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Congestion Mitigation through Schedule Coordination at JFK: An Integrated Approach

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Abstract

Most of the flight delays in the United States are created by large imbalances between demand and capacity at the busiest airports. Absent opportunities for significant capacity increases, airport congestion can only be mitigated by reducing peak scheduling levels through schedule coordination. This paper introduces an integrated approach to schedule coordination that jointly optimizes the rescheduling of flights at the strategic level and the efficiency of airport operations at the tactical level. Given an original schedule of flights created by the airlines in the absence of any demand management measure, a modified schedule is proposed to meet delay reduction objectives while minimizing the displacement from the original schedule. The modified schedule does not eliminate any flight from the original schedule and maintains all aircraft and passenger connections. An original iterative solution algorithm is developed to integrate airport stochastic queue dynamics and a dynamic control of arrival and departure service rates into an Integer Programming model of flight scheduling. The application of the model to one of the busiest US airports, John F. Kennedy (JFK) International Airport, suggests that very substantial delay reductions can be achieved through a moderate level of schedule coordination. In particular, peak expected arrival and departure delays can be reduced by as much as 33% and 55%, respectively, without modifying the scheduled time of 83% of the flights arriving at or departing from JFK and without shifting the scheduled time of any flight by more than 30 minutes.

Key words airport, capacity, delay, schedule coordination, demand management, integer programming, dynamic programming, queuing model

1 Introduction

Due to the combination of air traffic growth and limitations in airport capacity, airport congestion has become an increasingly important phenomenon worldwide. In the United States, flight delays reached an all-time peak in 2007 and induced nationwide costs of over \$30 billion during that calendar year [1]. Most of these delays originate in demand-capacity mismatches resulting from

airlines scheduling more flights than available capacity at airports and in the propagation of delays through the National Aviation System [8].

Flight delays can therefore be significantly mitigated by reducing the imbalance between demand and capacity at the busiest airports. This can first be achieved by increasing airport capacity through infrastructure expansion, the development of new air traffic management technologies, etc. However, such projects are investment-intensive and, more importantly, are either very time-consuming or even infeasible in the densest and most constrained regions. Delays can also be reduced through improvements in air traffic flow management. Typical levers include the allocation of available capacity to arriving and departing flights [14], the selection of runway configurations [5, 21], the control of the departure process [34, 22], the ground holding of departures in the Ground Delay Program [32, 17, 15, 2], etc. These approaches adjust the flow of aircraft to reduce congestion costs at the tactical level. However, they are generally inadequate for reasonably mitigating congestion at airports where demand and scheduling levels exceed capacity by a significant margin.

Absent opportunities for substantial capacity increases or improvements in operational efficiency, demand-capacity mismatches can only be significantly reduced through schedule coordination to reduce the number of flights scheduled at peak hours and to distribute flights more evenly over the course of the day. Most of the busy airports outside the United States operate under slot control policies that allocate slots administratively to carriers. In contrast, flight schedules have been weakly constrained at US airports since the phase-out of the High Density Rule, effective in 2007. In 2008, hourly flight caps were introduced at a few airports, including JFK. However, these caps have been loosely enforced and have been criticized as being too high to substantially mitigate congestion [11, 26, 16].

Determining the “optimal” stringency of demand management measures remains an open question. Any form of schedule coordination involves complex tradeoffs in a multi-stakeholder environment. Schedule coordination can lead to significant delay reductions at busy airports [30] and thus reduce the congestion costs borne by airlines and passengers [36, 35]. On the other hand, it constrains flight schedules and may create distortions in airline competition. The design and assessment of demand management measures therefore requires careful analysis of their effects on airline competitive scheduling and on airport congestion.

This paper introduces a congestion mitigation tool that optimizes schedule coordination to achieve policy objectives of delay reduction while minimizing interference with airline competition. We develop a *Schedule Coordination Model* that, given an original schedule of flights resulting from airlines’ decisions in the absence of any demand management measure, reschedules flights more evenly through the course of the day to meet delay reduction targets. It is based on the well-known observation that, for a given number of flights scheduled in a day, the more evenly they are distributed over its course, the lower expected delays will be [30, 20]. The smoothed schedule produced by the Schedule Coordination Model is chosen “as close as possible” to the

original schedule. We apply the model to JFK using scheduling data from 2007, when no flight cap was in place at this airport. Results suggest that delays can be substantially mitigated through even a moderate level of schedule coordination. In particular, peak departure delays can be reduced by over 50% while (i) no flight originally scheduled is eliminated, (ii) all aircraft itineraries are left unchanged, (iii) all passenger connections are maintained and (iv) no flight is displaced by more than 30 minutes.

1.1 Literature Review

The body of literature on demand management falls into three categories: models of airport operations, economic analyses of demand management and models of airline scheduling.

In the first category, capacity estimates have been developed [14, 33] and subsequently used in *descriptive* models of airport congestion that quantify the relationships between flight schedules and delays [19, 29, 25]. These models consider flight schedules as fixed. Therefore, they do not directly inform on how demand should be managed to reduce delays.

The problem of regulating access to commercial airports has also been the focus of numerous economic studies [10]. Some compare quantity-based (*e.g.*, slot controls) to price-based (*e.g.*, congestion pricing, slot auctions) capacity allocation mechanisms [7, 4, 9]. Others aim at determining the optimal stringency of demand management measures for different market structures [6, 12, 27]. These studies provide important insights on the economic performance of demand management policies. However, they typically consider simplified operational settings and fail to capture the complexity and variability of airport operations and of airlines' networks of flights.

Last, recent studies modeled the effects of demand management measures on airline schedules and, in turn, on airport congestion. Vaze and Barnhart developed a game-theoretic framework of airline frequency competition under slot control and congestion pricing constraints [36]. They found that these measures would result in delay reductions at US airports as well as an increase in operating profits of carriers. However, the time-scale of this study was a full day of operations, and thus too coarse to account for the dynamics of the formation and propagation of delays during the course of the day. Pyrgiotis and Odoni simulated the effects of scheduling limits at the busiest US airports on airlines' schedules by minimizing the displacement from an original schedule of flights planned in the absence of any demand management measure [30]. They demonstrated that substantial delay reductions could be achieved under "mild" scheduling constraints while keeping airlines' networks of flights and passengers' itineraries unchanged. Finally, Zografos, Salouras and Madas optimized the allocation of airport capacity to airlines at slot-controlled airports by minimizing the difference between the requested and allocated scheduled times [37]. They showed that significant efficiency improvements can be achieved to better accommodate airlines' preferences through the slot allocation process at congested European airports.

1.2 Contributions of this Paper

The main contribution of this paper is the development of an integrated approach to congestion mitigation that is both *tactical* and *strategic*. We jointly optimize the coordination of flight schedules at the strategic level and the utilization of airport capacity at the tactical level. The approach combines (a) estimates of airport capacity; (b) stochastic and dynamic queuing models of airport congestion; (c) a dynamic control of runway configurations and of arrival and departure service rates that optimizes airport efficiency at the tactical level; and (d) an Integer Programming model of flight scheduling. We believe that it represents the first attempt to integrate airport stochastic queue dynamics and operating procedures into a flight scheduling model aimed at mitigating congestion at the strategic level.

From a methodological standpoint, we develop a bi-level iterative approach that enables the integration of a stochastic and dynamic queuing model of airport congestion into any Integer Programming model of flight scheduling. First, we integrate a *deterministic* queuing model of airport congestion into the scheduling model. This provides an optimal schedule of flights, given deterministic queue dynamics. Then, we evaluate this solution using a *stochastic* queuing model. Iterating between these two phases determines, in turn, the optimal schedule of flights given stochastic queue dynamics.

Moreover, we develop a Tail Number Reconstruction Model that reconstructs aircraft itineraries, using information available in the Aviation Performance Metrics (APM) database. This database, maintained by the Federal Aviation Administration (FAA), reports extensive information on most commercial flights operated in the United States. However, it is incomplete when it comes to reporting aircraft tail numbers, which identify the aircraft used to operate each flight. Our Tail Number Reconstruction Model imputes missing data by optimizing the routing of aircraft, given available APM data. In turn, the reconstructed aircraft itineraries are integrated into the Schedule Coordination Model in order to maintain the connectivity of airlines' networks of flights in our scheduling model.

From a practical standpoint, this paper provides a congestion mitigation tool that optimizes and simulates "Level 2 coordination". Under this type of schedule coordination, airlines submit their flight schedules at the subject airport to a schedule facilitator (in this case, the FAA), who may then propose some adjustments to reduce anticipated delays [10]. This type of intervention is currently in place at a few busy US airports where scheduling levels exceed capacity significantly. However, no standardized procedure is applied and flight rescheduling typically takes place on an *ad hoc* basis, often through voluntary compliance by the airlines. The Schedule Coordination Model developed in this paper provides a general tool that optimizes the rescheduling of flights under this type of coordination. In addition, the application of the model informs on the extent to which delays can possibly be reduced through schedule coordination while minimizing interference with the original flight schedules submitted by the airlines.

