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Flight operations recovery: New approaches considering passenger recovery

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Abstract The sources of disruption to airline schedules are many, including crew absences, mechanical failures, and bad weather. When these unexpected events occur, airlines recover by replanning their operations. In this paper, we present airline schedule recovery models and algorithms that simultaneously develop recovery plans for aircraft, crews, and passengers by determining which flight leg departures to postpone and which to cancel. The objective is to minimize jointly airline operating costs and estimated passenger delay and disruption costs. This objective works to balance these costs, potentially increasing customer retention and loyalty, and improving airline profitability.

Using an Airline Operations Control simulator that we have developed, we simulate several days of operations, using passenger and flight information from a major US airline. We demonstrate that our decision models can be applied in a real-time decision-making environment, and that decisions from our models can potentially reduce passenger arrival delays noticeably, without increasing operating costs.

Keywords Irregular airline operations · Disruption management · Passenger recovery.

1. Airline operations: Problem description and motivation

Although it is fairly difficult to estimate the cost of schedule disruptions, the New York Times reported in 1997 that the impacts of irregularities encountered by a single major US carrier "exceeded $400 million per year in crew overpay, lost revenue and passenger hospitality costs". Shavell (2000) estimates the total direct disruption costs in 1998 for the domestic operations of the 10 major US airlines as $1.83 billion, $858 million of which is attributed to flight cancellations

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and $909 million to flight delays. (For a comprehensive list of potential causes of schedule disruptions see Filar et al. (2000).)

Most cancellations and delays can be attributed to two major sources of disruption, namely, shortages of airline resources (such as crews, aircraft, ground personnel, gates, etc.); and airport and airspace capacity shortages.

- *Airline resource shortages* include unscheduled aircraft maintenance, crew absence due to sickness or to upstream schedule disruptions, longer than scheduled aircraft turn times due to lack of ground resources, and longer than expected passenger embarking and disembarking times.
- *Airport and airspace capacity shortages* result typically from weather conditions that require aircraft to operate under Instrument Meteorological Conditions with more spacing needed between aircrafts in the air, thereby reducing airport throughput. When the number of departures and arrivals at an airport exceed the airport's airfield capacity, flight legs get delayed and/or cancelled, generating irregularities and passenger schedule disruptions.

1.1. Airline operations control centers

Airlines have developed Operations Control Centers (AOCCs) to manage operations of aircraft, crews, and passengers centrally; control the safety of operations; and exchange critical information with governmental authorities and other airlines (Clarke et al. (2000), Clarke (1998) and Grandeau et al. (1998)).

Operations controllers face a myriad of options, including holding delayed flight legs until resources are ready to be operated; canceling flight legs and using resources differently; postponing the departure times of flight legs departing a hub airport to prevent connecting passengers from missing their connections; or not waiting for connecting passengers, resulting in *disrupted passengers*, that is, passengers who must be reaccommodated on itineraries other than planned because of missed connections or flight leg cancellations.

If operations controllers delay flight departures for too long, they generate substantial flight departure delays. These delays can propagate throughout the schedule and disrupt passengers later in the day, making it difficult to find good recovery itineraries.

For effective schedule recovery decision-making, it is necessary for operations controllers, at any time t of the day of operations, to have knowledge of: (1) where aircrafts are and their future maintenance requirements; (2) where crews are, whether they are disrupted or not, their schedules and the remaining duty, and flight time before they are disrupted; and (3) where passengers are, their disruption status, and planned arrival times. We refer to this information collectively as the *Airline System State* at time t.

Beyond the system state, controllers need forecasted *gate-to-gate times* for each flight leg. Gate-to-gate time, which depends on weather conditions and congestion levels, comprises taxi-out time, en route time, and taxi-in time. Idris et al. (2002) propose a real-time forecasting model of taxi-out times, the most difficult component of gate-to-gate time to forecast because of the complex sequencing of departure queues. Taxi-in times are less difficult to predict, assuming gates are available when aircraft arrive. En route, or flying, times are predicted using forecasting models and real-time information obtained from the Enhanced Traffic Management System (ETMS), or the Air Traffic Control System Command Center (ATCSCC) (http://www.fly.faa.gov/Products/Information/information.html). This information is critical to airline recovery, as it allows the estimation of aircraft and crew ready times.

Before implementing operational decisions, the operations controllers consult with a number of groups, including

- *Crew planners* to check the legalities of proposed decisions with respect to affected crews.
- *Customer service coordinators* who access the consequences of operations decisions on passenger schedules.
- *Dispatchers* who follow a group of aircraft, providing flight plans to pilots and updating them on any new information concerning the flight.
- *The air traffic control group* which provides visibility of the state of the system at a given time.

Although customer service coordinators are consulted, passenger disruptions rarely drive operational decision-making. Studies show, however, that arriving on time is the service characteristic most valued by passengers (Mitra, 2001). Providing reliable service to passengers is therefore important to (1) attract high-value passengers who are sensitive to on-time reliability; (2) increase customer loyalty and customer retention rates, as satisfied customers are less likely to defect (Suzuki, 2000); and (3) reduce direct and indirect costs resulting from passenger disruptions.

In this paper, we propose airline recovery decision models that select flight leg departure times and cancellations that, like conventional models, minimize operating costs, but are extended to include the resulting delay and disruption costs experienced by passengers.

1.2. Contributions

In this paper, we propose a new approach to airline schedule recovery in which the objective is to find the optimal trade-off between airline operating costs and passenger delay costs. We develop alternative optimization models and using them generate recovery plans that select flight departure times and flight cancellations, assign aircraft and reserve crews to each flight leg as necessary, and ensure the compliance of crew regulations and aircraft maintenance requirements. We evaluate our recovery solutions using data representing the operation of a large US airline, and an airline operations control center simulator that we have developed. Rerunning days of operations assuming flight decisions are taken as determined by one of our recovery models, we demonstrate that passenger-centric models can be solved in real time and hence, utilized for operational recovery.

For 3 days of operations with different levels of disruption, our simulation results indicate that noticeable reductions in passenger delays and disruptions are achievable. This suggests that our approach can lead to decisions that reduce passenger delays and disruptions, while concurrently controlling operating costs and recovering aircraft and crew schedules.

1.3. Paper outline

In Section 2, we review schedule recovery options and related literature. We present integrated airline recovery models and solution approaches in Section 3. These approaches are designed to identify flight departure times and cancellation decisions that optimize the balance between airline operating costs and passenger costs. In Section 4, we validate our proposed approaches using airline data provided by a major US airline and an Airline Operations Controller Center simulator that we have built. We quantify potential reductions in passenger delays by comparing the performance of our models' recovery decisions to actual airline operations.

