</td>
<td>Los Angeles</td>
<td>3</td>
<td>3</td>
<td>EWR</td>
</tr>
<tr>
<td>4</td>
<td>San Francisco</td>
<td>3</td>
<td>4</td>
<td>BOS</td>
</tr>
<tr>
<td>5</td>
<td>Moscow</td>
<td>3</td>
<td>5</td>
<td>AMS</td>
</tr>
<tr>
<td>6</td>
<td>Milan</td>
<td>3</td>
<td>6</td>
<td>BOS</td>
</tr>
<tr>
<td>7</td>
<td>Chicago</td>
<td>3</td>
<td>7</td>
<td>FUK</td>
</tr>
<tr>
<td>8</td>
<td>Sao Paolo</td>
<td>3</td>
<td>8</td>
<td>DLG</td>
</tr>
<tr>
<td>9</td>
<td>Melbourne</td>
<td>2</td>
<td>9</td>
<td>KPN</td>
</tr>
<tr>
<td>10</td>
<td>Belo Horizonte</td>
<td>2</td>
<td>10</td>
<td>SJU</td>
</tr>
<tr>
<td>11</td>
<td>Sacramento</td>
<td>2</td>
<td>11</td>
<td>JIO</td>
</tr>
<tr>
<td>12</td>
<td>Tampa</td>
<td>2</td>
<td>12</td>
<td>EVE</td>
</tr>
<tr>
<td>13</td>
<td>Orlando</td>
<td>2</td>
<td>13</td>
<td>FTY</td>
</tr>
<tr>
<td>14</td>
<td>Belo Horizonte</td>
<td>2</td>
<td>14</td>
<td>BRS</td>
</tr>
<tr>
<td>15</td>
<td>Phoenix</td>
<td>2</td>
<td>15</td>
<td>EMK</td>
</tr>
<tr>
<td>16</td>
<td>Nagoya</td>
<td>2</td>
<td>16</td>
<td>MIE</td>
</tr>
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<td>17</td>
<td>Lublin</td>
<td>2</td>
<td>17</td>
<td>BLS</td>
</tr>
<tr>
<td>18</td>
<td>Toronto</td>
<td>2</td>
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<td>HDS</td>
</tr>
<tr>
<td>19</td>
<td>Tenerife</td>
<td>2</td>
<td>19</td>
<td>BMI</td>
</tr>
<tr>
<td>20</td>
<td>Tehran</td>
<td>2</td>
<td>20</td>
<td>ITR</td>
</tr>
</tbody>
</table>

Table 2: Top-ranked nodes according to the number of airports in five unweighted air transportation networks; the airport network is not shown since each node corresponds to exactly one airport. The list is dominated by airports/regions from US and Europe. Alaska is ranked top for distance-based and region-based networks.
the network are gradually decreased with higher aggregation levels, meaning that the nodes are becoming closer to each other. The clustering coefficient is rather stable, ranging from 0.61 to 0.69. The assortativity values for all six network instances are negative, i.e. hub nodes in air transportation networks tend to connect to small ones. This also indicates that the network becomes more heterogeneous as its evolves from fine-granularity to more coarse aggregation level. Finally, the modularity of the networks, the fraction of the links which fall within the community minus the expected fraction of links if the links were distributed randomly, according to (Blondel et al. 2008), is rather stable as well, with an average value of 0.6783.

We have performed additional experiments to analyze whether these derived networks can be considered as small-world. In a small-world network (Watts and Strogatz 1998), nodes tend to form a large number of triangles, thus indicating a dense micro-scale connectivity; but, at the same time, this does not affect the average distance between pairs of nodes, which scales sub-linearly with the size of the network. This yields two-fold criteria to assess the small-world property of a network: first, an average clustering coefficient significantly higher than an equivalent random network, constructed with the same number of nodes and links; second, a similar average shortest path length (Watts and Strogatz 1998). Our experiments show that all networks considered in this study are small-world. The average shortest path length of the air transportation network ranges from 1.8 (country) to 2.8 (airport, city); while the clustering coefficients are from 0.62 (airport, city) to 0.69 (country). For the random network counterparts, however, we observe clustering coefficients between 0.01 (airport, city) and 0.21 (country), i.e. significantly lower than in the real-world networks.

