Article publicat / *Published paper*:

Cumelles, J.; Lordan, O.; Jose M Sallan. Cascading failures in airport networks. "Journal of air transport management", Maig 2021, vol. 92, art. 102026. DOI: 10.1016/j.jairtraman.2021.102026

Cascading failures in airport networks

Abstract

Cascading failure phenomena can appear in complex networks that distribute flows of information, people or goods, when flow going through nodes or edges exceeds the capacity of network nodes or edges. Cascading failure models from previous research are not adequate for airport networks, as flow is not continuous, and load has to be redistributed among close airports, rather than previously existing connections. With these constraints in mind, we have defined an algorithm to simulate the management of cascading failures in airport networks. We use the algorithm to evaluate the effectiveness of several selection rules of alternative departure and arrival airports to affected flights to reduce the impact of the cascading failure. We have applied the algorithm to the Oceanic Airport Network to assess the impact of several incidents. Results show that selection rules of arriving airports have significant impact in reducing the effect of incidents affecting central airports.

1 Introduction

The air transport industry has been growing until becoming an essential part of the everyday life in today's economy. Airline industry deregulation and liberalization has lead to a continuous growth of air transport (Wang et al., 2016; Burghouwt and de Wit, 2015; Goetz and Vowles, 2009). Air transport is generally considered safer and faster than other means of transport (Chambers, 2012), particularly to connect isolated rural areas and islands with urbanized areas, or to connect mutually distant locations such as cities in different continents (Rocha, 2017). Air transport has been shaped by historic, politic, geographic and economic factors (Guimerà et al., 2005), and is the result of the aggregation of routing decisions of airlines, that try to serve the air transport demand in the context of a competitive industry. The recent COVID-19 pandemic has been an important drawback for this trajectory of sustained growth. Beyond short-term effects like travel ban and border closures, the pandemic has brought some significant menaces for the airline industry in the future years. Some of these threats are the extensive use of teleworking by companies providing the demand of business travelers, the implementation of health screening controls that can make air travel less attractive for leisure passengers, and the likely lack of governmental support for full-service airlines (Suau-Sanchez et al., 2020).

An air transport network can be represented as an airport network, where nodes represent airports or cities and edges direct connections between nodes. This representation can be completed assigning weights to edges, usually representing intensity of connections (e.g. weekly frequency of flights). Following the pioneering study of Guimerà and Amaral (2004) for the global airport network, the topology of several regional airport networks has been examined by (Bagler, 2008) (India), (Guida and Maria, 2007) (Italy), (Wang et al., 2011) (China), (Hossain et al., 2013) (Australia) and (Tsiotas and Polyzos, 2015)

(Greece), among others. All of these studies conclude, with minor differences between them, that air transport networks have the small-world property (a small average path length together with a high average clustering coefficient) and a truncated scale-free degree distribution (Amaral et al., 2000). In airport networks well-connected nodes have high values of node degree while central nodes have high values of betweenness, therefore degree and betweenness are measures of local and global centrality, respectively. (Guimerà et al., 2005) found that for the world airport network the better-connected nodes are not necessarily the most central, resulting in anomalous values of centrality.

Air transport can be particularly affected by airport closure. This event can be triggered for environmental causes, accidents, security alerts, strikes or terrorist attacks, producing high costs for the airline industry (Lordan et al., 2014). One example of closure of airports by environmental causes is the ash plume from Iceland's Eyjafallajökull volcano. This event led to the progressive closure of large sectors of European airspace over a period of seven days, causing over 100,000 flights to be canceled (Wilkinson et al., 2011; Brooker, 2010). The effect of the closure of a particular airport depends of its role in the air transport network, i.e., the system shaped by airports and the flights that connect them.

The analysis of the impact of airport closure on a transport network is an example of operational resilience analysis (Ganin et al., 2016), which focuses in analyzing the evolution of a critical functionality for a class of adverse events. Two critical functionality measures have drawn researcher's attention: delays and loss of connectivity. Using passenger demand data, Voltes-Dorta et al. (2017a) analyze the vulnerability of the European air transport network from the perspective of passenger delays. They simulate the disruption of each of the 25 busiest airports and reallocating affected passengers in minimum delay itineraries. In Voltes-Dorta et al. (2017b) the same authors perform a case study analysis of the reallocation of passengers of the Palma de Mallorca airport. Cardillo et al. (2013) use schedules supply data to examine the passenger re-scheduling in a multi-layered airport network. The apparition of delays in an airport can trigger delays in other airports in the network on downstream flights. Du et al. (2018) analyse the delay propagation network using Granger causality analysis, and Zanin (2015) examine delay networks for a multi-layered model of the European airport network. From the connectivity loss perspective, the impact of airport closure can be analyzed through static robustness analysis, i.e., the study of the effect of the disconnection of a subset of nodes on network connectivity, usually measured as the size of the largest connected component. Chi and Cai (2004) performed a robustness analysis for the US airport network, and Lordan et al. (2014) detected the critical nodes of the world airport network using several node selection criteria. Both studies concluded that airport networks are robust to errors (isolation of nodes chosen at random), but not to attacks (isolation of important or central nodes). This behavior is typical of scale free networks (Albert et al., 2000). Static robustness analysis does not consider the dynamic effects that can occur after a network disruption. A small initial disruption can trigger secondary failures to other network components, leading to a cascading failure effect (Motter and Lai, 2002). This phenomenon is a significant threat to some networked systems, like the power grid (Kinney et al., 2005; Wang and Rong, 2011) or the Internet (Wang et al., 2014). Similar effects have been reported in some incidents in the air transport system, like the Eyjafallajökull volcano incident mentioned above. The first aim of this study is to create a model of cascading failures in airport transport networks. This model assesses the immediate impact of an incident involving the closure of a set of airports, evaluating the flights that have to be modified or canceled, and the airports that must be closed due to overload, until the incident ends and normal operations can be resumed. This model has to take into account the specificity of airport networks, specially when defining capacity and load of network components, and rules of flow redistribution compatible with air transport operations. Our second aim is to use the model to evaluate the effectiveness of several selection rules of alternative departure and arrival airports to reduce the impact of the incident. This approach extends the operational resilience analysis framework to the cascading effects of airport closure. If this analysis is performed beforehand, air navigation service providers (ANSPs) can define act more effectively when unanticipated events occur. In the case of anticipated events, such as meteorological hazards, the application of the algorithm to the specific situation can give a more precise guidance to mitigate impact event.

