Complementary Strengths of Airlines under Network Disruptions

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Abstract
Disruptions of air transportation systems, caused by events such as, extreme weather conditions or human-intended attacks, can lead to huge economic losses. Existing studies have modeled and estimated the robustness of air transportation networks under node/link failures, and found that networks disintegrate quickly under targeted attacks. The robustness of airline networks, however, has been largely neglected in the past, with investigating strongly spatially constrained regions and few airlines only.

In this study, we first investigate the robustness of more than 200 global airline networks, which cover almost 95 percent of worldwide air passenger transportation. We find that the robustness depends largely on the structure of the airline network. Second, we estimate how much these disruptions can be absorbed by other airlines using the notion of static complementary strength. In addition, with passenger data and rerouting considerations, we analyze how much of an airline disruption can be compensated by other airlines in reality. Results show that the traditional complementary strength clearly overestimates the robustness of the network; according to our more realistic model, many airlines are indeed easy to fail and the consequences of failures are not readily compensated by other airlines.

Our work contributes towards improving air transportation systems, by understanding the hidden threats of airline disruptions.

Keywords: Airline disruption, Network robustness, Air transportation

1. Introduction

Air transport systems can be studied from a complex network point of view, where airports are modeled as nodes and links exist between two airports if there is at least one direct flight connection [1, 2]. Due to convective weather conditions or human-intended interruptions (such as terrorist attacks, air traffic controller strikes or pilots strikes) or unexpected mechanical failures (such as aircraft component breakdown or runway systems failures), air transport systems can become vulnerable [3]. Such disruptions often lead to huge economic and social costs [4, 5]. The eruption of Eyjafjallajökull volcano in 2010, for instance, caused airlines losing approximately 1.7 billion US dollars and more than 10 million passengers were affected [6]. In order to avoid such high socio-economic costs, it is critical to assess the robustness of air transportation systems against disruptions [7, 8, 9]. Accordingly, understanding and improving the resilience of air transportation systems is a major challenge to ensure safe and efficient global transportation [10].

Related studies have analyzed air transportation network robustness mainly against node/link failures [11, 12, 13], where node failure refers to airport closure and link failure refers to the cancellation of a flight. Most of these techniques perform either random attacks or they attack nodes in the network using some type of node ranking as a guiding strategy, following traditional complex network-based view [14]. Examples for such rankings are degree (the number of incoming/outgoing links) or betweenness (the centrality of a node according to how many shortest paths it is located on). Other works also consider the closure of airports based on spatial distance from a given epicenter [12]; and link attacking strategies [13]. Moreover, all these studies focus on the negative effects of airport network disruptions, with a strong emphasis on airports. Finally, there is a large body of literature on other cyber-physical systems, e.g.,
Figure 1: An overview on the worldwide airport network for August 2015. Airports are represented by blue circles and direct flight connections by blue lines. The airline network for Lufthansa is highlighted in yellow color. Many of the connections for Lufthansa originate from the European airspace, particularly from the two Airports Frankfurt and Munich. (Data source: Sabre Airport Data Intelligence, ADI).

power-grids [15, 16, 17, 18, 19] and ground transportation networks [20, 21, 22, 23, 24] (see [25] for a recent review), or other transportation infrastructure elements [26, 27, 28, 29].

In this study, we investigate the robustness of individual airlines and the complementary strengths of airlines to compensate for airline network disruptions. We define a topology-induced notion of static complementary strength to evaluate the pairwise ability of airlines to help each other during disruptions. Extending this view towards a more realistic model, we take into account passengers and rerouting under disruptions. Based on worldwide airline data for August 2015, we show how the top 250 airlines are interconnected and how their complementary strength can be possibly exploited to prevent large-scale disasters. Our work contributes towards improving air transportation systems, by taking a novel view of airline disruptions and their complementary effects.

This paper is organized as follows. Section 2 summarizes the literature on resilience analysis of air transport networks. Individual airline networks and their robustness against disruptions is studied in Section 3. Section 4 assesses the complementary robustness of airline networks in a global context. Finally, conclusions are discussed in Section 5.

