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Endogenous Control of Service Rates in Stochastic and Dynamic Queuing Models of Airport Congestion

Alexandre Jacquillat
(corresponding author)
Ph.D. Candidate
Engineering Systems Division
Massachusetts Institute of Technology
Cambridge, MA USA
Email: alexjacq@mit.edu

Amedeo R. Odoni
Professor
Aeronautics & Astronautics and Civil and
Environmental Engineering
Massachusetts Institute of Technology
Cambridge, MA USA
Email: arodoni@mit.edu

Endogenous Control of Service Rates in Stochastic and Dynamic Queuing Models of Airport Congestion

Alexandre Jacquillat^{a,*}, Amedeo R. Odoni^b

^a*Massachusetts Institute of Technology, 77 Massachusetts Avenue, Building E40-246, Cambridge, MA 02139, USA*

^b*Massachusetts Institute of Technology, 77 Massachusetts Avenue, Building 33-218, Cambridge, MA 02139, USA*

Abstract

Airport congestion mitigation requires reliable delay estimates. This paper presents an integrated model of airport congestion that combines a tactical model of capacity utilization into a strategic queuing model. The model quantifies the relationships between flight schedules, airport capacity and flight delays, while accounting for the way arrival and departure service rates can be controlled over the day to maximize operating efficiency. We show that the model estimates well the average and variability of the delays observed at New York's airports. Results suggest that delays can be extremely sensitive to even small changes in flight schedules or airport capacity.

Keywords: airport, capacity, delay, queuing model, optimal control

1. Introduction

The design and assessment of airport congestion mitigation measures require efficient and reliable models of airport congestion to quantify flight delays under different demand and capacity scenarios. An important challenge in this class of models involves the representation and estimation of airport capacity. Airport capacity is defined as the expected number of movements that can be operated at the airport per unit of time under continuous demand (de Neufville and Odoni, 2013). Given the variability of airport operations, it is not a fixed quantity but depends on several operational factors, including weather conditions, the proportion of landings and takeoffs operated and the runway configuration in use (Gilbo, 1993; de Neufville and Odoni, 2013; Simaiakis, 2012). Some of these factors are not determined exogenously in advance. Instead, air traffic managers exercise a control over the runway configuration in use and the balance of arrivals and departures to make the best use of available capacity over the course of the day. However, existing models of congestion consider exogenous, often single-value capacity estimates and thus do not capture these controls exercised in practice.

*Corresponding author

Email addresses: alexjacq@mit.edu (Alexandre Jacquillat), arodoni@mit.edu (Amedeo R. Odoni)

This paper presents an original approach to airport congestion modeling that integrates recent, fine-grain characterizations of airport capacity and capacity utilization procedures into a strategic queuing model of airport congestion. We describe the formation and propagation of delays over the course of the day by means of a stochastic and dynamic queuing model. We formulate an efficient control of arrival and departure service rates as a function of flight schedules, operating conditions and observed queue lengths. This control simulates how service rates are selected over the day by air traffic managers to maximize airport efficiency in the short run, under capacity constraints. The model is then applied to the three primary airports in the New York Metroplex: JFK, Newark (EWR) and LaGuardia (LGA). We show that it approximates well the dynamics and magnitude of airport queues over the course of the day. In turn, the model provides a fast and flexible tool to forecast the evolution of delays at different airports under different demand and capacity scenarios.

1.1. Literature Review

Models of airport congestion fall into three categories: microscopic, mesoscopic and macroscopic models. Microscopic models consider each aircraft individually and reproduce precisely the physical layout of the airport and the sequencing of movements (Bilimoria et al., 2000; Sood and Wieland, 2003; George et al., 2011). These models are not well-suited to performing strategic planning under a wide range of scenarios. Mesoscopic models predict runway delays and taxi-in and taxi-out times using operational data, such as the runway configuration in use, short-term arrival demand, push-back schedules, etc. (Shumsky, 1995; Pujet et al., 1999; Simaiakis and Balakrishnan, 2014). These models have been applied to the design of procedures for optimizing surface operations (Simaiakis et al., 2014; Khadilkar and Balakrishnan, 2014). However, their heavy reliance on detailed operational data limits their applicability to modeling delays for strategic planning purposes when such data are not available. Finally, macroscopic models aggregate operations at the airport level to provide computationally efficient estimates of the relationships between flight schedules, airport capacity and flight delays in support of strategic planning (*e.g.*, to assess the benefits of capacity expansion or the impact of scheduling policies). Our research falls within this third category.

Existing macroscopic models of congestion are based on econometric models (Kwan and Hansen, 2010; Morrison and Winston, 2008; Xu, 2007), deterministic queuing models (Hansen, 2002), stochastic queuing models (Kivestu, 1974; Gupta, 2010; Pyrgiotis et al., 2013), or a combination thereof. In this paper, we consider a stochastic queuing model, which aims to capture the dynamics of formation and propagation of delays over the course of the day as well as the uncertainty and variability associated with airport operations. Previous research has shown that this model approximates well queue dynamics at major US airports (Pyrgiotis and Simaiakis, 2010; Lovell et al., 2007).

The delay estimates obtained with any queuing model depend critically on the estimates of the rates at which arrivals and departures are serviced, which are constrained by the capacity of the airport. In existing models, service rates are generally kept constant over the day (Pyrgiotis,

2011; Jacquillat, 2012) or varied using *ex post* operational data, such as meteorological conditions, reported capacity estimates, etc. (Hansen et al., 2009). Clustering techniques were developed recently to generate capacity profiles using probabilistic weather forecasts (Liu et al., 2008; Buxi and Hansen, 2011) and used *ex ante* in queuing models (Nikoleris and Hansen, 2012). These variations in service rates are exogenous and depend neither on flight schedules nor on observed congestion.

However, other important variations in arrival and departure service rates are *endogenous*, *i.e.*, they depend on the schedules of flights and on observed queue lengths. For instance, if a large number of landings are scheduled, then air traffic managers might decide to enhance the arrival throughput, at the expense of the departure throughput. As well, the arrival throughput might be enhanced if the observed arrival queue is longer than expected—or if the departure queue is shorter than expected. These controls are not taken into account in existing macroscopic models of airport congestion, although they might affect significantly the dynamics and the magnitude of delays. One recent application of a queuing model included variations in arrival and departure service rates that occur in response to changes in daily flight schedules caused by aircraft delays. However, these variations are introduced into the model manually and not systematically (Pyrgiotis and Odoni, 2014).

1.2. Contributions and Outline

The contributions of this paper fall into four categories:

- We develop an original approach to airport congestion modeling that integrates a tactical model of capacity utilization into a strategic model of airport congestion. We combine a control of arrival and departure service rates into a stochastic and dynamic queuing model. This approach can be applied to quantify airport congestion under different capacity expansion or flight scheduling scenarios, while accounting for the way airport operating procedures can react to such changes to maximize operating efficiency at the airport in the short run.
- We formulate an efficient control of arrival and departure service rates under stochastic queue dynamics and stochastic operating conditions. This control is based on a tactical decision-making support tool developed in previous research that optimizes the selection of runway configurations and the balance of arrival and departure service rates to minimize congestion costs (Jacquillat et al., 2013). In this paper, we formulate an approximate version of this control to incorporate it efficiently into our queuing model of airport congestion.
- We perform extensive comparisons with operational data at JFK, EWR and LGA to validate our model as a means of quantifying airport on-time performance. To the best of our knowledge, this represents the first attempt to compare the results of a macroscopic model of airport congestion to historical records of operations over a large sample of days. We develop estimates of on-time performance from historical records of operations. We show that

our model approximates well expected departure queue lengths and expected delays at the three airports. We also show that it provides good approximations of the range, hence of the variability, of departure queue lengths.

- We apply the model to study recent trends in scheduling and on-time performance at the New York airports. The analysis suggests that the large delay reductions observed between 2007 and 2011 can be largely attributed to the comparatively small reduction in demand over the period and, perhaps, to improvements in air traffic handling procedures.

The remainder of the paper is organized as follows. Section 2 presents the queuing model of airport congestion and the control of arrival and departure service rates. Section 3 compares the results of the model to historical records of operations at JFK, EWR and LGA. Section 4 discusses the opportunities and challenges associated with the application of the model in support of strategic planning and presents an example of such application. Section 5 concludes.

2. Model Presentation

The purpose of our model of airport congestion is to quantify the magnitude of delays and their evolution over the course of a day as a function of flight schedules and airport capacity. The model is *strategic*: it uses information that is available *before* a day of operations. It may then be used to test the impact of changes in flight schedules or in airport capacity on flight delays in support of airport congestion mitigation and airline scheduling.

2.1. Model Inputs

The model takes as inputs (a) the schedule of landings and takeoffs on a given day and (b) estimates of airport capacity.

Airport demand is aggregated per 15-minute period. Specifically, we divide a day of operations between 6 a.m. and 12 a.m. into $T = 72$ periods of length $S = 15$ minutes each and we consider the number of scheduled landings and takeoffs per period.

