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Creating Tomorrow

Airport Capacity Management Optimization vs Airline Fairness: an empirical study

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Abstract
This research aims to find relevant evidence on whether there is a link between air capacity management (ACM) optimization and airline operations, also considering the airline business model perspective. The selected research strategy includes a case study based on Paris Charles de Gaulle Airport to measure the impact of ACM optimization variables on airline operations. For the analysis we use historical data which allows us to evaluate to what extent the new schedule obtained from the optimized scenario disrupts airline planned operations. The results of this study indicate that ACM optimization has a substantial impact on airline operations. Moreover, the airlines were categorized according to their business model, so that the results of this study revealed which category was the most affected. In detail, this study revealed that, on the one hand, Full-Service Cost Carriers (FSCCs) were the most impacted and the presented ACM optimization variables had a severe impact on slot allocation (approximately 50% of slots lost), fuel burn accounted as extra flight time in the airspace (approximately 12 min per aircraft) and disrupted operations (approximately between 31% and 39% of the preferred assigned runways were changed). On the other hand, the comparison shows that the implementation of an optimization model for managing the airport capacity, leads to a more balanced usage of runways and saves between 7% and 8% of taxi time (which decreases fuel emission).

1. Introduction
Air transport has experienced constant growth throughout the twentieth century (Jiang et al., 2019). Despite several crises that have impacted the sector, air transport has proven to be resilient and been able to recover from many adverse events such as economic and political crises by demonstrating steady growth over the years. Last year, the world was hit by arguably the most striking crisis of all time, when the Covid-19 pandemic broke through. The aviation sector has been one of the most affected by this, as it has experienced a sharp decline in Europe, reaching about 65% fewer flights performed so far (EUROCONTROL, 2021). The only aviation sector that was positively impacted was the cargo sector, which witnessed a 10% increase in traffic. The most optimistic forecast predicts that traffic will recover almost completely to pre-Covid19 times (2019), by 2024 (EUROCONTROL, 2020). As reported by IATA, the aviation sector has lost about 11,9 billion to date , with 4,8 million of direct lost jobs and the revenue per passenger/kilometer dropping/falling by 70% (Airlines., n.d.; IATA, 2020). However, as the forecast shows, the traffic will slowly recover and bring to light the air traffic network capacity issues, as it was just before Covid-19 outbreak started. In this regard, airports play a crucial role as nodes of the air traffic network and as an interface between air and land, contributing to the growth of air traffic (Pacagnella et al., 2021). The forecasted growth in air traffic volumes in a post-Covid19 scenario will present new challenges to all stakeholders involved, as environmental, social, technical and land-use constraints will prevent airports from developing and expanding their capacities (Jacquillat & Odoni, 2018). The cost of delays, flight cancelations, lost slots due to capacity constraints affect the airline profitability (Cook et al., 2012). As reported by T2RL, (2016), the costs to airlines due to disrupted operations are estimated at $60 billion globally, representing 8% of the airline revenues in 2016. It is therefore in the interest of every airline to ensure efficient and effective operations at the airport to prevent any disruptions. The increase can be traced back to ancillary services that have become an integral part of the business model of all types of airlines (Warnock-Smith et al., 2017).

Ancillary revenue describes the additional revenue generated by an airline in parallel to the sale of its flight tickets (O'Connell & Warnock-Smith, 2013). This source of revenue can be generated through direct sales to passengers or indirectly as part of the travel experience (O'Connell & Warnock-Smith, 2013). Consequently, airlines and their operations are dependent on airport infrastructure. Airports are always looking for ways to cope with the increasing air traffic. In this context, there are long and short-term solutions to potentially solve the problem, but they often have the disadvantage of not being feasible in real operations (Scala, Mujica Mota, Wu, et al., 2021). Although there have been quite some studies about airport capacity management, that address various aspects of the problem (airspace sequencing, runway management, taxiway routing, gate allocation), few of them consider airline fairness in their model variables. Hence, this work will focus on the research question of how Airport Capacity Management (ACM) impacts airline operations. In this way, this study serves as a proof-of-concept for creating awareness on the variables that should be included when managing the capacity of airports while taking into account airlines interests. Thereby, this study is conducted by using a real case study which is Paris Charles de Gaulle Airport, and the flight data used refers to a pre-Covid19 scenario. The authors believe that the work will be relevant as the air traffic will be recovered in post-Covid19 scenarios.

The paper is structured as follows: in the next section a brief state of the art of the main studies related to airport capacity management and airline fairness is given; then the problem of airport capacity management is defined; followed by a description of the empirical study , with the relative results; next a section for discussion and interpretation of the results is provided; and lastly conclusions and future research directions are given.

2. Literature review on airport capacity management and airline fairness

This section presents a brief literature review of the recent development on airport capacity management that highlights the relevancy of this research. Moreover, studies on how airline fairness has been implemented to the problem of airport capacity management is presented. Finally, the contributions of this paper are listed.

2.1. Airport capacity management

Airports are intermodal interfaces between the air and the ground traffic, in this context, passengers and aircraft pass through several processes at the airport, which thus fulfills the interface function. Dray, (2020) refers to the airport capacity as the quantifiable production output of an airport. It can be stated that airport capacity is composed of various sub-capacities and that a capacity bottleneck in one component determines the total capacity of an airport. In the literature there are no standard definitions of airport capacity, however, Jacquillat & Odoni, (2018) generalize the term airport capacity by defining it as an interaction between the "existing infrastructure and the limited operational capabilities" of the airport. Based on these definitions, it can be stated that ACM refers to the coordination and administration of explicit tasks to address demand and capacity constraints at airports. The objective hereby is to maximize throughput, minimize congestion and improve resilience towards disruptions. In this work, we refer to ACM as the integration between airside and airspace operations with the aim of ensuring safe operations and maximizing the efficiency of existing infrastructure. In this context, Kjenstad et al., (2013) proposed arrival, departure and surface management, where they optimize in a sequential way the surface aircraft routing and the arrival and departure sequence. Bertsimas & Frankovich, (2016) tackled the airspace and ground operations problem by optimizing air and ground aircraft sequences by applying a two-stage solving method. Other studies that focused on similar problems can be found in Samà et al., (2013), Bosson et al., (2015) and Guépet et al., (2017). In Ma et al., (2019), airspace aircraft sequencing operations were integrated with airport ground operations at a macroscopic level. In this study, taxiways and terminals were modeled in low detail by considering them as nodes of a network characterized only by their capacity. The problem was solved with a heuristic that employs a sliding window approach. The extension of this work involves the use of simulation in combination with optimization for improving the robustness of the solution (Scala et al., 2020; Scala, Mujica Mota, Wu, et al., 2021).

