

A Queuing Model of Airport Congestion and Policy Implications at JFK and EWR

by

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Abstract

Since the phasing-out of the High Density Rule, access to major commercial airports in the United States has been unconstrained or, in the case of the airports of New York, weakly constrained. This largely unregulated demand combined with capacity constraints led to record delay levels in 2007, whose costs were estimated as in excess of \$30 billion a year. Mitigating airport congestion may be achieved through demand management measures. Quantifying the benefits of such measures requires careful modeling of flight delays as a function of flight schedules.

This thesis applies a stochastic and dynamic queuing model to analyze operations at JFK and Newark (EWR), two of the most congested airports in the United States. Two models are used to approximate the dynamics of the queuing system: a numerical model called DELAYS and a new Monte Carlo simulation model, which combines time-varying stochastic models of demand and capacity. These two models are then calibrated and validated using historical records of operations. In particular, they provide estimates of the average throughput rate at JFK and EWR under different weather conditions. The models are then shown to predict accurately both the magnitude of the delays and their evolution over the course of a day of operations. In addition, the Monte Carlo simulation model evaluates reasonably well the variability of the delays between successive days of operations.

These two models are then applied to a study of recent trends in scheduling and on-time performance at JFK and EWR. The analysis indicates that the significant delay reductions observed between 2007 and 2010 can be largely attributed to the relatively small reduction of airport demand over this period. In particular, it demonstrates the strongly nonlinear relationship between demand and delays when airports operate close to capacity. It also shows that, for a given daily number of flights, the more evenly they are distributed in a day, the lower the resulting delays are likely to be.

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Chapter 1

Introduction and Background

1.1 Airport Congestion in New York City

Since the deregulation of the US airline industry in 1978, air traffic operations have significantly increased worldwide while airport capacity has been lagging. Consequently, most commercial airports have experienced severe congestion, resulting in delays and cancellations. In particular, the New York region has been for decades one of the most congested aviation areas in the United States.

New York City is served by three primary airports: John F. Kennedy International Airport (JFK), Newark Liberty International Airport (EWR) and LaGuardia Airport (LGA), as well as the major general aviation airport of Teterboro and other secondary and general aviation airports. A map of the region is provided in Figure 1-1. Over the past decades, these airports have been facing increasing demand, which is due to many different factors, including the growth and the globalization of the economy, the growth of airline operations, the decrease of air fares etc. Two recent exceptions to this increase are to be noted: the post-9/11 air transportation crisis and the economic downturn between 2007 and 2010, which negatively affected air transportation demand. Nevertheless, approximately 30% more flights have been operated in the New York region in 2010 than in 1990.

However, airport capacity in the New York region is limited. Each of the primary airports is constrained in size and has fewer runways than the largest airports in the

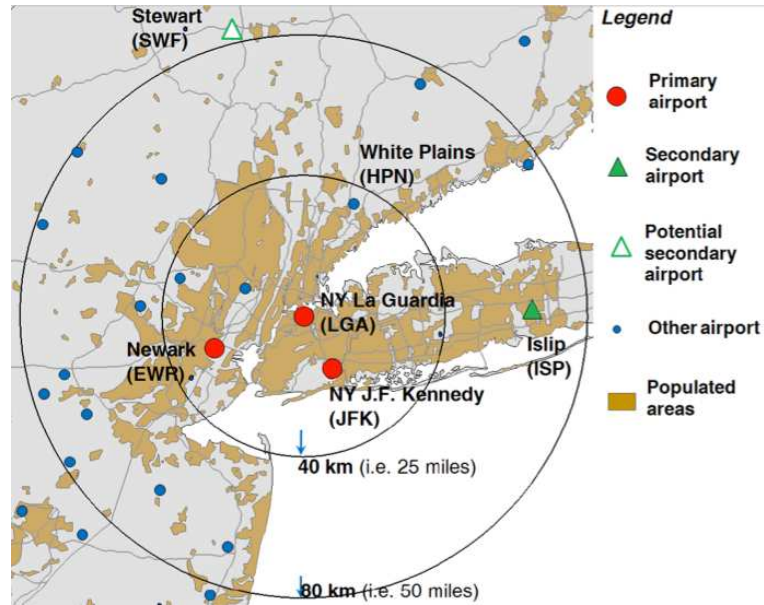


Figure 1-1: Airports in the New York metropolitan region (Bonney, 2008)

United States, as illustrated in Table 1.1. Because of the high urban density, any land expansion is extremely costly and infeasible in the short-term. The construction of new runways would also raise many environmental concerns¹. In addition, the region's airspace is very crowded because of the proximity of the different airports, which also constrains the operations at any single airport. Improvements in air traffic control procedures, including the implementation of NextGen, may enhance airport capacity but would not be sufficient to scale the system up to meet demand.

Table 1.1: New York's airports vs. Hartsfield-Jackson Atlanta International Airport (ATL), Chicago O'Hare International Airport (ORD) and Denver International Airport (DEN)

Airport	LGA	EWR	JFK	ATL	ORD	DEN
Number of Runways	2	3	4	5	7	6
Land Area (in Acres)	680	2,207	4,930	4,700	7,200	33,920

Demand growth and capacity limitations have resulted in important congestion in the New York region. Figure 1-2 shows that the three primary airports in New York have experienced the largest delays nationwide between 2007 and 2010. Moreover,

¹As an example, any runway expansion of JFK into Jamaica Bay is legally prohibited due to the presence of the federally-protected Gateway National Recreational Area.

delays originating from New York’s airports are known to propagate throughout the National Airspace System and therefore to deteriorate the on-time performance of the entire US air transportation system. Among the three primary airports in the New York region, JFK and EWR are the ones from which delays propagate the most, while, by contrast, many flights operated at LGA are regional.

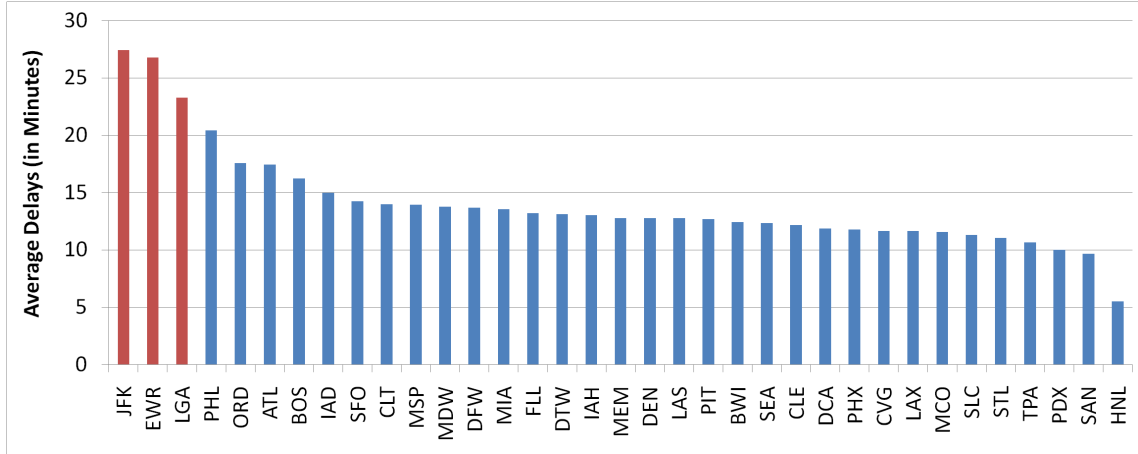


Figure 1-2: Average delays between 2007 and 2010 at the 35 major US airports (source: ASPM database)

High scheduling levels are responsible for most of the delays at JFK and EWR. Figure 1-3 shows the main causes of the delays experienced between 2007 and 2010 at JFK (Figure 1-3a) and EWR (Figure 1-3b), and compares them with the causes of the delays at the 35 major airports in the United States together (Figure 1-3c). Most of the flight delays in the United States are reported as National Aviation System delays, which include delays due to inefficient airport operations, to heavy traffic volume and to non-extreme weather conditions. In general, these delays are created by local demand-capacity mismatch. Note that the importance of these delays is larger at JFK and EWR than at other major US airports: National Aviation System delays indeed account for more than half of the delays at JFK and EWR and for only 40% of the delays on average in the United States. The two other important causes of delays are the propagation of delays from previous flight legs and inefficiencies in airlines’ operations (*e.g.* aircraft maintenance and fueling, baggage loading, crew delays etc.).

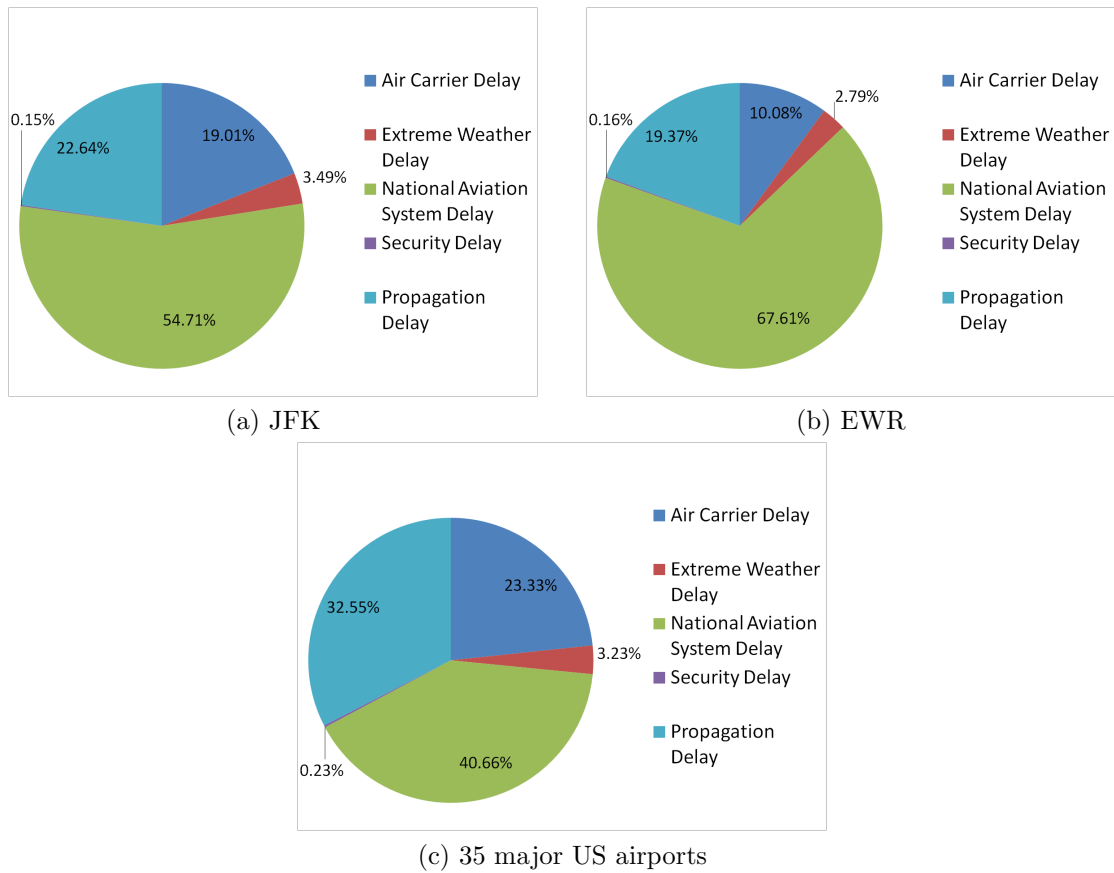


Figure 1-3: Cause of the flight delays between 2007 and 2010 (source: Bureau of Transportation Statistics)

The objective of this study is to quantify the relationship between flight schedules and flight delays at JFK and EWR, in order to test the impact of different demand scenarios on airport congestion.

1.2 Air Traffic Management in the United States

1.2.1 Air Traffic Management policies

Recent comparisons undertaken by the FAA and EUROCONTROL (Enaud et al., 2009) and supported by academic findings (Morisset, 2008) have indicated that the US and European airports achieve very different performance levels. On the one hand, more flights are operated in the United States than in Europe for comparable runway layouts. On the other hand, on-time performance is better in Europe than

in the United States, where, on average, delays are both larger and more variable. These differences are primarily due to differences in Air Traffic Management policies and practices.

First, airport demand is currently largely unregulated in the United States. Indeed, US airports do not declare their capacity and no schedule limitation policy is implemented. As a result, flight scheduling is weakly constrained: an airline remains free to schedule a landing or takeoff at any time, as long as it can obtain access to the airfield through an adequate number of gates and aircraft stands (Odoni, 2009). These policies rely on the assumption that the air transportation market will regulate itself and that delays will not grow beyond levels perceived as tolerable by aircraft operators.

Second, air traffic control procedures depend on weather conditions in the United States. Indeed, under good weather conditions (*i.e.* high ceiling and good visibility), referred to as “visual meteorological conditions” (VMC), flights are operated under “visual flight rules” (VFR). In this case, pilots are responsible for maintaining visual separations from preceding aircraft during the final phases of the flight. However, when the weather is poor - *i.e.* under “instrument meteorological conditions” (IMC) - air traffic controllers use “instrument flight rules” (IFR) to comply with a set of required minimum separations between aircraft. As a result, airport capacity is significantly larger under VMC than under IMC. By contrast, outside of the United States, IFR separations are applied in all weather conditions.

These two exceptional characteristics lead to high scheduling levels in the United States. Figure 1-4 shows the average number of scheduled flights for any 15-minute period of the day at JFK (Figure 1-4a) and EWR (Figure 1-4b) and estimates of the maximum throughput rates under VMC and IMC. Both airports operate very close to capacity and in some cases above their optimal capacity. In addition, scheduling levels exceed the airport’s IMC capacity during many periods of the day, which results in large delays if the weather deteriorates.

An important issue faced by the Federal Aviation Administration (FAA) is therefore how demand should be managed at JFK and EWR and whether a schedule

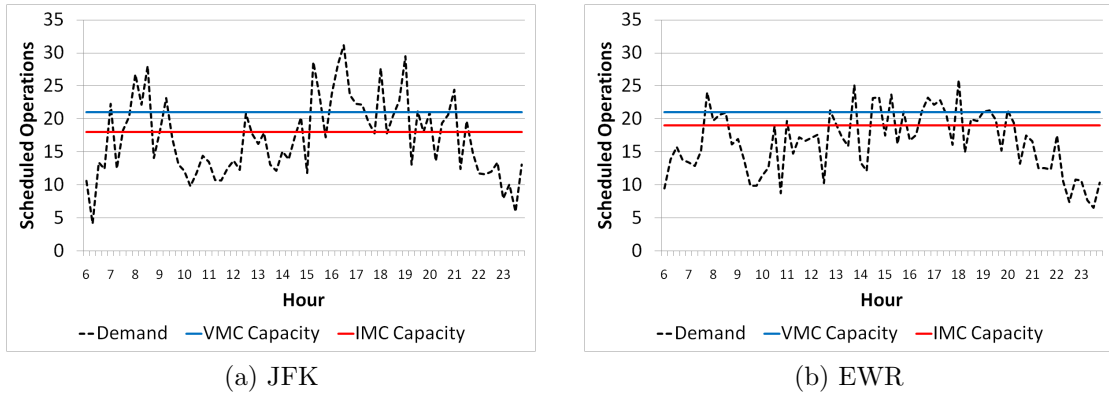


Figure 1-4: Average scheduling levels in August 2007 at JFK and EWR

limitation policy should be adopted.

Historically, regulatory authorities have attempted to limit scheduling levels at some congested airports in the United States. Most notably, the High Density Rule (HDR) was adopted in 1968 to restrict access to five busy airports, namely Washington/Reagan, Chicago/O’Hare, and the three primary airports in the New York region² by imposing schedule limitations. Initially, the process of slot allocation under HDR was quite similar to schedule coordination as practiced at the majority of busy airports outside of the United States: the number of hourly operations was restricted and slots were allocated through an administrative procedure by the FAA. However, the deregulation of the airline industry in 1978 made the implementation of this process extremely difficult as the number of available slots fell far short of satisfying the demand of all airlines. Therefore, the FAA switched in December 1985 to a buy-and-sell mechanism, which created a market for slots among competing airlines. However, in 2000, Congress enacted the Wendell H. Ford Aviation Investment and Reform Act of the 21st Century (AIR-21) phasing out the HDR³. The rationale was that the HDR distorted competition among airlines by unfairly favoring established ones against new entrants. In accordance with AIR-21, the phasing out of the HDR was completed in 2007.

Since then, the FAA has attempted to mitigate congestion by maintaining some restrictions on the number of operations at EWR, JFK and LGA. It designed a slot

²The rule was suspended at EWR in 1970.

³United States Code Service, 49 USCS 41715

allocation mechanism based on slot auctions to limit the negative effects of such restrictions on competition and to prevent fare increases. The Congestion Management Rule for JFK and EWR in October 2008 (Federal Aviation Administration, 2008a) proposed that some slots be relinquished annually and then allocated to the highest bidder for each slot. A similar rule was adopted for LGA (Federal Aviation Administration, 2008b). The legality of this slot auction plan was challenged by the Air Transport Association of America (ATA), which was joined by some airlines and the Port Authority of New York and New Jersey (PANYNJ). The ATA and its allies claimed that the plan exceeded the FAA’s statutory authority. The United States Court of Appeals for the District of Columbia Circuit granted a stay pending further order in 2008⁴, and the FAA eventually rescinded the rule (Federal Aviation Administration, 2009).

While considering alternatives, the FAA promulgated a temporary order in May 2008 that capped operations at both JFK and EWR at 81 scheduled flights and 2 unscheduled flights per hour. However, these limitations are substantially less restrictive than those in most airports worldwide. The Office of Inspector General of the US Department of Transportation argued that these limits have not managed to mitigate congestion at New York’s airports and recommended that the FAA reexamine them (Office of Inspector General, 2010).

1.2.2 Stakeholder Identification

The regulation of airport operations raises numerous economic, political and legal concerns because of the diversity of the stakeholders involved and the multiplicity of their interests. On the one hand, flight delays are extremely costly: their impact has been estimated to more than \$30 billion in 2007 (Ball et al., 2010), broken down as reported in Table 1.2. On the other hand, regulating airport demand also raises a large variety of economic concerns. This section identifies the main stakeholders and discusses how they may be affected by schedule limitations and flight delays.

⁴*Port Authority of New York and New Jersey v. Federal Aviation Administration*, United States Court of Appeals, District of Columbia Circuit, No. 08-1329, September 2008

Table 1.2: Costs of delays in 2007 (Ball et al., 2010)

Cost Component	Cost (in \$ billions)
Cost to Airlines	8.3
Cost to Passengers	16.7
Costs from Lost Demand	3.9
Total Direct Cost	28.9
Impact on GDP	4.0
Total Cost	32.9

In the United States, civil aviation is regulated by the Federal Aviation Administration (FAA). This agency was created in 1958 by an Act of Congress⁵ and became part of the US Department of Transportation in 1966. Its budget for the year 2010 was approximately \$16 billion. It is responsible for maintaining secure, safe and efficient air traffic operations. It is primarily in charge of establishing and enforcing standards ensuring aircraft and airport safety, issuing pilot certificates and developing and operating the air traffic control system. It also manages airport development and planning in collaboration with airport authorities. However, as indicated in Section 1.2, its authority to regulate demand at congested airports has not been established.

The primary airports in the New York region are managed and operated by the Port Authority of New York and New Jersey (PANYNJ). As previously mentioned, these airports are space constrained and any expansion of their runway systems is virtually infeasible. Their attractiveness to passengers depends on their ability to maintain safe, efficient and reliable operations. Schedule limitations may increase system reliability, but may also lead to lost throughput. In addition, they may impede the implementation of innovative capacity enhancement strategies.

The commercial airlines are major stakeholders. They aim primarily at attracting as many consumers as possible, while maintaining costs as low as possible. Intensified competition creates incentives for airlines to maximize the frequency of their operations on each market served. This generally results in large numbers of flights on many markets and in the use of small- and intermediate-sized aircraft (Belobaba

⁵*Federal Aviation Act of 1958*, Public Law 85-726; 72 Stat. 737

et al., 2009). In addition, airlines typically operate flights in a large and interconnected operational network, so that schedule changes at some congested airports may have consequences for a large number of flight legs. These considerations create a concern that regulatory action may restrict market flexibility and distort competition. Airlines are also concerned by the possibility that any slot allocation process may increase their operating costs or limit their ability to enter new markets. On the other hand, airport congestion increases travel times, crew costs and fuel emissions. In addition, delays may result into customer dissatisfaction and missed revenue opportunities. Altogether, delays cost airlines billions of dollars each year. They would therefore benefit greatly from carefully crafted policies that would mitigate congestion at busy airports.

Air taxi and general aviation operators are also importantly affected by the regulation of airport operations. Unlike major airlines, these operators often rely on last-minute scheduling of flights, which, of course, depends on runway availability. In addition, these unscheduled operations represent a very small fraction of airport operations and they are not the main contributors to runway congestion, which would raise issues of fairness in the slot allocation process.

Airline passengers constitute another major set of stakeholders. Flight delays also cost billions of dollars each year to them due to increased trip times, missed connections and unplanned expenses. Passengers have to adjust their departure and arrival times to the supply of flights: the higher the flight frequency, the more convenient air transportation is for passengers. In addition, schedule limitations may also drive up travel fares. Consequently, regulatory policies are likely to have complex impacts on passengers. Moreover, all market segments will not be equally affected. For instance, business passengers are less flexible than leisure passengers regarding their departure times and may be more sensitive to delays as well.

Air transportation also has important impacts on the environment and on surrounding communities. Although these considerations are primarily addressed in the design of an airport and its runway layout, they are also affected by the regulation of airport operations. Indeed, aircraft queues significantly contribute to fuel emissions

at airports and thereby reduce air quality. From this standpoint, schedule limitations may reduce environmental pollution. However, they may also shift operations to later at night or earlier in the morning, which may increase noise impacts on local communities.

Finally, economic activity in New York City depends, in no small measure, on the quality and the reliability of air transportation access to the city. More generally, the performance of the National Aviation System has important consequences for the US economy. For these reasons, local and federal governmental authorities are also key stakeholders.

In conclusion, demand management at US airports gives rise to acute tradeoffs involving a large variety of stakeholders. From the perspective of the FAA, these considerations are to be taken into account in the evaluation of the costs and benefits of any potential policy regulating or restricting airport flight schedules.

1.3 Thesis Outline

The objective of this study is to quantify the relationship between airport capacity, scheduling levels and flight delays at two primary airports in the New York region: JFK and EWR. To this end, we consider a numerical queuing model of airport congestion and we develop a macroscopic Monte Carlo simulation model, and we show that they estimate accurately the delays observed in practice at these airports. These models are then used to perform a case study at these airports.

This work is based on data reported in the Aviation System Performance Metrics (ASPM) database which is maintained by the FAA. The data are described in Chapter 2, which also discusses some limitations and gaps of this database.

In Chapter 3, we introduce a general dynamic and stochastic queuing model of airport operations and two approximation methods: an analytical approximation of the average delay called DELAYS (Kivestu, 1974) and a new Monte Carlo simulation model, which approximates the behavior of the queuing system by randomly sampling each takeoff and each landing individually in a day of operations. We also present

dynamic and time-varying models of airport demand and of airport capacity which are combined into the Monte Carlo simulation algorithm.

In Chapter 4, the models are calibrated and validated using historical records of operations at JFK and EWR in 2007. We show that they estimate well the magnitude of the delays at these airports as well as the dynamics of their formation and propagation over the course of one day of operations. We also show that they approximate well the variability of the delays between successive days of operations.

Chapter 5 then uses this model to analyze recent trends in demand and delays at JFK and EWR between 2007 and 2010 by comparing the observed delays with the model's predictions. We first present the evolution of scheduling levels at these airports over this period. Then, we show that the significant delay decrease observed between 2007 and 2010 is largely explained by the small reduction of the demand due to the economic downturn. Last, we demonstrate that the distribution of the flights over the course of the day also has an impact on the extent of congestion: for the same number of flights, "smoother" distributions lead to lower delays than uneven schedules.

These results are summarized in Chapter 6, which identifies the primary drivers of queue formation and propagation at congested airports. The chapter concludes with a brief discussion of how this model can be integrated into a broader study, which would compare the costs and benefits of a schedule limitation policy.

1.4 Literature Review

Several models of airport operations have been developed over the years. They generally fall into three categories: microscopic, mesoscopic and macroscopic.

First, microscopic models consider each aircraft individually and reproduce as precisely as possible airport operations, including the specificities of each airport's layout and the operating rules at gates, taxiways and runways. Examples include SIMMOD or TAAM (Odoni et al., 1997). Whereas they provide useful insights on how different airport procedures and tactical methods to reduce congestion compare to one

another, they are not well-suited to performing strategic evaluations and planning that considers a wide range of scenarios and alternatives.

Mesoscopic approaches consider flow dynamics at the tactical level. Movements are typically aggregated and operating procedures are not included in these models. Early studies have defined the departure process as a queuing system (Shumsky, 1995), and stochastic models have later improved the model's validity (Pujet et al., 1999). More recently, the takeoff rate has been determined as a function of the number of departing and arriving aircraft in the queue (Simaiakis and Balakrishnan, 2009). This work has been used to design efficient air traffic control procedures by specifying optimal pushback rates for different extents of airport congestion (Simaiakis, 2009), which result in smaller average taxi-out times. These techniques alleviate surface congestion and mitigate the environmental impacts of air transportation. However, they cannot be directly used in the assessment of the costs and benefits of a schedule limitation policy because they do not directly link scheduling levels and flight delays.

The relationship between airport demand and flight delays may be determined by macroscopic models, which typically consider low levels of detail and aggregate operations at the airport level. These models may then be used to test the impact of alternative schedules on system on-time performance.

Some of the models are based on econometric analyses; they evaluate delays as a function of scheduling levels and airport capacity as well as an array of contextual factors, including weather conditions, the number of gates and the runway configuration in use (Kwan and Hansen, 2010; Morrison and Winston, 2008; Xu, 2007). However, the econometric models do not describe the dynamics of delay formation and propagation over the course of the day. By contrast, other models of airport operations, based on queuing theory, predict the average delay levels over the course of a day of operations as a function of scheduling levels and airport capacity at each period of the day. They may be either deterministic (Hansen, 2002) or stochastic. In this study, stochastic models will be considered in order to take into account the variability and the uncertainty of the processes at stake. However, the main results of queuing theory (Gross and Harris, 1988) and its applications (Larson and Odoni,

1981) are obtained under steady-state conditions. Since both the demand rate and the service rate at an airport are typically highly variable in practice, the time to reach steady-state is often much longer than the time scale of the system in case of congestion (Odoni and Roth, 1983). Therefore, dynamic queuing models must be considered⁶.

A model of airport congestion which has received considerable attention is the $M(t)/E_k(t)/1$ queuing system, in which the demand process and the service process are respectively approximated as a Poisson process and an Erlang process. Given the computational intractability of this dynamic model, a numerical approximation called DELAYS has been developed (Kivestu, 1974) and algorithmically implemented (Gupta, 2010). DELAYS has been shown to accurately estimate taxi-out delays (Pyrgiotis and Simaiakis, 2010) and arrival delays (Lovell et al., 2007) and has also been used to model propagation of flight delays in a network of airports (Malone, 1995; Pyrgiotis, 2011) and to assess alternative demand management strategies (Fan, 2003; Pyrgiotis, 2011).

The same family of queuing models of flight delays has also been used to evaluate the extent to which congestion may be mitigated if scheduling levels are reduced. In particular, it has been shown that a small demand reduction at LaGuardia in 2000 to comply with the Wendell-Ford Aviation Act for the 21st Century resulted in significant delay reductions (Fan, 2003). This non-linear relationship between air transportation demand and flight delays (de Neufville and Odoni, 2003) provides the motivation for looking carefully into the relationship between flight schedules and delays in order to evaluate the potential of scheduling limits at some of the busiest airports in the United States.

⁶This also allows one to consider demand profiles which at some point exceed airport capacity.

Chapter 2

Presentation of the Data and Definition of Variables

The process of building, calibrating and validating a model of runway congestion requires the use of data on airport operations and delays. The most comprehensive database with information on activity at US airports is the Aviation System Performance Metrics (ASPM), which is maintained by the FAA¹. The purpose of this chapter is to define the quantities involved in our models of airport congestion and describe how they may be measured from available data. We also discuss potential data limitations and sources of data inaccuracies.

2.1 Presentation of the Database

The ASPM database provides data on all flights to and from 77 major US airports, including JFK and EWR. It offers two distinct modules:

- The “Individual Flights” module records information on every flight, including the times when departing aircraft leave the gate and take off and the times when arriving aircraft land and arrive at the gate. For each flight, both the scheduled time and the actual time are presented. Cancelled flights are not reported.

¹In the United States, airlines are required by law to provide the relevant data for their operations.

- The “Airport” module aggregates information per 15-minute period through the course of the day. It includes data on scheduling levels, on the number of movements which actually took place and on the average delays experienced at a given airport. These data can be compared to those from the “Individual Flights” module. It also presents estimates of the airport capacity for any period of the day. In addition, it includes data on the conditions of airport operations, including the runway configuration in use and the weather conditions.

Both modules provide extensive data on scheduled and actual operations, and may be used to characterize demand and delays at airports. However, they do not perfectly match with each other, thus creating some uncertainty about the actual situation.

First, the majority of the metrics presented in the ASPM database do not include unscheduled operations, such as general aviation and military flights. These flights nonetheless contribute to runway congestion and may increase delays experienced by scheduled aircraft. Only one metric in the “Airport” module, called “Operations for Efficiency Computation”, includes these flights. As shown in Table 2.1, approximately 5 % of flights are not reported in the rest of the database.

