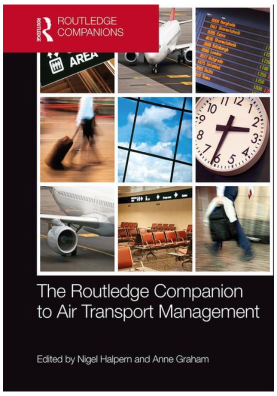

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Airline capacity planning and management

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Airline capacity planning and management

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Introduction

This chapter focuses on capacity planning and operational management for airlines (for airports, see Chapter 16). In general, the purpose of airline capacity planning is to respond to current and future travel demand of passengers (see Chapter 19). While the capacity of an airline is certain and can be planned, travel demand attracted to a particular airline is fairly uncertain. Travel demand typically depends on marketing, product offerings in the market, competition, and to some extent the market power (share) of an airline. Economies of density are identified in the literature for airlines running a hub-and-spoke network, while low cost carriers (LCCs) tend to run a point-to-point network on trunk routes and generate desired economies of scale (Button, 2002) (see Chapter 11 for a discussion of airline economies of density/scale). Since flights have various levels of demand, airlines respond to this capacity management issue by combining two techniques: the use of various fleets of different sizes, and the adjustment of service frequency on the route.

While airline capacity can be planned well ahead of operations, capacity management on the day of operation poses another challenge for airlines. Airline products (i.e. flight tickets) are offered according to a planned timetable that distributes the available capacity among routes, given certain capacity constraints. Unfortunately, daily operations are subject to stochastic disruptions from various sources, such as airport operating capacity (see Chapter 16), weather, air traffic control (see Chapter 4), aircraft availability and passenger processing. These disruptions cause varying levels of disturbance to airline operations. As such, an airline may need to reallocate capacity in its network to fulfil its transportation obligation to its customers. The management of daily capacity is called airline operations management, also known as disruption management in the industry.

Adjusting capacity allocation and flight frequency in a network gives rises to two challenging airline planning problems, namely schedule generation (SG) (also known as timetabling in the industry) and fleet assignment (FA). The issue of daily capacity management in airline operations then deals with the reallocation or withdrawal of capacity due to operational disturbances in disruption management. This chapter focuses on two main issues relating to airline capacity management: fleet assignment during schedule planning, and disruption management during operations.

Routes and network structure with uncertain demand

Uncertain demand and fleet capacity allocation

FA is critical in that it affects subsequent planning tasks in airline scheduling, including aircraft routing, crew pairing and crew rostering (Wu, 2010). FA also affects airline revenue management (RM) strategies. Hence, it has profound importance at an early stage of airline scheduling and capacity planning. For instance, route AC in Figure 15.1 has a forecast demand of 180, BC has 120, CD has 220 and CE has 80. The airline operating this network has three fleet types: Embraer 170 (80 seats), Airbus 320 (170 seats) and Airbus 330 (240 seats). It would be ideal to assign the Airbus 320 to route AC, Embraer 170 to route BC, Airbus 330 to CD and Embraer 170 to CE, based on the individual demand of sectors and the capacity of different fleet types. However, this assignment may not be entirely optimal from the RM perspective, unless routes AC and CD can be assigned the same fleet type (e.g. Airbus 330). By using the same fleet type, the airline can capture through revenues from A to D for services that are often priced higher due to the preferred shorter connection time at the hub airport C (Gopalan and Talluri, 1998; Sherali et al., 2006). This joint consideration of both a fleet assignment model (FAM) and RM can affect aircraft routing for this network.

Routes and airline network development

Travel demand between origin-destination (OD) airport pairs drives the development of airline networks (Burghouwt, 2007). The development of an airline network then drives the selection of aircraft fleets (fleet purchase) and fleet assignment to flight sectors in a network (Clark, 2001). As with the example shown in Figure 15.1, if the demand between airport F and H is high enough to sustain a non-stop flight (FH), then such a sector will be added to the network. Otherwise, a one-stop flight from F to H via hub G will be provided (i.e. FG and GH). The flight GH can then be flown with a larger aircraft if this outbound flight collects enough OD and connecting traffic from other inbound flights into G, including the traffic from F and locally from G. While this hub-and-spoke network development concept is straightforward, a key question in airline schedule planning is whether a flight sector should be provided in the network (capacity allocation) and which fleet should be used to maximise profits. This gives rises to the SG and FA problems that are commonly seen in airline scheduling.

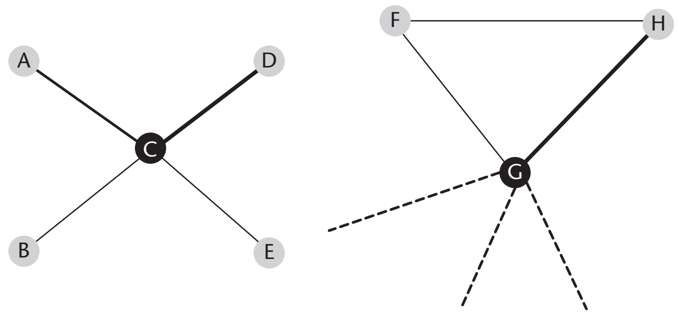

Figure 15.1 An example airline network

Source: Authors.

Fleet assignment models and profit maximization

Schedule generation and the integration with fleet assignment

The fleet assignment problem has been studied by airlines since the late 1980s. With the improvement in computing resources and solution algorithms, airlines have reported significant benefits by developing in-house FAMs (Abara, 1989; Rushmeier and Kontogiorgis, 1997; Subramanian et al., 1994). Mancel and Mora-Camino (2006) and Sherali et al. (2006) provide good reviews on the early development of FAMs, both in industry and academia. The basic flight leg-based fleet assignment model (LFAM) is provided by Hane et al. (1995) as follows:

$$\textit{Minimise} \sum_{i\in L}\sum_{f\in F} c_{f,i}x_{f,i} \text{ or } \textit{Maximise} \sum_{i\in L}\sum_{f\in F} r_{f,i}x_{f,i} - \sum_{i\in L}\sum_{f\in F} c_{f,i}x_{f,i} \tag{1.0}$$

