Chapter 4

A review of sustainability in aviation: a multi-dimensional perspective

Daniel Guimarans
Amsterdam University of Applied Sciences, Netherlands

Pol Arias
Loughborough University, United Kingdom
Queen Mary University of London, United Kingdom

Maurizio Tomasella
University of Edinburgh, United Kingdom

Cheng-Lung Wu
UNSW Sydney, Australia

Abstract

The notable growth of air transportation in recent years has led to increasingly congested airports and airspace. Working at nearly maximum capacity involves risks that normally translate into operational disruptions, increasing costs, and lower service quality. Airlines also participate in a highly competitive market, where margins are diminished and streamlined operations are key to reduce their corresponding costs. In this chapter, we review several studies and applications aimed at better managing existing infrastructure and operations. Many of these works are focussed on efficiently assigning resources to release unused capacity, reduce costs, and increase system's resilience to unexpected events for sustainable transport infrastructure development. We also explore several initiatives proposed to enhance airspace capacity (e.g. SESAR program), while reducing at the same time operational and environmental costs. Efficient management, together with these initiatives, are key to ensure a sustainable growth of the aviation sector in the next few decades.

Key Words: *Aviation, Air Transport, Capacity, Sustainability, Resilience, Disruption Management, Operations Research, Operations Management*

1. Introduction

In 2013, the International Civil Aviation Organisation (ICAO) reported over 3 billion passengers worldwide, a number anticipated to surpass 7 billion passengers by 2035 (IATA, 2017) (see Figure 1). These figures are confirmed by the forecast of main aircraft manufacturers, which predict a doubling in aircraft capacity over the next 15 years (Airbus, 2017; Boeing, 2017). This increasing pressure in the aviation network poses many challenges, as many airports and airspace will be hitting their capacity ceiling in the near future.

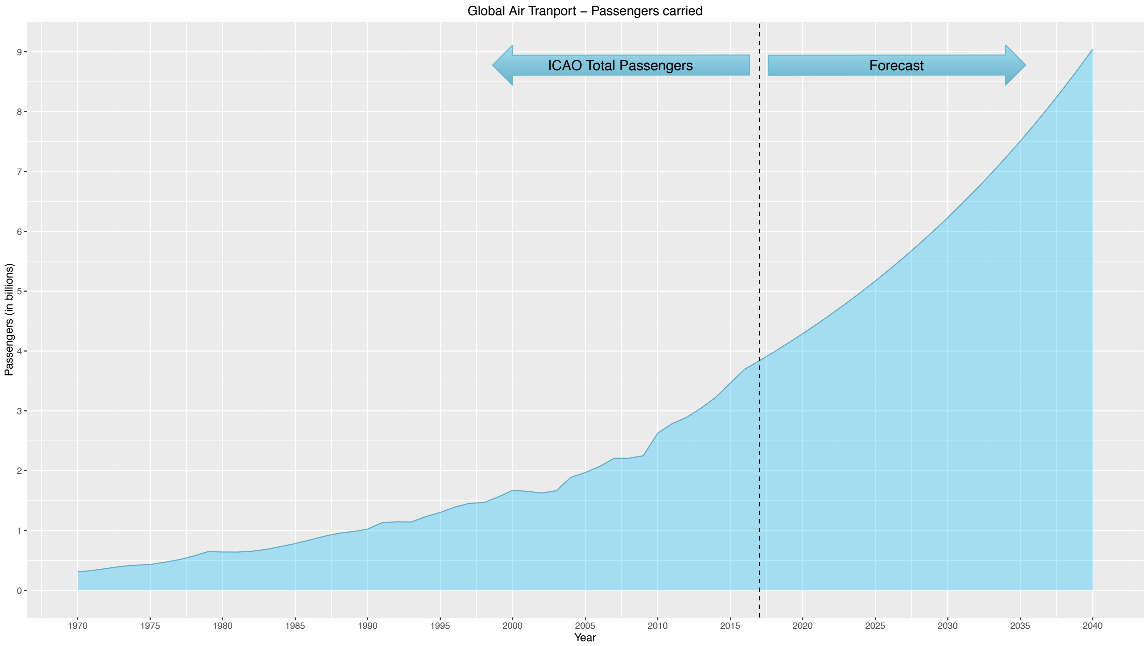

Figure 1: Reported and forecast global passenger traffic (in billion passengers).

Hence, the aviation network requires the introduction of operational policies and managerial directives to improve efficiency, new technologies that aim at incrementing existing capacity, and infrastructure investment in the form of new airports or capacity expansion plans in order to cope with air traffic trends. However, an uncontrolled growth may generate additional congestion issues (Janić, 2017). Effective Air Traffic Management (ATM) is required to avoid airspace congestion and, in particular, in Terminal Manoeuvring Areas (TMA) around busy airports. Bad management of these airspaces leads into additional noise and green-house gas emissions, already a sensitive issue in most countries. Delays derived from congestion may also prevent passengers from having access to their flights at the desired time and location, hindering the airports' major function in the network.

Air traffic is not divided evenly among all airports, with 50% of the measured traffic handled by 3% of the airports, and 90% of traffic handled at 24% of the airports (Gelhausen et al., 2013). It seems obvious that using remaining underutilised infrastructure would ease pressure off the most congested airports, but the reality is that geographical location of served markets, business models in aviation, interests and regulations deem this option as unsuitable. Additionally, legacy plays an important role that prevents this shift, as it has a major impact on the adaptability of aviation business models.

All these aspects require an approach that ensures sustainability of aviation operations in order to cope with demand growth. Sustainability is often simplified to just focussing on the evaluation of environmental costs, while in fact it has multiple dimensions, of which in this chapter we deliberately focus on the following:

- *Sustainable growth*: as a first step to quantify the required growth, it is important to determine current capacity, its limiting factors, and match it to forecast demand. A mismatch between demand and supply may easily derive into congestion issues (Janić, 2017). Better management of existing capacity can extend assets life with limited investment. Capacity studies may aid at directing infrastructure investments in the most efficient way.
- *Environmental sustainability*: aviation operations are known to have a significant impact in terms of green-house gas emissions and noise. Technology advances, results from projects such as SESAR (Eurocontrol, 2010a) and NextGEN (FAA, 2016), and optimisation of current operations may play a big role on reducing these emissions; e.g. reduced fuel consumption due to uninterrupted taxis, less gate blockages, point-to-point optimised trajectories, reduced TMA holding stacks, etc.
- *Socio-political sustainability*: aviation and airports in particular are main drivers of local and regional economies. This comes at a price: local residents often need to deal with high levels of noise, pollution, traffic congestion, etc. Thus, local authorities need to balance economic growth with regional developments, knowing that expansion of aviation activities has a major impact on urban planning, ground transportation and quality of living. Carefully analysing expansion projects to be undertaken by means of simulation may help determining the most efficient way of managing infrastructure; e.g. London multi-airport system (Irvine et al., 2015). The weight of legacy is also important, as new developments and policies may need to break with well-rooted practices that could be hindering efficiency (e.g. noise distribution around Amsterdam Schiphol airport or London Heathrow's alternating runway operations). New initiatives to

solve or work around these problems may face a lot of inertia from local economy, authorities, and communities.

- *Operational sustainability*: aviation operations rarely develop according to plan. The same nature of aviation implies the existence of inherent variability and uncertainty, mainly due to operational practices, congestion, weather conditions, legacy rights, etc. On the one hand, schedules and plans need to be developed in a way that allow revenues in a market where margins are generally quite low. On the other hand, these plans should also be *reliable*, that is, able to absorb most disturbances without causing a knock-on effect. Robust optimisation, simulation, and accurate forecasting should help mitigating disruption effects and reducing system's vulnerability. Nevertheless, regardless of industry's best efforts to avoid disruptions, they are inherent to aviation. Strategies should be developed to help operations get back to schedule in the minimum time possible, while mitigating adverse effects. That is, designing strategies to make aviation systems as *resilient* as possible. In order to limit the high involved costs (Eurocontrol, 2010b), disruption management policies should focus on efficiently using existing and available resources rather than introducing new ones (e.g. ferrying an empty aircraft), or outsourcing services only when strictly necessary (e.g. rebooking passengers with a different airline).

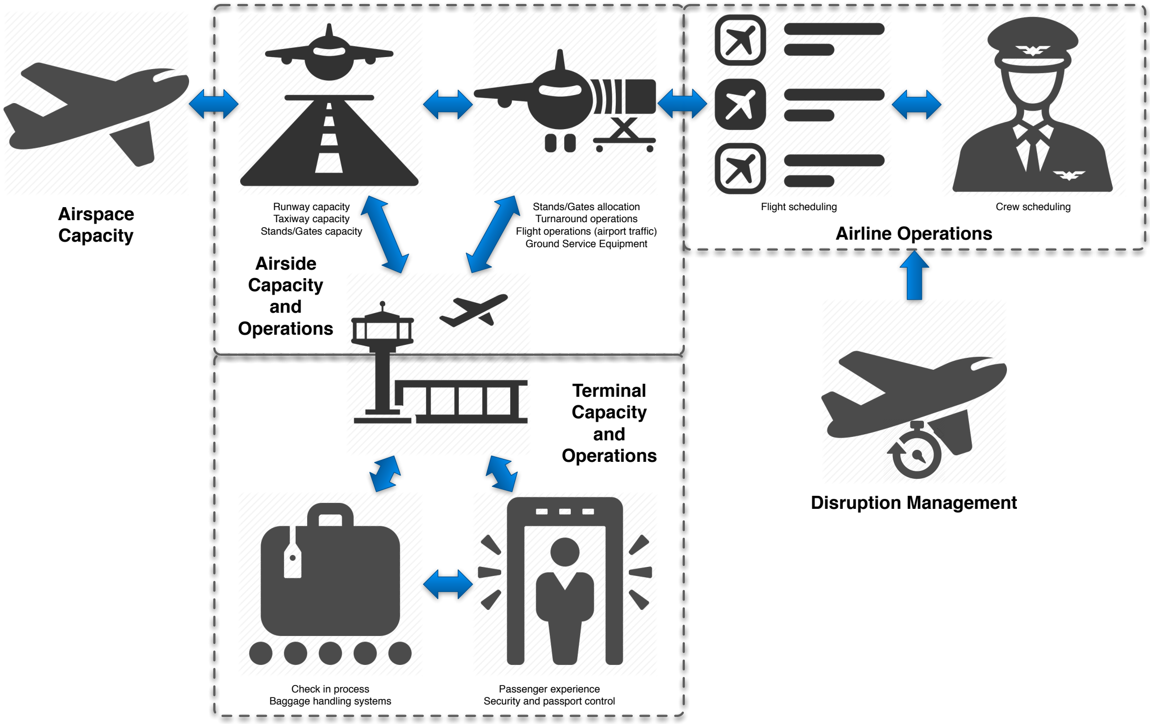

Figure 2: Overview of the topics covered in this chapter.