2. Schedule recovery options

With greater than ever computing power and capabilities in airline decision support, operations planners are constructing more and more efficient schedules with little built-in nonproductive, that is, slack, time. Consequently, controllers are faced with the increasingly difficult task of managing operations. With minimal slack, even short schedule delays cannot be absorbed and instead propagate throughout the network, with effects sometimes continuing beyond the current day of operations. To control delays and their propagation, operations controllers have a number of options available to them, the most common being aircraft swapping, flight cancellations, postponement of flight departures, and utilization of reserve crew (additional crews which can be called to replace disrupted crews) and spare aircraft (additional aircraft not required to operate the plan). Other actions that can be taken to mitigate the effects of schedule disruptions include using *move-up* crews (Chebalov and Klabjan 2002), prioritizing flights on the ground in the departing queue (Anagnostakis et al. 2003), and decreasing en route time.

2.1. Reserve crew, spare aircraft and aircraft swapping

Operations controllers have additional crew and aircraft resources available to prevent and recover from schedule disruptions. Reserve crews are often positioned at hub airports, crew bases, and other major airports (Sohoni et al. 2000). Spare aircrafts are typically positioned at maintenance stations to facilitate recovery from aircraft shortages (Grandeau et al. 1998). Beyond calling in these additional resources, operations controllers have the option of using existing resources differently, with aircraft swapping the most common mechanism for achieving this. To illustrate the idea of aircraft swapping, consider a bank of arriving flight legs, denoted by f_1, f_2, and f_3, arriving in sequence, and a connecting set of flight legs f_4, f_5, and f_6, departing in sequence, with one aircraft assigned to f_1 and f_4; another to f_2 and f_5; and finally, a third to f_3 and f_6. Assume that the first flight leg f_1 is delayed and the other flight legs arrive as planned. The result is a delayed departure of f_4 and potential missed connections for passengers connecting to other flights from f_4. Consider, however, an alternative operating strategy in which f_1 and f_6 are assigned to the same aircraft; f_2 and f_5 are assigned to an aircraft; and f_3 and f_4 are assigned to the same aircraft. With these swaps, it might be possible to manage the arrival delay of aircraft f_1 without delaying departing flight legs and disrupting passengers, as illustrated in Figure 1.

Operations controllers might also decide to swap aircraft with different types. Although such swaps provide interesting opportunities to mitigate delays and aircraft shortages, several considerations must be evaluated before swapping aircraft of different types. First, to leave crew schedules intact, pilots must be able to operate different aircraft types. This check has to be conducted for all crews scheduled to fly all swapped aircraft. Moreover, the operations controller has to forecast the impact of the changes on future operations. For example, different aircraft types are likely to have different seat capacities for all cabins, and reassigning a smaller aircraft to a flight might result in seat shortages and passenger schedule disruptions. These ripple effects have to be carefully analyzed as future disruption costs can outweigh the immediate benefits of swapping. Additionally, all swaps must allow aircraft maintenance requirements to be satisfied. Notwithstanding these restrictions, numerous swap opportunities often exist, especially for large airlines at a hub airport where it is not unusual to find up to 60 aircraft on the ground at the same time (Grandeau et al. 1998).

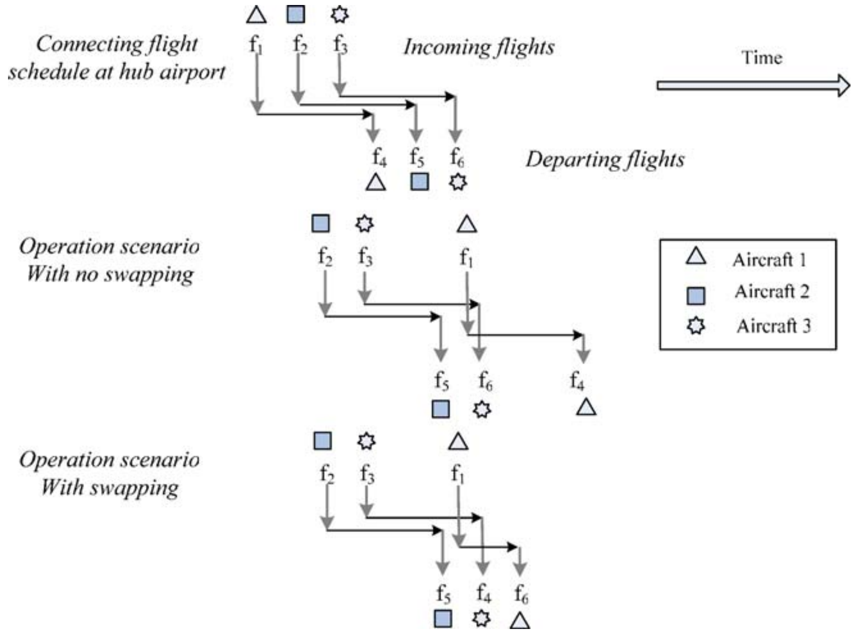

Fig. 1 Illustration of an aircraft/flight assignment swap to mitigate delays

2.2. Flight leg cancellation and departure postponement

Operations controllers sometimes have no other choice than to cancel flights. Reasons for cancellation include mechanical problems; crew absence, delays and disruptions; upstream flight leg delays; and reduced airport departure and landing capacity due to weather conditions.

In the United States, if weather reduces airport capacity greatly, airlines with flight legs scheduled to the affected airport are assigned landing slots under Ground Delay Programs (GDP). If the number of flight legs scheduled exceeds the number of assigned slots, then an affected airline might decide to cancel flight legs at that airport. Willemain (2002) shows that canceling the right flight legs can significantly decrease the average arrival delays of subsequent flights affected by the GDP.

Controllers must cancel flight legs that form a cycle in order to maintain *aircraft flow conservation*, often referred to as *balance*, at airports. Hub-and-spoke flight networks often include a number of potential cancellation cycles, each with a small number of flight legs. In fact, for large hub-and-spoke airline networks with a high degree of network connectivity, many cancellation cycles contain only two flight legs. If at least one spare aircraft is available at the destination of a candidate flight leg for cancellation, then the number of flight legs cancelled can be further reduced to one, without compromising aircraft balance requirements.

Additional recovery options regarding which flight legs to cancel, particularly at hub airports, are provided by aircraft swaps. Consider for example, an aircraft a_1 assigned to a late evening flight leg f_1, and an aircraft a_2 assigned to an early morning flight leg f_2. If a1 is unavailable but a_2 is available to operate f_1, operations controllers have the option of reassigning a_2 to f_1

and canceling f_2 (if a1 is still unavailable for f_2.) By canceling a morning flight leg rather than a late evening flight leg, passengers are not disrupted overnight and resulting delays are shortened significantly.