The remainder of this paper is organized as follows. Section 2 develops the Schedule Coordination Model. We introduce successively the flight scheduling framework, the stochastic queuing model of airport congestion and the dynamic control of arrival and departure service rates. We then describe the iterative solution algorithm that integrates stochastic queue dynamics and airport operating procedures into the scheduling framework at the strategic level. Section 3 presents the experimental setup at JFK. In this context, we also develop the Tail Number Reconstruction Model that reconstructs aircraft itineraries from APM data. Section 4 presents the results of the implementation of the model at JFK. The impacts of schedule coordination on flight schedules and flight delays are quantified. Finally, Section 5 summarizes the findings of the paper.

2 The Schedule Coordination Model

The Schedule Coordination Model takes as inputs (i) the original schedule of flights created by the airlines on a given day in the absence of any demand management measure and (ii) estimates of airport capacity. It generates a schedule of flights that minimizes the displacement from the original schedule, while ensuring that the connectivity of flights is maintained and that delays are kept below predefined delay reduction targets. We use the demand-smoothing framework based on Integer Programming developed by Pyrgiotis and Odoni [30]. The framework provides a methodology for producing a schedule of flights which does not eliminate any flight, while leaving all aircraft itineraries unchanged and maintaining all passenger connections. However - and most importantly - we integrate delay reduction objectives *within* the scheduling algorithm instead of applying predetermined schedule limits.

For this purpose, we integrate into the Schedule Coordination Model a stochastic and dynamic queuing model of airport congestion that quantifies, for any schedule of flights, the probabilistic distribution of arrival and departure queue lengths over the course of the day. In order to integrate this model into the scheduling framework, we impose constraints on arrival and departure *queue lengths*. Note that constraints on *delays* can be mapped into constraints on *queue lengths* by approximating the expected delay by the ratio of the expected queue length over the average service rate at the airport.

A schematic formulation of the model is given as follows, where A_{MAX} and D_{MAX} denote the limits that are placed on expected arrival and departure queue lengths, respectively. Note that the formulation applies reduction targets to *peak expected* queue lengths. This formulation can easily be modified to apply reduction targets to *total* expected queue lengths or to estimates of peak *maximal* (e.g., 95th percentile) queue lengths.

minimize	Schedule Displacement
subject to	No flight eliminated
	Scheduled block-times unchanged
	Aircraft connections maintained
	Passenger connections maintained
	Peak expected arrival queue length lower than A_{MAX}
	Peak expected departure queue length lower than D_{MAX}

In addition, we integrate into the Schedule Coordination Model a control of runway configurations and of arrival and departure service rates that optimizes the dynamic allocation of available capacity to arriving and departing aircraft over the course of the day [21]. In turn, the Schedule Coordination Model optimizes the rescheduling of flights at the strategic level and maximizes, at the same time, the efficiency of airport operations at the tactical level. *Jointly* optimizing flight schedules and the utilization of airport capacity is crucial as the latter is a function of the former. Consider, for instance, a period of the day during which a large number of takeoffs has been scheduled and let us assume that schedule coordination lowers this departure peak in order to reduce departure delays. Then the allocation of airport capacity to arriving and departing aircraft at the considered period may have to change. Given the inherent tradeoff between arrival and departure throughput, it may indeed be beneficial to lower the departure service rate and increase the arrival service rate to best serve the changed balance between arrival and departure demand.

A schematic representation of the integrated approach is provided in Figure 1.

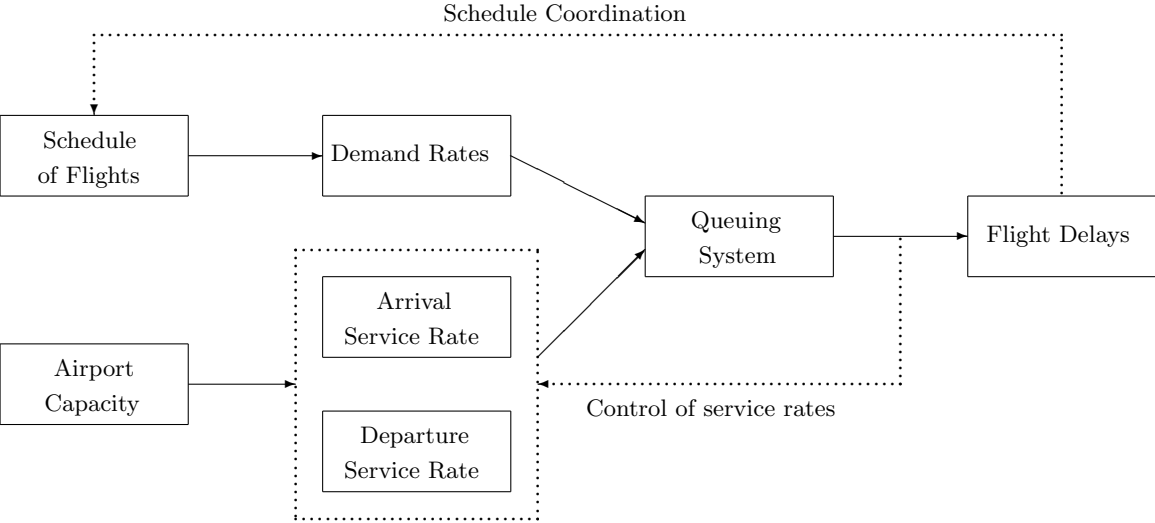


Figure 1: Representation of the integrated approach of the Schedule Coordination Model

2.1 Scheduling Framework

We first introduce the Integer Programming framework of the scheduling model. It builds on the model developed in [30]. We denote by A the airport where schedule coordination is applied (in this case, JFK)¹. We divide a day of operations into T periods of length 15 minutes each. We denote by F the number of flights that are included in the scheduling model. This includes all flights that arrive at A or that leave from A , as well as all flights that are flown by an aircraft that visits A during the day. For instance, if an aircraft flies the itinerary $A \rightarrow B \rightarrow C$, then *both* flights $A \rightarrow B$ and $B \rightarrow C$ are included in the model. This is because the rescheduling of flight $A \rightarrow B$ might require a change in the scheduled time of flight $B \rightarrow C$ to maintain a feasible connection between both flights. We define below the sets, parameters, variables and constraints of the scheduling model.

2.1.1 Sets

$$\begin{aligned}\mathcal{F} &= \text{the set of flights, } \{1, \dots, F\}; \\ \mathcal{T} &= \text{the set of time intervals, } \{1, \dots, T\};\end{aligned}$$

2.1.2 Parameters

$$\begin{aligned}S_{it}^{\text{arr}}/S_{it}^{\text{dep}} &= \begin{cases} 1 & \text{if flight } i \text{ is originally scheduled to land / take off in period } t \\ 0 & \text{otherwise} \end{cases} \\ A_i^{\text{arr}}/A_i^{\text{dep}} &= \begin{cases} 1 & \text{if flight } i \text{ is scheduled to land at / take off from airport } A \\ 0 & \text{otherwise} \end{cases} \\ z_{ij} &= \begin{cases} 1 & \text{if flight } i \text{ and flight } j \text{ are flown by the same aircraft} \\ & \text{and if flight } j \text{ is the immediate successor of flight } i \\ 0 & \text{otherwise} \end{cases} \\ t_{ij}^{\text{min}} &= \text{the minimum aircraft turnaround time between flight } i \text{ and flight } j \\ t_{ij}^{\text{max}} &= \text{the maximum aircraft turnaround time between flight } i \text{ and flight } j \\ \text{pax}_{ij} &= \begin{cases} 1 & \text{if there is at least 1 passenger connecting from flight } i \text{ to flight } j \\ 0 & \text{otherwise} \end{cases} \\ \tau_{ij}^{\text{pax}} &= \text{the minimum passenger connection time between flight } i \text{ and flight } j\end{aligned}$$

The parameters t_{ij}^{min} , t_{ij}^{max} and τ_{ij}^{pax} are expressed as numbers of 15-minute periods. For instance, if an aircraft connection requires a turnaround time of at least 45 minutes, then we set the corresponding value of t_{ij}^{min} to 3.

¹The model can be easily extended to apply schedule coordination simultaneously at several airports.

2.1.3 Variables

$$\begin{aligned}
 x_{it}/y_{it} &= \begin{cases} 1 & \text{if flight } i \text{ is rescheduled to land / take off in period } t \\ 0 & \text{otherwise} \end{cases} \\
 u_i &= \text{the displacement of flight } i \\
 \delta &= \text{the } \textit{maximal} \text{ displacement of any single flight} \\
 \Delta &= \text{the } \textit{total} \text{ displacement of all flights}
 \end{aligned}$$

The displacement variables u_i , δ and Δ are also expressed as numbers of 15-minute periods. Moreover, the value of u_i can be positive or negative, thus allowing any flight to be rescheduled later or earlier in the day.

2.1.4 Objective

The objective of the Schedule Coordination Model is to minimize the *maximal* displacement δ that any flight will sustain in order to meet the expected queue length targets A_{MAX} and D_{MAX} . Among all feasible schedules that can be obtained under this objective, we select one that minimizes the *total* displacement Δ . In other words, we consider a two-stage formulation where we first determine the minimal value of the maximal displacement, denoted by δ^* , and then we minimize the total displacement Δ among all feasible solutions satisfying the constraint $\delta = \delta^*$. This choice is motivated by equity concerns, as it ensures that no flight will incur a disproportionately large displacement [30].