In general, the aforementioned studies focused on improving the decision-making process through a system-wide exchange of data, increasing the system's capacity through improved management of traffic flows, and raising the situational awareness among participants in airspace and ground operations.
The present work is based on the works of Ma et al., (2019) and Scala, Mujica Mota, Wu, et al., (2021), where both ACM are formulated and solved by using optimization techniques. The novelty of this study is that it considers the airline's point of view as a critical evaluation factor.

2.2. Airline fairness in airport capacity management problems

In this section we present a literature review of studies that address airspace and airport management problems when airline fairness is considered. We divide this section into three subcategories: slot allocation, aircraft emissions, operations disruptions.

2.2.1. Slot allocation

EU, (2016) defines slots as a limited time interval during which flights are authorized to operate (take-off or landing) at the airport, allocated to particular airline corporations. Whereas the International Civil Aviation Organization (ICAO, 2012) describes a slot as the takeoff and landing rights at an airport. At the European level, slot allocation is based on the Council Regulation (EEC) No. 95/93 on standard rules for the allocation of slots at community airports (EU, n.d.). Considering the scarcity of airport capacity, the significance of coordinating arrival and departure times and slot allocation at busy and highly congested airports is growing (de Wit & Burghouwt, 2008). Many airports do not have sufficient runway capacity to satisfy the overall demand for slots, as the required number of take-offs and landings at peak times of the day is higher than the existing airport capacity itself (de Wit & Burghouwt, 2008). Bard & Mohan, (2008) focused on the relocation of arrival slots, introducing a model that aims to allocate incoming flights in the ground delay program (GDP) to available arrival windows in a total cost minimized manner. Ribeiro et al., (2018) established a novel multi-objective priority-based slot allocation model (PSAM). Based on the key performance indicators of airport declared capacities and requested slots of the airline, a schedule is constructed, with the aim to minimize the displacement of slots regarding the requirements of the IATA guidelines. The work of Ivanov et al., (2017) focuses explicitly on Air Traffic Flow Management (ATFM). In their two-level mixed-integer optimization model, they investigate the possibility of distributing ATFM delays. The objective hereby is to minimize propagated delays and subsequently maximize airport slot adherence of regulated flights by the airline. However, Miranda & Oliveira, (2018) shed light not only on the strategies and models used to allocate scarce airport slots, but also on the study from the point of view of the airlines. Hereby they examined the relationship between the control of slots and their incentives to commit themselves to service quality. Further studies explicitly examine slot constraints or loss of slots, for which influencing variables were considered, such as extra pushback time (Liu et al., 2017; Sun et al., 2018) and extra entry time of the aircraft (Schummer & Abizada, 2017). Androutsopoulos & Madas, (2019) take it a step further and include the fairness of airlines. In their work, they extended the strategic scheduling model to ensure that each airline has its fair share of congestion.

2.2.2. Aircraft emissions

The reduction of kerosene consumption plays an essential role from both an ecological and an economic point of view. In the field of air traffic management, the focus was on reducing the amount of greenhouse gas emissions. The majority of literature examines the relationship between the use of the taxiways and the generated emissions since fuel consumption and emissions are directly dependent on aircraft ground movements. Thus, significant fuel and emissions savings can be achieved through targeted optimization of taxiing traffic on the ground. Simaiakis et al., (2014) argue that the upsurge of taxi times, as well as fuel consumption and emissions can be traced back to the airport surface congestion. They conducted a field study at the Boston Logan International Airportemploying the K-control method, which resulted in fuel consumption of 12000-15000 kg/day, while the gate pushback time increased by 4.4 minutes. Based on the K-control method, Lian et al., (2019) discusses the influence of extensive departure taxi-out times at airports. They propose a Dynamic Pushback Control method based on the predicted taxi-out time. This is designed to rationally distribute operating time and achieve the necessary trade-off between fuel consumption reduction and gate holding times. Rodríguez-Díaz et al., (2019) constructed a bi-objective model for aircraft ground scheduling. In addition to reducing delays, this model aims to reduce aircraft noise and fuel consumption. They used a real case study, Madrid-Barajas airport, and demonstrated significant improvements of up to 4.5% decrease in fuel consumption.

2.2.3. Operations disruptions

The continuing growth of air traffic has resulted in the increasing logistical complexity of air transport (Kang & Hansen, 2018; Wang et al., 2019). Furthermore, air traffic is also a system characterized by operational fluctuations. Regular short-term and mostly unforeseeable events can easily lead to minor or major flight irregularities (Jimenez Serrano & Kazda, 2017). Flight irregularities include any phenomena that noticeably disrupt flight operations (Wang et al., 2019). As a result, routine handling processes cannot be carried out as planned, causing previously optimized flight schedules to be interrupted and resulting in severe delays (ACRP, 2012). In this context, disrupted operations can be defined as a representation of irregularities and interruptions of in-flight operations caused by unscheduled events or phenomena. Therefore, they require special measures and capabilities for the organization and re-organization of handling processes in the air transport (Jimenez Serrano & Kazda, (2017). One of the first studies on disrupted operations is provided by Clarke, (1998), where a decision-making framework was developed that addresses the question of how airlines can re-assign aircraft for scheduled flights after a disruptive event. Rosenberger et al., (2000) introduced a stochastic model of daily flight operations. The aim of this model is to evaluate crew rotations or procedures for handling operational disturbances during random events caused by weather or mechanical errors. Other studies have examined the impacts of ACM on tactical response capabilities of the airline, such as flight delay, cancellation or diversion. In Løve et al., (2002) a heuristic was implemented for the reassignment of aircraft to flights, delaying or flights cancelations due to unforeseen events. Abdelghany et al., (2004) developed a model for planning flight schedules by considering air traffic delays. They extended this work by developing a model that simulates and optimizes the schedule in case of irregular occurrences (Abdelghany et al., 2008). Malandri et al., (2020) developed a discrete event simulation model for arrival, departure and turnaround operations assessing the impact of rerouted flights to other airports on the ground operations, focusing on ground handling workload.

2.3. Paper contributions

Theoretically, the relationship between ACM and airline operations has been approached from different perspectives. In this context, we have reviewed many studies about airport operations that focus on improving their effectiveness and efficiency with the aim of enhancing airport capacity, both for airspace and ground areas. Despite the many studies that consider airline fairness in terms of slot allocation, emissions and operations disruptions, they have always considered airspace and ground operations independently. In this work, we overcome this aspect by considering integrated airspace and ground airport operations (ACM) and evaluating how Air Traffic Management (ATM) tactical decisions affect the airline's operations.

