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Airport Ground Access Reliability and Resilience of Transit Networks: a Case Study

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Abstract

Airport ground access is one of the key determinants influencing air travellers' airport choice. The continuous growth of air travel demand and the consequent induced road congestion have encouraged the development of efficient transit systems approaching the airport, thus promoting a modal shift from individual cars to greener transport alternatives. In addition, transit systems must be resilient and reliable to air travellers, since the cost of missing a flight is high. In this paper, resilience aspects of transit systems accessing airport areas are discussed and some indexes have been set up to estimate the transit network resilience. Three different transit systems to get to a large regional Italian airport (Automated People Mover, Airport Shuttle Bus, Bus Line) are modelled and the system resilience has been estimated for each scenario by using the proposed indexes.

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Keywords: Airport ground access; Network resilience; Network reliability; Public transport; Impacts

1. Introduction

Air traffic has been rapidly growing in recent years. In 2015, around 3.5 billion people used it (+6.4% w.r.t. 2014), 50 million tons of freight were carried and the number of departures reached approximately 34 million globally (ICAO, 2015). The growth of air travellers caused an increase in airport ground access traffic and its related issues – e.g., an

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airport with 45 million passengers per year may generate eight million kilometres of ground access travel in one day (Cooganet et al, 2008) – drawing airport operators and policy makers attention.

Airport ground access describes the ground transportation system that provides access to and from the airport for people – passengers, employees, visitors, contractors – and goods. It affects directly airport operational and financial performances. In addition, surface access may be considered by airlines when deciding whether to serve a specific airport. Therefore, reliable, robust and attractive ground access alternatives are important airport requirements.

Airport ground access can be classified into three categories: private vehicles, transit systems and non-motorised modes (cycling or walking). Among these three categories, private car is the most used as it is perceived as the one offering more comfort, convenience, personal security and reliability (Budd, 2016). However, the intensive use of cars for those trips has led to severe traffic congestion problems around airports and remarkable environmental externalities, such as atmospheric pollution due to vehicle emissions and localized noise (Postorino and Mantecchini, 2014, 2016). Recently, there has been a growing pressure in both EU and US to promote the development of reliable transit systems accessing the airport, thus encouraging a shift toward more sustainable transport modes and reducing private car use. Furthermore, through the 1998 "A Deal for Transport" White Paper and the next 2003 "The future for Air Transport Paper" White Paper, UK airports were tasked to set targets to increase the percentage of trips by transit systems at the expenses of private vehicles (DETR, 1998; Department for Transport, 2006).

To be an attractive option, transit system should meet consumer needs and preferences. Several studies have identified relevant factors associated with airport ground access mode choice, particularly journey time, distance and ease of baggage handling as well as the trip purpose are key determinants in passengers' mode choice (Budd, 2014). Tam et al (2005) found that travel time reliability is the most important factor, where reliability refers to travel condition stability and predictability. Some studies showed that price is less important than time if a new, more reliable public transport system is available to access the airport (Jou et al., 2011). In addition, passengers are more willing to pay for improved travel time reliability, because lower travel time reliability depicts a higher possibility of late appearance at the airport, leading to a higher chance of missing the flight (Koster et al., 2011).

In case of transit system disturbances, such as strikes or infrastructure failures, it is crucial that passengers are still enabled to reach the airport without missing their flight. The ability of a system to adsorb, adapt to and rapidly recover from a disruptive event is called resilience. (Mattson, 2015). The more resilient the system is, the more it minimises the magnitude and duration of the impacts caused by a disruption, thus reducing negative experiences for passengers and, in some cases, costs for operators.

In this study, we analyse the resilience of the transit network accessing the airport as the magnitude and duration of the deviation of selected indicators from baseline performance levels. Particularly, delays on passengers, generalized costs and changes in the volume-over-capacity ratio after a disruption are proposed to measure the effects of unplanned service disruptions. Analyses of delays allow predicting the share of passengers who risk missing the flight, while the volume-over-capacity ratio allows understanding the different levels of system congestion and the network recovery time. The impacts of service disruption are modelled by BusMezzo, a simulation tool modelling the interactions between public transport operations and travellers' choices, included the opportunity for passengers to switch their route after supply changes. Different sources of public transport operation uncertainty are modelled, including traffic conditions, vehicle capacities, dwell times and vehicle schedules. Each traveller is modelled as an adaptive decision maker who moves forward in the transit system by undertaking successive decisions (Cats et al., 2011).