2 Models of cascading failures

Motter and Lai (2002) define a global load-based cascading model for analyzing cascading failures on complex networks. The basic assumption of this model is that flows of energy or information between nodes are transmitted along the shortest paths connecting them. Then L_i^0, the initial *load* of node i, is defined as the total number of shortest paths from all vertices to all other that pass through the node. In later formulations of this model (Dou et al., 2010), load is equal to node betweenness. The capacity, or maximum flow that a node is able to transmit, is defined as $C_i = (1 + \alpha) L_i^0$, where $\alpha \geq 0$ is a tolerance parameter. If a disruption leading to the isolation of one or several nodes occurs, node loads may change. In a iteration t of the cascading process, all nodes with $L_i^t > C_i$ are overloaded, then removed from the network. This causes a new load redistribution, which may lead to new overload of nodes in the next iteration. The cascading process finishes when no new nodes are overloaded. The damage caused by this process is measured with the parameter $G = N'/N$ where N and N' are the sizes of the largest connected component before and after the cascading process, respectively. Crucitti et al. (2004) propose an alternative model where the overload of a node degrades the communication through edges incident to that node, so shortest paths will go through other nodes. In this model, overloaded nodes are not removed from the network, and and the damage caused by a cascade is quantified in terms of decrease of global efficiency.

The models described above are adequate to represent cascading phenomena where flows between nodes are transmitted trough the shortest paths connecting them, and consequently flow redistribution takes place at the global level. This is an unrealistic assumption for air transport operations, where redistribution of flows takes place at the local level, as the congestion of an airport causes redistribution of traffic to neighboring airports. Wu et al. (2008) define a local weighted flow redistribution model. In this model, the load or flow going through node i is equal to $L_i^0 = k_i^\theta$, where k_i is the degree of node i and θ is an adjustable parameter. Node capacity is equal to $C_i = CL_i^0$, where $C > 1$ is a threshold parameter characterizing network tolerance. Once a node i is disconnected or overloaded, its load L_i^t is redistributed among their neighbors proportionally to the load of each neighbor L_j^t:

$$\Delta L_j^{t+1} = L_i^t \frac{L_j^t}{\sum_{m \in \Omega_i} L_m^t} \tag{1}$$

where Ω_i is the set of neighbors of i. In this new iteration, the nodes to be overloaded will be those which hold:

$$L_j^{t+1} = L_j^t + \Delta L_j^{t+1} > C_j \tag{2}$$

Similarly to the global load-based models, the redistribution of loads may lead to further overload of other nodes. Wang and Chen (2008) define a similar model of local weighted flow redistribution for edge overload.

3 Cascading failures model for air transport networks

3.1 Algorithm definition

The models defined in the previous section are not adequate to represent realistically cascading failures in air transport networks. A common assumption of these models is of continuous flow along the network, while the air transport network is a temporal network of scheduled flights. An implication of this modeling is that airport load is equal to the number of planes parked in the airport. Second, air traffic management establishes that load redistribution has to be made considering spatial considerations. Aircraft departures or arrivals will be rerouted to airports close to the original location with available capacity. Third, although airports with high degree should have high capacity, in this model airport capacity (the maximum number of aircraft that can be parked to be operative) is an exogenous parameter, rather than proportional to initial load.

Taking into account this considerations, we define a cascading failures model that takes into account the specificity of air traffic management. In this model, an airport $\mathbf{a}$ is modeled as a tuple with elements $\{L(t), C\}$. Load $L(t)$ is equal to the number of planes in the airport at time t, and C is airport capacity, defined as the maximum number of planes that can be parked at the airport to carry out normal operations. The value of C is specific for each airport, and is set to zero for attacked airports. If $L(t) < C$ the airport is open, allowing normal operations. If $C \leq L(t) \leq 1.3C$, the airport is *saturated*: in a saturated airport only can land active flights with arriving airports closed, and with no alternative open airport. No flights can depart from saturated airports. If $L(t) > 1.3C$ the airport is *closed*, meaning that has too much load even for emergency operations. For each airport is defined a set $\mathcal{N}$ of secondary airports where traffic can be redirected in case of saturation of closure. Airports belonging to this set must be closer than a distance R from the original airport. A flight $\mathbf{f}$ is modeled as a tuple with elements $\{i, j, t_d, t_a, s\}$, where i and t_d are the departing airport and departing time, and j and t_a are the arrival airport and arrival time. Variable s represents the state of the flight, which can be non-active (not yet departed), active (on flight), landed, canceled or in emergency. Emergency flights are those flights on air in the moment that the incident starts that have no airport to land, as all alternative airports are closed. This does not necessarily mean that the flight has to crash, but it is certainly an effect to be avoided, for instance varying the parameter R.

The algorithm uses a discrete time variable t, defined by time intervals t_s for a the time horizon starting in T_{min} and ending at T_{max}. If an attack has occurred between $t - t_s$ and t, we set to zero the capacity of attacked airports, so that no flight can arrive or depart to these airports. Then, we start examining the flights scheduled to depart between t and $t + t_s$. For flights departing from saturated airports, the algorithm tries to assign a new non-saturated departing airport with non-zero load. Doing this we try to get enough load in arriving airports to start future flights. Then we check if the arrival airport for those flights is saturated of closed. In that case, we try to assign a new arrival airport.

If it is not possible to assign a new departing or arriving airport, the flight is canceled. Once departing flights are examined, we proceed to register landing flights. We assume that any incident between t and $t + t_s$ will affect airports at $t + t_s$. Finally, we look for active flights that should be landing on closed airports, and we try to find an alternative arrival airport for these flights. If it is not possible, the flight is in emergency. If we cannot assign an airport to a flight in emergency before its landing time, we have a major incident generated by the cascading failures process. The pseudo code of the algorithm is presented in Algorithm 1. The assignment of a new departing airport for flights in saturated airports may limit the scope o the simulated incident, possibly reducing the load of saturated airports so that they can be open again.

The algorithm requires defining selection rules for alternative departing and arriving airports. We have defined two rules for selecting a departing airport i^*, that prioritize airports with high load. Rule MD1 selects an airport from $\mathcal{N}_i$ randomly, with a probability proportional to its load. This rule is similar to the local redistribution rule defined in Wu et al. (2008), and tries to reduce the load of most congested airports by increasing the number of departing flights. MD2 selects the airport with minimal slack $C_{i^*} - L_{i^*}(t)$. When applying MD2, we try to reduce load from airports which are closer to saturation. We have defined three rules for selecting an alternative arrival airport j^*. Rule MA1 selects the airport of set $\mathcal{N}_j$ closest to j. MA2 selects the airport of maximal $C_{j^*} - L_{j^*}(t)$. This rule has a logic analogous to MD2, but now we are locating arriving flights in airports with low load. MA3 selects the airport of minimal $L_{j^*}(t)\, d_{jj^*}$, where d_{jj^*} is the distance between the original arrival airport j and the selected new arrival airport j^*. This measure looks for airports which are closer to the initial destination, and with low load. Rules MA1 and MA2 lead to preferring open airports to saturated airports, if the former are available, as alternative landing airports. Ties between candidate airports are broken randomly.