Table 2.1: Comparison between the number of flights reported in the ASPM database and the total number of operations in 2010

Airport	JFK	EWR
All Flights (“Efficiency Computation”)	401,490	404,165
Reported Flights (“Metric Computation”)	382,131	383,989
Proportion of Reported Flights	95.2%	95.0%

Second, flight delays are not exclusively due to local runway congestion. Indeed, an aircraft may be delayed before it demands the usage of the runway (*e.g.* because of delays in previous flight legs, mechanical problems etc.). Consequently, the time at which a flight is planned to be operated may be readjusted dynamically over the course of the day. The ASPM database reports data provided by two sources:

- The schedule: published in advance of the day of the flight, it comes from the

Computer Reservation System. It represents the time at which the operation was supposed to take place when the flight was originally planned.

- The latest flight plan filed before departure: created less than 24 hours prior to departure, the flight plan may be updated over the course of the day if major changes occur. Obviously, for the majority of flights, the planned time is equal to or later than the scheduled time; nonetheless, some flights are rescheduled earlier than originally.

Flight plan filing varies from one airline to another and from one day of operations to another and there is no standardized procedure in this respect. In addition, if a flight plan is updated after takeoff, this change is not reported in the ASPM database. Therefore, the extent to which flight plans account for previous disturbances cannot be known with perfect accuracy.

Last, records of actual times of operations also involve some uncertainty. The ASPM database separates flights into two categories: the *OOOI flights* and the *non-OOOI flights*. The gate-out, wheels-off, wheels-on and gate-in times of OOOI flights are automatically recorded by aircraft equipped with ACARS sensors. For the other flights, however, these data are not available and they are thus estimated by the ASPM; these calculations essentially use information from air traffic controllers and approximations that use median values among OOOI flights. Table 2.2 shows that in August 2010 a large proportion of flights were reported as non-OOOI flights, which contributes to the uncertainty these data are subject to.

Table 2.2: OOOI and non-OOOI flights in August 2010

Airport	JFK	EWR
Proportion of OOOI flights	61.9 %	66.7 %

2.2 Quantities of interest

In this study, system performance is primarily characterized by operation delays, which are modeled as a function of airfield demand and airport capacity. Consequently, these three variables must be carefully defined and identified from available data. This section compares data from the “Airport” module and data from the “Individual Flights” module and illustrates the nature and the extent of differences between data from the original schedule and data from the flight plan. To these ends, a specific day of operations is considered as an example: Wednesday, August 4, 2010 at JFK.

The airfield demand: It is defined as the number of aircraft demanding the use of the runway system per unit of time. It is estimated by the number of scheduled departures and arrivals for any time period of the day.

In the “Airport” module, these quantities are directly available. In the “Individual Flights” module demand is computed by aggregating flights on the basis of their scheduled gate-out times for departures and gate-in times for arrivals. Figure 2-1 shows that the estimated demand differs slightly depending on which module is considered. These differences may be due to a lack of uniformity in the aggregation of departures and arrivals: the departure (resp. arrival) time considered in the “Airport” module may not correspond to the scheduled gate-out (resp. gate-in) time for all flights. In addition, flights reported in the “Airport” module include the small number of cancelled flights.

The evaluation of demand also depends on whether the original schedule or the flight plan is considered. Both sources lead to the same total number of flights but their distribution through the course of the day is slightly different, as illustrated in Figure 2-2. Unsurprisingly, the most notable differences occur in the afternoon, when previous events may have led to changes in the flight plans.

The capacity: For the purposes of this study, capacity is defined as the average number of aircraft movements/operations which may be sustainably operated per unit

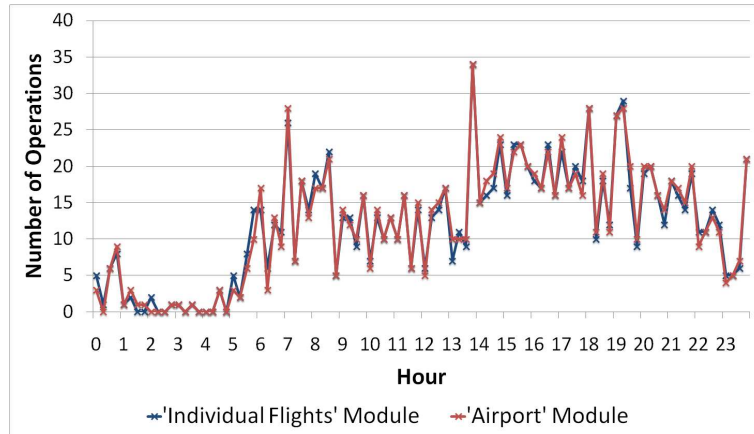


Figure 2-1: Demand Profile at JFK on Wednesday, August 4th 2010, from the “Airport” module and from the “Individual Flights” module

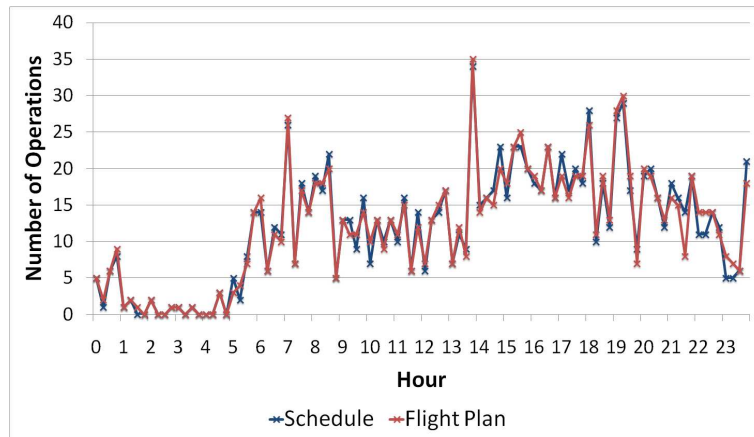


Figure 2-2: Demand Profile at JFK on Wednesday, August 4th 2010, from the original schedule and from the flight plan

of time at an airport². It is primarily determined by airport infrastructure - especially the runway system - and air traffic control procedures, including safety requirements. Several models have been developed to estimate capacity from inputs and data on airport operations through theoretical (Blumstein, 1959) and empirical approaches (Gilbo, 1993).

The ASPM database itself provides estimates of the departure capacity and the arrival capacity of the airport based on air traffic reports, respectively called “Average

²Alternative definitions of airport capacity accounting for the level of service may be considered; as an example, the practical hourly capacity is defined as the average number of operations which can be handled per hour with an average delay per operation less than 4 minutes (de Neufville and Odomi, 2003).

Departure Rate” and “Average Arrival Rate”. The total capacity estimate is obtained by summing up these two quantities and shown as the “ASPM Capacity” graph in Figure 2-3. For any period of the day, this estimate can be compared to the number of flights which were actually operated. The ASPM database provides three different data sources on actual operations, which are also shown in Figure 2-3:

- The “Operations for Efficiency Computation” in the “Airport” module;
- The “Operations for Metric Computation” in the “Airport” module; and
- The total number of flights reported in the “Individual Flights” module.

According to the ASPM documentation, the “Operations for Efficiency Computation” include all the flights which actually took place, including general aviation and military flights, whereas the “Operations for Metric Computation” only reports scheduled flights. Consequently, the total number of “Operations for Efficiency Computation” (1205 on August 4, 2010) is larger than the total number of “Operations for Metric Computation” (1155) over the entire day. The flights reported in the “Individual Flights” module are exactly the same as the ones reported as “Operations for Metric Computation” in the “Airport” module and the total number of flights (1155) over the entire day matches exactly in both cases.

However, as shown in Figure 2-3, the patterns are different. Notably, the data reported as “Operations for Metric Computation” often make little sense: as can be seen in the figure, the number of actual operations exceeds airport capacity by a wide margin during some periods. On the other hand, there seems to be a very good match between the “Individual Flights” module and the “Operations for Efficiency Computation” reported in the “Airport” module; the small differences between these series seem to be due solely to the inclusion of unscheduled flights in the latter.

Most importantly, we have concluded on the basis of extensive experience with the ASPM data that the estimates of airport capacity which are reported in the database overestimate the rate at which flights may be sustainably operated. Indeed, it can be seen from Figure 2-3 that during peak afternoon hours, when the airport operates

under continuous demand, fewer movements than the total reported ASPM capacity were actually operated at JFK on August 4, 2010. For this reason, we will not use the ASPM capacity, as reported in the ASPM database, as an input to our queuing model, but instead we will consider the airport capacity as a degree of freedom which we will adjust to match the magnitude of the delays observed in practice (see Section 4.1.2).

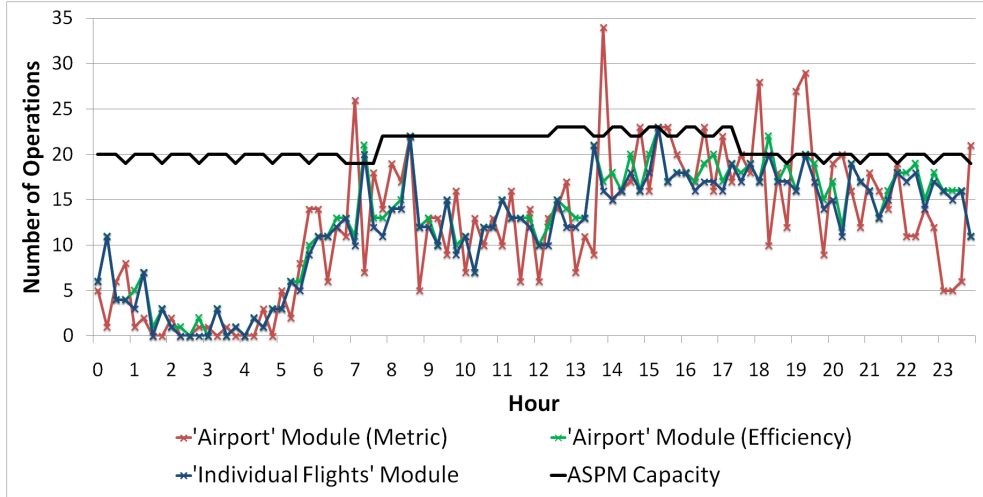


Figure 2-3: Actual Operations at JFK on Wednesday, August 4th 2010, from the “Airport” module and from the “Individual Flights” module

Operation Delay: The departure (resp. arrival) delay is estimated by the difference between the actual wheels-off (resp. gate-in) time and the scheduled wheel-off (resp. gate-in) time, if positive. In other words, if $Off(i)$ and $In(i)$ respectively represent the wheels-off time and the gate-in time of flight i , its delay is computed as follows:

$$\text{Departure Delay } (i) = \max(0, \text{Act. Off } (i) - \text{Sch. Off } (i))$$

$$\text{Arrival Delay } (i) = \max(0, \text{Act. In } (i) - \text{Sch. In } (i))$$

In addition, an aggregate measure of delays for a given period of the day can be defined in several ways. In particular, the average flight delay - including both departure delays and arrival delays - may be calculated among the flights which were scheduled during the considered period or among the flights which actually took place during it. For a period \mathcal{P} , they are respectively given by:

$$\text{Average Delay} = \frac{\sum_{\text{Sch. Off } (i) \in \mathcal{P}} \text{Dep. Delay } (i) + \sum_{\text{Sch. In } (i) \in \mathcal{P}} \text{Arr. Delay } (i)}{\text{Number of Scheduled Operations during } \mathcal{P}} \quad (2.1)$$

$$\text{Average Delay} = \frac{\sum_{\text{Act. Off } (i) \in \mathcal{P}} \text{Dep. Delay } (i) + \sum_{\text{Act. In } (i) \in \mathcal{P}} \text{Arr. Delay } (i)}{\text{Number of Actual Operations during } \mathcal{P}} \quad (2.2)$$

Figure 2-4 shows these two measures and airfield demand for August 4th 2010. Note that when aggregating delays on the basis of the schedule, as computed in equation (2.1), the average delays (in blue) are large at times when the system is actually congested (between 7 p.m. and 9 p.m. for instance) whereas if the flights are aggregated on the basis of the actual operations, as in equation (2.2), then delays (in red) are higher in some periods when the demand is very low and the queue is actually decreasing (between 9 p.m. and 11 p.m.). Therefore, aggregating the flights on the basis of the schedule leads to more realistic delay patterns.

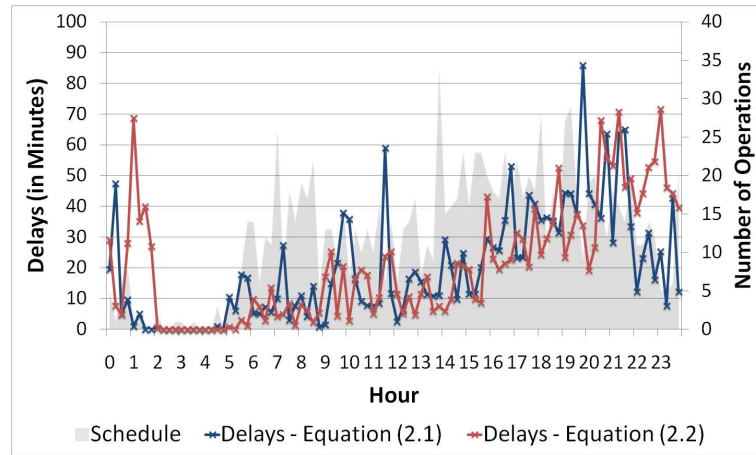


Figure 2-4: Operation Delays at JFK on Wednesday, August 4th 2010, using two distinct ways of aggregating delays per 15-minute periods

In addition, these delays may be computed by comparing the actual operation time of a flight with either its scheduled time or the time reported in its flight plan. Figure 2-5 compares the two corresponding series. It shows that delays calculated against the original schedule are larger than delays calculated against the flight plan

in the late morning and in the late afternoon, when some aircraft may have been previously delayed and may not have recovered from these delays. Therefore, using the flight plan in the computation of delays eliminates upstream delays to some extent.

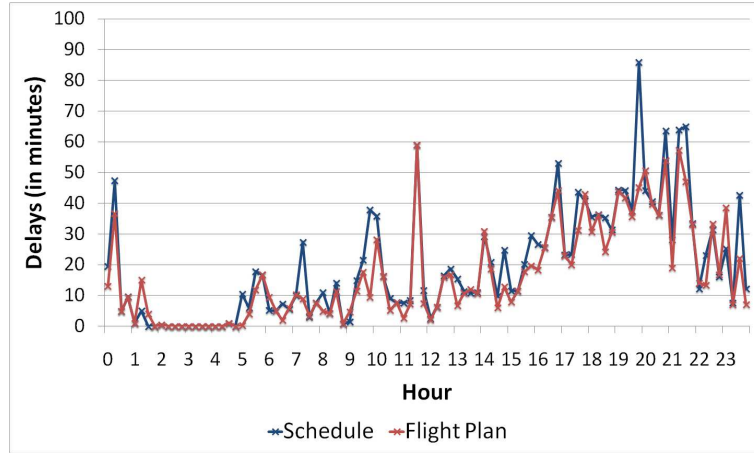


Figure 2-5: Operation Delays at JFK on Wednesday, August 4th 2010, calculated against the original schedule and against the flight plan

In conclusion, local runway congestion is better estimated by (1) aggregating flights according to their scheduled time instead of the time when they were actually operated and (2) using the flight plan instead of the original schedule as a baseline. Under these conditions, the average delays computed from the “Individual Flights” module may be compared to the delays presented in the “Airport” module. Figure 2-6 shows these two series of delays. Note that the data do not match perfectly: even though delay levels and patterns are reasonably close to each other in both cases, some differences may be noted.

In summary, there exist some differences between the different data reports available in the ASPM database. First, data in the “Airport” module and in the “Individual Flights” module differ noticeably from each other. Several alternative ways may also be used to define the main quantities of interest. Based on the observations described in this chapter, and unless otherwise explicitly stated, the following choices will be made henceforth:

- The “Individual Flights” module will be used to define the airfield demand, the number of actual operations and the flight delays. This choice is motivated by

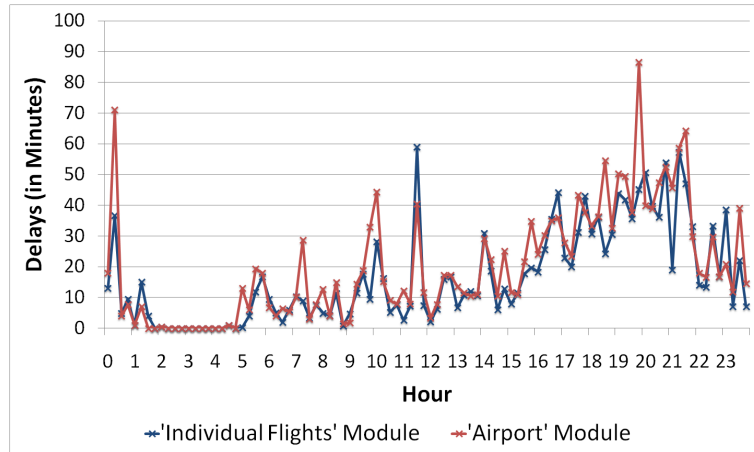


Figure 2-6: Operation Delays at JFK on Wednesday, August 4th 2010, from the “Airport” module and from the “Individual Flights” module

the larger flexibility in the use of the data and the prevention of some data inconsistencies underlined above. (Note, however, that this module provides no information when it comes to unscheduled operations and cancelled flights.) The “Airport” module will still be used to determine the contextual factors of airport operations, such as the runway configuration in use and the weather conditions.

- The flight plan is used to compute airport demand and delays, because it reduces the extent of upstream disturbances. However, this has three major limitations. First, since the flight plan is not actually known days ahead, long-term planning considers flight schedules. Second, delays computed against the flight plan, though better capturing local runway congestion, are not directly related to delays experienced by passengers. Third, there is no uniform procedure of issuance of the flight plan. The procedure may vary from one airline to another and from one day of operations to another.

This discussion highlights sources of uncertainty in the available data about both scheduled and actual operations. In the macroscopic approach adopted in this study, little attention is given to such details, but the data limitations must be understood.

Chapter 3

Presentation of the Models of Airport Congestion

This chapter introduces the queuing model of airport operations which is used to evaluate flight delays at a given airport as a function of airport demand and capacity. Two numerical approximation models of the queue dynamics are then presented: the analytical model called DELAYS (Kivestu, 1974) (Section 3.2) and an alternative model based on Monte Carlo simulation (Section 3.3).

3.1 A dynamic $M(t)/E(t)/1$ Queuing Model

Airport operations can be modeled by considering 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, 2003). Physically, departing aircraft are queuing on the ground, primarily on the taxiways; arriving aircraft are queuing in the terminal airspace or in the en route airspace, or on the ground at the origin airport, if a Ground Delay program is implemented. A virtual single queue with both types of movements is assumed here.

A schematic representation of the runway system at JFK and EWR is provided in Appendix A.

A typical process for a given aircraft at a given airport is described in Figure 3-1:

the aircraft first arrives in the queuing system when it is ready to land and leaves it when it actually lands. It then goes through a similar process when it departs from the airport. The arrival and departure delays that it experiences are equal to the times it spends in the queue while it undergoes these processes.

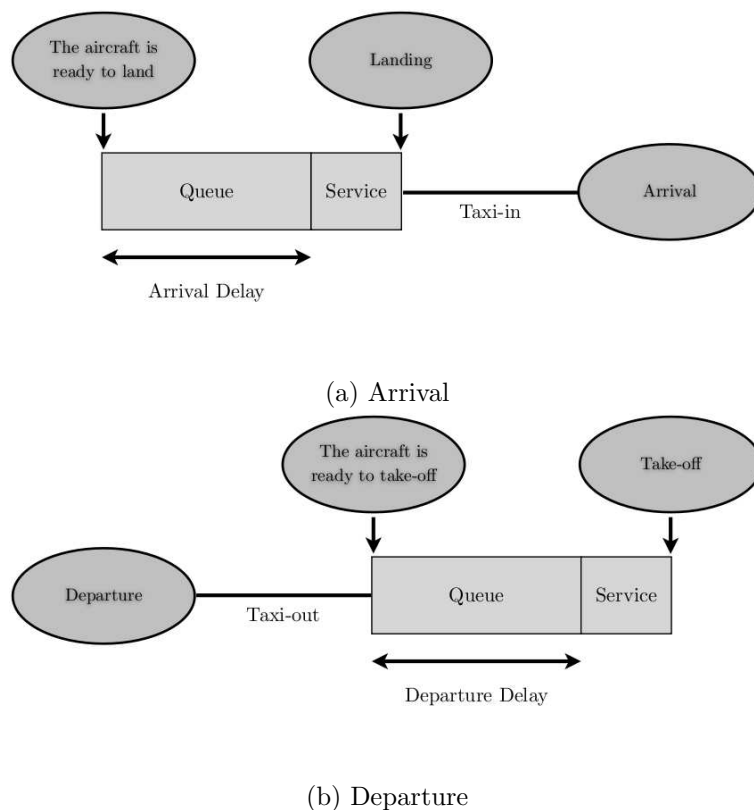


Figure 3-1: Demand process: arrival and departure of a single aircraft

A day of operations is divided into 96 15-minute periods.

The model takes as inputs:

- the demand profile, *i.e.* the number of scheduled flights at each period of the day, including both departures and arrivals
- the capacity profile, *i.e.* the airport capacity at each period of the day

The model computes flight delays at each period of the day as a function of the demand and capacity profiles.

Note that the capacity profile is not known beforehand in practice. For any period of the day, the number of flights which can be operated depends on the weather

conditions and an array of other factors, including the runway configuration in use, the air traffic control procedures, the aircraft mix etc. These operating conditions are not known in advance. Two different approaches will be considered to address this issue:

- Flat capacity profiles may be considered. For instance, the model may be used to compute the *VMC delays*, *i.e.* the delays if the weather is good during an entire day of operations. Similarly, it may be used to compute *IMC delays* or delays associated with any pre-specified capacity profile that includes some combination of VMC and IMC time intervals.
- A dynamic model of airport capacity is introduced in section 3.3.3 to take into account the uncertainty and the variability of the airport capacity.

The queuing model is stochastic and dynamic: both the demand and the service are modeled as time-varying random processes. Therefore, it takes into account the variability of the actual queuing processes.

The scope of this model is macroscopic: the detailed operational procedures at each airport are not considered by the model. For example, air traffic controllers may implement various strategies to operate flights and to mitigate congestion at the tactical level, which result in changes in the service process. In this macroscopic model, these aspects are not taken into account and it is assumed that the stochasticity of the demand and service processes account for these sources of uncertainty.

More specifically, the model considered is an $M(t)/E_k(t)/1/FCFS/\infty$ model:

1. The demand process is modeled as a Poisson process with time-varying intensity. This provides a mathematical representation of the times when aircraft demand use of a runway, either for a takeoff or for a landing. The stochasticity of this process is motivated by the uncertainty regarding the times at which aircraft are ready to take-off or to land and join the queue. Indeed, these times are determined by several factors which are largely uncertain and variable, including airline operations, the operations in passenger buildings, on-time performance at other airports, etc.

In this study, the term “airport demand” refers to the demand for use of the runways, *i.e.* the number of flights scheduled at an airport, including both departures and arrivals. This demand is primarily determined by the business decisions the airlines make, based on the underlying passenger (or cargo) demand for air travel. Airport demand (the number of flights scheduled) does not necessarily change at the same rates (or, even, in the same direction) as passenger demand, especially at slot controlled airports. This study focuses on the airport demand and on its effects on airport delays, and does not consider passenger demand.

2. The service times are defined by the airport capacity and modeled as an Erlang random variable. That is to say, the time between two consecutive movements is assumed to follow an Erlang distribution with a fixed parameter k . When $k = 1$, this results in an exponential distribution (and the service process is then a Poisson process); when $k = \infty$, the process is deterministic. In-between, the service process is a random variable whose variability is lower than the variability of a Poisson process. This is motivated by the fact that the service rate is strongly influenced by considerations such as safety requirements and air traffic control procedures.

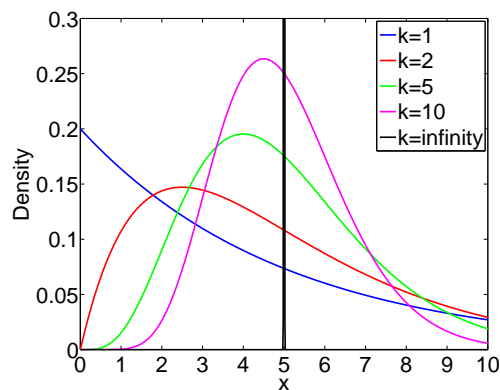


Figure 3-2: Erlang distribution with different orders k and with mean 5

The service rate is airport-specific and primarily determined by the number of runways and their geometric layout.

3. A single-server model is used, which represents the runway system as a whole. In particular, the queue includes both departing and arriving aircraft.
4. The aircraft are served on a first-come first-served basis.
5. The queue capacity is infinite.

On the basis of Assumptions 3 and 4, the runway system is modeled as a single server, with all aircraft joining a single virtual queue and being served in a first-come first-served order. This is, of course, a significant simplification of reality, consistent with the macroscopic nature of our model. At a multi-runway airport, aircraft generally queue up at a number of active runways (typically 2 or 3 at JFK and EWR, depending on the runway configuration being used) with some runways serving exclusively arrivals or departures, and others mixed operations. However, in the case of JFK and EWR (see airport layouts in Appendix A) the simplification of using a single server is partly justified by the interdependence of operations on different runways, especially at EWR, during peak air traffic hours in a typical day. Operations are often conducted on configurations consisting of two parallel (closely-spaced in the case of EWR) and one intersecting runways, and air traffic control procedures are aimed at optimizing the global service rate of aircraft for any given runway configuration and a given mix of departures and arrivals.

Note, however, that this choice is far from perfect in modeling the actual operations at JFK and EWR. Indeed, flights may be operated simultaneously on different runways, which challenges the single-server assumption. In addition, arrivals are often given priority over departures by air traffic controllers, both for safety and efficiency reasons, which challenges the first-come first-served assumption. Therefore, the accuracy of the single-server approximation depends on the runway configuration in use, the demand for arrivals and departures and the air traffic control procedures. In two recent studies, the departure throughput rate has been quantified as a function of departure demand and of the arrival throughput rate for given runway configurations at Boston Logan International Airport (BOS) (Simaiakis and Balakrishnan, 2011) and at EWR (Pyrgiotis, 2011). In the latter study, delays at EWR have been computed

with two servers, one used for departures and the other one for arrivals (Pyrgiotis, 2011). This approach compensates to some extent for the limitations of our model. In conclusion, we shall continue to use throughout this work the single-server model, consistently with Assumptions 3 and 4, but the above considerations may be sources of some inaccuracies.

With the 5 assumptions outlined above, the time-varying demand rate and service rate are respectively denoted by $\lambda(t)$ and $\mu(t)$.

An Erlang process with order k and rate μ is equivalent to the sum of k successive phases each with a negative exponential distribution with a rate parameter equal to $k\mu$. Therefore, the service process is equivalent to k independent and successive service phases, each one being Markovian. Each additional aircraft joining the queue is equivalent to k additional phases in the service. Thus, at each time t , the state of the system may be described by the number of phases in the system; if n designates the number of aircraft in the system, that is to say both in the queue and in the service facility, and if j represents the number of remaining phases in the current service, the state is given by:

$$m = \max(n - 1, 0) + j.$$

If $n = 0$, then j is fixed to 0.

The resulting state-transition diagram is shown in Figure 3-3.

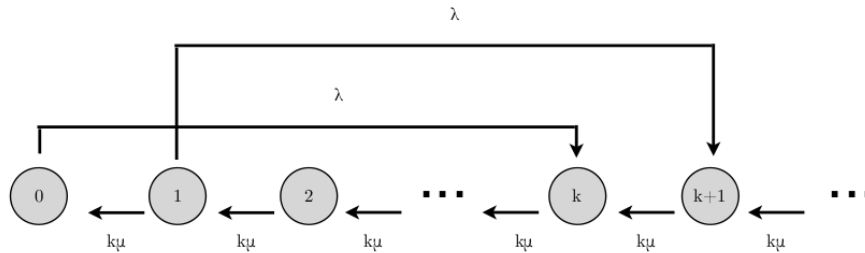


Figure 3-3: State-transition diagram of the $M/E_k/1$ model

The queuing system is assumed to be empty initially. This is a realistic assumption in practice if one chooses an appropriate local time (such as 3 a.m. or 4 a.m. or 5

a.m. at practically any US airport).

During a day of operations, the system's evolution is described by the system (3.1) of the Chapman-Kolmogorov first-order differential equations. In these equations, N denotes the queuing capacity of the system (including the customer being served) and $P_i(t)$ the probability of being in state i at time t .

$$\begin{aligned}
\frac{dP_0(t)}{dt} &= -\lambda(t)P_0(t) + k\mu(t)P_1(t) \\
\frac{dP_i(t)}{dt} &= -(\lambda(t) + k\mu(t))P_i(t) + k\mu(t)P_{i+1}(t) && \forall i \in \{1, \dots, k\} \\
\frac{dP_i(t)}{dt} &= \lambda(t)P_{i-k}(t) - (\lambda(t) + k\mu(t))P_i(t) + k\mu(t)P_{i+1}(t) && \forall i \in \{k+1, \dots, (N-1)k\} \\
\frac{dP_i(t)}{dt} &= \lambda(t)P_{i-k}(t) - k\mu(t)P_i(t) + k\mu(t)P_{i+1}(t) && \forall i \in \{(N-1)k+1, \dots, kN-1\} \\
\frac{dP_{kN}(t)}{dt} &= \lambda(t)P_{k(N-1)}(t) - k\mu(t)P_{kN}(t)
\end{aligned} \tag{3.1}$$

With a queuing capacity equal to N , the number of states in the system is equal to $kN+1$. In order to model an infinite queue capacity, N must be set very large and, as a consequence, the computational times needed to solve the system numerically increase quickly. In cases of severe congestion, the numerical solution may be extremely time-consuming.