In the following sections, the transit system model is shortly introduced and the methodology used to evaluate impacts is described (2). An application to the large-regional Italian "Bologna Marconi" Airport is then presented (3), followed by some concluding remarks (4).

2. Methodology

2.1. Transit system model and implementation

Transit system performance results from complex and mutual interactions among several components, which influence the way the system evolves over time. To model such complexity, the dynamic nature of both public transport supply and demand has been considered as shortly explained in the following sections. A general introduction concerning transit system dynamic aspects can be found in the book edited by Gentile and Nökel (2016).

2.1.1. Supply

The transit network is represented by a direct graph $G(S, E)$ where S is the set of nodes - corresponding to stops - and E is the set of links connecting stops. Pedestrian links are also introduced, which allow transfers between stops. A transit line (or simply line) is defined as a sequence of stops or stations, $l = (s_{l1}, s_{l2}, \dots, s_{l|l|})$, where $s_{l1} = o_l$ is the origin stop and $s_{l|l|} = d_l$ is the destination stop. One or more lines may use the same link. Lines associated to their timetables represent runs. Transit vehicles follow a schedule that consists of sequences of runs, so delays on a given run may propagate to another one. The link travel time, defined on each link as the time between two subsequent stops, may vary depending on the current traffic conditions. It can be divided into two components: running times along the link and delays at intersections. The running time is a random variable with distribution derived from empirical observations. Delays at intersections are estimated by stochastic queue models. Similarly, each node (stop) is associated with a dwell time, which is the time required for a vehicle to stop for boarding and alighting passengers. Again, dwell time can be modelled as a random variable, as it varies depending on the number of passengers, vehicle and stop type.

2.1.2. Demand

Passenger demand is represented by an Origin/Destination (OD) matrix at stop level. Trips begin at an origin stop and passengers have to choose their path to a pre-defined destination stop, according to the final destination. The traveller's path is defined as a sequence of stops from the origin to the destination, that is $j = (s_{j1}, s_{j2}, \dots, s_{j|j|})$, where the origin stop is $o_j = s_{j1}$ and the destination stop is $d_j = s_{j|j|}$. When travelling, passengers can make successive path choice decisions, which depend on the evolving public transport system conditions. The dynamic path choice model includes three decision steps: connection, boarding and alighting. A connection decision takes place when the traveller chooses the start and/or alighting point of the trip and depends on the features of alternative paths connecting each candidate stop with the traveller's final destination stop. The traveller can choose to stay at the same stop for a connection or walk to a nearby stop and wait there for another transit service or walk directly to the final destination. A boarding decision takes place when travellers are waiting at a given stop. When the vehicle arrives, the traveller can decide whether to board it or stay at the stop and wait for another vehicle. Finally, once on-board the traveller makes an alighting decision, which may change depending on new information. The rating of alternative paths depends on traveller's preferences and expectations, evaluated by using the concept of path utility. Traveller's decisions are represented with a multinomial Logit model and the deterministic part of the utility of path i for passenger n, v_{in}, is defined as:

$$v_{in} = \beta^{wait} t_{in}^{wait}(t) + \beta^{ivt} t_{in}^{ivt}(t) + \beta^{walk} t_{in}^{walk} + \beta_t^{trans} trans_i \tag{1}$$

where t_{in}^{wait} and t_{in}^{ivt} are the waiting time and in-vehicle time respectively; t_{in}^{walk} is the walking time; $trans_i$ is the number of transfers; $\beta^{(.)}$ are the corresponding weights. More information on the dynamic route choice model including congestion effects are in Cats et al. (2016).