In the ACM framework, we define three airline fairness variables, namely missed slots, emissions, disrupted operations and we evaluate the extent to which they are affected either positively or negatively, by tactical ATM decisions. We will use these new insights to redefine the objectives of the ACM problem.

Moreover, we will conduct a thorough analysis by considering the different airline business models, which will provide us with further insights into the correlation between ATM decisions and airline fairness.

In conclusion, the literature review revealed the following assumptions/limitations: the research on ACM has focused more on the impact on airports rather than on the perspective of airlines or the airline business models. Therefore, this study will conduct further research and investigation on the aspects of ACM and its impact on the airline operations from the airline business model's perspective.

3. Problem description

In this work, the ACM problem is studied. For this purpose, the ACM is defined as the integration of the landing aircraft sequencing in the airspace near an airport and aircraft movement congestion on the ground of an airport (Scala et al., 2020; Scala, Mujica Mota, & Delahaye, 2021; Scala, Mujica Mota, Wu, et al., 2021). The operations involved in this problem are as follows: aircraft arrival sequencing in the airspace (i.e., the Terminal Maneuvering Areas, TMA); runway operations (i.e., aircraft arrivals and departures); aircraft occupancy of the taxiway and terminal gates; and aircraft departure sequencing. Figure 1 illustrates a schematic overview of the problem.

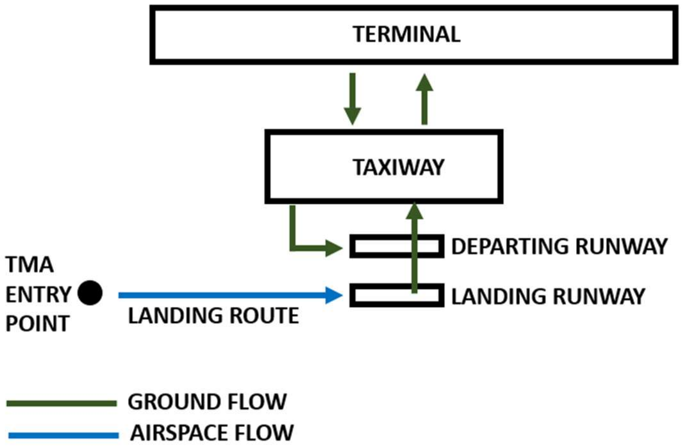

Figure 1. ACM schematic overview *(Scala, Mujica Mota, & Delahaye, 2021)*.

The tactical decisions of the ATM are:

- Airspace delay (advance), defined as the time stamp given by air traffic controllers (ATCOs) at the entry point of the TMA to the aircraft. Given an already defined flight plan, aircraft could be delayed or advanced;
- Speed modification in the airspace, defined as the speed to be maintained when entering the TMA; here the speed could be adjusted by either decreasing or increasing the already planned speed;
- Landing runway assignment, defined as the choice of the runway to use for landing;
- Departure runway assignment, defined as the choice of the runway to use for departure;
- Ground delay, defined as the delay given to aircraft before they leave the parking stand.

The ACM problem has been formulated as a mathematical problem by defining an objective function, constraints and decision variables. The objective function of the optimization model takes into account the airspace performance and the airside performance in terms of conflicts. An airspace conflict is defined as violation of the separation minima between consecutive aircraft, while airside conflicts are defined as capacity overloads. The objective function is represented by the weighted sum of the airspace and airside performance (1). The weights $Y_{airspace}$ and $Y_{airside}$ are assigned to the airspace and airside performance, respectively. These weights can be adjusted to drive the optimization process by focusing on one of the two components. The objective function aims at minimizing the airspace and airside ground side performance, therefore, an optimal solution will lead to 0.

$$\text{Objective function} = Y_{airspace} \times \text{Airspace performance} + Y_{airside} \times \text{Airside performance} \tag{1}$$

The airspace and airside performance represent the constraints of the optimization model. Airspace performance is identified by aircraft separation conflicts and sequence order conflicts (2). Aircraft separation conflicts are defined as the violation of the separation minima between consecutive aircraft (3). Sequence order conflicts are detected to prevent an aircraft overtaking another one (4).

$$\text{Airspace performance} = \text{Airspace conflicts} + \text{Order of sequence conflicts} \tag{2}$$

Airspace conflicts and order of sequence conflicts are formulated as follows:

Airspace conflicts: let be A a given set of landing aircraft, i and j consecutive pair of aircraft, S_{ij} the separation minima between the leading aircraft type i and the trailing aircraft type j and D_{ij} the distance between aircraft type i and aircraft type j. For details about the values of D_{ij}, please refer to (Scala, Mujica Mota, Wu, et al., 2021). In this way, conflicts are detected and calculated as:

$$\text{Airspace conflicts} = \{1, D_{ij} < S_{ij}, \forall i, j \in A \;\; 0, otherwise \tag{3}$$

Sequence order conflicts: let be $l_{(u,v)}$, $l=1,..,n$, a given set of links $order_{fu}^{l}$ and $order_{fv}^{l}$ the positions of the aircraft i on the link entry u and on the link exit v, respectively. The sequence order conflicts are calculated as:

$$\text{Sequence order conflicts} = \sum_{l=1}^{n} \left(\sum_{i \in A} \; order_{iv}^{l} - order_{iu}^{l} \right) \tag{4}$$

The airside performance is identified by the runway conflicts, taxiway and terminal overload (5). The runway conflicts are calculated in a similar way as the airspace ones, the only difference is that airspace and runways have different separation minima standards [4] (6).

$$\text{Airside performance} = \text{Runway conflicts} + \text{Taxiway overload} + \text{Terminal overload} \tag{5}$$

Runway conflicts: let be A a given set of aircraft, i and j a consecutive pair of aircraft, S_{ij} the separation minima between aircraft type i and aircraft type j and D_{ij} the detected time difference between aircraft type i and aircraft type j. For details on the values of D_{ij}, please refer to Scala, Mujica Mota, Wu, et al., (2021). In this way, conflicts are formalized with the following function:

$$\text{Runway conflicts} = \{1, \; if \; D_{ij} < S_{ij}, \forall i, j \in A \;\; 0, \; otherwise \tag{6}$$

Taxiway and terminal overload are calculated in terms of max and average overloads (5-8).

