Simulating Airline Operational Responses to Environmental Constraints

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Summary

This dissertation describes a model that predicts airline flight network, frequency and fleet changes in response to policy measures that aim to reduce the environmental impact of aviation. Such airline operational responses to policy measures are not considered by existing integrated aviation-environment modelling tools. By not modelling these effects the capability of the air transport system to adjust under changing conditions is neglected, resulting in the forecasting of potentially misleading system and local responses to constraints.

The model developed follows the overriding principle of airline strategic decision making, i.e., airline profit maximisation within a competitive environment. It consists of several components describing different aspects of the air transport system, including passenger demand forecasting, flight delay modelling, estimation of airline costs and airfares, and network optimisation. These components are integrated into a framework that allows the relationships between fares, passenger demand, infrastructure capacity constraints, flight delays, flight frequencies, and the flight network to be simulated. Airline competition is modeled by simulating a strategic game between airlines competing for market share, each of which maximizes its own profit.

The model is validated by reproducing historical passenger flows and flight frequencies for a network of 22 airports serving 14 of the largest cities in the United States, using 2005 population, per capita income and airport capacities as inputs. The estimated passenger flows and flight frequencies compare well to observed data for the same network (the R^2 value comparing flight segment frequencies is 0.62). After validation, the model is applied to simulate traffic growth and carbon dioxide and nitrogen oxide emissions within the same network from 2005 to 2030 under a series of scenarios. These scenarios investigate airline responses to (i) airport capacity constraints, (ii) regional increases in costs in the form

of landing fees, and (iii) major reductions in aircraft fuel burn, as would be achieved through the introduction of radically new technology such as a blended wing body aircraft or advanced open rotor engines.

The simulation results indicate that, while airport capacity constraints may have significant system-wide effects, they are the result of local airport effects which are much greater. In particular, airport capacity constraints can have a significant impact on flight delays, passenger demand, aircraft operations, and emissions, especially at congested hub airports. If capacity is available at other airports, capacity constraints may also induce changes in the flight network, including changes in the distribution of connecting traffic between hubs and the distribution of true origin-ultimate destination traffic between airports in multi-airport systems. Airport capacity constraints are less likely to induce any significant increase in the size of aircraft operated, however, because of frequency competition effects, which maintain high flight frequencies despite reductions in demand in response to increased flight delays. The simulation results also indicate that, if sufficiently large, regional increases in landing fees may induce significant reductions in aircraft operations by increasing average aircraft size and inducing a shift in connecting traffic away from the region. The simulation results also indicate that the introduction of radically new technology that reduces aircraft fuel burn may have only limited impact on reducing system CO_2 emissions, and only in the case where the new technology can be taken up by the majority of the fleet. The reason for this is that the reduced operating costs of the new technology may result in an increase in frequency competition and thus aircraft operations.

In conclusion, the modelling of airline operational responses to environmental constraints is important when studying both the system and local effects of environmental policy measures, because it captures the capability of the air transport system to adjust under changing conditions.

Declaration

This dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration except where specifically indicated in the text. No part of the work contained in this dissertation has been submitted to any other university or place of learning for any other qualification. In compliance with the regulations of the Degree Committee, this dissertation contains approximately 46 000 words with 26 figures and 3 tables.

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And finally, *Soli Deo Gloria*. All Glory to God.

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Acronyms and Abbreviations

ACIM	Air Carrier Investment Model
AERO-MS	Dutch Civil Aviation Authority Aviation Emissions and Evaluation of Reduction Options Modelling System
AIM	Cambridge University Aviation Integrated Modelling Project
ATL	Atlanta Hartsfield-Jackson International Airport
APMT	MIT Aviation Environmental Portfolio Management Tool
APU	Auxiliary Power Unit
ASAC	Aviation System Analysis Capability
ASM	Available Seat Miles
ASPM	Aviation System Performance Metrics
ATA	Air Transport Association
ATC	Air Traffic Control
BADA	Base of Aircraft Data
BOS	Boston General Edward Lawrence Logan International Airport
BUR	Burbank Bob Hope Airport
CAEP	Committee on Aviation and Environmental Protection
CCSP	United States Climate Change Science Program
CLE	Cleveland-Hopkins International Airport
CVG	Cincinnati/Northern Kentucky International Airport
DAL	Dallas Love Field Airport
DCA	Ronald Reagan Washington National Airport
DEN	Denver International Airport
DFW	Dallas/Fort Worth International Airport

DOT	United States Department of Transport
DTW	Detroit Metropolitan Wayne County Airport
ETS	Emissions Trading Scheme
EU	European Union
EWR	Newark Liberty International Airport
FAA	United States Federal Aviation Administration
FESG	ICAO CAEP Forecasting and Emissions Support Group
FLL	Fort Lauderdale/Hollywood International Airport
GAO	United States Government Accountability Office
GDP	Gross Domestic Profit
HOU	Houston William P. Hobby Airport
IAD	Washington Dulles International Airport
IAE	Cambridge University Institute for Aviation and the Environment
IAH	Houston George Bush Intercontinental Airport
IATA	International Air Transport Association
ICAO	International Civil Aviation Organisation
IGSM	MIT InteGrated Systems Model
IPCC	Intergovernmental Panel on Climate Change
JFK	John F. Kennedy International Airport
LAX	Los Angeles International Airport
LGA	LaGuardia Airport
LMI	Logistics Management Institute
LTO	Landing Take-Off Cycle
MDW	Chicago Midway International Airport
MHT	Manchester-Boston Regional Airport