Subject to:

$$\sum_{f\in F} x_{f,i} = 1 \forall i \in L \tag{1.1}$$

$$y_{f,a,t^-} + \sum_{i\in I(f,a,t)} x_{f,i} - y_{f,a,t^+} - \sum_{i\in O(f,a,t)} x_{f,i} = 0 \,\forall f,a,t \tag{1.2}$$

$$\sum_{a\in A} y_{f,a,O^-} + \sum_{i\notin CL(f)} x_{f,i} \le N_f \,\forall f \in F \tag{1.3}$$

$$x_{f,i} \in \{0,1\}, \forall f \in F, \textit{and} \,\forall i \in L$$

$$y_{f,a,t} \ge 0, \forall f,a,t$$

The basic LFAM aims at minimising the total costs of FA, including passenger spill costs, spill recapture, passenger carrying costs and aircraft operating costs (aggregately modelled by the cost term, $C_{f,i}$ in (1.0)), given the assignment of fleet *f* to flight leg *i*, $r_{f,i}$. An alternative objective function is to maximise expected profit contribution by incorporating the estimated expected revenues from fleet assignment $x_{f,i}$ (modelled by the revenue term, $r_{f,i}$ in (1.0)). Constraints (1.1) ensure that each flight is only covered by exactly one fleet type. This type of constraint arises in many planning and recovery problems, and is commonly termed the flight coverage constraint. Constraints (1.2) impose flow balance for the aircraft (fleet) across the planning horizon. Constraints (1.3) ensure that the size of each fleet is respected in the solution.

While airlines have long realised the importance of FA in schedule planning, the importance of SG has attracted less attention in the literature until recently. Gopalan and Talluri (1998) note the important role that SG may play and how the outcome of SG may affect fleet assignments and aircraft routings. Since airlines can change flight times in the timetable, research has found that the performance of FAM can be significantly improved if SG is incorporated or integrated with FAM. Belanger et al. (2006) and Rexing et al. (2000) use the concept of time windows to allow flexibility in setting flight departure times at the SG stage. Multiple copies of the original flight departure time are created to allow flexibility in choosing the optimal departure time in order to improve FAM results. Lohatepanont and Barnhart (2004) combine SG and FAM so the timetable is optimised according to the potential gains in FAM. More recently, Sherali et al. (2013) extend the process of integrating SG and FAM to further integrate with the aircraft routing model (ARM), while Pita et al. (2013) propose an integrated SG and FAM by explicitly considering the operational costing of aircraft and passenger delays under airport congestion scenarios.

Moving from LFAM to origin-destination fleet assignment model (ODFAM)

As illustrated by Figure 15.1 earlier, FAM results can affect how flights are connected by different fleets in aircraft routing optimisation, and accordingly how airline tickets are offered in the market. Perhaps more importantly, the FAM affects how tickets are priced in RM systems of airlines. Earlier basic FAMs in the literature predominantly focused on LFAM that treated each flight leg independently without explicit consideration of the interdependencies of passenger spills due to FA and the implications on network revenues that an airline network can leverage (Barnhart et al., 2002). For an example of possible network effects on airline revenue management strategies and the comparison with LFAM, readers are referred to Barnhart et al. (2002).

An itinerary-based fleet assignment model (IFAM) is proposed by Barnhart et al. (2002) that incorporates a passenger mix model (PMM) in LFAM. PMM is developed to minimise passenger spill and carrying costs by capturing the network effects of passenger booking subject to flight capacity constraints and booking spills in the RM system. IFAM differs from the LFAM in that IFAM incorporates the PPM model by adding the PPM term in the objective function of LFAM:

$$\sum_{p\in P}\sum_{r\in P}(\widetilde{fare}_p - b_p^r\widetilde{fare}_r)t_p^r, \tag{2}$$

where $\widetilde{fare}_p$ ($\widetilde{fare}_r$) is the fare of itinerary p (r), b_p^r represents the recapture rate of passenger spill from p to r, and t_p^r denotes the number of spilled passengers from itinerary p to r. Further constraints are also added in the IFAM formulation to consider seat capacity allocation in the FAM part of the IFAM framework (Barnhart et al., 2002).

Recognising the fundamental importance of the interdependencies between flight sectors in FAM and RM, efforts have been focused on two areas: modelling passenger flows in the network and improving the revenue calculation (estimation) in FAM. Yan et al. (2007) combines SG and a passenger flow model (PFM) with FAM so to further exploit the potential gains of flight scheduling and FAM on passenger flows across an airline network. Jacobs et al. (2008) extend the basic LFAM and incorporate the network flow aspects of uncertain yield management in airline RM systems. This ODFAM formulation specifically incorporates RM systems that deal with passenger flows in the FAM framework to account for the probabilistic aspect of yield management in RM.

Dumas and Soumis (2008) develop a PFM that can be used to find an approximation of the expected passenger flows on an airline network given demand forecast data and an assumed booking process. Specifically, the PFM by Dumas and Soumis (2008) considers random distributions of itinerary demand, time distribution of itinerary bookings, and the estimation of passenger spill to a given itinerary. This PFM is then used in Dumas et al. (2009) to improve the outcome of FAM by focusing on the estimation of revenue loss that is commonly adopted in FAM to drive the passenger revenue component in the objective function of FAM. In the improved calculation, Dumas et al. (2009) are able to use the PFM to model spill and recapture between itineraries and account for leg interdependency of revenues.

Barnhart et al. (2009) focus on enhancing the revenue modelling part of LFAM by a different formulation called the subnetwork fleet assignment model (SFAM). The motivation of SFAM is the concern that assumptions made on the revenue estimation in the literature are too simplistic to reflect the complexity of RM systems commonly used by airlines, potentially leading to suboptimal FAM results. The generic fleet assignment model (GFAM) proposed by Barnhart et al. (2009) is shown to be the generalised form of LFAM. Two factors are considered in formulating

SFAM: improving revenue modelling by partitioning a network into subnetworks, and reformulating GFAM into SFAM. The expected revenue function $r(x;h)$ in FAM is often provided in a linear form of fleet assignment *x* under fare structure *h* in the literature. The expected revenue is then approximated by $r(x;h) = \sum_{i \in L} \sum_{f \in F} r_{f,i} x_{f,i}$ in LFAM. The simplified and implicit assumption in the estimation of expected revenue lies in the allocation of the revenue share that a particular flight sector *i* receives in a possible multi-sector itinerary booking.