Airport capacity depends on three factors, primarily: the weather conditions at the airport, the proportion of landings and takeoffs operated and the runway configuration in use. In order to capture these dependencies, we represent the capacity of each runway configuration by means of an *Operational Throughput Envelope*, which characterizes the non-increasing relationship between the *average* number of arrivals and the *average* number of departures that can be operated per 15-minute period in the presence of continuous demand, in the runway configuration considered (Simaiakis, 2012). This representation takes into account the variability of the traffic mix, including different aircraft types, different sequencing of arrivals and departures, etc. We specify one Operational Throughput Envelope for each runway configuration in “Visual Meteorological Conditions” (VMC) and another one in “Instrument Meteorological Conditions” (IMC)—we use VMC and IMC as surrogates of “good” and “poor” weather conditions, respectively.

2.2. $M(t)/E_k(t)/1$ Queuing Models

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 (de Neufville and Odoni, 2013). Aircraft join the queue when they demand the usage of the runway system to land or to take off. Departing aircraft are queuing on the ground, primarily on the taxiways. Arriving aircraft are queuing in the terminal airspace, in the en-route airspace, or at the origin airport if a Ground Delay Program is implemented. The model returns the probability distribution of the number of arriving and departing aircraft queuing at the end of each period $t = 1, \dots, T$, which we denote by a_t and d_t , respectively.

We represent the arrival queue and the departure queue as two distinct $M(t)/E_k(t)/1$ queuing systems. The demand process and the service process are respectively modeled as a Poisson processes and as an Erlang process of order k . The smaller the value of k , the more variable the service processes. These two queues are not independent since the arrival and departure service rates are subject to the same weather-related constraints and are negatively correlated: increasing the arrival throughput reduces the departure throughput, and conversely. This relationship is captured in the model. However, the stochastic evolution of the arrival queue is assumed to be independent of that of the departure queue. For instance, on a given day and for given values of the arrival and departure service rates, the arrival queue might be longer than expected while the departure queue might be shorter than expected.

This model is stochastic and dynamic: both demand and service are time-varying random processes. In combination they are intended to capture the uncertainty and the variability associated with the actual queuing processes. For instance, the number of aircraft that demand the usage of the runway system during a particular period depends on several uncertain factors, including airline operations, operations in passenger buildings, on-time performance at other airports, etc. As well, the number of landings and takeoffs that can be operated over a period depends on the aircraft mix, the sequencing of landings and takeoffs, human factors in airport operations, etc.

The dynamics of each $M(t)/E_k(t)/1$ queuing model can be described by a system of first-order differential equations. We solve it off-line and store the queue transition probabilities in a look-up table. This allows us not to re-solve it every time we apply the model.

We introduce a practical queue capacity denoted by N . In other words, each of the arrival and departure queues can hold up to N aircraft in the model. The value of N should be chosen sufficiently large to approximate a queue with infinite queue capacity, *i.e.*, to avoid underestimating delays. At the same time, large values of N also mean larger computational times to run the model.

We assume that the demand rates and the service rates are constant over each 15-minute period of the day. The arrival and departure demand rates are equal to the expected number of arriving and departing aircraft that will join the queuing system per period, *i.e.*, to the number of scheduled landings and takeoffs per period. The arrival and departure service rates, *i.e.*, the

expected number of landings and takeoffs that can be operated per period, are constrained by the capacity of the airport. These service rates are not determined in advance, but are dynamically adjusted by air traffic managers over the day to maximize the efficiency of airport operations. This control is typically based on flight schedules, on meteorological conditions and also on arrival and departure queue lengths, which are precisely modeled in this paper. In order to capture the endogenous relationship between arrival and departure queue lengths, on the one hand, and arrival and departure service rates, on the other, we integrate a dynamic control of arrival and departure service rates into our queuing model. We present this control in the next section.

2.3. Control of Arrival and Departure Service Rates

The control of arrival and departure service rates optimizes the utilization of airport capacity to minimize congestion costs, for any schedule of flights. The application of this control, in turn, integrates tactical decisions made by air traffic managers into our strategic queuing model of airport congestion. A schematic representation of this endogenous control is provided in Figure 1.

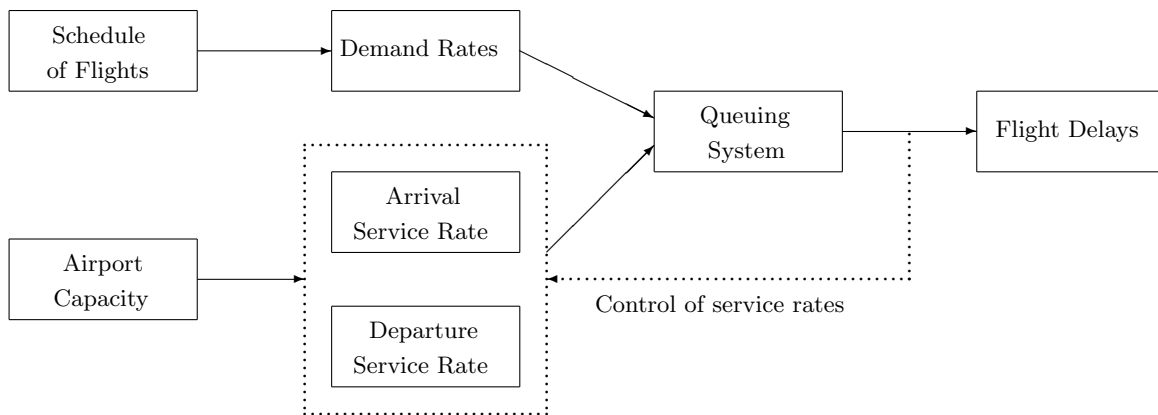


Figure 1: Control of arrival and departure service rates in queuing models of airport congestion

In previous research, we developed a control of runway configurations and of arrival and departure service rates under stochastic operating conditions (Jacquillat et al., 2013) that optimizes the dynamic allocation of available capacity to arriving and departing flights at the tactical level. It is formulated as a finite-horizon Dynamic Programming model. At the beginning of each 15-minute period t , the runway configuration and the arrival and departure service rates are jointly selected. The runway configuration, along with observed weather conditions, determines the Operational Throughput Envelope for the next period, *i.e.*, the set of achievable arrival and departure service rates. The service rates are then selected among this set. The control is exercised as a function of a five-dimensional state variable that includes the arrival and departure queue lengths, the runway configuration in use, weather conditions (which impact the efficiency of airport operations) and winds (which might restrict the set of runways that can be used). The objective of the control

is to minimize congestion costs. This control mechanism has been shown to provide significant operational benefits (Jacquillat et al., 2013).

However, the computational requirements of the full control outlined above prevent it from being used repeatedly with different flight schedules or different capacity estimates and thus limit its applicability in support of strategic planning. Therefore, we have also developed an approximate version of the control to ensure computational efficiency of the model. The purpose of this simplification is to approximate the arrival and departure queue lengths that minimize congestion costs at the tactical level, without accounting for all the operational details that need to be considered in the full control.

The simplified control is obtained by grouping runway configurations into clusters of “similar” configurations. The objective of this clustering approach is to approximate how the trade-off between arrival and departure throughput varies with runway configurations, but at a more aggregate level than in the full control. Specifically, we cluster runway configurations based on the number of runways they use to operate landings and takeoffs and on their physical layout. We estimate the average capacity of the airport for each cluster of runway configurations, *i.e.*, we consider a *single* Operational Throughput Envelope for each cluster. Table 1 shows the clusters considered at the three New York airports. For instance, at JFK, “Type 2” configurations, which allocate two runways to arrivals and one runway to departures, achieve the highest arrival throughput while “Type 3” configurations, which allocate one runway to arrivals and two runways to departures, achieve the highest departure throughput when few arrivals are operated.

Table 1: Runway configuration clusters at JFK, EWR and LGA

	“Type 1” Conf.	“Type 2” Conf.	“Type 3” Conf.
Characterization	1 arrival runway 1 departure runway	2 arrival runways 1 departure runway	1 arrival runway 2 departure runways
JFK	31R 31L 13L 13R	13L, 22L 13R 31L, 31R 31L	22L 22R, 31L 4R 4L, 31L
EWR	22L 22R 4R 4L 29 22R	11, 22L 22R 4R, 11 4L 4R, 29 4L	22L 22R, 29
LGA	31 4 22 31 22 13 4 13	—	—

We assume that the schedule of use of runway configurations clusters is exogenously determined in advance—obtained from the full control with a representative schedule of flights and from the actual patterns of runway configuration usage at the airports. Specifically, we assume that JFK operates in a “Type 3” configuration in the morning and in the late afternoon, and in a “Type 2”

configuration between 11:45 and 17:00, in order to best serve the arrival peak in this time window. As well, we assume that EWR operates in a “Type 1” configuration in the morning and in a “Type 2” configuration from 10:30 onward and that LGA operates in a “Type 1” configuration for the entire day. Subsequently, the simplified control is restricted to the selection of arrival and departure service rates at the beginning of each 15-minute period, under capacity constraints defined by the Operational Throughput Envelope of the runway configuration in use. This simplification captures the trade-off between arrival and departure service rates and approximates the selection of runway configurations.