3.2 Toy model application

To illustrate the algorithm, we present a toy model with four airports, labeled from A to D (Table 1) and eight scheduled flights, labeled from 1 to 8 (see Table 2). We will examine the effect of a closure of airport B at 10:00, remaining closed the rest of the day (see Table 3). Before the closure of B, flights 1 to 4 have departed normally. The closure of B at 10:00 does not affect flight 1, but affects flights 2 and 3, which are rerouted to airport C. Arrival times of both flights need to be recalculated. This re-routing is affecting flight 4 critically, as it is expected to land in C, which is now closed. The alternative airport B is not available, so this flight is in emergency. At 10:10 has to depart flight 5 with destination to B. As B is closed, this flight is rerouted to A before departing. Flight 6 has to be canceled, as it is departing from a closed airport C with no alternative. Flight 7 has to be also canceled, as the alternatives for airport B are unavailable: airport C is closed and airport A has no load. Finally, flight 8 has to be also canceled as its departing airport D has no load, and it has no alternative airport available.

4 Case Study: Oceanic Airport Network

We simulate the cascading process in the Oceanic Airport Network (OAN). We have considered flights in the OAN between airports with at least 1 Km of asphalt runway between 4 and 17 August 2014. The resulting airport network, where two airports (nodes)

```
t ← T_min
while t < T_max do
    Departing flights:
    for flights with t_d ≥ t and t_d < t + t_s do
        saturated or closed departing airport:
        if L_i (t) > C_i then
            select new departing airport i* ∈ 𝒩_i
            i ← i*
            if L_j (t) > C_j then
                select new arriving airport j* ∈ 𝒩_j
                j ← j* recalculate arriving time
            end
        end
        if i = ∅ or j = ∅ then
            cancel flight
        else
            flight is active
            L_i (t) ← L_i (t) − 1
        end
    end
    Landing flights:
    for flights with t_a ≥ t and t_a < t + t_s do
        if flight is in emergency then
            flight has major incident
        else
            flight is landed
            L_j (t) ← L_j (t) + 1
        end
    end
    Rerouting active flights:
    for flights with t_d < t and t_a > t + t_s do
        active flights with closed arriving airport:
        if L_j (t) > 1.3C_j then
            select new arriving airport j* ∈ 𝒩_j
            if j* = ∅ then
                flight is in emergency
            else
                recalculate arriving time
            end
        end
    end
    t ← t + t_s
end
```

Algorithm 1: Cascading failures algorithm

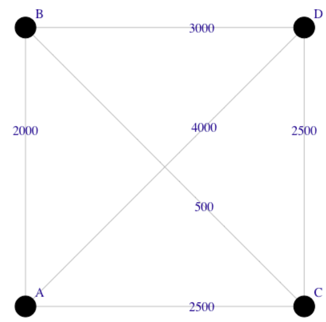

Figure 1: Toy model: distances between airports (in kilometers).

Airport i	$L_i(0)$	C_i	$\mathcal{N}_i$
A	3	3	B
B	0	2	A, C
C	0	2	B
D	2	2	—

Table 1: Toy model: initial load, capacity and secondary airports.

are connected by a link when there is at least a direct flight between them, has $N = 169$ nodes and $E = 726$ edges. In Figure 2 we present the geographical position of the airports of the network, and all direct connections between these airports. We measure airport centrality by degree (number of connections), strength(number of flights arriving and departing) and betweenness. In all rankings of centrality the airports of Auckland (AKL), Brisbane (BNE), Cairns (CNS) and Sydney (SYD) are in the top-five ranking. Port Moresby (POM) has a high ranking of betweenness, and Melbourne (MEL) of degree and strength.

We have checked the effectiveness of several selection rules of new arriving and departing airports, checking the six possible combinations of rules MD1 and MD2 for departing airports and MA1, MA2 and MA3 for arriving airports. We have applied the combinations of rules to the following incidents:

- Closure of five and ten airports of maximum degree (deg), maximum strength (str), maximum betweenness (btw) and random selection (rnd).

Flight	Origin	Destination	ETD	ETA
1	A	C	08:10	10:40
2	A	B	08:20	10:30
3	A	B	08:40	10:50
4	D	C	09:30	12:45
5	D	B	10:10	13:15
6	C	D	12:00	14:50
7	B	D	13:00	17:50
8	D	C	15:25	16:05

Table 2: Toy model: scheduled flights

Time	Event	A	B	C	D	1	2	3	4	5	6	7	8
08:00	Start	3	0	0	2	N	N	N	N	N	N	N	N
08:10	Depart 1	2	0	0	2	A	N	N	N	N	N	N	N
08:20	Depart 2	1	0	0	2	A	A	N	N	N	N	N	N
08:40	Depart 3	0	0	0	2	A	A	A	N	N	N	N	N
09:30	Depart 4	0	0	0	1	A	A	A	A	N	N	N	N
10:00	Closure B					A	A	A	A	N	N	N	N
10:00	Reroute 2 new arrival C (arrival time 10:40)					A	A	A	A	N	N	N	N
10:00	Reroute 3 new arrival C (arrival time 10:50)					A	A	A	A	N	N	N	N
10:00	Flight 4 cannot land on C, and B is closed: emergency								E	N	N	N	N
10:10	Reroute 5 new arrival A (arrival time 13:15)					A	A	A	E	A	N	N	N
10:10	Depart 5	0	0	0	0	A	A	A	E	A	N	N	N
10:30	Arrival 2	0	0	1	0	A	L	A	E	A	N	N	N
10:40	Arrival 1	0	0	2	0	L	L	A	E	A	N	N	N
10:50	Arrival 3	0	0	3	0	L	L	L	E	A	N	N	N
12:00	Cancel 6: only alternative departing is B, which is closed					L	L	L	E	A	C	N	N
13:00	Cancel 7: only alternative departing is A, which has no load					L	L	L	E	A	C	C	N
13:15	Arrival 5	1	0	3	0	L	L	L	E	L	C	C	N
15:25	Cancel 8: departing airport is closed and alternative B is closed	1	0	3	0	L	L	L	E	L	C	C	C

Table 3: Operations of the toy model with closure of B at 10:00. Columns A to D show load of each airport at each time, and columns 1 to 8 show flight state (N: non-active, A: active, L: landed, C: cancelled, E: emergency).

- Closure of all airports of the following territories: New Zealand (NZ), Western Australia (WA), Tasmania and Victoria (TV) and Papua and New Guinea (PNG). These territories are labeled in black, red, green and orange in Figure 2.

