Resilience of Cities Towards Airport Disruptions at Global Scale

Abstract
Improving the efficiency and resilience of air transportation is one of the major challenges in the 21st century. Large cities are often in the catchment area of multiple airports. Accordingly, the services at these airports can be complementary or competitive; an airport-specific view of resilience neglects the effects of such interactions. In this study, we analyze the resilience of cities in the presence of airport disruptions. The major research question we address is: How much would the air accessibility of complete cities lose under the outage of a single airport? We perform a study at the global level, comparing the resilience of 5,000 largest cities. Two types of passenger-focused measures are proposed to quantify the impact of airport disruption on the air accessibility of cities: the unaffected passengers and the reroutable passengers. We find that some countries have resilient cities, while others are more vulnerable to airport disruptions. Our study contributes to the literature by a unique combination of city-view, accurate airport-to-city aggregation with road driving distance, and presence of real passenger data.

Keywords: Airport failure; City global resilience; Reroutable passengers

1. INTRODUCTION
Given a steadily increasing demand for human mobility, ambitious goals have been set for air transportation, in terms of quality and affordability, environment, efficiency, safety, and security [European Commission 2001]. With the rapid development of economic globalization, resilience of transportation systems to disruptions becomes increasingly important, for improving passenger’s safety and avoiding huge economic losses. The eruption of Eyjafjallajoekull volcano in 2010 caused airlines lost approximately 1.7 billion US dollars and more than 10 million passengers were affected [Wilkinson, Dunn, and Ma 2012]. An overnight snowstorm on March 12, 2013 disrupted the transport system across northwestern Europe; in particular Frankfurt airport was closed and airlines canceled about 700 flights. In December 2017, an electrical fire in a tunnel beneath Atlanta’s Hartsfield-Jackson airport (the busiest airport in the world), broke its main and backup power systems, leading to a power outage of nearly 11 hours. Power outage and failed computing systems can also have large impacts on airlines. For instance, for Delta Airlines lost 150 million USD in August 2016 due to a five-hour power outage, caused by computer crash[1] Therefore, it is critical to understand the complexity and emergent behavior of air transportation systems.

Network science provides powerful tools for understanding the structures and dynamics of complex socio-economic systems, including air transportation [Barabasi 2013, Newman 2010, Zanin and Lillo 2013, Vitali et al. 2012]. Accordingly, throughout the last decade, many studies have analyzed the delay propagation [Fleurquin, Ramasco, and Eguiluz 2013], epidemic spreading [Gomes et al. 2014], temporal evolution [Kotegawa et al. 2011, Wandelt and Sun 2015, Wong et al. 2019], port (airport) adaptation to climate-related disasters [Xiao et al. 2015, Wang and Zhang 2018, Randrianarisoa and Zhang 2019], and, particularly, the impact of large-scale disruptions [Caschili, Medda, and Wilson 2015, Caschili, Reggiani, and Medda 2015, Wandelt et al. 2019].

The majority of studies on air transportation network resilience focus on the airport network, where nodes represent single airports and links correspond to direct flights between airports. It has been shown that worldwide airport network is rather resilient to random failures (i.e., random malfunctioning airports of any size), while targeted attack[2] (i.e., intentionally disrupt large, critical airports) can break the network quickly [Sun, Wandelt, and Cao 2017, Sun, Cao, and Wandelt 2017].

[2]The term attack is not to be understood literally here. For complex networks, the word attack is used for distinction from random failures, which do not prefer critical nodes.
Figure 1: Multiple airport region for the city of London: Luton Airport (LTN), Stansted Airport (STN), Heathrow Airport (LHR), City Airport (LCY), Southend Airport (SEN), Gatwick Airport (LGW), and Southampton Airport (SOU). From the city center of London (blue circle), a total of six commercial airports can be reached within a free-flow road travel time less than 100 minutes. Each airport is visualized with its IATA code and the free-flow road travel time in minutes. The black lines highlight the routes from the city center to the airports.