2. Literature review

The robustness of worldwide air transport network as a single layer, i.e., ignoring airlines, was analyzed with comparison of several different robustness measures and attacking strategies [30]. It was found that degree and Bonacich based attacks harm passenger weighted network most; with a new notation of robustness metric originating from the function of air transport: Unaffected passengers with rerouting. The robustness of US air transport network was studied [31], using attacking strategies based on degree, betweenness, closeness, and HITS (Hyperlink Induced Topic Search), with the size of giant component as the robustness measure. A new exploration/exploitation search technique for a computationally efficient attacking model was proposed in [3]; four real-world domestic air transport networks were presented to analyze the scalability of the proposed techniques. With an estimated number of stranded passengers in the giant component as a robustness metric, Louzada et al. proposed reroute of flights within certain distances of original destination airports in order to improve the resilience of worldwide air transport system under targeted node attacks [32]. Robustness of Australian air transport network was investigated under random attacks and degree/betweenness/strength targeted attacks, with the size of giant component and network reachability as robustness measures [33]. The worldwide air transport network was studied under random attacks as well as degree and betweenness-based attacks; with shortest average path length and the size of giant component as robustness measures [34]. The flight routes addition/deletion problem was introduced and algebraic connectivity was used as the...
Table 1: Excerpt of airline list in our study. Overall, these airlines cover more than 90 percent of all passengers traveled in August 2015. The topological parameters differ significantly among these airlines. ASPL=Average shortest path length, ADEG=Average Degree.

<table>
<thead>
<tr>
<th>ID</th>
<th>IATA Name</th>
<th>Passengers</th>
<th>Nodes</th>
<th>Links</th>
<th>Density</th>
<th>ASPL</th>
<th>ADEG</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AA AMERICAN AIRLINES INC.</td>
<td>13.19 Mio (4.03%)</td>
<td>186</td>
<td>1049</td>
<td>3.05%</td>
<td>2.28</td>
<td>11.3</td>
</tr>
<tr>
<td>2</td>
<td>DL DELTA AIR LINES INC.</td>
<td>13.05 Mio (8.01%)</td>
<td>249</td>
<td>1162</td>
<td>1.88%</td>
<td>2.28</td>
<td>9.3</td>
</tr>
<tr>
<td>3</td>
<td>WN SOUTHWEST AIRLINES CO.</td>
<td>13.03 Mio (11.99%)</td>
<td>95</td>
<td>1281</td>
<td>14.34%</td>
<td>1.97</td>
<td>27.0</td>
</tr>
<tr>
<td>4</td>
<td>FR RYANAIR LTD.</td>
<td>8.78 Mio (14.67%)</td>
<td>180</td>
<td>2438</td>
<td>7.57%</td>
<td>2.20</td>
<td>27.1</td>
</tr>
<tr>
<td>5</td>
<td>UA UNITED AIRLINES INC.</td>
<td>8.66 Mio (17.31%)</td>
<td>193</td>
<td>967</td>
<td>2.61%</td>
<td>2.57</td>
<td>10.0</td>
</tr>
<tr>
<td>6</td>
<td>CZ CHINA SOUTHERN AIRLINES</td>
<td>7.6 Mio (19.63%)</td>
<td>134</td>
<td>994</td>
<td>5.58%</td>
<td>2.39</td>
<td>14.8</td>
</tr>
<tr>
<td>7</td>
<td>U2 EASYJET AIRLINE COMPANY L.</td>
<td>6.46 Mio (21.61%)</td>
<td>133</td>
<td>1430</td>
<td>8.15%</td>
<td>2.12</td>
<td>21.5</td>
</tr>
<tr>
<td>8</td>
<td>MU CHINA EASTERN AIRLINES</td>
<td>6.02 Mio (23.44%)</td>
<td>131</td>
<td>853</td>
<td>5.01%</td>
<td>2.34</td>
<td>13.0</td>
</tr>
<tr>
<td>9</td>
<td>TK TURKISH AIRLINES INC.</td>
<td>5.26 Mio (25.05%)</td>
<td>255</td>
<td>648</td>
<td>1.00%</td>
<td>2.09</td>
<td>5.1</td>
</tr>
<tr>
<td>10</td>
<td>LH DEUTSCHE LUFTHANSA AG</td>
<td>5.1 Mio (26.60%)</td>
<td>169</td>
<td>494</td>
<td>1.74%</td>
<td>2.15</td>
<td>5.8</td>
</tr>
<tr>
<td>11</td>
<td>EK EMIRATES</td>
<td>4.87 Mio (28.09%)</td>
<td>130</td>
<td>276</td>
<td>1.65%</td>
<td>2.07</td>
<td>4.2</td>
</tr>
<tr>
<td>12</td>
<td>CA AIR CHINA LIMITED</td>
<td>4.71 Mio (29.53%)</td>
<td>124</td>
<td>538</td>
<td>3.53%</td>
<td>2.21</td>
<td>8.7</td>
</tr>
<tr>
<td>13</td>
<td>NH ALL NIPPON AIRWAYS CO. LT.</td>
<td>4.43 Mio (30.88%)</td>
<td>76</td>
<td>260</td>
<td>4.56%</td>
<td>2.42</td>
<td>6.8</td>
</tr>
<tr>
<td>14</td>
<td>AF AIR FRANCE</td>
<td>3.95 Mio (32.09%)</td>
<td>151</td>
<td>369</td>
<td>1.63%</td>
<td>2.21</td>
<td>4.9</td>
</tr>
<tr>
<td>15</td>
<td>BA BRITISH AIRWAYS P.L.C.</td>
<td>3.83 Mio (33.26%)</td>
<td>183</td>
<td>405</td>
<td>1.22%</td>
<td>2.60</td>
<td>4.4</td>
</tr>
<tr>
<td>...</td>
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<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>250</td>
<td>DG SOUTH EAST ASIAN AIRLINES</td>
<td>0.18 Mio (93.98%)</td>
<td>15</td>
<td>32</td>
<td>15.24%</td>
<td>1.81</td>
<td>4.3</td>
</tr>
</tbody>
</table>