The resulting control is formulated as follows. At each period $t = 1, \dots, T$, the decision-maker observes (i) the arrival queue length at the end of period $t - 1$, denoted by $a_{t-1} \in \{0, \dots, N\}$, (ii) the departure queue length at the end of period $t - 1$, denoted by $d_{t-1} \in \{0, \dots, N\}$ and (iii) the weather state, denoted by $w_t \in \{VMC, IMC\}$. The runway configuration cluster for period t , denoted by RC_t , is given. The decision-maker selects the arrival service rate for period t , denoted by μ_t^a . The upper bound for this choice depends on the runway configuration cluster and weather conditions and is denoted by A_{RC_t, w_t} . This choice is discretized, so the arrival rate is chosen in the set $\{0, 1, \dots, A_{RC_t, w_t}\}$. Once the arrival rate is selected, the departure service rate μ_t^d is determined by the Operational Throughput Envelope. Congestion costs are assumed to depend quadratically on arrival and departure queue lengths. The objective function is therefore expressed as $\sum_{t=1}^T a_t^2 + \sum_{t=1}^T d_t^2$. 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 :

$$J_t(a_{t-1}, d_{t-1}, w_t) = \min_{\mu_t^a \in [0, A_{RC_t, w_t}]} \left(E[a_t^2] + E[d_t^2] + E[J_{t+1}(a_t, d_t, w_{t+1})] \right), \forall t = 1, \dots, T_0 \quad (1)$$

The simplification of the control reduces considerably the dimensionality of the model and therefore accelerates its solution. In the original control, the state space had 5 dimensions: the arrival and departure queue lengths (which can each take $N + 1$ values), the runway configuration in use (we denote the number of runway configurations by $|\mathcal{RC}|$), the weather state (VMC or IMC) and the wind state (we denote the number of wind states $|\mathcal{WS}|$). In the simplified control, the size of the state space is reduced by a factor of $|\mathcal{RC}| \times |\mathcal{WS}|$, (*i.e.*, by a factor of 100, approximately). The decision state had 2 dimensions in the original model: the selected runway configuration (which could take $|\mathcal{RC}|$ values) and the arrival service rate. In the simplified model, the decision is restricted to the selection of the arrival service rate, which can take $A_{RC_t, w_t} + 1$ values at each period t —we denote by \bar{A} an upper bound of the values A_{RC_t, w_t} . In turn, the simplification reduces the size of the decision space by a factor $|\mathcal{RC}|$ (*i.e.*, by a factor of 10, approximately). These simplifications, in turn, reduce the computational requirements of the control by several orders of magnitude. Table 2 summarizes the size of both models.

Table 2: Size of the original and simplified controls

Model	Original Model	Simplified Model
Number of states	$(N + 1)^2 \times \mathcal{RC} \times 2 \times \mathcal{WS} $	$2 \times (N + 1)^2$
Number of decisions (upper bound)	$(\bar{A} + 1) \times \mathcal{RC} $	$\bar{A} + 1$
Number of periods	T	T

2.4. Model of Weather Conditions

We model weather variations at the airports as follows. We consider 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, denoted by π , is unbiasedly estimated by the empirical proportion of days that have only VMC periods. The weather “profile” on VMC/IMC days is modeled by means of a Markov chain, with transition matrix:

$$\begin{array}{cc} & \begin{array}{cc} VMC & IMC \end{array} \\ \begin{array}{c} VMC \\ IMC \end{array} & \left(\begin{array}{cc} 1 - p & p \\ q & 1 - q \end{array} \right) \end{array}$$

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 initial state of the system is sampled from the stationary distribution of the Markov chain, *i.e.*, a VMC/IMC day starts in “state” VMC (resp. IMC) with probability $\frac{p}{p+q}$ (resp. $\frac{q}{p+q}$).

Note that the purpose of this simple weather model is *not* to describe exactly weather conditions at an airport on any given day but rather to approximate weather profiles in our queuing model. We showed in previous research that this model captures relatively well the aggregate weather dynamics at the New York airports. Specifically, the model predicts that the number of consecutive periods in VMC (resp. IMC) for VMC/IMC days follows a geometric distribution with parameter p (resp. q). We obtained a very good fit between these model-derived distributions and the empirical distributions, as confirmed by a chi-squared test (Jacquillat, 2012).

3. Model Implementation

We implement our queuing model of airport congestion with the endogenous control of service rates developed in this paper at the three primary New York airports. We first describe our experimental setup for the model implementation and develop on-time performance metrics from available operational data. We then compare the queue lengths and delays predicted by the model to those observed in practice. Specifically, we show that our model provides good estimates of the

expected value and the variability of the departure queue lengths (Section 3.3) and of the expected value of arrival and departure delays (Section 3.4) at JFK, EWR and LGA.

Before proceeding further, we underline the objectives of such comparisons. As previously mentioned, our model is strategic in scope. It is based on information that is available before the day of operations and does not consider real-time operational information, such as the runway configuration actually in use, wind conditions, the occurrence of delays at other airports, the pushback times of departing flights, etc. Therefore, the delay estimates that it provides are expected to be less accurate than estimates based on such real-time information at the tactical level (see (Feron et al., 1997; Simaiakis and Balakrishnan, 2014)). The objective of the model is to capture, at a macroscopic level, the dynamics of formation and propagation of delays over the course of the day and the magnitude of flight delays at peak morning and afternoon hours.

3.1. Experimental Setup

We apply the model to the 4-month period from June to September 2007 (henceforth “Summer 2007”). Data on flight schedules, airport operations and flight delays are obtained from the Aviation Performance Metrics (APM) database (Federal Aviation Administration, 2013). Details on the use of this database for our purposes are provided in (Jacquillat, 2012).

The VMC and IMC Operational Throughput Envelopes for each runway configuration cluster are obtained from (Simaiakis, 2012). These envelopes are computed with operational data from the year 2007 and shown in Figure 2. The figure also shows dots that correspond to observed counts of scheduled departures and arrivals per 15-minute period, their size being proportional to the frequency of the observations. Note, first, that scheduling levels often exceed airport capacity, even in VMC. This is likely to create significant delays. Obviously, the imbalances between demand and capacity are even larger in IMC. In addition, the proportion of arrivals and departures is variable. Therefore, the optimal combination of arrivals and departures to be processed may vary from one period to another. This underscores the need for integrating our control of arrival and departure service rates into the model of airport congestion.

We estimate the parameter k of the Erlang random variables that describe the service times by the ratio of the squared sample mean of the service time over the sample variance of the service time. This ensures that the theoretical and empirical distributions of the service times have the same mean and the same variance. This leads to the use of $k = 3$ for the cases described here.

We use a value of the practical queue capacity for (each of) the arrival queue and the departure queue of $N = 50$ aircraft. With this value, delay estimates for the whole day are obtained in about one minute on a laptop computer. At the same time, the probability of the modeled queues to be full is very small, which minimizes the downward bias introduced by the practical queue capacity.

We apply the model to each one of the days of Summer 2007 and quantify the resulting probability distributions of queue lengths. This is motivated by potential nonlinear variations of delays with flight schedules, as suggested by steady-state queuing theory (de Neufville and Odoni, 2013),