In the following sections, we provide an overview on the above-mentioned sustainability dimensions for most aviation processes. Figure 2 provides the conceptual schema of the topics covered in this chapter. We start in Section 2 with a brief description of airspace capacity and main projects aimed at solving and managing congestion. Our review mainly adopts an Operational Research (OR) / Management Science (MS) perspective, a focus we maintain throughout the chapter. Therefore, we review OR/MS proposals whose goal is to maximise efficiency and sustainability of operations given current capacity limitations. In Section 3, we study airport capacity and that of its key constraining elements, namely the runway(s) system and buffer capacity linked to stands and gates. We also discuss technology enablers and the adaptability of airports to ever-changing operating requirements. The following section focusses on sustainability of airport operations, from aircraft turnaround to terminal processes and resource allocation. This review covers technology and policy implementations aimed at mitigating environmental effects while guaranteeing the required level of service to the airport customers. Section 5 presents an overview of mechanisms and procedures airlines may implement to reduce their vulnerability to unexpected perturbations in their plans. On the contrary, the following section studies strategies for airlines to cope with disruptions once they happen, trying to minimise the time required to resume regular operations. Finally, we point at some promising areas of current and future research on sustainable aviation operations.

2. Airspace capacity

The increasing pressure in the air transport network due to traffic growth is aggravating congestion problems, especially in European and American airports and airspace. Figure 3 provides an example of the saturation the European airspace experiences on any given day. Airspace capacity is normally defined as the number of aircraft that can fit into Air Traffic Control (ATC) sectors in a specific time frame, given separation and safety standards (Nosedal et al., 2014). When traffic exceeds the arrival and/or departure airports' capacity, or that of the different air sectors the flight needs to traverse, congestion-caused delays start to arise throughout the network.

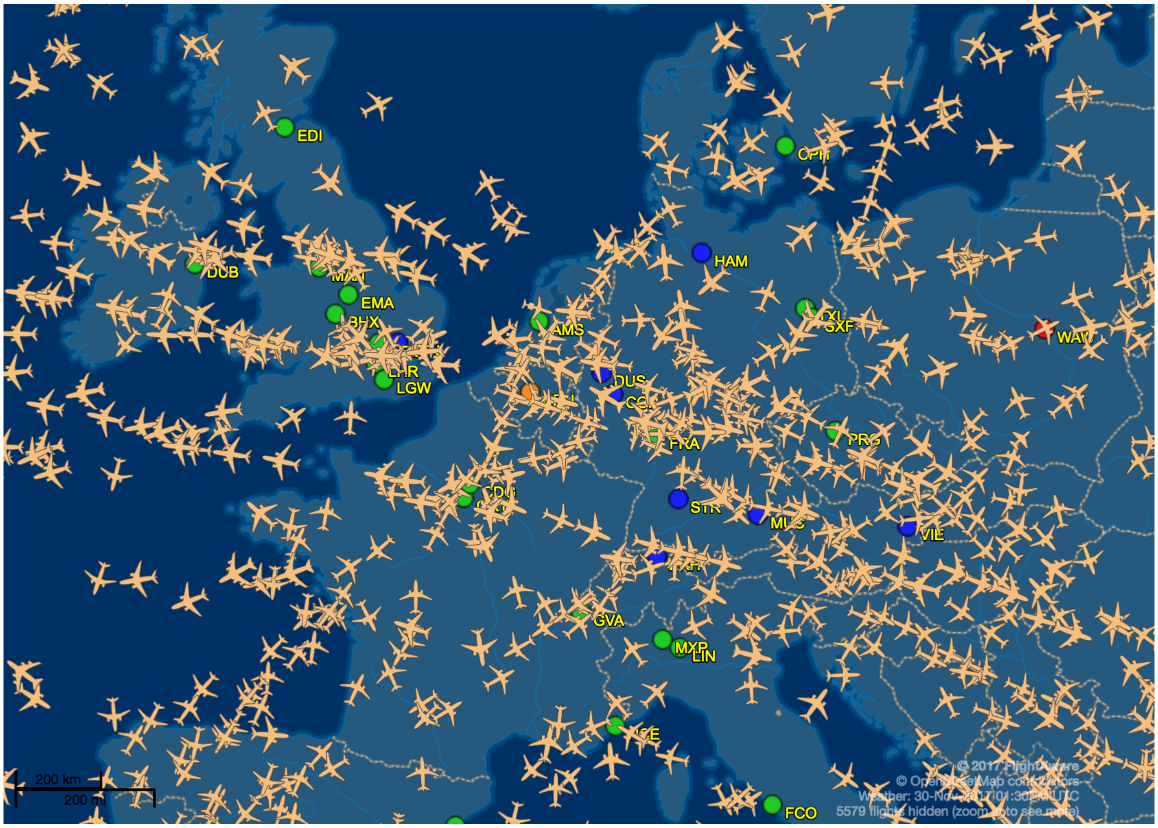

Figure 3: Saturation of European airspace, around the four busiest airports in Europe: London Heathrow (LHR), Paris Charles de Gaulle (CDG), Amsterdam Schiphol (AMS), and Frankfurt (FRA). (Source: www.flightaware.com)

Initiatives like SESAR in Europe (Eurocontrol, 2010a), and NextGEN in the USA (FAA, 2016), are aimed at enabling a better utilisation of the existing airspace capacity. These programs promote the introduction of new technologies and standards to effectively increase or better manage current airspace capacity. In Europe, where the problem of airspace capacity is more acute, the SESAR program has led to redefining airspace regions based on operational requirements, regardless of existing country boundaries (Eurocontrol, 2008). These new standards allow managing the airspace as a single continuum and the introduction of so-called Business Trajectories (BTs), or "free routes".

Generally, if an imbalance is predicted between traffic demand and available capacity at either airports or the airspace, ATM authorities may issue a regulation to maximise the flow in regulated sectors. Alternatively, controllers may issue instructions at the operational or tactical level consisting of holding planes in stacks, or applying either route diversions or speed variations (Nosedal et al., 2014). The former may be more desirable than the latter due to their lower cost in economic and safety terms (Agustín et al., 2010). When such delays are imposed on departing flights, they are often known as *green delays*, due to savings on fuel consumption, gas emissions, and noise reduction when compared to airborne delays. However, as most aircraft are used for consecutive flights, these delays may still have an impact on the airline's network, their operations, and crew availability.

Given the benefits of transferring airborne delays to the ground, there is a large body of research devoted to the subject. Agustín et al. (2010) provide a comprehensive overview on the different problem variants and the methodologies used to tackle them. Seminal works focussed on solving the ground-holding problem for a single or multiple airports, while more recent works have incorporated air sectors flow management. According to the authors, this is so because the problem was first studied in USA, where airspace congestion is less acute than in Europe. Whichever the case, air traffic saturation may pose an important challenge for sustainability of current and forecast operations. Without initiatives like SESAR or NextGEN, airspace congestion, and especially airport capacity limitations, could be seriously hindering air transport performance in the immediate future.

3. Airport capacity and constraints

Airport capacity may be broadly defined as the volume of operations an airport can handle in a given time frame. Although a conclusive definition of capacity is lacking, it is still the main driving concept for airport management at operational, tactical and strategic level.

The work of Idris (2001) examined the interaction between key elements of an airport, including runways, taxiways, stands, and gates. Focussing on departures at Boston's Logan Airport, the author concluded that runways constitute the main bottleneck in the flow of airport operations and their management critically impacts the system's efficiency. The next capacity constraining resource is represented by the airport stands (parking positions), as it is normally assumed that an airport will have enough taxiway capacity to absorb the runway flow.

This section thus discusses principally runway/taxiway capacity and its impact on airport capacity. The section concludes with further thoughts on the role of stand and gate capacity and their impact on airport capacity, as well as considerations of long-term airport capacity management issues.

3.1. Runway / taxiway capacity

Defining capacity of an airport system is a key element for carrying out daily operations. It is used for tactical decisions such as the number of slots offered at the airport (i.e. available time periods for landing/take-off operations) and controlling daily operations. Despite its importance, the definition of a generally accepted procedure to calculate capacity seems elusive (Janić, 2017). The International Air Transport Association (IATA) proposed several alternative capacity definitions (Pitfield & Jerrard, 1999):

- *Declared capacity* is the stated limiting capacity of the airport in aircraft movements (i.e. either departures or arrivals) per hour.
- *Sustained capacity* is the maximum runway throughput that can be achieved over a sustained period of time when aircraft operate under instrument flight rules (IFR), under a specific traffic mix, in good weather conditions, with good air traffic and runway management, but in accordance with safety requirements and with an acceptable maximum delay for an agreed limited period of time. Acceptable delays are those airlines can accept, due to their compatibility with their schedules and aircraft utilisation policies. Tolerance for higher delays may increase the airport capacity, but at the cost of increasing congestion and making it less attractive for airlines.
- *Unconstrained capacity* is the maximum runway throughput which can be achieved under ideal conditions, considering only safety requirements.