2.1.5 Constraints

The scheduling constraints are provided below. Constraint (1) (resp. Constraint (2)) defines the displacement of any flight as the difference between its rescheduled arrival (resp. departure) time and its original arrival (resp. departure) time. In addition, the combination of Constraints (1) and (2) ensures that scheduled block times are left unchanged. Constraints (3) and (4) state that each flight is assigned to exactly one scheduled departure time and to one scheduled arrival time. Constraints (5) and (6) force aircraft turnaround times to be larger than the minimum turnaround times and smaller than the maximum turnaround times that are imposed. Finally, Constraint (7) ensures that passenger connecting times are kept larger than the minimum time required to connect between two flights at each of the airports visited by the flights in \mathcal{F} .

$$\sum_{t \in \mathcal{T}} tx_{it} = \sum_{t \in \mathcal{T}} tS_{it}^{\text{arr}} + u_i \quad \forall i \in \mathcal{F} \quad (1)$$

$$\sum_{t \in \mathcal{T}} ty_{it} = \sum_{t \in \mathcal{T}} tS_{it}^{\text{dep}} + u_i \quad \forall i \in \mathcal{F} \quad (2)$$

$$\sum_{t \in \mathcal{T}} x_{it} = 1 \quad \forall i \in \mathcal{F} \quad (3)$$

$$\sum_{t \in \mathcal{T}} y_{it} = 1 \quad \forall i \in \mathcal{F} \quad (4)$$

$$\left(\sum_{t \in \mathcal{T}} ty_{jt} - \sum_{t \in \mathcal{T}} tx_{it} \right) z_{ij} \geq t_{ij}^{\text{min}} \quad \forall i, j \in \mathcal{F} \quad (5)$$

$$\left(\sum_{t \in \mathcal{T}} ty_{jt} - \sum_{t \in \mathcal{T}} tx_{it} \right) z_{ij} \leq t_{ij}^{\text{max}} \quad \forall i, j \in \mathcal{F} \quad (6)$$

$$\left(\sum_{t \in \mathcal{T}} ty_{jt} - \sum_{t \in \mathcal{T}} tx_{it} \right) \text{pax}_{ij} \geq \tau_{ij}^{\text{pax}} \quad \forall i, j \in \mathcal{F} \quad (7)$$

We add the following two constraints, which respectively define the maximal displacement of flights and the total displacement of flights.

$$|u_i| \leq \delta \quad \forall i \in \mathcal{F} \quad (8)$$

$$\sum_{i \in \mathcal{F}} |u_i| \leq \Delta \quad (9)$$

The remaining constraints to be included in the formulation are the queuing constraints. We describe in the next section our model of airport congestion.

2.2 Stochastic Queue Dynamics

We model the relationship between flight schedules and flight delays by means of a *stochastic* and *dynamic* queuing model. We characterize the airport as a queuing system. Service is provided by the runway system, which is generally the main bottleneck of operations at congested airports [11]. Aircraft join the queue when they demand the use of the runway system to land or to take off at the airport. We model the arrival queue and the departure queue by means of two distinct $M(t)/E_k(t)/1$ queuing systems, *i.e.*, the demand processes and the service processes are respectively modeled as Poisson processes and as Erlang processes of order k . We use a value of $k = 3$ [20]. The stochasticity of the model is intended to capture the uncertainty and the variability associated with the actual queuing processes. The model has been found to approximate well the magnitude and dynamics of delays at busy US airports [31, 24, 20].

We divide a day of operations between 6 a.m. and 12 a.m. into 72 15-minute periods. We assume that the demand rates and the service rates within each 15-minute period are constant.

Demand rates are determined by the number of landings and takeoffs scheduled per 15-minute period. With the notations introduced in the previous section, the arrival (resp. departure) demand rate at airport A during any period t is equal to $\sum_{i \in \mathcal{F}} A_i^{arr} x_{it}$ (resp. $\sum_{i \in \mathcal{F}} A_i^{dep} y_{it}$).

Service rates are determined by airport capacity. However, they are not exogenously determined in advance. They depend instead on operating decisions made by air traffic controllers through the course of the day. These decisions are typically based on flight schedules, on meteorological conditions and on observed arrival and departure queue lengths. We integrate into the model of airport congestion a control of arrival and departure service rates. For any schedule of flights, the control optimizes the dynamic allocation of airport capacity to arriving and departing aircraft at the tactical level to minimize congestion costs. The details are presented in the next section.

2.3 Dynamic Control of Arrival and Departure Service Rates

We represent the capacity of an airport, in a given runway configuration, by means of a piece-wise linear *Operational Throughput Envelope*, which determines the non-increasing relationship between the average number of landings and the average number of takeoffs that can be operated per unit of time [33]. Given that airport throughput is significantly impacted by weather conditions, we consider one VMC envelope and one IMC envelope for each runway configuration. A schematic representation of these envelopes for a given runway configuration is provided in Figure 2. Points 1 and 2 represent two pairs of achievable average arrival and departure service rates in VMC and Point 3 represents a pair of achievable average service rates in IMC.

We consider a dynamic programming model of the control of runway configurations and of arrival and departure service rates [21]. At the beginning of each 15-minute period, the runway configuration and the arrival and departure service rates are jointly selected. First, the runway configuration, along with the weather conditions observed at the airport, determines the Operational Throughput Envelope, *i.e.*, the set of achievable arrival and departure service rates. Second, arrival and departure service rates are selected among the set of achievable service rates determined by the Operational Throughput Envelope. The control is exercised as a function of observed arrival and departure queue lengths, of the runway configuration in use, of weather conditions, which impact the efficiency of airport operations, and of winds, which might restrict the set of runways that can be used. In [21] this control has been shown to provide significant operational benefits.

However, the computational requirements of the full control outlined above prevent it from being used repeatedly with different flight schedules. Computational efficiency is necessary to enable successful integration of the control into the Schedule Coordination Model. Therefore, we implement an approximate version of the control. For this purpose, we assume that the schedule of use of runway configurations is exogenously determined in advance. It is obtained from the

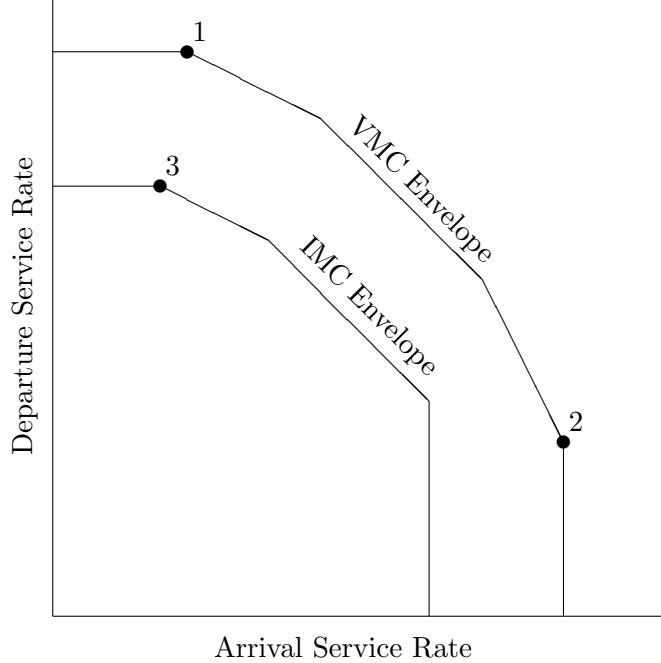


Figure 2: Representation of the VMC and IMC Operational Throughput Envelopes of an airport in a given runway configuration

application of the full control developed in [21] with the schedule of flights on a representative day. Subsequently, the schedule of use of runway configurations is treated as fixed and the control is restricted to the selection of arrival and departure service rates at the beginning of each 15-minute period. For the observed weather conditions (VMC or IMC), the service rates are constrained by the corresponding Operational Throughput Envelope of the runway configuration in use. This simplification reduces considerably the dimensionality of the decision space and therefore accelerates the dynamic programming algorithm.

The resulting control can be formulated as follows. At each period $t = 1, \dots, T$, the decision-maker observes (i) the arrival and departure queue lengths at the end of the previous period, respectively denoted by a_{t-1} and d_{t-1} and (ii) the weather conditions, denoted by $w_t \in \{VMC, IMC\}$. The runway configuration for period t , denoted by RC_t , is given. The decision-maker selects the arrival rate for period t , denoted by μ_t^a . The upper bound for this choice depends on the runway configuration and weather conditions and is denoted by A_{RC_t, w_t} . The departure service rate is subsequently determined by the Operational Throughput Envelope. Congestion costs are assumed to depend quadratically on arrival and departure queue lengths. Moreover, we weight the costs associated with arrival delays by a factor $\alpha \geq 1$ in order to capture the potentially larger costs of arrival delays than departure delays. The objective function is therefore expressed as $\alpha \sum_{t=1}^T a_t^2 + \sum_{t=1}^T d_t^2$. The Bellman equation is then formulated as follows, where $J_t(a_{t-1}, d_{t-1}, w_t)$

represents the cost-to-go of being in state (a_{t-1}, d_{t-1}, w_t) at the beginning of period t :

$$J_t(a_{t-1}, d_{t-1}, w_t) = \min_{\mu_t^a \in [0, A_{RC_t, w_t}]} \left(\alpha \mathbb{E}[a_t^2] + \mathbb{E}[d_t^2] + \mathbb{E}[J_{t+1}(a_t, d_t, w_{t+1})] \right), \forall t = 1, \dots, T \quad (10)$$