IFAM improved LFAM by modelling the revenue function with an itinerary variable *p* that replaces individual sector variable *i* in the formulation, along with capacity side constraints and more detailed fare structures (Barnhart et al., 2002). SFAM uses the subnetwork concept and partitions an airline network into *k* subnetworks to transform the revenue function to $r\left(x;\sum_{k=1}^{K} h^k\right) = \sum_{k=1}^{K} r\left(x;h^k\right)$ for a specific fare structure h^k for subnetwork k. SFAM is then formulated by transforming the fleet assignment decision variable $x_{f,i}$ in (1) to a composite decision variable ω_j for fleet assignment configuration *j*. In essence, SFAM builds a stronger revenue estimation framework that is fully incorporated in the FAM formulation. This leads to better FAM results that are more consistent to RM strategies and passenger bookings observed in the industry.

RM-driven fleet assignment

Given the sequential airline schedule planning paradigm, decisions made earlier in the scheduling process can have profound impacts on schedule execution and airline revenues. From the perspective of airline capacity management, and more specifically FA, decisions of fleeting can affect RM strategies (and revenues), aircraft routing, crewing and flight operations. Berge and Hopperstad (1993) question the suitability of FAM results on the day of operation given the long lead time (two to three months in advance) that FAM results are produced and the potential mismatch of FAM results and the continuing realisation of ticket booking levels up to the day of departure. A demand-driven dispatch (D^3) concept is then developed to take advantage of the updated ticket booking levels some time before the departure day, and accordingly adjusts FAM results to better suit realised demands. This type of RM-driven FAM tries to better match capacity allocation among flights via re-fleeting (re-FA) with updated booking demand forecasts during a booking period.

Although it appears ideal for RM to re-FA, the snowballing effects of re-FA due to the sequential schedule planning process cannot be ignored. Bish et al. (2004) then examine two key questions in RM-driven FAM, including timing (when re-FA by aircraft swapping should be carried out) and frequency (how often re-FA should be conducted). Arguably, with later timing and higher frequency, the re-FA can achieve better revenues because of superior demand forecasts and better matching between demand and capacity. However, late re-FA may greatly disturb aircraft routing and crew rosters, leading to higher schedule planning costs that are not always clear during the re-FA process. Regarding the inclusion of RM components in FAM, Wang and Meng (2008) is perhaps the most extensive with respect to RM modelling in FAM. A dynamic programming model that contains a continuous-time network yield management problem with D^3 is developed to integrate RM components when solving FAM. A small example implementing the integrated framework is provided by Wang and Meng (2008) to demonstrate this idea.

The idea of RM-driven FAM is further extended by Jiang and Barnhart (2009) and Warburg et al. (2008) with the concept of dynamic airline scheduling. Through flight retiming and re-FA, coupled with updated booking demand forecasts, dynamic scheduling aims to better match fleet capacity with stochastic travel demand that is gradually realised during the booking period. Flight retiming can generate new connection opportunities for offering new itineraries in the market, while re-FA can swap aircraft types among flights so to match new demand forecast with capacity while flight booking is in progress. In both papers, retiming and re-FA are reported to generate synergy when they are applied simultaneously, and result in significant profit gains for case study airlines. The dynamic airline schedule concept is further extended to include robustness from schedule generation (SG), in which the number of potentially connecting itineraries is maximised by using revenues as weighting factors (Jiang and Barnhart, 2013). This robustness is then embedded in the dynamic scheduling environment so the timetable can be more easily modified, reflecting changing demand in the booking period.

Incorporating robustness in FAM and integrated capacity planning

Since FAM is solved early in the process of airline schedule planning, FAM results greatly affect subsequent scheduling tasks. Accordingly, researchers have focused on improving the robustness of FAM, and have recently extended this pursuit by integrating FAM with follow-up scheduling tasks. Early efforts of achieving robustness in FAM are through embedding schedule recovery options in FAM.

A simple recovery approach that has received academic and industry interest is aircraft swapping. A swap can be performed if two aircraft are planned to be on the ground at the same airport at the same time. If one aircraft is delayed, the other can be swapped to perform the alternate aircraft route. Ageeva (2000) presents a scheduling approach that aims to maximise aircraft swapping opportunities. Kang (2004) uses the concept of subnetwork to improve the robustness of the complete schedule. The subnetworks are given by a partitioning of the flights. In the scheduling process, each aircraft routing, crew pairing and passenger itinerary is constructed using flights of a single subnetwork. This idea tries to isolate the impact of disruptions. Ideally, a disruption will only affect a single subnetwork, and as a result only have an impact on a subset of aircraft, crew and passengers. Rosenberger et al. (2004) focus on creating short cycles in FAM, so when disruption occurs, short flight cycles (i.e. a pair of flights out and back to a hub) can be cancelled without affecting aircraft routing. The concept of station purity in FAM is developed by Smith and Johnson (2006), where the types of fleets that can be assigned to a single hub are limited by some criteria. By this, Smith and Johnson (2006) demonstrate that flow-on benefits from FAM make crew scheduling, maintenance scheduling (aircraft routing) and disruption recovery simpler, with reduced operational costs.

Paradigm shift in airline scheduling

Airline scheduling is substantially driven by corporate resource utilisation and profit maximisation. Airline scheduling generally refers to the whole process of generating an airline schedule, including schedule generation, fleet assignment, aircraft routing, crew pairing and crew rostering. Due to the large-scale nature of real-world airline scheduling problems, airline scheduling has been approached by a divide-and-conquer philosophy. This strategy involves solving tasks sequentially, where the output of one task is used as the input to subsequent tasks (Bazargan, 2012; Wu, 2010; Wu and Maher, 2017).

The most notable drawback of this approach is that the solution quality (also the solution space) of a subsequent task heavily depends on the solution of the previous task. Often, the sequential approach lacks consideration of interdependence between tasks in airline scheduling. A characteristic of the sequential approach is the fixing of solutions for use as input to subsequent stages. This process typically results in suboptimal or even infeasible solutions across planning stages. As an example, Barnhart et al. (1998) state that the optimal FAM result in their case study did not always yield feasible aircraft maintenance routing solutions.

Additionally, the pursuit of corporate profit maximisation also pushes airlines to maximise asset utilisation, leaving little buffer for disruptions. As a result, airlines incur high operating costs due to disruption management actions, although the optimised schedule may have the potential to generate maximum profits with the least costs. The paradigm of airline scheduling, recognising the weakness of current scheduling practice, has gradually shifted to integrated schedule planning and robust scheduling.