When given options, operations controllers will try to cancel a set of flight legs assigned to the same crew, so that crews are not disrupted. They can also, if possible, cancel flight legs with crews terminating their workday so that reserve crews are not needed. Finally, if cancellations require reserve crews, then operations controllers prefer to cancel flight legs such that the disrupted crews can quickly and inexpensively be repositioned to recommence their assigned work later.

Although cancellations are sometimes necessary, operations managers often have the option not to cancel flights, and instead wait for the missing resources to be available or replaced. In some cases, controllers will choose to postpone the departure of a flight leg even beyond its *ready time* at is, the earliest time at which the departure is possible. This has the potential advantage that late connecting passengers are not left behind, obviating the need to reaccommodate these disrupted passengers on alternative flight legs, and avoiding the associated room, meal, and passenger good-will costs.

2.3. Aircraft recovery literature

In operations, making the right operational decisions is particularly difficult because feasibility must be maintained for aircraft, crews, and passengers. Moreover, solutions must be generated quickly. According to Love, Sorensen, and Larsen (2001), recovery solutions need to be generated in less than 3 min, otherwise the recovery solution can become infeasible; and multiple scenario analyses, for example evaluating various weather scenarios, cannot be conducted.

It is current practice in the airline industry to determine recovery plans in a primarily sequential manner, first recovering aircraft, then crew, and then passengers (Filar J. et al. 2000). With respect to aircraft recovery, Jarrah et al. (1993) consider the aircraft schedule recovery problem and propose two network models to address aircraft shortages. The objective of the first model is to determine flight leg departure times that minimize total flight delay costs, and the second is to select flight leg cancellations that minimize cancellation costs. Cao and Kanafani (1997) develop a model to maximize airline profitability by assigning aircraft to flight legs or canceling flight legs, but their approach is limited to aircraft assigned to routes containing at most two flight legs. Thengvall et al. (1998) extend the approach of Jarrah et al. to consider flight leg departure scheduling and cancellations simultaneously. Their objective is to minimize total operating costs, but crew and passenger disruptions are not considered. Similarly, Andersson and Värbrand (2000) propose an aircraft recovery model that does not consider the effects of the recovery plan on passengers. Rosenberger, Johnson, and Nemhauser (2001), however, present an optimization model for aircraft recovery that models passenger connections, but does not fully captures passenger delays. Stojkovic et al. (2002) propose a model to select flight leg departure times, considering crew transfers, rest periods, passenger connections, and aircraft maintenance, but not including cancellation decisions.

A limitation of many of the existing models is that passengers are not modeled explicitly and hence, passenger delay costs are only approximate. Teodorovic and Guberinic (1984, 1990) model passenger delays explicitly but they assume that all passenger itineraries contain only a single flight leg. In the following sections, we maintain this modeling focus on passengers, but relax restrictive operating restrictions and incorporate flight departure postponement and cancellation decisions.

3. Passenger-centric aircraft and crew recovery

In this section, we propose airline recovery models to minimize (1) the sum of operating costs and disrupted passenger costs; and (2) the sum of operating costs and total passenger delay costs. Underlying these models is a flight schedule network representing flight legs with *flight arcs*, with each arc a corresponding to a flight leg f, the tail node of a representing the departure location of f at time d(t); and the head node of a representing the arrival location of f at time d(t) increased by the gate-to-gate time of f. For each possible departure time d(t) of f (we discretize time and allow departures every minute within the window of feasible departure times for f), we include in our network a copy t of arc a, representing the departure of arc a at time d(t).

The approach of generating copy arcs to represent flight leg departure time decisions has been employed extensively in various airline schedule recovery models. For example, Thengvall et al. (1998), Andersson and Varbrand (2000) and Yan and Young (1996) generate flight copies every m min for each flight. Bratu demonstrates that many of these flight copies are dominated, and hence are not needed to produce optimal scheduling decisions. Using these insights, he presents an algorithm that limits the generation of flight copies without compromising optimality. Applying his approach, we are able to eliminate many dominated copy arcs, thereby reducing model size to allow for real-time solution.

The decision variables common to our models are

$x_f^t =$ 1 if flight leg f is selected to depart at the departure time of the tth copy of flight f, and 0 otherwise;
$z_f =$ 1 if flight leg f is canceled; and 0 otherwise;
$y_t^{k,a}$ number of aircraft of type k on the ground at airport a at time t.

Additional notation common to our models are the set of fleet types K, the set of airport locations A, the set of flight arcs for fleet type k arriving at node n of airport a, denoted by $F_{n^-}^{k,a}$, and similarly, the set of flight arcs for fleet type k departing from node n of airport a, denoted by $F_{n^+}^{k,a}$. For fleet k at airport a, let b and e represent the first and last nodes (at the beginning and the end of the recovery planning period, respectively). For notational ease, assume that the time of node b is b and the time of node e is e. $N_b^{k,a}$ and $N_e^{k,a}$ represent the number of operational aircraft of type k at airport a at times b and e, respectively. $F_{b^+}^{k,a}$ is the set of flight arcs for aircraft type k at airport a departing node b and $F_{e^-}^{k,a}$ is the set of flight arcs for aircraft type k at airport a arriving at node e. $N(k, a)$ represents the set of nodes with both inflow and outflow at airport a for fleet type k. We denote o_f^t as the delay costs incurred by the aircraft and crews assigned to copy t of flight leg f.

3.1. Reserve crews and crew feasibility

Crew schedules can be disrupted for a number of reasons, including missed connections; depletion of available flying or duty time; or flight cancellations. To remedy this, airlines have 25–30% additional personnel (Sohoni et al. 2002) in the form of reserve crews.

To allow for the assignment of reserve crews in our models, we let R be the set of crews; $f_c(m)$ be the mth flight leg to be operated by crew c in the current day of operations; n_c as the number of flight legs in the duty assigned to crew c; and $M(c, m, t)$ as the set of copies of flight leg $f_c(m+1)$ to which crew c has insufficient time to connect from the tth copy of flight leg $f_c(m)$, *and* the set of copies of flight leg $f_c(m+1)$ that if assigned to crew c will result in violation of one or more work rules. We denote $I(f_c(m))$ as the set of flight copies of flight leg $f_c(m)$. We let decision variable q_m^c equal 1 if a reserve crew is needed to operate the mth flight leg in crew c's planned operations; and equal 0 otherwise. If crew c has insufficient time to connect to the next scheduled flight leg, a reserve crew is needed, as captured by the following constraints:

$$x^t_{f_c(m)} + \sum_{u \in M(c,m,t)} x^u_{fc(m)} - q^c_{m+1} \leq 1, \forall c \in R, \quad \forall m = 1, \ldots, n_c - 1, \forall t \in I(f_c(m))$$