We have computed the total number of closed airports and the proportion of modified (with a different departure and/or arrival airport), canceled and emergency flights out of total flights for each of the 14 days between 4 and 17 August 2014 for $R = 100$ and $R = 600$ kilometers. The maximum number of flights was 2707 (on 8 August), and the minimum 1820 (on 9 August). To examine the effect of R with more detail, we evaluated the effect of a sequence of values of R from 50 to 600 kilometers with a step of 50 on two specific incidents (the closure of the ten airports of highest degree and of Tasmania and Victoria) in the day of highest traffic (8 of August). The results of this evolution are presented on Figure 3. In an additional analysis (not shown here), we observed that increasing R above 600 did not change the results significantly for the OAN network. The results of the analysis performed showed a regular pattern regarding affected flights and closed airports, therefore we can conclude that the algorithm yields consistent results.

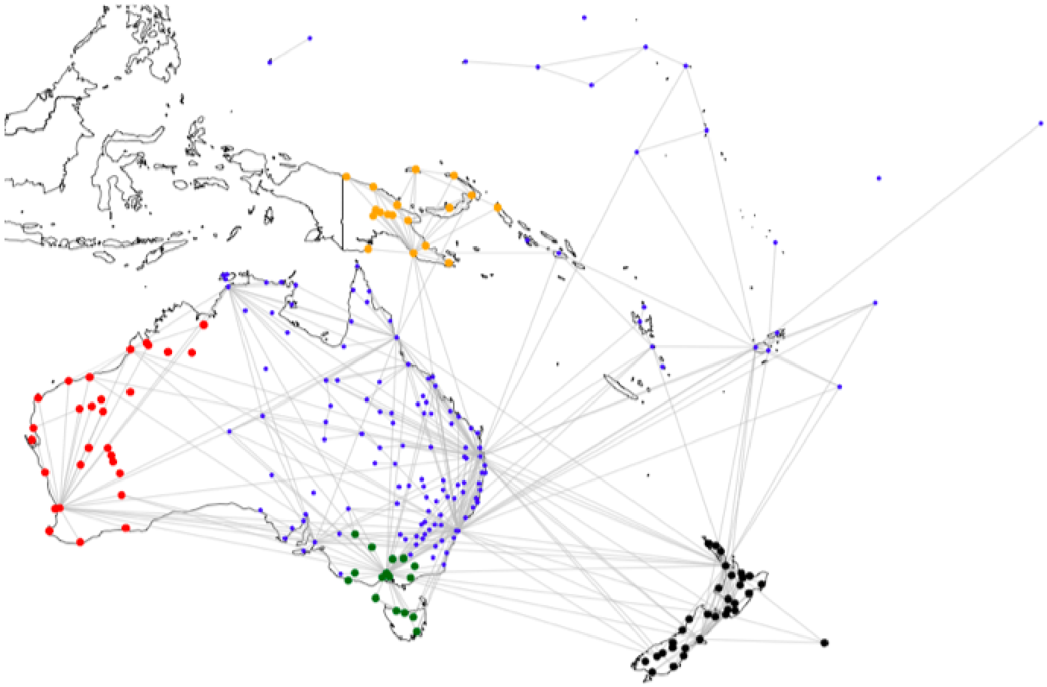

Figure 2: A map of the Oceanic Airport network, presenting the airports of the network and the direct connections between them. Colors distinguish each of the territories of the OAN: New Zealand (black), Western Australia (red), Eastern Australia (blue), Tasmania and Victoria (green) and Papua and New Guinea (orange).

In Figures 4 and 5 we present the results, averaged by the 14 days examined, of the impact caused by the removal of the ten airports of largest degree (deg), strength (str), betweenness (btw) and random selection (rnd), and by the closure of all airports of four territories: New Zealand (NZ), Western Australia (WA), Tasmania and Victoria (TV) and Papua New Guinea (PNG) for $R = 100$ and $R = 600$ kilometers. On a real setting, the value of $R = 100$ would be a realistic one for reallocating passengers. The values of $R = 600$ are reported to show the evolution of the cascading failure as R increases. In Figure 4 we present the average value of closed airports, and in Figure 5 we present the average number of modified, canceled and emergency flights for the same incidents. We also present the values of mean and standard deviation of affected flights and closed airports for attacks based on central nodes in Table 4, and for closures of territories in Table 5.

The initiating incident that causes most damage is the closure of central nodes, selected either by degree, strength or betweenness. These incidents are the ones affecting more flights and closing more airports. The three centrality measures have a similar impact, much larger than selection of random nodes or the closure of a whole territory. These results are similar to the obtained for the evaluation of static robustness in air transport networks (Lordan et al., 2014), and are in line to theoretical predictions for scale free networks (Albert et al., 2000). The closure of territories has a global impact intermediate between the closure of ten random airports and the closure of central nodes.

The R parameter defines the number of alternative airports for each affected flight: the larger the value of R, the larger the set of alternative departing or arriving airports will be. We can observe the effect of varying R for two specific incidents (labeled deg and TV on Figures 4 and 5) on Figure 3. The panels of the left on Figure 3 present the proportion of