The most intuitive form of integrated planning is the combination of two related planning problems, such as FAM and ARM (Barnhart et al., 1998), while the most complex involves optimisation problems that encompass the complete airline planning process, such as the one developed by Papadakos (2009). With a better understanding of solution algorithms and improved computing resources, the benefits of integrated planning can be realised.

The goal of integrated planning is to address the limitations of the sequential planning paradigm by considering multiple resources or tasks simultaneously. Further, the consideration of multiple resources provides the opportunity to impose extra planning conditions to improve operational performance.

Integrating crew scheduling and aircraft routing

A very important direction of integrated planning is the simultaneous scheduling of crew and aircraft. Crew wages and fuel costs represent the two largest costs to an airline (see Chapter 11). As such, the improved planning solution given by combining the optimisation of crew and aircraft will have a significant impact on the profitability of an airline.

The combination of crew scheduling and aircraft routing is presented by Cordeau et al. (2001). In the airline planning context, a connection is defined as two flights that can potentially be operated by the same crew or aircraft consecutively. Specifically, given flight i and flight j, the connection (i, j) is valid if: (i) the destination of i is the same as the origin of j; and (ii) the time between the arrival of i and the departure of j is greater than the minimum connection time at an airport, called the turn time for aircraft and sit time for crew.

The minimum sit time for crew is typically longer than the minimum turn time for aircraft. This leads to the definition of a short connection, which is a connection where the difference in the arrival of flight i and the departure of flight j is less than the minimum sit time but at least as long as the minimum turn time. Crew are permitted to use a short connection if an aircraft also uses the same connection. A key contribution of Cordeau et al. (2001) is the improved use of short connections in crew pairing, leading to lower planning and operational costs. The mathematical model integrating the crew pairing model (CPM) and ARM provided by Cordeau et al. (2001) is:

$$\textit{Minimise} \sum_{f \in F} \sum_{\omega \in \Omega^f} c_\omega \theta_\omega + \sum_{k \in K} \sum_{\omega \in \Omega^k} c_\omega \zeta^r_\omega \tag{3.0}$$

Subject to:

$$\sum_{f \in F} \sum_{\omega \in \Omega^f} a^i_\omega \theta_\omega = 1 \left(i \in N \right), \tag{3.1}$$

$$\sum_{k \in K} \sum_{\omega \in \Omega^k} a^i_\omega \zeta_\omega = 1 \left(i \in N \right), \tag{3.2}$$

$$\sum_{k\in K}\sum_{\omega\in\Omega^k} b_\omega^{ij}\zeta_\omega - \sum_{f\in F}\sum_{\omega\in\Omega^f} b_\omega^{ij}\theta_\omega \leq 0\left((i,j)\in C\right), \tag{3.3}$$

$$\sum_{\omega\in\Omega^f}\theta_\omega = 1\left(f\in F\right), \tag{3.4}$$

$$\sum_{\omega\in\Omega^k}\zeta_\omega = 1\left(k\in K\right), \tag{3.5}$$

$$\theta_\omega \in \{0,1\}\left(f\in F;\omega\in\Omega^f\right)$$

$$\zeta_\omega \in \{0,1\}\left(k\in K;\omega\in\Omega^k\right)$$

The objective (3.0) of this problem is to simultaneously minimise the cost of aircraft routing and crew pairing. The variables θ_ω (ζ_ω) equal 1 to indicate the use of flight route (crew pairing) ω. Constraints (3.1) and (3.2) ensure that all flights in the network are operated by exactly one crew and aircraft, respectively. These constraints are the flight coverage constraints. Constraints (3.3) enforce the condition that crew can only use a short connection if an aircraft is also using the same connection. Finally, constraints (3.4) and (3.5) ensure that each crew and aircraft are assigned to exactly one path through the network.

An important aspect that is presented in the above model is the use of variables to identify paths through a network. These paths are described as aircraft routings and crew pairings. Thus, a path is a sequence of flights that is performed by a single crew or aircraft over a predefined time period. Given that the total number of paths is exponential in the number of flights, it is not practical to completely enumerate all variables (i.e. paths). This difficulty is addressed by the use of the solution technique, column generation (Desaulniers et al., 2005).

Column generation is a solution technique used to solve linear programs by dynamically generating variables. Linear programs that are suitable for the application of column generation typically contain a large number of variables, most of which are expected to be zero in the optimal solution. The column generation solution algorithm initialises a restricted master problem (RMP), containing only a subset of all variables, and a sub-problem. The master problem solves to find an upper bound on the optimal solution and the sub-problem is tasked with identifying new variables that, when added to the master problem, will reduce the upper bound. When integer variables are present in the problem, the optimal solution is found using the related technique of branch-and-price.

Using problem (3) as an example, the RMP is given by (3.0)–(3.5), but formulated with only a subset of the variables θ_ω and ζ_ω . This is achieved by replacing the sets Ω^f and Ω^k with $\bar{\Omega}^f$ and $\bar{\Omega}^k$, respectively, where the latter are subsets of the former. Given a solution to the RMP, the sub-problem, which is a resource-constrained shortest-path problem, is solved to identify variables from $\bar{\Omega}^f\backslash\Omega^f$ and $\bar{\Omega}^k\backslash\Omega^k$ to add to the RMP. The linear program is solved to optimality when no additional variables that could improve the solution to the RMP can be identified in the sub-problem. As mentioned above, branch-and-price would then be required to find the integer optimal solution.

Integrating fleet assignment, aircraft routing and crew scheduling

Given the fundamental nature of the FAM within the airline planning process, the integration with other planning stages is expected to provide improved planning solutions. Haouari et al. (2009) integrate FAM with ARM so to provide higher quality solutions to the ARM by using a network flow-based approach. Since some constraints in FAM and ARM overlap (such as the constraints of aircraft flow balance and aircraft counts), many FAM elements can be replaced by ARM elements. Papadakos (2009) draws upon this idea and extends upon the work of Cordeau et al. (2001) and Mercier et al. (2005) to develop an integrated model that incorporates FAM, ARM and CPM:

$$\textit{Minimise} \sum_{f\in F}\sum_{r\in R^f} c_r^+ v_r + \sum_{f\in F}\sum_{p\in P^f} c_p \omega_p \tag{4.0}$$