Taxiway and terminal overloads: let be C the capacity, O_t the aircraft occupancy for each discrete time increment $t \in T$; and T the entire time frame considered, the max and average (taxiway/terminal) overload are given by:

$$\text{Taxiway/Terminal overload} = \text{Max overload} + \text{Average overload} \tag{7}$$

$$\text{Max overload} = \{max_{t \in T}(Overload_t), if \; O_t > C \; 0, otherwise \tag{8}$$

$$\text{Average overload} = \frac{\sum_{t \in T} \; Overload_t}{T} \tag{9}$$

$$\text{Overload} = \{O_t - C, if \; O_t > C \; 0, otherwise \tag{10}$$

The decision variables of this problem refer to the tactical ATM decisions mentioned previously. Given a set of flights F, for each flight f, where $f \in F$:

Airspace delay (advance):

$$t_f \in T_f \text{ where } T_f = \{T_f^o + j\Delta T \mid (\Delta T_{min})/\Delta T \leq j \leq (\Delta T_{max})/\Delta T \;, j \in Z\} \tag{11}$$

where ΔT_{min} and ΔT_{max} are the minimum and maximum values that can be assigned to t_f, and ΔT is a discretized time increment. In this case ΔT_{min} is -5 min, ΔT_{max} is +30 min and ΔT is 5 s.

Speed modification in the airspace:

$$s_f \in S_f \text{ where } S_f = \{S_f^0 + j\Delta S \mid |j| \leq (\Delta S_{max} - \Delta S_{min})/\Delta S,\ j \in Z\} \tag{12}$$

where ΔS_{min} and ΔS_{max} are the minimum and maximum values that can be assigned to s_f and ΔS is a discretized increment. In this case ΔS_{min} is $0.9S_f^0$, ΔS_{max} is $1.1S_f^0$ and ΔS is $0.01S_f^0$.

Landing runway assignment:

$$l_{rf} \in LR_f \tag{13}$$

Where LR_f is the set of available landing runways.

Departure runway assignment:

$$d_{rf} \in DR_f \tag{14}$$

Where DR_f is the set of available departure runways.

Airside delay:

$$pb_f \in PB_f \text{ where } PB_f = \{pb_f^0 + j\Delta T \mid 0 \leq j \leq (\Delta PB_{max})/\Delta T,\ j \in Z\} \tag{15}$$

where ΔPB_{max} is the maximum value that can be assigned to PB_f, and ΔT is a discretized time increment. In this case ΔPB_{max} is +15 min and ΔT is 5 s.

3.1. Airline fairness variables

In this study, we identified three variables that represent airline fairness in the context of the ACM. These variables are the following:

- *Missed slots*, any delay that occurs to the scheduled landing time/departure time (SLT/SDT) that exceeds 10 minutes (Cohor, 2021);
- *Emissions* (fuel burned), given by the extra time spent on the airspace (delay) and on the airside (taxiway), which leads to more fuel being burned than necessary;
- *Operations disrupted*, change in planned assigned runway that results in a change in taxiway route, as this can potentially add additional time in performing airside operations.

This study aims to quantitatively evaluate each of these variables after the ACM is solved by using optimization techniques. The airline fairness variables and the tactical ATM decision are directly correlated. The missed slots variable is directly correlated with the airspace delay, airside delay and tactical ATM decisions. The more delay is given to aircraft, both in the airspace and in the airside, the more likely the flight will lose its own landing/departure slot. Emissions are directly correlated with the airspace delay, as the more aircraft flying in the airspace, the more fuel is burned. Moreover, a change in the planned landing/departure runway could potentially increase the taxiway time, which would increase emissions. Flying at higher speed also impacts the fuel burned by aircraft, however, this was not considered in this work. Lastly, the variable disrupted operations is directly related to the landing/departure runway change. By changing the assigned runways the taxiway routes will also change, leading potentially to extra taxiway times.
The analysis conducted in this paper, not only considers airline fairness variables, but also distinguishes the airlines according to their business model, giving more insights on which category is more affected by the ACM problem optimal solution. In this paper, we distinguished between Full-Service Cost

Carriers (FSCCs), Low-Cost Carriers (LCCs), Cargo Carriers (CaC), Charter Carriers (ChC), and Regional Carriers (RC).

4. Empirical study: CDG case study

The analysis conducted in this study deals with a real case study, namely Paris Charles de Gaulle (CDG) Airport. CDG Airport is one of the major airports in Europe, due to its size, number of passengers transported and air traffic movements. It is the hub of the French carrier Air France and transported 76.2 million passengers in 2019, connecting 328 destinations in 119 countries (Paris Aeroport, n.d.-b).

4.1. CDG airport airside and airspace

CDG airport has four parallel runways. They operate as independent runways, meaning that they can accommodate air traffic movements simultaneously. In real operations two of the runways are used only for landings and the other two only for departures. CDG airport is constituted by three terminals and a complex taxiway network. However, in this study, terminals and taxiway network are characterized by their capacity and occupancy time. Taxiway times are calculated as averages of surveilled taxi times, while terminal times are derived by the original schedule and represent the aircraft turnaround times. Tables 1 and 2 display the capacity of these components and the average times of the taxiway used in the optimization model. Figure 2 depicts the top view of the CDG airside.

Table 1. Ground component capacity

Ground component	Capacity
Landing runway	1
Departing runway	1
Taxiway network	20
Terminal 1	11
Terminal 2	89
Terminal 3	55

Table 2. Average taxiway times [s]

	Runways			
	Landing runways (taxi-in time)		Departure runway (taxi-out time)	
Terminals	27R	26L	26R	27L
Terminal 1	400	535	720	1400
Terminal 2	730	500	890	760
Terminal 3	680	530	880	710

Figure 2. CDG airside.

The TMA of CDG considered in this case study only included aircraft arrival routes. CDG has two routes coming from the north and two coming from the south, with a total of four different entry points for arrivals. Each of the two southern and northern routes converge into two merging points, resulting in two descending paths for each of the two landing runways. Therefore, based on the coming direction (route entry point) and on the landing runway, there are 8 paths in total, as demonstrated in Figure 3.