2.1.3. Implementation

The supply and demand models have been implemented by using an event-based mesoscopic traffic simulator – for both individual and transit transport systems – called BusMezzo (Toledo et al. 2010). BusMezzo simulates transit vehicles individually as objects characterized by specific attributes (length, number of seats, capacity, leaving rules from stops) and according to a list of scheduled trips. Trip chaining can also be modelled explicitly. Links are divided into two parts: a running part and a queuing part. Travel times on the running part are computed by speed-density functions. At the queuing (downstream) part of the link, queue servers process the arriving vehicles, which are forced to line up in single queues waiting to move out of the link according to a selected service time distribution. Separate queue servers with their corresponding capacities are used for turning movements to capture link connectivity and lane channelling. Passengers at stops are generated by following a Poisson arrival process with arrival rates specified in time-dependent OD matrices. As an event-based simulator, the time clock of the simulation progresses from one event to the next one according to a chronological list of events that refers to the relevant objects (vehicles). During the simulation, each object updates passenger loads and computes the maximum number of passengers that may board at each stop.

2.2. Network resilience due to service disruptions

The transit network resilience is measured as the change in the system generated by a disruption. Some performance indicators describe both the disrupted and the baseline states, by enabling the identification of the most suitable scenario able to adsorb the impacts caused by the disturbance – in terms of both magnitude and duration – i.e. the most resilient condition. More in detail, the resilience of the airport ground access transport network is studied by imposing the closure of a segment of the transit system serving the airport. Then, the impacts caused on air passengers, whose flight departing time imposes a tight constraint, are estimated. Three performance indexes have been set up for the transit network resilience analysis: delays on passengers (*DEL*), loss of convenience (or Inconvenience, *INC*) and change in volume-over-capacity ratio (*VOC*) throughout the network. The first two indexes measure impacts on passengers potentially leading to severe consequences (e.g., missing the flight), while the last one has been used to estimate the recovery time, i.e. the time the system needs to reach again a baseline working condition.

DEL enables the estimate of the share of passengers who risk missing their flight. Delay experienced by passenger n using the transit system to reach the airport is computed as the difference between the total travel time in the disrupted scenario s_d and the total travel time in the baseline scenario s_b:

$$DEL_n = TT_n(s_d) - TT_n(s_b) \tag{2}$$

INC reflects the discomfort perceived by users and is computed as the difference between the network generalized cost (*GC*) in the disrupted scenario s_d and the baseline one s_b:

$$INC = GC(s_d) - GC(s_b) \tag{3}$$

The generalized cost for scenario s is defined as:

$$GC = \mathrm{E}[t_n^{ivt}] + \gamma^{wait} * E[t_n^{wait}] + \gamma^{walk} * \mathrm{E}[t_n^{walk}] + \gamma^{waitfs} * \mathrm{E}[t_n^{waitfs}] + \gamma^{tr} * trans_n \tag{4}$$

where $E[\cdot]$ is the expected value of time, averaged on all passengers; t_n^{waitfs} is the time spent waiting for the second transit vehicle, in case it is not possible to board the first one because of vehicles capacity constraints; $\gamma^{(\cdot)}$ are the trade-off values $\beta^{(\cdot)}/\beta^{inv}$. Monetary costs have not been considered as it has been assumed that in case of unplanned disruptions air travellers are cost insensitive for the ground access part of their air journey.

Finally, for vehicle m moving on link e at time t in the scenario s, *VOC* is given by:

$$VOC_m(e,t|s) = \frac{V_m(e,t)}{C_m} \tag{5}$$

where $V_m(e,t)$ is the number of passengers riding vehicle m (of capacity C_m) moving on link e during time window t. VOC measures the on-board link saturation level. High saturation levels cause on-board overcrowding and some passengers may experience denied boarding and thus prolonged waiting times. Impacts of link closure are evaluated by comparing VOC in the base scenario s_b and in the disrupted one s_d through the Actual Difference Ratio (*ADR*) measure:

$$ADR(t|s_d) = \frac{\sum_{e\in E}\sum_{m\in M_{tes_d}}(VOC_m(e,t|s_d) - VOC_m(e,t|s_b))}{\sum_{e\in E} M_{tes_d}} \tag{6}$$

where M_{tes_d} is the whole number of vehicles travelling on link e during time window t in scenario s_d. *ADR* is used to estimate the recovery time. More in details, when the passenger queue – causing vehicle overloading with respect to the baseline scenario – has run out, then *ADR* is zero. The time needed to reach again the baseline condition measures the network recovery time from disruption. The shorter such time is, the more the network is resilient.