Subject to:

$$\sum_{f\in F}\sum_{r\in R^f} e_{lr} v_r = 1, \forall l \in L \tag{4.1}$$

$$\sum_{p\in P^f} a_{lp}\omega_p - \sum_{r\in R^f} e_{lr} v_r = 0, \forall l \in L, \forall f \in F \tag{4.2}$$

$$\sum_{p\in P^f} s_p^{ij}\omega_p - \sum_{r\in R^f} s_r^{ij} v_r \le 0, \forall (i,j) \in S^f, \forall f \in F \tag{4.3}$$

$$q_m - q_{m^-} + \sum_{r\in R^f} \left(e_{mr}^+ - e_{mr}^-\right) v_r = 0, \forall m \in M^f, \forall f \in F \tag{4.4}$$

$$\sum_{m\in \hat{M}^f} q_m + \sum_{r\in R^f} \hat{e}_r v_r \le n_f, \forall f \in F \tag{4.5}$$

$$v_r \in \{0,1\}, \forall r \in R^f, \forall f \in F$$

$$q_m \ge 0, \forall m \in M^f, \forall f \in F$$

$$\omega_p \in \{0,1\}, \forall p \in P^f, \forall f \in F$$

In this formulation, the objective is to minimise costs. Constraints (4.1) ensure that each sector is assigned to exactly one route of a single fleet. Constraints (4.2) assign leg l to be included in one crew pairing for fleet f if and only if l is assigned to that fleet. Constraints (4.3) cover short crew connections if and only if the two consecutive flights are operated by the same aircraft. Constraints (4.4) describe the aircraft flow balance, which is essential in FAM and ARM. Constraints (4.5) limit the use of aircraft to the fleet size available. Salazar-Gonzalez (2014) operationalises the fully integrated model by Papadakos (2009) to solve the schedule planning problem of a regional Spanish carrier.

Solving integrated planning problems

The above two problems present the integration of crew and aircraft. This integration is modelled by constraints (3.3) in the Cordeau et al. (2001) model, and constraints (4.2) and (4.3) in the Papadakos (2009) model. These constraint sets introduce a large number of additional constraints that are not present in the individual aircraft routing and crew pairing problems. The ability to handle this increase in problem size is an important challenge of integrated planning.

Relaxing the integration constraints allows the crew and aircraft problems to be solved independently. This idea is exploited by applying the solution technique of Benders' decomposition

(Benders, 1962). The crew and aircraft problems are solved independently using a master/slave solution algorithm. Using Cordeau et al. (2001) as an example, the aircraft problem is formulated with constraints (3.2) and (3.5) and the crew problem is formulated with constraints (3.1), (3.3) and (3.4). The solution to the aircraft problem is fixed and then provided to the crew problem as input, greatly simplifying the relationship between the resources that is defined by constraint (3.3). Using this fixed input, the solution to the crew problem generates additional constraints that are added to the aircraft problem. This may appear similar to the sequential solution approach, such as Dunbar et al. (2012) and Weide et al. (2010). However, the sequential approach is a heuristic while the Benders' decomposition algorithm finds the optimal solution to the integrated problem. The use of Benders' decomposition is demonstrated by Cordeau et al. (2001) and Papadakos (2009) to be an effective solution approach to improve the solving performance of the integrated problem.

Airline capacity and disruption management

Disruptions to airline operations are commonplace. In 2015, 79.92 per cent of all arriving flights in the United States were on time, with the 10-year average on-time performance to December 2015 reported as 77.82 per cent (Bureau of Transportation Statistics, 2016). The on-time performance results demonstrate that schedule perturbations are an unavoidable part of airline operations. In response to the persistent nature of delays, airlines engage in the process of disruption management – a class of practices and decision-making processes designed to address the impact of schedule perturbations by managing airline capacity reallocation and sometimes performing re-optimisation.

Disruption management can be categorised into two classes – proactive and reactive disruption management. Proactive disruption management, commonly termed robust planning, is characterised by the development of airline planning solutions that are expected to be less susceptible to flight delays. A key example is the allocation of buffer times (increasing slack) between the arrival and departure of an aircraft (AhmadBeygi et al., 2008; Eggenberg, 2009; Wu, 2006). Proactive disruption management also includes embedding potential recovery possibilities into the planning solution. Examples of this technique include reducing the number of flights an aircraft performs away from a hub (short cycles) (Rosenberger et al., 2004) and providing aircraft swapping opportunities (Ageeva, 2000). Reactive disruption management, also termed airline recovery, is characterised by the repair of flight schedules, aircraft routings and crew pairings following a disruptive event (Clausen et al., 2010). In general, proactive disruption management aims to provide planning solutions that will reduce the potential impact of schedule disruptions, while reactive approaches respond to disruptions on the day of operations and provide tools and techniques to minimise the resulting impact.

Proactive disruption management

The main aim of proactive disruption management is to efficiently allocate resources while minimising the expected impact of schedule perturbations. The areas of airline planning that have seen significant progress in the development of proactive disruption management approaches are aircraft routing and crew scheduling.

Many of the developments in proactive disruption management have arisen from the integration of aircraft and crew. The integration of aircraft and crew with a focus on restricted and short connections is presented by Cordeau et al. (2001) and Mercier et al. (2005). An extension of this work to include flight retiming is developed by Mercier and Soumis (2007). Additionally, proactive disruption management approaches that minimise a delay measure in an integrated aircraft and crew planning problem have been developed by Dunbar et al. (2012) and Weide et al. (2010). Alternatively, the concept of recoverable robustness is introduced for the tail assignment and maintenance planning problems by Froyland et al. (2014) and Maher et al. (2014).

In airline planning, there is a trade-off between the most efficient use of resources and the susceptibility of the planned solution to schedule disruptions. When planning solutions are found without considering the possibility of disruptions, the result is the most efficient use of resources with the lowest cost. However, such planning solutions are typically brittle and are highly susceptible to disruptions. In contrast, proactive disruption management approaches aim to identify alternative solutions that may appear to be suboptimal with respect to efficient resource usage and cost, but are expected to provide improved operational performance. The value of proactive disruption management techniques is realised only on the day of operations. The expectation is that the increase in planning costs due to using proactive disruption management planning techniques can be compensated by a decrease in operational costs.

Proactive approaches to reduce flight delay propagation

The use of proactive disruption management to avoid flight delays is a major focus of research. There are two categories of flight delays: primary and secondary delays. Primary delays are those that are caused by disrupting events such as inclement weather, late passengers or unscheduled maintenance. Secondary delays are those that occur as the result of previously delayed flights, commonly caused by aircraft routing, crewing and passenger connections in the network.