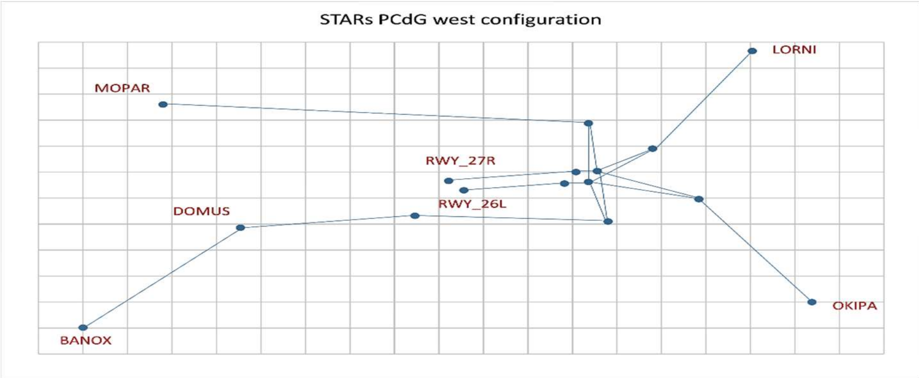

Figure 3. CDG airspace TMA landing routes.

4.2.Airlines types operating at CDG

Since in this paper we study the impact of ACM optimization within the framework of tactical ATM decisions on airlines, we will provide an overview of the airlines flying at CDG, classifying them according to their business model. In CDG there are more than 150 airlines operating (Paris Aeroport, n.d.-a), in Figure 4 and we can see the traffic share per airline type. In Figure 4, we can observe that FSCCs dominate, carrying 84% of the traffic, followed by LCCs, which carry 10% of the operations. The CaC, ChC and RC carriers each contribute 2% to the traffic. Table 3 displays the contribution to the traffic by airline type, broken down into arrival, departure and total number of flights.

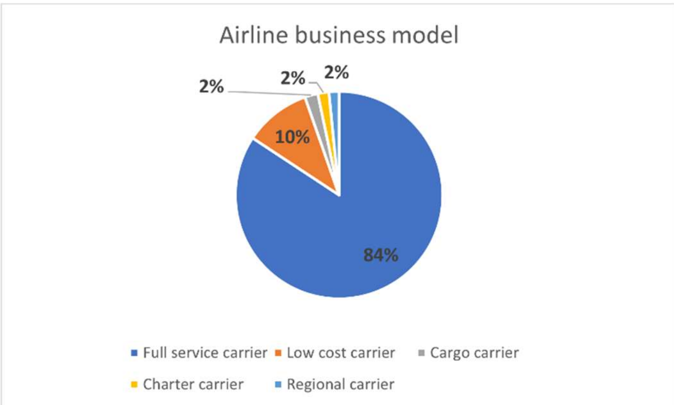

Figure 4. Airline business model categories.

Table 3. Traffic share by airline type.

Airline type	Traffic		
	Arrival	Departure	Total
FSCC	466	476	942
LCC	61	57	118
CaC	8	9	17
ChC	9	9	18
RC	10	10	20

4.3. Experiments and results

In this study, we will analyze how airlines are affected by an ACM optimization process. The ACM solution method is based on the work of Scala, Mujica Mota, Wu, et al., (2021). Two scenarios are analyzed based on the parameter "separation minima". In the first scenario S1, this parameter keeps its default value, while in the second scenario S2, its value has been increased by 30%. The change of this parameter is equivalent to the relaxation of one of the constraints, namely the airspace conflicts, as they directly depend on the setting of the minimum allowed separation between aircraft. Table 4 summarizes the scenario evaluated.

Table 4. Scenarios evaluated

Scenario	Separation minima increase value
S1 (Default)	0%
S2	+30%

4.3.1. Missed slots

We define an arrival or departure slot as a time window of 10 minutes assigned to an aircraft in which it is supposed to land or take off. Therefore, we define a *missed slot* when an aircraft misses the opportunity of using this time window. In the ACM, decisions such as airspace delay or airspace delay directly affect the variable *missed slots*. In Table 5, the values of the variable *missed slots* are shown for each scenario. Table 5 displays that the most affected airline type is the FSCC, which obtains a high number of *missed slots in both scenarios*. The most affected operations, for each of the airline types, are the arrivals. FSCC are also affected by the ACM solution as the percentage of *missed slots* are even higher than FSCC. While the CaC, ChC and RC airline types present high values of percentage of *missed slots*, their absolute values are rather small, as they do not represent a big share of the total traffic (see Table 3). Overall, these results show that for both scenarios S1 and S2, about 50% of slots are missed. Therefore, we can infer that the solutions to the ACM problem impact the airlines' slot allocation planning, which might lead to the slot being lost for the next planned season and might also have negative economic consequences.

Table 5. *Missed slots* per scenario.

Scenario	Airline type	Missed slots					
		Absolute value			Percentage value		
		Arrival	Departure	Total	Arrival	Departure	Total
S1	FSCC	306	153	459	65.66%	32.14%	48.72%
	LCC	43	26	69	70.49%	45.61%	58.47%
	CaC	4	3	7	50.00%	33.33%	41.17%
	ChC	7	6	13	77.77%	66.66%	72.22%
	RC	6	1	7	60.00%	10.00%	35.00%
	Total	366	189	555	66.06%	33.68%	49.77%
S2	FSCC	306	166	472	65.66%	34.87%	50.10%
	LCC	38	20	58	62.29%	35.08%	49.15%
	CaC	2	3	5	25.00%	33.33%	29.41%
	ChC	6	5	11	66.66%	55.55%	61.11%
	RC	10	3	13	100.00%	30.00%	65.00%
	Total	362	197	559	65.34%	35.11%	50.13%

4.3.2. Disrupted operations

In this work we define *disrupted operations* as any deviation from the airside planned operations. In this context, we consider as airside operation the landing/departing runway assignment. Given a preplanned assigned gate, the change in the landing/departing runway changes the taxiway routing from runway to gate. In order to quantify the *disrupted operations*, we compare the two scenarios with the originally planned schedule, Table 6 summarizes the results obtained.

Table 6. *Disrupted operations* values as runways changes.

Scenario		Runway changes	
		Absolute value	Percentage value
S1	Landing runway	267	48.45%
	Departure runway	85	15.12%
	Total	352	31.54%
S2	Landing runway	299	54,16%
	Departure runway	134	23.84%
	Total	433	38.79%

Table 6 points out that the most changed runways are the ones for landing, by 48.45% and 54.16% in S1 and S2, respectively. The departure runways are changed to a lesser extent by 15.12% and 23.84% for S1 and S2, respectively. Fewer changes in runways occur in S1 compared to S2, obtaining in total 31.54% against 38.79% in S2. This can be seen also by the graph in Figure 5, where the runway assignment of the original and the two scenarios is demonstrated. Runway 27R and 26L are used for landings, while Runway 27L and 26R are used for departures. We can notice that in the two optimized scenarios the runways are more evenly distributed than in the original schedule, with a disproportion especially in the runways between Runway 26L (located in the south), which accommodates more than twice the number of landings, and Runway 27R (located in the north).The departure runways assignment does not change much between original schedule and the scenarios S1 and S2, confirming the results from Table 5.