Table 2 reports the top 20 nodes in the aggregated networks, ranked according to the number of airports in each of them mapped. The highest-ranked city is London, which is served by five (rather large) airports: STN (London Stansted), YXU (London Municipal Airport), LTN (London Luton Airport), LGW (London Gatwick Airport) and LCY (London City Airport). However, London is a rather exceptional case of a multi-airport city, given that the majority of cities only have one or two airports. The aggregation by Haversine distance is dominated by airport BET (Bethel Airport), located in Alaska, US, followed by LHR (London Heathrow, UK) and EWR (Newark Liberty International Airport, New Jersey, USA). In general, at the Haversine-distance aggregation level, we already find several larger airport regions. At the regional level Alaska (US-AK) is ranked first, containing 132 airports. This latter result deserves further discussion. The size of areas identified by ISO 3166-2 codes is rather heterogeneous: while US-AK covers around 1.7 million km$^2$, other regions are significantly smaller - for instance DE-BR (Brandenburg in Germany) only covers 30,000 km$^2$. Therefore, the aggregation based on such regions should be understood from an administration-induced point of view, where the (regional) government can make decisions on the development of their airports, or at least provide incentives to set a direction for future development. Similarly, the nodes aggregated at the country level are to be understood as under control of the national government and national authorities. Not surprisingly, US is ranked top in our list with more than 500 active airports used for passenger transportation. Altogether, it can be seen that the country ranking according to the number of airports largely coincides with their respective sizes, since larger countries often need more airports to ensure an efficient passenger transportation.
4.2. Node importance

After having discussed some global properties of the reconstructed networks, we here descend to the micro-scale to analyse the importance of individual nodes. Several standard metrics are available to quantify the node importance from a complex network point of view, the most important and well-known being the degree and the betweenness centrality. The degree centrality of a node reflects its number of direct neighbors, normalized by the total number of nodes. Passengers of an airport with a high degree centrality can reach more airports within one step, i.e., using a single flight. The betweenness centrality, on the other hand, measures how frequently a node appears on the shortest paths of a network.

We firstly discuss the degree centrality. Figure 3 presents the top ten nodes ranked according to this metric, for the six aggregated air transportation networks. One can observe that the majority of important nodes is located in Western Europe and Northern America. London and Amsterdam, for instance, are top-ranked according to their degree centrality at city level, but at airport level DXB and FRA are more influential than LHR. In fact, London is an excellent example for a multiple-airport region, composed of 4–5 larger passenger airports around Greater London. These airports together, aggregated at the city level and higher, make this region very well-connected in the worldwide network, while most of the MAR airports inside London are not well-connected alone, except from LHR. This small example shows how the aggregation of airports in a MAR can significantly change the properties from a complex network point of view. In order to further analyze the transition of regions through different

![Maps showing different aggregation levels](image-url)
aggregation levels, essentially investigating the fractality of the network, Figure 4 visualizes the dependencies between both concepts through the hierarchical analysis of the top ten degree nodes in the six aggregated air transportation networks. While seven airports (LAX-Los Angeles International Airport, JFK-John Kennedy International Airport, CDG-Paris Charles De Gaulle Airport, LHR-London Heathrow Airport, FRA-Frankfurt Airport, DXB-Dubai International Airport, and AMS-Amsterdam Airport Schiphol) are important at all levels of aggregation, i.e. they form complete columns in Figure 4, other nodes only appear temporally.

Next, we discuss the importance of nodes as indicated by their betweenness centrality values. Figure 5 presents the scatter plot of degree vs. betweenness centrality in the six aggregated air transportation networks. All aggregation layers present a weak linear correlation ($R^2$ between 0.64 and 0.71) between both centralities, with the exception of a quadratic relationship in the case of the country network ($R^2$ of 0.90); both metrics thus agree on the identification of the most important hubs. An interesting question is whether the betweenness centrality of a node is strongly connected to the number of airports aggregated into that node; in other words, do more airports lead to higher centrality values? Figure 6 shows the scatter plots between the number of airports and betweenness centralities in the six aggregated air transportation net-
works at a semi-log scale. Surprisingly, no correlation is observed, thus indicating that putting more airports into a region does not necessarily increase the importance of that region. While uncommon from a pure network perspective, this is easily explainable when economical factors are taken into account, since an important prerequisite for successful MARs is a rather complementing set of destinations served by the airports. This insight is important for understanding the economical forces behind the growth of specific MARs.

Figure 6.: Scatter plot between the number of airports and betweenness centralities in the six aggregated air transportation networks at a semi-log scale. With the levels of aggregation going from single airports to country entities, betweenness centralities do not scale up.

Figure 7.: Robustness analysis of the six aggregated air transportation networks, with different attacking strategies: Intentional attacks (degree-based (deg), betweenness-based (betw)), as well as random failures (rand1, rand2, and rand3 are three random attacks to the network). The networks are robust against random failures, but disintegrate quickly under intentional attacks.
Figure 8.: Identification of attack-relevant nodes and their geographical origin. For each continent we show the percentage of attacked nodes for a given number of failed nodes, when attacking the network by betweenness centrality. It can be seen that the airports from Asia (AS) and Europe (EU) are the most important nodes during the attack, while airports from North America (NA) and Africa (AF) are less important. The only exception for North America are US-based regions, which are often attacked as one of the first nodes.