Finally, we integrate a simple model of weather variations into the control of arrival and departure service rates and into the stochastic queuing model of airport congestion. We use “Visual Meteorological Conditions” (VMC) and “Instrument Meteorological Conditions” (IMC) as surrogates of “good” and “poor” weather conditions, respectively. We introduce two categories of days: *all-VMC days* that have only VMC periods, and *VMC/IMC days* that have some VMC and some IMC periods. The probability that a given day is all-VMC is unbiasedly estimated by the empirical proportion of days that have only VMC periods. The weather “profile” on VMC/IMC days is modeled as a two-state Markov chain, with transition matrix:

$$\begin{array}{cc} & \begin{array}{cc} VMC & IMC \end{array} \\ \begin{array}{c} VMC \\ IMC \end{array} & \begin{pmatrix} 1-p & p \\ q & 1-q \end{pmatrix} \end{array}$$

The probability p (resp. q) represents the probability that, for a VMC/IMC day, period $t+1$ is in IMC (resp. VMC) given that period t is in VMC (resp. IMC). We estimate p (resp. q) by its maximum likelihood estimator, *i.e.*, the empirical ratio of the number of transitions from VMC to IMC (resp. from IMC to VMC) over the number of periods in VMC (resp. in IMC). The model of weather variations has been shown to replicate quite accurately historical records of weather conditions at JFK [20].

2.4 Integration of Deterministic Queue Dynamics into the Scheduling Model

Unfortunately, the stochastic and dynamic queuing model of airport congestion described in Section 2.2 and the control of arrival and departure service rates presented in Section 2.3 cannot be directly integrated into the Integer Programming scheduling model. This is because (a) the probabilistic evolution of arrival and departure queues depends *endogenously* on the schedule of flights, and (b) the stochastic relationship between flight schedules and flight delays is *nonlinear* [11]. In other words, changes in flight schedules, *i.e.* changes in the decision variables, induce nonlinear changes in the probabilistic dynamics of arrival and departure queues. This relationship cannot be expressed through a set of linear constraints in the scheduling model.

In contrast, we can easily integrate *deterministic* queue dynamics into our Integer Programming scheduling framework. In this section, we describe the corresponding parameters, variables and constraints. In the following section, we describe how we use this formulation to solve the Schedule Coordination Model with *stochastic* queue dynamics.

We first define the following set:

$$\mathcal{S}_t = \begin{array}{l} \text{the set of linear segments of the VMC Operational Throughput Envelope} \\ \text{of the runway configuration in use during period } t \end{array}$$

The VMC Operational Throughput Envelope of the runway configuration in use at period t can then be expressed by the following set of linear equations, where α_s , β_s and γ_s denote the parameters defining each linear segment of the envelope:

$$\alpha_s x + \beta_s y \leq \gamma_s, \forall s \in \mathcal{S}_t$$

We add two pairs of variables:

$$\begin{array}{l} \mu_t^a / \mu_t^d = \text{the arrival / departure service rate selected during period } t \\ a_t / d_t = \text{the arrival / departure queue length at the end of period } t \end{array}$$

Finally, we add 3 constraints. Constraint (11) ensures that, at any period t , the arrival and departure service rates lie within the bounds defined by the VMC Operational Throughput Envelope of the runway configuration in use. In addition, it provides a degree of freedom as any set of arrival and departure service rates that satisfies the constraint can be selected (*e.g.*, Point 1 or Point 2 or any other point of the VMC envelope in Figure 2). This integrates the control of service rates into the Integer Programming framework. Constraints (12) and (13) define the *deterministic* dynamics of arrival and departure queues. The arrival (resp. departure) queue length at the end of period t is simply equal to the sum of the arrival (resp. departure) queue length at the end of period $t - 1$ and the number of landings (resp. takeoffs) scheduled during period t , *i.e.* $\sum_{i \in \mathcal{F}} A_i^{arr} x_{it}$ (resp. $\sum_{i \in \mathcal{F}} A_i^{dep} y_{it}$), minus the number of landings (resp. takeoffs) operated during period t , *i.e.*, μ_t^a (resp. μ_t^d).

$$\alpha_s \mu_t^a + \beta_s \mu_t^d \leq \gamma_s \quad \forall t \in \mathcal{T}, \forall s \in \mathcal{S}_t \quad (11)$$

$$a_t = a_{t-1} + \left(\sum_{i \in \mathcal{F}} A_i^{arr} x_{it} \right) - \mu_t^a \quad \forall t \in \mathcal{T} \quad (12)$$

$$d_t = d_{t-1} + \left(\sum_{i \in \mathcal{F}} A_i^{dep} y_{it} \right) - \mu_t^d \quad \forall t \in \mathcal{T} \quad (13)$$

2.5 Iterative Solution Algorithm

At this point, we have developed an Integer Programming model that can determine the optimal schedule of flights meeting delay reduction targets under *deterministic* queue dynamics. However, we aim at finding the optimal schedule meeting delay reduction targets under *stochastic* queue dynamics. Previous research has shown that deterministic queuing models lead to significantly smaller

delay estimates than stochastic queuing models [19]. Therefore, solving the Schedule Coordination Model with deterministic queue dynamics would lead to an overly optimistic schedule. Indeed, a schedule of flights might meet the delay reduction targets with deterministic queue dynamics, but *not* with stochastic queue dynamics.

Nonetheless, it has also been found that delays estimated with stochastic and deterministic queuing models exhibit some degree of collinearity [19]. Whereas stochastic delays are larger than deterministic delays, the dynamics of formation and propagation of delays through the course of the day are similar under deterministic and stochastic queue dynamics. We therefore make the following assumption: given two distinct schedules of flights, the one that leads to the smallest peak deterministic delays will also lead to the smallest peak expected stochastic delays. Under this assumption, for any given schedule displacement, the schedule that minimizes peak deterministic delays will also be the schedule that minimizes peak expected stochastic delays.

Using this assumption, we develop an iterative bi-level solution algorithm to the Schedule Coordination Model. At the higher level, we determine, for a given value of the maximal displacement δ and/or of the total displacement Δ , a schedule that minimizes peak *deterministic* delays. Using the Integer Programming framework developed above, we minimize the following expression:

$$q_{\text{MAX}} := M \left[\max \left(\frac{1}{A_{\text{MAX}}} \max_{t \in \mathcal{T}} a_t, \frac{1}{D_{\text{MAX}}} \max_{t \in \mathcal{T}} d_t \right) \right] + \sum_{t \in \mathcal{T}} \left(\frac{a_t}{A_{\text{MAX}}} + \frac{d_t}{D_{\text{MAX}}} \right), \quad (14)$$

where $M \gg 1$ is a very large scalar. In other words, we first minimize the largest arrival and departure queue lengths that are incurred during the day, with the arrival (resp. departure) queue length “normalized” by a factor A_{MAX} (resp. D_{MAX}). The purpose of the normalization is to capture the relative “cost” of increasing the expected arrival (resp. departure) queue length vis-à-vis the target levels A_{MAX} (resp. D_{MAX}). Among all schedules that minimize the largest normalized queue lengths, we select the one that minimizes the “total” normalized queue length, expressed as $\sum_{t \in \mathcal{T}} \left(\frac{a_t}{A_{\text{MAX}}} + \frac{d_t}{D_{\text{MAX}}} \right)$.

At the lower level, we use the resulting schedule of flights to simulate delays using *stochastic* queue dynamics. We determine in this way whether the optimal displacement is larger or smaller than the considered displacement (see details in the next two paragraphs). If the peak expected stochastic delays are found *larger* than the expected queue length targets A_{MAX} and D_{MAX} , then the displacement has to increase, *i.e.*, schedule coordination has to be more aggressive in order to meet the targets. If, however, the stochastic delays are found *smaller* than the queue length targets, then the optimal displacement is smaller than the considered displacement, *i.e.*, schedule coordination might be less aggressive and targets might still be met. This approach is based on the non-increasing relationship between displacement and delays.

Figure 3 presents the algorithm that determines the optimal maximal displacement δ^* by iteratively updating a lower bound of δ^* , denoted by $\underline{\delta}$. We initialize the algorithm with a value of

$\underline{\delta} = 0$, *i.e.*, no flight is displaced. We optimize the control of arrival and departure service rates and we estimate stochastic delays with the original schedule of flights. If the queue length targets are met, then the optimal maximal displacement δ^* is equal to 0. Otherwise, we increase the value of $\underline{\delta}$ to 1. We obtain the schedule that minimizes peak delays for a value of $\delta = 1$. Note that we do not impose any restriction on the total displacement at this point, and therefore Constraint (9) is relaxed. Using the modified schedule, we re-optimize the control of service rates and we simulate stochastic delays. If the queue length targets are met, then the optimal maximal displacement δ^* is equal to 1. Otherwise, we increase the value of $\underline{\delta}$ to 2, and repeat the process until the targets are met.