An airport's runway capacity or maximum throughput is normally expressed as the hourly rate of aircraft operations which may be reasonably accommodated by the runway system, be it single or a combination of runways. This capacity is mainly dependent on the runway occupancy times and separation standards applied to successive aircraft in the traffic mix. Other elements affecting runway capacity include availability of exit taxiways, aircraft types operating at the airport, sequencing of aircraft, ATC policies, weather conditions, runway configuration and spacing between parallel runways, mode of operation (segregated or mixed), etc. The airport capacity is normally tied to runway capacity, as this is identified as the main constraint for airport operations (Idris, 2001). Although other criteria may also be applied (e.g. terminal capacity for passengers, availability of stands, noise restrictions, night curfews, etc.), in practice declared capacity is typically set to 85-90% of maximum runway throughput (Zografos et al., 2017), i.e. 85-90% of sustained runway capacity under given local conditions.

Declared capacity and, by extension, runway capacity, play a critical role in the main demand management mechanism: slot scheduling. In practice, declared capacity controls the number of slots available for allocation per unit of time. A poor allocation scheme may lead to congestion problems (Zografos et al., 2017). These translate into additional costs due to delays, fuel consumption, and increased noise and emissions. These issues may be aggravated as a consequence of the inability of an airport to match requested slots with those eventually allocated to airlines, generally due to capacity shortage over certain periods. The close interdependency of slot scheduling and declared capacity levels turns estimation of airport capacity into a key procedure to ensure sustainability of operations for all the involved stakeholders.

Runway capacity may be determined by means of analytical and/or simulation models. Analytical models tend to be over-simplified mathematical representations of airport and airspace characteristics, and are mainly used for policy analysis, strategy development and cost-benefit evaluation (Bazargan et al., 2002). On the other hand, simulation models permit obtaining more realistic estimates of capacity and have been widely used to study different airports and their corresponding expansion projects (Bazargan et al., 2002; Irvine et al., 2015; Pitfield & Jerrard, 1999).

Monte-Carlo (MC) simulation models are among the most popular approaches to study the airport environment and determine runway capacity. For example, Pitfield & Jerrard (1999) used MC simulation to estimate the unconstrained capacity at the Rome Fiumicino International Airport. More recently, Irvine et al. (2015) also used MC simulation to evaluate the different alternatives to increase capacity at London's multi-airport system. The authors carried out an extensive study to determine the capacity increase derived from: developing a new hub airport in the Thames Estuary; constructing a third runway at Heathrow or extending one of its existing runways; expanding Heathrow westwards; building a second runway either at Gatwick or Stansted; or, optimising runway utilisation at Heathrow by permanently operating in mixed-mode (i.e. permanent arrival/departure operation instead of departure-only during certain periods). Interestingly, the authors evaluate the proposals beyond the obtained maximum capacity and consider additional factors, such as noise increase. Hence, although the new hub airport would be the most effective way to increase capacity, the estimated financial and environmental costs indicate a poor rate of return. Mixed-mode operations at Heathrow represents the least expensive option and yields a small increase of capacity, but imposes an additional noise burden on airport residents. In light of these results, the authors conclude that any future decision about airport capacity "needs to consider not only the practicalities of airport operations and optimal airfield configurations and locations, but also the myriad socio-economic and environmental implications of any development at both local and global scales".

In comparison to MC simulation, discrete-event simulation models try to replicate more accurately traffic flows and aircraft movements within the airport. This allows representing actual constraints, uncertainties and interactions, although at a higher computational and development cost. This kind of techniques have also been used to determine capacity and study scheduling policies at different airports (Bazargan et al., 2002).

Runway capacity and, by extension, airport capacity require efficient management to cope with current and forecast demand. Ensuring an effective matching of existing capacity to demand is crucial to support medium and long-term growth in a sustainable way (Janić, 2017). Short-term approaches to enable a more efficient utilisation of existing runway capacity include economic-based (e.g. pricing congestion) and operational solutions (e.g. scheduling). Technical, technological and operational innovations (e.g. time-based approach) permit increasing runway capacity in the medium-term, while infrastructure investment (e.g. building new additional runways) and operational changes (e.g. multi-airport systems) represent a long-term approach to capacity increase (Fasone & Maggiore, 2014).

Charging (or pricing) congestion at airports usually implies raising the landing fees during the congestion period. These fees are applied to those aircraft more likely to impose excessive delays and related costs to successive aircraft (Janić, 2017). The main goal is to incentivise airlines to reschedule some flights to off-peak periods or, in some cases, prevent these flights from accessing the airport. As such, this approach does not increase the existing runway capacity, but provides a more efficient utilisation by releasing some capacity during peak periods. Mixing this congestion pricing with other externalities, such as noise or emissions, has proved relatively effective for capacity management and has deserved substantial efforts from the research community (Janić, 2005; 2017).

An optimal or pseudo-optimal schedule of runway operations may yield an operational increase of runway utilisation, as well as savings in fuel costs and a reduction of delays (Farhadi et al., 2014). These scheduling problems try to determine effective aircraft sequencing over one or multiple runways subject to operational constraints (e.g. adopted standard for aircraft separation). Most approaches have their roots on research works on machine scheduling, and make use of popular solution techniques such as dynamic programming, branch-and-X algorithms, or tailored heuristics and metaheuristics (Bennell et al., 2011). Most of these studies tend to focus on a quite limited problem, defining sequences for either arrivals or departures in isolation (Farhadi et al., 2014). However, they have proved effective when applied or tested at different airports. For example, Farhadi et al. (2014) developed different methods that yielded near-optimal schedules for the new Doha (Hamad) International Airport. Malik & Jung (2016) developed different methodologies aimed at real-time decision making that were later simulated on the east side of Dallas/Fort Worth International Airport. Rodríguez-Díaz et al. (2017) tackled the sequencing problem aiming at minimising the deviation from scheduled times, rather than maximising throughput or minimising the makespan for all scheduled operations. The authors reported their simulated annealing algorithm was able to improve by 30% the time delays registered at London Gatwick Airport.

Unfortunately, most approaches found in the literature for aircraft sequencing omit the inherent uncertainty present in real operations. Heidt et al. (2016) showed that protection against uncertainties during the plan design leads to considerably more reliable plans. Two different approaches may be adopted to deal with such uncertainty: stochastic optimisation can be used to obtain good average solutions, or robust optimisation can be used to compute more reliable schedules that are less sensitive to perturbations. As the authors state, such approaches have hardly been considered for solving runway scheduling problems. Given the uncertainty naturally involved in aviation, this gap shows a clear need for future research efforts devoted to achieve more robust and sustainable operations.

Usually, it is assumed there exists enough taxiway capacity to sustain runway operations. In particular, it is generally assumed that there are enough high-speed exits to absorb all scheduled traffic, without taxiway capacity or configuration imposing any constraint on runway operations (Bazargan et al., 2002). Nevertheless, Ravizza et al. (2012) proved that good taxiway management can have an influence on airport's efficiency and that a good estimation of taxi times can help mitigate delays and environmental effects of ground operations. In this line, several authors have developed models to either forecast taxi times, determine optimal taxi routes, or examine the influence of different surface management policies. On the one hand, predictive models that allow computing taxi times have been developed for specific airports, such as Barcelona-El Prat (Lordan et al., 2016), Stockholm-Arlanda and Zurich (Ravizza et al., 2012). Most of these studies focus on segregating the effects of route-specific decisions (adopted taxi route) from interaction-specific (traffic-related) aspects, in order to understand the dynamics of the specific airport system. On the other hand, some research has been devoted to solve the ground routing problem, consisting in scheduling aircraft movements between the runway(s) and the assigned parking stands, while respecting safety constraints (Guépet et al., 2016; Ravizza et al., 2014; Yu et al., 2013). Finally, other management initiatives to reduce aircraft fuel consumption and taxiway congestion have been studied (see Section 4.2). As these studies show, more predictable taxi times and reduced ground congestion, combined with efficient runway management, are the key for effective and sustainable capacity utilisation.

3.2. The role of stands and gates for airport capacity

A great portion of airport capacity is thus provided by an airport's aircraft processing capability for take-off and landing operations, particularly by runway capacity. The next level down in the hierarchy of most constraining airport resources (Idris, 2001) is surely represented by the number and types of aircraft stands (parking positions) and gates (for passenger boarding/disembarking), particularly the former. The number of aircraft stands available represents a form of buffering capacity of an airport in terms of aircraft processing. Airport capacity can be negatively impacted by stand shortage, especially during peak hours.

At the next level of (even more detailed) analysis, the number of gates of course also affect the capacity of the airport to process inbound/outbound passenger flows at the air/ground boundary. While many stands and related gates will be physically attached to the terminal - we speak then of *contact* stands/gates, *remote* stand locations are often used to enhance the available buffering capacity. They are in principle cheaper to build than additional contact stands, which require terminal extensions, and can affect airport capacity to some extent. On the other hand, they increase the operational complexity of the airfield, which tend to negatively impact passenger experience, with additional passenger movements to be realized by coach/bus connecting remote stands to either dedicated "remote" gates or one of the existing contact gates, when the latter are available for use.

Effective and efficient models and algorithms for the assignment of available stands and gates on the day of operation, especially at disrupted times, are crucial in all those situations where runway capacity is not saturated and the binding constraints to higher airport capacity are posed by a fully utilised apron buffering capacity. We will discuss some of these models and algorithms in Section 4.3.

3.3. Sustainable airport development in the long-term

When it comes to airport development (master planning), capacity – defined as units of service/production in a given time interval, e.g. aircraft movements per day - is not all that is required. Examples from other research areas do exist to shed additional light on this issue. For instance, research on manufacturing systems has long established (Koren et al., 1999) that functionality – i.e. "The purpose something is designed or expected to serve; the function or functions that something is designed to perform." (OED, 2017), also plays a key role. It does even more in environments where system requirements may change unpredictably and unexpectedly over time. Of course, capacity and functionality are tightly linked together and technology options available to system designers concur in determining long-term system success.