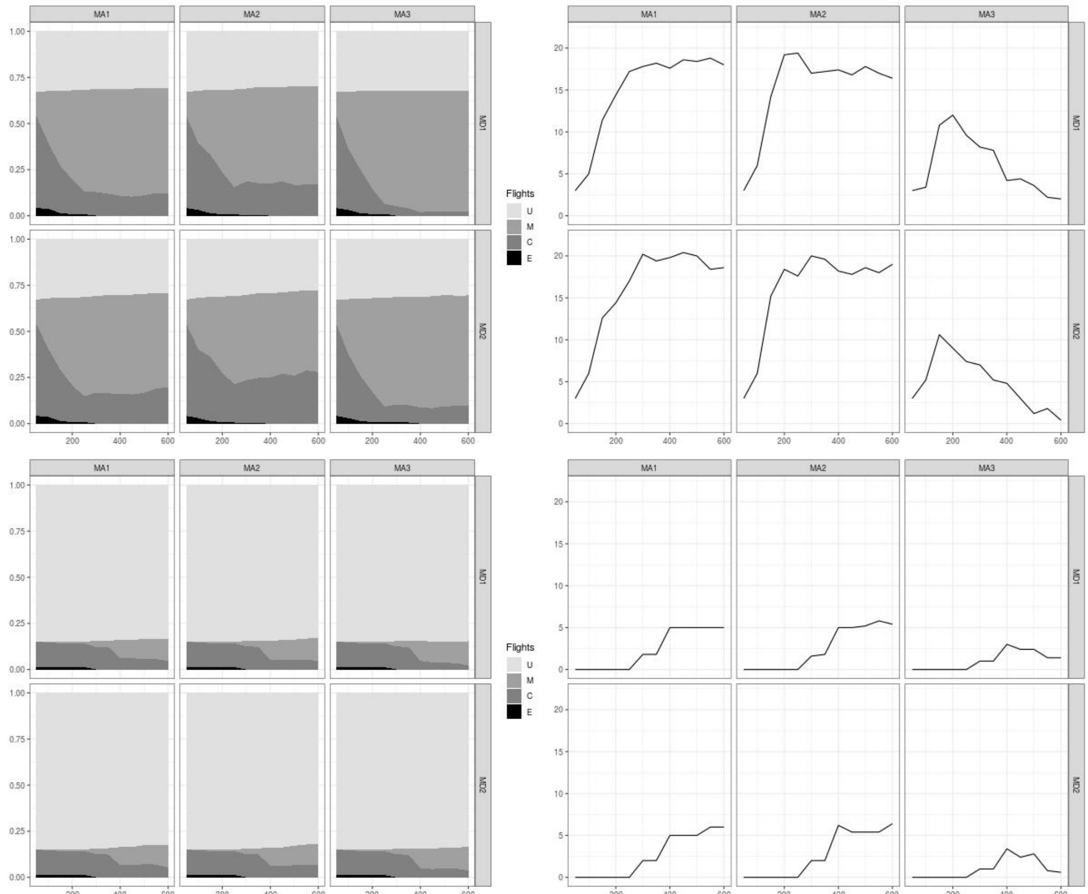

Figure 3: Sensitivity analysis of the algorithm for the closure of the ten airports of highest degree (upper row) and the closure of Tasmania and Victoria territory (lower row). The horizontal axis represents values of R. In the left panels, the vertical axis presents the fraction of unaffected (U), modified (M), canceled (C) and emergency (E) flights. In the right panel, the vertical axis represents the number of closed airports.

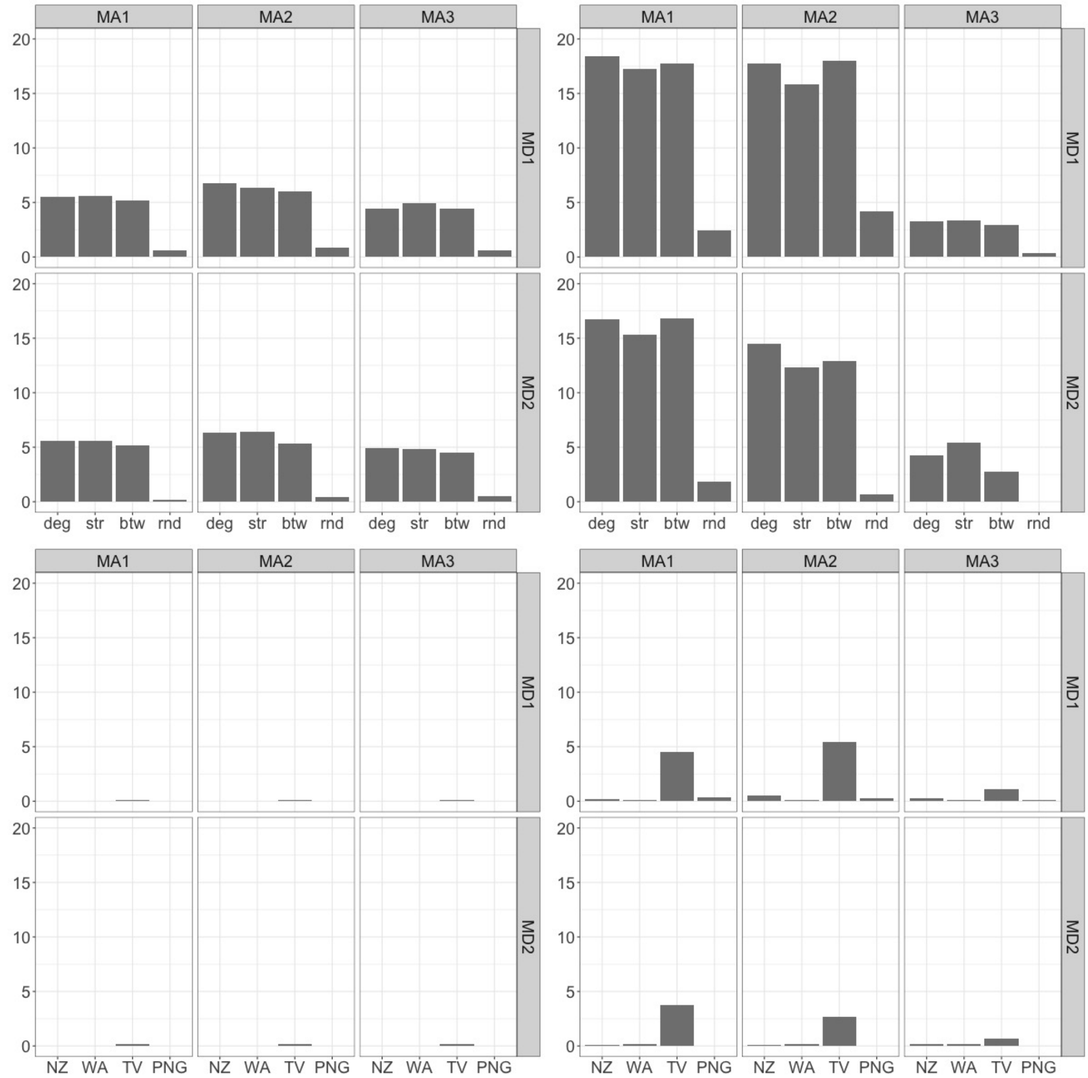

Figure 4: Average number of closed airports by cascading failures from several incidents with combinations of selection rules of departing and arriving airports. Left figures are computed with $R = 100$ and right with $R = 600$ kilometers.

flights in each state: as we increase R, canceled flights turn into modified flights, and the number of emergency flights decreases until going to zero. In both incidents, the number of affected flights remains approximately constant: around 70% for the deg incident, and around 20% for TV. The right panels of Figure 3 show the effect of increasing R on the number of closed airports: for the two incidents selected, we observe that the number of closed airports increases with R. The impact of increasing R can be thus summarized as follows: as we increase R the number of airports where flights can be rerouted increases, so the number of canceled flights lowers, and the number of modified (rerouted) flights increases. The rerouting of flights to airports not affected by the primary attack ends ups exhausting the capacity not used by regular flights in these airports, so these airports go into closed state, as can be observed in the right panel of Figure 3. Going again to Figures 4 and 5, we observe that the evolution describe for deg and TV applies for the rest of incidents affecting central nodes, but not for the closure of NZ, WA and PNG territories: for these incidents, the results for $R = 600$ are similar to the obtained for $R = 100$. Examining the values for these incidents in Table 5, when go from $R = 100$ to $R = 600$ we can observe a small increase of number of closed airports, an increase