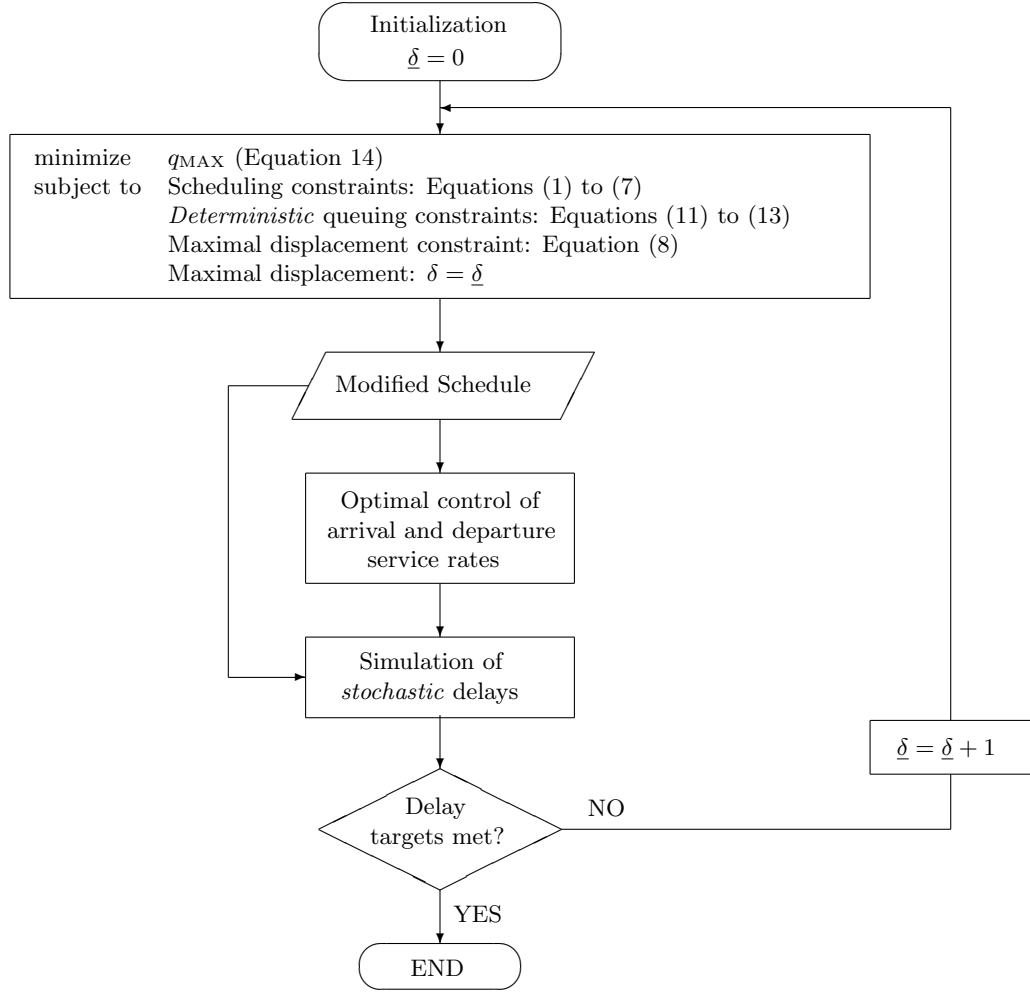


Figure 3: Determination of the optimal maximal displacement δ^*

Figure 4 shows the iterative algorithm that determines the optimal total displacement Δ^* , given the optimal maximal displacement δ^* . We denote by $\bar{\Delta}$ and $\underline{\Delta}$ an upper bound and a lower bound of Δ^* , respectively. We initialize the algorithm by setting $\bar{\Delta}$ to $F\delta^*$, which corresponds to the

situation where *all* flights are displaced by δ^* , and $\underline{\Delta}$ to 0, which corresponds to the situation where *no* flight is displaced. We proceed by dichotomy. At each iteration, we consider a tentative value of the total displacement, denoted by Δ^{try} , at the midpoint of $\overline{\Delta}$ and $\underline{\Delta}$. We find the schedule that minimizes peak deterministic delays for the value of $\Delta = \Delta^{\text{try}}$. Using this schedule, we optimize the control of arrival and departure service rates and we simulate stochastic delays. If the queue length targets are met, then the optimal total displacement is at most equal to Δ^{try} , so we set $\overline{\Delta}$ to Δ^{try} . Otherwise, the optimal total displacement is larger than Δ^{try} , so we set $\underline{\Delta}$ to Δ^{try} . We repeat this process until $\overline{\Delta}$ and $\underline{\Delta}$ have converged to the same value, which is then equal to the optimal total displacement Δ^* .

Note that the iterative algorithm relies on our assumption that the schedule that minimizes peak deterministic delays, for a given schedule displacement, is identical to the schedule that minimizes peak expected stochastic delays. In fact, this assumption may introduce an error in some instances. For example, there may exist, for a given displacement, a schedule of flights that reduces peak expected stochastic delays to a greater extent than the schedule minimizing peak deterministic delays. In such instances, the algorithm may not be able to find the exact optimal solution. Nonetheless, we expect such errors to be of second order. In general, the modified schedule of flights that we obtain is expected to be very close to the optimal schedule.

2.6 Summary

We have developed a Schedule Coordination Model that reschedules flights in order to meet delay reduction targets. The model minimizes the displacement from the original schedule, while preserving the networks of flights and keeping peak expected arrival and departure queue lengths below predetermined limits. Since we could not integrate stochastic queue dynamics into the Integer Programming formulation of the model, we have developed an original iterative approach. For any schedule displacement, we determine the schedule of flights that minimizes peak *deterministic* delays. We use this modified schedule to simulate *stochastic* delays. The comparison of the stochastic delays to the expected queue length targets informs on whether the considered displacement is too small or too large. Iterating this algorithm determines, in turn, a good approximation of the optimal displacement and of the optimal schedule meeting the expected queue length targets.

3 Experimentation Setup at JFK

We now apply our Schedule Coordination Model to the schedule of 05/25/2007 at JFK. This was one of the busiest days of the year 2007, with the number of scheduled flights corresponding to the 90th percentile of the distribution of the number of daily flights at JFK during that year. Flight schedules were obtained from the Aviation Performance Metrics (APM) database [13]. Among other metrics, the database reports, for each flight taking off or landing at the main airports in the

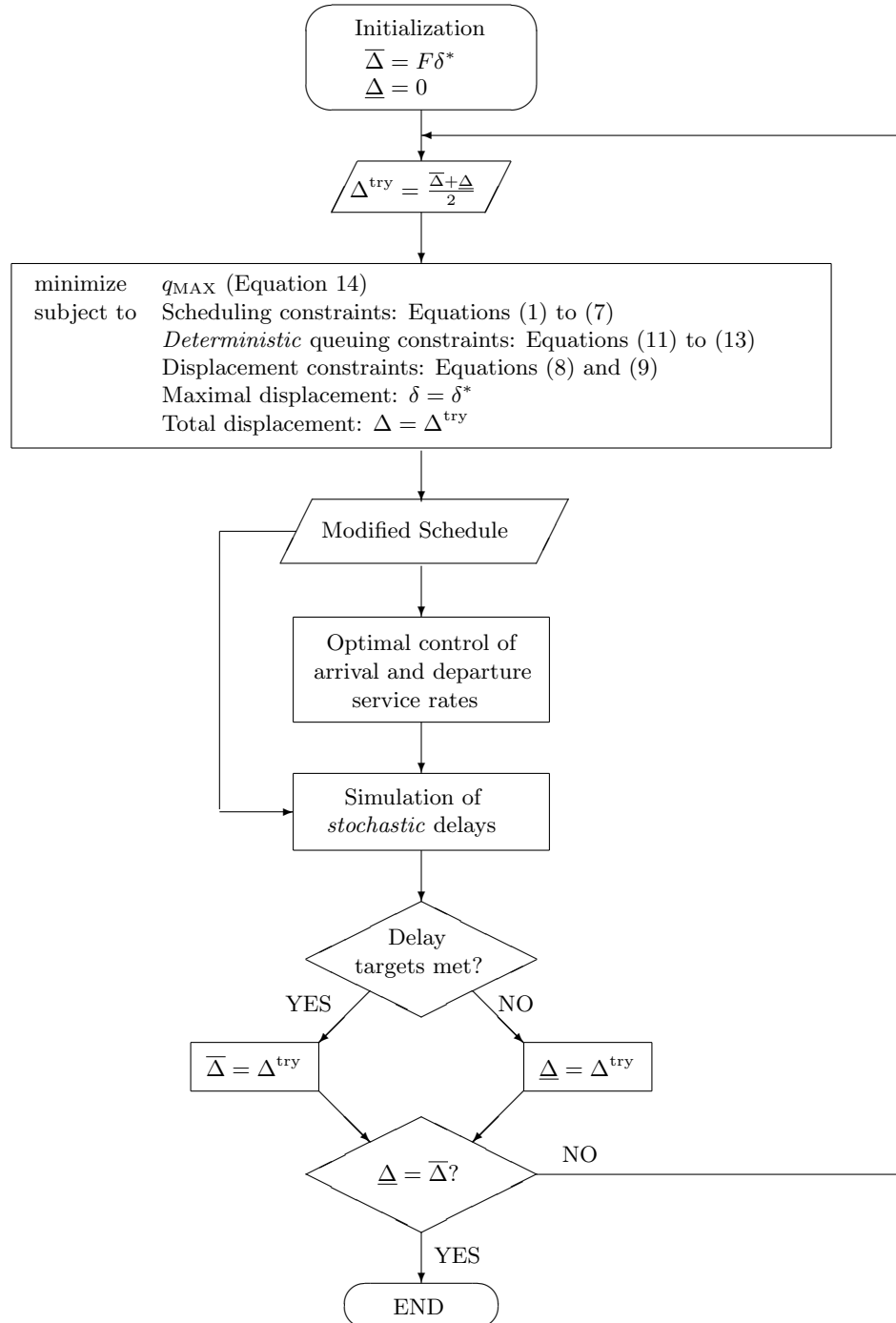


Figure 4: Determination of the optimal total displacement Δ^* , given the optimal value of the maximal displacement δ^*

United States, its origin, its destination and its scheduled takeoff and landing times, as well as the carrier operating the flight, the type of aircraft used (*e.g.*, A320, B777, etc.), the flight number and

the aircraft tail number.