In the realm of airport management, every time a new technology is developed, or a new law/regulation enforced, airport infrastructure choices must be made to ensure compliance with the novel requirements. More than a decade ago, when A380s started operating, airports were not necessarily equipped with the needed infrastructure, e.g. air-bridges/facilities for passenger boarding, size of contact stands/taxiways/etc. More recently, so called Standard 3 technologies have been mandated for automated screening of outbound baggage, which require vastly modified baggage flows and come with an array of technical specifications that render many existing airport baggage halls unsuitable for operation. There is currently a lack of OR/MS methodologies to aid airport master planning in such a way that airports are made more easily reconfigurable, in terms of time and cost, in the long run, while adapting to many such major changes in requirements. Methodologies of decision making / optimisation under uncertainty may play an important role in this sense. Existing manuals for airport development/master planning (see e.g. IATA, 2014b) fail to provide the needed support, as they: suggest very specific recommendations regarding state-of-the-art technologies; limit option choices available to decision makers to restricted feasible domains; and do not support the type of dynamic, sequential decision making – especially under uncertain evolutions of airport requirements, that would be required to tackle such decision support problems. We believe all the above provides for the identification of an interesting gap area for aviation researchers to tap into and make considerable impact on practitioners in the field.

4. Airport operations

Airport operations include: passenger terminal operations, such as check-in services, security screening and retail; aircraft ground operations, such as fuelling, catering and services for turnaround aircraft; and flight operations, such as aircraft ground movement control, take-off and landing. Since most major airports in the world are constrained by land size and capacity, with the forecast increase of demand in future aviation, there is a growing focus on utilising airport resources by providing efficient operations through technologies, streamlined procedures, collaborative decision making, and real-time information sharing (Bevilacqua et al, 2015; Salaris and Pascual, 2012). This section reviews some of the main contributions in these respects. The long-term goal of airport operations is to be resilient to operational disruptions and be sustainable in providing air services to the public.

4.1. Aircraft ground operations

Ground operations at the airport are aimed for providing efficient services that facilitate aircraft turnarounds whilst maintaining the integrity of flight schedules amid stochastic operational disruptions and delays.

A typical operation scenario may unfold as follows. An inbound aircraft arrives late at the destination airport. This arrival delay may cause disruption to aircraft turnaround operations because ground support personnel and vehicles have been planned according to flight timetables without explicitly considering delays. The same support personnel and vehicles have also been rostered to service other aircraft at a later stage - hence this disruption may cause ripple effects (delay propagation) to other aircraft which require the exact same ground resources to turn around. The airport operator then becomes concerned about gate allocation and potential gate blockage/conflicts that arise from flight and ground operation delays. Meanwhile, ground handling agents are trying to maintain the integrity of their ground staff and equipment rosters amid disruptions from flight operations, while airlines are busy maintaining the on-time departure and arrival performance of follow-up flights for the rest of the day. This scenario demonstrates the day-to-day challenges to stakeholders in ground operations on operational efficiency and allocation of limited resources. This and the next subsection provide perspectives on process efficiency improvement and coordination aspects with respect to aircraft ground and flight operations, while efficient allocation of some of the major resources in an airport is discussed in the remainder of the section.

Ground operations are procedural according to specific service requirements for turning around a particular type of aircraft. Hence, tasks in these service procedures are often highly coordinated and optimised by applying e.g. PERT (Project Evaluation and Review Techniques) and BPR (Business Process Reengineering) in the industry (Abd Allah Makhloof et al, 2014; Bevilacqua et al., 2015; Thorne, 2008; Wu, 2010). Disruptions to ground operations come from different sources such as equipment, passenger processing, baggage handling, airport congestion, and airline’s own operations (IATA, 2014a). These disruptions are almost unpredictable and some are unavoidable, so maintaining the efficiency of ground operations has become a major means for airlines to maintain flight on-time performance (Arikan et al., 2013; Wu, 2010).

Since major airports in the world are limited by land size and hard to expand capacity, technology and efficient process design provide a means to increase infrastructure capacity. Realising the importance of real-time operations monitoring and data sharing, Wu (2008) proposed the Aircraft Turnaround Management System (ATMS) framework that aimed for collecting ground operational data on site with mobile devices and share this data with stakeholders on real-time basis including ground handling agents, airport operators, airport towers and airlines. This concept is in line with the concept of Airport-Collaborative Decision Making (A-CDM) proposed by Eurocontrol (2017). Through the advance of computing and mobile technologies, applications of similar systems have been gradually adopted by airlines, ground handling agents and technology providers in the industry (Abd Allah Makhloof et al. ,2014; Avtura, 2017; Rockwell Collins, 2018; Salaris and Pascual, 2012). This technology significantly improves ground operations efficiency, and meanwhile provides better situational awareness for stakeholders in ground operations.

4.2. Flight operations

With an emerging goal to make airport operations ‘greener’, the consumption of fuel and energy in ground operations at airports has become a research focus more recently. The increased time aircraft spend at the gate due to airport ground congestion consumes more energy than expected. This congestion also causes aircraft to spend more time taxiing in and out between runway ends and airport terminal gates, burning more fuel than normal flight operations and aggravating the environmental impact (Simaiakis and Balakrishnan, 2010). In light of this, various technologies have been proposed to reduce fuel consumption during the phase of flight operations on the ground. Honeywell (2017) started a joint venture with Safran in 2013 to develop an electric taxiing solution for Airbus 320 family by using powers from the APU (auxiliary power unit) aboard an aircraft, while Wheeltug is also developing a similar system for airlines (Wheeltug, 2017). A semi-automatic robotic aircraft towing system (TaxiBot) is being developed by an Israeli company, aiming for providing taxi services without using fuel-powered APU (TaxiBot International, 2017). Given the advance of robotic technology and scheduling methodologies, Sirigu (2017) developed conflict-resolution algorithms which are designed to schedule autonomous taxibots for towing aircraft without burning fuel by running aircraft engines during the taxi phase of flight operations.

Past efforts in flight operations on the ground focussed more on the taxi phase of operations because of delays due to taxiway congestion, taxiing conflicts and long take-off queues at runway ends. Various optimisation models were developed to improve taxi operations and hence reduce the time spent running engines for taxiing. Traditional approaches consider the minimisation of taxi times, although some authors include industry-specific key performance indicators, like average delay and on-time performance (Guépet et al., 2016). Surprisingly, the authors found that industry punctuality indicators are in contradiction with the objective of reducing taxi times, therefore requiring more fuel and increasing emissions derived from their operations. Other approaches consider ground taxi operations with priorities (Yu et al., 2013) or the possibility to hold aircraft at the stands (Ravizza et al., 2014). More recently, research efforts have moved towards reducing taxi fuel burn by adjusting speed profiles for greener taxiing operations, such as the works by Chen et al. (2016), Zhang et al. (2015), and Weiszer et al. (2014). Finally, other management initiatives to reduce aircraft fuel consumption and taxiway congestion have been studied, mainly due to fewer implementation barriers and investment requirements. For example, Hao et al. (2017) analysed the gains obtained by holding aircraft at the gate until taxi can proceed uninterrupted to the departure runway. The authors report savings of about 1% in fuel consumption and as much as 2% reduction on taxi delay. All these developments help improving the efficiency of aircraft flight operations on the ground by reducing taxi delays and conflicts, and thus reducing fuel burn and the associated environmental impact caused by airport ground operations.

4.3. Stand and gate allocation

Amongst practitioners, profoundly different settings may exist with respect to stand and gate allocation. For instance, in the USA airlines tend to act as the problem owners, as they lease gates from airport operators, while in many airports in Europe and Asia, airport operators tend to have more control over resource assignment on the day of operation. In some of our projects, we have occasionally seen realities where even ground handlers take up control of stand and gate allocation. Zhang and Klabjan (2017) focus on the airline-centric system typical of the USA, and explicitly call for future works to provide models that are suitable to other perspectives, as this is currently lacking.

Early efforts in the literature mostly focussed on gate allocation to optimise airline operations. For instance, gates could be allocated to minimise the walking distance of connecting passengers and crew (Ding et al., 2005). From a gate utilisation perspective, Cheng et al. (2012) developed metaheuristic algorithms to optimise resource utilisation and passenger satisfaction, while Merve and Nilay (2012) and Murat et al. (2012) developed a stochastic optimisation approach to solve the same problem. With the shift of focus moving towards minimising the impact of stochastic disruptions to airport operations, Kim and Feron (2011) used the concept of robust scheduling in terminal gate assignment. Lim and Wang (2005) and Li (2008) considered stochastic flight delays in gate assignment by using stochastic programming.

More recently, Castaing et al. (2016) considered the inherent stochasticity of airline flight delays and used optimisation models to assign flights to gates in order to minimise the chance of gate blockage. Gate blockage occurs when an inbound aircraft arrives at a gate, but the gate is still occupied by an outbound aircraft. By considering inherent delays in the system, the expected impact of gate blockage could be reduced and this contributes to fewer and shorter connection delays to passengers, crew, and less aircraft idle time on taxiway (reducing fuel consumption).

4.4. Allocation of other ground service equipment and staff

A less considered aspect of resource allocation is ground staff and equipment allocation. Marintseva et al. (2015) is a relatively recent example of a work using dual values generated by optimisation models to assess the quality of personnel allocation in aircraft turnaround processes.

Only a handful of papers exist that look at the allocation of ground service equipment (GSE) supporting aircraft turnaround – e.g. passenger stairs, conveyor belts for baggage loading/unloading, pushback trucks, etc. Ansola et al. (2011) is an informative account of how turnaround operations can be managed more dynamically thanks to the availability of GSE location information, which in turn is supposedly provided by radio frequency identification (RFID) technologies and is assumed to be known with 100% certainty. Kuhn and Loth (2009) look at scheduling of airport service vehicles by integer programming. A genetic algorithm-based heuristic is presented to considerably reduce the computational time. Again, important stochastic elements of the real-world problem, such as GSE location information, are not taken into account. A similar consideration on perfect information regarding GSE location over time holds for both Andreatta et al. (2014) and Padrón et al. (2016). The former demonstrated a fast heuristic assigning every GSE on the airfield one task at a time, whilst targeting to improve robustness of turnaround operations - assuming perfect tracking and tracing of GSE all over the apron. On similar assumptions, the latter presented more recently a methodological approach for GSE scheduling based on combining constraint programming with large neighbourhood search and variable neighbourhood descent.