The most resilient scenario is then defined as the one that produces the smallest impacts computed as the changes between the baseline and disrupted situations.

3. Application

3.1. Ground access transit system description

The described approach has been applied to Bologna “Guglielmo Marconi” Airport, a large regional airport in Northern Italy. Located 6 km far from Bologna Central Rail Station, it is served by an aero-bus service (Airport Bus Shuttle, BLQ), connecting the train terminal to the airport in approximately 25 minutes. At the end of 2018, the Airport Bus Shuttle is planned to be partially or totally replaced by an Automated People Mover (APM), a driverless elevated tram system connecting the station to the airport in about 7 minutes, with only one intermediate stop (Lazzaretto). Furthermore, the airport is served by a Bus Line (81), which takes almost 35 mins and stops 1 km far from the airport (15 mins walk). In this application, the three transit systems – included the planned one – are modelled, each one with its own vehicle type, operating speed, travel time variability and dwell time functions to reflect the differences in the service characteristics. Key attributes of each transport mode are shown in Table 1. Although monetary costs have not been considered in the choice model, Table 1 reports ticket prices to give complete information on the transport modes. Real demand, timetables and walking distances between stops are used to model the network with BusMezzo. Finally, the baseline scenario refers to the activation of the APM service, which substitutes the BLQ service.

Table 1: Service features

TYPE	CAPACITY (pax/vehicle)	FREQUENCY (vehicles/hour)	SCHEDULED HEADWAY (min)	PLANNED TRAVEL TIME (min)	TICKET PRICE (€)
APM	50	8	7.5	7.5	7.50
BLQ	55	5	12	25	6.00
81	60	4	15	35	1.50

Real transit demand, in terms of passengers, refers to the airport busiest hour in the week. More in details, the whole air demand is computed by considering both the schedule of movements and aircraft capacity, with an average load factor of 0.85. The peak hour is on Friday, between 13:00 and 14:00, with a demand of 1600 air travellers. Transit users are assumed to be 15%, incremented by 5% in order to consider employees. As a result, 270 estimated passengers will arrive at the airport by transit systems in the considered time interval.

According to real data kindly made available by Bologna airport, the majority of passengers arrives 60-90 minutes before their scheduled flights (about 75%), while the remaining percentage is distributed between very early arrivals (2 hours and more before the scheduled flight) and rather late arrivals (30 mins before the scheduled flight). According to data and based on arrival rates at the airport, we assumed that passengers depart from the Central Rail Station between 2.5 and 1.5 hours before the scheduled take-off of their flight, i.e. in the time interval 10:30-11:30 AM.

The simulated disruption consists of downing the capacity to zero on the APM service between Lazzaretto intermediate stop and Airport for the entire simulation period. To allow passengers to arrive to the airport in any case, three different alternatives are considered to cope with the emergency. In the first one, an emergency shuttle is introduced between Lazzaretto and Airport stops (D1, Figure 1b); the second scenario simulates the re-introduction of the BLQ service between the Station and the Airport (D2, Figure 1c); in the last one both alternatives are considered (D3, Figure 1d). In all scenarios, the Bus Line service is functioning under normal operations. Note that the system is simulated at a time where the APM service has substituted BLQ and for such reason this latter is not operating in scenario D1.

Passengers are assumed to be aware of any change in the system, so they know about the disruption and they can decide which alternative to take based on their preferences, assumed to be constant throughout the simulation period. The choice of alternatives has been modelled by a multinomial Logit. Although the utility function coefficients have not been specifically estimated for the case study, suitable values can be found in the literature (such as the ones in Guo and Wilson, 2011; Nuzzolo et al., 2012; Wardman, 2014, proposing a review of public transport value of time studies), which fit well for the examined socio-economic context. Particularly, the values estimated in Cats et al.