However, the aircraft tail number, which identifies the aircraft operating a flight, is missing for approximately 40% of the flights reported in the database, including all international flights. This information is required to identify aircraft connections and to define the related constraints in the Schedule Coordination Model. For this reason, we implement in the next section a simple Tail Number Reconstruction Model that, given available information in the APM database, reconstructs aircraft itineraries to maximize the number of connections.

3.1 A Tail Number Reconstruction Model

Let us consider a single airline, denoted by AL and a single aircraft type, denoted by AC . Let us also consider a given week of operations, denoted by w . From the information available in the APM database, we identify the set of flights operated by airline AL and flown by aircraft type AC during week w . We denote this set by \mathcal{I} .

We introduce the following two parameters. In the definitions below, a direct connection between flight i and flight j means that flights i and j are flown by the same aircraft and that flight j is the immediate successor of flight i .

$$A_{ij}^{\text{TNR}} = \begin{cases} 1 & \text{if a direct connection between flight } i \text{ and flight } j \text{ is feasible} \\ 0 & \text{otherwise} \end{cases}$$

$$B_{ij}^{\text{TNR}} = \begin{cases} 1 & \text{if a direct connection between flight } i \text{ and flight } j \text{ was actually planned} \\ 0 & \text{otherwise} \end{cases}$$

A connection between flights i and j is assumed to be “feasible” if flight j departs from the airport where flight i arrived and if the difference between flight j ’s departure time and flight i ’s arrival time is larger than the minimum time required for the aircraft to turn around. A connection between flights i and j is identified as “actually planned” if the tail numbers of flights i and j are reported in the APM database, if they are identical to each other and if the difference between flight j ’s departure time and flight i ’s arrival time is small enough to ensure that the aircraft has not flown other flights between flight i and flight j .

The Tail Number Reconstruction Model determines aircraft itineraries that minimize the number of aircraft used to operate the set of flights in \mathcal{I} . It is a simplified version of the extensively studied Fleet Assignment Model (see, *e.g.*, [18, 23]), applied to the set of flights operated by airline AL with an aircraft type AC . In other words, the assignment of aircraft types to the scheduled flights is assumed to have already been performed by the airline and we determine the routing or aircraft that minimizes the aircraft count, or, equivalently, that maximizes the number of connections.

We therefore define the following binary variable:

$$z_{ij}^{\text{TNR}} = \begin{cases} 1 & \text{if a connection between flight } i \text{ and flight } j \text{ is imposed} \\ 0 & \text{otherwise} \end{cases}$$

The Tail Number Reconstruction Model can be formulated as follows. The objective function (15) maximizes the number of aircraft connections. Constraint (16) states that there cannot be a connection between any pair of flights if the connection is not feasible. Constraint (17) maintains the connections that were actually planned. Constraint (18) (resp. (19)) states that any flight can be immediately preceded (resp. followed) by at most one flight.

$$\text{maximize } \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I}} z_{ij}^{\text{TNR}} \quad (15)$$

$$\text{subject to } z_{ij}^{\text{TNR}} \leq A_{ij}^{\text{TNR}} \quad \forall i, j \in \mathcal{I} \quad (16)$$

$$z_{ij}^{\text{TNR}} \geq B_{ij}^{\text{TNR}} \quad \forall i, j \in \mathcal{I} \quad (17)$$

$$\sum_{i \in \mathcal{I}} z_{ij}^{\text{TNR}} \leq 1 \quad \forall j \in \mathcal{I} \quad (18)$$

$$\sum_{j \in \mathcal{I}} z_{ij}^{\text{TNR}} \leq 1 \quad \forall i \in \mathcal{I} \quad (19)$$

$$z_{ij}^{\text{TNR}} \in \{0, 1\} \quad \forall i, j \in \mathcal{I} \quad (20)$$

We applied the Tail Number Reconstruction Model over the week spanning from three days before to three days after the day considered in the Schedule Coordination Model (in this case, 05/25/2007). We considered the networks of flights operated by all airlines that operated at least 1% of all flights scheduled at JFK on 05/25/2007. For each of these airlines, we consider the aircraft types that operated at least 100 flights during the considered week, *i.e.*, between 05/22/2007 and 05/28/2007. We applied the Tail Number Reconstruction Model for each of these airlines and for each of these aircraft types during the considered week. Finally, we reconstructed the remaining itineraries (*i.e.*, the itineraries operated by the airlines that operated less than 1% of the flights at JFK on 05/25/2007 and the itineraries flown by aircraft types that operated less than 100 flights during the considered week) using a manual procedure similar to the one outlined by Pyrgiotis [28].

Since this procedure optimizes the routing of aircraft to minimize the number of aircraft used over a week of operations, it is expected to approximate the fleet assignment decisions made by the airlines. It is likely, however, that the resulting routing will not match exactly the one that was used by the airlines on the considered day. For instance, considerations such as aircraft maintenance routing and crew scheduling are not included in the model. Nonetheless, the procedure is quite conservative: since it maximizes the number of aircraft connections, it constrains the Schedule Coordination Model as much as possible. Therefore, the solution to the Schedule Coordination

Model with any alternative routing of aircraft is expected to induce a smaller displacement than the solution that we obtain with the optimized routing.

3.2 Schedule Coordination Model Setup

As described in Section 2.1, we include in the Schedule Coordination Model all flights operated by all aircraft that visited JFK at least once during this day. This includes $F = 1,645$ flights, among which 1,229 flights were scheduled to land at or take off from JFK.

The aircraft connections parameters z_{ij} are obtained from the results of the Tail Number Reconstruction procedure described in Section 3.1. Note that, by construction, all connections reported in the APM database are maintained. We use the *minimum* aircraft turnaround time between any pair of flights estimated by Pyrgiotis [28]. It is a function of the aircraft type, of the airline and of whether the airport is a hub airport for the airline or not. Moreover, we define the *maximum* turnaround time of any pair of successive flights as the turnaround time that was actually planned on 05/27/2007 plus 15 minutes. In other words, we impose the condition that no aircraft connection will incur an increase in its turnaround time of more than 15 minutes. This ensures that aircraft utilization remains very close to what was originally planned by the airline.

We obtained passenger connection data from a database developed by Barnhart, Fearing and Vaze [3]. It is based on a discrete choice model for estimating historical passenger route choices. We estimated the minimum passenger connection time at JFK as the 5th percentile of the distribution of all planned passenger connection times.

Finally, we obtained the VMC and IMC Operational Throughput Envelopes of JFK’s main runway configurations from Simaiakis [33]. These envelopes were used previously in developing the control of runway configurations and of arrival and departure service rates at JFK [21].

4 Implementation Results

4.1 Convergence of the Iterative Algorithm

In this section, we describe the convergence of the iterative algorithm developed in this paper. We use expected queue length targets equal to $A_{MAX} = 10$ and $D_{MAX} = 15$, *i.e.* we require that the expected arrival and departure queue lengths should not exceed 10 aircraft and 15 aircraft, respectively. Figure 5a shows the value of the maximal displacement δ and of the upper and lower bounds of the total displacement, $\bar{\Delta}$ and $\underline{\Delta}$, after each iteration of the algorithm. Figure 5b shows the peak expected arrival and departure queue lengths after each iteration as well as the expected queue length targets.

During the first three iterations, the value of the maximal displacement δ is updated (see Figure 3). After the first iteration, *i.e.* with the original schedule of flights on 05/25/2007, peak expected arrival and departure queue lengths are respectively equal to 13.7 and 32.3 aircraft.