Given the (often high) number of ground handling organisations working concurrently on the same apron, and often sharing in practice the same resources including GSE (as already discussed in Sections 4.1 and 4.2), decision support methods that enable collaborative decision making would enhance the coordination aspects that would otherwise mine the propagation of delays and other issues related to GSE handling and sharing. While airport operational databases and other data sources are being pulled together following the paradigm of A-CDM, OR/MS-grounded methodologies are not widely available to enable the interested parties to exploit the vast amount of available information at the best of their capabilities. Examples of works starting to go in such a direction are Okwir et al. (2017) and Fitouri-Trabelsi et al. (2013).

4.5. Terminal operations

Beyond the aircraft operations value chain analysed so far, two additional value chains take place in any airport, whose related activities mostly unfold within the physical boundaries of airport terminals – namely the passenger and baggage/cargo value chains. Operations such as passenger check-in, security check, passport control and boarding highly contribute to the so-called *passenger experience*, something which each airline targets differently from one another but which the airport operator is supposed to be ensuring to all passengers irrespectively, through the provision of a “good enough” shared infrastructure. Similarly, both inbound and outbound baggage operations contribute to the formation and realisation of the intended passenger experience. There are obviously some other more fundamental aspects to be considered in both value chains such as security, detection of threats, etc., that all go beyond simple passenger experience as enacted through efficient terminal operations.

Technologies have been developed in the last few decades to help improve the way departing passengers make their way to the aircraft. These technologies have impacted and enhanced considerably all the above cited processes – they include e.g. self-service kiosks, facilities for automated check-in, common use passenger processing systems (CUPPS), biometrics, passenger tracking, video surveillance, risk-based security, access control and queue management, etc. Other technologies have enhanced safety levels such as the previously mentioned Standard 3 specification for automated baggage screening (see Section 3.3).

A good amount of OR/MS literature exists to show airport operators and airlines some of the ways they could boost the potential from adoption of novel technologies, as well as to help them to simply streamline terminal processes. Reviewing this body of knowledge is out of scope for the present chapter. Partial pointers can be provided however to some of the relatively recent works addressing the various areas cited so far, though in isolation, for instance: van Dijk and van der Sluis (2006), Parlar and Sharafali (2008), Stolletz

(2010), and Mújica Mota (2015) for check-in processes; Lee and Jacobson (2011), Seo et al. (2012), and De Lange et al. (2013) on passenger security checking.

The main learning one can possibly draw from examining existing literature is that no considerable amount of work appears to have been done on planning/execution of terminal processes as an end-to-end holistic process for passenger experience delivery. Existing excellent OR/MS work targeting only one process area at a time, or two of them at maximum, does not enable airport operators to better coordinate the various processes over the day of operation – especially considering that some of these processes may be sharing at times one or more resources, e.g. human operators. This lack of decision support for cross-process coordination is something whose consequences can be experienced directly by any passenger during disrupted times. For instance, think of when an automated system for security checks halts due to technical faults, and queues form backwards inside the terminal, often reaching the already busy check-in concourses and, at times, even the airport outdoor spaces. A quick online search would also reveal the existence of a few software solution providers (see e.g. Copenhagen Optimization, 2017) who indeed sell decision support modules to optimise passenger terminal operations - but again in isolation, thus supporting the hypothesis that neither the world of practitioners seems to be equipped for a truly holistic optimisation of the end-to-end airport passenger experience.

Finally, as a related discussion, one of the main concerns for airport operators is to define what "good enough" an airport infrastructure should be to enable this holistic view of process management in airport terminals. Guidance indeed does exist on individual terminal processes, typically in the form of Levels of Service (LoS) that processes must comply with, as developed and published by sector bodies such as IATA and Airport Council International (ACI). Nonetheless, all LoS definitions and figures issued so far still focus on individual airport processes instead of end-to-end passenger flows (Correia et al., 2008).

5. Airline operations

Over the last few years, robust and dynamic OR methodologies have gained popularity among companies and researchers for scheduling airline operations. The main benefit of applying these techniques lies in having a responsive approach towards possible perturbations, as the model itself contemplates these disruptions and constructs a solution that allows to absorb them. There are two main areas of robust and dynamic applications in the airline industry: aircraft and crew scheduling.

The static aircraft routing problem has been widely studied in the literature, but, during recent years, the need to improve schedules being able to absorb external events affecting their daily routine has raised. One of the early works introducing robustness tackles the maintenance aircraft problem, where a set of flights must be allocated under maintenance restrictions. Ageeva (2000) presents a model that generates routes where aircraft will meet at a given airport two times, so they can be swapped in case of a disruption. Another approach is used by Lan (2003), where the author tackles the aircraft maintenance problem with passenger disruption, optimising the allocation of slack time between flights. To do so, historical data are used to derive the delays of each flight. Simulation approaches have been widely used to test if a schedule is robust enough. Rosenberg et al. (2002) introduced SimAir, a software specialised in airline simulations. One of its applications can be seen in Rosenberg et al. (2004), where they propose isolating hubs so a cancellation affects the minimum number of flights. The idea is to use many short cancellation cycles to provide a more robust schedule. A cancellation cycle is defined as a sequence of legs in a rotation in which the first leg departs from the same airport at which the last leg lands. Hence, if the planning incorporates shorter cycles, if a disruption took place, it would minimise the effect of cancelling flights. Mixing both optimisation and simulation techniques has been widely used, e.g. in Wu (2005) both techniques are used to create a schedule that is reliable enough allowing to increase the buffer time between flights. In most studies in the literature, optimisation and simulation techniques are used sequentially: first, the optimisation procedure is used to find an optimal solution and the result is later tested by using simulation. On the contrary, Guimarans et al. (2015) used simulation in the acceptance step of the algorithm to check if the solution is robust enough for the aircraft recovery problem. By doing so, the algorithm can detect undesired solutions earlier. In a recent work, Ahmed et al. (2017a) use a mixed-integer programming approach to solve the deterministic approach, and then applying MC simulation they create the delays for each aircraft and adapt the buffers so they minimise the impact on the schedule. Similarly, Ahmed et al. (2017b) present two mixed-integer quadratic programming models that generate a feasible solution whose robustness is checked using MC simulation, followed by an evolutionary algorithm that iteratively improves the solution given by the previous step.

Crew scheduling is a process that presents serious challenges and has attracted more attention from the research community in recent years. Among these challenges, De Armas et al. (2017) highlight that optimising the number of crews needed is hardly possible due to new regulations forcing airlines to a minimum number of crews. Hence, the aim of airlines is to distribute the workload evenly between crew members to ensure equity between workers. A higher number of crews with more balanced workloads may also increase planning robustness, as more resources and additional flexibility are introduced in the system to respond to disrupted scenarios. However, this solution may imply a higher operative cost. Schaefer et al. (2005) were among the first authors tackling robustness aspects of crew scheduling. The authors introduced a methodology to find the expected cost of scheduling crews under disruptions and find a lower bound to compare with the deterministic approach. In their paper, they assume that no flight is cancelled and that crews fly the same legs originally assigned to them, but with delayed arrival or departure times. Another approach to model robustness in crew scheduling is by maximising the number of move-up crews, which are crews that can be potentially swapped at a specific airport to provide for more flexibility in response to disruptions. This is studied by Shebalov and Klabjan (2006), who introduce an integer problem that is solved using Lagrangian relaxation. By comparing the results on scenarios with disruptions, they conclude that the total crew cost is reduced using the robust approach. Again, robustness techniques can be embedded during the search of a solution. A stochastic programming model for solving the crew scheduling problem is presented in Yen and Birge (2006). In their work, the authors implement a branching algorithm that uses crew plane changes as the branching method. Computational results are presented demonstrating the validity of their algorithm.

Muter et al. (2013) present a different application of robustness. In their case, an airline seeks to include new flights into an existing schedule by minimising the possible implication to the original plan. They formulate the crew pairing problem as a set covering formulation solved by column generation. Another widely used method is to calculate the worst scenario cost of random simulated scenarios. Lu and Gzara (2015) solve the crew pairing problem by generating random flight and connection times calculating the cost of the worst-case scenario. They apply Lagrangian relaxation for the nonlinear robust terms in the objective function, and the resulting linear problem is solved by applying a shortest path algorithm with resource constraints. A series of simulation experiments show the validity of their approach.

6. Disruption Management

The interest towards how to manage disruptions in the airline industry has been a focus of interest both in the research and airline industry. Airline operations constitute one of the most complex transportation systems and is commonly introduced as a network. This network is composed by the following entities:

- Airports are referred as system nodes, which are linked between them using arcs considered to be flights or legs. These airports can be inter-connected either by point-to-point (commonly seen in low cost airlines such as Ryanair) or hub-and-spoke configurations, where most of an airline's flights are based at a single main airport (Atlanta, London Heathrow, etc..).

- Aircraft are the main resource of the system, which provide the transportation method between nodes.
- Crew is assigned to a specific flight and aircraft family. The crew scheduling process is one of the most complex problems in the system as it tackles a vast number of constraints, such as those imposed by safety regulations or restrictive union agreements.
- Passengers define the demand between nodes. In case of disruption, passengers need to be re-allocated to new flights minimising the impact on their journey.

Due to its complexity, a disruption in one of the system's processes might have a massive impact on the overall network performance. A disruption is defined as a perturbation which interrupts a process, activity or event. In this case, a disruption in one of the network's flights will implicate a cascading effect of delays and cancellations in future flights. This is a common case in hub-and-spoke configurations, as flights are highly interconnected at the hub airport(s). Hence, disruption management techniques need to be applied. Yu and Qi (2004) provide a detailed explanation of disruption management based on different applications, including among them flight and crew scheduling.