Therefore, numerical approximations are developed to approximate the dynamics of this model. In the remainder of this chapter, the analytical approximation called DELAYS and a new model based on Monte Carlo simulation are successively introduced.

3.2 An analytical approximation: DELAYS

DELAYS is based on an analytical approximation scheme of the queuing system which describes its evolution through a system of difference equations instead of the system of the Chapman-Kolmogorov differential equations (Kivestu, 1974). The system is described by the number of aircraft in the queue when a service has been completed, so that the number of states in the system is reduced from $kN+1$ to $N+1$.

This model is based on the following dynamics. Between two successive services, a certain number of aircraft demand use of the runway system and join the queue. The

probability that during the service of aircraft j , x aircraft arrive in the queuing system is denoted by $\alpha_j(x)$. The state probabilities are denoted by $p_n(t_j)$ and they represent the probability that n aircraft are queuing when the service of the j^{th} aircraft is completed.

The difference equations are given by:

$$p_n(t_{j+1}) = p_0(t_j)\alpha_{j+1}(n) + \sum_{i=1}^{j+1} p_i(t_j)\alpha_{j+1}(n-i+1), \forall j \in \{0, \dots, N\} \quad (3.2)$$

with:

$$t_{j+1} - t_j = \frac{k+1}{k} \frac{1}{\mu(t_j)} \quad (3.3)$$

and:

$$\alpha_{j+1}(x) = \frac{\left(\frac{\lambda(t_j)}{\mu(t_j)}\right)^x e^{-\frac{\lambda(t_j)}{\mu(t_j)}}}{x!}, \forall x \geq 0 \quad (3.4)$$

These equations approximate the state probabilities for every time period of a day, which are used to evaluate the expected delay over the course of the day. Indeed, the average number of aircraft in the queue at time t is given by $L_q(t) = \sum_{i=1}^N (i-1)p_i(t)$. Consequently, Equation (3.5) provides an approximation of the average delay at time t :

$$W_q(t) = \frac{\sum_{i=1}^N (i-1)p_i(t)}{\mu(t)} \quad (3.5)$$

Kivestu's approximation assumes that an aircraft is served at the rate which prevails at the moment the aircraft demands service - instead of the rate which exists when it is actually served. This is accurate if the service rate varies slowly relative to the time each aircraft spends in the queue. In general, this is a reasonable assumption since variations of the service rate typically occur over long periods of time. For example, significant weather variations may take 1 to 2 hours to take effect, an amount of time which typically far exceeds the average flight delays. However, this assumption may be challenged in cases of sharp capacity variations and severe con-

gestion. More recently, (Gupta, 2010) has incorporated into DELAYS the notion of the *effective service rate* μ_{eff} which considers the short-term variations of the service rate that may take place between the time aircraft join the queue and the time they are served.

DELAYS has been implemented in software (Gupta, 2010; Pyrgiotis, 2011) which is computationally extremely efficient and requires less than one second to estimate the expected delays as a function of time of the day for an entire day of operations. It has been shown that the expected delays of the $M(t)/E_k(t)/1$ model are approximated very accurately by the DELAYS model (Malone, 1995; Gupta, 2010). In addition, DELAYS provides reasonable estimates of the state probabilities at each time period of the day. Therefore, this analytical model approximates very accurately and efficiently the dynamics of the $M(t)/E_k(t)/1$ model, for known demand and capacity profiles.

In order to compute the delays experienced by aircraft over extended periods of time (*e.g.* one month), this model may be used with inputs consisting of the average daily demand profile over the entire period and a flat capacity profile. The chosen capacity may be set successively equal to the airport capacity under VMC and the airport capacity under IMC. In other words, the VMC delays and the IMC delays are computed separately, for an “all VMC” day and an “all IMC” day, *i.e.* under the assumption that the weather does not change during an entire day of operations. The weighted average of these delay profiles can then be used to estimate the overall average delay, the weights being the proportion of days during which each period of the day was VMC or IMC over the set of days which is considered. This relies on the assumption that IMC periods tend to be consecutive and concentrated in time.

The approach outlined in the previous paragraph has some serious limitations. In order to compute the average delay accurately, it is necessary to have *a posteriori* knowledge of the weather conditions which were actually experienced at a given airport over a given period of time. This is a limitation when it comes to computing the expected delay in future months for different demand scenarios. In addition, the mere proportion of VMC and IMC for any given set of days does not provide information

on the timing, sequence and duration of VMC and IMC time periods during each day. But these factors (timing, sequence and duration) have a significant impact on airport congestion. If, for instance, the weather deteriorates during peak hours, the impact on delays is much more important than if the weather deteriorates at off-peak hours. Note, however, that more complex capacity models, which account to a larger extent for these effects, could be used with this model. In particular, some researchers have applied statistical clustering techniques to derive sets of typical day-of-operation capacity profiles, with each profile associated with a probability of occurring, which could then be used as inputs to the DELAYS model (Lin et al., 2008; Buxi and Hansen, 2011).

3.3 Monte Carlo Simulation

In this section, an alternative numerical approximation of the $M(t)/E_k(t)/1$ model is presented. It is based on Monte Carlo simulation and it samples the times at which each aircraft joins the queue and is served. These may be used to compute delay statistics such as the expected value and the standard deviation of the delays. All algorithmic implementations are done in MATLAB.

The development of this alternative model was motivated by two main objectives. First, the DELAYS model presented in section 3.2 captures the stochasticity of the demand and service processes, as long as their expected values for any time period of the day are known and specified. However, in practice, these expected values are subject to considerable uncertainty and in addition they may vary significantly from day to day. In fact, the average demand changes as a function of the day of the week, of short-term demand fluctuations due to holidays or special events, of the number of unscheduled operations etc. In addition, planned departure and arrival times may be dynamically readjusted over the course of the day if operations have been significantly disturbed, which also contributes to the uncertainty regarding airport demand. As well, the expected capacity depends on weather conditions, on the runway configuration in use, on air traffic control procedures, on the aircraft

mix, on the mix of departures and arrivals etc. The flexibility of the Monte Carlo simulation allows modeling the combination of these effects through more complex distributions. A model of airport demand and a Markovian model of airport capacity are respectively presented in Sections 3.3.2 and 3.3.3.

A second reason for using a simulation model is that this approach provides estimates of the variability of the delays from one day of operations to another: each simulation run represents one day of operations and the extent to which delays vary from one day to another over a month (or other extended period of time) may thus be measured.

3.3.1 General algorithm

A discrete-event simulation is used to sample demands and services over the course of one day. The algorithm is initialized at the beginning of the day with no aircraft in the system. The first aircraft then arrives and is immediately served. Throughout the day, each aircraft demanding access to the runway system joins the queue in the last position or is immediately served, if the queue is empty. Once an aircraft is served, it is removed from the queue and each remaining aircraft advances by one position in the queue. The new service then starts if the queue has not become empty.

The pseudo-code is given in Algorithm 1. A binary variable *event* is introduced at each iteration and represents the type of the next event: it is equal to 1 if the next event is a demand and to 0 if it is a service.

All delay statistics computed with this Monte Carlo simulation model and presented in Chapters 4 and 5 are obtained with 10,000 simulation runs.

The models of airport demand and airport capacity are presented in Sections 3.3.2 and 3.3.3, respectively.

3.3.2 Model of Airport Demand

A model of airport demand is developed in order to take into account the variations of the demand between successive days of operations. It attempts to capture the

Algorithm 1 General algorithm of the Monte Carlo simulation

Inputs: Demand profile, Capacity profile

1. Initialization: $t = 0$, *Queue* empty and *QueueLength* = 0
2. Generation of the first demand at time $t_D^{(0)}$: Update of the time $t = t_D^{(0)}$ and definition of *event* = 1
3. Queue update:
 - while** $t \leq Tmax$ **do**
 - \triangleright While the end of the day of operations is not reached
 - Empty* \leftarrow *QueueLength* == 0 \triangleright *Empty* is a binary variable
 - NextEmpty* \leftarrow *QueueLength* == 1 \triangleright *NextEmpty* is a binary variable
 - if** *event*=1 **then** \triangleright The next event is a demand
 - Add the aircraft at the end of *Queue*
 - if** *Empty* TRUE **then**
 - Start a new service, which ends at time t_S
 - end if**
 - Generate the next demand, at time t_D
 - else** \triangleright The next event is a service
 - Remove the aircraft from *Queue* and reorganize *Queue*
 - if** *NextEmpty* FALSE **then**
 - \triangleright After the aircraft is served, the queue is not empty
 - Start a new service, which ends at time t_S
 - end if**
 - end if**
 - Empty* \leftarrow *QueueLength* == 0
 - Time update:
 - if** *Empty* TRUE **then** \triangleright The queue is empty
 - $t = t_D$
 - event* = 1
 - else** \triangleright The queue is not empty
 - if** $t_S < t_D$ **then**
 - $t = t_S$
 - event* = 0
 - else**
 - $t = t_D$
 - event* = 1
 - end if**
 - end if**
 - end while**

Output: Times of demands, times of services and service time of each aircraft

variability of both the total number of flights in a day and of how these flights are distributed over the course of the day.

The average demand vector is denoted as (X_1, \dots, X_{96}) . For each 15-minute period i , X_i represents the average number of flights which are scheduled during period i over one month of operations. The demand vector (Y_1, \dots, Y_{96}) in effect on any given day is then sampled as follows:

1. The total number of flights scheduled in a day, denoted by N , is randomly sampled from the Poisson distribution with average $\sum_{i=1}^{96} X_i$. Figure 3-4 shows the histogram of the number of operations between 6 a.m. and midnight in July and August 2010 at JFK and the probability distribution function of this Poisson distribution. A chi-squared goodness-of-fit test with 3 degrees of freedom has been performed. The null hypothesis is that the number of flights per day follows a Poisson distribution. The results are reported in Table 3-4. The p-value is equal to 0.103, which indicates that, at a level of significance 0.05, the null hypothesis cannot be rejected, and consequently that the Poisson distribution provides an acceptable model for the total number of flights in a day.

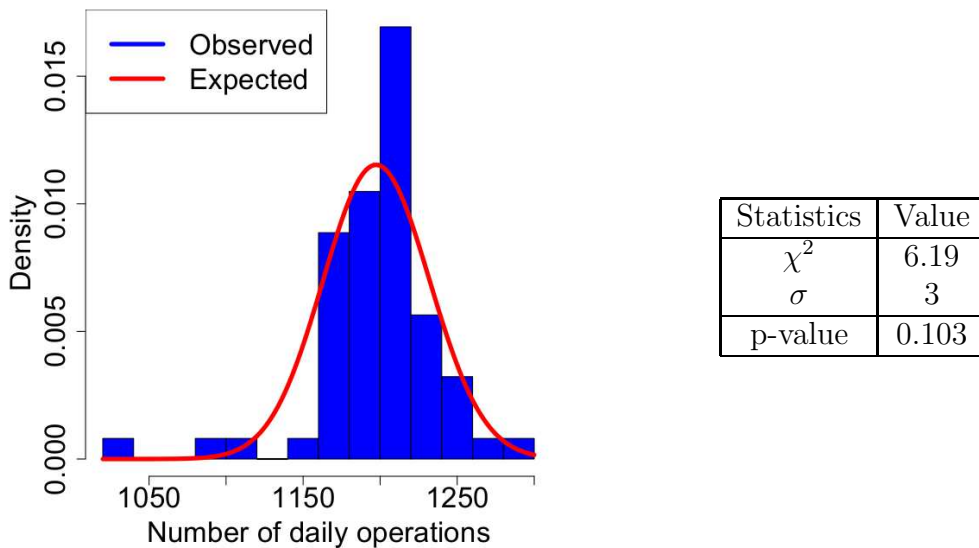


Figure 3-4: Histogram of the number of daily flights at JFK in July and August 2010 and the distribution function of the Poisson distribution

2. The N flights of the previous step are then distributed temporally over the course of the day in a manner consistent with the demand vector (X_1, \dots, X_{96}) , thus maintaining the typical pattern of peaks and valleys during the day of operations. For example, if X_i , for some particular time period i is equal to 2 per cent of $\sum_{i=1}^{96} X_i$, then a number of flights equal to 2 per cent of N will be allocated to time period i .
3. A perturbation, uniformly sampled from the five integers between -2 and +2 is then added to the number of flights allocated to each time period. In other words, for every time period i , the number of scheduled flights on a given day of operations is equal to $Y_i = \frac{X_i}{\sum_{i=1}^{96} X_i} N + U$, where U is uniformly sampled from $\{-2, -1, 0, 1, 2\}$. The reason for this perturbation is our desire to capture the day-to-day variability in demand due to general aviation flights, other unscheduled flights, flight cancellations due to mechanical problems, etc. The expected value of this perturbation term is equal to 0.
4. For every period i , the actual time when each of the Y_i flights demands the usage of the runway - *i.e.*, joins the queue - is independently sampled from the uniform distribution over the 15 minutes of each period. This is consistent with the Poisson model of the demand process.

Steps 1 to 3 sample flight schedules, which may be compared to field observations. Table 3.1 shows some statistics of the sampled demand and the observed demand at JFK for the 31 days of August 2010 for two separate periods of the day and for the entire day. The sampled demand matches quite accurately the average value, the variance and the range of the observed demand. Note that the low variance of the number of planned flights during a given period may still be consistent with the Poisson model of the demand process. It is likely that the number of aircraft joining the queuing system during any period of time - *i.e.* demanding use of the runway system - is more variable than the number of planned flights during the same period of time, because of the deviations from planned departure and arrival times over the course of one day of operations.

Table 3.1: Comparison of the sampled and the actual schedules at JFK in August 2010

Periods	Statistics	Model	Field Data
3:45 - 4:00 PM	Average	24.01	23.71
	Variance	2.59	5.76
	Minimum	20	19
	Maximum	28	28
8:45 - 9:00 PM	Average	13.00	13.10
	Variance	2.21	3.47
	Minimum	10	9
	Maximum	16	18
All day	Average	1,198	1,193
	Variance	1,189	1,095
	Minimum	1,047	1,089
	Maximum	1,354	1,292

3.3.3 Model of Airport Capacity

The capacity of the airport is modeled as a stochastic process that takes into account its variability over the course of each day. Since capacity variations are primarily due to weather variations, a dynamic model of weather conditions is developed. Two categories of days are introduced: *all-VMC days* that have only VMC periods, and *VMC/IMC days* that have some VMC and some IMC periods. The weather “profile” on VMC/IMC days is modeled by means of a Markov chain.

Given average capacity values of C_{VMC} (resp. C_{IMC}) operations per period in VMC (resp. IMC) conditions, the evolution of the capacity over the course of a day is thus modeled as follows:

1. Sampling of the weather conditions:
 - The day is all-VMC with probability π and VMC/IMC with probability $1 - \pi$. An unbiased estimator of π is the empirical proportion of days which have only VMC periods.
 - If the day is VMC/IMC, the weather conditions are modeled as a Markov

chain with transition matrix P given by:

$$P = \begin{matrix} & \begin{matrix} VMC & IMC \end{matrix} \\ \begin{matrix} VMC \\ IMC \end{matrix} & \begin{pmatrix} 1-p & p \\ q & 1-q \end{pmatrix} \end{matrix} \quad (3.6)$$

The transition diagram of this Markov chain is shown in Figure 3-5.

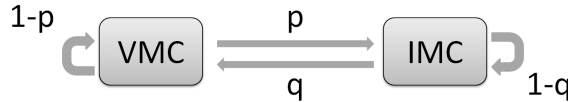


Figure 3-5: Transition diagram of the Markov chain on VMC/IMC days

The process starts at the beginning of each VMC/IMC day in the VMC state with probability τ and in the IMC state with probability $1 - \tau$. The probability τ is unbiasedly estimated as the empirical proportion of VMC/IMC days which start in the VMC state.

The probability p (resp. q) represents the probability that, for a VMC/IMC day, the weather conditions are IMC (resp. VMC) during period $i+1$ given that the weather is VMC (resp. IMC) during period i . Thus, the weather conditions at period $i+1$ only depend on the weather conditions at period i . For this 2-state Markov process it is known that the number of consecutive periods during which the weather is VMC (resp. IMC) follows a geometric distribution with parameter p (resp. q). This property was used to estimate the parameters p and q as the reciprocal of the average number of consecutive VMC and IMC periods during VMC/IMC days.

2. For each period, the airport capacity is uniformly sampled in the set $\{C_{VMC} - 1, C_{VMC}, C_{VMC} + 1\}$ (resp. $\{C_{IMC} - 1, C_{IMC}, C_{IMC} + 1\}$) under VMC conditions (resp. IMC conditions). In other words, a perturbation, equally likely to be -1, 0, or +1, is added to the capacity in each period; this takes into account short-term capacity variations, which may, for instance, be due to different runway

configurations being used or to variations in the aircraft mix.

The Markov model was then validated by comparing the empirical distribution of the number of consecutive VMC and IMC periods for VMC/IMC days in recent summer months with the model's predictions. For both distributions, a chi-squared goodness-of-fit test with 1 degree of freedom has been performed, the null hypothesis being that the number of consecutive periods in the same weather state follows a geometric distribution. The histogram of the number of consecutive VMC (resp. IMC) periods during VMC/IMC days and the results of the chi-squared tests are shown in Figures 3-6 (resp. 3-7) for JFK, with similar figures obtained for EWR.

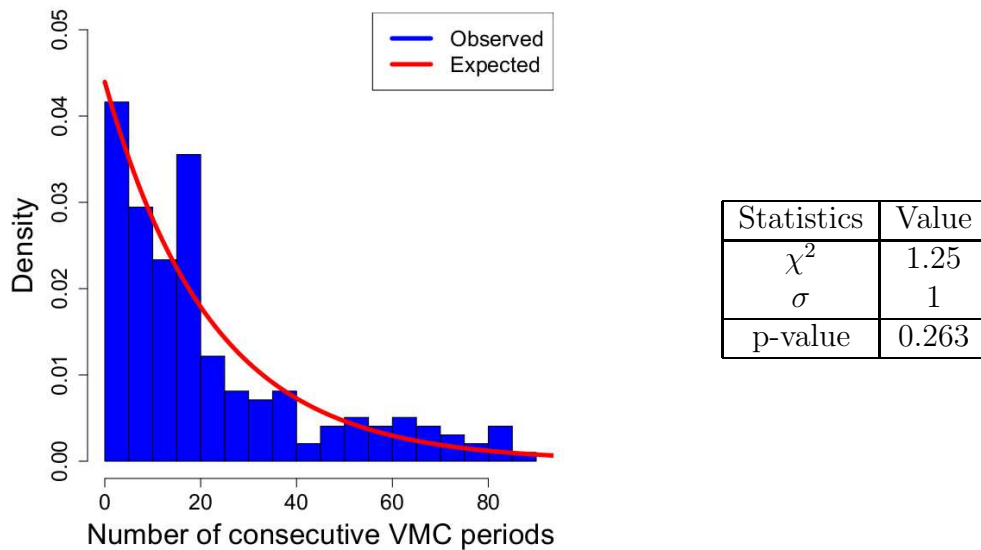


Figure 3-6: Histogram of the number of consecutive VMC periods at JFK in July and August during VMC/IMC days and the distribution function of the geometric distribution

Figure 3-6 shows that the geometric distribution provides an acceptable model for the number of consecutive VMC periods. The p-value is indeed equal to 0.263, so that the null hypothesis cannot be rejected at a level of significance 0.05.

However, Figure 3-7 shows that the number of consecutive IMC periods is not perfectly modeled by a geometric distribution. The p-value is indeed very low, so that the null hypothesis is rejected. This is mainly due to from the model's underestimation of the probability of a very large number of consecutive IMC periods, as shown in

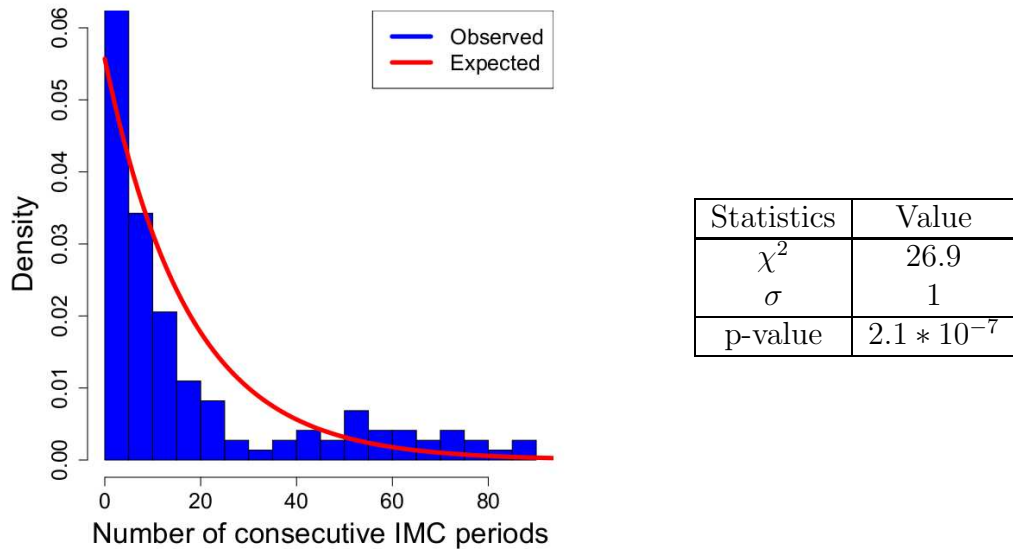


Figure 3-7: Histogram of the number of consecutive IMC periods at JFK in July and August during VMC/IMC days and the distribution function of the geometric distribution

the right end of Figure 3-7. In practice, there may indeed be some days during which the weather conditions are extreme, in which case it is very likely that flights will be operated under IMC for a long time. In this case, the transition probability between the IMC state and the VMC state is almost equal to 0. This challenges the assumption of the Markov model, according to which the transition probabilities are independent over time. We nevertheless assume that these days (that are characterized by extreme weather conditions) are outliers and cannot be fully accounted for by this simple model of weather variations.

The estimates of the parameters π , p , q and τ are reported in Table 3.2.

Table 3.2: Best estimates of the capacity model parameters for JFK and EWR

Airport	JFK	EWR
π	0.698	0.645
p	0.0440	0.0490
q	0.0557	0.0638
τ	0.618	0.595

One way to validate the model is by using it to estimate the expected fraction of

time occupied by VMC and by IMC periods, which we denote by ν_{VMC} and ν_{IMC} respectively, and comparing these estimates with the empirical fractions. The Markov chain which models the weather variations on VMC/IMC days is irreducible, positive recurrent and aperiodic, and thus ergodic. Therefore, there exists a steady-state probability distribution $\sigma = (\sigma_{VMC}, \sigma_{IMC})$ corresponding to the long-term average probability distribution of the weather conditions on VMC/IMC days. Since the proportion of VMC/IMC days is equal to $1 - \pi$, the expected proportions of VMC and IMC periods are obtained from the steady-state probability distribution, σ , of this Markov chain. We proceed as follows:

$$\begin{aligned}\nu_{VMC} &= \pi + (1 - \pi)\sigma_{VMC} \\ \nu_{IMC} &= (1 - \pi)\sigma_{IMC}\end{aligned}$$

This steady-state probability distribution σ of the 2-state Markov chain satisfies $\sigma = \sigma P$, where P is the transition matrix given in Equation (3.6). We therefore have:

$$\begin{aligned}\sigma_{VMC} &= (1 - p)\sigma_{VMC} + q\sigma_{IMC} \\ \sigma_{IMC} &= p\sigma_{VMC} + (1 - q)\sigma_{IMC}\end{aligned}$$

Since, in addition, $\sigma_{VMC} + \sigma_{IMC} = 1$, σ is obtained from the following system of equations:

$$\begin{cases} p\sigma_{VMC} = q\sigma_{IMC} \\ \sigma_{VMC} + \sigma_{IMC} = 1 \end{cases}$$

As a result, σ is given by:

$$\begin{aligned}\sigma_{VMC} &= \frac{q}{p+q} \\ \sigma_{IMC} &= \frac{p}{p+q}\end{aligned}$$

In conclusion, the expected fractions (or proportions) of VMC and IMC periods are equal to:

$$\nu_{VMC} = \pi + (1 - \pi)\frac{q}{p+q}$$

$$\nu_{IMC} = (1 - \pi)\frac{p}{p+q}$$

Table 3.3 shows these expected proportions of VMC and IMC periods at JFK and EWR in July and August and compares them with the empirical proportions. Again, the model slightly underestimates the proportion of IMC periods, because, as it was previously pointed out, it does not take into account extreme weather conditions. Nevertheless, the expected and empirical weather proportions are reasonably close to each other, which confirms the accuracy of the weather model developed in this section.

Table 3.3: Expected and empirical proportion of VMC and IMC periods at JFK and EWR in July and August

Airport	JFK		EWR	
Weather State	VMC	IMC	VMC	IMC
Expected Proportion	0.867	0.133	0.846	0.154
Empirical Proportion	0.910	0.090	0.881	0.119

Figure 3-8 shows sampled capacity profiles for one all-VMC day and for one VMC/IMC day according to this model, with hypothetical VMC and IMC capacities respectively equal to 20 and 17 movements per 15-minute period.

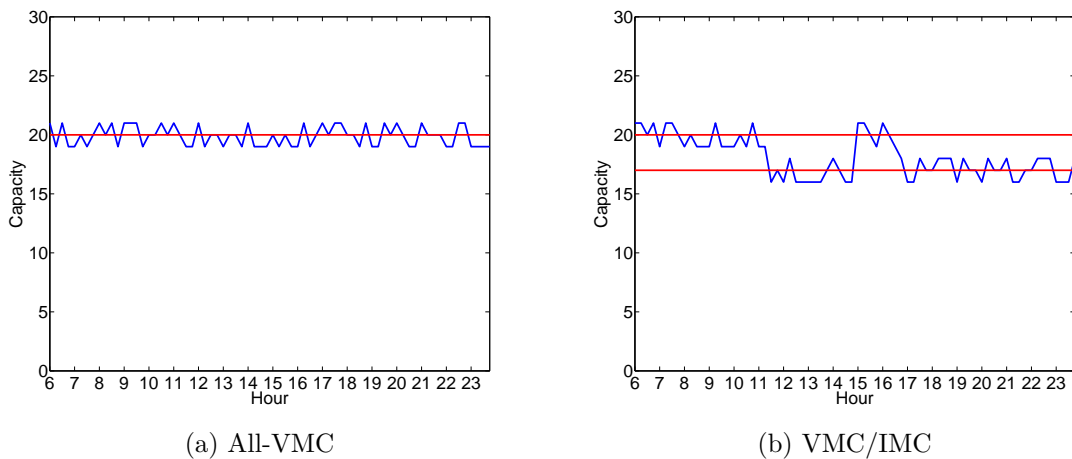


Figure 3-8: Sampled capacity profiles

3.4 Summary

Airport operations are macroscopically modeled by means of an $M(t)/E_k(t)/1$ queuing model. This model is stochastic and dynamic, *i.e.*, it considers the uncertainty and the variability over time associated with both the demand and the service processes.

Two numerical methods have been presented to approximate the dynamics of the system:

- DELAYS (Kivestu, 1974; Gupta, 2010) provides an analytical approximation of the average delays for each time period of the day. It is computationally very fast and efficient. The average delays are computed as the weighted average of the VMC and the IMC delays. Other performance metrics can also be computed.
- The Monte Carlo simulation model, described in this chapter, samples randomly each landing and each takeoff individually for an entire day of operations. It may be used to compute various statistics, including the average delay and the standard deviation of the delays between successive simulation runs. In this discrete-event simulation model, the profiles of the average demand and the capacity of the airport are sampled according to the models presented in Sections 3.3.2 and 3.3.3. Therefore, this model takes into account the day-to-day variability of the demand and of the capacity, as well as the variability of demand and capacity within the course of each day of operations.

Chapter 4

Calibration and Validation of the Models

The objective of this chapter is to calibrate and to validate the queuing models of airport congestion introduced in chapter 3 as tools for estimating the average value and the variability of air traffic delays at JFK and EWR. The analytical approximation DELAYS (Section 3.2) and the Monte Carlo simulation model (Section 3.3) are both considered in this chapter.

In the first section, the models are calibrated using historical records of operations at JFK and EWR from July 2007, with respect to delay magnitude. In other words, the model parameters are adjusted so that the expected value of the delays, as computed by the model, provide reasonably accurate estimates of the magnitude of the delays experienced in practice at these airports in July 2007. It is shown that the accuracy of the predictions depends to only a very limited extent on whether DELAYS or the Monte Carlo simulation method is used as the approximation method.

Then, the models are validated using data from August 2007. We demonstrate that both DELAYS and the Monte Carlo simulation model estimate accurately the average delays observed in practice at JFK and EWR, as well as their evolution over the course of a day of operations. In addition, we show that the Monte Carlo simulation model predicts with reasonable accuracy the variability of the delays between successive days of operations at JFK and EWR.

4.1 Calibration of the Models

4.1.1 Need for Calibration

The un-calibrated models have the following characteristics:

- The demand is defined as the number of planned operations for each time period of the day; this number is obtained from the “Individual Flights” module of the ASPM database.
- The airport capacity is given by the value reported in ASPM database; it is obtained by summing up the “Average Departure Rate” and the “Average Arrival Rate”, from the “Airport” module.
- The Erlang order k , which describes the variability of the service process, is unknown.
- The delay is computed as the weighted average of, on the one hand, the departure delay - *i.e.* the difference between the actual wheels-off time and the planned wheels-off time for departing aircraft - and, on the other hand, the arrival delay - *i.e.* the difference between the actual gate-in time and the planned gate-in time for arriving aircraft. The aggregate measures are computed as in Equation (2.1).