Wandelt, and Linke 2017). For instance, PEK (Beijing Capital International Airport) is the second busiest airport in the world. Such hub nodes are critical for the structure of air transportation and they are inherently priorities for targeted attacks. Takebayashi and Onishi 2018) examine the policies for the reliever airport to regain traffic when the main airport is dysfunctional due to a catastrophe, with the two airports linked by high-speed rail. Other studies investigate the resilience of the air transportation city network, where nodes represent cities and links correspond to direct flights between cities. The aggregation of airports into cities relies on the concept of Multiple Airport Regions (MARs). A MAR is defined as a group of two or more major commercial airports in a metropolitan region, serving an overlapping share of latent passengers (de Neufville 1986). After combining the airports nearby a city into a MAR, which is usually performed by simple spatial distance aggregation (e.g., a distance between city center and airport of 50 - 250 km) (Xia et al. 2019), the city network is analyzed with similar techniques as the airport network described above. To sum up, existing studies usually analyze the effects of node (or link) failures to the airport network or the city network.

In this study, we investigate the effect of single airport outages on the air accessibility of global cities. As an example, consider the area of Greater London, which is being served by seven airports, all of which can be reached in 100 minutes by car (Figure 1). Naturally, the roles of these airports for London are transitioning between competition and cooperation. On one hand, some airports offer similar destinations, essentially competing for passengers. On the other hand, airports also offer complementary services. Please note that airports are not exclusively aggregated to one city, but can be shared by multiple cities. For instance, airport SOU (Southampton Airport) from Figure 1 is aggregated to the city of London and the city of Southampton, among others. While this might be counter-intuitive, we believe that the methodology underlying our study is rational. Other studies have used the line-by-sight distance (Loo, Ho, and Wong 2005, O’Connor and Fuellhart 2016, Bonnefoy, de Neufville, and Hansman 2010, Hansen and Du 1993), which can greatly overestimate or underestimate the actual travel time in presence of specific geographical
conditions and transportation infrastructure. According to the time-threshold in this study, Southampton is accessible from the city center of London within 99 minutes. In fact, there are suggestions to further remove burden from the Greater London area by building new international hubs as far away as Birmingham (and then connect Birmingham to London via a high-speed rail line); Birmingham being 206 km outside of London Center, compared to 112 km for Southampton.

In Figure 2, this situation is visualized for our London example. For each airport pair \((ap_1, ap_2)\) around London, we compute \(D(ap_1) \cap D(ap_2)\), where \(D(ap)\) denotes the set of destinations for airport \(ap\). A larger value (red cell) indicates that most destinations of \(ap_1\) are not covered by \(ap_2\); while a smaller value (cell with light color) indicates that \(ap_1\) does not have many new destinations compared to \(ap_2\). For instance, consider the two airports Gatwick Heathrow (LGW) and Stansted Airport (STN): \(|D(LGW)| = 178, |D(STN)| = 158, |D(LGW) \cap D(STN)| = 90, and \(|D(LGW) \cup D(STN)| = 248\). Accordingly, \(\frac{|D(LGW) \cap D(STN)|}{|D(LGW) \cup D(STN)|} = \frac{90}{248} = 0.36\). This example highlights the importance of analyzing the effects of airport outage in a MAR towards the accessibility to the global air transportation system.

The remainder of this paper is structured as follows. Section 2 presents the methodology used throughout our study. We present the results on the resilience of global cities in Section 3. Section 4 summarizes the major contributions and discusses directions for future work.

2. METHODOLOGY AND DATA PREPARATION

The data preparation for the worldwide airports and cities used in this study is presented in Section 2.1 and Section 2.2 separately; Section 2.3 presents the methodology to aggregate the airports to multiple airport region of a city.

2.1. Airport Data Preparation

The airport data used in this study comes from two distinct sources: The locations of airports come from http://ourairports.com, a community-run website for collecting information on airports around the world. The website reports the location, name, country, runway lengths, navigation types and other information for each airport. Ourairports.com is considered as one of the major and complete (open-source) airport datasets, which is updated on a daily basis by a strong community of pilots and other volunteers. In our own preliminary experiments, we have not found anything else as complete. We also performed some comparison with the commercial Jeppesen airport database. The dataset from ourairports.com contains many more airports (52,865) than Jeppesen (13,669). The reason is that not all airports in ourairports.com provide scheduled service; the airports with scheduled service are distinguishable by a column in their database; for our study we only analyzed those airports with scheduled service.