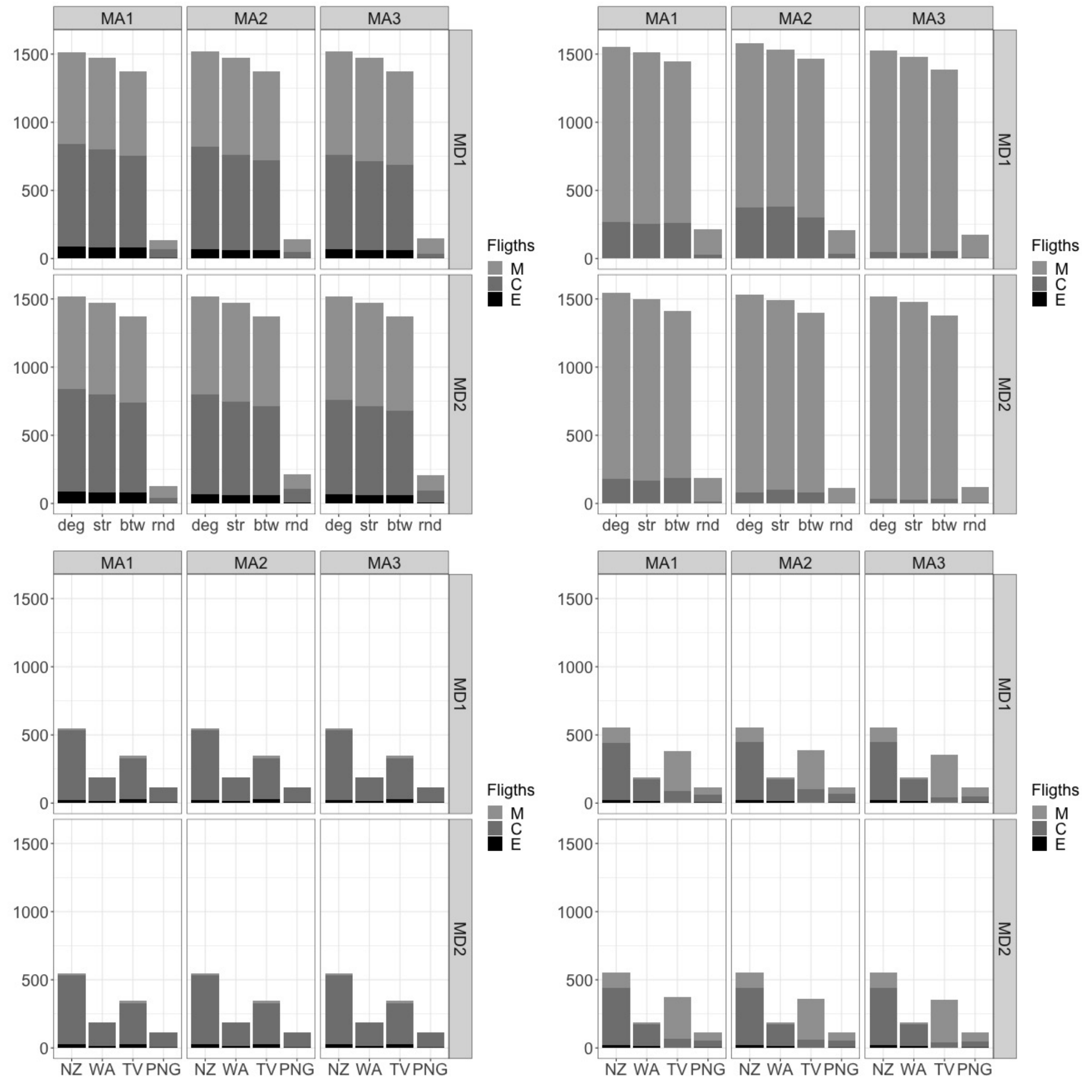

Figure 5: Average number of modified (M), canceled (C) and emergency (E) flights affected by cascading failures from several incidents with combinations of selection rules of departing and arriving airports. Left figures are computed with $R = 100$ and right with $R = 600$ kilometers.

R	var.	deg	str	btw	rnd
100	M	713.310 (124.005)	717.155 (123.926)	658.250 (107.453)	95.417 (113.375)
	C	731.190 (151.225)	688.917 (149.346)	648.500 (113.115)	63.488 (70.981)
	E	73.036 (12.928)	67.226 (13.149)	66.369 (12.507)	2.750 (5.068)
	CA	5.595 (1.291)	5.619 (1.211)	5.095 (0.989)	0.524 (0.799)
600	M	1377.571 (241.571)	1337.012 (238.641)	1260.405 (179.963)	154.131 (143.268)
	C	164.869 (138.742)	160.500 (137.786)	153.167 (114.719)	16.655 (22.649)
	E	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
	CA	12.500 (6.572)	11.595 (5.687)	11.869 (6.868)	1.571 (2.208)

Table 4: Mean and standard deviation across all days and selection rules for total number of modified (M), canceled (C) and emergency (E) flights and of closed airports (CA) for degree (deg), betweenness (btw) and random (rnd) attacks.

R	var.	NZ	WA	TV	PNG
100	M	13.881 (5.574)	0.000 (0.000)	20.190 (30.927)	0.000 (0.000)
	C	508.869 (67.922)	170.000 (41.199)	299.643 (55.239)	108.643 (7.007)
	E	24.607 (3.868)	15.786 (2.287)	29.310 (5.490)	3.786 (1.665)
	CA	0.000 (0.000)	0.000 (0.000)	0.143 (0.352)	0.000 (0.000)
600	M	108.893 (63.276)	11.000 (11.420)	301.905 (41.838)	57.845 (14.790)
	C	420.560 (105.133)	157.560 (45.228)	67.250 (30.004)	52.452 (14.793)
	E	21.964 (6.861)	17.083 (4.037)	0.012 (0.109)	3.179 (1.909)
	CA	0.214 (0.441)	0.143 (0.352)	3.024 (1.932)	0.119 (0.326)

Table 5: Mean and standard deviation across all days and selection rules for total number of modified (M), canceled (C) and emergency (E) flights and of closed airports (CA) for New Zealand (NZ), Western Australia (WA), Tasmania and Victoria (TV) and Papua New Guinea (PNG).

of modified flights and the persistence of a significant volume of emergency flights. An explanation for this behavior can be obtained if we examine the map of Figure 2: there we can see that New Zealand, Western Australia and Papua New Guinea are territories more isolated than Tasmania and Victoria, so for these territories the increase of R to 600 Km offers less possibilities to reach airports to reroute flights.

The most effective action for minimizing the effect of cascading failures involves selecting alternative arrival airports minimizing the product of load and distance to affected airport (MA3). In Figure 3 we observe that using MA3 reduces the total number of closed airports for the specific incident analyzed. In Figure 4 we observe the same pattern for the other incidents analysed.