The simplest approach to minimise the impact of flight delays involves the generation of aircraft routings and crew pairings that only use connections with a longer buffer time between consecutive flights. A more sophisticated approach applying this concept in an optimisation model is presented by Eggenberg (2009). The presented approach solves the maintenance routing problem to maximise the total slack or maximise the minimum slack between flight connections. It is noted that in an unconstrained problem, the maximum total slack may be infinite. However, the ARM by Eggenberg (2009) includes flight coverage constraints, and a constraint on the maximum number of aircraft ensures that the maximum total slack is finite. The approach developed by Eggenberg (2009) aims to better distribute connection slack across all flight connections. Flight retiming was employed by Lan et al. (2006) to reduce the prevalence of propagated delay in the solution to the aircraft routing problem. A more involved approach using estimates for the probability of propagated delay in the tail assignment problem is presented by Dovica (2014).

An example of propagated delay is presented in Figure 15.2. The horizontal axis represents time and the vertical axis is the location of an airport. The diagonal lines are flights and those of the same colour are operated by the same aircraft. In Figure 15.2, aircraft VH-435 experiences a primary delay when operating flight AR242 from BNE to MEL. This primary delay is greater than the buffer time planned for the next flight to be operated by VH-435, which is flight AR328 from MEL to SYD. As a result, some of the original primary delay on flight AR242 is propagated onto the subsequent flight for VH-435, flight AR328.

A proactive disruption management approach that considers the probability of delay propagation is presented by Dovica (2014). Using historical data, Dovica (2014) computes the

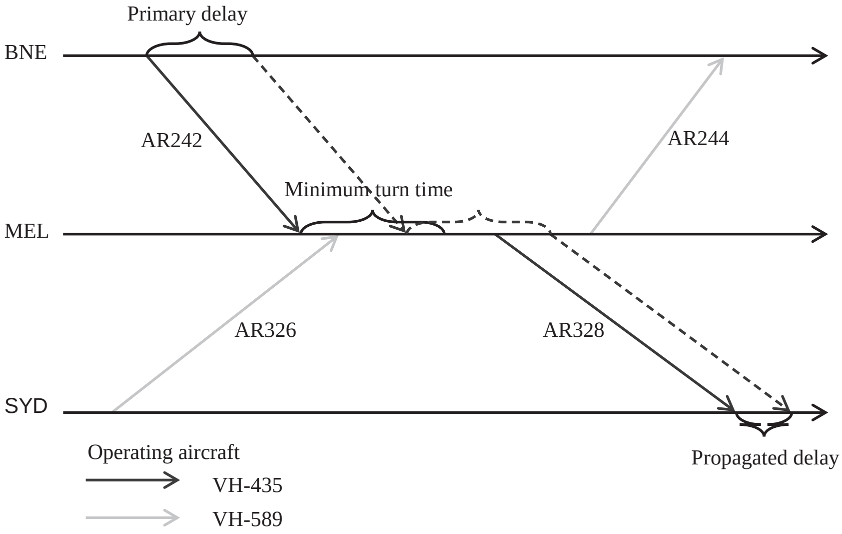

Figure 15.2 Example of propagated delay

Source: Authors

probability of delay propagating between two consecutive flights. This computed probability is used to minimise the expected propagated delay. An interesting aspect of this work is that secondary flight delays are considered as a variable in the model, not as a historical data input. By considering flight delays as variables in the model, the actual delays that could be experienced are better represented. The resulting optimisation problem is then solved to minimise the probability of propagated delay. This approach attempts to more effectively use buffer times to address delays while ensuring a high utilisation of aircraft.

An integrated planning approach that explicitly minimises a propagated delay measure is presented by Dunbar et al. (2012). The amount of expected delay propagation for a given aircraft routing ω and crew pairing δ is computed using the following equations, respectively:

$$d_j^R = max\left\{d_i^R - \left(s_{ij}^R - p_{ij}^R\right), 0\right\} \forall (i, j) \in \omega, \tag{5}$$

$$d_j^P = max\left\{d_i^P - \left(s_{ij}^P - p_{ij}^P\right), 0\right\} \forall (i, j) \in \delta. \tag{6}$$

The optimisation problem presented by Dunbar et al. (2012) is an integrated aircraft routing and crew planning problem. The integration of aircraft and crew is achieved using an iterative algorithm. This algorithm treats each resource separately, but uses the solution for the alternate resource as input. Most importantly, the delay propagation with respect to crew is considered in the aircraft problem with the following modification to equation (5):

$$d_j^R = max\left\{d_i^R - \left(s_{ij}^R - p_{ij}^R\right), d_k^P - \left(s_{kj}^P - p_{kj}^P\right), 0\right\}, \tag{7}$$

where (*i, j*) is part of an aircraft routing and (*k, j*) is part of a crew pairing. For the aircraft routing problem, the crew pairings are fixed as given. As such, all crew pairing connections (*k, j*) are known and each term $d_k^P - \left(s_{kj}^P - p_{kj}^P\right)$ is fixed. Similarly, the propagated delay for each flight in a crew pairing is identified with fixed aircraft routings by using the following equation:

$$d_j^P = max\left\{d_i^P - \left(s_{ij}^P - p_{ij}^P\right), d_k^R - \left(s_{kj}^R - p_{kj}^R\right), 0\right\}, \tag{8}$$

where (i, j) is now part of a crew pairing and (k, j) is part of an aircraft routing.

The integrated planning approach by Dunbar et al. (2012, 2014) is effective in reducing the expected propagated delay when the approach is used in robust airline scheduling. Most importantly, the use of the iterative algorithm is valuable in improving robustness in relatively small runtimes. While the iterative algorithm is effective, the algorithm does not guarantee optimality. As such, exact solution approaches that provide a similar decomposition, such as Benders' decomposition, can be a valuable future research direction.

Reactive disruption management recovery

Unexpected events regularly cause flight delays that require direct intervention by an airline. Recovery is the term given to the reactive disruption management techniques employed by an airline on the day of operations to mitigate the impact of schedule perturbations. Airline recovery is a complex capacity management process that is commonly performed in a series of sequential stages that is analogous to that of the planning counterpart (Clausen et al., 2010). The stages of airline recovery typically consist of schedule, aircraft, crew and passenger recovery. Similar to the planning process, airline recovery solves each stage in order with the solutions to the preceding stage fixed and used as input for the following stage. The complexity of the airline recovery problem is similar to airline planning. However, while planning is performed over many months, a recovery solution is required within minutes or hours, depending on the scale of disruptions. Additionally, because disruptions can significantly affect the planned schedule, feedback is required in the airline recovery problem to repair any infeasibilities that result from using fixed inputs between the stages.