(2011), also in line with the ones in Wardman (2014), have been assumed proper for this case: $\beta_a^{wait} = -0.07$, $\beta_a^{walk} = -0.07$, $\beta_a^{ivt} = -0.04$, $\beta_a^{trans} = -0.334$. Although trip fare is not considered in this analysis, we assume that, according to some surveys, 4% of the demand uses the Bus Line because of cost savings.

In order to allow a warm-up period, the supply is simulated from 9:30. For each scenario, 10 simulations are carried out to obtain a standard error of less than 5% for passenger travel time.

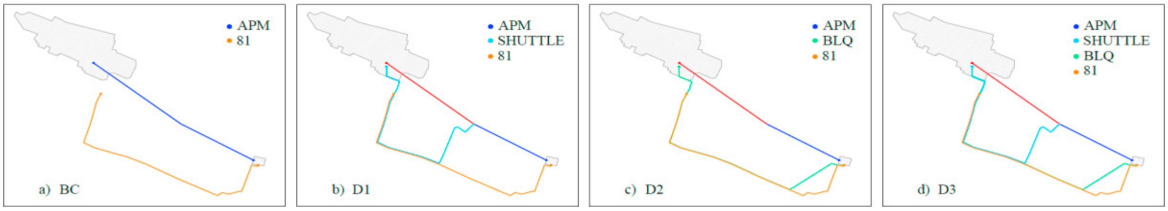
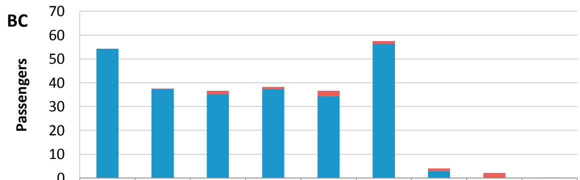


Figure 1: Baseline scenario BC (a) and disrupted scenarios D1 (b), D2 (c) and D3 (d). In red: disrupted link

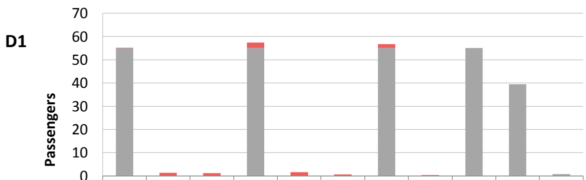
3.2. Results

In the baseline scenario (Figure 1a), the average passenger travel time is 8 minutes. The majority of transit passengers (65%) arrive between 11:00 and 12:00, i.e. 60 to 120 minutes before the flight departure (Figure 2a). After the disruption, passengers are forced to reroute and are affected by delays. In the disrupted scenario D2, the average passenger travel time increases by 13 minutes, but users are still able to reach the airport within acceptable time (Figure 2c). Differently, the adoption of the Emergency Shuttle solution (D1) generates only a slight increase in the average travel time (8 mins), but vehicle capacity plays a key role and more than 60% of passengers are forced to wait at the stop for a second vehicle because the first one is full. Most passengers arrive after 12:00 AM and 15% of them arrives less than half an hour before the departure (after 12:30), risking to miss the flight (Figure 2b). Scenario D3 (Figure 2d) may avoid capacity problems but it is a more expensive alternative for the service provider. According to travellers' preferences modelled by the discrete choice approach, BLQ is chosen by 51% of passengers while the remaining part chooses the Emergency Shuttle. However, also in this case some passengers arrive less than one hour before their flight departure.