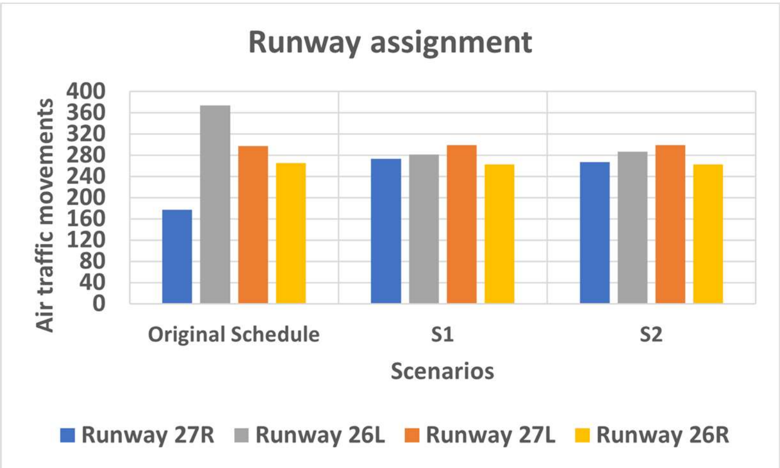

Figure 5. Runway assignment comparison between the original schedule and the optimized scenarios.

4.3.3. Emissions

Emissions related to aircraft fuel consumption are defined by two variables*: extra time flown in the airspace* and *extra taxiway operations in the airside*. The first variable is directly related to the airspace delay used in the ACM, since any delay provided to aircraft will result in longer flight time for the aircraft leading to burning more fuel and creating more emissions. The second variable depends on the runway and terminal assignment, as the taxiway time will differ accordingly. In the ACM described in this work, the runway, both for landings and departures, can be changed affecting the taxiway time.
Table 6 summarizes the main findings about the emissions generated in the airspace and in the airside. The indicators chosen for the evaluation of the airspace emission are the *total and average extra time flown in the airspace*; while concerning the airside we calculated the *total taxiway time and the taxiway time delta,* which indicates the difference of the total taxiway time between the original schedule and the two scenarios. Regarding the airspace emission indicators, the larger their value, the more emission will be released. Similarly, for the airside emission indicators, if the total taxi time for the scenarios S1 and S2 are greater than the original schedule, a positive value of *taxiway time delta* will be generated, which is translated into an extra taxiway time. Conversely, a negative value of taxi time delta represents a reduction in taxiway time. Emission-wise, a positive *taxiway time delta* means more fuel burned and therefore more emissions, and vice versa for a negative *taxiway time delta*.
As it can be seen in Table 6, S1 obtained a higher *total extra time flown in the airspace* (8136.16) than in S2 (7915.08), which is also reflected in a higher *average extra time flown in the airspace per aircraft*. The average values per aircraft are 12.73 and 12.38 for S1 and S2, respectively. The standard deviation is relatively high for both S1 and S2 compared to their average values, indicating high variability in the operations.
Regarding the airside emission indicators, we obtained negative values for the taxiway time delta in both scenarios S1 and S2, meaning that the ACM reduces the emissions due to the aircraft taxiing on the ground. S1 reduces the *total taxiway time* by 7.8% and S2 by 8.1% compared to the original schedule. On the one hand, ACM improves the airside emissions but, on the other hand, worsens them for the airspace emissions.

Table 6. Comparison between the original schedule, S1 and S2 scenarios in terms of emissions generated in the airspace and in the airside.

	Original schedule	S1	S2
Total extra time flown in the airspace [min.]	-	8136.16	7915.08
Average extra time flown in the airspace per flight (standard deviation) [min.]	-	12.73 (10.62)	12.38 (10.55)
Total taxiway time [min.]	5089.55	4687.80	4673.58
Taxiway time delta [min.] (%)	-	-401.75 (-7.8%)	-415.96 (-8.1%)

5. Discussion

By conducting this empirical study on the relation between ACM, tactical ATM decision, and airline operations, we found that ACM has significant impact on airline operations in terms of *missed slots*, *disrupted operations* and *emission*. Most of the results revealed the negative impact on airlines, however, we also found positive aspects which led us to identify the following trade-offs:

- Airline *missed slots* vs Air Traffic Controllers workload: The results indicated that airlines were affected by airspace and ground delay as they missed around 50% of their slots, which had a negative impact. Nevertheless, the optimized solution of the ACM brought advantages to the air traffic controllers by reducing their workload as they will obtain schedules without conflicts.

- D*isrupted operations* of airlines vs runway utilization balance: For many airlines, the landing and departure runways were changed, meaning that a different taxiway routing would take place. Since the terminal was retained as planned, it becomes clear that this would not be ideal, especially for FSCC airlines that have more traffic and therefore more influence on operations (e.g., Air France for CDG) . Conversely, the results demonstrated a more balanced runway utilization, which enhances the efficiency of the infrastructures and avoids potential bottlenecks on the taxiways.
- *Emissions* generated in the airspace vs *emissions* generated in the airside: We found that airspace was affected by extra emission generated by delays given in the airspace. At the same time, the balanced use of the runway reduced taxiway time, which, in turn, reduced airside emissions. A more detailed study on the extent of the emission generated in the airspace and in the airside would be beneficial to evaluate this trade-off.

In conclusion, the abovementioned trade-offs highlight the advantages and disadvantages of implementing the ACM. These trade-offs highlight the different perspective of stakeholders on ACM implementation , with airport operators and air traffic controllers benefiting at the expense of the airlines. This suggests that a thorough solution to the ACM could be achieved if the airline's point of view was also taken into account.

6. Conclusions

In this paper, we have conducted an empirical study to evaluate the impact of implementing the ACM problem on airline operations. To assess the impact, we have defined three main variables, namely *missed slots*, *disrupted operations* and *emissions*. These variables affect the airlines from an operational and economical point of view. The obtained results revealed that these variables are negatively affected as we determined that around 50% of slots were missed by airlines, between 31% and 39% of the taxiway routing operations were modified and extra emissions were generated in the airspace (about extra 12 minutes of time flown in the airspace). The specific case study highlighted that the most affected airline type was the FSCC, which amplifies the negative impact, as these airlines account for the largest share of the airport's traffic. This work sheds light on potential trade-offs that arise when considering different stakeholders' point of view such as airport operators, air traffic controllers and airlines.