The first known review tackling irregular operations in the airline industry was introduced by Clarke (1998). It provides an extensive study on processes and decision frameworks on how airlines deal with such events. A more recent study by Ball et al. (2007) updates the work of Clarke (1998), and gives an extensive description of all the costs and main features in airline irregular operations. Another overview is given by Kohl et al. (2007), where the authors define disruption management not as a single problem, but rather as an ongoing process which needs to be monitored. All literature agrees that the objectives in disruption management can be hard to adopt and quantify, but a common convention is to fulfil passengers' needs, quantify the cost of the disruption, and get back to normal operations. There has been a lot of interest on how to use and quantify these objectives. Two main lines of research can be observed: on the one hand, creating a more robust schedule for flights, aircraft and crews, which can absorb more perturbations or even work with different scenarios; on the other hand, once the disruption has occurred, the goal is minimising the time required to get back to normal operations, which in turn reduces the total of the disruption.

Due to the high complexity of the system, disruption management was initially divided in three different problems, which tackle specific features. Clausen et al. (2010) introduce a review of these sub-problems:

- The Aircraft Recovery Problem (ARP) aims at reducing the disruption from the aircraft perspective, by swapping, delaying, or cancelling flights assigned to the aircraft.
- The Crew Recovery Problem (CRP) re-arranges the crews of each flight after a perturbation occurs – typical issues involved are e.g. crews not being able to fly as scheduled due to labour-related restrictions.
- The Passenger Recovery Problem (PRP) looks at minimising the cost of re-assigning all affected passengers until they reach their destination, and is normally formulated in combination with the ARP.

Due to its complexity, recovery of the entire system is generally solved hierarchically, with decisions made for one resource defining constraints for subsequent recovery problems. The following sections provide a brief overview on developments tackling the three recovery sub-problems separately, as well as some attempts to solve different combinations in a more integrated way.

6.1. Aircraft recovery

The ARP is the most studied of the three sub-problems, possibly because its constraints are less complex than e.g. those to be considered in the CRP.

Early research on the ARP is presented by Teodorović and Guberinić (1984), which minimises passenger delay by retiming and swapping aircrafts. They use a network flow model and branch-and-bound to solve the problem. Teodorović and Stojković (1990) proposed an improved approach based on dynamic programming, which allows cancellations and minimises the total number of them.

A more complex model is introduced by Løve et al. (2002), which allows swapping aircraft from different fleets by using a local search-based heuristic. Another feature of the problem is tackled by Yan and Lin (1997), presenting a model to solve the multi-fleet ARP with the temporary closure of a specific airport. The model, as in previous works, allows swaps, cancellations and delays, but the authors do not consider diverting flights to other airports.

More recent works, such as Eggenberg et al. (2010), typically use data from existing companies to verify and improve their recovery step.

6.2. Crew recovery

The CRP aims at reassigning as quickly as possible all the crew personnel affected by a perturbation. This is regarded as possibly the most complex recovery problem, as there are many constraints attached to it (e.g. flight hours, resting periods, etc.). If the problem is tackled separately, the main assumption is that it is solved after knowing the aircraft schedule. Moreover, crew scheduling is generally split into two sub-problems, respectively the crew pairing and the crew rostering sub-problems. Crew pairing (i.e. combination of tasks within a working period, which may extend over several days) aims at optimising the number of crews for a given flight schedule. On the other hand, crew rostering assigns pairings to specific crew members.

Wei et al. (1997) were among the pioneers to tackle the CRP with fixed schedules. They formulated the problem as a crew pairing problem which minimises the time it takes to recover from the disruption. A perturbation is induced in the original schedule and, by using their mathematical model, they repair the solution considering the existing pairings. On the other hand, Medard and Sawhney (2007) state that the problem needs to be solved by creating the pairings and assigning them to a specific crew in a single step. To do so, they use a column generation approach improved with a shortest path algorithm.

While most research focusses exclusively on optimising the two problems, they are part of the airline complete schedule. Hence, Stojković and Soumis (2001) introduce the possibility of delaying flights to reschedule crews, taking advantage that the flights have been previously rearranged. The problem is formulated as an integer nonlinear multi-commodity network flow model. Although disruptions are highly complex to quantify, Yu et al. (2003) present the architecture of the solver (CrewSolver) created for Continental Airlines to solve the CRP, and state that it saved Continental Airlines approximately up to $40 million.

6.3. Integration of passenger recovery

Passenger recovery may be the least complex operation in a disrupted scenario, due to available options to reallocate passengers in different flights, or even rebook them with a different airline. However, it may become a challenging process due to limitation of seats if airlines do not agree to cooperate. In the literature, the PRP is commonly studied merging it with crew or aircraft recovery.

Bratu and Barnhart (2006) introduce two passenger recovery approaches, which integrate crew and aircraft recovery features. In their model, they also allow delaying or cancelling flight departures, assigning reserve crews, and assigning new aircraft to flights. Crew recovery is not fully tackled, but instead they model restrictions for the reserve crew. Bisaillon et al. (2011) present a more complex algorithm. The authors use their approach to solve a combination of fleet assignment, aircraft routing, and passenger reallocation. The introduced heuristic alternates between construction, repair, and improvement phases, which iteratively destroy and repair parts of the solution.

A common problem faced by companies and researchers is the amount of computational time needed to solve such problems. Thus, sometimes it is assumed an airline will use a solution if is “good enough”, provided that it requires low computational times. To deal with this issue, Jafari and Zegordi (2011) introduce a mathematical model to solve the ARP with passenger recovery. They define a recovery scope (i.e. time until all changes caused by the disruption have been carried out), introduced by Guo (2005), to solve smaller parts of the schedule, allowing them to solve bigger problems. Their model permits flight re-timing, aircraft swapping, use of reserve aircraft, cancellations, and passenger reassignment. More recently, Sinclair et al. (2016) model the combined aircraft and passenger recovery problem as a mixed-integer formulation. Due to its complexity, they use a large neighbourhood search introduced by Sinclair et al. (2014) to solve large instances of both ARP and PRP, and then use a post-optimisation column generation heuristic. Moreover, the model allows to take only into account the passenger recovery problem if needed.

Finally, Marla et al. (2017) tackle the ARP and PRP introducing a new mechanism called “flight planning”, which allows speed changes during flight. Their problem is based on the formulation from Bratu and Barnhart (2006), including the possibility of speed change. In this more recent work the focus is on aircraft and passenger disruptions, but the same approach can be applied, with little modifications, to look at crews. Using data from a European airline, the authors manage to reduce passenger disruptions by approximately 66%–83%, incurring in an increase of fuel burn between 0.152% and 0.155%. The total cost savings for the airline is approximately 5.7%– 5.9%, which is better than the approaches typically adopted in practice.

7. Conclusions

Aviation is currently facing many challenges to cope with the constant growth of air traffic. These challenges are likely to increase in the near future, as demand is forecast to grow substantially. Most of these problems stem from operating near current capacity ceilings at airports and airspace, an issue generally aggravated by poor capacity management practices. In the present chapter, we have reviewed several initiatives aimed at releasing some pressure off the system by means of the introduction of new technologies, operating policies, and efficient management of resources.

As observed in our review, many OR works focus on managing air transport operations more efficiently. These studies originate from the industry need to reduce costs in an extremely competitive market. Reduced margins force companies to seek more efficient resource management strategies to sustain their operations and meet market demands. An increasing concern for environmental impact in terms of green-house emissions and noise pollution is also driving many stakeholders to look for alternatives on how to manage assets and better utilise the system's current capacity. This is so in order to serve global and regional economies and local communities, while minimising the adverse effects of their operations.

Air transport is inherently uncertain, as many agents need to converge to ensure smooth and streamlined operations. Its own nature makes it also more vulnerable to external factors, such as weather conditions, that may hinder or even impede performance over some time periods. Strict safety regulations, legacy rights, and policies may also limit the system's capacity. All these elements are at the root of deviations from planned operations and disruptions in the network. The ability of the different stakeholders to overcome these perturbations on their plans is key to ensure the continuity of their operations. Although most efforts are currently focussed on designing reliable and robust schedules able to absorb certain amount of variability, or developing recovery plans that allow returning to normal operations in the minimum possible times, a complete understanding of the influence of different factors giving rise to delays and major disruptions is still lacking. Due to the network structure, where all agents are very closely interconnected, these undesired effects quickly propagate to other parts of the network. A better understanding of propagation mechanisms and disruption sources may help increasing the predictability of these events, and the development of proactive mitigating strategies. Given the frequency and consequences of disruptions in the network, such topics constitute a major research avenue for the future with a potential major impact on the aviation industry.

In this chapter, we have identified many other lines that are the focus of current and future research. Major projects like SESAR and NextGEN grant the development of new technologies, standards, and operational procedures to ensure the sustainability of aviation operations. The OR literature is also rich on new strategies for reducing or managing congestion more efficiently. However, most of these approaches are based on deterministic models that ignore or simplify the uncertainty linked to many variables in air transport problems. The development of methodologies able to cope with uncertain or incomplete information is clearly a must for the industry. Their integration with management systems and protocols like A-CDM opens a whole range of research possibilities. Finally, simulation has proved an effective tool for studying aviation systems. A closer integration with other OR techniques would bring these methodologies one step closer to solving many of aviation's current challenging problems.

References

Abd Allah Makhloof, M., Elsayed Waheed, M., and Usama A. El-Raouf Badawi, 2014. Real-time aircraft turnaround operations manager. Production Planning & Control, 25(1), pp. 2-25.

Ageeva, Y., 2000. Approaches to incorporating robustness into airline scheduling. PhD. Dissertation. Massachusetts Institute of Technology (MIT).

Agustín, A., Alonso-Ayuso, A., Escudero, L.F., and Pizarro, C., 2010. Mathematical Optimization models for Air Traffic Flow Management: A review. In: Bui, A., and Tseveendorj, I., ed. Combinatorial Optimization in Practice. Paris, France: Hermann Informatique; pp. 141-177.