To identify the reserve crews needed due to cancellations, we introduce the following additional notation. Let $a1_c(m)$ be the origin airport of the mth flight leg $f_c(m)$ in crew c's schedule; $a2_c(m)$ be the destination airport of the mth flight leg $f_c(m)$ in crew c's schedule; $\gamma^a_{a1_c(m)}$ equal 1 if the origin of the mth flight leg in crew c's planned operations is a, and equal 0 otherwise; and $\gamma^a_{a2_c(m)}$ equal 1 if the destination of the mth flight leg in crew c's planned operations is a, and equal 0 otherwise. We let decision variable r_m^c equal 1 if a reserve crew is needed to operate the mth flight leg in crew c's schedule due to a cancellation; and equal 0 otherwise. Just prior to the departure of any flight leg $f_c(m)$ in crew c's schedule, if the number of arrivals at airport a (the departure location of flight leg $f_c(m)$) does not exceed the total number of departures from a at that time, a reserve crew is needed at airport a, as captured by the following constraints:

$$\sum_{m=1,\ldots,i} \sum_{t \in I\ (f_c(m))} \left(x^t_{fc(m)} \gamma^{a1_c(i)}_{a1_c(m)} - x^t_{f_c(m)} \gamma^{a1_c(i)}_{a2_c(m)} \right) - \sum_{m=1,\ldots,i} r^c_m \gamma^{a1_c(i)}_{a1_c(m)} \leq 0, \forall c \in R, \forall i = 1, \ldots, n_c$$

To ensure that the number of reserve crews utilized does not exceed the number available, let $E(a, k)$ denote the number of reserve crews on duty at airport a for aircraft type k; A' *be the set of airport locations where the airline has reserve crews*; and δ_c^k equal 1 if crew c operates aircraft of type k. The reserve crew *count constraints* are then expressed as:

$$\sum_{c \in R} \sum_{m=1,\ldots,n_c} \left(r^c_m + q^c_m \right) \gamma^a_{a1_c(m)} \delta^k_c \leq E(a, k) \quad \forall a \in A', \forall k \in K$$

Note that if operations forecasts indicate that a crew has accumulated too much delay to complete its duty, our model might preemptively replace the crew before its time runs out to match the availability of reserve crews. We define e_m^c as the cost associated with calling a reserve crew to operate the mth flight leg of crew c's schedule, with e_1^c large because we will not, by definition, replace crew c with a reserve crew at the start of the day. Note that these costs include approximations of the costs associated with appropriately repositioning the original, stranded crews.

While our approaches do not consider how to recover disrupted crews, models to repair crew schedules can be used as complements to our approach (Desaulniers et al. (1997), Lettovsky (1997) and Yu et al. 2003).

3.2. Passenger-centric models

Disrupted passengers experience on average much higher delays than nondisrupted passengers, accounting for almost half of the total passenger delays and most of the severely delayed passengers (Bratu).

$$Minimize \left(\sum_{p \in P} s_p \times n_p \times \lambda_p + \sum_{f \in F} \sum_{t \in I(f)} \left(o_f^t + (n_f - \sum_{p \in P} n_p \beta_f^p \lambda_p) \times d_f^t \right) \times x_f^t + \sum_{c \in R} \sum_{m=1,\dots,n_c} e_m^c \times \left(r_m^c + q_m^c \right) \right)$$

For one major US airline in August 2000, Bratu estimates that 85% of the passengers who experienced more than 4 h of arrival delay were disrupted. This provides the motivation for our first model, called the *Disrupted Passenger Metric* model, in which we minimize the sum of operating and disrupted passenger costs.

We let decision variable λ_p equal 1 if planned itinerary p is disrupted, and equal 0 otherwise. We approximate the associated passenger disruption costs by the product of the number of disrupted passengers and an estimated cost per disrupted passenger, denoted by s_p for itinerary p. To facilitate tractability of our model, s_p does not rely on knowledge of the actual delay to passengers, and hence, can represent only an *approximation* of the true disruption costs. (We subsequently relax this assumption and examine the implications.) For a detailed algorithm to compute these approximate passenger disruption costs, see Bratu.

Let P denote the set of passenger itineraries, L the set of local itineraries (that is, itineraries containing exactly one flight leg), C the set of connecting itineraries. F the set of flights and $I(f)$ the set of flight copies of flight f, $IT(p)$ the set of flight legs in itinerary p, $IT(p, n)$ the nth flight leg in itinerary p, and n_p the number of passengers on itinerary p. Considering the set of planned connecting flight legs from flight leg f, we let $MC(f, t)$ denote the subset of connecting flight legs for which there is insufficient time to connect with the tth copy of flight leg f. Let n_f represent the number of passengers whose itineraries terminate with flight leg f; β_f^p equal 1 if itinerary p terminates with flight leg f, and equal 0 otherwise; and d_f^t equal the delay cost per non-disrupted passenger assigned to copy t of flight leg f. A lower bound on the total delay cost associated with copy t of flight leg f is then $n_f d_f^t$. We assume that itineraries contain two or fewer flight legs, however, it is straightforward to extend the formulation to include itineraries with more than two flight legs.

Our *Disrupted Passenger Metric* model, denoted as DPM, can be written as follows:

subject to:

$$\sum_{(f,t) \in F_{n^-}^{k,a}} x_f^t + y_{n^-}^{k,a} - \sum_{(f,t) \in F_{n^+}^{k,a}} x_f^t - y_{n^+}^{k,a} = 0 \quad \forall k \in K, \forall a \in A, \qquad \forall n \in N(k,a) \tag{1}$$

$$\sum_{(f,t) \in F_{b^+}^{k,a}} x_f^t + y_{b^+}^{k,a} = N_b^{k,a} \quad \forall k \in K, \forall a \in A \tag{2a}$$

$$\sum_{(f,t) \in F_{e^-}^{k,a}} x_f^t + y_{e^-}^{k,a} = N_e^{k,a} \quad \forall k \in K, \forall a \in A \tag{2b}$$

$$\sum_{t \in I(f)} x_y^t + z_f = 1 \qquad \forall f \in F \tag{3}$$

$$x_{IT(p,1)}^t + \sum_{u \in MC(IT(p,1),t)} x_{IT(p,2)}^u - \lambda_p \le 1$$

$$\forall p \in C \qquad \forall t \in I(IT(p, 1)) \tag{4}$$

$$\lambda_p \geq z_f \qquad \forall p \in P, \forall f \in IT(p) \tag{5}$$

$$x^t_{fc(m)} + \sum_{i \in M(c,m,t)} x^u_{fc(m)} - q^c_{m+1} \leq 1, \forall c \in R, \forall m = 1, \ldots, n_c - 1, \forall t \in I(f_c(m)) \tag{6}$$