Through conducting this study, we learned that variables such as emissions and airlines fairness in terms of slots allocation should be included in an ACM optimization model to provide a more complete solution. This lays the foundation for a future research direction in which the ACM will be extended by considering the previously mentioned variables.

These variables could be considered as cost factors in the ACM objective function, coming up with a multi-objective ACM problem. Due to the contrasting nature of these objectives, methods such as the Pareto front could be implemented for obtaining good solutions.

References

Abdelghany, K. F., Abdelghany, A. F., & Ekollu, G. (2008). An integrated decision support tool for airlines schedule recovery during irregular operations. *European Journal of Operational Research*, *185*(2), 825–848. https://doi.org/10.1016/j.ejor.2006.12.045

Abdelghany, K. F., Shah, S. S., Raina, S., & Abdelghany, A. F. (2004). A model for projecting flight delays during irregular operation conditions. *Journal of Air Transport Management*, *10*(6), 385–394. https://doi.org/10.1016/j.jairtraman.2004.06.008

ACRP. (2012). Guidebook for Airport Irregular Operations (IROPS) Contingency Planning. In *Guidebook for Airport Irregular Operations (IROPS) Contingency Planning*. https://doi.org/10.17226/14667

Airlines. (n.d.). *The impact of COVID-19 on aviation*. Retrieved June 2, 2021, from https://airlines.iata.org/news/the-impact-of-covid-19-on-aviation

Androutsopoulos, K. N., & Madras, M. A. (2019). Being fair or efficient? A fairness-driven modeling extension to the strategic airport slot scheduling problem. *Transportation Research Part E: Logistics and Transportation Review*, *130*, 37–60. https://doi.org/10.1016/j.tre.2019.08.010

Bard, J. F., & Mohan, D. N. (2008). Reallocating arrival slots during a ground delay program. *Transportation Research Part B: Methodological*, *42*(2), 113–134. https://doi.org/10.1016/j.trb.2007.07.005

Bertsimas, D., & Frankovich, M. (2016). Unified optimization of traffic flows through airports. *Transportation Science*, *50*(1), 77–93. https://doi.org/10.1287/trsc.2015.0590

Bosson, C., Xue, M., & Zelinski, S. (2015). Optimizing integrated arrival, departure and surface operations under uncertainty. *Proceedings of the 11th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2015*.

Clarke, M. D. D. (1998). Irregular airline operations: a review of the state-of-the-practice in airline operations control centers. *Journal of Air Transport Management*, *4*(2), 67–76. https://doi.org/10.1016/S0969-6997(98)00012-X

Cohor. (2021). *Paris Charles de Gaulle Airport*. https://www.cohor.org/en/aeroport-paris-charles-de-gaulle-cdg/

Cook, A., Tanner, G., & Lawes, A. (2012). The hidden cost of airline unpunctuality. *Journal of Transport Economics and Policy*, *46*(2), 157–173. https://www.jstor.org/stable/24396360?seq=1

de Wit, J. G., & Burghouwt, G. (2008). Slot allocation and use at hub airports, perspectives for secondary trading. *European Journal of Transport and Infrastructure Research*, *8*(2), 147–164. https://doi.org/10.18757/ejtir.2008.8.2.3339

Dray, L. (2020). An empirical analysis of airport capacity expansion. *Journal of Air Transport Management*, *87*, 101850. https://doi.org/10.1016/j.jairtraman.2020.101850

EU. (n.d.). *EUR-Lex - 31993R0095 - EN - EUR-Lex*. Retrieved June 2, 2021, from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:31993R0095

EU. (2016). *Research for TRAN Committee - Airport slots and aircraft size at EU airports*.

EUROCONTROL. (2020). *EUROCONTROL Five-Year Forecast 2020-2024 European Flight Movements and Service Units Three Scenarios for Recovery from COVID-19*.

EUROCONTROL. (2021). *Comprehensive Assessment of COVID-19's Impact on European Air Traffic*. https://www.eurocontrol.int/publication/eurocontrol-comprehensive-assessment-covid-19s-impact-european-air-traffic

Guépet, J., Briant, O., Gayon, J. P., & Acuna-Agost, R. (2017). Integration of aircraft ground movements and runway operations. *Transportation Research Part E: Logistics and Transportation Review*, *104*, 131–149. https://doi.org/10.1016/j.tre.2017.05.002

IATA. (2020). *European Air Transport COVID-19 Impacts and Expected Recovery to be Worse than other Global Regions*. https://www.iata.org/en/pressroom/pr/2020-12-10-01/

ICAO. (2012). *WORLDWIDE AIR TRANSPORT CONFERENCE (ATCONF)*. www.icao.int/meetings/atconf6.

Ivanov, N., Netjasov, F., Jovanović, R., Starita, S., & Strauss, A. (2017). Air Traffic Flow Management slot allocation to minimize propagated delay and improve airport slot adherence. *Transportation Research Part A: Policy and Practice*, *95*, 183–197. https://doi.org/10.1016/j.tra.2016.11.010

Jacquillat, A., & Odoni, A. R. (2018). A roadmap toward airport demand and capacity management. *Transportation Research Part A: Policy and Practice*, *114*, 168–185. https://doi.org/10.1016/j.tra.2017.09.027

Jiang, Y., Liao, F., Xu, Q., & Yang, Z. (2019). Identification of technology spillover among airport alliance from the perspective of efficiency evaluation: The case of China. *Transport Policy*, *80*, 49–58. https://doi.org/10.1016/j.tranpol.2019.05.004

Jimenez Serrano, F. J., & Kazda, A. (2017). Airline disruption management: Yesterday, today and tomorrow. *Transportation Research Procedia*, *28*, 3–10. https://doi.org/10.1016/j.trpro.2017.12.162

Kang, L., & Hansen, M. (2018). Assessing the impact of tactical airport surface operations on airline schedule block time setting. *Transportation Research Part C: Emerging Technologies*, *89*, 133–147. https://doi.org/10.1016/j.trc.2018.01.018

Kjenstad, D., Mannino, C., Nordlander, T. E., Schittekat, P., & Smedsrud, M. (2013). Optimizing AMAN-SMAN-DMAN at Hamburg and Arlanda airport. *SIDs 2013 - Proceedings of the SESAR Innovation Days*.