4.3. Network robustness

Air transport, like all other critical infrastructures, is required to maintain the highest fault tolerance (Freeman, Seiler, and Balas 2013; Zhang et al. 2011a; Lee, Yoo, and Park 2014), since disruptions have huge economic and societal impacts (Ball et al. 2006). For instance, due to an overnight snowstorm on March 12, 2013, Frankfurt airport was closed and airlines cancelled about 700 flights. The 2010 ash cloud over Europe, caused by eruption of Icelandic volcano Eyjafjallajökull, is estimated to have caused losses of approx. 3.3 billion Euro for large European airlines (Mazzocchi et al. 2010). Therefore, robustness analysis is a critical and important issue in air transport, especially for the deployment of future improvements. In this study, we quantify the robustness of the network against random failures and targeted attacks by measuring the size of the giant component, as often performed in related studies (Lordan et al. 2014; Wang et al. 2014).

Figure 7 presents the results of the robustness analysis for the six aggregated air transportation networks, under both intentional and random attacks. Intentional attacks disable nodes based on certain network metrics: we here consider node degree and betweenness, as previously defined. Essentially, the robustness curve of the networks for random failures is along the diagonal line, which means that worldwide air transportation networks are rather robust against random failures. Under intentional attacks, as induced by degree and betweenness rankings, the network breaks
down into isolated components much faster. In general, networks at higher aggregation levels, e.g., distance-based MARs and country networks, are more robust than the fine-grained counterparts, e.g., airport and city networks. One possible explanation is that the aggregated networks have a higher link density, see Table 1.

The results of Figure 7 for the betweenness attack can be disaggregated by regions, to investigate how the spatial location of nodes is relevant for intentional attacks - see Figure 8. Here, we record the number of nodes from each continent, once the network is attacked according to node betweenness. We can observe that airports in Asia and Europe are often attacked earlier in the attack process. Therefore, it can be understood as more important for the robustness of air transportation networks. This is surprising, since US airports play crucial roles in international air transportation, at least from an economical point of view. Further analysis reveals that inside North America, there a few airports which are highly important from the topological point of view, but most airports are less important and are being attacked in the end of the attacking process. For instance, many of these airports are located on smaller islands in the Caribbean Ocean, or in rural areas. Most of these airports also have a rather low passenger traffic.

4.4. Communities

In complex networks, the notion of community has been developed to identify nodes which are densely connected within a group, yet sparsely connected with other groups in the network. The detection of communities helps to understand the underlying
structures of the network and identifying hidden properties between nodes (Palla et al. 2005; Zhou 2003). In this study, we use the widely-known Louvain method (Blondel et al. 2008) to identify communities in the network. The Louvain method is a greedy one, in that it attempts to optimize the modularity of partitions in the network using a sequential procedure, which starts with smaller communities and gradually analyzes larger ones. Figure 9 presents the community structures in the six aggregated air transportation networks. We find that the communities of the networks largely coincide with the administrative regional boundaries. The number of communities is stable for all aggregation levels (usually around 10 communities are identified by the Louvain method). One interesting insight is that the West-African coast belongs to the community of Western Europe in all aggregation levels, while the rest of Africa is strongly connected to the Arabian region, with connections up to India.

4.5. Further discussion on network fractality

So far, we have derived the worldwide air transportation network instances at six different aggregation levels: airports, cities, spatial distance with radii of 100 km and 200 km, regional network, and country network. While these have been selected according to their operational relevance, and to their previous use in the literature, they are nevertheless arbitrary thresholds. One may then ask whether there are better aggregation scales.

The approach here presented is an example of a more general fractal analysis, a topic by and large studied in complex network theory. Nodes in a network are aggregated according to different criteria, for then analysing how several relevant structural metrics evolve during the process. In spite of many works dealing with this problem, there is no clear consensus on the way a fractal analysis should be conducted, as networks are usually not embedded in a space, and thus, distance has no clear meaning (Song et al. 2007; Li, Yu, and Zhou 2014; Watanabe, Mizutaka, and Yakubo 2015; Wei and Wang 2016). Airports are nevertheless located in space, simplifying the aggregation process.

In order to identify the transitional patterns of the fractality, we evaluate the properties of the network for a large set of radii with 10 km interval, ranging from 10 km to 490 km, yielding a total of 49 network instances. We set the upper limit to 490 km, since too many airports would be clustered together for larger radii and we think larger radii have less practical implications in reality, especially regarding the operational interactions between airports inside a MAR (Bonnefoy, de Neufville, and Hansman 2010).