$$\sum_{m=1,\ldots,i} \sum_{t \in I\ (f_c(m))} \left(x^t_{fc(m)} \gamma^{a1_c(i)}_{a1_c(m)} - x^t_{f_c(m)} \gamma^{a1_c(i)}_{a2_c(m)} \right) - \sum_{m=1,\ldots,i} r^c_m \gamma^{a1_c(i)}_{a1_c(m)} \leq 0, \quad \forall_c \in R, \forall i = 2, \ldots, n_c \tag{7}$$

$$\sum_{c \in R} \sum_{m=1,\ldots,n_c} (r^c_m + q^c_m) \gamma^a_{a1_c(m)} \delta^k_c \leq E(a, k) \forall a \in A', \forall k \in K \tag{8}$$

$$\begin{array}{ll} 0 \leq \lambda_p \leq 1 & \forall p \in P \\ 0 \leq r^c_m, q^c_m \leq 1 & \forall m = 1, \ldots, n_c, \forall c \in R \\ x^t_f \in \{0, 1\} & \forall f \in F, \forall t \in I(f) \\ z_f \geq 0 & \forall f \in F \\ y^{k,a}_n \geq 0 & \forall k \in K, \forall a \in A, \forall n \in N(k, a) \end{array}$$

Constraints (1) and (2) enforce aircraft flow balance for each node and ensure that planes are positioned to operate flight legs scheduled at the end of the recovery planning period. It is possible to assign to a flight leg an aircraft of a type different from that in the plan (as in Thengvall et al. 2001), however, problem size increases because the x variables must then record the type of aircraft originally assigned to each flight leg. Spare aircraft can be modeled by adding the number of spare aircraft to the right-hand side of constraints (1), (2a), and (2b). Constraints (3) guarantee that each flight leg is assigned to an aircraft or cancelled. Itineraries with insufficient connection time (constraints 4) or with one or more canceled flight legs (constraints 5) are classified as disrupted. The objective is to minimize the sum of passenger disruption costs and airline operating costs. Constraints (6)–(8) are the reserve crew constraints described in Section 2.1.

Variables x are binary but y need only be nonnegative real because constraints (1), (2a), and (2b) together with integrality of the x variables, ensures integrality of y (Barnhart et al. 1995). Because constraints (3) and the binary restrictions on x guarantee z to be binary, we define z to be nonnegative real variables. Moreover, because x are binary variables, λ_p binary can be relaxed as specified in the model earlier, and because x are binary, constraints (6) and (7) allow us to relax binary requirements on the q and r variables.

As an alternative to DPM in which delay costs are only approximate, we develop another model, referred to as the *Passenger Delay Metric* model, denoted as PDM. In PDM, delay costs are more accurately computed by explicitly modeling passenger disruptions, recovery options, and delay costs.

We let each passenger type represents the set of passengers at the same location at the start of the recovery-planning period, and destined to the same location with the same arrival time. For each passenger type p, we generate a list of candidate recovery itineraries $R(p)$, including the planned itinerary, recovery itineraries, and a virtual itinerary that models passengers reaccommodated by other airlines. Note that a flight leg f followed by flight leg g corresponds to potentially several itineraries, each with different combinations of copies of flight legs f and g.

In this model, decision variable ρ^r_p is the number of type p passengers ultimately served on itinerary r, and d^r_p is the total cost of delay incurred when a type p passenger is reaccommodated on itinerary r. In contrast to DPM, the objective of PDM is to minimize the sum of *passenger delay* costs and operating costs. In this case, delay costs can capture relevant hotel costs and ticket costs if passengers are recovered by other airlines. Harder to estimate, but possible to include are delay costs to the passenger and costs of future lost ticket sales (Narasimhan, 2001).

Similar to DPM, we let decision variable λ_p equal 1 if passenger type p is disrupted and equal 0 otherwise. Again, for ease of exposition, we assume that itineraries contain two or fewer flight legs, however, it is straightforward to extend the formulation to include itineraries with more than two flight legs.

Let S_f denote the number of seats on flight leg f. For each flight leg f and itinerary r, let δ_f^r equal 1 if flight leg f is in itinerary r, and equal 0 otherwise.

Our *Passenger Delay Metric* model, denoted as PDM, is formulated as:

$$\textit{Minimize} \quad \left(\sum_{p \in P} \sum_{r \in R(p)} d_p^r \times \rho_p^r + \sum_{f \in F} \sum_{t \in I(f)} o_f^t \times x_f^t + \sum_{c \in R} \sum_{m=1,\ldots,n_c} e_m^c \times \left(r_m^c + q_m^c \right) \right)$$

subject to:

$$\sum_{(f,t) \in F_{n^-}^{k,a}} x_f^t + y_{n^-}^{k,a} - \sum_{(f,t) \in F_{n^+}^{k,a}} x_f^t - y_{n^+}^{k,a} = 0 \forall k \in K, \forall a \in A, \forall n \in N(k,a) \tag{1}$$

$$\sum_{(f,t) \in F_{b^+}^{k,a}} x_f^t + y_{b^+}^{k,a} = N_b^{k,a} \quad \forall k \in K, \forall a \in A \tag{2a}$$

$$\sum_{(f,t) \in F_{e^-}^{k,a}} x_f^t + y_{e^-}^{k,a} = N_e^{k,a} \quad \forall k \in K, \forall a \in A \tag{2b}$$

$$\sum_{t \in I(f)} x_f^t + z_f = 1 \qquad \forall f \in F \tag{3}$$

$$x_{IT(p,1)}^t + \sum_{u \in MC(IT(p,1),t)} x_{IT(p,2)}^u - \lambda_p \leq 1 \forall p \in C \forall t \in I(IT(p,1)) \tag{4}$$

$$\lambda_p \geq z_f \qquad \forall p \in P, \forall f \in IT(p) \tag{5}$$

$$x_{fc(m)}^t + \sum_{u \in M(c,m,t)} x_{fc(m)}^u - q_{m+1}^c \leq 1, \quad \forall c \in R, \forall m = 1, \ldots, n_c - 1, \forall t \in I(f_c(m)) \tag{6}$$

$$\sum_{m=1,\ldots,i} \sum_{t \in I\ (f_c(m))} \left(x_{fc(m)}^t \gamma_{a1_c(m)}^{a1_c(i)} - x_{f_c(m)}^t \gamma_{a2_c(m)}^{a1_c(i)} \right) - \sum_{m=1,\ldots,i} r_m^c \gamma_{a1_c(m)}^{a1_c(i)} \leq 0, \quad \forall_c \in R, \forall i = 2, \ldots, n_c \tag{7}$$