Robustness measure to optimize the network robustness; with the Virgin America network as a case study [35, 36, 37]. Essentially, all these measures investigate node/link failures and largely ignore the multi-layer structure.

Individual structures of seven US largest passenger airline networks were analyzed [13]: the networks’ resilience to random node/edge deletion and targeted node deletion based on degree/betweenness were examined as well. The size of giant component and a relative global travel cost were used to quantify the network performance under various deletion processes. Cardillo et al. analyzed the resilience of European air transport network against random edge failures (flight cancellation), with each airline as an interdependent network [38]. The re-scheduling of the passengers who are affected by random edge failures has been considered; rescheduled passengers are divided into three groups: those who cannot fly, those who can fly via an alternative path with the same airline, the ones who have to switch airlines. It was shown that the multi-layer structure strongly reduces the system’s resilience under disruptions. Note that this paper focused on the effects of layered structures on the resilience of the European air transport. Zhao et al. evaluated the robustness of multiplex networks under layer node-based random and targeted attacks [39], with the size of giant component as the robustness measure. It was found that layer node-based attack makes the multiplex networks less robust. These works are most similar to ours, yet, none of them focuses on the complementary effects at the world-wide scale.

Verma et al. analyzed the resilience of the worldwide airport network and revealed that it is a redundant and resilient network for long distance air travel, but otherwise breaks down completely due to removal of short insignificant connections [40]. The eruption of volcano Eyjafjallajökull, the September 11th terrorist attacks, and geographical disruptions in the worldwide air transport system were investigated; effective distance [41] was used to quantify the impact of these disruptions on the network [12].

3. Individual airline networks and their robustness

We present an overview of the airlines used in our study in Table 1: the names of all 250 airlines and their IATA codes are summarized in Table 3 in the Appendix. In total, we analyze the top 250 airlines, ranked by the number of passengers travelled in August 2015. All data was obtained from the Sabre Airport Data Intelligence (ADI, http://www.airdi.net). The number of passengers ranges from around 0.18 Mio (for South East Asian Airlines) to 13.19 Mio (for American Airlines). The largest network in our study, regarding the number of nodes, is Turkish Airlines with 255 airports. The density of networks varies between 1% (for sparse networks) and 17% (for dense networks). The average shortest path length, which represents the average number of hops between all airports inside the airline network, is usually between 1.8 and 2.5. The average degree varies significantly among airline networks in our study. Note that both traditional airlines and low-cost carriers are considered in our study. There are significant
differences between traditional airlines and low-cost carriers: While traditional airlines are often characterized by hub-and-spoke network structures, large route networks, large fleet size with multiple types of aircraft, as well as differentiated products serving wide arrays of passengers, including short-medium-long haul flights; low-cost carriers generally have point-to-point network structures, low operating costs, decreased ticket prices, and less comforts, with focus on short and medium haul flights. With continued growth, low-cost carriers are expanding their operations at major airports/cities as well and this triggers more direct competition between traditional airlines and low-cost carriers. The results in our study show that a clear mix of both types of networks is emerging.