5 Conclusions

Cascading failure phenomena can appear in complex networks that distribute flows of information, people or goods, when flow going through nodes or edges exceeds the capacity of network elements. Previous research has defined models where flow is redistributed globally or locally. In global redistribution rules flows are proportional to betweenness (Motter and Lai, 2002; Crucitti et al., 2004), and in local redistribution to degree (Wu et al., 2008; Wang and Chen, 2008). These models are not adequate to model cascading failures in airport networks, because flow is not continuous, and criteria for redistributing load has to consider close airports, rather than previously existing connections.

We have defined an algorithm to simulate the management of cascading failures in airport networks (see pseudo code in algorithm 1). The algorithm tries to reduce the impact of an incident of the network assigning alternative departure or arrival airports to affected flights with several alternative rules. The impact of the incident can be measured by the proportion of affected flights (modified, canceled or in emergency) and number of closed airports. This algorithm is a tool to perform an operational resilience analysis of a transport network, helping to allocate resources and define rules of action to act when an unanticipated airport closure event occurs. In the case of anticipated events, like meteorological hazards, the algorithm can be run with the specific boundary conditions of the event, and therefore provide a more specific guidance to mitigate the cascading closure of airports.

We have applied the algorithm to the Oceanic Airport Network, assessing the effectiveness of several rules of selection of alternative airports in three types of incidents: closure of central airports, of random airports or a whole territory. Results show that the closure of central airports has a much larger impact than random airports, and that selection rules are effective to reduce the number of overloaded airports and proportion of canceled flights. The selection rule MA3, based on minimizing the product of load and distance to affected airport, is the most effective to mitigate cascading failures, reducing the total number of airports closed (see Figure 4). Another way of mitigating the impact of the cascading failure is increasing the value of the parameter R, the maximum distance between the scheduled and the re-assigned departure or arrival airport. The increase of R increases the possibility to find an alternative airport to land, and reduces the probability that a flight on air in the moment of starting the incident goes to emergency state. These results show the importance of considering spatial and temporal properties of airport networks in network robustness analysis.

A possibility of reducing the load of some airports, thus mitigating the magnitude of the cascading effect, is to delay the departure of some flights. This delay increases the load of the departing airport, possibly advancing the moment the airport is saturated or closed, but can alleviate the load of the arrival airport, as one or more flights can depart before the delayed flight arrives. Further research can consider the possibility of introducing delays to alleviate the impact of the cascading effect. This can be specially useful to model incidents that close airports for a short time lapse.

The methodology used to define this algorithm can be extended to other transportation networks, such as maritime or road networks, and to study other phenomena affecting the performance of transportation networks, like jamming transitions or delay propagation.

References

Albert, R., Jeong, H., Barabasi, A., 2000. Error and attack tolerance of complex networks. Nature 406, 378–82. URL: http://www.nature.com/nature/journal/v406/n6794/abs/406378A0.htmlhttp://www.ncbi.nlm.nih.gov/pubmed/10935628, doi:10.1038/35019019.

Amaral, L.a.N., Scala, A., Barthelemy, M., Stanley, H.E., 2000. Classes of small-world networks. Proceedings of the National Academy of Sciences 97, 11149–11152. URL: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=17168{&}tool=

pmcentrez{&}rendertype=abstracthttp://www.pnas.org/cgi/doi/10.1073/pnas.200327197, doi:10.1073/pnas.200327197.

Bagler, G., 2008. Analysis of the airport network of India as a complex weighted network. Physica A: Statistical Mechanics and its Applications 387, 2972–2980. URL: http://linkinghub.elsevier.com/retrieve/pii/S0378437108001131, doi:10.1016/j.physa.2008.01.077.

Brooker, P., 2010. Fear in a handful of dust: aviation and the Icelandic volcano. Significance 7, 112–115.

Burghouwt, G., de Wit, J.G., 2015. In the wake of liberalisation: long-term developments in the EU air transport market. Transport Policy 43, 104–113. URL: http://dx.doi.org/10.1016/j.tranpol.2015.05.006http://linkinghub.elsevier.com/retrieve/pii/S0967070X15000621, doi:10.1016/j.tranpol.2015.05.006.

Cardillo, A., Zanin, M., Gómez-Gardeñes, J., Romance, M., García del Amo, A.J., Boccaletti, S., 2013. Modeling the multi-layer nature of the European Air Transport Network: Resilience and passengers re-scheduling under random failures. The European Physical Journal Special Topics 215, 23–33. URL: http://link.springer.com/10.1140/epjst/e2013-01712-8, doi:10.1140/epjst/e2013-01712-8.

Chambers, M., 2012. Transportation safety by the numbers. URL: https://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/by_the_numbers/transportation_safety/index.html. accessed: 2017-07-02.

Chi, L.P., Cai, X., 2004. Structural Changes Caused By Error and Attack Tolerance in Us Airport Network. International Journal of Modern Physics B 18, 2394–2400. URL: http://www.worldscientific.com/doi/abs/10.1142/S0217979204025427, doi:10.1142/S0217979204025427.

Crucitti, P., Latora, V., Marchiori, M., 2004. Model for cascading failures in complex networks. Physical Review E 69, 045104. URL: http://arxiv.org/abs/cond-mat/0309141{%}0Ahttp://dx.doi.org/10.1103/PhysRevE.69.045104https://link.aps.org/doi/10.1103/PhysRevE.69.045104, doi:10.1103/PhysRevE.69.045104, arXiv:0309141.

Dou, B.L., Wang, X.G., Zhang, S.Y., 2010. Robustness of networks against cascading failures. Physica A: Statistical Mechanics and its Applications 389, 2310–2317. URL: http://dx.doi.org/10.1016/j.physa.2010.02.002http://linkinghub.elsevier.com/retrieve/pii/S0378437110001007, doi:10.1016/j.physa.2010.02.002.

Du, W.B., Zhang, M.Y., Zhang, Y., Cao, X.B., Zhang, J., 2018. Delay causality network in air transport systems. Transportation Research Part E: Logistics and Transportation Review 118, 466–476. URL: https://doi.org/10.1016/j.tre.2018.08.014https://linkinghub.elsevier.com/retrieve/pii/S1366554518301042, doi:10.1016/j.tre.2018.08.014.

Ganin, A.A., Massaro, E., Gutfraind, A., Steen, N., Keisler, J.M., Kott, A., Mangoubi, R., Linkov, I., 2016. Operational resilience: concepts, design and analysis. Scientific

Reports 6, 19540. URL: http://www.nature.com/articles/srep19540, doi:10.1038/srep19540, arXiv:1508.01230.

Goetz, A.R., Vowles, T.M., 2009. The good, the bad, and the ugly: 30 years of US airline deregulation. Journal of Transport Geography 17, 251–263. URL: http://linkinghub.elsevier.com/retrieve/pii/S0966692309000386, doi:10.1016/j.jtrangeo.2009.02.012.