Since the airport data does not have any information on the destinations, we merge this dataset with flight leg data from the Sabre Airport Data Intelligence (ADI, http://www.airdi.net). ADI reports the number of passengers
and the number of departures per year for each scheduled airport pair. We extract all airports from ADI for the year 2015, keep those listed in http://ourairports.com, filter all airports with less than 50,000 passengers per year. Finally, for each pair of scheduled airports, we convert the number of passengers and the number of departures to daily values. The remaining airports obtained by the filtering step are visualized in Figure 3. In total, we have 2,340 scheduled airports for the analysis in this study.

2.2. City Data Preparation

For a collection of cities in the world, we refer to the World Cities Database (https://simplemaps.com/data/world-cities). The data is provided as a CSV file, containing information on cities’ location, name, country, continent, estimated population and others. We sort all cities decreasingly by the estimated population and extract the top 5,000 cities. According to the source data, we select all cities with a population larger than 25,000, at the time of 2015. The total population of all 5,000 selected cities covers roughly two billion people. The cities used throughout our study are visualized in Figure 4.

2.3. Aggregating Airports to Cities

Traditionally, MARs are defined based on spatial distance threshold. Threshold values range between 50 km to 250 km; airports within this distance are aggregated to a MAR. The rationale for such simplified distance-induced aggregation criterion is easily being questioned: When analyzing networks at large scale, it becomes intricate to compute all exact distances between airports (and city centers). Perhaps more importantly, for passengers airport accessibility is a measure of the costliness of reaching an airport using available transportation systems (Reggiani, Nijkamp, and Lanzi 2015). The costs depend, in addition to distance, on the availability as well as the quality of land-side transportation systems. Recent advances in open Geographical Information Systems (GIS) and increased computational resources, allow us to overcome this unnatural definition of airport aggregation and compute accurate driving time in this study instead (Sun et al. 2017). Our automatic routing algorithms are based on Openstreetmap (OSM), which has become one of the premier resources of worldwide transportation infrastructure. OSM is a community-based effort, started in 2004, which is mainly run by volunteer mappers with the goal to create an editable map of the world.
Over time, OSM has become a highly accurate representation of the transportation infrastructure in the majority of populated areas (Haklay and Weber 2008, Neis and Zielstra 2014, Wandelt, Wang, and Sun 2017, Poppinga 2018). In this study, we use the road network modeled in OSM for routing between city centers and airports. Our routing implementation is based on the Open Source Routing Machine (OSRM) (Luxen and Vetter 2011). Within OSRM, scalable techniques have been implemented for routing vehicles with different speed profiles over OSM data. It is released as a small standalone server application (see http://project-osrm.org/). Technically, OSRM performs shortest path calculation based on contraction hierarchies, which allows queries to scale up very well to continent scale. OSRM allows for accurate free-flow time estimations, given that it directly exploits road-specific maximum speed information from OSM. We extracted the driving time for each airport-city pair in our study, by querying for the fastest driving connection between the latitude/longitude pairs of both places. It should be noted that the result is an estimation of the minimum free-flow time between the two points, without any information about road blocks, congestion, or other additional (temporary) road conditions.

Figure 5 shows the correlation between spatial distance proxy, as in previous related studies (Loo, Ho, and Wong 2005, O’Connor and Fuellhart 2016, Bonnefoy, de Neufville, and Hansman 2010, Hansen and Du 1993), and estimated driving time (used in our study). It can be seen that, while there is an overall linear correlation between both variables, the deviation of driving times can be rather large for a specific distance. For instance, at a fixed distance of 50 km, the shortest driving time is 40 minutes and the longest driving time is 120 minutes. Treating both cases identical, as done in existing studies, yields misleading results.

For each city in the dataset, we compute the driving time to all airports. If the driving time from the city center to the airport is less than 120 minutes, we aggregate the airport to the city. For all airport-city pairs, we enforce that airport and city have to be located in the same country, with the only exception of participating countries in the European Schengen area. For cities in the latter countries, we assume that cities can also aggregate airports in other Schengen countries. For instance, people in the border region of Western Germany frequently take international flights from AMS (Amsterdam Schiphol), instead of farther away German airports. In reality, other countries could be taken into consideration, e.g., UK and England, under an airport disruption at either Belfast or Dublin. Future studies could perform a more fine-grained analysis with an improved distinction of viable cross-border traffic.

As indicated above, both, our airports and Openstreetmap, are typical open-source data and they have been increas-
Figure 5: Correlation between spatial distance proxy (x-axis) and estimated driving time (y-axis) for all city-airport pairs in our study. Each blue point is a city-airport pair; the red line is a linear regression curve; the Pearson correlation coefficient is 0.93 and the p-value is 0.