In Figure 2, we visualize four traditional airline networks selected in this study: British Airways, Emirates, Turkish Airlines, and Deutsche Lufthansa; while Figure 3 shows three low-cost-carrier networks: Southwest Airlines, Easyjet Airlines and Ryanair. For each airline we show the airports as green codes and direct flights as green links. Moreover, we highlight important airports, so-called hubs, with red circles. Since there exists no standard definition of a hub airport, we have chosen the following criteria: An airport is a hub, if it is connected to at least 50% of the other airports in the airline network. For large networks, this high threshold ensures that only very central airports are taken into consideration. It can be seen that the structures of traditional airline networks have at most two hubs; while there are multiple hubs in the low-cost-carrier networks. Moreover, all networks have very diverse topological properties,
Figure 4: Scatter plot of airline network properties against the number of hubs in the airline network, where an airport is considered a hub, if it is connected to more than 50% of the other airports in the airline network. Low-cost carriers are highlighted with red color and traditional carriers with blue color. Opposed to other studies (with less data), a clear separation between low-cost and traditional carriers cannot be confirmed. (Data source for low-cost carriers: https://en.wikipedia.org/wiki/List_of_low-cost_airlines).

distinguishable from their visualizations alone. Some traditional airlines, such as Turkish Airlines are essentially built around a single hub airport, in this case Istanbul Ataturk Airport. Other low-cost-carriers, such as Southwest Airlines are constructed with a larger backbone of hubs, distributed over the region of operation. Note that there seems to be a transition from hub-and-spoke network structure to peer-to-peer network structure, rather than a clear cut.

In order to further explore the relationship between the number of hubs and other network properties, we report additional correlations in Figure 4. We investigate the following airline network properties: Number of airports (nodes), number of direct flights (links), network density, and the total number of passengers using the airline network. None of these four properties reveals a strong correlation with the number of hubs in the network. We conclude that the number of hubs used by an airline is not so much a topology-based decision, but rather affected by its business model. In addition, Figure 4 distinguishes traditional airlines (blue) and low-cost carriers (red). In opposition to other studies, which usually rely on less data, we cannot find a clear distinction between both types of airlines: We have traditional airlines with a high number of hubs, e.g., ZH (Shenzen Airlines) and XG (Sunexpress Deutschland), as well as, low-cost carriers with a smaller number of hubs in their network. Therefore, the traditional view, that all low-cost carriers have substantial differences to traditional airlines [42, 43, 44], should be taken with caution when analyzing robustness. Assessing the robustness of airline networks rather depends on analyzing the networks separately with
their induced topological and functional properties, no matter being low-cost or traditional.

The robustness of airline networks is substantially influenced by the number of hubs and other factors. In order to measure the topological impact of node failures, the relative size of the giant component is often used: How many nodes are in the largest component after an attack, compared to the number of nodes in the largest component before an attack took place. The attacking strategy, inducing the order of node removal, varies throughout studies, but most frequently the following three are used: Random, degree, and betweenness. Random strategies simulate node failures without a particular pattern. It was shown that complex networks are often resilient against random node removal. Targeted strategies, based on degree and betweenness, remove important nodes in the network first and therefore provide more of a worst-case perspective on network robustness.

In Figure 5, we visualize the robustness curves for the top 15 airline networks used in our study and compare the effect of all three introduced attack strategies. We can see that all airlines are rather robust against random attacks but susceptible for targeted attacks. This implies that all airline networks are robust on daily operations, but once being attacked with sufficient knowledge about the network topology, the network breaks down fast. The differences between degree-based and betweenness-based attacks are minor; particularly, neither of the two strategies clearly outperforms the other. The ability to break down airport networks with attacking a few nodes, emphasizes the need to better understand the individual and complementary effects of airline network disruptions. The R value in Figure 5 is computed according to the methodology presented in [45]. Given a network with N nodes, the robustness is defined as $R = \frac{1}{N} \sum_{Q=1}^{N} s(Q)$, where $s(Q)$ is the size of the giant component (GC size) after removing Q nodes. The range
of valid R values ranges from 0.0 to 0.5. Vulnerable networks have smaller R values and resilient networks larger R values.