Guida, M., Maria, F., 2007. Topology of the Italian airport network: A scale-free small-world network with a fractal structure? Chaos, Solitons & Fractals 31, 527–536. URL: http://linkinghub.elsevier.com/retrieve/pii/S0960077906001792, doi:10.1016/j.chaos.2006.02.007.

Guimerà, R., Amaral, L.A.N., 2004. Modeling the world-wide airport network. The European Physical Journal B - Condensed Matter 38, 381–385. URL: http://www.springerlink.com/openurl.asp?genre=article{&}id=doi:10.1140/epjb/e2004-00131-0, doi:10.1140/epjb/e2004-00131-0.

Guimerà, R., Mossa, S., Turtschi, A., Amaral, L.a.N., 2005. The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles. Proceedings of the National Academy of Sciences of the United States of America 102, 7794–9. URL: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1142352{&}tool=pmcentrez{&}rendertype=abstract, doi:10.1073/pnas.0407994102.

Hossain, M., Alam, S., Rees, T., Abbass, H., 2013. Australian Airport Network Robustness Analysis : A Complex Network Approach, in: Australasian Transport Research Forum 2013 Proceedings, pp. 1–21.

Kinney, R., Crucitti, P., Albert, R., Latora, V., 2005. Modeling cascading failures in the North American power grid. The European Physical Journal B 46, 101–107. URL: http://arxiv.org/abs/cond-mat/0410318{%}0Ahttp://dx.doi.org/10.1140/epjb/e2005-00237-9http://www.springerlink.com/index/10.1140/epjb/e2005-00237-9, doi:10.1140/epjb/e2005-00237-9, arXiv:0410318.

Lordan, O., Sallan, J., Simo, P., Gonzalez-Prieto, D., 2014. Robustness of the air transport network. Transportation Research Part E: Logistics and Transportation Review 68, 155–163. doi:10.1016/j.tre.2014.05.011.

Motter, A.E., Lai, Y.C., 2002. Cascade-based attacks on complex networks. Physical Review E 66, 065102. URL: https://link.aps.org/doi/10.1103/PhysRevE.66.065102, doi:10.1103/PhysRevE.66.065102, arXiv:0301086.

Rocha, L.E., 2017. Dynamics of air transport networks: A review from a complex systems perspective. Chinese Journal of Aeronautics 30, 469–478. URL: http://arxiv.org/abs/1605.04872http://linkinghub.elsevier.com/retrieve/pii/S1000936117300171, doi:10.1016/j.cja.2016.12.029, arXiv:1605.04872.

Suau-Sanchez, P., Voltes-Dorta, A., Cugueró-Escofet, N., 2020. An early assessment of the impact of COVID-19 on air transport: Just another crisis or the end of aviation as we know it? Journal of Transport Geography 86, 102749. URL: https://doi.org/10.1016/j.jtrangeo.2020.102749, doi:10.1016/j.jtrangeo.2020.102749.

Tsiotas, D., Polyzos, S., 2015. Decomposing multilayer transportation networks using complex network analysis: a case study for the Greek aviation network. Journal of Complex Networks 3, 642–670. URL: http://dx.doi.org/10.1093/comnet/cnv003http://comnet.oxfordjournals.org/lookup/doi/10.1093/comnet/cnv003, doi:10.1093/comnet/cnv003.

Voltes-Dorta, A., Rodríguez-Déniz, H., Suau-Sanchez, P., 2017a. Passenger recovery after an airport closure at tourist destinations: A case study of Palma de Mallorca airport. Tourism Management 59, 449–466. URL: http://linkinghub.elsevier.com/retrieve/pii/S0261517716301613, doi:10.1016/j.tourman.2016.09.001.

Voltes-Dorta, A., Rodríguez-Déniz, H., Suau-Sanchez, P., 2017b. Vulnerability of the European air transport network to major airport closures from the perspective of passenger delays: Ranking the most critical airports. Transportation Research Part A: Policy and Practice 96, 119–145. URL: http://dx.doi.org/10.1016/j.tra.2016.12.009http://linkinghub.elsevier.com/retrieve/pii/S0965856416300234, doi:10.1016/j.tra.2016.12.009.

Wang, J., Bonilla, D., Banister, D., 2016. Air deregulation in China and its impact on airline competition 1994–2012. Journal of Transport Geography 50, 12–23. URL: http://dx.doi.org/10.1016/j.jtrangeo.2015.03.007http://linkinghub.elsevier.com/retrieve/pii/S0966692315000472, doi:10.1016/j.jtrangeo.2015.03.007.

Wang, J., Jiang, C., Qian, J., 2014. Robustness of Internet under targeted attack: A cascading failure perspective. Journal of Network and Computer Applications 40, 97–104. URL: http://dx.doi.org/10.1016/j.jnca.2013.08.007, doi:10.1016/j.jnca.2013.08.007.

Wang, J., Mo, H., Wang, F., Jin, F., 2011. Exploring the network structure and nodal centrality of China's air transport network: A complex network approach. Journal of Transport Geography 19, 712–721. URL: http://linkinghub.elsevier.com/retrieve/pii/S0966692310001328, doi:10.1016/j.jtrangeo.2010.08.012.

Wang, J.W., Rong, L.L., 2011. Robustness of the western United States power grid under edge attack strategies due to cascading failures. Safety Science 49, 807–812. URL: http://dx.doi.org/10.1016/j.ssci.2010.10.003, doi:10.1016/j.ssci.2010.10.003.

Wang, W.X., Chen, G., 2008. Universal robustness characteristic of weighted networks against cascading failure. Physical Review E 77, 026101. URL: https://link.aps.org/doi/10.1103/PhysRevE.77.026101, doi:10.1103/PhysRevE.77.026101.

Wilkinson, S.M., Dunn, S., Ma, S., 2011. The vulnerability of the European air traffic network to spatial hazards. Natural Hazards 60, 1027–1036. URL: http://www.springerlink.com/index/10.1007/s11069-011-9885-6, doi:10.1007/s11069-011-9885-6.

Wu, Z.X., Peng, G., Wang, W.X., Chan, S., Wong, E.W.M., 2008. Cascading failure spreading on weighted heterogeneous networks. Journal of Statistical Mechanics: Theory and Experiment 2008, P05013. URL: http://stacks.iop.org/1742-5468/2008/i=05/a=P05013?key=crossref.3f1867440b40feb5c4e8cc4a67f0d2fe, doi:10.1088/1742-5468/2008/05/P05013.

Zanin, M., 2015. Can we neglect the multi-layer structure of functional networks? Physica A: Statistical Mechanics and its Applications 430, 184–192. URL: http://dx.doi.org/10.1016/j.physa.2015.02.099https://linkinghub.elsevier.com/retrieve/pii/S0378437115002289, doi:10.1016/j.physa.2015.02.099, arXiv:1503.04302v1.