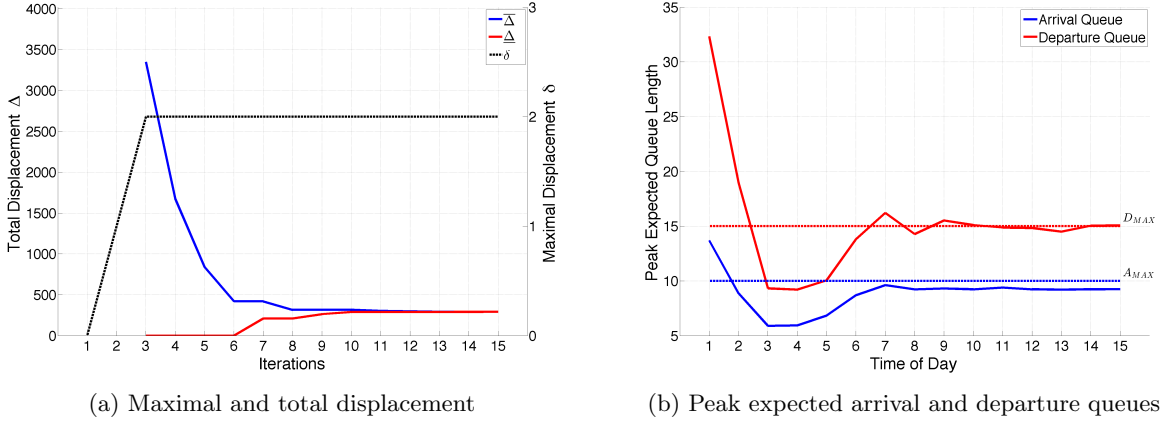


Figure 5: Convergence of the algorithm: displacement and queue lengths per iteration

After the second iteration, *i.e.* with a maximal displacement of 1 15-minute period, the queue length targets are still not met as the expected departure queue length peaks at 19 aircraft. At the third iteration, a schedule that meets the queue length targets is found with a value of the maximal displacement $\delta = 2$. Therefore, the optimal maximal displacement δ^* is equal to 2. In the remaining iterations, we apply the algorithm shown in Figure 4 to minimize the total displacement. The algorithm adjusts the upper and lower bounds of the total displacement to find the schedule that leads to expected delays as close as possible to the queue length targets. The algorithm terminates when the upper and lower bounds converge to the same value. In this case, the optimal total displacement is equal to $\Delta^* = 293$ 15-minute periods.

Note that the optimal solution is obtained after 15 iterations. As described in Section 2.5, each iteration consists in (i) the application of the Integer Programming scheduling model, which provides a modified flight schedule, (ii) the optimization of the control of arrival and departure service rates using the dynamic programming model and (iii) the simulation of arrival and departure queue lengths using our stochastic and dynamic queuing model. We implemented the Integer Programming scheduling model in GAMS 24.0 using CPLEX 8 and the control of arrival and departure service rates and the simulation of arrival and departure queues in MATLAB 8.1. The average time of each iteration is equal to 10 minutes on an Intel(R) Core(TM) i7 running at 2.6 GHz 16 GB RAM. In total, the 15 iterations terminate in approximately 2 hours and 30 minutes. This computational time is perfectly acceptable in view of the strategic nature of the model. Moreover, a close-to-optimal solution is found after only 10 iterations, a 33% computational improvement. Indeed, the range between the upper bound and the lower bound of the total displacement is lower than 10% after 10 iterations. Therefore, a modified schedule that meets the queue length targets while minimizing the changes from the original schedule of flights is obtained quickly after a small number of iterations.

4.2 Effects of Schedule Coordination on Flight Schedules

In this section, we describe how the schedule of flights is modified through schedule coordination. As in the previous section, we use expected queue length targets equal to $A_{\text{MAX}} = 10$ aircraft and $D_{\text{MAX}} = 15$ aircraft. The results from the previous section indicate that a schedule that meets these targets is obtained with a maximal displacement of 2 15-minute periods and with a total displacement of 293 periods. In particular, no flight is eliminated and all aircraft connections and all passenger connections are maintained. Among the 1,229 flights scheduled to land at or to take off from JFK, the scheduled time of 1,019 flights, *i.e.*, 83%, is not modified. Among the 1,645 flights considered in the model, the scheduled time of 1,453 flights (or 88%) is left unchanged, the scheduled time of 151 flights is shifted by 15 minutes and the scheduled time of 71 flights is shifted by 30 minutes.

Figure 6 depicts the original schedule of arrivals and departures on 05/25/2007 (Figure 6a) and the coordinated schedule (Figure 6b). As expected, schedule coordination reduces peak scheduling levels by rescheduling flights more evenly through the course of the day. Whereas over 30 flights were originally scheduled during some periods of the day, no more than 25 flights are scheduled at any period after schedule coordination. Moreover, schedule coordination affects differently the arrival schedule and the departure schedule depending on whether more landings or takeoffs are scheduled. For instance, a large number of departures are scheduled at JFK in the morning while arrival demand lies below capacity. As a result, the Schedule Coordination Model smooths the morning schedule of takeoffs but leaves the arrival schedule almost unchanged.

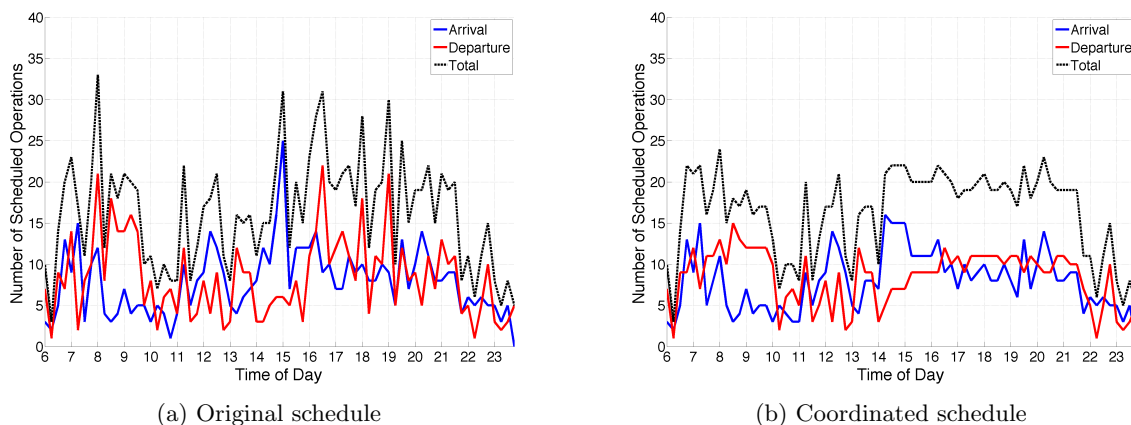


Figure 6: Original and coordinated schedules of flights ($A_{\text{MAX}} = 10$ and $D_{\text{MAX}} = 15$)

Please note that the coordinated schedule is not distributed evenly over the course of the day. This is an important observation that underlines the advantages of our integrated approach. It is well known that, for a given number of scheduled flights, expected delays will be the smallest when the flights are evenly distributed over the course of the day. But a “flat” schedule would

generally induce a larger displacement than the solution produced by the Schedule Coordination Model. Instead, the model maintains some peaks and valleys in the schedule of flights, albeit of smaller magnitude than the corresponding variations in the original schedule. This is far more realistic and consistent with airline preferences than a flat schedule. The optimal schedule exhibits above-capacity scheduling levels at some peak morning and afternoon hours and a schedule slack at off-peak hours. As well, the relative proportion of arrivals and departures is also maintained. The coordinated schedule, like the original schedule, has a departure peak in the morning and an arrival peak in early afternoon. Thus, the optimal schedule lies “closer” to the original schedule than a flat schedule.

These results underscore the importance of integrating queue dynamics into the Schedule Coordination Model. Indeed, the optimal schedule may maintain some peaks and slacks in the schedule and may thus differ from a schedule obtained by simply flattening the schedule of flights through the imposition of schedule limits. Therefore, for a given schedule displacement, applying *ex post* flight caps may not result in a delay-minimizing schedule of flights. Put another way, for given delay reduction targets, the Schedule Coordination Model developed in this paper will generally produce a solution that induces smaller changes to the original schedule of flights than a solution that caps the number of arrivals, the number of departures and the total number of flights scheduled per 15-minute period of the day.

4.3 Effects of Schedule Coordination on Flight Delays

The smoothing of flight schedules through schedule coordination reduces the imbalances between airport demand and capacity. This section quantifies the resulting reductions in flight delays. We define, in Table 1, 5 different scenarios by imposing 5 increasingly stringent sets of expected queue length targets A_{MAX} and D_{MAX} . For each test, the table reports the optimal displacement², the peak expected queue lengths and the average arrival and departure delays. In the first test, we impose no constraint on arrival and departure delays. The original schedule is therefore left unchanged and the expected arrival and departure queue lengths peak at 13.7 aircraft and 32.3 aircraft, respectively. In the four remaining tests, we progressively reduce the limits A_{MAX} and D_{MAX} that are placed on expected queue lengths. As a result, the minimal schedule displacement required to meet the queue length targets increases and flight delays decrease.

Note that very substantial delay reductions can be achieved through a limited level of schedule coordination. The peak expected arrival and departure delays can be reduced by 12% and 39%, respectively, without displacing any flight by more than 15 minutes. This corresponds to respective declines in the *average* delays during the whole day by 5% and 21%. Further delay reductions can be achieved by displacing some flights by 30 minutes, while keeping the total displacement Δ^*

²The values of the maximal displacement δ^* and of the total displacement Δ^* are given as numbers of 15-minute periods.