Ahmed, M.B., Ghroubi, W., Haouari, M. and Sherali, H.D., 2017a. A hybrid optimization-simulation approach for robust weekly aircraft routing and retiming. Transportation Research Part C: Emerging Technologies, 84, pp. 1-20.

Ahmed, M.B., Mansour, F.Z. and Haouari, M., 2017b. A two-level optimization approach for robust aircraft routing and retiming. Computers & Industrial Engineering, 112, pp. 586-594.

Airbus, 2017. Growing Horizons – Global Market Forecast. Technical report.

Andreatta, G., De Giovanni, L., and Monaci, M., 2014. A Fast Heuristic for Airport Ground-Service Equipment-and-Staff Allocation. Procedia – Social and Behavioral Sciences, 108, pp. 26-36.

Ansola, P.G., Higuera, A.G., Pastor, J.M., and Otamendi, F.J., 2011. Agent-based decision-making process in airport ground handling management. Logistic research, 3(2), pp. 133-143.

Arikan, M., Deshpande, V., Sohoni, M., 2013. Building reliable air-travel infrastructure using stochastic models of airline networks. Operations Research, 61 (1), pp. 45-64.

Avtura, 2017. http://avtura.com. Accessed on 30 October 2017.

Ball, M., Barnhart, C., Nemhauser, G., and Odoni, A., 2007. Air transportation: Irregular operations and control. Handbooks in operations research and management science, 14, pp. 1-67.

Bazargan, M., Fleming, K., and Subramanian, P., 2002. A simulation study to investigate runway capacity using TAAM. Proceedings of the 2002 Winter Simulation Conference, pp. 1235-1243. San Diego, USA.

Bennell, J., Mesgarpour, M., and Potts, C., 2011. Airport runway scheduling. 4OR: A Quarterly Journal of Operations Research, 9(2), pp. 115-138.

Bevilacqua, M., Ciarapica, F.E., Mazzuto, G. and Paciarotti, C., 2015. The impact of business growth in the operation activities: a case study of aircraft ground handling operations. Production Planning & Control, 26(7), pp. 564-587.

Bisaillon, S., Cordeau, J.F., Laporte, G. and Pasin, F., 2011. A large neighbourhood search heuristic for the aircraft and passenger recovery problem. 4OR: A Quarterly Journal of Operations Research, 9(2), pp. 139-157.

Boeing, 2017. Current Market Outlook 2017-2036. Technical report.

Bratu, S. and Barnhart, C., 2006. Flight operations recovery: New approaches considering passenger recovery. Journal of Scheduling, 9(3), pp. 279-298.

Castaing, J., Mukherjee, I., Cohn, A., Hurwitz, L., Nguyen, A., and Muller, J. J., 2016. Computers & Operations Research, 65, pp. 189-199.

Chen, J., Weiszer, M., Stewart, P., and Shabani, M., 2016. Toward a more realistic, cost-effective, and greener ground movement through active routing part I: Optimal speed profile generation. IEEE Transactions on Intelligent Transportation Systems, 17(5), pp. 1196–1209.

Cheng, C., Sin, C. H., and Kwan, C., 2012. The use of meta-heuristics for airport gate assignment. Expert Systems and Applications, 39(16), pp. 12430–12437.

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), pp. 67-76.

Clausen, J., Larsen, A., Larsen, J. and Rezanova, N.J., 2010. Disruption management in the airline industry—Concepts, models and methods. Computers & Operations Research, 37(5), pp. 809-821.

Copenhagen Optimization, 2017. http://copenhagenoptimization.com. Accessed on 30 October 2017.

Correia, A. R. , Wirasinghe, S. C. , and de Barros, A. G., 2008. Overall level of service measures for airport passenger terminals. Transportation Research Part A: Policy and Practice, 42(2), pp. 330–346.

de Armas, J., Cadarso, L., Juan, A. A., and Faulin, J., 2017. A multi-start randomized heuristic for real-life crew rostering problems in airlines with work-balancing goals. Annals of Operations Research, 258(2), pp. 825-848.

De Lange, R., Samoilovich, I., and Van Der Rhee, B., 2013. Virtual queuing at airport security lanes. European Journal of Operational Research, 225(1), pp. 153–165.

Ding, H., Lim, A., Rodrigues, B., and Zhu, Y., 2005. The over-constrained airport gate assignment problem. Computers & Operations Research, 32(7), pp. 1867–1880.

Eggenberg, N., Salani, M. and Bierlaire, M., 2010. Constraint-specific recovery network for solving airline recovery problems. Computers & Operations Research, 37(6), pp. 1014-1026.

Eurocontrol, 2008. Evaluation of Functional Airspace Block (FAB) initiatives and their contribution to performance improvement. Technical report.

Eurocontrol, 2010a. SESAR – The future of flying. Technical report.

Eurocontrol, 2010b. Planning for delay: Influence of flight scheduling on airline punctuality. Trends in Air Traffic, vol. 7. Technical report.

Eurocontrol, 2017. Airport CDM Implementation. Technical report.

FAA, 2016. NextGEN Priorities – Joint Implementation Plan. Technical report.

Farhadi, F., Ghoniem, A., and Al-Salem, M., 2014. Runway capacity management - An empirical study with application to Doha International Airport. Transportation Research Part E: Logistics and Transportation Review, 68, pp. 53-63.

Fasone, V., and Maggiore, P., 2014. Airport development and sustainability: a case of multi-airport system in Italy. International Journal of Sustainable Aviation, 1(1), pp. 13-24.

Fitouri-Trabelsi, S., Nunes Cosenza, C.A., Zelaya Cruz, L.G., and Mora-Camino, F., 2013. An Operational Approach for Ground Handling Management at Airports with Imperfect Information. Proceedings of the 19th International Conference on Industrial Engineering and Operations Management. Valladolid, Spain.

Gelhausen, M.C., Berster, P., and Wilken, D., 2013. Do airport capacity constraints have a serious impact on the future development of air traffic? Journal of Air Transport Management, 28, pp. 3-13.

Guépet, J., Briant, O., Gayon, J.P., and Acuna-Agost, R., 2016. The aircraft ground routing problem: Analysis of industry punctuality indicators in a sustainable perspective. European Journal of Operational Research, 248(3), pp. 827 – 839.

Guimarans, D., Arias, P., and Mota, M. M. (2015). Large Neighbourhood Search and Simulation for Disruption Management in the Airline Industry. In: Mújica Mota, M., Flores, I., and Guimarans, D., ed. Applied Simulation and Optimization. Berlin, Germany: Springer International Publishing; pp. 169-201.

Guo, Y. (2005). Decision support systems for airline crew recovery. PhD. Dissertation. University of Paderborn.

Hao, L., Ryerson, M., Kang, L., and Hansen, M., 2017. Estimating fuel burn impacts of taxi-out delay with implications for gate-hold benefits. Transportation Research Part C: Emerging Technologies, 80, pp. 454-466.

Honeywell, 2017. https://www.honeywell.com/newsroom/pressreleases/2013/12/airbus-signs-mou-with-honeywell-and-safran-to-develop-electric-taxiing-solution-for-a320-family. Accessed on 30 October 2017.

Heidt, A., Helmke, H., Kapolke, M., Liers, F., and Martin, A., 2016. Robust runway scheduling under uncertain conditions. Journal of Air Transport Management, 56, pp. 28-37.

Idris, H., 2001. Observation and analysis of departure operations at Boston Logan International Airport. PhD. Dissertation. Massachusetts Institute of Technology (MIT).

International Air Transport Association (IATA), 2014a. Airport Handling Manual. Technical report.

International Air Transport Association (IATA), 2014b. Airport Development Reference Manual. Technical report.

International Air Transport Association (IATA), 2017. IATA 20-year Air Passenger Forecast. Technical Report.

Irvine, D., Budd, L., and Pitfield, D., 2015. A Monte-Carlo approach to estimating the effects of selected airport capacity options in London. Journal of Air Transport Management, 42, pp. 1-9.

Jafari, N. and Zegordi, S.H., 2011. Simultaneous recovery model for aircraft and passengers. Journal of the Franklin Institute, 348(7), pp. 1638-1655.

Janić, M., 2005. Modelling airport congestion charges. Transportation Planning and Technology, 28(1), pp. 1-26.

Janić, M., 2017. Analysing and modelling some effects of solutions for matching the airport runway system capacity to demand. Journal of Air Transport Management, 65, pp. 166-180.

Kim, S. H., and Feron, E., 2011. Robust gate assignment. Proceedings of the AIAA guidance, navigation, and control conference. Portland, USA.

Kohl, N., Larsen, A., Larsen, J., Ross, A. and Tiourine, S., 2007. Airline disruption management—perspectives, experiences and outlook. Journal of Air Transport Management, 13(3), pp. 149-162.

Koren, Y., Heisel, U., Jovane, F., Moriwaki, T., Pritschow, G., Ulsoy, G., and Van Brussel, H., 1999. Reconfigurable Manufacturing Systems. CIRP Annals, 48(2), pp. 527-540.

Kuhn, K., and Loth, S., 2009. Airport Service Vehicle Scheduling. USA/Europe Air Traffic Management Research and Development Seminar (ATM2009). Napa, USA.

Lan, S., 2003. Planning for robust airline operations: Optimizing aircraft routings and flight departure times to achieve minimum passenger disruptions. PhD. Dissertation. Massachusetts Institute of Technology (MIT).

Lee, A.J., and Jacobson, S. H., 2011. The impact of aviation checkpoint queues on optimizing security screening effectiveness. Reliability Engineering and System Safety, 96(8), pp. 900–911.

Li, C., 2008. Airport gate assignment: New model and implementation. arXiv preprint arXiv:0811.1618. Cornell University.

Lim, A., and Wang, F., 2005. Robust airport gate assignment. Proceedings of 17th IEEE International Conference on Tools with Artificial Intelligence. Hong Kong, China.