There are numerous actions that can be performed to mitigate the effects of schedule disruptions. The possible types of actions include, but are not limited to, delaying or cancelling flights (schedule recovery), changing the aircraft operating a flight (aircraft recovery), and changing the crew operating a flight (crew recovery). These actions aid the airline to manage capacity in operations by changing flight capacities (cancelling or changing aircraft types), and accordingly the crew that are required to operate the updated schedule.

Aircraft recovery

In response to the complexity of airline recovery, early research was directed towards aircraft recovery. One of the first examples of aircraft recovery was presented by Teodorović and Guberinic (1984). A feature of the model presented by Teodorović and Guberinic (1984) is the use of only flight delays as a recovery policy. The limited use of recovery policies in early aircraft recovery problems was driven by the lack of computing resources to solve more complex problems in the required short runtimes. A prominent example of aircraft recovery problems with limited use of actions is the development of delay-only and cancellation-only models by Jarrah et al. (1993). A more comprehensive view of the aircraft recovery problem is presented by Thengvall et al. (2000), which incorporates aircraft swapping, flight delays and cancellations.

An interesting feature included in the model of Thengvall et al. (2000) is the objective of minimal deviation from the planned aircraft routings. This objective aids in forming solutions that are more human-friendly, and are expected to be more intuitive and easily implementable by operation controllers of airlines. Similar to the planning stages, advances in recovery problems have been made through the integration of related optimisation problems. Eggenberg et al. (2010) is a notable example, with the inclusion of maintenance routing constraints in the aircraft recovery problem.

An important feature of aircraft recovery problems is the structure design of the underlying network that is used to model airline schedule and resource connections. Three main network designs are the most prevalent – time–line, time–band and connection networks. The time–line network, used by Jarrah et al. (1993), Yan and Yang (1996) and Thengvall et al. (2000), provides an accurate description of the recovered schedule. However, this accurate description comes with a trade-off, typically resulting in very large problem formulations. The time–band network, as presented by Argüello (1997) and Eggenberg et al. (2010), attempts to address the large networks required to describe recovered schedules by aggregating activities into discrete time-bands. Finally, the connection network, which is also popular for airline planning problems, is used by Rosenberger et al. (2003) as an accurate and concise description of the recovered schedule and related activities.

Integrated schedule and aircraft recovery model

The motivation for combining schedule and aircraft recovery is that flight delays and cancellation decisions rely on the availability of aircraft to operate the recovered schedule. Performing schedule and aircraft recovery separately requires a feedback process between the two problems to ensure that a feasible solution for both schedule and aircraft can be provided. Consider the aircraft recovery problem presented by Rosenberger et al. (2003):

$$\textit{Minimise} \sum_{p \in P} \sum_{r \in R_{(p,f)}} c_r X_r + \sum_{f \in F} b_f K_f \tag{9.0}$$

Subject to:

$$\sum_{r \in R_{(p,f)}} X_r = 1 \forall p \in P, \tag{9.1}$$

$$\sum_{r \ni f} X_r + K_f = 1 \forall f \in F, \tag{9.2}$$

$$\sum_{r \in R_u} X_r \le 1 \forall u \in U, \tag{9.3}$$

$$\sum_{r \in R_a} \left| H(r,a) \right| X_r \le \alpha_a \forall a \in A, \tag{9.4}$$

$$X_r \in \{0,1\} \forall r \in R_{(p,f)}, p \in P,$$

$$K_f \in \{0,1\} \forall f \in F.$$

This model captures the main features of the aircraft recovery problem – flight delays and cancellations and the rerouting of aircraft. The objective of the aircraft recovery problem is to minimise the cost of flight delays and cancellations. The cost parameter c_r in the objective function (9.0) is the unit cost of operating aircraft routing *p*, which includes the cost of delaying flights on that route. The parameter b_f represents the cost of flight cancellations. This cost typically includes direct costs, such as lost revenues, and indirect costs, such as loss of passenger goodwill. Constraints (9.1) state that each aircraft can be assigned at most one routing. Constraints (9.2) state that each flight must be included in exactly one flight routing or is cancelled. An important feature of aircraft recovery is the management of available airport slots and capacity. These necessary restrictions are imposed by constraints (9.3) and (9.4).

There are many similarities between the aircraft routing planning and aircraft recovery problems. Specifically, the aircraft routing problem requires flight coverage constraints. Compare the aircraft routing and scheduling model presented by Desaulniers et al. (1997):

$$\text{Minimise} \sum_{k\in K}\sum_{p\in\Omega^k} c_p^k \theta_p^k, \tag{10.0}$$

Subject to:

$$\sum_{k\in K}\sum_{p\in\Omega^k} a_{ip}^k \theta_p^k = 1 \,\forall i \in N, \tag{10.1}$$

$$\sum_{p\in\Omega^k} \left(d_{sp}^k - o_{sp}^k\right)\theta_p^k = 0 \,\forall k \in K, \forall s \in S^k, \tag{10.2}$$

$$\sum_{p\in\Omega^k} \theta_p^k = n^k \,\forall k \in K, \tag{10.3}$$

$$\theta_p^k \geq 0 \,\forall k \in K, \forall p \in \Omega^k,$$

$$\theta_p^k \text{ integer} \,\forall k \in K, \forall p \in \Omega^k.$$

The aircraft routing and scheduling model of Desaulniers et al. (1997) minimises the expected routing cost. In this model, *k* represents the set of all aircraft types. As such, all aircraft of the same type are considered identical. In comparison to the aircraft recovery problem, only a single aircraft type is considered, but each aircraft is individually identified. Assuming that in the above model each individual aircraft is a unique type, then $n^k = 1 \forall k \in K$. This makes the routing model of Desaulniers et al. (1997) and recovery problem of Rosenberger et al. (2003) in (9) directly comparable.

The main differences between the aircraft routing and recovery problem are given by the additional flexibility permitted in the latter. Namely, flight cancellations are permitted – modelled in constraint (9.1) – but are not permitted in the routing model, as indicated by constraint (10.1). Additionally, in recovery, flight delays are considered in the generation of recovery aircraft routes. There are also further restrictions that must be considered in the recovery problem. In particular, the recovery problem must manage the scarce resource of airport capacity (see Chapter 16).