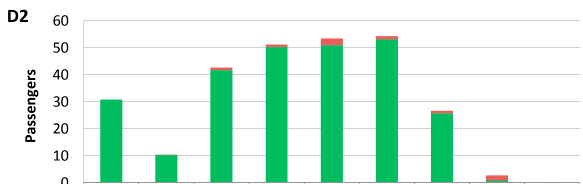
	10:40-10:50	10:50-11:00	11:00-11:10	11:10-11:20	11:20-11:30	11:30-11:40	11:40-11:50	11:50-12:00	12:00-12:10
81		0,1	1,5	0,7	2,1	1,1	1	2,2	0,1
APM	54,3	37,4	35,1	37,5	34,5	56,4	3,1		

a)

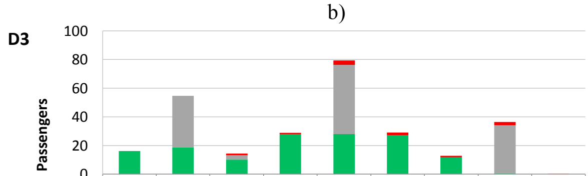


	11:00-11:10	11:10-11:20	11:20-11:30	11:30-11:40	11:40-11:50	11:50-12:00	12:00-12:10	12:10-12:20	12:20-12:30	12:30-12:40	12:40-12:50
81	0,1	1,4	1,2	2,4	1,6	0,7	1,7	0,4			
SHUTTLE	55			55			55		55	39,4	0,8

b)



	10:50-11:00	11:00-11:10	11:10-11:20	11:20-11:30	11:30-11:40	11:40-11:50	11:50-12:00	12:00-12:10	12:10-12:20
81		0,1	1	0,9	2,5	1,2	1	1,9	0,1
BLQ	30,7	10,2	41,6	50,2	50,9	53	25,6	0,7	



	10:50-11:00	11:00-11:10	11:10-11:20	11:20-11:30	11:30-11:40	11:40-11:50	11:50-12:00	12:00-12:10	12:10-12:20
81	0	0	1,1	0,9	3,1	2,1	1,2	2,2	0,2
SHUTTLE	0	36,1	3	0	48,3	0	0	33,6	0
BLQ	16,2	18,5	10,2	28	28	27	11,7	0,5	0

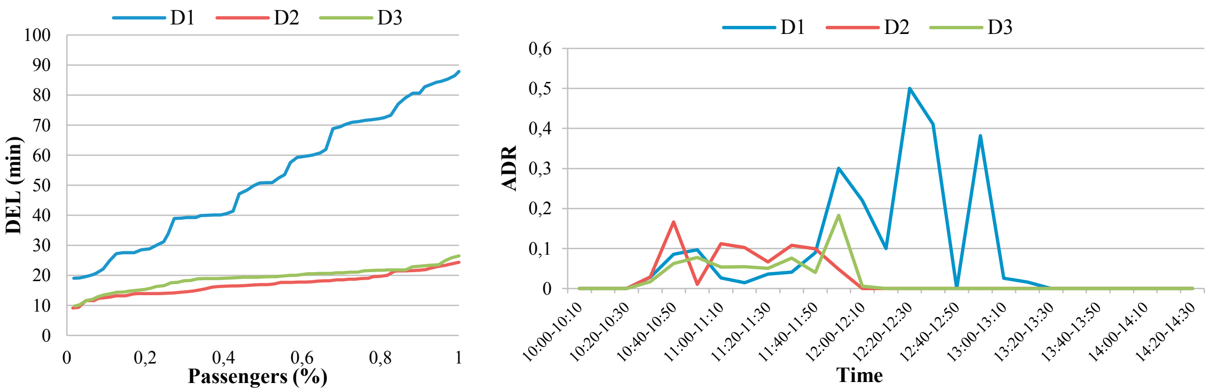
c) d)

Figure 2: Passengers arrival time

To measure the magnitude of delays experienced by passengers, indicator DEL (Eq. 2) has been computed. As Figure 3a shows, in scenario D1 delays are significantly higher and 30% of passengers experience more than one hour of delay. Conversely, in scenario D2 delays are in the range 10 - 30 minutes while scenario D3, providing both Emergency Shuttle and BLQ alternatives, generates almost the same average delay as scenario D2.