Figure 4-1 shows the average delays predicted by the un-calibrated model and compares them with the operation delays which were measured at JFK and EWR in July 2007. DELAYS is used as the approximation method in this case. Two extreme values of the Erlang order k are considered: $k = 1$ and $k = \infty$. Note that the model greatly underestimates the delays experienced at both JFK and EWR. At JFK, for instance, peak delays were larger than 60 minutes on average in July 2007, while the model predicts that their expected value is approximately equal to 20 minutes. As well, computed delays are lower than 10 minutes at EWR, while peak delays have been larger than 50 minute in practice.

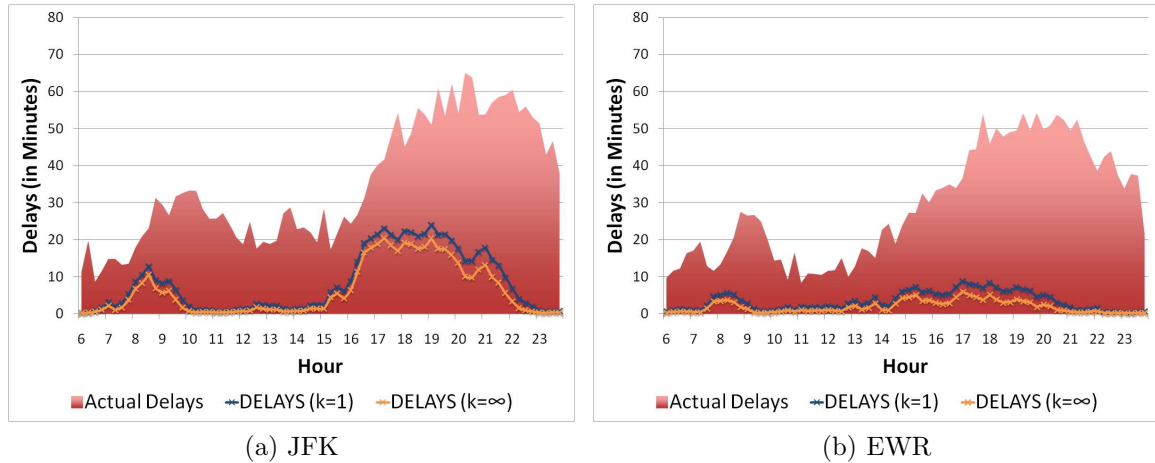


Figure 4-1: Results of the un-calibrated model in July 2007

4.1.2 Calibration Steps

The difference between the delays actually observed in practice at JFK and EWR in August 2007 and the delays predicted by the un-calibrated model may be due to the combination of three factors:

- The number of scheduled flights may underestimate the number of flights which actually contribute to airport congestion.
- The capacity values reported in the ASPM database may overestimate the throughput rate which may be sustained over significant periods of time.
- The average delays observed in practice may be larger than the delays which are due to runway congestion at JFK and EWR.

The objective of the calibration of the model is therefore to determine three quantities: the demand for use of the runways, the service provided by the runway system - including its capacity, and the actual delays incurred by aircraft using the runways. The two former ones are the inputs to the model, and therefore determine the delays predicted by the model. The latter one is the quantity which the model's outputs are trying to estimate and should be compared to. This section presents and discusses the main choices which have been made to determine these quantities and to estimate the model parameters.

Demand process

In addition to commercial flights, demand for use of the runways includes unscheduled operations, such as general aviation and military flights. Indeed, these flights contribute to congestion because they occupy the runway system during their operation. As shown in table 2.1, they represent approximately 5% of the total air traffic volume at JFK and EWR, *i.e.* 50 to 100 flights per day. It is assumed that, on average, the temporal distribution of these flights through the course of the day is the same as the distribution of the scheduled flights; in other words, if 2% of the daily flights are scheduled between 3 PM and 3:15 PM, then 2% of the unscheduled flights also demand use of the runway system during this time interval.

Including these unscheduled operations increases the demand; as a consequence, the computed delays will be larger and thus closer to the reported ones.

Service process

When it comes to the capacity of the runway system, we have chosen to disregard the capacity estimates for each part of the day that are given in the ASPM database. The reason is that these estimates are determined rather subjectively by the air traffic control system and often seem overly optimistic (Figure 2-3). Instead, we have adjusted by trial-and-error the runway capacities under VMC and under IMC with the objective of matching as closely as possible the average delays observed in practice at JFK and EWR. In other words, we estimate the *sustained throughput rate*, which is defined as the average service rate (*i.e.*, capacity) which, if sustained over extended periods of time, results in delay levels similar to those which are observed in practice.

This led to the use of $k = 3$ for the cases described here. Note that this choice is subject to some uncertainty, as service times are rounded up to an integer number of minutes (*i.e.*, 1 minute, 2, 3) in the database, so that the precision of the service time data is limited. Moreover, the fact that both airports typically operate with two or three simultaneously active runways creates problems of data interpretation because of the assumption (Chapter 3) of a single-server system.

Actual Delays

We are interested here in the delays that can be attributed to *local* runway system congestion. Indeed, we wish to compare the model's outputs to field data on actual local delays. But the available data are contaminated by delays due to many factors other than the relationship between local demand and local runway system capacity. These factors may include mechanical problems with the aircraft, late-arriving cockpit or cabin crews, delayed passengers in terminal buildings and, most important, late-arriving aircraft due to "upstream" delays on earlier flight legs. It is therefore necessary to select carefully the data on which the estimates of actual local delays are based. As indicated in Chapter 2, we have assumed that the unimpeded arrival time of a flight is given by the time predicted in the flight plan. On the departure side, the local delay is assumed to be given by the taxi-out delay only, instead of the sum of the gate delay and the taxi-out delay. These choices eliminate to a large extent, upstream delays and delays from other causes. Note, however, that this is a far from perfect procedure. For example, some of the gate delays that departures suffer are indeed caused by local congestion: if many aircraft are already queued for takeoff on the taxiway system, air traffic controllers may decide to delay the departure of more aircraft from the gates to avoid aggravating further the congestion of the airfield.

In addition, we subtract from the delay data any "residual" delays, *i.e.* delays suffered for various unknown reasons during non-congested periods of the day. Thus, we assume, in effect, that no delays should exist during these very low-traffic periods.

We have used these procedures in estimating the actual local delays, but must underline that these estimates are subject to considerable uncertainty and should be treated only as approximate. As detailed in Chapter 2, the ASPM database itself is not fully reliable in some respects, in the first place. Moreover, the estimation of the true value of local congestion delays is affected by such complexities as the practice of schedule padding by airlines, the use of different surface congestion management techniques at different airports and the initiation of Ground Delay Programs when severe congestion is predicted.

4.1.3 Calibration Results

The procedures described in Section 4.1.2 have been implemented at JFK and EWR with data from July 2007. Figure 4-2 shows the demand profiles that were used as inputs to the model (in black) for JFK (Figure 4-2a) and EWR (Figure 4-2b). The demand profiles are further broken down into scheduled departures, scheduled arrivals and unscheduled flights. In addition, we estimate the sustained throughput rates, as defined in Section 4.1.2 under “Service process”. These rates essentially amount to our best estimates of expected runway capacity at JFK and EWR per 15-minute period. They are given in Table 4.1.

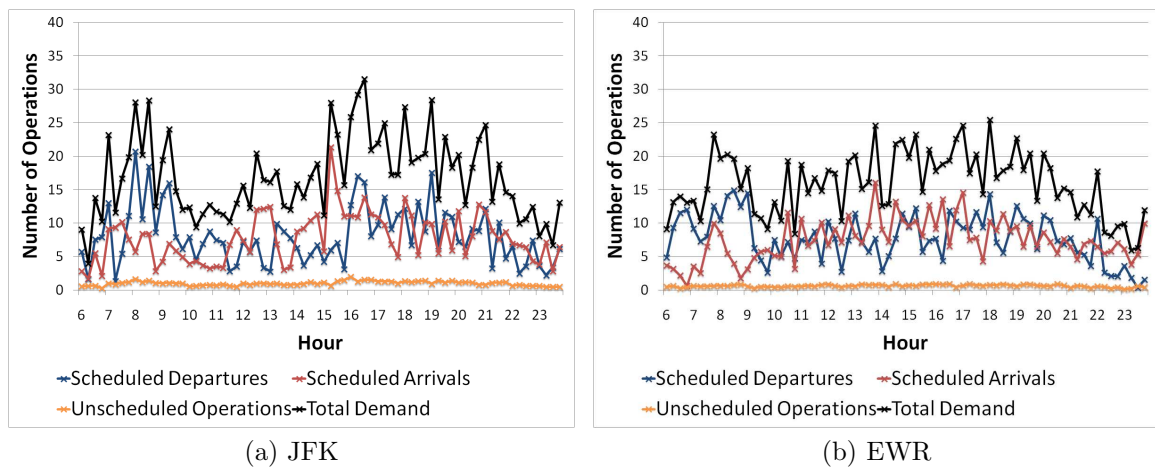
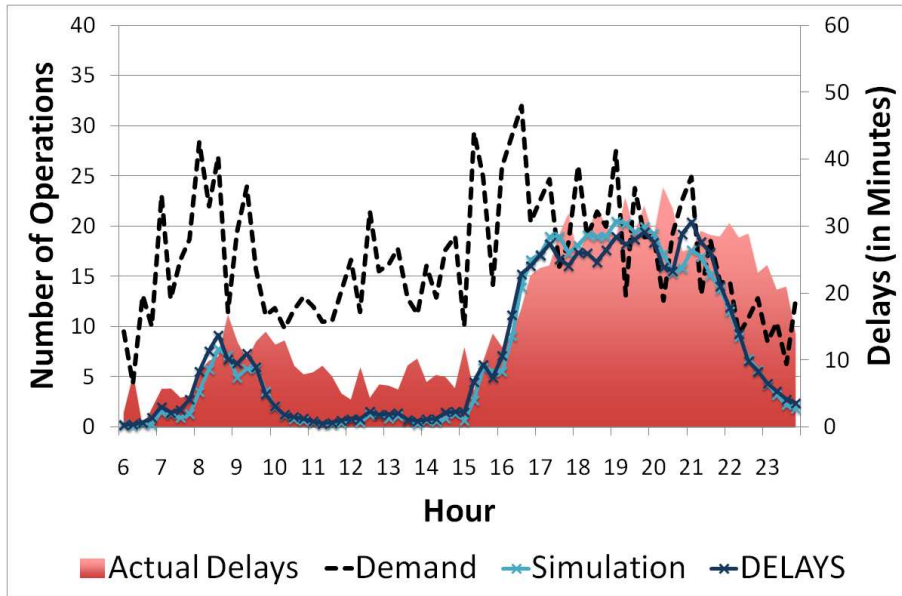


Figure 4-2: Average demand profiles at JFK and EWR in July 2007

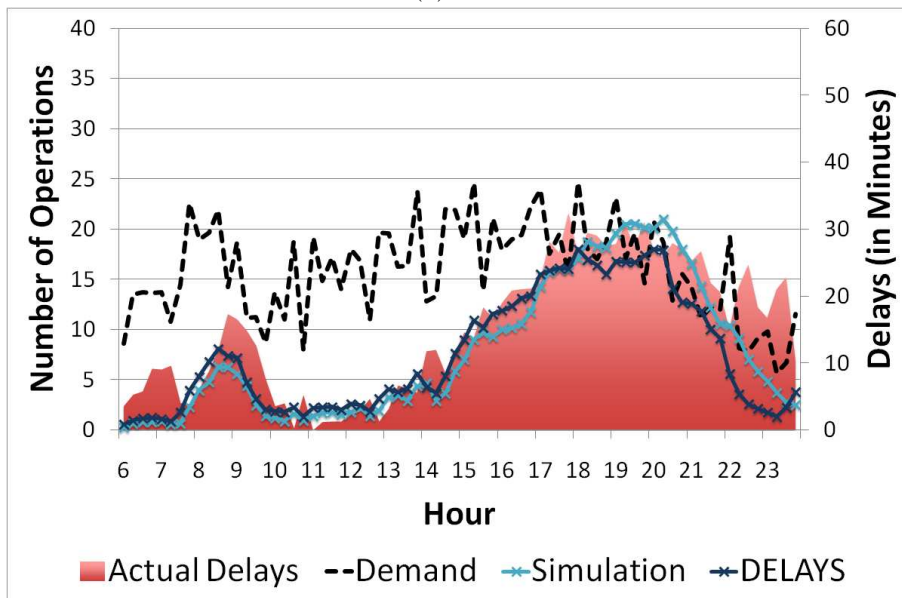
Table 4.1: Values of the service rate considered

Airport	Weather	Capacity
JFK	VFR	21 per 15 minutes
	IFR	18 per 15 minutes
EWR	VFR	19 per 15 minutes
	IFR	16 per 15 minutes

Figure 4-3 shows the results of the calibrated model for JFK (figure 4-3a) and for EWR (figure 4-3b) and the delays actually observed in practice at these airports in July 2007. The results of both DELAYS and the Monte Carlo simulation model are shown in these figures.



(a) JFK



(b) EWR

Figure 4-3: Predicted and Actual Delays at JFK and EWR in July 2007

Note, first, that DELAYS and the Monte Carlo simulation model provide very similar estimates of the expected value of flight delays at JFK and EWR in July 2007. Thus, the predicted delays do not depend significantly on whether one method or the other is applied. This confirms that the two numerical models, which approximate the dynamics of the $M(t)/E_k(t)/1$ queuing model, are consistent with each other.

Moreover, the delays that these models predict approximate very well the delays

that were actually experienced at JFK and EWR in July 2007. In general, these delays tend to form in the morning, dissipate around noon and return again in the afternoon with large delays experienced during the evening hours. These patterns are predicted well by the models. It is also noteworthy that the expected value of the delays computed by the models is close to the average actual flight delays throughout the day and, especially, during the peak delay periods.

Actual delays cannot, of course, be predicted with perfect accuracy because of the complexity of the processes at stake and because of the multiple sources of uncertainty. For instance, the delays observed late at night (after 22:00) at both airports are much higher than predicted by the models. The reason, we believe, is that the delays observed during that period are associated with a small number of aircraft which suffer “propagated delay”, *i.e.* delay due to the ripple effect of congestion earlier in the day that affects aircraft which visit JFK or EWR multiple times in the course of a day (Pyrgiotis, 2011). Moreover, the model seems to underestimate the delays suffered around noon, after the morning peak, especially at JFK. This may be due, in part, to similar propagation of delays experienced earlier in the morning. In addition, the imbalance of departures and arrivals at JFK between 8 a.m. and 10 a.m. observed in Figure 4-2a may also explain, in part, the model’s underestimation of these delays. Nevertheless, it is clear that the calibrated model captures quite well the dynamics of formation and propagation of delays over the course of one day of operations and estimates well the extent of congestion observed at JFK and EWR in July 2007.

4.1.4 Sensitivity to Model Parameters

Through the calibration of the model, as outlined in Section 4.1.2, several model parameters have been estimated. Given the uncertainty which these estimations are subject to, we conduct sensitivity analyses to investigate the effects that changes in the input estimates may have on the magnitude of the delays predicted by the model. We specifically focus on two questions in this section:

- To which extent does the magnitude of the predicted delays depend on the

estimate of the airport capacity?

- To which extent does the magnitude of the predicted delays depend on the variability of the service process?

Airport Capacity

The sustained throughput rate has been estimated by comparing the model's outputs with the delays observed in practice at JFK and EWR. Since airport capacity may not be estimated with perfect accuracy and certainty, it is important to analyze the extent to which the model's predictions may change if alternative estimates are considered.

Figure 4-4 shows the expected value of the delays predicted by the Monte Carlo simulation model at JFK (Figure 4-4a) and EWR (Figure 4-4b) in July 2007, for different combinations of VMC and IMC capacity estimates. For example, the "Cap. 22/19" graph for JFK in Figure 4-4a corresponds to the case in which the VMC capacity of JFK is assumed to be 22 movements per 15 minutes and the IMC capacity 19 movements per 15 minutes. Note that even marginal variations of capacity lead to significant changes of the predicted delays when the runway system operates close to capacity. In some cases, if the estimate of the capacity of the runway system is reduced by 1 flight per 15-minute period (or 4 per hour), the expected value of the peak delays may increase by as much as 15 to 20 minutes.

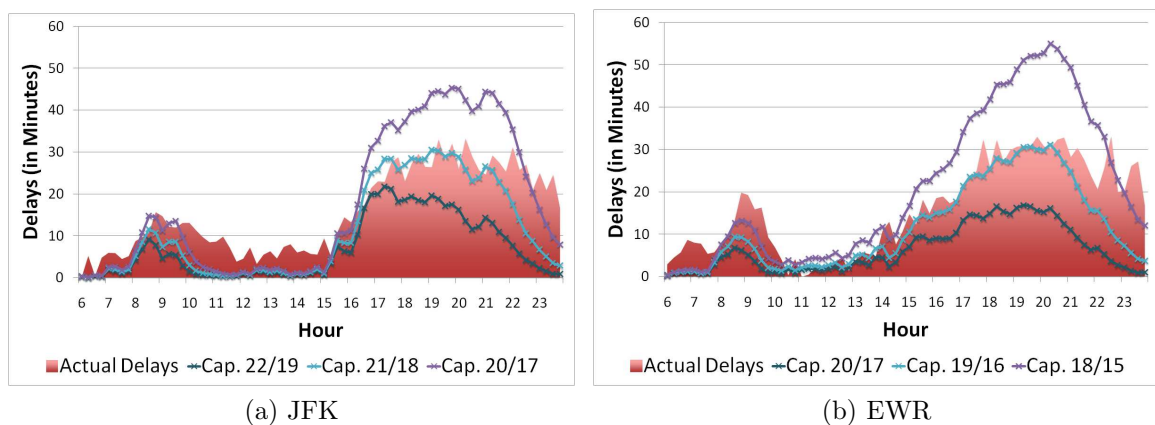


Figure 4-4: Average delays and predicted delays with different VMC and IMC capacity estimates, at JFK and EWR in July 2007

Variability of the service process

One indicator of the variability of the service process is the Erlang order k : the smaller k , the more variable the service process. Figure 4-5 shows the expected value of the delays predicted by the Monte Carlo simulation model at JFK (Figure 4-5a) and EWR (Figure 4-5b) in July 2007, for different values of k . Note that the smaller k , the larger the average delays are. In other words, for the same values of airport capacity (*i.e.* for the same average service time), a more variable service process results in larger delays than a less variable one. At peak hours, the difference between the two extreme cases at EWR may be as large as 6 minutes, or approximately 20% of the predicted delays. The adopted value of $k=3$ seems to be a reasonable choice, in any event.

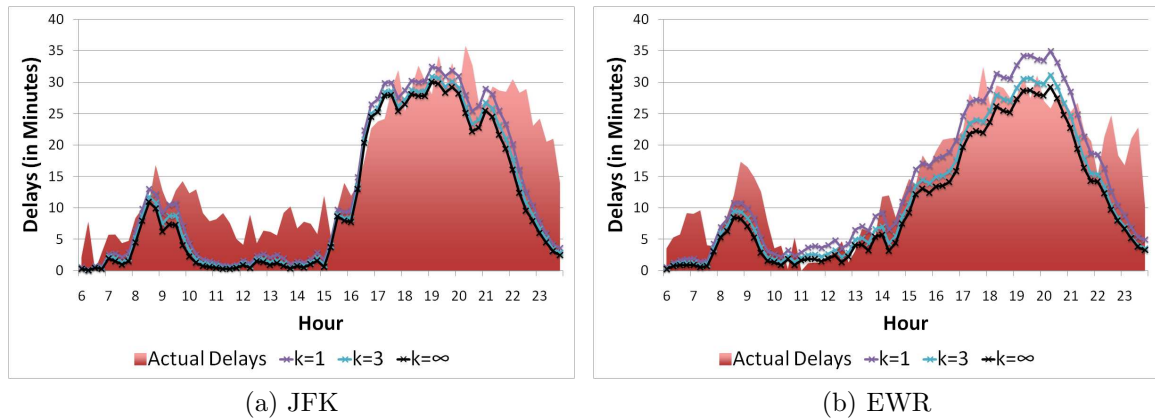


Figure 4-5: Average delays and predicted delays with different Erlang orders, at JFK and EWR in July 2007

Conclusion

In conclusion, the delays predicted by the models are very sensitive to changes in the model's inputs. We have demonstrated that the expected value of the delays depends critically on the estimate of the airport capacity and, to a lesser extent, on the variability of the service process (for a fixed value of the airport capacity). Changes in other model parameters might have similar effects, including changes in demand estimates or alternative choices in the definition of airport demand and capacity in the Monte Carlo simulation (Sections 3.3.2 and 3.3.3).

The estimation of the models' inputs may thus have significant effects on its outputs, and therefore the predicted delays should be treated as approximate. Sensitivity analyses should always be conducted to account for some of the uncertainty associated with the models' inputs.

4.1.5 A note on Airport Capacity

In this study, we have estimated the *sustained throughput rate*, defined as the average service rate which, if sustained over long periods of time, creates delays of a level similar to the one observed in practice at JFK and EWR. Table 4.2 compares this estimate to two alternative evaluations of airport capacity. It reports:

- Our estimate of the sustained throughput rate;
- The estimate of the maximum throughput rate at EWR, defined as the maximal number of flights which may be operated per unit of time. It is evaluated by computing the 95th percentile highest value of observed throughput (Odoni et al., 2011).
- A range of capacity estimates obtained by the Office of Inspector General (OIG) of the US Department of Transportation (Office of Inspector General, 2010).

Table 4.2: Comparison of capacity estimates

Airport	Weather	Sustained Rate	Maximum Rate	OIG range
JFK	VFR	21	N/A	19-22
	IFR	18	N/A	16-17
EWR	VFR	19	21	21-23
	IFR	16	19	15-17

Note, first, that the sustained throughput rate obtained is lower than the maximum throughput rate at EWR. In other words, delays observed at EWR are larger than those which would be experienced if the airport could operate sustainably at its maximum throughput rate. In addition, our capacity estimates fall within the range of the evaluations of the OIG, with the exception of the VMC capacity at EWR.

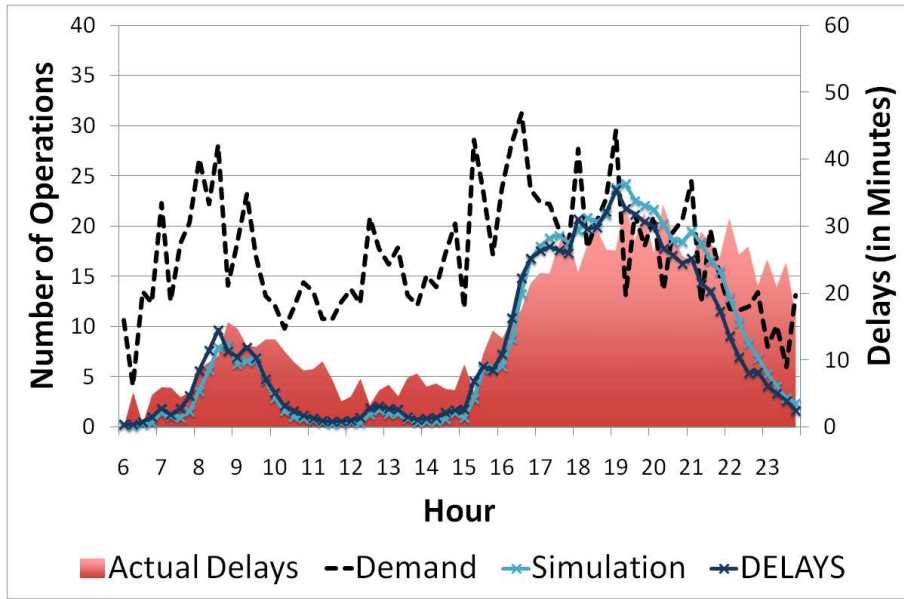
4.2 Validation of the Model

The calibrated models can now be validated by predicting the expected local delays and the variability of these delays at JFK and EWR in the month of August 2007 and then comparing the predictions with the reported actual delays. We consider as fixed the parameters of the model that were estimated during the model calibration stage which was presented in Section 4.1. In particular, the airport capacity is given by the values reported in Table 4.1. We only change the estimate of the airport demand, which is given by the average number of planned flights for any period of the day in August 2007 at JFK and EWR. The new outputs of this model are compared to the delays actually experienced at these airports in August 2007. We show that the delays predicted by the model approximate very well both the magnitude and the variability of the reported delays.

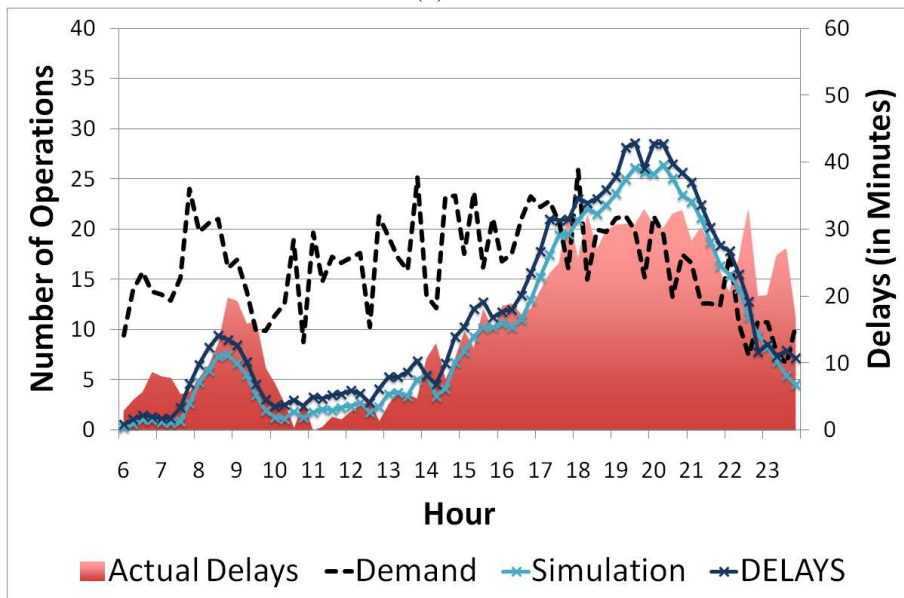
4.2.1 Validation of the Model with respect to Delay Magnitude

The expected value of the delays predicted by the model in each 15-minute period of a day in August 2007 turns out to be a good approximation of the average delays actually observed in practice. Figure 4-6 presents the results for JFK (Figure 4-6a) and for EWR (Figure 4-6b) for August 2007. The figures show the average delays observed in practice and the expected value of the delays predicted by the model. The results of both DELAYS and the Monte Carlo simulation model are presented in these figures. Note that these results are similar to those obtained for July 2007 (Figure 4-3) and that the model predicts well the magnitude of the delays and their evolution over the course of one day of operations. Exactly as in the calibration stage, the predictions are least accurate during the late night hours (after 22:00) at both airports and during late morning at JFK.

A first measure of the model's accuracy is the difference between the average delay over an entire day of operations predicted by the model and the average delay observed in practice. Table 4.3 compares these statistics for the 18-hour period between 6 a.m.



(a) JFK



(b) EWR

Figure 4-6: Predicted and Actual Delays at JFK and EWR in August 2007

and 12 a.m., as well as lists the absolute and relative differences between them. The average delays are well estimated by the model: indeed, the model's error is lower than 10%, which corresponds to an absolute error equal to 2 minutes at most. Given the model's macroscopic nature, this level of accuracy is entirely adequate.

Another measure of the model's performance is the correlation between the time series of predicted and actual delays pictured in Figure 4-3. A regression analysis

Table 4.3: Predicted and observed average delay (in minutes) between 6 a.m. and 12 a.m. in August 2007

Airport	JFK		EWR	
Actual Delays	22.46		20.97	
Method	DELAYS	Simulation	DELAYS	Simulation
Predicted Delays	20.29	20.48	23.22	20.68
Absolute Error	2.18	1.99	2.25	0.29
Relative Error	9.69%	8.85%	10.72%	1.38%

was performed comparing the actual delay profile - *i.e.* the average actual delay for every 15-minute period of the day, and the predicted delay profile - *i.e.* the expected value of the delay computed by the model for every 15-minute period of the day. The correlation between these time series is a measure of the accuracy with which the model predicts the evolution and fluctuations of delays over the course of the day.

Figure 4-7 shows scatter diagrams for the actual and predicted demand profiles in August 2007 at JFK (Figure 4-7b) and JFK (Figure 4-7a). (The predictions of the Monte Carlo simulation are shown in the figure.) It demonstrates that the actual and predicted delays are quite similar for most of the 15-minute intervals. This is confirmed by the high values of the correlation coefficient between the actual and the predicted delay profiles reported in Table 4.4.