Figure 6: Number of cities versus the number of airports aggregated for a city. Most cities in our study have one airport. Two cities (Antwerpen and Oxford) have ten airports within their range. Note that the y-axis is log-scaled for the sake of magnitude comparison.

ingly used in the literature in recent years. These open-source datasets have been built and maintained by volunteers and they are released with open-content licenses. The aim of these open-source projects is exactly to promote anyone to use and share these geospatial data. The free-use and sharing of data sources is just the spirit of open-source projects, which is rather different from commercial data/service providers, such as OAG database. The high data acquisition cost of OAG prohibits large numbers of researchers to access the data who are interested in solving challenging problems. We believe that research findings based on (accurate) open-source data, can better enable the dissemination of knowledge in a fair and open way across the research community in the future.

3. RESULTS

After aggregating all airports to nearby cities, we obtain 3,511 cities having at least one airport reachable within two hours of driving time. Out of these, a total of 1,568 cities have at least two airports as a choice for their population. The two cities with the largest number of reachable airports are Antwerpen and Oxford with ten airports, followed by fourteen cities that can reach nine airports, e.g., New York, Brussels, Cologne, Wuppertal, Liege, Gent, Eindhoven, Newark, Reading, Luton, Paterson, Arnhem, ’s-Hertogenbosch, and Maastricht.
Table 1: Number of cities with a given number of aggregated airports (from 2 to 10) at the country level. Top 20 countries according to the total number of cities are shown.

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Figure 6 visualizes the number of cities aggregating a given number of airports. It is interesting to note that the perfect powerlaw-fit underlying the results in Figure 6 with the exception of cities with 8–9 airports. Table 1 reports the number of cities with 2–10 airports for selected 20 countries. The countries were chosen regarding the total number of cities in this study. It can be seen that cities with many airports are particularly prevalent in United States (USA), Germany (DEU), and Great Britain (GBR), followed by China (CHN), France (FRA), Italy (ITA), and South Korea (KOR).

In order to analyze the dependency between the number of airports and population, we performed additional experiments and the results are shown in Figure 7. It can be seen that the median of the population slightly increases with the number of airports aggregated into a city. Nevertheless, it should be noted that the variation of population is much larger than this trend: For cities with one airport, we have outliers with population ten times as high as the cities with ten airports. So there exists no strong correlation for all cities. In a similar way, we assess the dependency between the number of airports and the number of destinations and the results are shown in Figure 8. We find that the number of destinations grows significantly with the number of airports, indicating a complementary operation. Another explanation is that cities with many airports are located around areas with larger populations and
with manifold travel destinations, which are served by the airports around these cities. 

In the following, we assess the resilience of cities towards disruptions at their major airports. Here, we choose the major airport as the airport with the largest number of destinations. During the disruption, we simulate that all passengers traveling from a city via the disrupted airport have to find an alternative airport offering the same destination. We distinguish two types of passengers here.

1. The percentage of so-called unaffected passengers: These passengers are not affected by the airport closure. A large fraction of unaffected passengers indicates that the airport disruption has a small effect on the travelers. A small fraction, on the other hand, shows that the airport disruption is potentially hazardous.

2. The percentage of so-called reroutable passengers: These passengers can be rerouted through other airports and still make their journeys under disruptions. A large fraction of reroutable passengers indicates that the airport disruption has a smaller effect on the travelers; while a small fraction of reroutable passengers indicates significant operational problems.

Figure 9 visualizes the results of these two types of passengers under disruptions. We can see that the resilience of cities under disruptions varies considerably, from rather resilient cases, e.g., Yokohama and Moscow, to very fragile cities, e.g., Barcelona, Taipei, and Nairobi. This highlights that the choice of airports around a city, and also the assignment of destinations (overlap) is crucial for obtaining cities resilient to air transportation disruptions.

Figure 10 further aggregates the results at the country level. It can be seen that some countries have rather resilient cities, e.g., Japan (JPN), Russia (RUS), and Italy (ITA). Cities from other countries are much more vulnerable to disruptions at their main airports, e.g., Mexico (MEX), Indonesia (IDN), and India (IND). The country-level insights are interesting, given that they very likely represent structural properties of the government’s city planning.