The Inconvenience INC (Eq. 3) has been computed by assuming $\gamma^{wait} = 1.75$, $\gamma^{walk} = 2$, $\gamma^{waitfs} = 2$ and a transfer penalty γ^{tr} equivalent to approximately 8 min in-vehicle time (according to Wardman, 2014). INC values confirm that scenario D1 is the one causing more difficulties to passengers (Table 2). Users perceive the availability of the Emergency Shuttle 5 time more uncomfortable than scenario D2. Then, from passengers' point of view, it is better to have a unique service from the Station to the Airport (BLQ) than both alternatives as in D3. This apparently surprising result can be explained by considering that passengers consider transfers as journey interruptions, always poorly desirable due to the discomfort associated to carrying baggage, waiting time and potential queues at stops.

For each scenario, figure 3b shows the ADR trend. Data are averaged over time slices of 10 mins. Trends have a similar pattern for all disruption scenarios. As the generation of passengers starts (10:30 AM), ADR increases. Afterward, the difference between the baseline scenario and the disrupted ones progressively decreases reaching zero. Scenarios D2 and D3 have almost the same trend, while scenario D1 shows considerable higher impacts. At the beginning of the simulation, impacts are reasonable, but they increase more and more after the end of the generation of passengers (value of 0.5). As pointed out before, this is linked to the limited capacity of the Emergency Shuttle service, which is not able to satisfy the demand and forces passengers to wait for a second vehicle. Figure 3b allows computing the recovery time (Table 2), that is the time required for the network to return to the undisrupted conditions (baseline scenario), i.e. the time at which ADR=0. For scenarios D2 and D3, the recovery time is 1.5 hours (12:00 AM), computed from the generation of the first passenger. For scenario D1, the system is again standard operational 3 hours after the beginning of passenger generation (1:30 PM). These results suggest that the aftermath of disruption lasts up to 4 times compared to other scenarios, thus confirming scenario D1 as the worst alternative.



a) b)

Figure 3: a) Delay b) ADR index evolution for each scenario.

Table 2: Indexes to measure resilience for scenarios D1, D2 and D3

	D1	D2	D3
INC (minutes)	116,1	22,5	29,6
Recovery time (minutes)	180	90	90

4. Conclusions

The analysis proposed in this work focused on the estimation of several impacts produced by unplanned disruptions of the transit systems serving an airport. Estimates of passenger delays and costs, as well as the network recovery time, have been proposed to measure the transit network resilience. In fact, the main, desirable property that passengers – mainly air travellers – are asking when moving by transit systems is reliability, in addition to the opportunity offered to bypass road traffic congestion and plan a safe and comfortable journey to access the airport. When disruptions prevent from arriving as planned, discomfort is very high particularly because air travellers have no other choices but to use another transit alternative or taxis – which is much more expensive. Furthermore, late arrivals generate high stress levels because the risk to miss the flight is high.

The indexes proposed here to measure the transit network resilience have been tested on three scenarios simulating a disruption in one of the transit system leg. Particularly, for a given disruption, some possible transit system scenarios to cope with the emergency have been tested: a shuttle service from the disruption point to the airport; a direct aero-bus service, which does not serve the disrupted point; the combination of both shuttle and aero-bus service. A standard bus service, with several intermediate stops, is also available for all scenarios. The starting hypothesis is that travellers are aware of the disruption when it begins. One interesting result is that the simplest solution– i.e. the introduction of a substitute service between the disrupted point and the airport, generally adopted by service providers – is the worst scenario. Recovery time is very high if compared to other solutions, as well as delays and costs for travellers. The other two scenarios are much better, by showing a higher resilience as measured by the proposed indexes. Particularly, although the scenario with both shuttle and aero-bus service provide a wider set of alternatives, its resilience is not better than the resilience of the system with only the aero-bus service. This confirms that passenger discomfort is very high when there are transfers, as in the shuttle solution where passengers have to transfer from the disrupted APM service to the shuttle one. The proposed analysis of transit system resilience helps identifying scenarios that produce fewer impacts on passengers and airports and can be used to provide guidelines for infrastructure and service investment decisions that reduce costs for both passengers and service providers. Future studies may consider the probability to miss the flight as a function of the arrival time and the inclusion of monetary costs in the utility function.

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