Lordan, O., Sallan, J., and Valenzuela-Arroyo, M., 2016. Forecasting of taxi times: The case of Barcelona-El Prat airport. Journal of Air Transport Management, 56, pp. 118-122.

Løve, M., Sørensen, K.R., Larsen, J. and Clausen, J., 2002. Disruption management for an airline—rescheduling of aircraft. In: Cagnoni S., Gottlieb J., Hart E., Middendorf M., Raidl G.R. (eds). Applications of Evolutionary Computing. Berlin, Germany: Springer International Publishing; pp. 315-324.

Lu, D. and Gzara, F., 2015. The robust crew pairing problem: model and solution methodology. Journal of Global Optimization, 62(1), pp. 29-54.

Malik, W., and Jung, Y., 2016. Exact and heuristic algorithms for runway scheduling. Proceedings of 16th AIAA Aviation Technology, Integration, and Operations Conference, pp. 1-10. Washington, USA.

Marintseva, K., Yun, G. and Kachur, S., 2015. Resource allocation improvement in the tasks of airport ground handling operations. Aviation, 19(1), pp. 7-13.

Marla, L., Vaaben, B. and Barnhart, C., 2011. Integrated disruption management and flight planning to trade off delays and fuel burn. Transportation Science, 51(1), pp. 88-111.

Medard, C.P. and Sawhney, N., 2007. Airline crew scheduling from planning to operations. European Journal of Operational Research, 183(3), pp. 1013-1027.

Merve, S., and Nilay, N., 2012. Stochastic optimization models for the airport gate assignment problem. Transportation Research Part E: Logistics and Transportation Review, 48(2), pp. 438–459.

Mújica Mota, M., 2015. Check-in allocation improvements through the use of a simulation–optimization approach. Transportation Research Part A: Policy and Practice, 77, pp. 320-335.

Murat, G. H., Kaan, E. O., İbrahim, E., Fatih, B. M., and Onaran, G. B., 2012. A stochastic neighborhood search approach for airport gate assignment problem. Expert Systems and Applications, 39(1), pp. 316–327.

Muter, İ., Birbil, Ş.İ., Bülbül, K., Şahin, G., Yenigün, H., Taş, D. and Tüzün, D., 2013. Solving a robust airline crew pairing problem with column generation. Computers & Operations Research, 40(3), pp. 815-830.

Nosedal, J., Piera, M.A., Ruiz, S., and Nosedal, A., 2014. An efficient algorithm for smoothing airspace congestion by fine-tuning take-off times. Transportation Research: Part C: Emerging Technologies, 44, pp. 171-184.

Okwir, S., Ulfvengren, P., Angelis, J., and Ruiz, F., 2017. Managing turnaround performance through Collaborative Decision Making. Journal of Air Transport Management, 58, pp. 183-196.

Oxford English Dictionary (OED), 2017. http://www.oed.com/view/Entry/54950742?redirectedFrom=functionality#eid. Accessed on 30 October 2017.

Padrón S., Guimarans D., Ramos J.J., and Fitouri-Trabelsi S. (2016). A bi-objective approach for scheduling ground-handling vehicles in airports. Computers & Operations Research, 71, pp. 34- 53.

Parlar, M., and Sharafali, M., 2008. Dynamic Allocation of Airline Check-In Counters: A Queueing Optimization Approach. Management Science, 54(8), pp. 1410-1424.

Pitfield, D., and Jerrard, E., 1999. Monte Carlo comes to Rome: a note on the estimation of unconstrained runway capacity at Rome Fiumucino International Airport. Journal of Air Transport Management, 5, pp. 185-192.

Ravizza, S., Atkin, J., Maathuis, M., and Burke, E., 2012. A combined statistical approach and ground movement model for improving taxi estimations at airports. Journal of the Operational Research Society, 64, pp. 1347-1360.

Ravizza, S., Atkin, J. A. D., and Burke, E. K., 2014. A more realistic approach for airport ground movement optimisation with stand holding. Journal of Scheduling, 17(5), pp. 507–520.

Rockwell Collins, 2018. https://www.rockwellcollins.com/Data/News/2016-Cal-Yr/IMS/FY16IMSNR17-AirTQM.aspx. Accessed on 19 February 2018.

Rodríguez-Díaz, A., Adenso-Díaz, B., and González-Torre, P., 2017. Minimizing deviation from scheduled times in a single mixed-operation runway. Computers & Operations Research, 78, pp. 193-202.

Rosenberger, J.M., Johnson, E.L., and Nemhauser, G.L., 2004. A robust fleet-assignment model with hub isolation and short cycles. Transportation Science, 38(3), pp. 357-368.

Rosenberger, J.M., Schaefer, A.J., Goldsman, D., Johnson, E.L., Kleywegt, A.J., and Nemhauser, G.L., 2002. A stochastic model of airline operations. Transportation Science, 36(4), pp. 357-377.

Salaris, M. V., and Pascual, S. P., 2012. Benefits of turnaround integration into the airport business trajectory: TITAN. Presentation at the AIRDEV Airport Development Conference. http: web.tecnico.ulisboa.pt/~vascoreis/ projects/airdev/Presentation_V_SALARIS.pdf. Accessed on 30 October 2017.

Seo, S., Choi, S., and Lee, C., 2012. Security Manpower Scheduling for Smart airports. In: J. Park J., Chao H.C., Obaidat, M., and Kim, J., ed. Computer Science and Convergence. Dordrecht, Netherlands: Springer International Publishing; pp. 31–42.

Schaefer, A.J., Johnson, E.L., Kleywegt, A.J., and Nemhauser, G.L., 2005. Airline crew scheduling under uncertainty. Transportation Science, 39(3), pp. 340-348.

Shebalov, S. and Klabjan, D., 2006. Robust airline crew pairing: Move-up crews. Transportation Science, 40(3), pp. 300-312.

Simaiakis, I., and Balakrishnan, H., 2010. Impact of congestion on taxi times, fuel burn, and emissions at major airports. Transportation Research Record: Journal of the Transportation Research Board, 2184, pp. 22–30.

Sinclair, K., Cordeau, J.-F., and Laporte, G., 2014. Improvements to a large neighborhood search heuristic for an integrated aircraft and passenger recovery problem. European Journal of Operational Research, 233, pp. 234–245.

Sinclair, K., Cordeau, J.F. and Laporte, G., 2016. A column generation post-optimization heuristic for the integrated aircraft and passenger recovery problem. Computers & Operations Research, 65, pp. 42-52.

Sirigu, G., 2017. Planning and reconfigurable control of a fleet of unmanned vehicles for taxi operations in airport environment. PhD. Dissertation. Politecnico di Torino.

Stojković, M., and Soumis, F., 2001. An optimization model for the simultaneous operational flight and pilot scheduling problem. Management Science, 47(9), pp. 1290-1305.

Stolletz, R., 2010. Operational workforce planning for check-in counters at airports. Transportation Research Part E: Logistics and Transportation Review, 46(3), pp. 414-425.

TaxiBot International, 2017. http://www.taxibot-international.com. Accessed on 30 October 2017.

Teodorović, D. and Guberinić, S., 1984. Optimal dispatching strategy on an airline network after a schedule perturbation. European Journal of Operational Research, 15(2), pp. 178-182.

Teodorović, D. and Stojković, G., 1990. Model for operational daily airline scheduling. Transportation Planning and Technology, 14(4), pp. 273-285.

Thorne, A., 2008. The Measurement of Aircraft Turnaround Performance. MPhil Dissertation. University of Cambridge.

van Dijk, N.M., and van der Sluis, E., 2006. Check-in computation and optimization by simulation and IP in combination. European Journal of Operational Research, 171(3), pp. 1152-1168.

Wei, G., Yu, G. and Song, M., 1997. Optimization model and algorithm for crew management during airline irregular operations. Journal of Combinatorial Optimization, 1(3), pp. 305-321.

Weiszer, M., Chen, J., Ravizza, S., Atkin, J., and Stewart, P., 2014. A heuristic approach to greener airport ground movement. Proceedings of IEEE Congress on Evolutionary Computation (CEC), pp. 3280–3286. Beijing, China.

Wheeltug, 2017. http://www.wheeltug.com/about.php. Accessed on 30 October 2017.

Wu, C. L., 2005. Inherent delays and operational reliability of airline schedules. Journal of Air Transport Management, 11(4), pp. 273-282.

Wu, C. L., 2008. Monitoring aircraft turnaround operations – framework development, application and implications for airline operations. Transportation Planning and Technology, 31(2), pp. 215–228.

Wu, C. L., 2010. Airline Operations and Delay Management- Insights from airline economics, networks and strategic schedule planning. Ashgate Publishing.

Yan, S. and Lin, C.G., 1997. Airline scheduling for the temporary closure of airports. Transportation Science, 31(1), pp. 72-82.

Yen, J.W. and Birge, J.R., 2006. A stochastic programming approach to the airline crew scheduling problem. Transportation Science, 40(1), pp. 3-14.

Yu, G. and Qi, X., 2004. Disruption management: framework, models and applications. World Scientific.

Yu, G., Argüello, M., Song, G., McCowan, S.M., and White, A., 2003. A new era for crew recovery at continental airlines. Interfaces, 33(1), pp. 5-22.

Yu, J., Zhihua, L., and Honghai, Z., 2013. A collaborative optimization model for ground taxi based on aircraft priority. Mathematical Problems in Engineering, 2013, pp. 1–9.

Zhang, T., Ding, M., Zuo, H., Zeng, L., and Sun, Z., 2015. A two-stage airport ground movement speed profile design methodology using particle swarm optimization. International Journal of Mathematical, Computational, Physical, Electrical and Computer Engineering, 9(9), pp. 15–21.

Zhang, D., and Klabjan, D., 2017. Optimization for gate re-assignment. Transportation Research Part B: Methodological, 95, pp. 260-284.

Zografos, K., Madas, M., and Androutsopoulos, K., 2017. Increasing airport capacity utilisation through optimum slot scheduling: review of current developments and identification of future needs. Journal of Scheduling, 20(1), pp. 3-24.