Lian, G., Zhang, Y., Xing, Z., Luo, Q., & Cheng, S. (2019). A new dynamic pushback control method for reducing fuel-burn costs: Using predicted taxi-out time. *Chinese Journal of Aeronautics*, *32*(3), 660–673. https://doi.org/10.1016/j.cja.2018.12.013

Liu, L., Zhang, Y., Liu, L., & Xing, Z. (2017). Congestion pricing for aircraft pushbackslot allocation. *PLoS ONE*, *12*(1), e0170553. https://doi.org/10.1371/journal.pone.0170553

Løve, M., Sørensen, K. R., Larsen, J., & Clausen, J. (2002). Disruption management for an airline - Rescheduling of aircraft. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *2279 LNCS*, 315–324. https://doi.org/10.1007/3-540-46004-7_31

Ma, J., Delahaye, D., Sbihi, M., Scala, P., & Mujica Mota, M. A. (2019). Integrated optimization of terminal maneuvering area and airport at the macroscopic level. *Transportation Research Part C: Emerging Technologies*, *98*. https://doi.org/10.1016/j.trc.2018.12.006

Malandri, C., Mantecchini, L., Paganelli, F., & Postorino, M. N. (2020). Impacts of unplanned aircraft diversions on airport ground operations. *Transportation Research Procedia*, *47*, 537–544. https://doi.org/10.1016/j.trpro.2020.03.129

Miranda, V. A. P., & Oliveira, A. V. M. (2018). Airport slots and the internalization of congestion by airlines: An empirical model of integrated flight disruption management in Brazil. *Transportation Research Part A: Policy and Practice*, *116*, 201–219. https://doi.org/10.1016/j.tra.2018.06.008

O'Connell, J. F., & Warnock-Smith, D. (2013). An investigation into traveler preferences and acceptance levels of airline ancillary revenues. *Journal of Air Transport Management*, *33*, 12–21. https://doi.org/10.1016/j.jairtraman.2013.06.006

Pacagnella, A. C., Hollaender, P. S., Mazzanati, G. V., & Bortolotto, W. W. (2021). Efficiency drivers of international airports: A worldwide benchmarking study. *Journal of Air Transport Management*, *90*, 101960. https://doi.org/10.1016/j.jairtraman.2020.101960

Paris Aeroport. (n.d.-a). *Airlines directory - Paris Aéroport*. Retrieved June 25, 2021, from https://www.parisaeroport.fr/en/passengers/flights/airlines

Paris Aeroport. (n.d.-b). *Paris-Charles de Gaulle - Network in France - Groupe ADP - Paris Aéroport*. Retrieved June 25, 2021, from https://www.parisaeroport.fr/en/group/group-strategy/our-strategy/in-brief/platforms/paris-charles-de-gaulle

Ribeiro, N. A., Jacquillat, A., Antunes, A. P., Odoni, A. R., & Pita, J. P. (2018). An optimization approach for airport slot allocation under IATA guidelines. *Transportation Research Part B: Methodological*, *112*, 132–156. https://doi.org/10.1016/j.trb.2018.04.005

Rodríguez-Díaz, A., Adenso-Díaz, B., & González-Torre, P. L. (2019). Improving aircraft approach operations taking into account noise and fuel consumption. *Journal of Air Transport Management*, *77*, 46–56. https://doi.org/10.1016/j.jairtraman.2019.03.004

Rosenberger, J. M., Schaefer, A. J., Goldsman, D., Johnson, E. L., Kleywegt, A. J., & Nemhauser, G. L. (2000). SimAir: A stochastic model of airline operations. *Winter Simulation Conference Proceedings*, *2*, 1118–1122. https://doi.org/10.1109/WSC.2000.899074

Samà, M., D'Ariano, A., & Pacciarelli, D. (2013). Rolling horizon approach for aircraft scheduling in the terminal control area of busy airports. *Transportation Research Part E: Logistics and Transportation Review*, *60*, 140–155. https://doi.org/10.1016/j.tre.2013.05.006

Scala, P., Mujica Mota, M., & Delahaye, D. (2021). Air Traffic Management during Rare Events Such as a Pandemic: Paris Charles de Gaulle Case Study. *Aerospace*, *8*(6), 155. https://doi.org/10.3390/aerospace8060155

Scala, P., Mujica Mota, M., Ma, J., & Delahaye, D. (2020). Tackling Uncertainty for the Development of Efficient Decision Support System in Air Traffic Management. *IEEE Transactions on Intelligent Transportation Systems*, *21*(8), 3233–3246. https://doi.org/10.1109/TITS.2019.2924981

Scala, P., Mujica Mota, M., Wu, C. L., & Delahaye, D. (2021). An optimization–simulation closed-loop feedback framework for modeling the airport capacity management problem under uncertainty. *Transportation Research Part C: Emerging Technologies*, *124*, 102937. https://doi.org/10.1016/j.trc.2020.102937

Schummer, J., & Abizada, A. (2017). Incentives in landing slot problems. *Journal of Economic Theory*, *170*, 29–55. https://doi.org/10.1016/j.jet.2017.04.003

Simaiakis, I., Khadilkar, H., Balakrishnan, H., Reynolds, T. G., & Hansman, R. J. (2014). Demonstration of reduced airport congestion through pushback rate control. *Transportation Research Part A: Policy and Practice*, *66*(1), 251–267. https://doi.org/10.1016/j.tra.2014.05.014

Sun, F., Qian, J., & Qian, G. (2018). Optimization of aircraft pushback slot allocation under multi-hotspot restriction. *Proceedings of 2018 the 8th International Workshop on Computer Science and Engineering, WCSE 2018*, 19–23. https://doi.org/10.18178/wcse.2018.06.004

T2RL. (2016). *Shaping the future of Airline Disruption Management (IROPS)*. https://amadeus.com/documents/en/airlines/white-paper/shaping-the-future-of-airline-disruption-management.pdf

Wang, Y., Zhan, J., Xu, X., Li, L., Chen, P., & Hansen, M. (2019). Measuring the resilience of an airport network. *Chinese Journal of Aeronautics*, *32*(12), 2694–2705. https://doi.org/10.1016/j.cja.2019.08.023

Warnock-Smith, D., O'Connell, J. F., & Maleki, M. (2017). An analysis of ongoing trends in airline ancillary revenues. *Journal of Air Transport Management*, *64*, 42–54. https://doi.org/10.1016/j.jairtraman.2017.06.023