In Table 2, we summarize the robustness of airlines networks for a specific case study: We investigate how many airports need to fail in order to reduce the size of the giant component down to 20%, in other words, 80% of the airports cannot be reached any longer. As we can see, the majority of airlines is very vulnerable. On average, 2–4 airports need to be removed from the network. In concordance with our previous findings, we can see that there is no clear distinction between traditional airlines and low-cost carriers. The most resilient airline network in our study is Ryanair (FR): The network of Ryanair can withstand outages at multiple airports without completely breaking down. Possible explanations are discussed as follows.

Nowadays, low-cost airlines play important roles in the worldwide air transportation, with Southwest airlines dominating in the United States and Ryanair in Europe. The robustness of low-cost airlines is mainly due to the point-to-point model of the network (see Figure 3), rather than the hub-and-spoke model for traditional full-service airlines (see Figure 2). The majority of the nodes in the network of low-cost airlines have very low values of betweenness centralities, compared to traditional carriers’ networks. In the latter, disruptions on airports with high betweenness usually affect the whole network. In most airlines, like Lufthansa, there are only a few outstanding hubs with extraordinarily high betweenness values. Once they fail, the whole network breaks down. Low-cost airlines do not have these single points of failures in their network and are therefore more robust against targeted attacks and random failures.

### Table 2: Aggregation of airlines by the number of nodes required to be failed in order to reduce the relative size of the giant component down to 20% (i.e., 80% of the airports cannot be reached any longer). Low-cost carriers are highlighted in bold. Nodes are being attacked by decreasing degree, i.e., from hubs to non-hubs.

<table>
<thead>
<tr>
<th>Nodes</th>
<th>Reduction of the giant component size down to 20%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2L 8L 9Q 9U AT AY B2 BT CM CX DD DT EK EL ET EU EY FB FI FV FZ G9 GF HF HX IB J2 JP JU KA KL KM KQ KU KY LG LO LP LY ME MI MS NX OA OK OS PR PS QA QR RJ RO SA SN SQ SU T0 TG TK TR UL WA WK WY</td>
</tr>
<tr>
<td>2</td>
<td>0B 16 17 2P 4Z 7F AF AM AU BA BK BR C5 CI CL CT EI EP EW FD FM GH HA HQ I2 KC KK LA LH LX MH NI OD P5 PN QB S7 SY TA TP TU V0 VW W3 WZ Y7</td>
</tr>
<tr>
<td>3</td>
<td>3O 5D 5J 7C 7R 9I 9R AC AK AV AZ CU DP DV HG HO HV HY JO KE MQ NZ OU OZ PC PG PX RE SE SJ TO VN VS YS ZL ZW</td>
</tr>
<tr>
<td>4</td>
<td>3M 4O AH AR AX CP D7 G5 G8 GA GE JL NC O6 QF QG QS QX R3 SK SV TS UN VA VB XQ YV</td>
</tr>
<tr>
<td>5</td>
<td>9C 9E 9W A3 AS B6 EH G7 IW JQ JT NH PK QK WG WS Y4 ZB</td>
</tr>
<tr>
<td>6</td>
<td>4U 6E BV 19 IR IX KD UT</td>
</tr>
<tr>
<td>7</td>
<td>9K CA DL EV F7 G4 JJ LS R2 SG ST UA UX YX</td>
</tr>
<tr>
<td>8</td>
<td>AA BE DB GS JD OO OS S5 U6 YC</td>
</tr>
<tr>
<td>9</td>
<td>3U 6Y AB DE F9 G3 NK TB V7 WF</td>
</tr>
<tr>
<td>10</td>
<td>AD DY VV XG</td>
</tr>
<tr>
<td>&gt;10</td>
<td>SC YW MF X3 HU ZH CZ MU WN W6 H1 U2 FR</td>
</tr>
</tbody>
</table>
Figure 6: Visualization of static complementary strengths between top 100 airlines. Lower values (visualized by white color) indicate less complementary strength (i.e., less potential for cooperation and competition between two airlines); while larger values (towards red color) indicate more complementary strength (i.e., large market overlap between two airlines).