Table 1: Displacement and delays for different expected queue length targets

Test	Queue Length Targets		Optimal Displacement		Peak Queue Lengths		Average Delay	
	A_{MAX}	D_{MAX}	δ^*	Δ^*	Arrival	Departure	Arrival	Departure
1	–	–	0	0	13.7 A/C	32.3 A/C	9.1 min.	21.5 min.
2	13	25	1	38	12.9 A/C (-5.8%)	24.2 A/C (-25.1%)	8.9 min. (-2.38%)	19.0 min. (-11.40%)
3	12	20	1	104	12.0 A/C (-12.4%)	19.6 A/C (-39.4%)	8.6 min. (-5.32%)	17.0 min. (-21.00%)
4	10	15	2	293	9.2 A/C (-32.8%)	14.5 A/C (-55.2%)	7.7 min. (-15.59%)	12.9 min. (-40.15%)
5	8	10	2	837	6.7 A/C (-51.3%)	9.6 A/C (-70.4%)	5.8 min. (-36.80%)	8.6 min. (-60.06%)

relatively low. Tests 4 and 5 indicate that the peak expected arrival and departure delays can be reduced by as much as 30% to 50% and 50% to 70%, respectively. This corresponds to reductions in the average arrival delay by 4 to 5 minutes per flight, or 15% to 35%, and reductions in the average departure delay by 10 to 13 minutes per flight, or 40% to 60%.

Figure 7 shows the evolution of the expected arrival (Figure 7a) and departure (Figure 7b) queue lengths over the course of the day under the original schedule and the coordinated schedules from Tests 3, 4 and 5. The coordinated schedules correspond to respective expected queue length targets equal to $A_{MAX} = 12$ and $D_{MAX} = 20$, to $A_{MAX} = 10$ and $D_{MAX} = 15$ and to $A_{MAX} = 8$ and $D_{MAX} = 10$. As suggested in Table 1, schedule coordination results, in these cases, in very substantial delay reductions. The reductions in peak expected arrival and departure delays are estimated at 10% to 50% and at 40% to 70%, respectively. Note, also, that schedule coordination results in a slight extension of the peak scheduling periods. For instance, the arrival peak scheduled originally at 14:45 is smoothed between 14:00 and 15:00 (Figure 6). As a result, queues may form earlier with the coordinated schedules than with the original schedule. For instance, afternoon departure delays become significant around 3 pm after schedule coordination, while they remain very low until 4 pm under the original schedule. However, the magnitude of these delays remains much more manageable under the coordinated schedule. Instead of increasing almost instantaneously to over 30 aircraft, the expected departure queue length increases at a lower rate up to 10 to 20 aircraft, depending on the scenario considered. The queue lengths then become stable until the end of the evening peak under the coordinated schedules.

4.4 Sensitivity of the Optimal Displacement to Queue Length Targets

Finally, we investigate the sensitivity of the optimal schedule displacement to the delay reduction targets. Figure 8 shows the optimal values of the maximal displacement δ^* and the total displacement Δ^* as a function of the expected queue length targets A_{MAX} and D_{MAX} . In this figure, we impose the same constraint on the arrival and departure queue lengths, *i.e.* we set $A_{MAX} = D_{MAX}$.

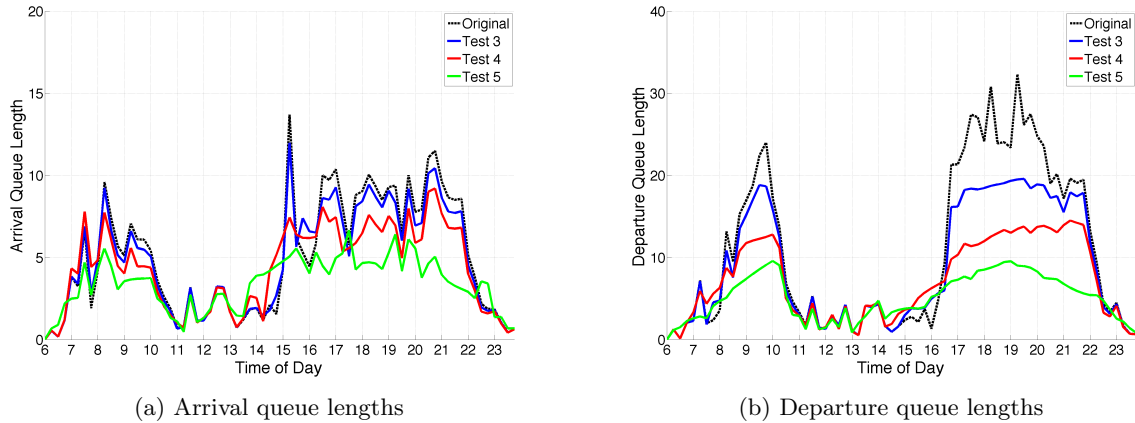


Figure 7: Expected arrival and departure queue lengths before and after coordination

Note that, under this assumption, the constraint on the departure queue length is the most likely to be binding as the departure queue was more peaked than the arrival queue under the original schedule (see Figure 7).

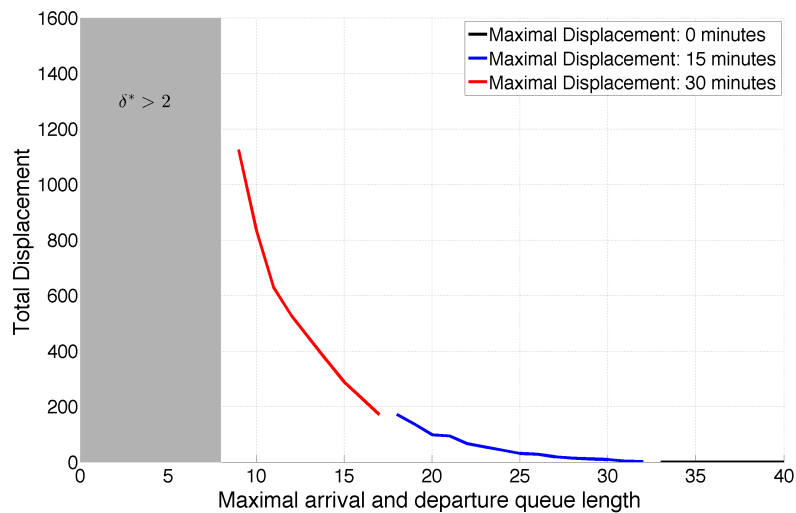


Figure 8: Sensitivity of the optimal displacement as a function of $A_{MAX} = D_{MAX}$

Note that the optimal schedule displacement increases exponentially as delay reduction targets become more stringent. In other words, significant delay reductions can be achieved through limited interference with the schedule of flights, while the most stringent delay reduction objectives may require disproportionately large displacements of flights.

First, peak expected departure delays can be reduced by nearly 50% with a small schedule displacement. Expected queue length targets as low as $A_{MAX} = D_{MAX} = 18$ aircraft can be met without displacing any flight by more than 15 minutes ($\delta^* = 1$). Further delay reductions can

be achieved by displacing some flights by 30 minutes, while keeping the total displacement Δ^* relatively low. For instance, imposing expected queue length targets equal to $A_{\text{MAX}} = D_{\text{MAX}} = 15$ aircraft reduces peak expected departure delays by 54% with a total displacement equal to 289 15-minute periods.

In contrast, the most stringent delay reduction targets induce significantly larger schedule displacements. For instance, reducing the peak expected departure queue from 20 aircraft to 10 aircraft requires an increase in the optimal total displacement from 98 to 836 15-minute periods. In addition, the most aggressive delay reduction objectives cannot be achieved without substantially interfering with airlines' schedules. For instance, the expected arrival and departure queue lengths cannot be kept below 8 aircraft at any time of the day without displacing some flights by more than 30 minutes. Moreover, further reducing the queue length targets might require even more substantial changes in the planned network of flights, including the elimination of some flights. In other words, the most stringent delay reduction targets cannot be met through Level 2 coordination and would require more aggressive demand management strategies. Nonetheless, the results from this section suggest that limited changes in airlines' schedules through Level 2 coordination can result in very substantial mitigation of airport congestion.

5 Conclusion

We have developed an integrated approach to airport congestion mitigation that jointly optimizes the rescheduling of flights through schedule coordination at the strategic level and the efficiency of airport operations at the tactical level. We have introduced and implemented a *Schedule Coordination Model* that optimizes and simulates Level 2 coordination. The model provides a feasible schedule of flights that meets delay reduction objectives while minimizing the changes in airlines' schedules. To the best of our knowledge, this is the first study that attempts to integrate stochastic airport queue dynamics and a tactical model of airport capacity utilization into a strategic flight scheduling model. To this end, we have developed an original solution algorithm that iteratively optimizes the rescheduling of flights under deterministic queue dynamics and evaluates flight delays under stochastic queue dynamics.

The application of the model to JFK suggests that very large delay reductions can be achieved with limited interference with the flight schedules of airlines. In particular, we have shown that peak arrival and departure delays can be reduced by as much as 33% and 55%, respectively, without eliminating any flight, without modifying the scheduled time of over 80% of the flights arriving at or departing from JFK and without shifting the scheduled time of any flight by more than 30 minutes. In addition, the proposed schedule maintains all aircraft connections and all passenger connections.

In summary, this paper has shown that even a moderate level of schedule coordination can provide large system-wide benefits by reducing substantially the congestion costs borne by airlines, passengers and society. An important next step in this line of research consists in investigating

the longer-term, dynamic impacts of schedule coordination on airlines' strategic planning. Future work can therefore investigate the problem of congestion mitigation from the perspective of the airlines in a competitive environment. The integrated approach developed in this paper provides a methodology for addressing these issues.

Acknowledgments

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