4. CONCLUSIONS

In this study, we explored the resilience of cities in the global air transportation network to single airport disruptions. The major contributions of our study are summarized as follows.

1. We aggregate airports to cities based on an accurate free-flow driving time estimation, compared to traditional spatial constraints. As shown in Figure 5, spatial constraints are only an inaccurate proxy for the accessibility from a city center.
2. We report statistical properties about the derived city-airport regions, including the country-level distributions, correlation between the number of airports and city population (Figure 7) versus the number of destinations (Figure 8). The latter is more positively correlated with the number of airports than the former. Furthermore, we find that the cities follow a powerlaw-distribution, regarding the number of aggregated airports (Figure 6).

3. We identify the general phase transition for cities when their largest airports are disrupted (Figure 9), distinguishing the unaffected passengers and the reroutable passengers. The majority of cities can be found along a log-curve.

In addition to demonstrating that (open) big data can empower researchers to perform transport network-resilience analysis at an unprecedented level of scale, our study yields useful implications for the industry and governments. Given that resilience is an important performance indicator for an airport or a city, our analysis will help airport managers and policy makers monitor the network performance against that of other airports and cities. Furthermore, presumably management and policy practices will have an impact on the spatial transformation of air transport systems in the form of, e.g., connectivity and resilience changes. To see such an impact, measuring resilience by quantifying and visualizing the overwhelming data is a first step. This in turn will assist managers and policy makers for i) better monitoring and planning of their initiatives, and ii) optimal management and control of the transformation. The implications include facilitation of networking and routing decisions, identification of business opportunities (e.g. if a city is ranked low, there may be opportunities for improvements and investments), and designing strategies to improve the competitive positions of airports/cities. Another important implication of our analysis is for assessing the competitive airport environment that each city faces. Effective competition of an airport may come not only from airports in the same city, but also from airports located in neighbour cities. Moreover, multiple airports in the same city can help each other in case of major disruptions. Management and policy practices should be designed with this complementary in mind.

For our study, we made a set of simplifying assumptions; some of which are caused by lack of data and others simply by the planet-wide coverage of this study. Future work could address these limitations as follows:

1. This study measured the accessibility of airports based on driving time; the literature, usually only computes line-by-sight distance-based accessibility for large-scale studies. Future work could take into account the actual travel costs, degree of convenience, travel frequency and other factors. However, it should be noted that obtaining such data at planet-scale is very challenging, given the lack of a commonly used, global database for such purposes.
2. Similarly, any disruptions will have different effects on different passenger types. For instance, business/first class passengers will probably prefer other transportation options than the majority of economy class passengers. With additional ticket/price data, future work could analyze this effect further. Moreover, even the type of airline could be used for making decisions regarding the viable alternatives, e.g., low-cost carrier versus traditional airlines.

3. We did not consider a time constraint for the connectivity during disruptions, since from the data available to us we can only tell whether two airports are connected and how many passengers took that connection. Nevertheless, a review of the well-established literature on airport connectivity (e.g., [Burghouwt and Veldhuis 2006, Zhu, Zhang, and Zhang 2018, Burghouwt and de Wit 2005]) indicates that a viable connection may involve some realistic assumptions such as the maximum transit time (e.g., within 4 hours) and maximum number of stops allowed; for a literature survey see [Burghouwt and Redondi 2013]. The incorporation of further connection criteria is an important area of future research.

4. Throughout this study we assume that cross-border traffic takes place inside Schengen area only. In reality, other countries could be taken into consideration, e.g., UK and England, under an airport disruption at either Belfast or Dublin. Future studies could perform a more fine-grained analysis with an improved distinction of viable cross-border traffic.

5. All airports in our study have a sufficient infrastructure to cope with typical international services. The only exception are wide-body aircraft such as A380. Given that we do not have information about aircraft types and runway configurations for all airports at planet scale, we did not make decisions regarding specific fleets and the availability of adequate runways on each airport. It is an interesting and important extension, which could be considered in future work, given available data.

6. We analyze the robustness of air transportation on its own. This is motivated by the lack of infrastructure/schedule data for alternative transportation modes around the world. Future work can aim for a comprehensive analysis of multi-modal robustness at larger scales. But the existing, available datasets do not allow for such studies yet. Only giant companies like Google could perform such studies at planet scale, and still face large computational challenges. Our study should be seen as a first step towards planet-scale city resilience of air transportation.

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