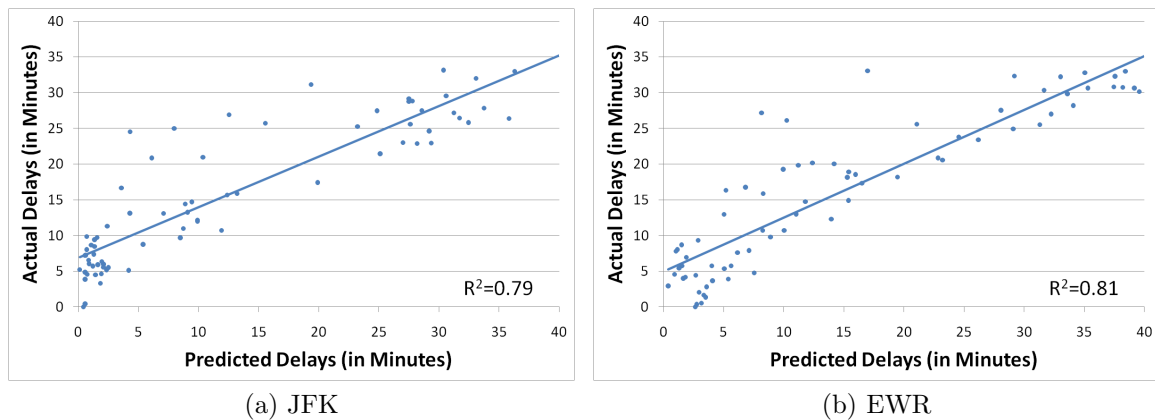


Figure 4-7: Actual delays vs. predicted delays at EWR in August 2007

In summary, the simulation model estimates well the magnitude of the queues at the two airports and captures accurately their dynamics.

Table 4.4: Correlation between the actual and predicted delay profiles over the course of a day in August 2007

Airport	JFK		EWR	
Method	DELAYS	Simulation	DELAYS	Simulation
Pearson's correlation	0.834	0.889	0.887	0.898
Coefficient of determination R^2	0.695	0.790	0.786	0.806

4.2.2 Validation of the Model with respect to Delay Variability

One of the objectives of the Monte Carlo simulation model is to predict the variability of the delays from one day of operations to another. This topic has attracted only limited attention to date despite the fact that delay variability is a very important aspect of airport performance and reliability. For instance, if delays from day to day tend to stay close to their long-term average values, then they can be anticipated with reasonable accuracy and airlines may be able to accommodate them through adjustments in their operations or schedules. If, however, delays are extremely variable from day to day, knowing the average long-term delay is of limited value. The likelihood of very large deviations from the average on any particular day is now much higher and schedule reliability lower.

The variability of the delays is typically measured by the following two quantities:

- The range of the delays, *i.e.* the difference between the highest and the lowest delays experienced during a given period of time.
- The standard deviation of the delays, *i.e.* the extent to which the daily average of delays varies between successive days of operations over a longer period of time - typically one month.

In this section, we compare the range and the standard deviation of the delays observed in practice at JFK and EWR in August 2007 to the model's predictions. According to queuing theory, the average and the variability of the delays (*i.e.*, the expected value and standard deviation, respectively) are correlated to each other, but

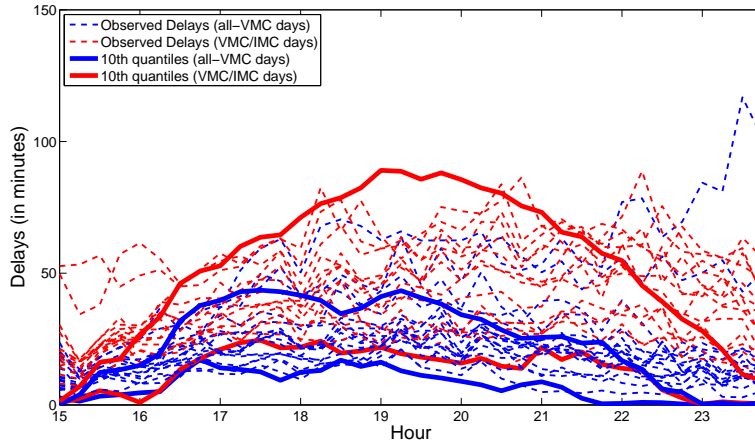
their exact mathematical relationship under transient conditions is unknown.

We compute the predicted range of delays by considering the 10th quantile of the simulation results. In general terms, a data point is said to be at the τ^{th} quantile of a data set if it is larger than a proportion of $\frac{\tau}{100}$ of the data points in the set and if it is smaller than a proportion of $1 - \frac{\tau}{100}$. We thus eliminate simulation runs with average delays larger than 90% of the other runs and those with average delays less than 10% of the other runs. This procedure robustly eliminates outliers in the evaluation of the range of flight delays. Figure 4-8 compares this predicted range (in full lines) to the range of delays observed in practice at JFK (Figure 4-8a) and EWR (Figure 4-8b) during peak afternoon hours (*i.e.* between 3 p.m. and 12 a.m.). The dashed lines in this figures represent the delays observed at these airports on each day of August 2007. The days are separated according to the distinction introduced in Section 3.3.3: *all-VMC days* are represented in blue and *VMC/IMC days* are represented in red.

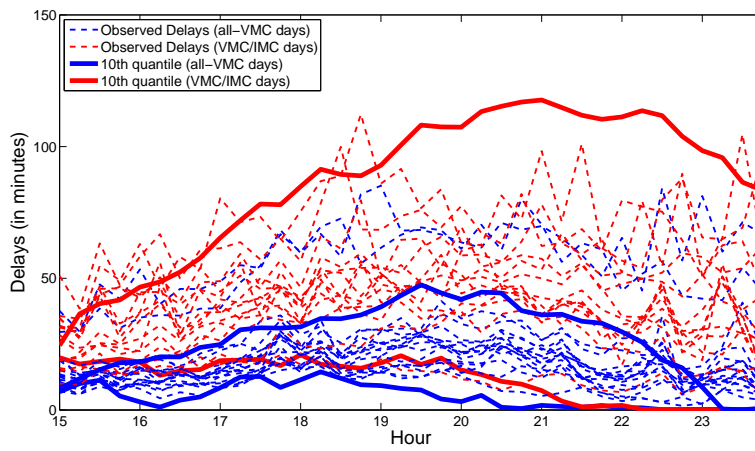
Figure 4-9 compares the standard deviation of the delays predicted by the model with the standard deviation observed in practice at JFK (figure 4-9a) and EWR (figure 4-9b) in August 2007 for all 15-minute periods of the day.

Note, first, that delay variability is large at both JFK and EWR. First, the range of the delays is very large. Even for days during which all flights are operated under VMC, peak delays may be very different from one day of operations to another. For instance, at JFK, they may be as low as 20 minutes and as large as 60 minutes. Unsurprisingly, the range of the delays is even larger if days with some IMC periods are considered. In addition, the standard deviation of the delays at peak hours is approximately equal to 20 minutes, roughly the same order of magnitude as the average delays during these hours - which are slightly larger than 30 minutes. Note also that the standard deviation of the delays is largest in the afternoon when the average delays are also the largest. As a result, runway congestion not only creates large delays on average, but also increases the variability of delays around their average value.

Figures 4-8 and 4-9 show that these aspects of delay variability are captured well by the model. First, the range of the delays is well approximated by the model for

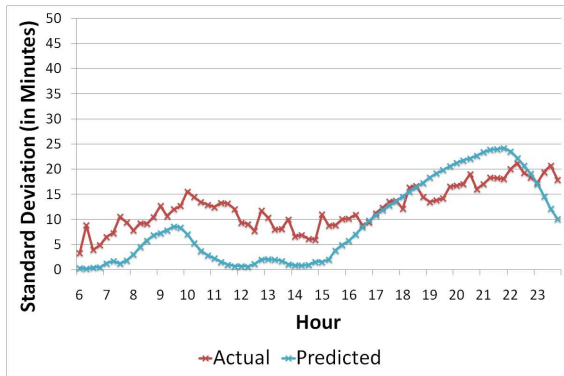


(a) JFK

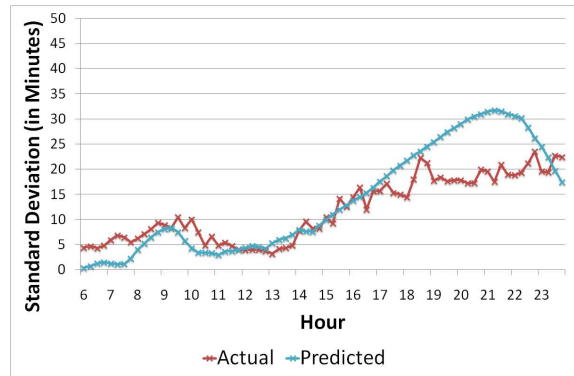


(b) EWR

Figure 4-8: Comparison of the range of delays at JFK and EWR in August 2007



(a) JFK



(b) EWR

Figure 4-9: Comparison of the standard deviation of delays at JFK and EWR in August 2007

both categories of days. There is only a very limited number of days where observed delays do not fall within the range predicted by the model, and at the same time the upper and lower bounds estimate reasonably the maximum and the minimum delays observed in practice. In addition, the predicted and actual standard deviations of the delays are of the same order of magnitude, and they evolve similarly in the course of the day.

In summary, the Monte Carlo simulation model estimates accurately the variability of the delays across a set of many days of operations. This model may therefore be used not only to predict the average value of flight delays, but also their dispersion around this average. In particular, it may be used to quantify the probability that on-time performance will be below a given threshold on a given day.

4.3 Conclusion

In this chapter, the $M(t)/E(t)/1$ queuing model of airport congestion has been calibrated and validated using historical records of airport operations at JFK and EWR in Summer 2007. The month of July 2007 has been used for calibration and the month of August 2007 has been used for validation.

It has been shown that the two numerical approximation models of the $M(t)/E_k(t)/1$ queuing model presented in Chapter 3, *i.e.* DELAYS and the Monte Carlo simulation model, estimate accurately the magnitude of the delays at these airports and the dynamics of their formation and their propagation over the course of the day. Sensitivity analyses have indicated the extent to which the magnitude of the delays depends on the average and the variability of the service process. First, even incremental changes in capacity result in substantial changes in delays when the system operates close to capacity. In particular, weather variations result in significant delay variations. All else being equal, the more variable the service process, the larger delays are on average.

In addition, the Monte Carlo simulation model has been shown to estimate accurately the variability of the delays. Both the range and the standard deviation of the

predicted delays match well with those which are observed in practice. Therefore, the simulation model may be used to quantify the extent to which the level of service varies from one day of operations to another. In particular, it may be used to evaluate the likelihood that the level of service during a particular day will be worse than a given threshold - given an average number of flights scheduled at the airport.

This model may now be used to analyze the evolution of performance levels at JFK and EWR between 2007 and 2010 and to evaluate the impact that alternative schedules may have on on-time performance.

Chapter 5

Policy Implications

In Chapter 4, the queuing models have been calibrated and validated using data from July and August 2007. We have shown that they estimate accurately the magnitude and the variability of the delays for these two months. In this chapter, we use this model to analyze trends in scheduling and on-time performance at JFK and EWR between 2007 and 2010. First, we present the evolution of airport demand and delays at both airports over this period. We then apply the model with average demand profiles from 2007 to 2010 and we show that the large delay reductions observed at JFK and EWR since 2007 have been primarily due to changes in flight schedules. In particular, we demonstrate that the relationship between airport demand and delays is highly nonlinear at congested airports. In addition, for a given number of flights, their distribution over the course of the day may have significant effects on flight delays. Finally, we use the Monte Carlo simulation model to quantify the effects of a slot control policy on the average and the variability of airport delays.

5.1 Demand and Delay Trends between August 2007 and August 2010 at JFK and EWR

In this section, we analyze trends in scheduling and delays at JFK and EWR between August 2007 and August 2010.

Figure 5-1 (resp. Figure 5-2) shows the changes, percent-wise, of the average number of flights operated in a day and of the average local delays¹ between July 2007 and July 2008, 2009 and 2010 (resp. August 2007 and August 2008, 2009 and 2010) at JFK (Figures 5-1a and 5-2a) and EWR (Figures 5-1b and 5-2b). Note that airport demand, as measured by the number of aircraft movements, has declined slightly at both JFK and EWR between 2007 and 2010. At the same time, very significant delay reductions have been observed at both airports. The decline in delay has been much larger, percent-wise, than the decrease in the demand: whereas the demand has decreased by approximately 5 to 10%, the local delays in August 2010 were, on average, about one half of what they were in August 2007, both at JFK and EWR².

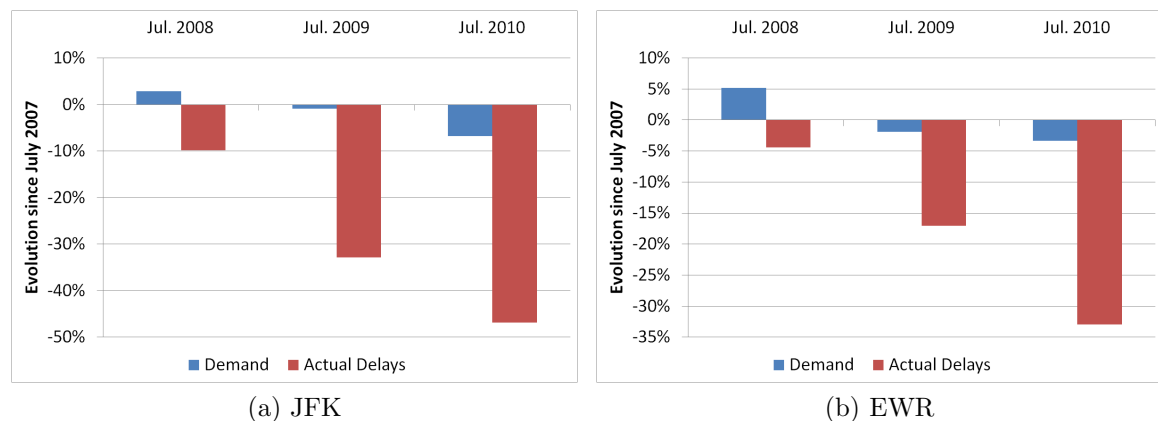


Figure 5-1: Evolution of average demand and delays from July 2007 onwards

This reduction of airport demand at both JFK and EWR between 2007 and 2010 is primarily due, we believe, to the combination of the economic downturn during this period, which has affected air transportation demand negatively and the implementation of schedule caps at these airports from May 2008 onwards. Figure 5-3 (resp. Figure 5-4) shows the number of scheduled departures and arrivals at JFK (resp. EWR) during all 1-hour periods between 6 a.m. and 12 a.m. for the months of August 2007-2010. Each point in these scatter plots corresponds to an observed count of scheduled departures and arrivals, its size being proportional to the frequency of

¹The actual delays represent the local congestion delays defined in Section 4.1.2 and modeled in this study.

²Obviously, the total flight delays have also declined substantially over the same period of time.

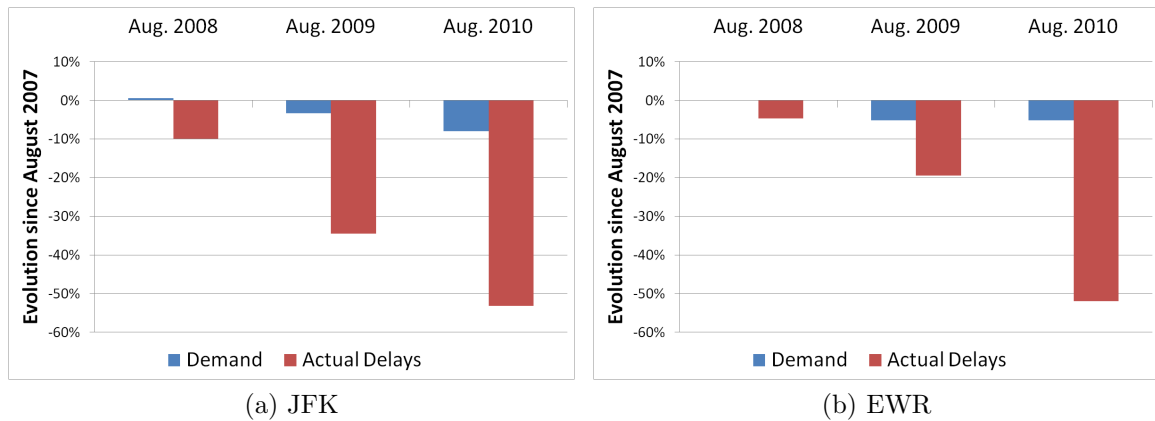


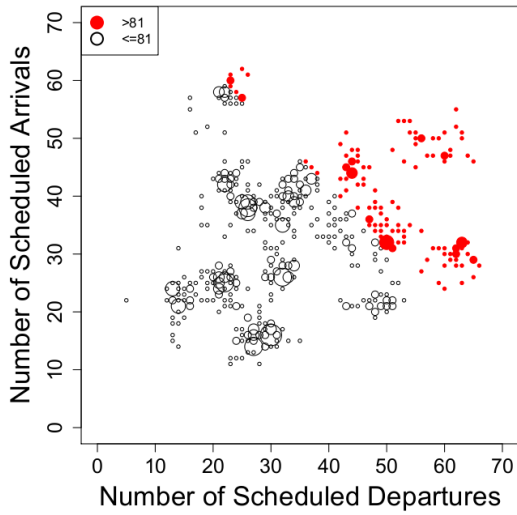
Figure 5-2: Evolution of average demand and delays from August 2007 onwards

each observation. The red points indicate 1-hour periods during which more flights than the the recommended cap of 81 operations have been scheduled.

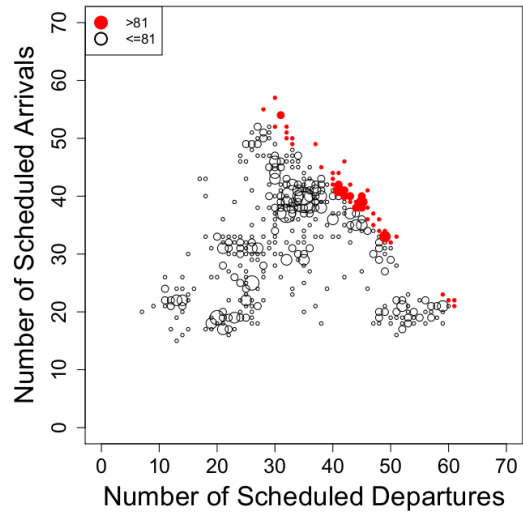
Note that the proportion of time during which the number of scheduled operations exceeded 81 was significantly larger in 2007 than in 2008, 2009 and 2010. In particular, while approximately the same number of flights were scheduled in August 2008 as in August 2007 at both airports, as indicated in Figure 5-2, the 81-slot limit was exceeded much less often in August 2008 than in August 2007. Therefore, the implementation of the recommended cap in 2008 has resulted in smoothing the demand on an *hourly basis* over the course of a day. This may explain, in part, the delay reduction between August 2007 and August 2008 observed at both JFK and EWR in Figure 5-2.

Note, also, that the schedule caps have not been strictly enforced since 2008 at JFK. Indeed, there have been on average 1 to 2 hours per day in August 2009 and August 2010 with more than 81 movements scheduled at JFK. By contrast, this limit was almost never exceeded at EWR in August 2009 and 2010 (Figures 5-4c and 5-4d).

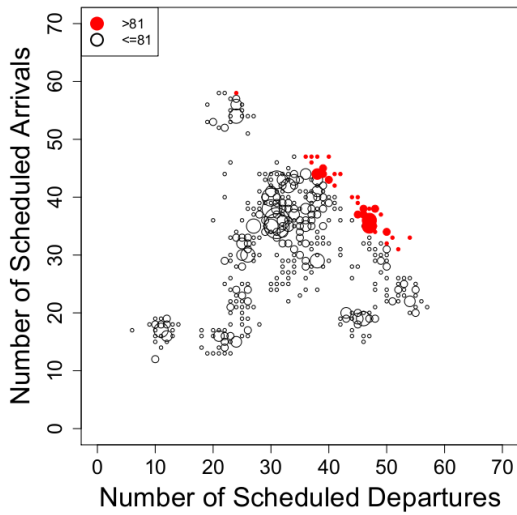
However, the number of scheduled operations exceeds airport capacity much more often if flights are aggregated on a 15-minute basis. Figure 5-5 shows the scatter plots of scheduled departures and arrivals aggregated on a 1-hour basis (Figure 5-5a) and on a 15-minute basis (Figure 5-5b) at EWR in August 2009. As shown in Figure 5-4c, scheduling levels never exceeded the 81-flight hourly cap during this month. Note, however, that more than 20 flights are scheduled during a significant number of 15-minute periods.



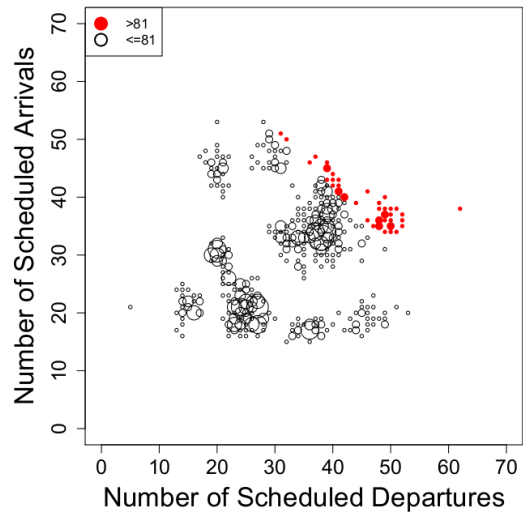
(a) August 2007



(b) August 2008



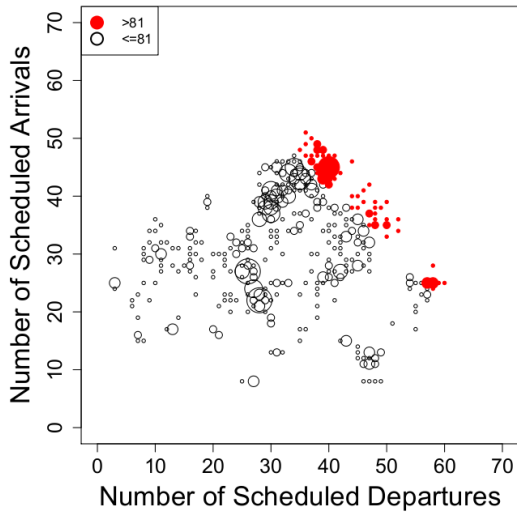
(c) August 2009



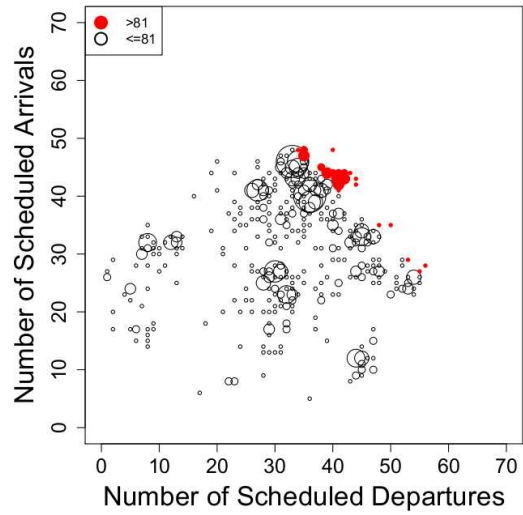
(d) August 2010

Figure 5-3: Number of scheduled flights during all 1-hour periods at JFK between August 2007 and 2010

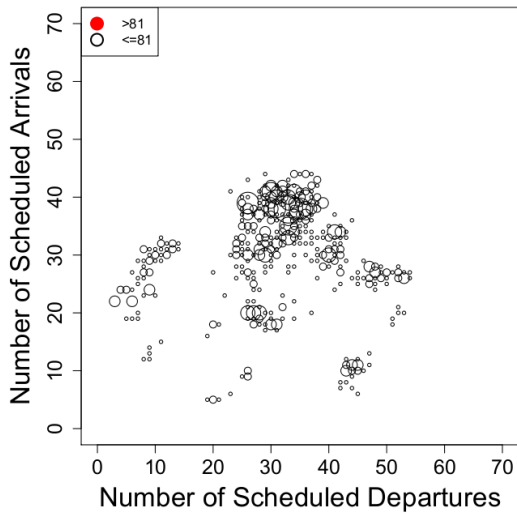
Table 5.1 reports the proportion of 1-hour periods with more than 81 scheduled flights and the proportion of 15-minute periods with more than 20 scheduled flights in August 2007, 2008, 2009 and 2010 at JFK and EWR. Note that, although the proportion of time during which scheduling levels exceed the 81-flight hourly cap has substantially decreased over time, the proportion of 15-minute periods with above-capacity scheduling has remained approximately the same over these years. In August



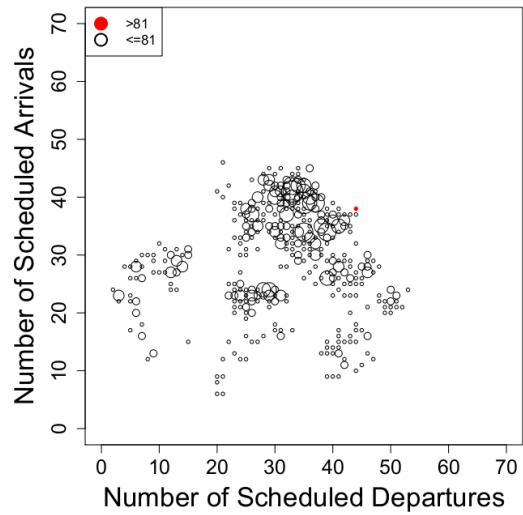
(a) August 2007



(b) August 2008



(c) August 2009



(d) August 2010

Figure 5-4: Number of scheduled flights during all 1-hour periods at EWR between August 2007 and 2010

2009 and 2010, the number of scheduled operations almost never exceeded the 81-operations cap at EWR, and it did so on average between 1 and 2 one-hour periods of the day at JFK; however, schedules exceeded 20 flights in more than 25% of the 15-minute periods per day on average at these two airports. Therefore, the implementation of the hourly caps at JFK and EWR has not reduced scheduling levels on a 15-minute basis.

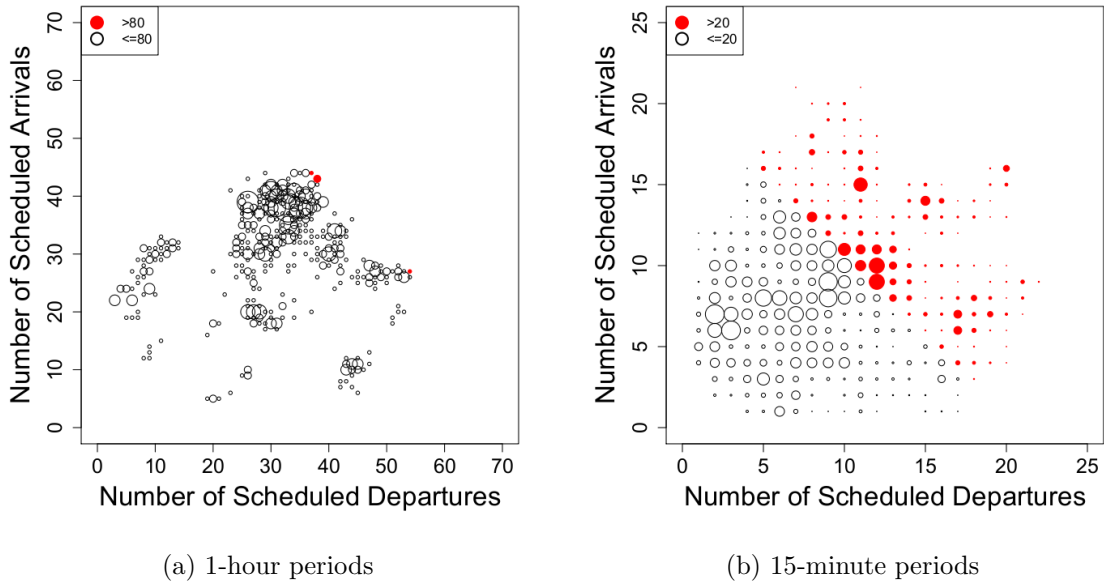


Figure 5-5: Number of scheduled flights at EWR in August 2009

Table 5.1: Proportion of 1-hour periods with more than 81 scheduled flights and proportion of 15-minute periods with more than 20 scheduled flights

Airport	JFK		EWR	
	1-hour	15 minute	1-hour	15-minute
August 2007	22.8%	33.9%	14.9%	31.8%
August 2008	10.2%	31.7%	6.6%	33.5%
August 2009	8.4%	32.3%	0%	29.3%
August 2010	8.1%	27.6%	0.2%	30.0%

The main takeaway from this section is twofold. First, demand has slightly decreased at both JFK and EWR between 2007 and 2010 and, at the same time, average delays have declined substantially. The objective of Section 5.2 is to determine the extent to which this delay reduction may be explained by changes in demand. Second, the implementation of hourly schedule caps at these airports from May 2008 has resulted in reducing hourly scheduling levels, but airport capacity is very often exceeded on a 15-minute basis. Section 5.3 quantifies the effect of these changes in the distribution of flights over the course of one day of operations on airport delays.

5.2 Relationship between Scheduling Levels and Delay Magnitude

The objective of this section is to determine the extent to which the delay decrease observed at JFK and EWR between 2007 and 2010 can be attributed to changes in airport demand. To this end, we use the queuing model presented in Chapter 3 and validated in Chapter 4 with the average demand profiles of the eight months from July and August 2007 to July to August 2010. The other input parameters are identical for all months. In particular, the runway system capacity estimates are the same in all cases, as reported in Table 4.1. Therefore, the observed changes in predicted delays are solely due to the changes in airport demand between 2007 and 2010. If the model predicts an evolution of delays of similar magnitude to the one observed in practice, then the delay decrease can be attributed primarily to the changes in demand between 2007 and 2010. If, on the other hand, the model predicts a delay reduction which 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.

Figures 5-6 and 5-7 show the average delays observed at JFK and EWR between July and August 2007 and July and August 2010, and compares them to the model's predictions. The results of both DELAYS and the Monte Carlo simulation model are presented.