$$\sum_{c \in R} \sum_{m=1,\ldots,n_c} \left(r_m^c + q_m^c \right) \gamma_{a1_c(m)}^a \delta_c^k \leq E(a,k), \qquad \forall a \in A', \forall k \in K \tag{8}$$

$$n_p \times (1 - \lambda_p) = \rho_p^p \qquad \forall p \in P \tag{9a}$$

$$\sum_{p \in P} \rho_p^r \leq \sum_{p \in P} n_p \times (1 - \lambda_r) \qquad \forall r \in P \tag{9b}$$

$$\sum_{r \in R(p)} \rho_p^r = n_p \quad \forall p \in P \tag{10}$$

$$\sum_{p \in P} \sum_{r \in R(p)} \delta_f^r \times \rho_p^r \leq S_f \times (1 - z_f) \quad \forall f \in F \tag{11}$$

$$
\begin{array}{ll}
0 \le r_m^c, q_m^c \le 1 & \forall m = 1, \ldots, n_c, \forall c \in R \\
0 \le \lambda_p \le 1 & \forall p \in P \\
\rho_p^r \in \mathbb{Z}^+ & \forall p \in P \forall r \in R(p) \\
x_f^t \in \{0, 1\} & \forall f \in F, \forall t \in I(f) \\
z_f \ge 0 & \forall f \in F \\
y_n^{k,a} \ge 0 & \forall k \in K, \forall a \in A, \forall n \in N(k, a)
\end{array}
$$

Constraints (1)–(3) are the same as those in *DPM*. Constraints (10) ensure that all passengers are transported to their destinations, but constraints (11) limit the number of passengers transported on each flight leg to the capacity of that leg, and further, disallow any passenger if the leg is canceled. Constraints (4) and (5) set λ_p to 1 if itinerary p is not feasible. If λ_p is 1, constraints (9a) ensure that passengers of type p are served on itineraries different from those originally planned; otherwise type p passengers are served as planned. Similarly, constraints (9b) ensure that no passengers are served on disrupted itineraries. Finally, constraints (6)–(8) are the reserve crew constraints described in Section 3.1. Just as in DPM, these constraints, combined with integrality conditions on x, allow us to relax the binary requirements on q and r.

3.3. Ensuring satisfaction of maintenance requirements

To limit problem size and achieve real-time solutions, we do not enforce aircraft maintenance requirements in our models, but instead, given the flight departure and cancellation decisions of the DPM and PDM models, we try to generate aircraft routings that position *maintenance critical aircraft* at maintenance stations at the end of the day. Maintenance critical aircraft must undergo maintenance at the end of the day of operations, or else be grounded due to safety regulations imposed by government authorities. For each solution to DPM and PDM, we check to ensure that all maintenance critical aircrafts are positioned at appropriate maintenance stations at the end of the day of operations. If one or more maintenance critical aircraft is not positioned correctly, we alter our DPM or PDM model to include constraints prohibiting the rerouting of these aircrafts, and resolve the modified model to generate new solutions. We repeat this process until all maintenance critical aircrafts are positioned appropriately at the end of the day of operations. (Arguello et al. (1997), Thengvall et al. (1998), Rosenberger et al. (2001) and Bratu describe aircraft rerouting approaches.)

4. Model evaluation

We develop an Airline Operations Control Center Simulator to evaluate the potential impact of decisions generated by our airline recovery models on a major US airline's operations during August 2000. Other simulators containing modules involving airline operations have been developed by Clarke et al. (2004) and Rosenberger et al. (2002). For our evaluation, we use airline flight operations data from the Airline Service Quality (ASQP) database, and actual passenger booking and no-show data provided by a major U.S. airline. The airline data represent domestic US operations involving 302 aircraft of four different fleet types; 83,869 passengers on 9,925 different passenger itineraries per day; 74 airports in the domestic United States; and three hub airports. Of the 83,869 passengers 55,424 are local (that is, have single-leg itineraries) and 28,445 are connecting through one or more of the hubs. The simulation is in Matlab using OPL Studio to solve the recovery models and AWK to extract data from the ASQP database. The AOCC simulator is run on an OptiPlex GX1 desktop containing 128RAM.

4.1. Airline operations control center simulation

Our airline operations control center simulation is designed to mimic the decision-making process within the AOCC. Our simulation differs from actual operations at the center, however, in that simulated flight leg departure and cancellation decisions are based on the solutions to our recovery models. Hence, after the start of the day, simulated operations and actual airline operations can, and most often do, diverge.

In our simulation, we define the *simulated airline system state* at any time t, like the airline system state, to represent the status of each aircraft, crew, and passenger at that time. Given decisions taken at time t, we compute the earliest departure time for each flight leg based on the availability of relevant aircraft and crew resources. The earliest departure times are determined by two types of delays, namely, *nonpropagated* and *propagated.*

Nonpropagated delays result independently of previous delays to the aircraft. For example, an independent delay occurs when ground holds from ground delay programs are issued; when aircraft experience mechanical problems; or when crew unavailability delays the departure of a flight. Propagated delays, resulting from lack of sufficient slack time in aircraft flight schedules, are the delays experienced by an aircraft as independent delay is propagated downstream to subsequent flight legs of that aircraft.

To compute nonpropagated and propagated delays in our simulation, we begin by analyzing *actual* airline operations for each day d of operations. Consider an aircraft that operates two consecutive flight legs f and g, with the minimum turn time between these flight legs denoted by MTT. Denote the arrival time of flight leg f as AAT(f), the planned departure time of flight leg g as PDT(g), and the actual departure time of g as ADT(g). Then, the propagated delay associated with g, denoted as PD(g), is Max(AAT(f) + MTT − PDT(g);0); and the non-propagated delay associated with g, denoted NPD(g), is Max(ADT(g) − PDT(g) − PD(g);0). (If g is the first flight leg of the day, PD(g) is assumed to be 0.)

We assume that in our simulated AOCC environment each flight leg experiences the same non-propagated delays as computed for actual operations. The rationale is that nonpropagated delays (ground delays programs, crew illness, mechanical failure) are, for the most part, independent of cancellation and flight departure postponement decisions. Given the nonpropagated flight leg delays (assuming that nonpropagated delays of canceled flights are 0), we then compute within the simulation, the propagated delays resulting from the decisions generated by our recovery models. Summing the nonpropagated and propagated delays for each flight leg yields the total flight leg delay, and hence, defines the simulated state of aircraft in the system.