Figure 10 presents the evolution of several topological metrics as a function of the radius \( \delta \). We can observe that, as the aggregation distance expands, both the number of nodes (airports) and links (flight connections) gradually decrease; while the density of the network smoothly increases. This is rather straightforward, since, as more nodes are merged together, intra-links among these merged nodes disappear; while, on the other hand, inter-links intensify. The assortativity coefficient is negative during the whole process with a rather low coefficient of variation (the ratio of the standard deviation to the mean is 0.03910), i.e. major airports in the worldwide air transportation networks tend to connect small ones at all aggregation scales. When the radius is 60 km, the assortativity reaches its lowest value (around -0.2006); then the assortativity value increases until the radius is 260 km, afterwards it starts to decrease gradually. It is interesting to identify these two transitional thresholds for the radius. Firstly, because
they are quite close to the standard values considered in the literature (i.e. 100 km and 200 km), thus indicating that the latter ones are also reflected in the network structure. Secondly, the fluctuating behavior of the assortativity indicates that during the node merging process, the connectivity patterns of the networks change adaptively. Finally, the modularity values and the number of communities are computed using the well-known Louvain method (Blondel et al. 2008). It can be seen that the modularity values decrease slightly, with a very small coefficient of variation (0.0018). The number of communities reduces slightly as the aggregation radius increases.

The evolution of the six topological metrics here presented only yields a first glimpse of the more complex problem of the fractality in the air transport system. Future works will have to dig deeper into this problem, especially regarding the relationships between fractality and its operational consequences.

5. Conclusions

In this contribution, we have extensively and comprehensively explored the structural properties of the worldwide air transportation network at multiple aggregation levels: airports, cities, spatial distance with a radius of 100 km, spatial distance with a radius of 200 km, regional network and country network. At each level, nodes have either been aggregated according to a distance measure, or to the corresponding administrative boundary. We have further presented the results of aggregating nodes according to a continuous distance function, thus introducing (to the best of our knowledge, for the first time in air transport) a fractality analysis. With respect to previously published studies, we have here introduced a statistical physics approach to the aggregation problem: the aggregation is thus not just guided by arbitrary and external criteria (e.g. fixed distance thresholds), but by the same topology of the system. This allows for a better understanding of the multi-scale structure of the air transport, and on the role that each element (here, airports) plays within the macro-scale structures it is part

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fractality.png}
\caption{Fractality analysis for the structure of the worldwide air transportation networks, with the radius ranging from 10 km to 490 km. Evolution of six network properties is recorded: number of nodes (decreasing), number of links (decreasing), density (increasing), assortativity (fluctuating), modularity (slightly decreasing), and number of communities (slightly decreasing).}
\end{figure}
Finally, we presented a detailed analysis of the relationship between the fractality of the system and its resilience, opening the door to a better understanding of the effects of major airport closures and to the development of optimized contingency plans. The major findings are summarized below.

(1) **Network structure:** The network structure varies significantly between different aggregation levels. The number of nodes ranges from 231 in country network to 3097 in the airport network. The country network is much denser (21%) than the city network (1%). Accordingly, the average shortest path length in the country network is approx. one step shorter than in all other aggregation levels. The clustering coefficient is rather stable and ranges between 0.61 and 0.69.

(2) **Node importance:** The importance of nodes in the aggregated networks changes gradually with the aggregation level. While few nodes are important at all levels of aggregation, *e.g.* LHR/London/Great Britain or JFK/NewYork/US, others only become important at some specific scales, *e.g.* SIN/Singapore or Canada. We also find that node degree and betweenness are rather uncorrelated at all aggregation levels.

(3) **Network robustness:** The degree and the betweenness of a node provide necessary information to reduce the functionality of the network, as measured by the size of the giant component. In general, networks at higher aggregation levels, *e.g.* distance-based MARs and country networks, are more robust than the fine-grained counterparts, *e.g.* airport and city networks. Moreover, our analysis reveals that the airports in Asia and Europe are often more important from a robustness point of view.

(4) **Communities:** Previous research works were not conclusive on whether communities induced by the air transportation structure coincide with geographical and political boundaries. We find that indeed most communities follow geographical boundaries, with few exceptions. Furthermore, the number of communities and their structures do not change significantly from fine-grained to coarse aggregation levels, thus indicating that the community structure is a rather stable property of air transportation networks.

(5) **Fractality:** Further fractality analysis of the worldwide air transportation networks shows that the networks become denser but with fluctuating assortativity patterns. We identified two transitional thresholds for the radius. Both are quite close to the standard values considered in the literature (*i.e.* 100 km and 200 km), thus indicating that the latter ones are also reflected in the network structure.

Our current study focuses on topological properties of the worldwide air transportation networks at six different aggregation levels; as well as how the networks evolve from fine-grained to coarse granularity. In future works, the analysis could be complemented with weight information, using for instance information about the number of passengers or number of flights for each direct connection. The temporal evolution of the multi-scale properties of the network could also be studied further, in order to derive policy implications (Gil-Alana, Barros, and Assaf 2013). Moreover, additional measures of network robustness could be used (Chow et al. 2015; Pien et al. 2015).

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