We adapt this definition for our purpose, by taking into account the existence of MAR in a network as follows. Two airports from different airlines are considered to be complementary, if their distance is less than 50km. This is a standard value chosen from the literature [49]. This translates into the following definition:

$$ S_{CS_{S_2 \rightarrow S_1}} = \frac{\text{Airports in } S_1 \text{ which have a complementary airport within 50km in } S_2}{\text{Airports in } S_1} $$

Based on this definition, we computed the pairwise complementary strength for the top 100 airlines in our study (ranked by the number of passengers). The results are presented in Figure 6. For each airline, we can read off the complementary strength to all other airlines. A lower value indicates few complementary strength, and thus, less potential for cooperation and competition. High values, on the other hand, indicate that both airlines work on markets.
with a large overlap. We can identify three large clusters in Figure 6. The largest cluster (on the top center) consists of airlines serving mainly the European market. We can see how three airlines (Lufthansa, British Airways, and Air France) are strongly complementary to many other European airlines in our study. This is important, since it indicates that these airlines are the major backup options for the European air transportation systems. Similarly, in the second largest cluster, which can be found in the lower-left, we find many airlines from America, and three of them are strongly complementary to all other airlines in the cluster: American Airlines, Delta Airlines, and United Airlines. The third largest cluster, located in the right of the chart, essentially resembles Asian airlines. The most relevant airlines as backups, from a complementary strength point of view are China Southern, Air China, and China Eastern. Apart from the three major clusters, we observe a vertical band spanning up between airlines KLM to Lufthansa, additionally including Etihad Airways, Qatar Airways, Emirates, Turkish Airlines, Air France, and British Airways. All these airlines have significantly higher complementary strengths to all other airlines, than the average; and we conclude that they have considerable impacts on the resilience of the complementary air transportation systems.

The previously used static complementary strength captures the dependencies between two airlines from a static point of view and quantifies how much one airline can be a backup for another. However, this view is purely based on topology, without taking into account real passengers in the airline networks. In the following, we develop a more realistic complementary strength measure for estimating the effect of an airline disruption, in presence of other airlines. Given a set of disrupted airline networks and a set of non-disrupted airline networks, we want to estimate the number of passengers from disrupted airlines which can travel by switching towards a non-disrupted airline. In order to avoid our model becoming too complex, we make a few simplifications as follows. First, since we do not have information about the number of free seats for flights of airlines, we assume that approx. 80 percent of a flight is booked, which is an average value obtained from Sabre airline data; similar assumptions were made in related work [50]. Second, we assume that passengers can travel freely between airports using ground transportation; a threshold of 50km is used as above.

9
Figure 7: Visualization of passenger-centric complementary strengths between top 100 airlines. Lower values (visualized by white color) indicate less passenger-centric complementary strength (i.e., the disruption of one airline cannot be compensated by other airlines); while larger values (towards red color) indicate more complementary strength (i.e., the disruption of one airline could be partly compensated by others).

Based on these simplifications, the passenger-centric complimentary strength is computed as sketched in Algorithm 1. First, we create a capacity network that collects the free capacity among airport pairs as provided by the non-disrupted airlines (Lines 3–8). Next, we iterate over all direct flights in the disrupted airline networks and assign them the network without violating capacity constraints (Lines 9–30). In addition, we take into account the concept of multiple airport regions within 50 km (Line 11–12) and only reassign passengers if their flight takes at most two hops and the overall flight distance is not increased by more than 50% (Line 16).

We describe the outcome of our experiments regarding passenger-centric complementary strengths of pairwise airline networks next. Given Algorithm 1, we compute for all pairs of airlines the passenger-centric complementary strength. We report the results in Figure 7. Compared to the results obtained by static complementary strength (Figure 6), we can identify only very few significant complementary strengths. Most of these dependent airline pairs are located in North America, where local airlines serve largely overlapping regions. In these cases, the disruption of
one airline can be partly compensated by the free capacity of others. Yet, the differences with the purely topological measure are striking. We conclude that the failure of a single airline cannot be compensated by other single airlines, despite a large overlap of airports (after MAR consolidation).