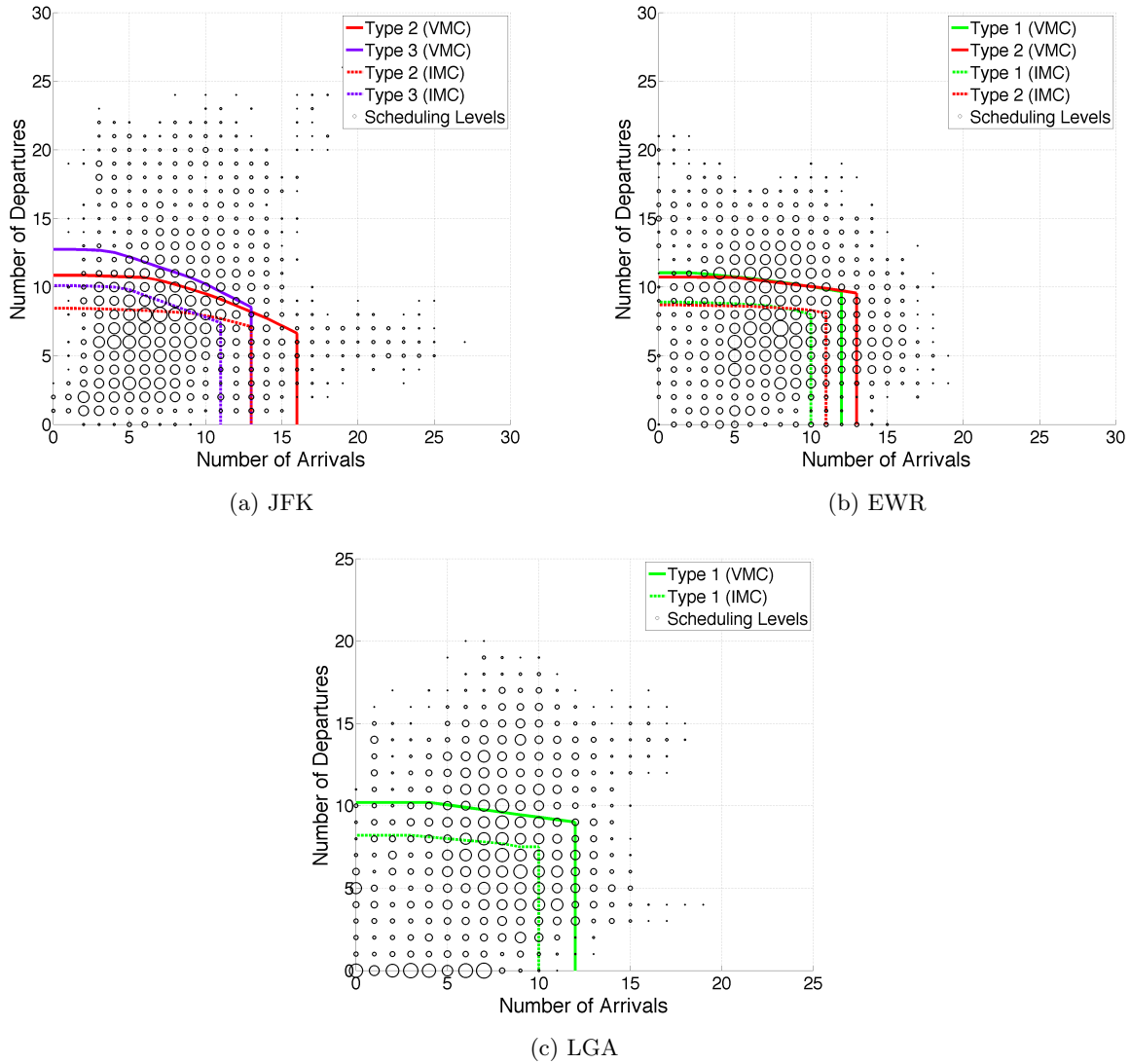


Figure 2: Capacity and scheduling levels in Summer 2007 (Simaiakis, 2012)

so the use of the average demand profile might not provide an accurate indication of the distribution of delays during the period of interest. We then compare the model’s outputs to on-time performance observed in practice during the considered period.

3.2. Measures of Airport On-Time Performance

In order to compare our model’s predictions to actual operations, we develop estimates of airport on-time performance from available records of operations. Note, at the outset, that establishing apples-to-apples comparisons is not straightforward. We are interested here in identifying and estimating delays that can be attributed to local runway congestion. But the available data are contaminated by delays due to an array of other factors, including the propagation of upstream

delays, constraints at other airports, delays in passenger buildings, mechanical failures and safety incidents. The on-time performance metrics presented below aim to eliminate such external delays. It should be noted, however, that the values of these metrics are subject to uncertainty and must be treated only as approximate.

Figure 3 shows the different phases of a flight and defines the main quantities of interest. We denote the set of all flights on a given day by \mathcal{F} . For any flight $i \in \mathcal{F}$, we denote its gate-out time by OUT_i , its wheels-off time by OFF_i , its wheels-on time by ON_i and its gate-in time by IN_i . We also consider its taxi-out time $TO_i = OFF_i - OUT_i$, its airborne time $AIR_i = ON_i - OFF_i$ and its taxi-in time $TI_i = IN_i - ON_i$. For each of these seven quantities, we consider both the planned time, which we denote by a superscript P , and the actual time, which we denote by a superscript A . (We will address further below some complications related to planned times.) For instance, OUT_i^P (resp. OUT_i^A) denotes the planned (resp. actual) gate-out time of flight i . Finally, we define, for any flight i , its gate-out delay δ_i^{OUT} , its wheels-off delay δ_i^{OFF} , its wheels-on delay δ_i^{ON} and its gate-in delay δ_i^{IN} as follows:

$$\begin{aligned}\delta_i^{OUT} &= \max(OUT_i^A - OUT_i^P, 0) = (OUT_i^A - OUT_i^P)^+ \\ \delta_i^{OFF} &= \max(OFF_i^A - OFF_i^P, 0) = (OFF_i^A - OFF_i^P)^+ \\ \delta_i^{ON} &= \max(ON_i^A - ON_i^P, 0) = (ON_i^A - ON_i^P)^+ \\ \delta_i^{IN} &= \max(IN_i^A - IN_i^P, 0) = (IN_i^A - IN_i^P)^+\end{aligned}$$

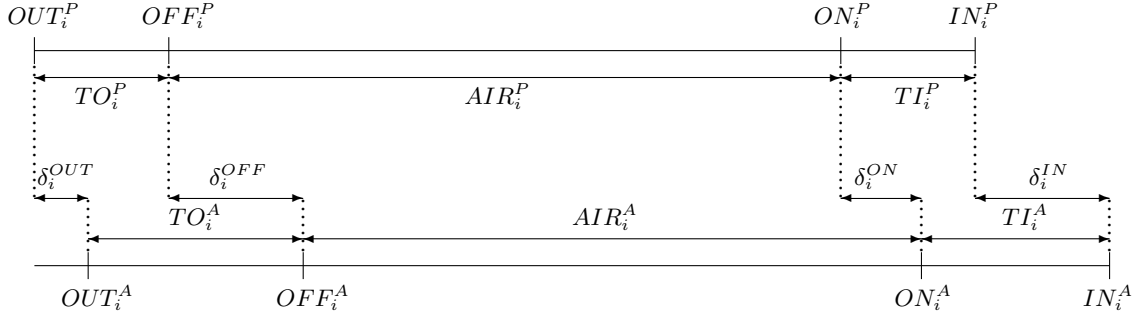


Figure 3: Breakdown of scheduled and actual flight times

We now derive estimates of the departure queue length at the end of each period $t = 1, \dots, T$, *i.e.*, at time tS , where S denotes the length of each period (in this case, 15 minutes). To do so, we assume that no departure metering procedure is in place—a reasonable assumption in 2007. In other words, we assume that aircraft leave the gate as soon as they are ready to depart. In the absence of runway congestion, departing aircraft would take off at time $OUT_i^A + TO_i^P$, *i.e.*, a duration equal to their unimpeded taxi-out time TO_i^P after they leave the gate. The departure queue consists of all aircraft that would have taken off at time tS in the absence of congestion, but that have not taken off yet at that time. Specifically, our estimate of the actual departure queue

length at the end of period t , denoted by \widehat{d}_t , is obtained as follows:

$$\widehat{d}_t = \left| \{i \in \mathcal{F} \mid OUT_i^A + TO_i^P \leq tS \ \& \ OFF_i^A > tS\} \right|$$

Unfortunately, estimating the arrival queue length from available records of operations is almost impossible. Indeed, there is no record of when arriving aircraft demand the usage of the runway. Physically, aircraft can be “queuing” in the terminal airspace, in the en-route airspace or at the origin airport, which complicates the estimation of the number of queuing aircraft at any time.

Next, we develop estimates of average arrival and departure delays per period $t = 1, \dots, T$. We first define the set \mathcal{A}_t (resp. \mathcal{D}_t) as the set of flights that are scheduled to land (resp. to take off) during period t :

$$\begin{aligned} \mathcal{A}_t &= \{i \in \mathcal{F} \mid (t-1)S \leq ON_i^P < tS\} \\ \mathcal{D}_t &= \{i \in \mathcal{F} \mid (t-1)S \leq OFF_i^P < tS\} \end{aligned}$$

The estimation of arrival delays requires the elimination of upstream delays incurred by the aircraft. For instance, if an aircraft incurs a departure delay at its origin airport (resulting from delays in previous flight legs, congestion at the departure airport or any other reason), then this departure delay must be removed from the estimation of the arrival delay of the flight. However, this is complicated by the practice of schedule padding by the airlines. Indeed, airlines might plan airborne times that are *longer* than the unimpeded airborne time, in order to improve their on-time performance (Skaltsas, 2011). We therefore correct our estimates of arrival delays accordingly. For each route terminating at the considered airport, we estimate the unimpeded airborne time by the 10th percentile of all actual airborne times on the considered route, which we denote by AIR^{MIN} . We then remove any surplus in the scheduled airborne time, *i.e.*: $(AIR^P - AIR^{MIN})^+$. In turn, we obtain the average arrival delay during period t , denoted by $\widehat{\delta}_t^A$, as follows:

$$\begin{aligned} \widehat{\delta}_t^A &= \frac{1}{|\mathcal{A}_t|} \sum_{i \in \mathcal{A}_t} \left((IN_i^A - IN_i^P)^+ - \left[(OFF_i^A - OFF_i^P)^+ - (AIR_i^P - AIR_i^{MIN})^+ \right]^+ \right)^+ \\ \widehat{\delta}_t^A &= \frac{1}{|\mathcal{A}_t|} \sum_{i \in \mathcal{A}_t} \left(\delta_i^{IN} - \left[\delta_i^{OFF} - (AIR_i^P - AIR_i^{MIN})^+ \right]^+ \right)^+ \end{aligned}$$