First, DELAYS and the Monte Carlo simulation model both predict very similar evolutions of delay averages over the period of time considered. This confirms the earlier observation that the two models provide consistent approximations of the $M(t)/E_k(t)/1$ queuing model. The small differences are, we believe, essentially due to the different weather conditions which were observed at JFK and EWR during the months considered. Indeed, we approximate average delays with the DELAYS model using the *a posteriori* observations of the timing, sequence and duration of VMC and IMC periods at these airports, while, by contrast, the Monte Carlo simulation considers an axiomatic and *a priori* model of weather variations. Therefore, if the

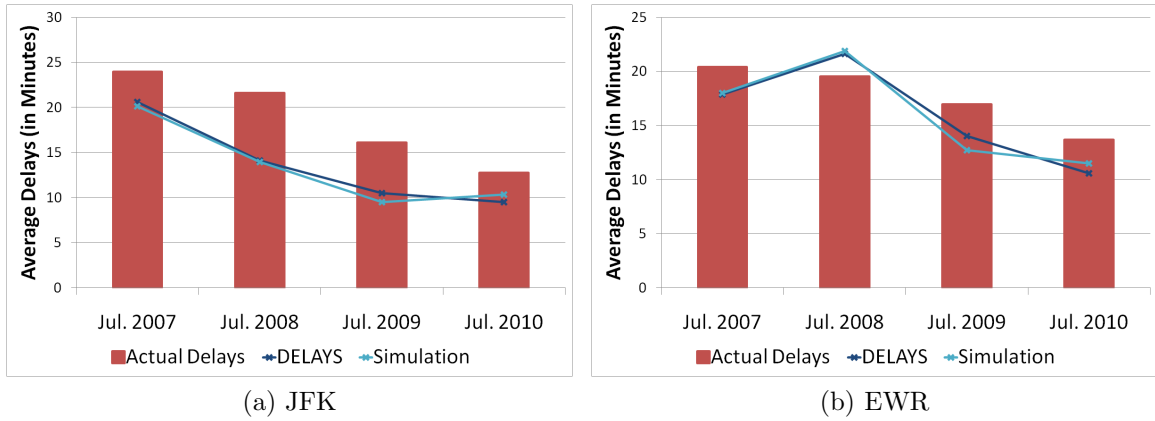


Figure 5-6: Comparison of the predicted and actual average delays from July 2007 to July 2010

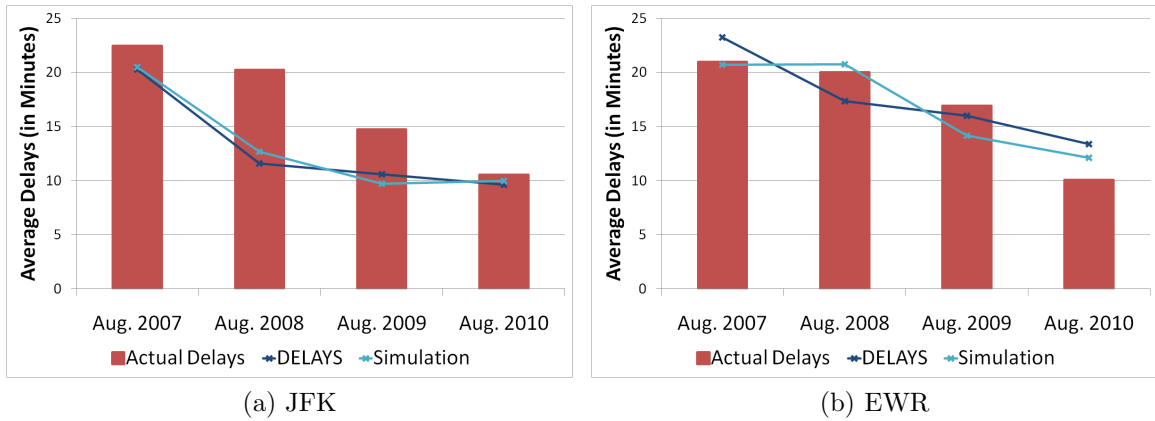


Figure 5-7: Comparison of the predicted and actual average delays from August 2007 to August 2010

weather has been particularly bad in practice in a given month, the delays predicted by DELAYS are likely to be larger than the delays predicted by the Monte Carlo simulation model. However, Figure 5-6 and 5-7 show that these differences are small.

In addition, it can be seen that the two models overall predict delay reductions of a magnitude similar to what was observed at JFK and EWR between 2007 and 2010. Indeed, they both approximate reasonably well the evolution of the actual delays over time. Nonetheless, some fluctuations may be observed and the accuracy of the estimates varies from month to month. In particular, the model seems to underestimate the delays at JFK in 2008 and 2009. The reason, we believe, is that, due to their macroscopic nature, the models do not consider a number of factors that

may influence significantly airport operations and ultimately an airport's on-time performance. Moreover, the estimates of the sustained throughput rate considered in this study are only approximate, and in practice the capacity of the runway system is subject to variations and uncertainty. For instance, delays significantly larger than the model's predictions may be indicative of a particularly poor performance of an airport during the month considered, and vice versa.

A more detailed presentation of the results of the Monte Carlo simulation model between 2007 and 2010 is provided in Appendix B. As indicated above, the results of the DELAYS model during this period are very similar to the simulations. Since the model slightly underestimates the delays at JFK in 2008 and 2009, we show in these figures results at JFK with two sets of capacity estimates: the values of the sustained throughput rate considered in this study (21 flights per period under VMC and 18 under IMC), and a set with slightly lower capacity values (20 flights per period under VMC and 17 under IMC). For EWR, we have solely considered the values of the sustained throughput rate considered in this study (19 flights under VMC and 16 under IMC). These more detailed graphs confirm the results observed in Figures 5-6 and 5-7: the model predicts a magnitude of delays which matches well the ones observed in practice at JFK and EWR between 2007 and 2010.

Overall, the model estimates accurately the delay decrease that has been experienced at JFK and EWR between 2007 and 2010. Table 5.2 reports the change, percent-wise, of the demand, the actual local delays and the delays predicted by the two numerical models between July and August 2007 and July and August 2010 at JFK and EWR. The models predict delay decreases that are remarkably similar to the ones observed in practice, with the exception of August 2007 vs. August 2010 at EWR, where the actual delay decrease has been slightly greater than the prediction.

These results suggest that the decrease in delays that has been observed at JFK and EWR over the past few years is primarily due to the reduction of the demand. Indeed, the queuing model predicts a delay reduction similar to the one observed in practice, and this predicted delay reduction results solely from the changes in demand between 2007 and 2010.

Table 5.2: Percent of change of the demand and of the delays at JFK and EWR between 2007 and 2010

Airport	JFK		EWR	
Month	July	August	July	August
Total Demand	-6.84%	-8.02%	-3.37%	-5.16%
Actual Delays	-46.90%	-53.15%	-32.93%	-52.02%
Predicted Delays (DELAYS)	-54.00%	-52.67%	-40.72%	-42.33%
Predicted Delays (Simulation)	-48.69%	-51.30%	-36.14%	-41.56%

Since the demand reduction over this period has been much more limited than the delay decrease, the relationship between demand and delays at congested airports is highly nonlinear. In other words, small changes in demand result in large changes in the magnitude of the delays, when the airports are operated close to their capacity.

This observation has been well established in the literature of queuing theory under steady-state conditions (Larson and Odoni, 1981). Indeed, the average delay under steady-state conditions is known to be proportional to $\frac{1}{1-\rho}$, where ρ is the ratio of demand over capacity. The nonlinear relationship between demand and delays is illustrated in Figure 5-8, which shows the expected delay as a function of the utilization ratio ρ under steady-state conditions. When ρ is close to 1 (*i.e.* when demand is close to capacity), small changes in ρ (*i.e.*, if capacity is fixed, small changes in demand) result in large delay variations.

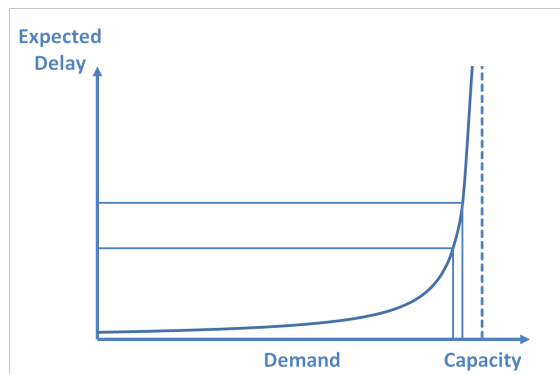


Figure 5-8: Non-linear relationship between the utilization ratio and the expected delay under steady-state conditions

This study extends this nonlinear relationship between demand and delays to the

operation of airports under dynamic conditions, in which the demand and service rates are time-varying and steady-state is not reached. Over the period 2007-2010, delays at JFK and EWR have decreased non-linearly in response to small declines in demand. Conversely, if demand increases again over the next few years, delays are likely to increase much more rapidly under existing operating conditions.

5.3 Impact of the distribution of flights within a day

In Section 5.2, we argued that the delay decrease which has been observed at JFK and EWR between 2007 and 2010 can be attributed primarily to changes in demand. In addition to the reduction of the number of scheduled flights, illustrated in Figures 5-1 and 5-2, their distribution over the course of the day may also have an effect on airport congestion. It is reasonable to expect that, for any given total number of flights, the more unevenly they are distributed in a day of operations, the larger the delays will be on average. Indeed, if too many flights demand use of the runway within a very limited period of time, long queues are likely to be formed and to propagate through time.

5.3.1 An example

To test the impact of the distribution of flights in the course of one day of operations, we have selected two days of operations at JFK: Sunday, July 22nd 2007 and Tuesday, July 26th 2008. During these two days, almost exactly the same number of flights were operated between 6 a.m. and 12 a.m., as indicated in Table 5-9. The hourly demand profile on these two days is shown in Figure 5-10, which indicates that the distribution of these flights was much more uneven on 07/22/2007 than on 08/26/2008. The peak scheduled demand levels were much higher on 07/22/2007: for instance, 115 flights were planned between 4 p.m. and 5 p.m., a number which greatly exceeds JFK's capacity. In addition, the 81-flight cap, which has been recommended by the FAA

beginning in May 2008, was exceeded during 7 one-hour periods on 07/22/2007. By contrast, the schedule on 08/26/2008 was much smoother: the 81-flight cap was exceeded during only 3 periods and the maximal number of movements planned in any hour was 89.

Figure 5-9: Total number of flights between 6 a.m. and 12 a.m. on 07/22/2007 and on 08/26/2008 at JFK

Day	Number of Planned Flights
07/22/2007	1257
08/26/2008	1258

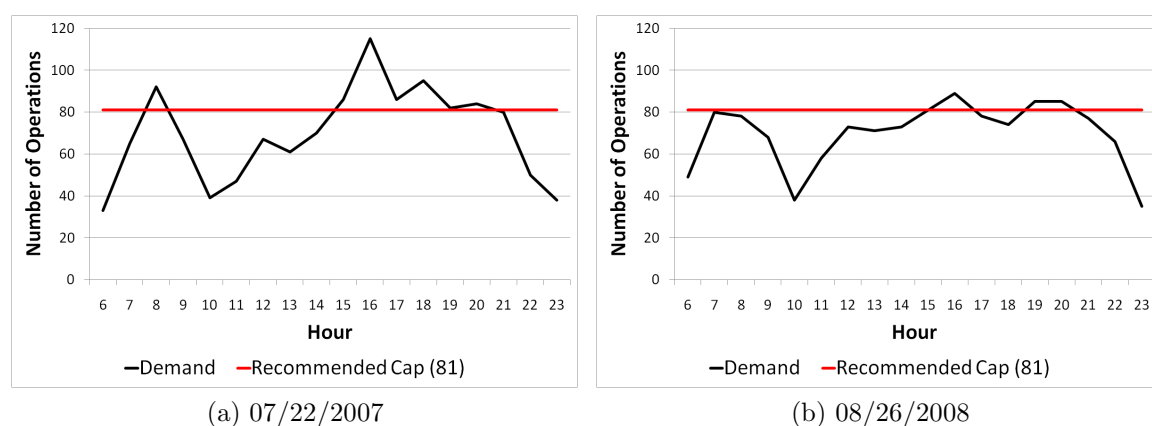


Figure 5-10: Planned demand on 07/22/2007 and on 08/26/2008 at JFK

We now wish to test the effect that these different schedules have had on airside delay performance at JFK. To this end, we compare the magnitude of the delays on these two days. Operations on both days were conducted under VMC, so that weather fluctuations were not a factor and did not bias the results. Figure 5-11 shows the actual and predicted delays on each of these days. Since the schedules of flights and the weather conditions on this particular day are *a posteriori* known, we have used DELAYS to compute the expected value of the delays, with the same estimate of the airport capacity (21 per 15-minute period) in both cases. Note that delays at JFK are significantly larger on 07/22/2007 than on 08/26/2008, and also that the model predicts delays which are of a similar magnitude to those observed in practice on both of these days. Table 5.3 shows that the model predicts a difference between the average delays on these days which is very similar to the one observed in practice.

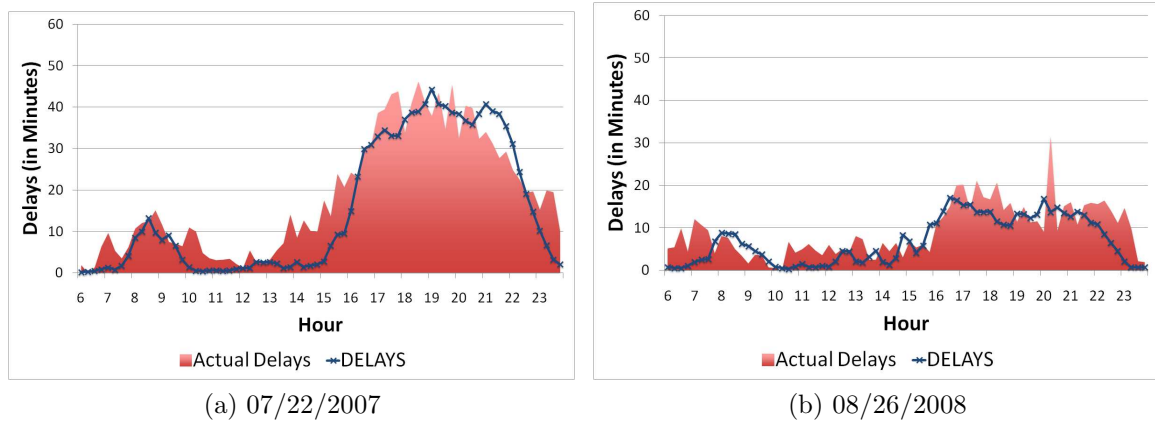


Figure 5-11: Actual and predicted delays on 07/22/2007 and on 08/26/2008 at JFK

Table 5.3: Average delays at JFK on 07/22/2007 and on 08/26/2008

Metrics	Actual Delays	Predicted Delays
07/22/2007	20.88 minutes	18.33 minutes
08/26/2008	9.31 minutes	8.05 minutes
Absolute Difference	11.57 minutes	10.28 minutes
Relative Difference	55.42%	56.07%

This comparison shows that the distribution of flights over the course of the day may have a very significant effect on airport congestion, and that this effect is well captured by the queuing model considered in this study. For a given total number of flights, a “smoother” distribution may result in much lower delays than a more uneven one.

5.3.2 Average distribution of flights at JFK and EWR

We now analyze the average distribution of flights at JFK and EWR and its evolution between August 2007 and 2010.

Figure 5-12 presents the average proportion of flights planned on weekdays during any one-hour period of the day at JFK (Figure 5-12a) and EWR (Figure 5-12b) between August 2007 and August 2010. If the schedule were perfectly even, 5.56% of flights would be planned during every period. As can be seen, the schedules at both JFK and EWR include peaks and valleys: more flights are scheduled in the early

morning and in the afternoon than in the late morning or in the late evening.

In addition, note that the distribution of flights over the course of the day has changed significantly at JFK between August 2007 and August 2010. Indeed, scheduling peaks were noticeable in August 2007 at 8 a.m. and 4 p.m., during which more than 7.5 % of the daily flights were planned. Flight schedules were more evenly distributed in August 2008 and August 2009: during every period of the day, less than 7% of the daily volume of flights were planned in these 2 months. However, the distribution of flights seems to have become more uneven again by August 2010.

In contrast, the changes in the distribution of flights during the day seem to have been quite limited at EWR between August 2007 and August 2010. Indeed, the proportion of flights planned at peak hours has remained the same over these years, ranging between 6% and 7% throughout.

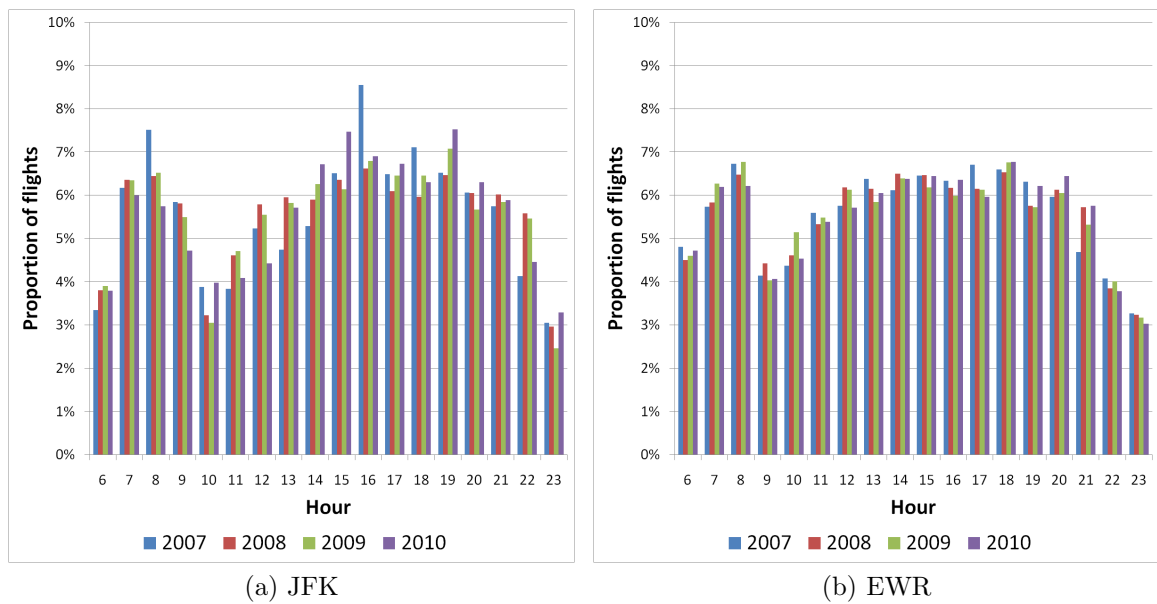


Figure 5-12: Proportion of flights during every hour at JFK and EWR between August 2007 and August 2010

In order to quantify the effect of the flight distributions on airport congestion, we consider eight different demand profiles four each for JFK and EWR with:

- the same total number of flights (1,200 flights between 6 a.m. and 12 a.m.)
- different distributions of flights over the course of the day: the 1,200 flights

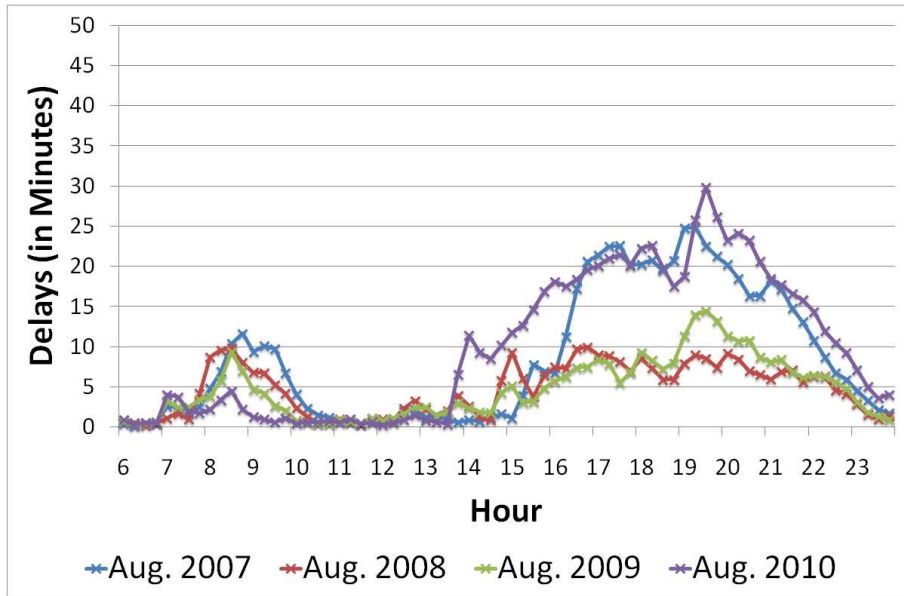
are distributed proportionally to the distributions observed at JFK and EWR between August 2007 and August 2010 and shown in Figure 5-12

We use the queuing model to compare the expected value of the delays under these different demand scenarios. Since in all cases the total number of flights in a day is the same, the potential differences are only due to the different distributions of the flights over the course of the day. Figure 5-13 shows the delays predicted by the Monte Carlo simulation model with the distributions observed at JFK (Figure 5-13a) and EWR (Figure 5-13b) between August 2007 and August 2010.

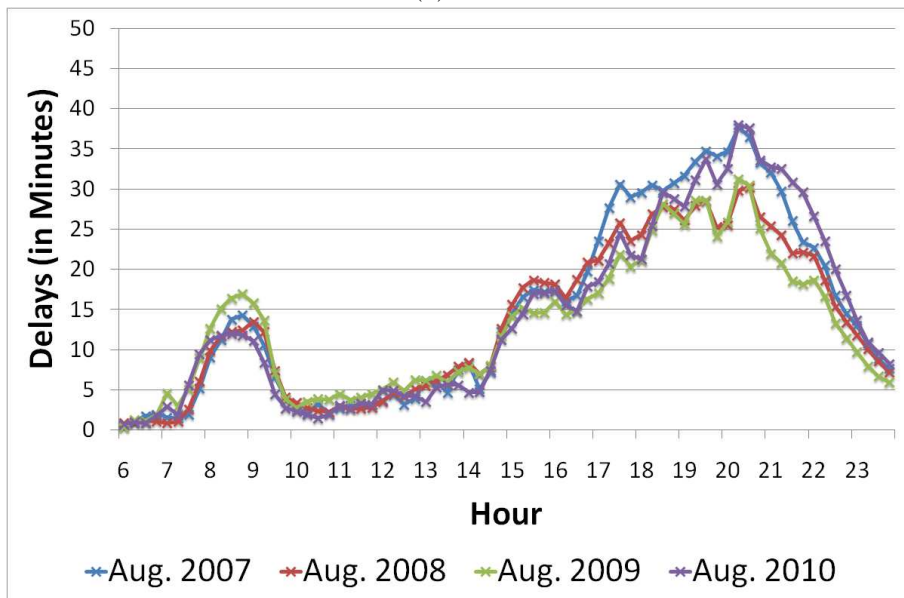
First, note that the distribution of flights has an important effect on average delays at JFK. Indeed, the expected value of the peak delays varies from 10 minutes with the flight distribution from August 2008 to more than 30 minutes, with the distribution from August 2010. More generally, for the same total number of flights, average delays are much smaller with distributions from August 2008 and 2009 than from August 2007 and 2010; this result confirms that the schedule has been much smoother in August 2008 and August 2009 than in August 2007 and 2010:

As expected, the differences at EWR are much more limited. Nevertheless, although differences in flight distributions have been negligible, as indicated in Figure 5-12b, average delays may vary from a year to another by 5 minutes at peak hours, which corresponds to a relative difference larger than 10%.

Interestingly, the distribution of flights over the day at both JFK and EWR has been smoother in 2008 and 2009 than in 2007, and more uneven again in 2010. First, the introduction of flight caps in May 2008 contributed to reducing peak scheduling levels. Since the average number of daily flights did not decline between 2007 and 2008, and, in fact, even increased in some cases, as shown in Figures 5-1 and 5-2, the flight caps resulted in smoothing the airport demand. In other words, approximately the same number of flights were scheduled, but were distributed more evenly over the course of the day, in part because of the schedule limitations. These trends are confirmed by Figure 5-14 and Table 5.4, which report the average number of scheduled flights per hour in the afternoon at JFK in August 2007, 2008 and 2010: the total number of flights scheduled in the afternoon remained similar between 2007



(a) JFK



(b) EWR

Figure 5-13: Predicted average delays with the distributions of flights observed at JFK and EWR from August 2007 to August 2010 and the same total number of flights in the day (1,200 flights)

and 2008, but less flights were scheduled during the peak period in 2008 than in 2007. However, between 2008 and 2010, the demand declined significantly because of the economic downturn, and the results from this section suggest that this demand reduction mostly occurred at off-peak periods. This is also confirmed by Figure 5-14

and Table 5.4. Indeed, the total number of flights scheduled in the afternoon decreased between August 2008 and August 2010, but the number of flights scheduled between 2 p.m. and 9 p.m. remained approximately the same. Therefore, airlines eliminated primarily off-peak flights, which are generally less profitable than peak-hour flights.

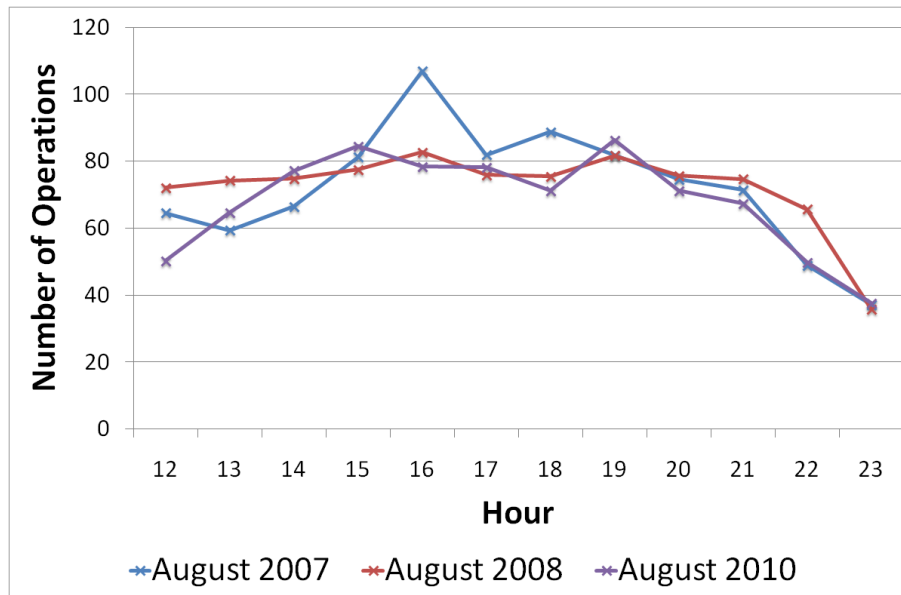


Figure 5-14: Average number of flights per hour in the afternoon at JFK in August 2007, 2008 and 2010

Table 5.4: Average number of flights in the afternoon at JFK in August 2007, 2008 and 2010

Time Window	August 2007	August 2008	August 2010
12 p.m. - 2 p.m.	124	146	115
2 p.m. - 9 p.m.	581	544	547
9 p.m. - 12 a.m.	157	176	155
12 p.m. - 12 a.m.	863	866	816

Table 5.5 reports the average and peak delays with distributions from August 2007 to August 2010 at JFK and EWR, and the same total number of flights. These results, of course, depend on the total number of flights which is assumed for the entire day. The choice of 1,200 flights here is arbitrary (but reasonable for these two airports) and any other choice would have led to different average delays. Nonetheless, the results underline the fact that the distribution of flights may have a substantial effect on

delays. As shown, delays are on average approximately 50% larger with distributions from August 2007 and 2010 at JFK than with distributions from August 2008 and 2009 at JFK.

Table 5.5: Average and peak delays (in minutes) with different distribution of flights and the same total number of flights in the day (1,200 flights)

Airport	JFK		EWR	
Metrics	Average Delays	Peak Delays	Average Delays	Peak Delays
August 2007	9.93	24.83	15.50	37.61
August 2008	5.30	9.94	14.05	30.23
August 2009	5.30	14.43	13.50	31.24
August 2010	11.39	29.85	14.93	37.94

Therefore, the distribution of flights over the course of the day has an important impact on the formation and the propagation of queues at congested airports, and variations of flight distributions at JFK and EWR between 2007 and 2010 have contributed to changes in delays over this period.

5.4 Conclusions

In this chapter, we have quantified the impact of flight schedules on airport delays. In particular, we have shown that both the total number of flights operated in a day and their distribution over the course of the day have an impact on delays.

First, the more flights are scheduled in a day, the larger the average delays will be. The application of the queuing model to JFK and EWR has demonstrated clearly that the relationship between demand and delays is highly nonlinear when an airport operates close to capacity. As a result, the delay reductions that have been observed at JFK and EWR between 2007 and 2010 can be largely attributed to the relatively small decline in flight demand at these two airports during the same period of time.

Second, for a given total number of flights in a day, the more evenly they are distributed over its course, the smaller the average delays will be. In particular, the institution of the 81-movement caps at JFK and EWR in May 2008 resulted

in smoother schedules in August 2008 and 2009 than in August 2007, which has contributed to the delay reductions observed at JFK and EWR during this period. However, scheduling levels have remained very high during a large number of 15-minute periods and this has contributed to the continuing high (on an absolute scale) level of delays at these airports. Therefore, a slot control system at JFK and EWR might be more effective if it specified limits on a 15-minute, rather than on an hourly, basis.

Chapter 6

Conclusion

6.1 Summary of the Results

In this thesis, we have modeled airport operations at a macroscopic level at JFK and EWR, two of the most important and most congested airports in the United States. To this end, we have used a stochastic and dynamic $M(t)/E_k(t)/1$ queuing model. Two approximation methods have been considered:

- an analytical approximation scheme called DELAYS (Kivestu, 1974; Gupta, 2010), which approximates the expected value of the delays through the course of one day of operations; and
- a new Monte Carlo simulation model introduced in this study, which samples randomly each landing and each takeoff in a day and which may be used to evaluate the expected value and also the probability distribution of flight delays.