In our simulation, given a day of operations spanning a time duration T, we assess the simulated airline system state at various times, denoted as $t_1, t_2, \ldots, t_e$. At each time t_i, we populate our recovery models with data reflecting the current simulated system state, and solve the planning model to determine the flight leg departure times and cancellations for the remaining flight legs in the current day of operations. Although decisions are generated for the rest of the day, the only decisions that are implemented are those that fall within the period from t_i to t_{i+1}, referred to as stage i. In each subsequent stage, the simulated airline system state is updated, recovery models are resolved, solutions are generated for the remainder of the day, and associated decisions are implemented for the current stage. This process repeats until the last-stage decisions at the end of the day of operations are implemented.

In addition to the airline system state defining critical information about the status of each aircraft, crew, and passenger, the following set of data is needed to achieve each stage *i* solution:

- Minimum aircraft turn times: We compute these for each fleet type at each airport by selecting the minimum actual turn times observed for the airline in August 2000.
- Crew duties for the day of operations: Because we do not have actual crew assignments, we generate these to satisfy airline regulations and practices, while keeping crews together with the same aircraft as much as possible.
- Number of reserve crews: Based on data obtained by an airline operations control center, we assume that the number of reserve crews positioned at each hub airport equals 20% of the number of flights scheduled at that hub. At each stage we check whether a crew is disrupted. If a crew is disrupted either a reserve crew is called or remaining flights in the crew schedule are canceled. The results of the decision models, DPM and PDM, recommend which decision to take to minimize costs and satisfy feasibility.
- Crew and delay costs: We estimate the hourly crew cost for each fleet type using data reported by the airline during 2000; and we approximate the cost of assigning a reserve crew to a flight leg as this estimated hourly crew cost multiplied by the leg's total gate-to-gate time. Leisure passenger costs are set at \$19.50 per passenger hour and business passenger costs at \$34.50 per passenger hour, as recommended by the FAA (1997). Considering the passenger mix of the airline we investigate, the average delay per passenger per hour (in 2000 dollar equivalents) is computed as \$24.11. Using the methodology described by Bratu we estimate \$121.76 to be the total cost of a disrupted passenger, that is, the estimated average passenger delay in August 2000 multiplied by the estimated passenger delay cost per hour.

With our simulation we consider multiple days of operation, with levels of schedule disruption varying from low to high. In each case, we allow aircraft swaps only among aircrafts of the same fleet type; we force aircraft counts of the beginning and the end of the simulation period to equal actual aircraft counts for each fleet type; and we compare the associated *actual* delays and costs of the selected day of operations with our simulated results.

Computing aircraft, crew, and nondisrupted passenger delays is straightforward, given the actual or simulated flight leg arrival times. Computing delays for disrupted passengers, however, is more complicated, involving knowledge of the actual itineraries taken by disrupted passengers. This information is provided as a byproduct of the PDM solution, but not of the DPM solution or of actual operations. Hence, for these cases, we employ a specialized algorithm, referred to as the Passenger Delay Calculator (Bratu), to optimize itinerary assignments of disrupted passengers and compute the corresponding minimum delays. The framework of the simulator is represented in Figure 2.

4.2. Case study results

4.2.1. High levels of disruption

We first evaluate our recovery models for a day d1 of operations with relatively high levels of disruption, that is, with a high incidence of delays and cancellations relative to other days in August 2000. Flight operation statistics for d1 are summarized in Table 1, with "15OTP" representing the percentage of flight legs arriving within 15 min of scheduled arrival time, and "45FD" representing the percentage of flight legs delayed at least 45 min beyond scheduled arrival time.

Table 1 Actual flight leg operations: statistics for day d1

Duration of simulation	1 day
15OTP	64.0%
45FD	21.6%
Percentage of flights delayed	61.1%
Number of flights canceled	60
Avg. delay per operated flight (min)	26.9
Number of flights	1,063

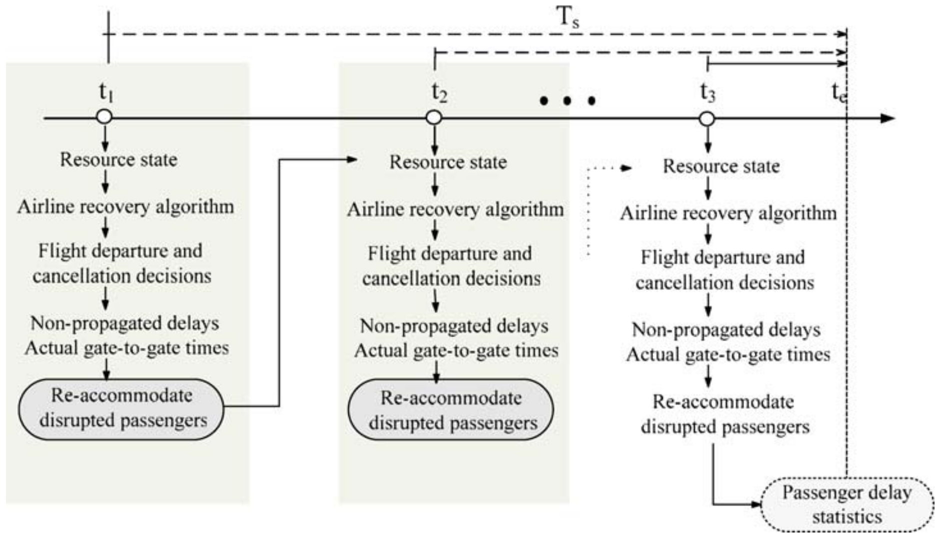

Fig. 2 Simulator framework

Table 2 Problem characteristics and running time for day d1

	PDM	DPM
Number of constraints	24,654	21,212
Number of variables	495,742	23,675
Number of LPs solved	232,113	2,765
Average solution time (sec)	5,042	201

In Table 2, we report the sizes and solution times of our recovery models for day d1. PDM requires excessive solution time, but DPM is solvable in real time.

Dividing the day of operations into 16 stages and running our simulator for each of the recovery models, we compare in Table 3 our simulated results with actual operations (denoted as BC for Base Case).

As expected, the average delays experienced by nondisrupted passengers in our simulations are higher than actual delays because our recovery models postpone flight departures beyond actual departures. This is more than offset by the reductions achieved with DPM in the number of disrupted passengers and in the average total passenger delay. Compared to actual operations,

Table 3 Airline recovery model performance compared to BC for day d1

	BC	PDM	PDM to BC (%)	DPM	DPM to BC (%)
Passenger delay (min)	49.5	38.1	−23.0	38.9	−21.4
Disrupted passengers	5,989	4,126	−31.1	4,055	−32.3
Missed connections	1,305	1,341	2.8	1,253	−4.0
Cancellations	4,684	2,785	−40.5	2,802	−40.2
Overnight passengers	1,010	367	−63.7	373	−63.1
Delay of disrupted passengers (min)	374.4	306.0	−18.3	314.9	−15.9
Delay of nondisrupted passengers (min)	24.5	25.4	3.5	25.0	2.1
Canceled flights	60	40	−33.3	40	−33.3
Passengers per canceled flight	78	71	−8.5	72	−8.0

we achieve with DPM a potential reduction of 63.1% in the number of passengers disrupted overnight, and a reduction of 15.9% in the delay experienced by these passengers.