Finally, we estimate the average departure delay during period t , denoted by $\widehat{\delta}_t^D$, as the average taxi-out delay of all aircraft scheduled to take-off during period t . In other words, we remove the gate delay from the recorded wheels-off delay, as most gate delays are not due to runway congestion

(*e.g.*, propagation from upstream disturbances, mechanical failures, delays in passenger buildings).

$$\widehat{\delta}_t^D = \frac{1}{|\mathcal{D}_t|} \sum_{i \in \mathcal{D}_t} \left((OFF_i^A - OFF_i^P)^+ - (OUT_i^A - OUT_i^P)^+ \right)^+$$

$$\widehat{\delta}_t^D = \frac{1}{|\mathcal{D}_t|} \sum_{i \in \mathcal{D}_t} (\delta_i^{OFF} - \delta_i^{OUT})^+$$

As previously mentioned, these estimates of departure queue lengths and arrival and departure delays are only approximate. Although the procedures outlined above do eliminate to a large extent delays that cannot be attributed to local runway congestion, they are still imperfect. On the arrival side, our estimation of arrival delays does not account for the possibility of en-route congestion. Even though most of the delays occur at the airports, this might create some measurement errors. More broadly, we do not consider Air Traffic Flow Management procedures in these macroscopic estimates. On the departure side, our restriction to taxi-out delays does not allow us to consider potential gate delays that are due to local runway congestion (*e.g.*, if gate pushbacks are slowed as a result of ground congestion). Conversely, some of the taxi-out delays that we attribute to local runway congestion may in truth be due to other causes (*e.g.*, safety incidents or pilot decisions).

3.3. Model of Departure Queue Lengths

In this section, we compare the departure queue lengths predicted by the model d_t to those observed in practice \widehat{d}_t at JFK, EWR and LGA in Summer 2007. Our estimates of actual departure queue lengths are obtained from APM data according to the procedures outlined in Section 3.2. Figure 4 shows the expected departure queue length for each of the 72 periods of the day as predicted by the model, as well as the average departure queue length observed at the airports. Note, first and foremost, that the model evaluates quite accurately both the dynamics of departure queues over the course of the day and their magnitude at peak hours. At JFK and EWR, departure queues tend to form in the morning—between 7 a.m. and 10 a.m., dissipate around noon and return again in the afternoon—from 4 pm onward. In contrast, LGA seems to be congested almost continuously from 8 a.m. to 9 p.m., which is due to its almost “flat” daily demand profile. These patterns are predicted well by our model. Moreover, the model predicts peak-hour queues of a similar magnitude to those observed in practice. Specifically, modeled queue lengths are within 2-3 aircraft from those observed at the airports at peak morning and afternoon hours, which corresponds to a relative difference within 20% (see Table 3). Given the strategic nature of the model and the uncertainty associated with our queue length estimates, this level of accuracy is entirely adequate.

The most significant errors of the model arise in the late afternoon and, to a lesser extent, in the late morning at JFK. We believe that this stems from the fact that a larger share of flights get delayed over the course of the day, resulting in later shifts in demand. As a result, many aircraft demand the usage of the runway system later than originally planned. In turn, the airports seem to recover from congestion less quickly than predicted by the model. Note that these effects are

observed at all three airports, even though the underestimation of late-afternoon departure queues seems to be the highest at EWR.

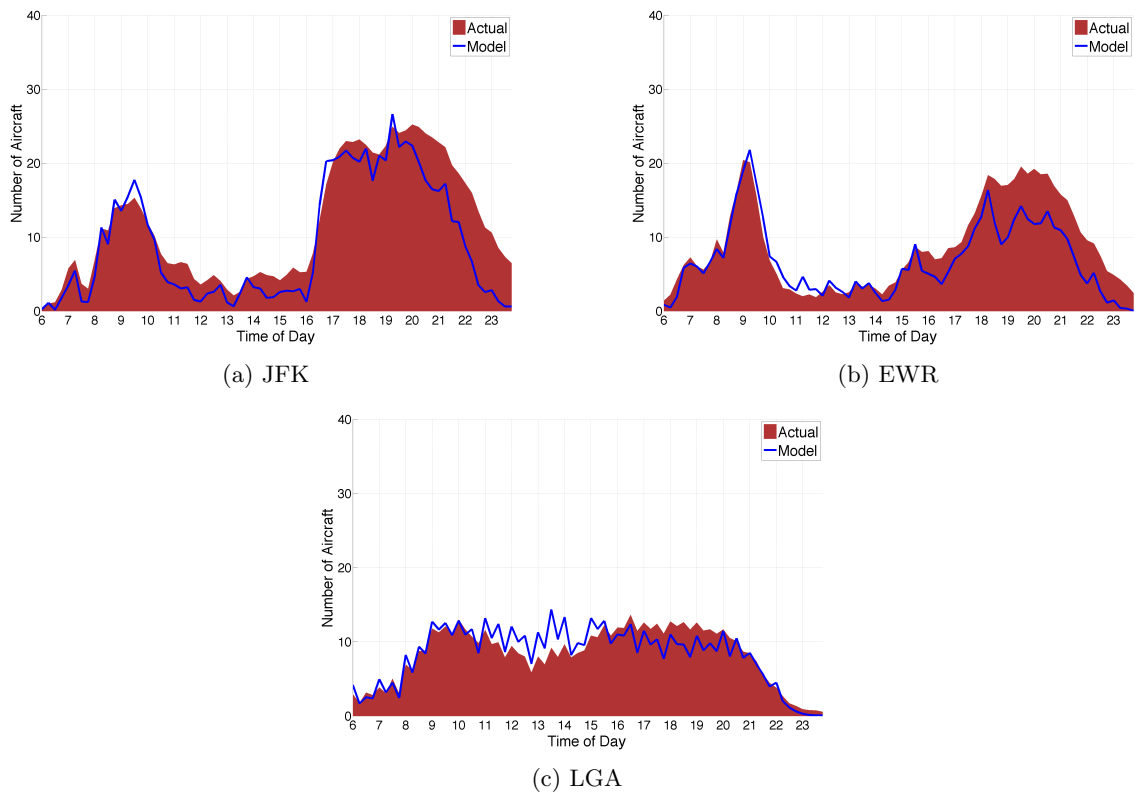


Figure 4: Average departure queue lengths in Summer 2007

Table 3: Statistics on modeled and actual departure queue lengths

Airport	Peak morning queue			Peak afternoon queue		
	Model	Actual	Error	Model	Actual	Error
JFK	17.7	15.3	+15.7%	26.6	25.2	+5.6 %
EWR	21.8	20.4	+6.7%	16.4	19.5	-16.1%
LGA	13.2	13.0	+1.2%	14.3	13.6	+5.3%

In addition to providing estimates of the expected queue lengths, our model also provides estimates of the variability of the queue lengths over the course of the day. This topic has attracted only limited attention to date despite the fact that delay variability is a very important measure of performance and reliability. Indeed, the system-wide impacts of flight delays depend, to no small extent, on their variations from day to day. If delays are relatively similar from day to day, then it might be possible for the airlines and airport operators to anticipate them and limit their impacts. If, on the other hand, delays are extremely variable from day to day, then the knowledge of expected

delays is only of limited value for planning schedules and operations.

Figure 5 compares the range of departure queue lengths observed in practice to the model's predictions. We compute the 5th and 95th percentiles of the distribution of departure queue lengths d_t obtained from our model, which we represent in full, red lines. Each dashed line corresponds to the departure queue length \hat{d}_t observed on a given day between June and September 2007 at the airports. The comparison shows that at all three airports considered, the model estimates well the range of delays that is observed. First, observed departure queue lengths lie outside the predicted range only on a very limited number of days. Second, the bounds defined by the 5th and 95th percentiles of the distribution of d_t are relatively close to the smallest and largest departure queue lengths observed in practice. Finally, note that the variability of delays is the largest at times when the average delays are also the largest. This suggests that runway congestion not only creates large delays on average, but also increases their variability.