In Figure 8, we report passenger-centric complementary strengths of each airline against all other airlines, where airlines are distinguished by the total number of passengers. This scenario simulates the disruption of one airline and estimates up to what extend all other airlines together can compensate for the failure. We can see that the median of passenger-centric complementary strength is around 0.2, which means that for many airlines, only 20% of the passengers can be recovered by other airlines after rerouting, while 80% are stranded because of the airline disruption. Only the failures of a few smaller airlines can be compensated to more than 50%. Copa Airlines (CM) has the smallest passenger-centric complementary strength, which serves as a major international airline for Panama. In case of a disruption in Tocumen International Airport (the hub of CM), the disruptions cannot be counterbalanced at all by other existing airlines. Note that our perspective is rather from passenger who could have a free choice on alternative airlines. In other words, we always have something like a system optimum in mind, where all airlines could help each other. The reality could be much different.

A comparison between the robustness of airport networks and airline networks is visualized in Figure 9. We can see that the airport network breaks down very fast under targeted degree-based and betweenness-based attacks; and it is almost completely disintegrated after attacking the top 300 nodes. The airline network, on the other hand, is slightly more robust under targeted attacks, since other airlines can accommodate some passengers from disrupted airlines.

5. Conclusions

Several studies have analyzed the robustness of air transportation networks under node/link failures, finding that the network is rather vulnerable under targeted attacks involving multiple airports. The robustness of airline networks,
however, has been largely neglected in the past. In this study, we first investigate the robustness of single airline networks to failures at their critical airports. Second, we estimate how much these disruptions can be absorbed by other airlines, from a topological view and taking into account passenger data as well. Our major findings are summarized as follows:

1. The structure of airline networks largely differs, between single-hub structure and more peer-to-peer organization. While this finding is not new by itself, we show the traditional belief, that low-cost carriers always follow point-to-point structures, cannot be hold up. In the opposite, we find a clear mix of both types of networks among traditional and low-cost carriers.

2. The network structure is critical for the resilience against airport disruptions inside the airline network. For some airlines in our study, e.g. Emirates (EK), British Airways (BA), and Turkish Airlines (TK), the robustness measure of R value is around 0.01, which means that the network breaks down with only a very few nodes being disrupted. In comparison, other airlines, such as Hainan Airlines (HU), Ryanair (FR), and China Southern (CZ), can withstand attacks to more than five airports, without completely being disintegrated.

3. Analysis of the static complementary strength between airline networks suggests that there exists a large redundancy and disruptions in one airline could be compensated by other larger airlines. Particularly, we identify three larger clusters of airlines which potentially support each other over Northern America, Europe, and Asia.

4. Extending topological analysis by taking into account passengers and rerouting under disruptions, we find that the real ability of airlines to absorb disruptions is significantly smaller than estimated from the static complementary strength. This shows that further work is necessary in order to design more resilient networks and give incentives to airlines to cooperate in case of disruptions.

We discuss a few limitations of our study, which directly lead towards a set of future research opportunities. First, we did not take into account the effect of airline alliances. Although airline alliances have handled more than half of international passengers and it is often claimed that they have created greater choices together with better connectivity for passengers, there are also wide criticisms that airline alliances actually reduce passengers’ choices as well as competition between carriers at hub airports serving certain routes. In general, airlines from the same alliance are more likely to cooperate with each other in case of disruptions. Particularly, it would be interesting to analyze
two distinct scenarios: 1) Airlines from the same alliance can provide complementary help, while 2) all airlines help compensate each other in case of disruptions. Moreover, our passenger-centric complementary strength computation is based on a greedy assignment. More efficient and realistic assignments, including travel mix and congestion effects, could be developed to obtain an even better model of real world behavior. Finally, other aspects of modeling critical infrastructures, see [25] for a detailed review, could be integrated into our study.

Acknowledgments

This paper is supported by the National Natural Science Foundation of China (Grants No. 61650110516, No. 61601013, No. 61521091 and No. 91538204).

References


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[37] P. Wei and D. Sun, “Weighted algebraic connectivity: An application to airport transportation network,” in *18th IFAC World Congress Milano (Italy)*, 2011.


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Table 3: IATA code and names of airlines in this study.