Dynamic models of airport demand and airport capacity have also been developed and combined into the Monte Carlo simulation model. They capture the uncertainty regarding scheduling levels and airport capacity, and their variability from one day of operations to another.

Both DELAYS and the Monte-Carlo simulation model have been calibrated and validated using historical records of airport operations at JFK and EWR. First, we

have shown that both models provide similar estimates of the expected value of the delays. Then, we have demonstrated that both the predicted magnitude of the delays and the predicted evolution of the delays over the course of the day are very close to what has been observed at these airports. In addition, the Monte Carlo simulation model estimates accurately the variability of the delays across a set of many days of operations at JFK and EWR. This model may therefore be used not only to predict the average value of flight delays, but also their dispersion around this average. In particular, it can be used to quantify the probability that on-time performance will be below a given threshold on a given day.

The *sustained throughput rate* has been defined as the average service rate which, if sustained over long periods of time, leads to delays which are at a level similar to those observed in practice. The sustained throughput rate is essentially the effective long-term capacity of the runway system in VMC and in IMC and can be estimated by adjusting the service rates at an airport until the delays predicted by the models are of about the same magnitude as the actual ones. The sustained throughput rate at EWR has been shown in our analysis to be slightly lower than the estimated the maximum throughput rate there.

The two models have been used to conduct a case study on scheduling and delays at JFK and EWR between 2007 and 2010. It has been shown that both airports operate very close to capacity, and that under these conditions the relationship between demand and capacity on the one hand and delays on the other is highly nonlinear. In other words, the magnitude of the delays is extremely sensitive to even small changes in:

- the number of scheduled flights in a day of operations: the more flights, the larger the delays;
- the distribution of flights over the course of the day: all else being equal, the more evenly flights are distributed, the lower the delays; and
- the capacity of the airport: the larger the capacity, the lower the delays.

We have shown that the large delay reductions observed at JFK and EWR between 2007 and 2010 can be largely attributed to changes in flight schedules, and in particular to the relatively small decline in airport demand at these two airports during that same period of time. Conversely, if airport demand increases again over the next few years, then flight delays are likely to grow at a faster rate.

6.2 Contribution of the Thesis

The major contributions of the thesis are:

- A general framework for using ASPM data was presented and sources of data uncertainty were identified.
- A new approximation scheme of the $M(t)/E_k(t)/1$ queuing model based on Monte Carlo simulation was developed. This model is macroscopic in nature. The calibration of its parameters is easy. It can be used to compute the expected value of delays for any period of a day. In addition, it provides the means for computing delay variability.
- A stochastic model for simulating flight schedules and associated uncertainty was developed and tested. Given an average demand vector, *i.e.* the average number of scheduled flights for every period of a day, the model samples randomly demand vectors, thus taking into account the variability of flight schedules from one day of operations to another, due to demand changes as a function of the day of the week, of short-term demand fluctuations, of different numbers of unscheduled operations, etc., as well as deviations from the scheduled departure and arrival times over the course of one day of operations.
- A Markov chain model of airport capacity was developed and tested. Given average service rates under VMC and IMC, it samples randomly the evolution of airport capacity over the course of one day of operations. In particular, this model captures capacity variations due to changes in weather conditions.

- DELAYS and the Monte Carlo simulation model were applied to study recent trends in scheduling and delays at JFK and EWR. It was shown that the delay decline over the period 2007-2010 was primarily due to changes in flight schedules. The effects of scheduling levels and the distribution of flights over the course of a day on flight delays were also quantified.

6.3 Further Research

The highly nonlinear relationship between demand and delays demonstrated in this thesis provides the motivation for looking carefully into the potential of scheduling limits at some of the busiest airports in the United States. Indeed, a limited reduction in scheduling levels may result in large delay reductions. In this case, the benefits of the improvements of system on-time performance and reliability might outweigh the economic losses associated with the implementation of and the compliance with scheduling limits. The queuing model presented in this thesis can be used to quantitatively estimate the effects of such limits on airport congestion. On the other hand, scheduling constraints at airports also engender costs to the stakeholders involved, as they may result in changes in flight schedules and potentially in the elimination of some flights. Moreover, because of the complexity of the air transportation system, there may be additional effects on competition and fares, as well as changes in environmental impacts. The question of setting slot limits at congested airports in Europe and in the United States has been widely discussed (Czerny et al., 2008), but only one recent paper (Ball et al., 2011) has attempted to quantitatively determine optimal scheduling limits.

The queuing simulation model presented in this paper can therefore be integrated into a broader study which would compare the benefits associated with reduced congestion - both locally and nationwide - due to scheduling limits, with the costs that such policies would engender for airlines, airports, passengers and other stakeholders. This analysis would determine whether an airport might benefit from the imposition of scheduling limits and, if so, what the optimal limits would be.

Appendix A

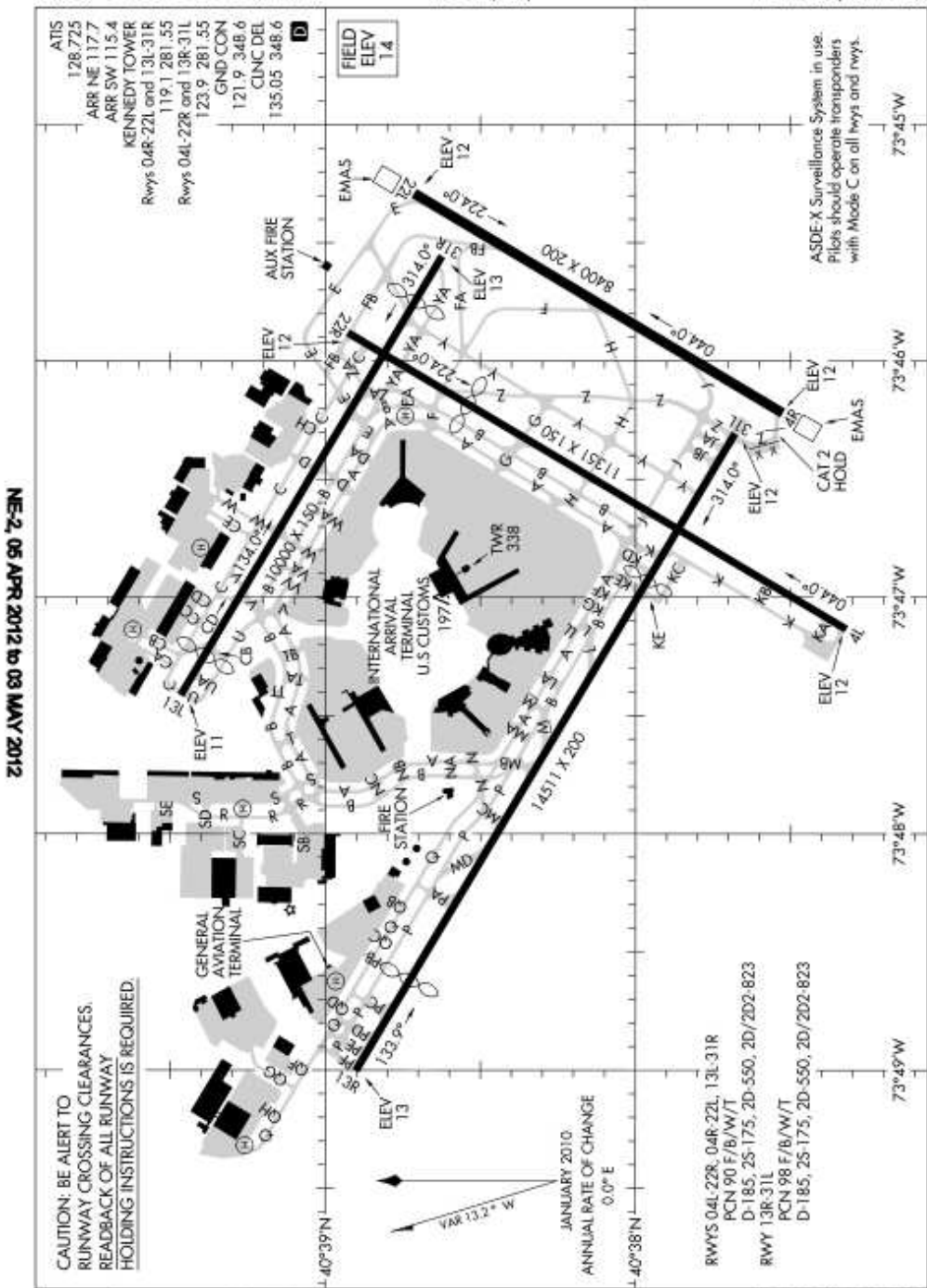
Airport Diagrams

12096

AIRPORT DIAGRAM

AL-610 (FAA)

NEW YORK / JOHN F. KENNEDY INTL (JFK)
NEW YORK, NEW YORK



NE-2, 05 APR 2012 to 03 MAY 2012

NE-2, 05 APR 2012 to 03 MAY 2012

AIRPORT DIAGRAM

12096

NEW YORK, NEW YORK
NEW YORK / JOHN F. KENNEDY INTL (JFK)

Figure A-1: Airport Diagram: JFK

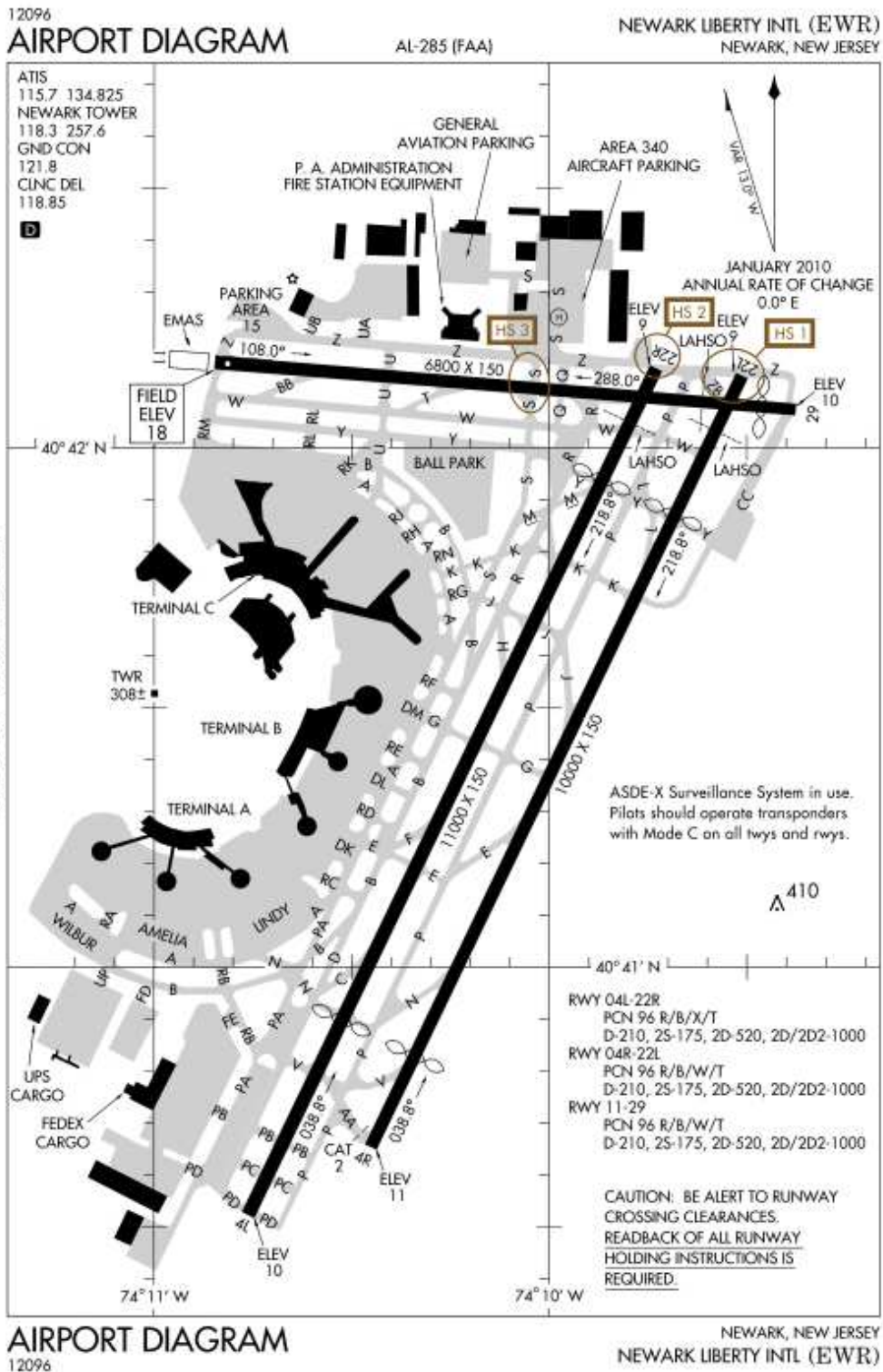
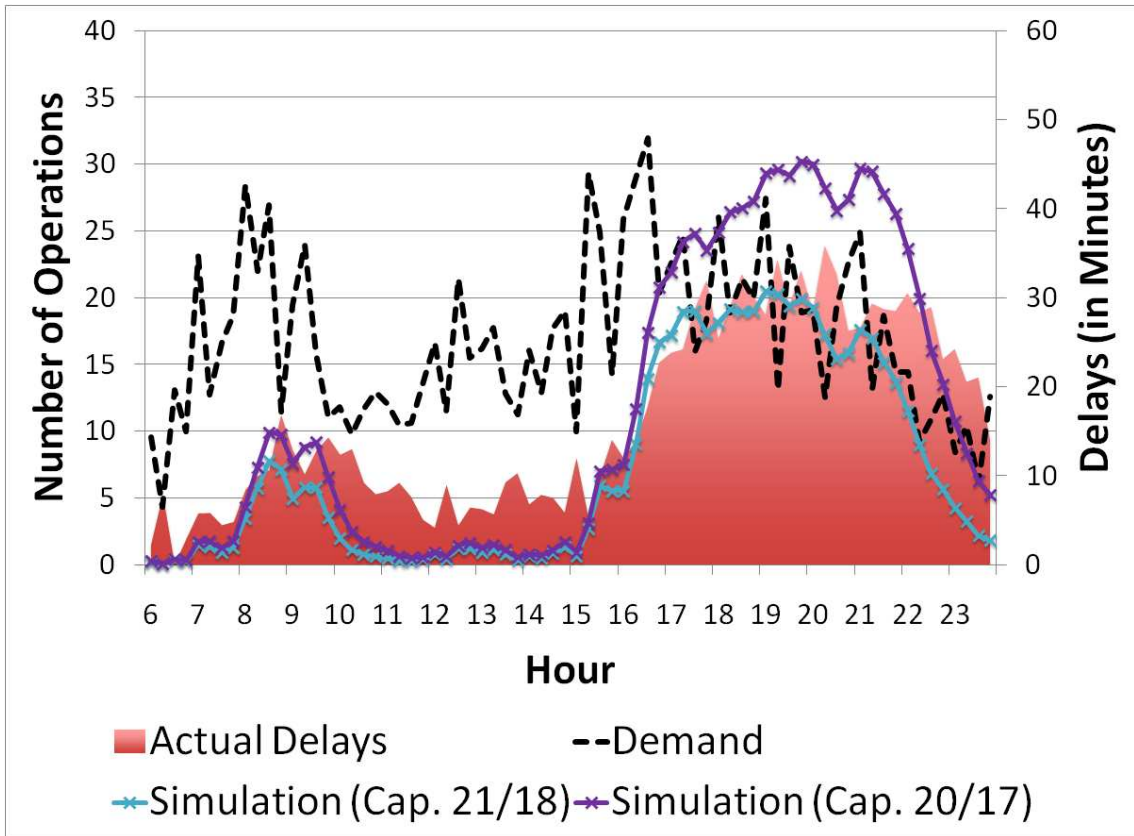