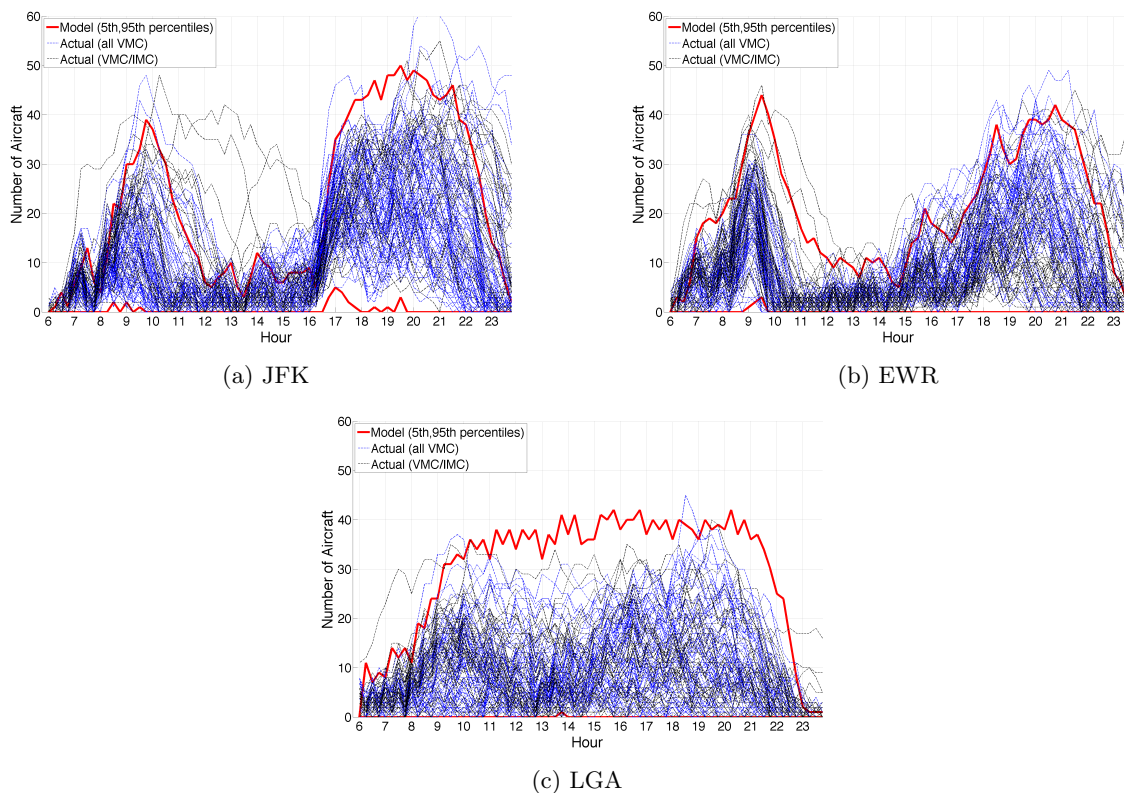


Figure 5: Variability of departure queue lengths in Summer 2007

3.4. Model of Arrival and Departure Delays

In this section, we compare the expected arrival and departure delays predicted by our model to the average delays $\hat{\delta}_t^A$ and $\hat{\delta}_t^D$ experienced at the airports. The purpose of this comparison is twofold. First, we aim to confirm our findings from the previous section to increase our confidence

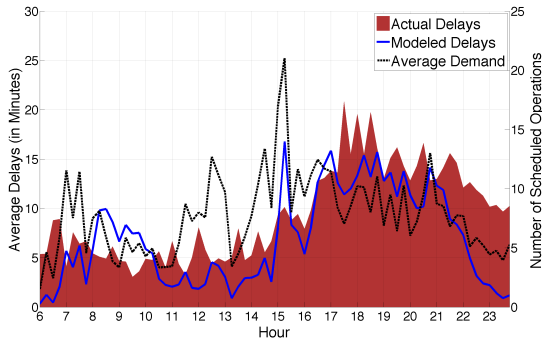
in our model’s ability to estimate departure delays at the airports. Second, we investigate our model’s ability to estimate arrival delays. Whereas no estimate of arrival queue lengths could be obtained from available data, we developed estimates of arrival delays in Section 3.2 that enable such comparison. Note, however, that these comparisons are subject to more uncertainty than those from the previous section, as delay estimates are more noisy than queue length estimates.

Figure 6 compares the expected value of the delays predicted by the model to the average delays observed in practice at JFK (Figures 6a and 6b), EWR (Figures 6c and 6d) and LGA (Figures 6e and 6f) between June and September 2007. Expected modeled delays are obtained by dividing expected queue lengths by the average service rates. We also plot the average number of flights scheduled. These results suggest that the model approximates very well the timing, dynamics and magnitude of the delays at the three airports and confirm the insights obtained in the previous section. First, the model predicts well the evolution and fluctuations of delays over the course of the day. Second, the most significant errors, percent-wise, occur at the least congested periods, such as late evening hours, when traffic is low. Third, the model approximates quite accurately the magnitude of flight delays, especially at peak hours. Table 4 reports the expected arrival and departure delays predicted by the model (a) over an entire day of operations and (b) during the peak delay period between 5 p.m. and 9 p.m., and the corresponding average delays observed in practice. The error of our model lies within 20% at JFK, within 30% at EWR and within 15% at LGA. With the exception of peak departure delays at EWR, this corresponds to an error in average delays of only 2-3 minutes.

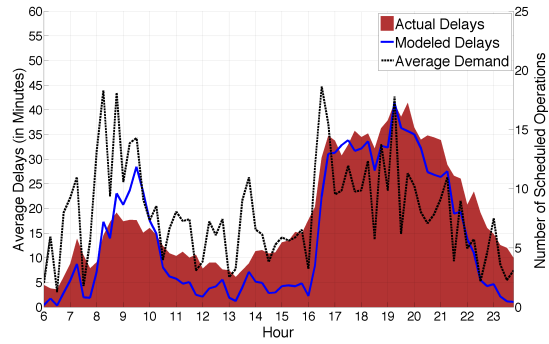
Table 4: Statistics on modeled and actual delays

Airport	Type	Average delays			Average peak delays		
		Model	Actual	Error	Model	Actual	Error
JFK	Arrivals	8.1 min	9.9 min	-18.2%	13.2 min	15.6 min	-15.2%
	Departures	18.3 min	21.6 min	-15.0%	33.3 min	36.0 min	-7.2%
EWR	Arrivals	5.7 min	7.1 min	-19.8%	7.4 min	9.9 min	-25.5%
	Departures	13.1 min	16.1 min	-18.8%	18.8 min	26.8 min	-29.7%
LGA	Arrivals	6.9 min	6.4 min	+7.3%	7.1 min	8.4 min	-15.7%
	Departures	17.1 min	16.2 min	+5.5%	19.0 min	20.9 min	-9.1%

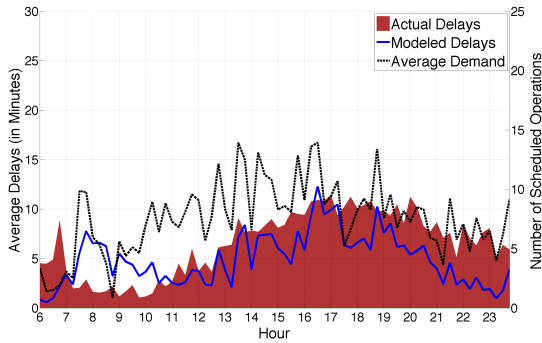
In particular, our model estimates accurately the relative magnitude of arrival and departure delays. Indeed, it predicts arrival delays of about half the magnitude of departure delays at JFK, EWR and LGA, that are observed in practice. (Please note the different scales of the y-axes in Figures 6a, 6c and 6e, on the one hand, and Figures 6b, 6d and 6f, on the other.) This is an important result that stems from the integration of our control of arrival and departure service rates into our queuing model of airport congestion. In order to illustrate this point, we compare our model to a baseline model where no control is exercised and the service rates are kept constant throughout the day of operations. Specifically, the baseline model considers equal values for the



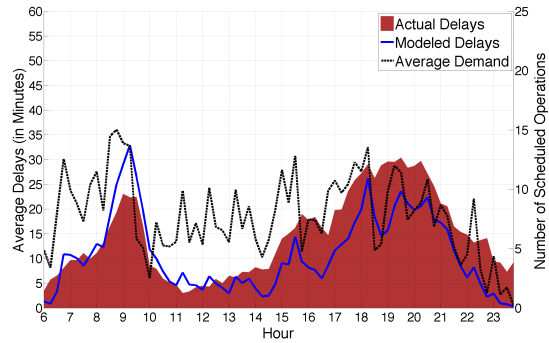
(a) JFK – Arrival Delay



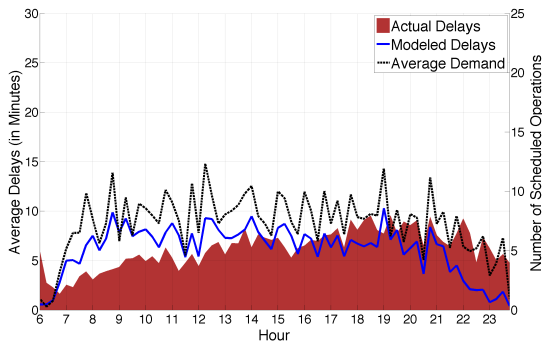
(b) JFK – Departure Delay



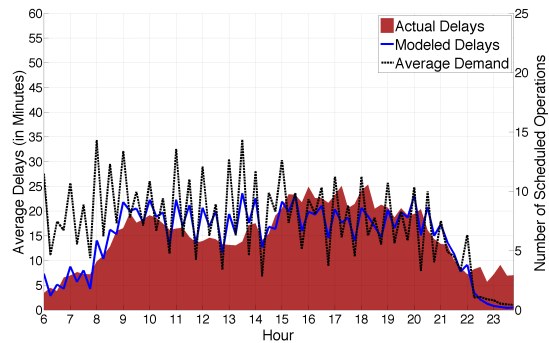
(c) EWR – Arrival Delay



(d) EWR – Departure Delay



(e) LGA – Arrival Delay



(f) LGA – Departure Delay

Figure 6: Predicted and actual delays at JFK, EWR and LGA in Summer 2007

arrival service rate and the departure service rate, equal to the capacity of the airport when it serves arrivals and departures in equal numbers. This is the modeling assumption that is most widely used in macroscopic models of airport congestion. Figure 7 shows the expected arrival (Figure 7a) and departure (Figure 7b) delays resulting from the application of the two models at JFK, as well as the average delays incurred in practice. Similar results are obtained at EWR and LGA.