Crew recovery

Crew recovery is a very complex part of the airline recovery process. This is due to the large number of crew members and the complex working rules that must be satisfied. Early attempts developing crew recovery problems focused on the sequential recovery process, specifically using a modified flight schedule and aircraft routings as inputs. Examples of crew recovery with a fixed flight schedule include Medard and Sawhney (2007), Nissen and Haase (2006), Stojković et al. (1998) and Wei et al. (1997). Similar to the planning process, using fixed inputs from preceding stages results in suboptimal, or even infeasible, solutions. As such, it is important within the crew recovery problem to consider flight delays and cancellations. The use of flight cancellations is considered by Lettovsky et al. (2000) and the modelling of flight delays for crew recovery is presented by Stojković and Soumis (2001). A further development of the crew recovery problem to include both flight delays and cancellations is presented by Abdelghany et al. (2004). A novel aspect of the work by Abdelghany et al. (2004) is the use of a rolling time horizon in the solution algorithm. The rolling time horizon breaks the complete crew recovery problem into a number of smaller problems that are expected to be easier to solve.

Integrated airline recovery

Similar to airline planning, there is a growing interest in the integration of airline recovery stages. The greatest impediment to the development of an integrated problem is the very restricted short time frames that are given to find an implementable solution in practice. However, many attempts have been made to develop partially and completely integrated airline recovery problems.

Many approaches developed for aircraft and crew recovery exhibit a partial integration with schedule recovery decisions. Examples of such partial integration are presented in the previous sections. Extending upon partially integrated approaches, there has been increasing interest in the integration of larger and more complex stages. In particular, the development of optimisation problems that integrate aircraft and crew recovery is a current research interest. Many integrated recovery problems extend models and solution algorithms developed for crew or aircraft recovery. For example, the model and solution methods presented by Abdelghany et al. (2004) are extended by Abdelghany et al. (2008) to include aircraft recovery decisions. In an integrated aircraft and crew recovery problem presented by Maher (2016), only a discrete set of delays at 15-minute intervals is considered due to the large number of possible delayed departure times for each flight. Discretisation of departure times is a common approximation approach employed in airline planning and recovery in order to improve the solving performance of the developed algorithm.

Passenger recovery

Passenger recovery is a very complex part of the recovery process. During the airline planning stage, potential passenger itineraries are identified for revenue management based upon business decisions reflecting possible market demands in an airline network. Passenger itineraries, which are formed by flights from the original flight schedule, result in a different network structure for passenger flows compared to the network constructed for aircraft and crew. In the event of a disruption, the networks for passenger flow and aircraft movements are affected in different ways. For aircraft, a disruption changes the departure times of the affected flights. As such, the flights still exist (assuming no cancellations), but the set of feasible connections to subsequent flights may change. In regard to passengers, the change in the feasible connections for aircraft may cause some passenger itineraries to become ineligible.

Passenger recovery typically occurs as the final stage of the sequential recovery process. This timing is chosen in an effort to address the complexity of the optimisation problem. At the end of the sequential recovery process, all schedule, aircraft and crew recovery decisions have been made and fixed. As such, all eligible and ineligible itineraries of affected passengers are known so the passenger recovery problem is modelled as an assignment problem.

A very difficult optimisation problem results from the integration of passenger recovery with schedule, aircraft and crew recovery. An itinerary recovery problem is modelled and incorporated into the integrated airline recovery problem developed by Petersen et al. (2012). Alternatively, for those airlines that only provide point-to-point services, an itinerary recovery model may be overly complex. As such, the reallocation approach by Maher (2015) greatly simplifies the passenger recovery process.

The management of passengers, such as rebooking or providing alternative transport, in recovery systems is becoming more important from the airline perspective. Challenge ROADEF (2009) focused on optimisation techniques for an integrated aircraft and passenger recovery problem. The most successful contribution in the challenge was a heuristic approach developed by Bisaillon et al. (2011). Building on the success of this approach, Sinclair et al. (2014) refine the large neighbourhood search solution algorithm of Bisaillon et al. (2011) to achieve improved solving performance. While the solution algorithm of Sinclair et al. (2014) finds good solutions in short runtimes, it is possible that they are far from optimal. A post-processing step is introduced by Sinclair et al. (2016) to improve the final solution quality. This is achieved by applying column generation to a modified version of the original aircraft and passenger recovery problem. The results of Bisaillon et al. (2011), Sinclair et al. (2014) and Sinclair et al. (2016) demonstrate the difficulty of solving recovery problems and the value of heuristic approaches.

Conclusion

Airline capacity management is a challenging topic that will receive ongoing attention in industry and academia. This chapter presents key concepts of airline capacity management focusing on the state-of-the-art airline fleet assignment model development and airline schedule recovery. There has been a long history of research into fleet assignment, with many of the developments flowing through to other critical schedule planning stages, such as crew scheduling and aircraft routing. A current focus of research for airline planning is the development of integrated planning approaches.

While the aim of airline schedule planning is to efficiently use available resources, achieving this goal is complicated as a result of uncertainties that emerge in daily operations. Proactive and reactive disruption management techniques have been developed to reduce the impact of schedule perturbation and minimise operating costs. Similar to the planning stages, there is much interest in the development of integrated approaches for disruption management. The knowledge gained in solving the capacity planning problems can be transferred to solving recovery problems that airlines face on a daily basis.

An important direction of future research is the handling of uncertainty in capacity planning using integrated models. In particular, airline fleet planning and purchase decision-making will receive more attention. As suggested by List et al. (2003) and Rosskopf et al. (2014), airlines still face the commercial risks of purchasing fleets based on uncertain long-term forecasts. Further, the growing pressure to reduce environmental impacts from operations (see Chapters 17 and 25) can drive different fleet purchasing behaviour of airlines, for example by purchasing fuel-efficient fleets.

The availability of airline planning data is important for continued research. Recently, Akartunali et al. (2013a, 2013b) proposed a framework aimed at developing benchmark research data. Freely available benchmark data will promote further research in airline planning and will provide a common base for the comparison of planning methods and algorithms. Ultimately, further research will achieve the necessary advances to improve the efficient deployment of airline resources and the effective management of capacity in daily operations.

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