Flight legs canceled on day d1 by DPM exhibit two important differences with actual operations, namely: canceled flight legs are scheduled to depart earlier on average (2:37 PM compared to 4:23 PM); and fewer passengers are disrupted per canceled flight (72 passengers with DPM and 78 passengers in actual operations). From this, we conclude that our decision models better anticipate the effects of delay propagation, resulting in the cancellation of earlier flights that effectively dampen downstream propagation of delay, thereby reducing the number of disrupted passengers.

Figure 3 shows the percentage difference in actual average passenger delay and that achieved with DPM, as a function of the number of optimization stages in our simulation. It is important to reoptimize often enough to adjust to changes in the system, but the benefit of reoptimization decreases as the number of stages increases, with very little benefit beyond 12 stages.

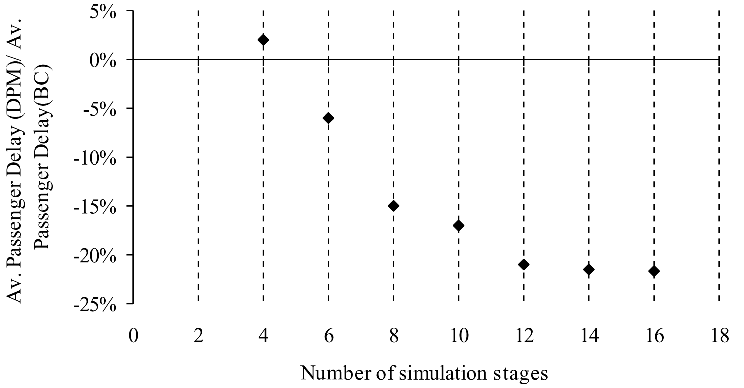

Fig. 3 Changes in average passenger delay for DPM as a function of number of simulation stages

Table 4 Actual flight leg operations: statistics for day d2

Duration of simulation	1 day
15OTP	71.6%
45FD	11.4%
Percentage of flights delayed	53.2%
Number of flights canceled	29
Avg. delay per operated flight (min)	13.8
Number of flights	1,061

4.2.2. Average levels of disruption

Table 4 summarizes the flight operations statistics for day d2, a day in August 2000 with average levels of disruption. In Table 4, we compare the DPM results to actual operations (*BC*) on *d2*, using 16 stages in our simulation.

Comparing the results of DPM to actual operations, we are able to reduce the number of disrupted passengers by 19.4% (644 passengers) and the number of passengers missing their connections by 36.7% (471 passengers). These reductions are partially achieved by increasing the delay experienced by nondisrupted passengers; however, the increase in average delay for these passengers compared to actual delay is only 0.2 min (1.6%).

Because the objective of DPM to reduce passenger disruptions can be achieved by judiciously postponing flight leg departures, on-time performance (as measured by 15OTP) is 2.9% lower for DPM than for actual operations. Assuming hourly average passenger delay costs of $24.11, we estimate that compared to actual operations, passenger delay costs are reduced by $65,699 with DPM (requiring at most 273.2 seconds to solve). This analysis highlights the inadequacy of 15OTP as a proxy for passenger schedule reliability.

4.2.3. Low levels of disruption

Table 6 summarizes the flight operations statistics for day d3, a day with low levels of disruption in August 2000. In Table 7, we compare actual operations for day *d3* (*BC*) to simulation results using DPM and 16 stages. Compared to actual operations, our simulation with DPM produces 17.2% fewer disrupted passengers who stayed overnight and reduces average passenger delay by 5.2%.

5. Conclusion

We develop a new approach to airline schedule recovery in which the objective is to find the optimal trade-off between airline operating costs and passenger delay costs. We generate recovery plans that suggest flight departure times and flight cancellations, assigning aircraft and reserve crews, if necessary, to flight legs, while complying with crew regulations and satisfying aircraft maintenance requirements. We propose two optimization models each minimizing airline operating costs jointly with some measure of passenger costs. The passenger costs considered are (1) passenger disruption costs in the model DPM; and (2) passenger delay costs in the model PDM. Our airline recovery models are evaluated using an AOCC simulator that we have developed, which reruns days of operations assuming flight leg decisions are taken as suggested by one of our optimization models. We find that PDM cannot be solved in real time for day-long decision windows and days with relatively high levels of disruption, whereas DPM is fast enough to be used by operations controllers to recover from airline irregularities in real time. DPM could

Table 5 Airline recovery model performance compared to BC for day d2

	BC	DPM	DPM/BC (%)
Passenger delay (minutes)	23.8	21.8	−8.2
Disrupted passengers	3,321	2,677	−19.4
Missed connections	1,285	814	−36.7
Cancellations	2,036	1,863	−8.5
Overnight passengers	500	278	−44.4
Delay of disrupted passengers (minutes)	262.2	254.1	−3.1
Delay of nondisrupted passengers (min)	13.9	14.2	1.6
Canceled flights	29	27	−6.9
Passengers per canceled flight	70	69	−1.4

Table 6 Actual flight leg operations: statistics for day d3

Duration of simulation	1 day
15OTP	89.4%
45FD	3.6%
Percentage of flights delayed	34.0%
Number of flights canceled	9
Avg. delay per operated flight (min)	5.9
Number of flights	1074

Table 7 Airline recovery model performance compared to BC for day d3

	BC	DPM	DPM/BC (%)
Passenger delay (min)	10.7	10.1	−5.2
Disrupted passengers	1,757	1,541	−12.3
Missed connections	981	785	−20.0
Cancellations	776	756	−2.6
Overnight passengers	209	173	−17.2
Delay of disrupted passengers (min)	233.1	230.4	−1.2
Delay of nondisrupted passengers (min)	5.9	6.0	1.5
Canceled flights	9	9	0.0
Passengers per canceled flight	86	84	−2.6

nonetheless be used to solve smaller instances that can be partitioned. More powerful computers and more efficient combinatorial algorithms, such as parallel metaheuristics, can also be used to reduce the search time to find an acceptable solution matching the AOCC response time. For 3 days of operations with different levels of disruption, using DPM we generate solutions with noticeable reductions in passenger delays and disruptions. We conclude that better operations decisions can be generated in real time to reduce passenger delays and disruptions, while recovering airline resource schedules and controlling airline operating costs.

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