Note that the control of service rates has a significant effect on the dynamics and magnitude of arrival and departure delays. Specifically, the baseline model greatly overestimates departure delays

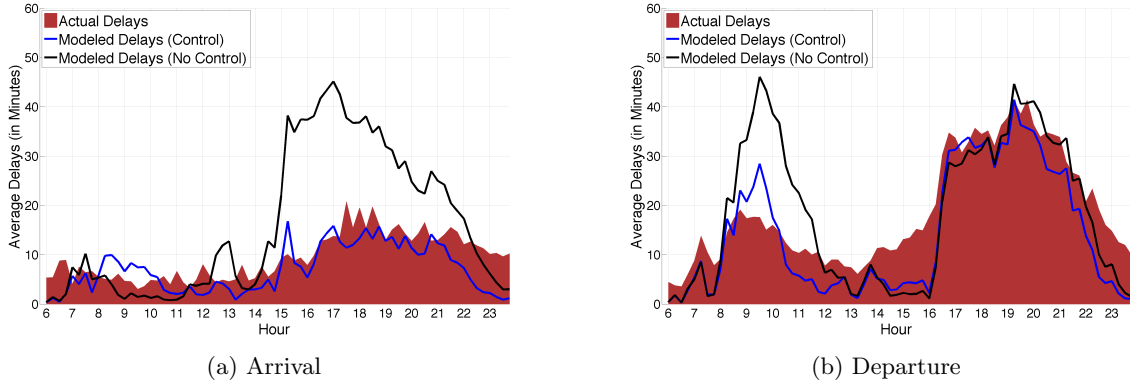


Figure 7: Modeled delays with and without the control of service rates at JFK in Summer 2007

in the morning and arrival delays in the afternoon. This is mostly because JFK faces a departure peak in the morning and an arrival peak in early afternoon. In turn, most of available capacity is used to operate departures in the morning and arrivals in early afternoon (around 3 pm). The baseline model, which considers fixed values of arrival and departure service rates, fails to capture how service rates are varied with the schedules of flights. In contrast, our control of arrival and departure service rates replicates the dynamic allocation of airport capacity to operate landings and takeoffs efficiently. In turn, the integration of this tactical control improves significantly the predictive power of our macroscopic queuing model of airport congestion at the strategic level.

4. Model Application

The model developed in Section 2 and validated in Section 3 as a tool for estimating arrival and departure delays at busy US airports can then be applied to investigate the impact of changes in flight schedules or in airport capacity on on-time performance. We first study recent trends in scheduling and on-time performance at the three New York airports by considering the changes in flight schedules between 2007 and 2011 into the model. We then discuss opportunities and challenges associated with the application of the model in support of strategic planning.

4.1. Recent Trends in Scheduling and On-time Performance

Airlines' schedules at JFK, EWR and LGA have undergone important changes since 2007. Figure 8 shows the average schedules at JFK (Figure 8a), EWR (Figure 8b) and LGA (Figure 8c) in Summer 2007, 2008 and 2010. Note, first, that the schedules of flights at JFK were smoother in 2008 than in 2007. Approximately the same total number of flights was scheduled at JFK in Summer 2008 as in Summer 2007 but peak-hour scheduling levels were significantly lower in 2008 than in 2007. This is mostly due to the introduction of schedule limits in May 2008 that capped the number of scheduled flights per hour at 81 at JFK and EWR (Federal Aviation Administration,

2008). In contrast, the number of scheduled flights per hour has been capped at 75 since 2000 at LGA and hourly schedules at EWR were less peaked in 2007 than at JFK, so smaller changes were experienced between 2007 and 2008 at these two airports. Second, the three airports experienced a small decline in demand between 2008 and 2010, estimated at 8.6% at JFK, 6.6% at EWR and 3.3% at LGA. This is mostly due to the economic downturn and, perhaps, to a recent profitability-based trend of “capacity discipline” in the US airline industry (Wittman and Swelbar, 2014).

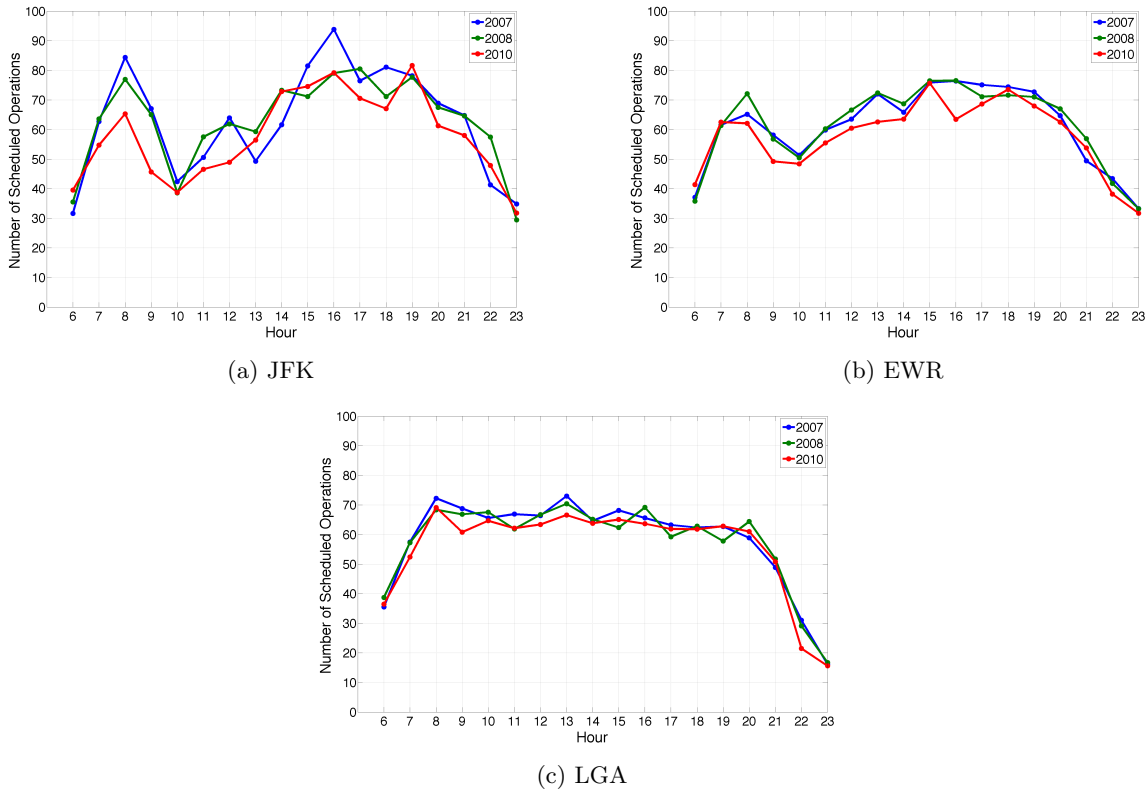


Figure 8: Average number of flights scheduled per hour in Summer 2007, 2008 and 2010

At the same time, substantial delay reductions have been observed in practice since 2007. At the three airports, the local departure delays were 25% to 50% lower in Summer 2011 than in Summer 2007. In order to understand the extent to which this very large decrease in delays can be attributed to the comparatively small changes in scheduling described in Figure 8, we apply our model of airport congestion with the schedules of flights from the 5 Summer periods between 2007 and 2011. The other input parameters, including the runway system capacity estimates (Figure 2), are left unchanged. Any change in modeled delays is thus due to changes in flight schedules. We then compare the evolution in average arrival and departure delays obtained with the model to that observed in practice. If the model predicts an evolution of delays similar to the one observed in practice, then the delay decrease can be attributed primarily to the changes in demand during the

considered period. If, on the other hand, the model predicts a delay reduction that is significantly smaller than the one observed in practice, then the reduction of the delays observed in practice is likely to be due to other factors than the changes in demand, including an improvement of airport traffic-handling performance. The results are summarized in Figure 9 and Table 5.