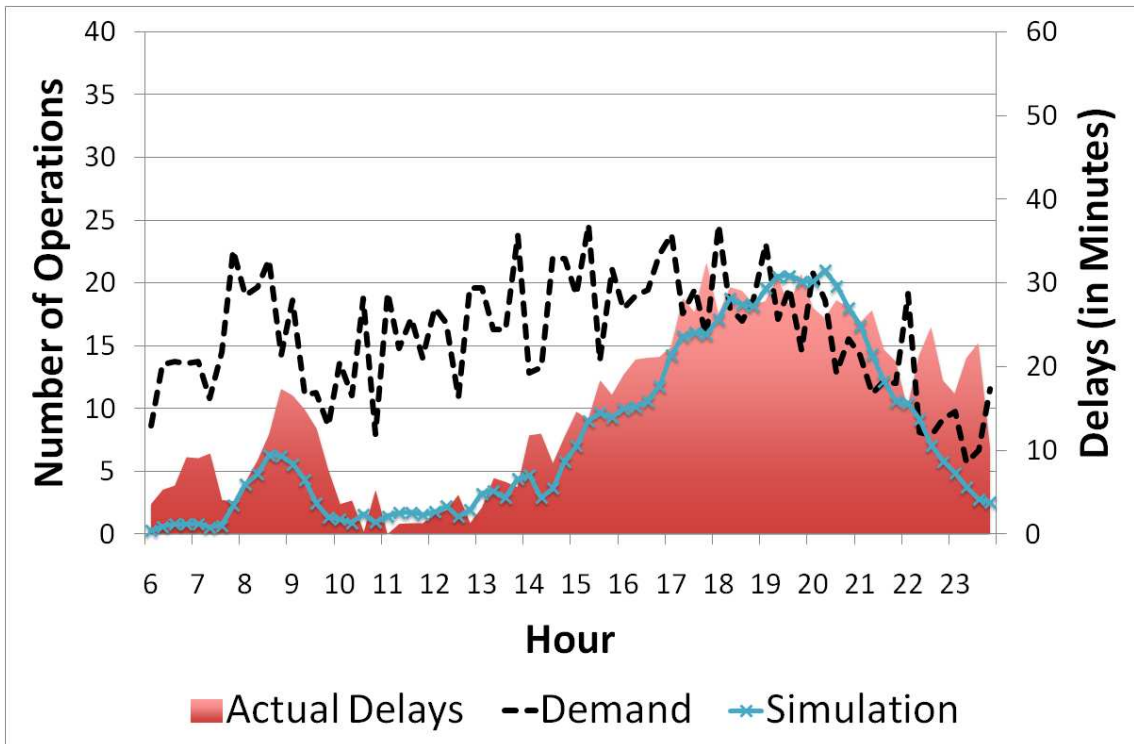
Figure A-2: Airport Diagram: EWR

Appendix B

Results of the Monte Carlo simulation model

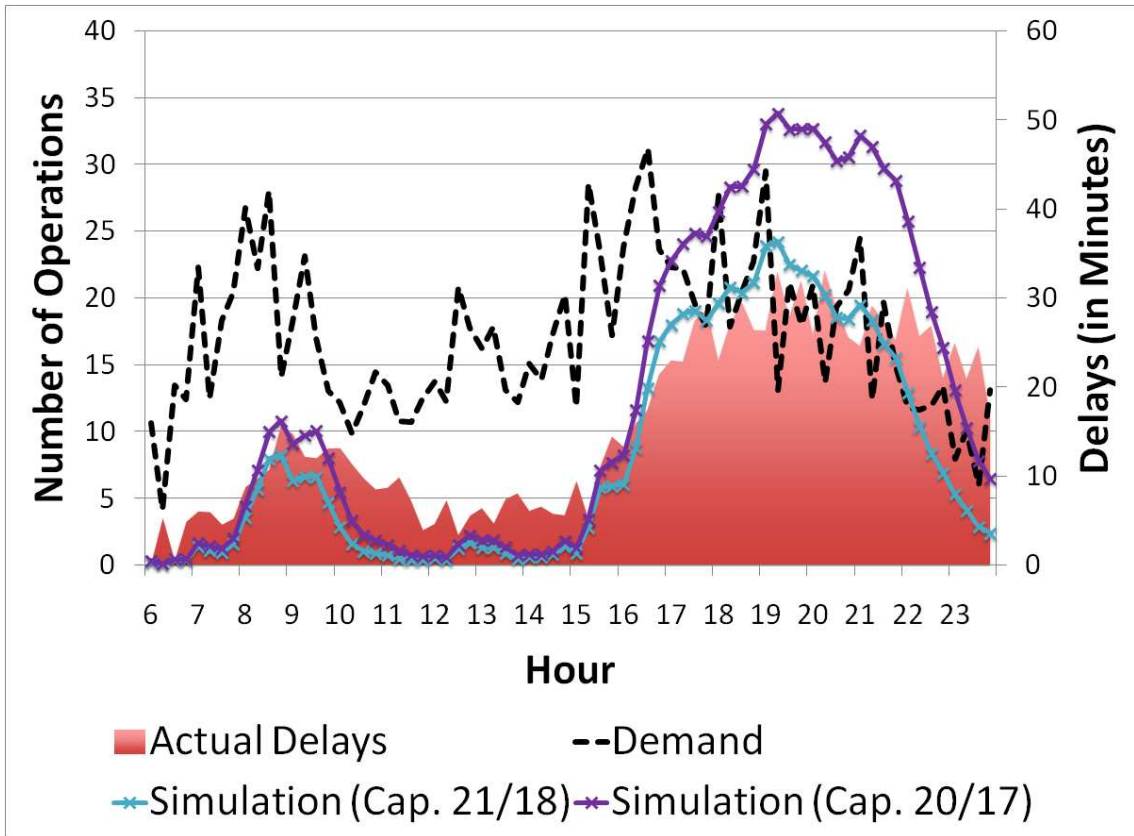


(a) JFK

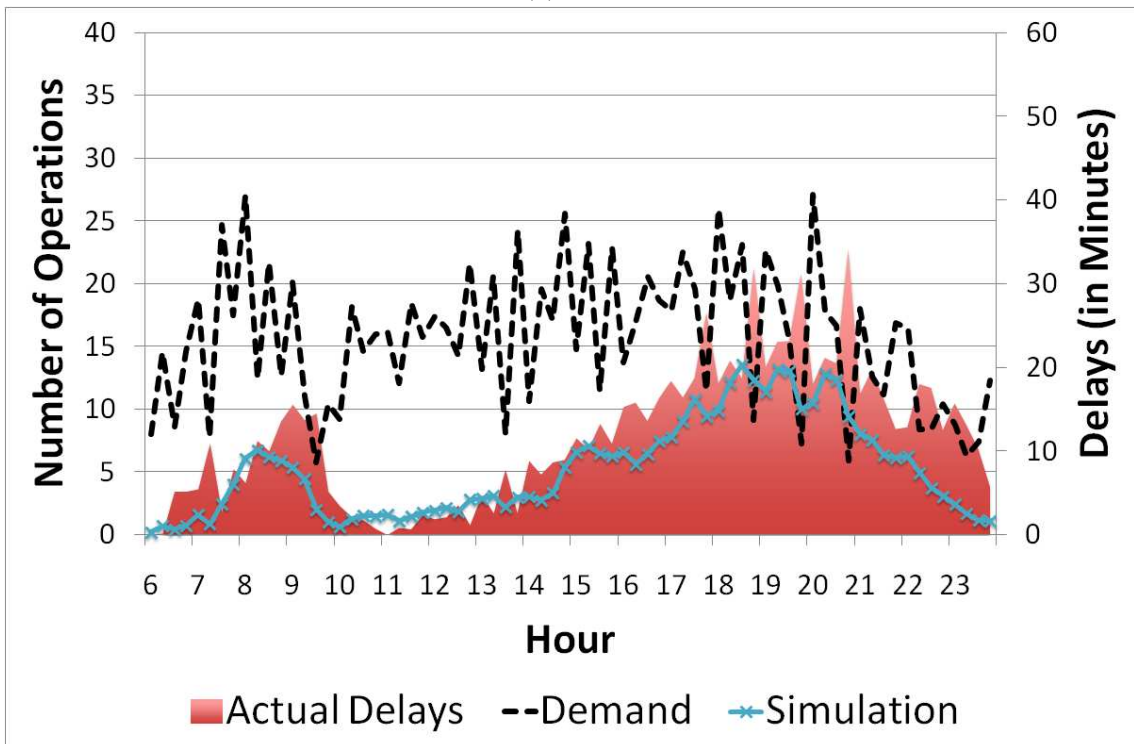


(b) EWR

Figure B-1: Results of the Monte Carlo simulation model in July 2007

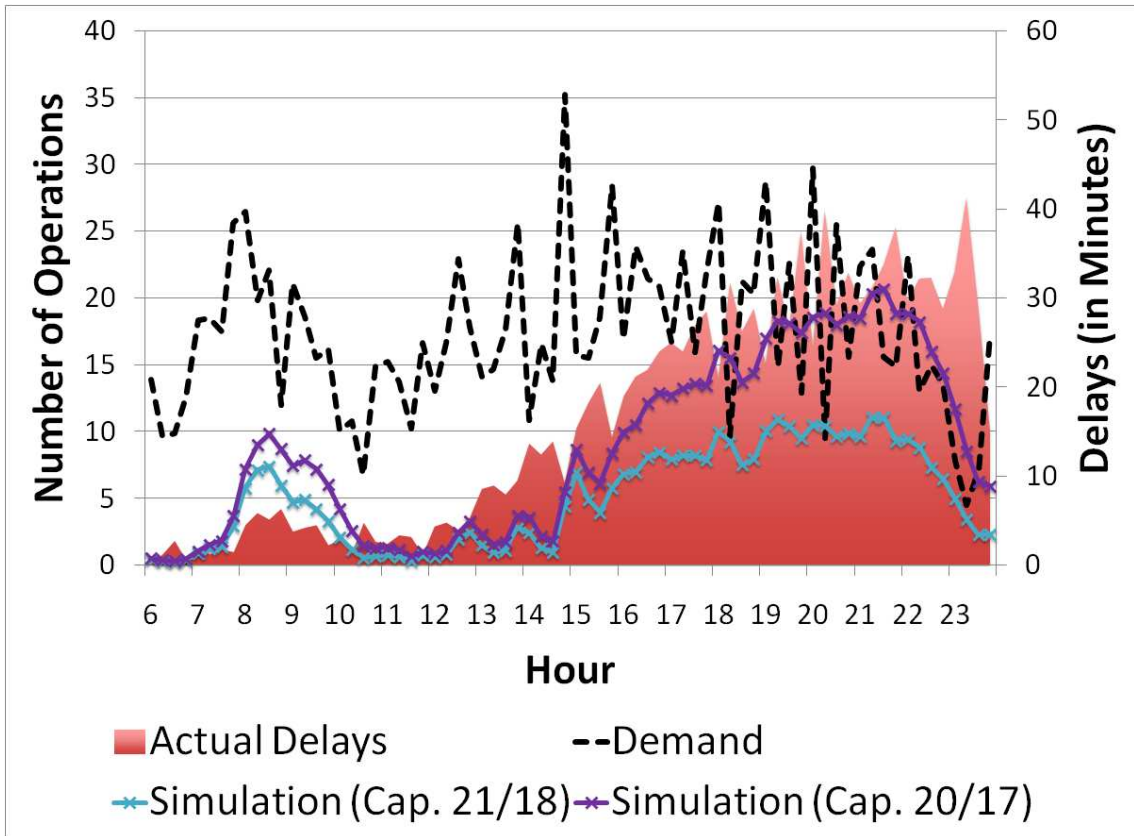


(a) JFK

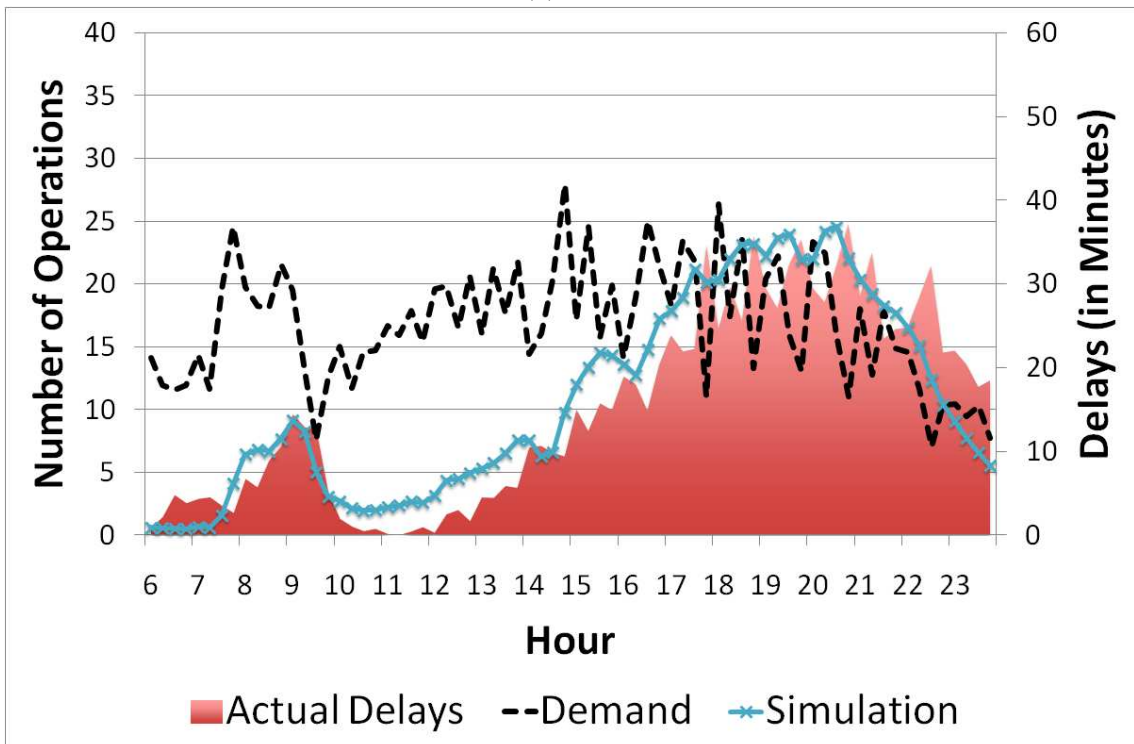


(b) EWR

Figure B-2: Results of the Monte Carlo simulation model in August 2007

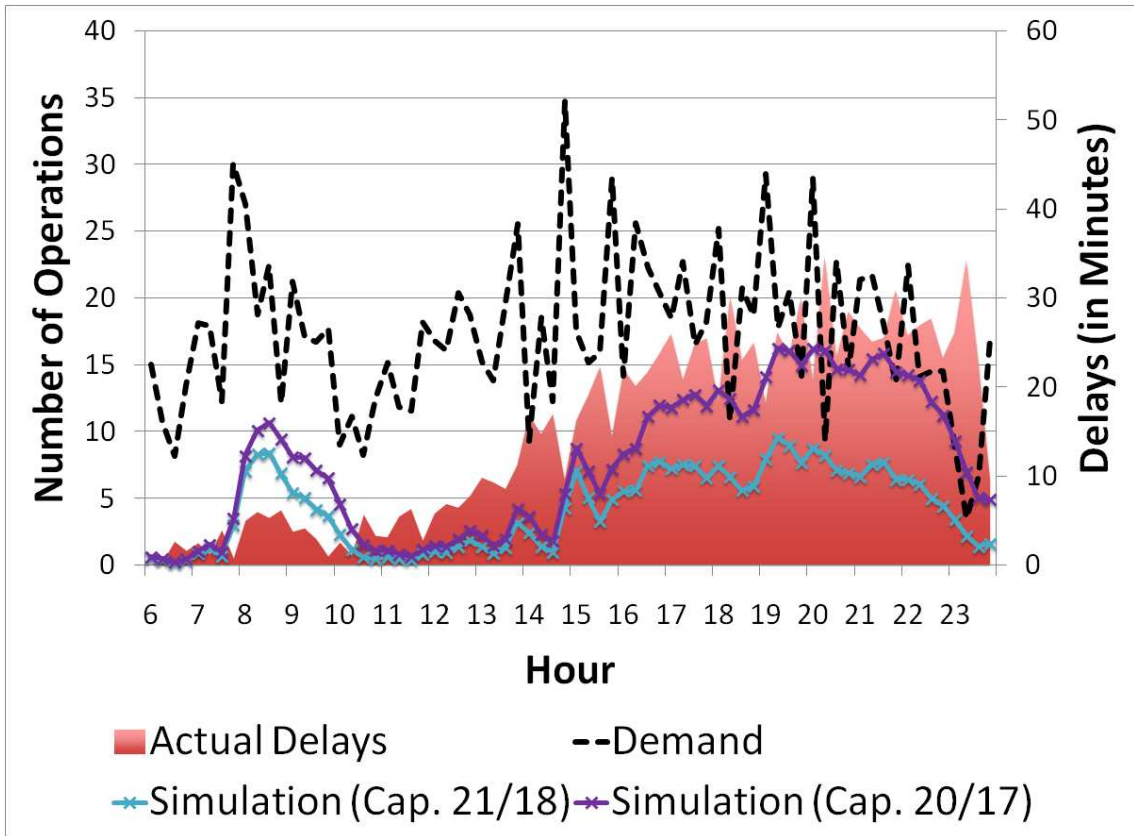


(a) JFK

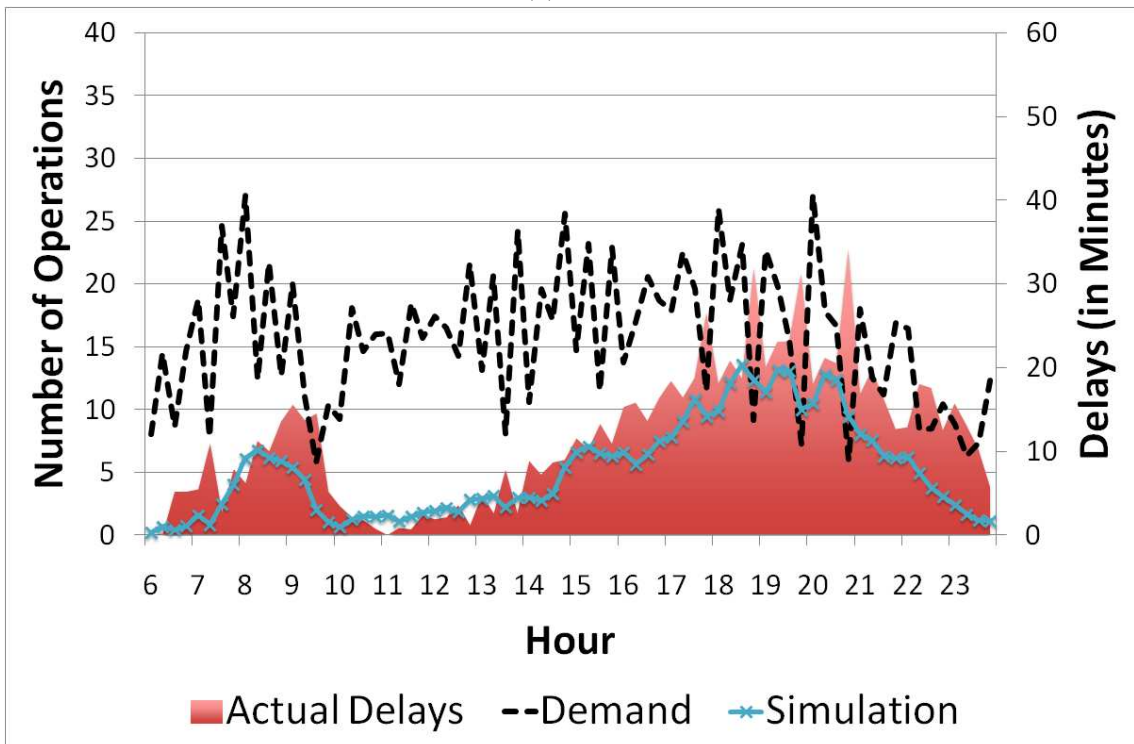


(b) EWR

Figure B-3: Results of the Monte Carlo simulation model in July 2008

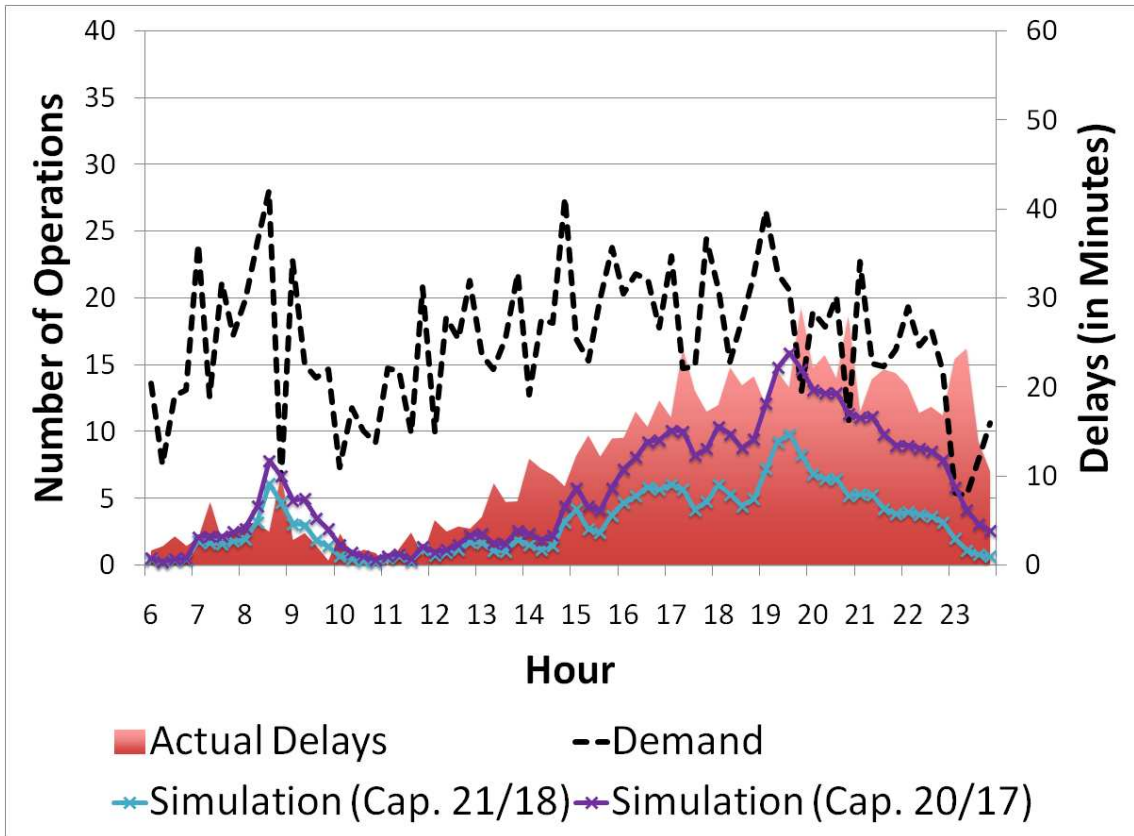


(a) JFK

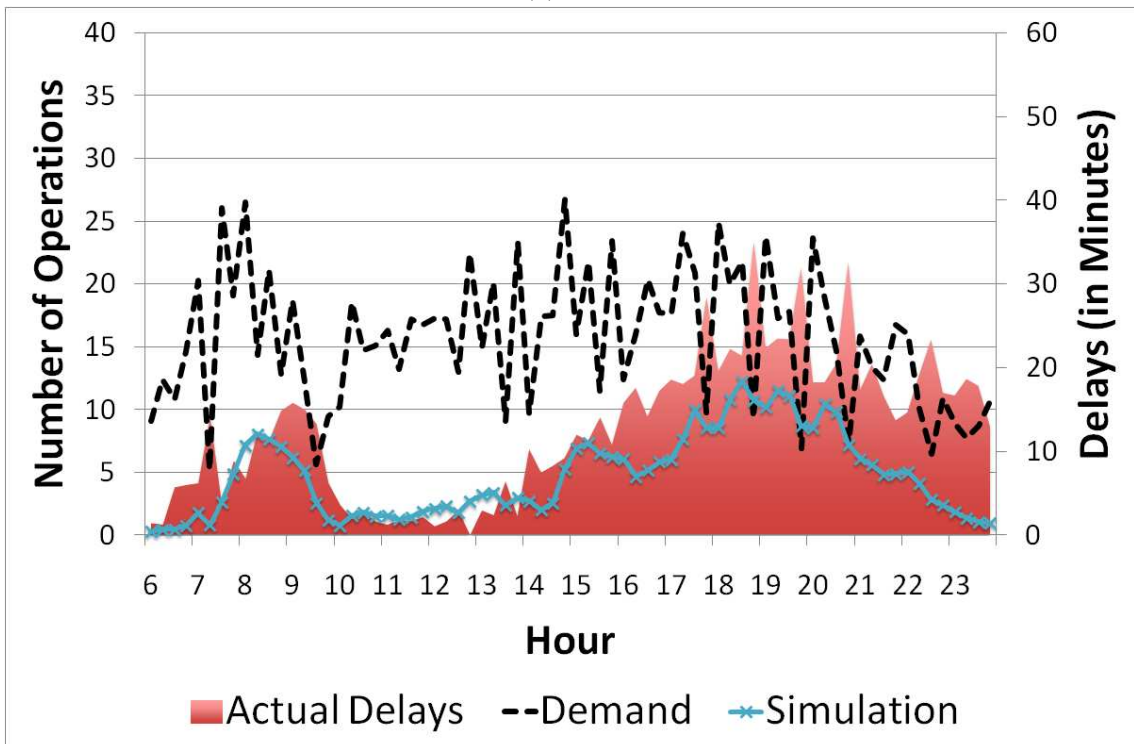


(b) EWR

Figure B-4: Results of the Monte Carlo simulation model in August 2008

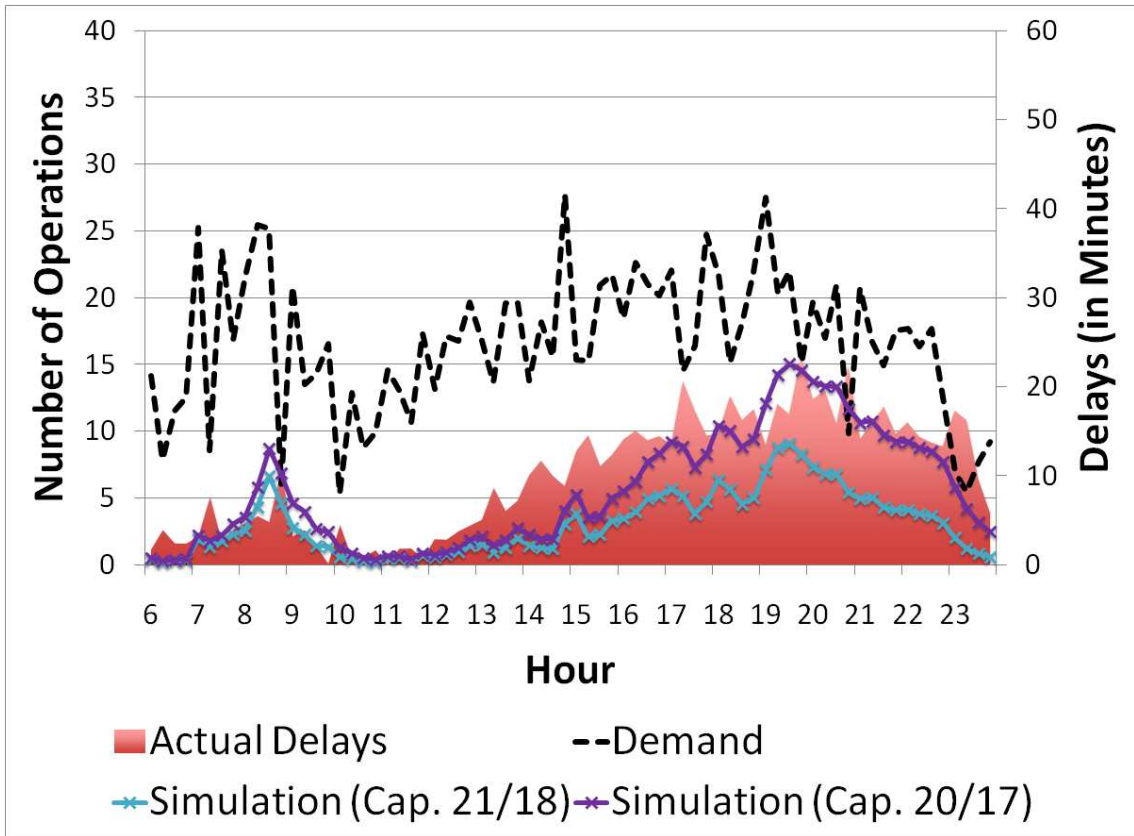


(a) JFK

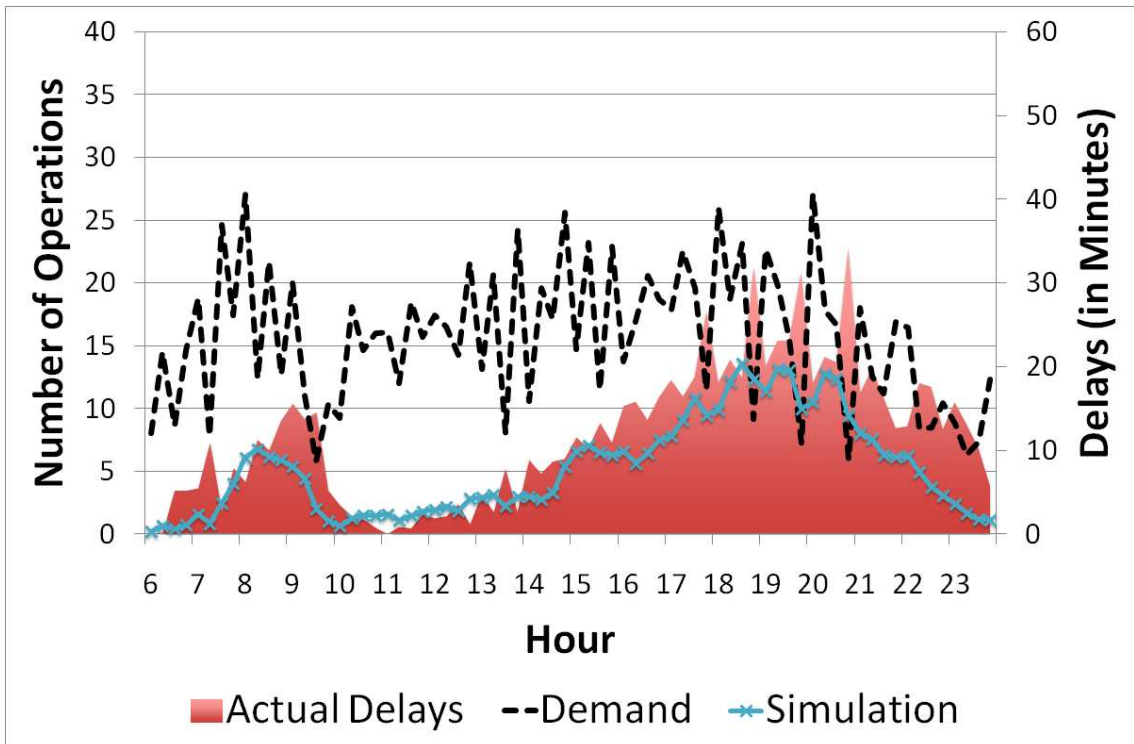


(b) EWR

Figure B-5: Results of the Monte Carlo simulation model in July 2009

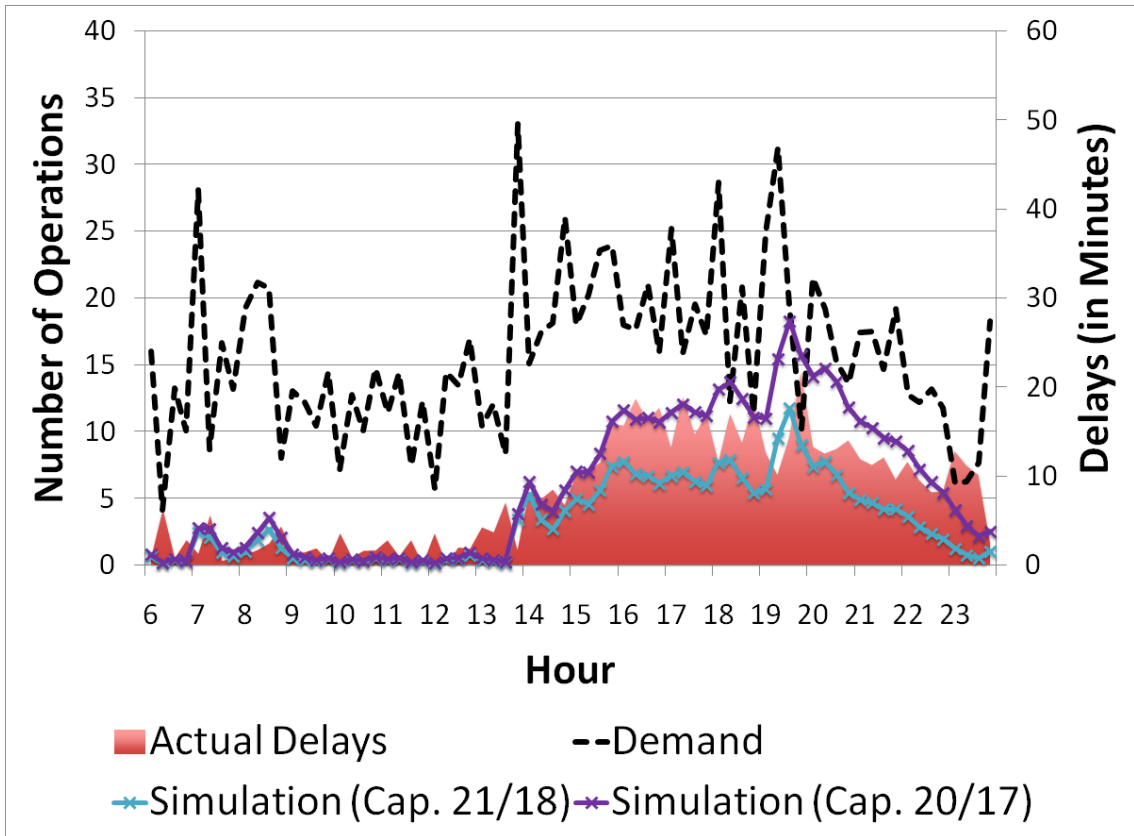


(a) JFK

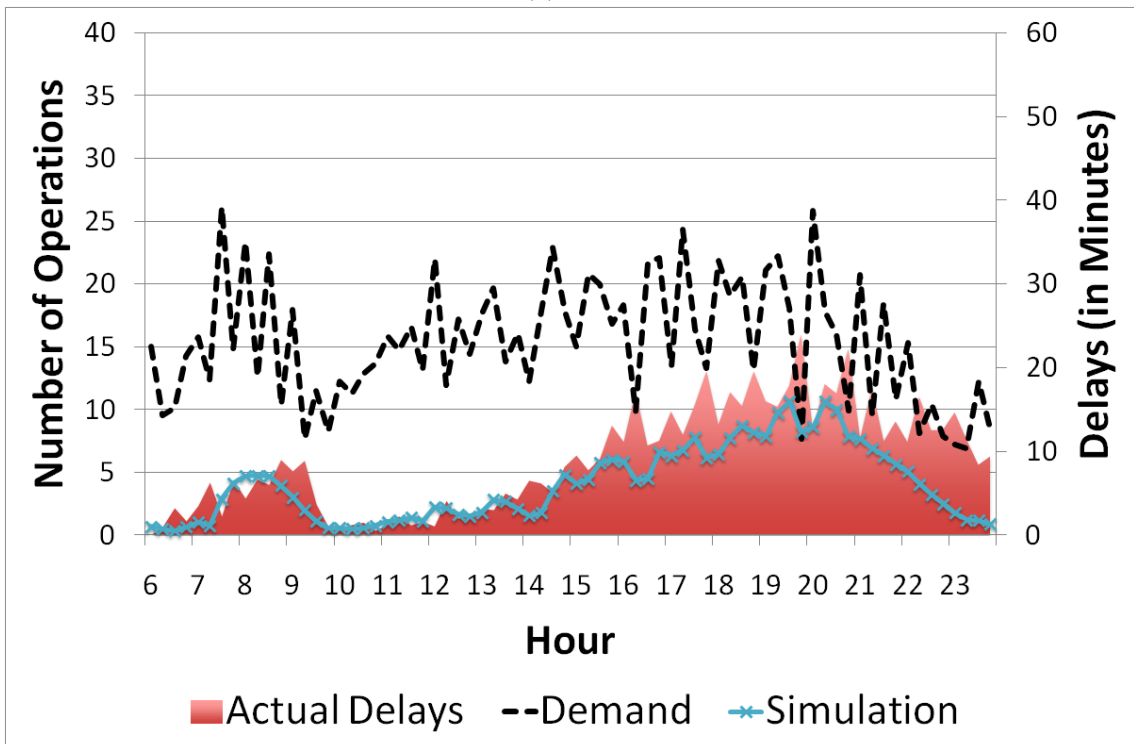


(b) EWR

Figure B-6: Results of the Monte Carlo simulation model in August 2009

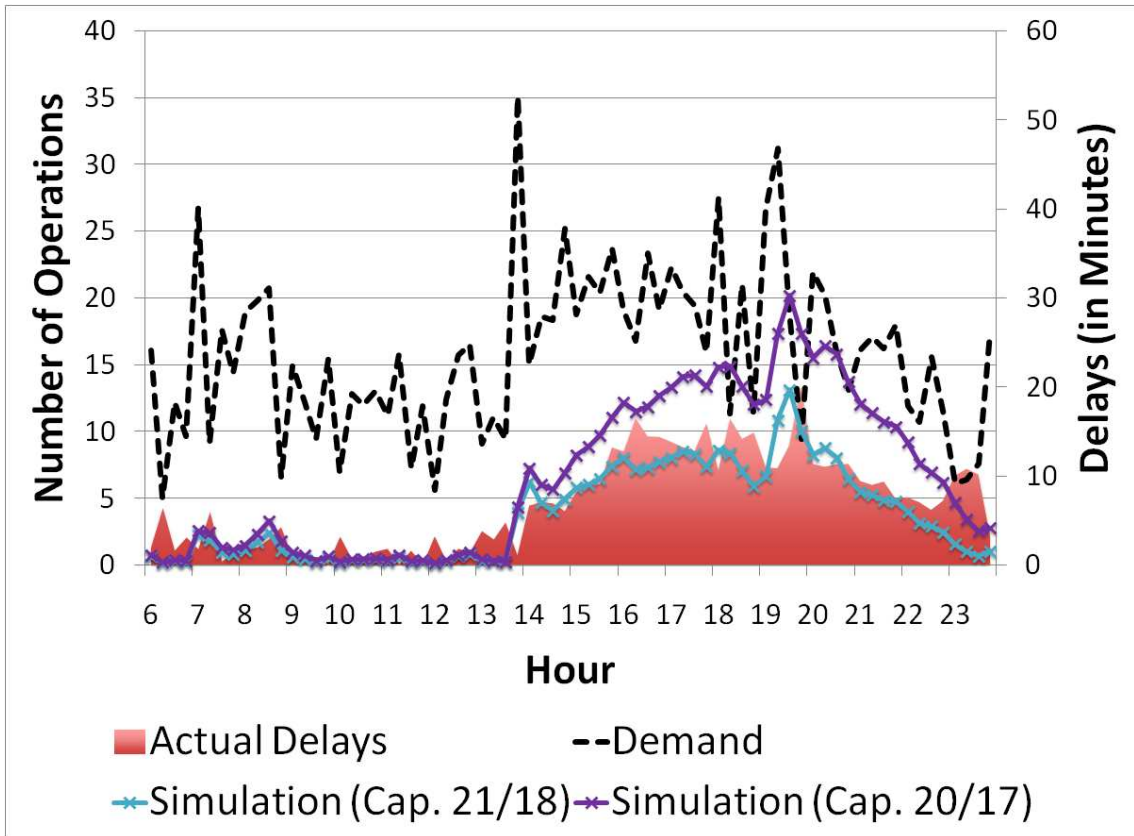


(a) JFK

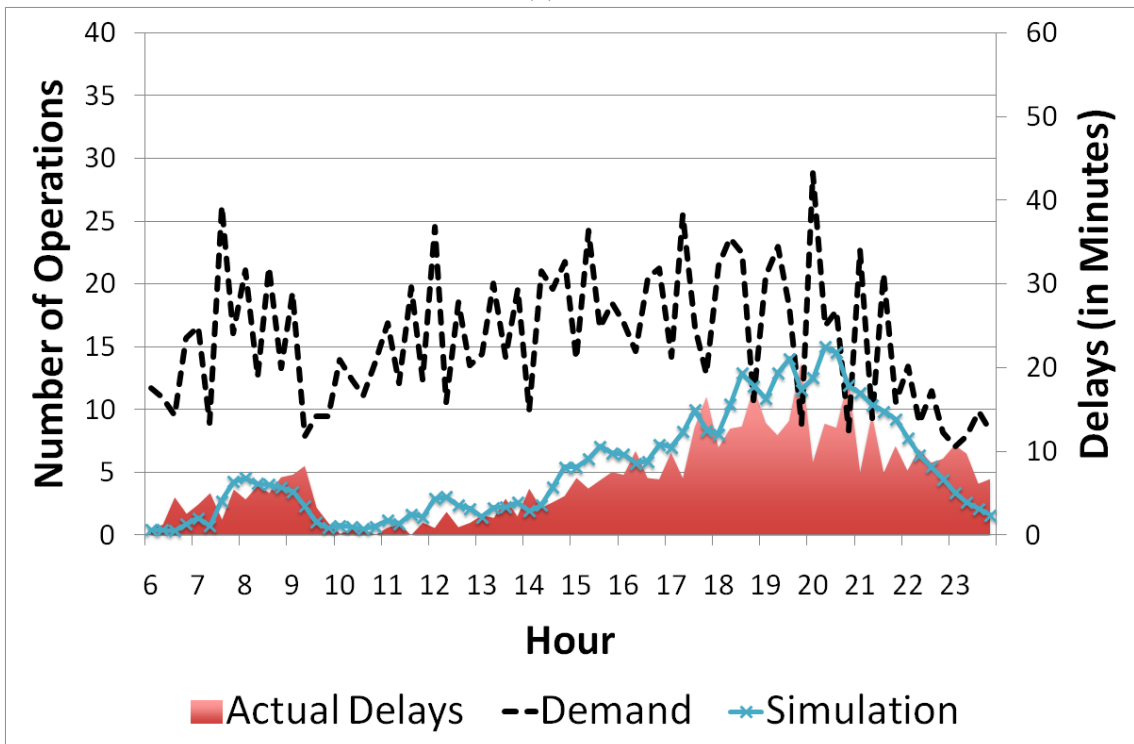


(b) EWR

Figure B-7: Results of the Monte Carlo simulation model in July 2010



(a) JFK



(b) EWR

Figure B-8: Results of the Monte Carlo simulation model in August 2010

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