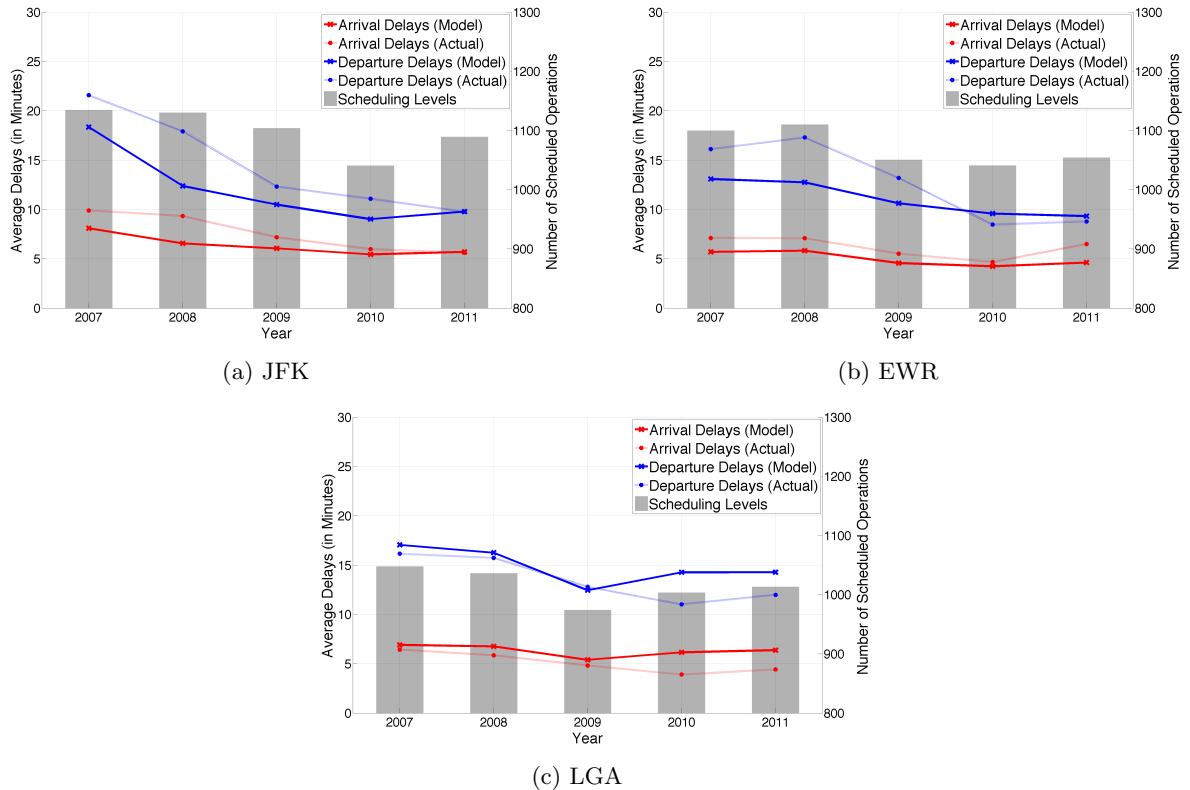


Figure 9: Predicted and actual average delays from Summer 2007 to Summer 2011

The main observations are twofold. First, the model does predict large delay reductions between 2007 and 2011 at the three airports and, in most cases, of an order similar to those observed in practice. Second, the delay reductions observed in practice tend to be larger than those predicted by the model, especially at EWR and LGA.

Note, first, that the model predicts reductions in arrival and departure delays of 30% to 50% at JFK, of 25% at EWR and of 10% to 15% at LGA between Summer 2007 and Summer 2010, when the demand was the lowest. This suggests that the small decline in demand observed during the period might explain very large declines in average delays. Queuing theory has established that delays vary non-linearly with demand when an airport operates close to capacity in steady-state conditions (de Neufville and Odoni, 2013). Our results suggest that the nonlinear relationship between scheduling levels and delays is also very much valid for the stochastic and dynamic queuing model with an endogenous control of service rates considered in this paper. In turn, airport on-time

Table 5: Percent of change in demand and delays between 2007 and 2011

Airport	Year	Demand	Arrival delays		Departure delays	
			Model	Actual	Model	Actual
JFK	2007	Baseline	Baseline	Baseline	Baseline	Baseline
	2008	-0.4%	-19.0%	-5.7%	-32.5%	-17.0%
	2009	-2.7%	-25.2%	-27.4%	-42.8%	-42.9%
	2010	-8.3%	-32.8%	-39.6%	-50.8%	-48.7%
	2011	-4.0%	-29.5%	-43.2%	-46.6%	-54.7%
EWR	2007	Baseline	Baseline	Baseline	Baseline	Baseline
	2008	+0.9%	+2.1%	-0.1%	-2.6%	+7.3%
	2009	-4.5%	-20.0%	-22.5%	-18.9%	-18.2%
	2010	-5.3%	-25.7%	-34.1%	-26.8%	-47.5%
	2011	-4.1%	-19.0%	-8.5%	-28.7%	-45.5%
LGA	2007	Baseline	Baseline	Baseline	Baseline	Baseline
	2008	-1.1%	-2.1%	-9.2%	-4.7%	-2.6%
	2009	-7.0%	-21.9%	-25.2%	-27.0%	-20.8%
	2010	-4.2%	-10.9%	-39.3%	-16.3%	-31.8%
	2011	-3.3%	-7.7%	-31.2%	-16.3%	-25.9%

performance is expected to be extremely sensitive to even small changes in demand.

It is noteworthy that departure delays declined significantly at JFK between Summer 2007 and Summer 2008, according to both the model and actual data. As previously discussed, approximately as many flights were operated during these two periods (see also Table 5). The improvements in on-time performance were therefore primarily due to changes in the *distribution* of the flights over the course of the day. By comparison, delays were of similar magnitude in Summer 2007 and Summer 2008 at EWR and LGA, where smaller scheduling changes were observed over this time period. These results indicate that on-time performance is sensitive not only to the total number of flights scheduled in the day, but also to their distribution over the day. Specifically, for any given number of flights scheduled in a day, the more evenly they are distributed over its course, the smaller the average delays will be.

Finally, the actual delay reductions between 2007 and 2011 have been larger than the model's predictions at the three airports. For instance, the model slightly underestimates arrival and departure delays in Summer 2007 at EWR but slightly overestimates them in Summer 2011. In particular, significant delay reductions have been observed at EWR between Summer 2009 and Summer 2010, while flight schedules were similar. As well, on-time performance seems to have improved at LGA between 2009 and 2010, even though demand was larger in 2010. This may suggest that the efficiency of operations has improved over the time period considered. Examples of such improvements might include increases in airport capacity resulting from improved air traffic management procedures, improved surface congestion management, etc. This is a topic that certainly deserves further future research.

4.2. A Note On the Application of the Model

The model of airport congestion developed in this paper can be used in support of strategic planning to estimate future arrival and departure delays under different demand and capacity scenarios. To perform such analyses, one needs to consider: (a) the schedules of flights and (b) estimates of airport capacity. The nonlinear relationship between flight schedules, airport capacity and flight delays identified in the previous section requires careful determination of these inputs.

On the demand side, the model can, first, be applied to estimate delays on a given day, with the schedule of flights produced by the airlines on that day. It can also be used to evaluate the impact of changes in demand or of scheduling policies on airport on-time performance. In contrast to our application in the previous section, however, this involves modeling future or hypothetical changes in flight schedules. Therefore, our model of airport congestion can be combined with models that develop airline schedules under a range of assumptions for the purpose of evaluating the impact of projected demand growth (or demand decline) on (i) airline schedules of flights and (ii) airport congestion. A similar approach could be used to quantify the impact of scheduling policies (Jacquillat and Odoni, 2013).

On the capacity side, the model requires the estimation of the Operational Throughput Envelopes of the airport's main runway configurations (or runway configuration clusters). We envision that our model of airport congestion would be combined with an empirical model of capacity estimation, such as the one developed by Simaiakis (2012). At airports where no significant changes in capacity are foreseen, historical data of operations can be used to generate Operational Throughput Envelopes. The model can also be applied to quantify the benefits of investments in additional capacity, such as the construction of a new runway. This would require an evaluation of the capacity increases resulting from such investments. This could be done through the combination of human-in-the-loop experiments (Barnett et al., 2010) and of empirical capacity estimations techniques (Simaiakis, 2012).

5. Conclusion

We presented an original approach to airport congestion modeling that integrates an endogenous control of arrival and departure service rates into a stochastic and dynamic queuing model. The control simulates the tactical utilization of available capacity and provides a systematic means of selecting arrival and departure service rates in any queuing model of airport congestion, for any schedule of flights and for any estimates of airport capacity. In turn, the resulting model of airport congestion provides a fast and flexible tool to quantify on-time performance at the strategic level at different airports under different demand and capacity scenarios.

We implemented the model at JFK, EWR and LGA, three of the most congested airports in the United States. We developed empirical estimates of airport on-time performance and compared our model's outputs to historical records of operations at the airports. We showed, first, that the

model predicts accurately the expected value and the variability of departure queue lengths for each period of the day at the three airports. Second, we showed that the model estimates well the timing, dynamics and magnitude of expected arrival and departure delays. Third, the application of the model has demonstrated that flight delays are very sensitive both to the number of daily flights and to the distribution of flights over the course of the day, when an airport operates close to capacity. Results suggested that the delay reductions that have been observed at JFK, EWR and LGA over the past few years can be primarily attributed to the comparatively small changes in scheduling and, to a lesser extent, to improvements in air traffic handling procedures.

Acknowledgments

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