MIA	Miami International Airport
MIP	Mixed Integer Program
MIT	Massachusetts Institute of Technology
NASA	National Aeronautics and Space Administration
nmi	Nautical Miles
OAG	Official Airline Guide
OAK	Metropolitan Oakland International Airport
O-D	True origin-ultimate destination
ONT	Ontario International Airport
ORD	Chicago O'Hare International Airport
PARTNER	The Partnership for AiR Transportation Noise and Emissions Reduction
PHL	Philadelphia International Airport
PVD	Providence Theodore Francis Green State Airport
RPM	Revenue Passenger Mile
SEA	Seattle-Tacoma International Airport
SFO	San Francisco International Airport
SJC	Norman Y. Mineta San Jose International Airport
SLC	Salt Lake City International Airport
SNA	John Wayne-Orange County Airport
STL	Lambert-St Louis International Airport
TAF	FAA Terminal Area Forecast
U.S.	United States

1 Introduction

The development of the powered aircraft in 1903 was to revolutionise intercity transportation. For the first time, the possibility arose for passengers and freight to be transported by air instead of over land or sea, making previously impossible trips not only possible, but practical and even attractive. However, it was not until after the Second World War, more than 40 years later, that long distance intercity travel would cease to be dominated by rail. It took technological innovations during and after the Second World War, most notably the development of the jet engine, for aircraft to become sufficiently cost effective for aviation to compete with rail. By the 1950s, advancements in aircraft technology along with government investment in aviation infrastructure (particularly airports) led to aviation taking over from rail to become the most important mode of transport for commercial intercity passenger travel in the United States (Schäfer *et al.*, 2009). The growth of aviation in other industrialised countries and regions followed similar trends. Between 1960 and 2005, worldwide scheduled passenger air travel grew from 109 billion passenger-kilometres travelled to 3.7 trillion – an average growth rate of over 8% per year (ICAO, 2006-2). Because of the growing demand to travel as income levels rise and people can afford to travel more, and because of the continuing trend to shift from slower to faster modes of transport across all distances (Schäfer *et al.*, 2009), forecasts for future growth in passenger air transport are also high. The Airbus Global Market Forecast from 2007 to 2026 (Airbus, 2007) and the Boeing Current Market Outlook from 2006 to 2026 (Boeing, 2007) both predict growth rates of around 5% per year. By 2050 conservative estimates predict a 30-110% growth in passenger kilometres travelled over 2005 levels (Berghof *et al.*, 2005), while more aggressive estimates predict an increase of an order of magnitude (Schäfer, 2006).

To serve this anticipated growth in demand for air travel, there must be an increase in air traffic (number of aircraft movements). In a deregulated system such as is in place in most industrialised nations and many developing economies, airlines allocate aircraft to routes in such a way as to maximise profit across their networks. Airline strategic planning is a complex process of optimising flight operations within a competitive environment in which airlines try to capture market share by reducing fares and increasing flight frequencies. Hub-and-spoke networks are a key component of such optimised operations. In hub-and-spoke networks airlines route passengers through central hub airports instead of on non-stop flights between cities. Hub-and-spoke operations thus enable airlines to serve multiple markets using fewer flights than can be achieved through point-to-point networks, in which all cities are connected by non-stop flights only. Airline hub-and-spoke operations were pioneered by Delta Air Lines in 1955, with a hub in Atlanta, in an effort to compete with Eastern Airlines (Delta Air Lines, 2009-1). After the deregulation of the U.S. airline industry in 1978, this model was adopted by several other airlines because of the cost savings associated with it. Economies of scale in servicing passengers and aircraft at the hub airports allow airlines to take advantage of reduced traffic servicing costs, while the greater number of passengers flying to and from the hub airports allow airlines to take advantage of economies of scale associated with the lower operating costs, per passenger kilometre, of larger aircraft types. However, passenger travel times and distances increase because passengers are flying via a hub, where they must connect. Airlines also compete by increasing non-stop frequencies between city pairs in order to increase market share. There is therefore a trade-off between the benefits of hub-and-spoke operations in terms of reduced traffic servicing costs and aircraft operating costs per passenger kilometre on the one hand, and the benefits of point-to-point operations in terms of reduced passenger-kilometres flown and increased market share on the other hand. As demand in a market increases, point-to-point operations typically become more profitable as airlines are able to take advantage of the economies of scale associated with the lower operating costs per passenger kilometre of larger aircraft types without the need to operate a hub-and-spoke network. Maximum profit is typically achieved through a combination of hub-and-spoke operations and point-to-point operations. The result is a complex network of flights offered by competing airlines to serve the available demand, which adjusts under changing conditions.

While necessary to serve increasing passenger demand, growth in air traffic is expected to have a number of negative consequences, including increasing flight delays, air quality and noise impacts, and impact on global climate change. Flight delays result when traffic growth is constrained by the air traffic system capacity. Airport and airspace capacity already constrain flight operations at many major airports in the United States and Europe. In the United States, average arrival delays were greater than 15 minutes at 23 airports in 2006, with LaGuardia Airport experiencing 21 minutes of average delay per flight (FAA, 2008). In Europe, average arrival delays were greater than 15 minutes at 10 airports in 2006, with London Luton Airport experiencing 18 minutes of average delay per flight (EUROCONTROL, 2007). In the industrialised world, where airport capacity expansion is limited by local community resistance and environmental restrictions, system capacity is likely to become an increasingly binding constraint on growth in air traffic. Flight delays are also increasing in developing regions, such as China (Cao, 2004) and India (Times of India, 2008), although in these regions system capacity is expected to grow with increasing air traffic, at least initially.

Of potentially greater concern is that the growth in air traffic is expected to produce a significant environmental impact, including air quality and noise impacts, and global climate change, as reported by the IPCC (1999), Cairns *et al.* (2006) and Reynolds *et al.* (2007). Nitrogen oxides (NO_x) and particulate emissions in the vicinity of airports have significant impacts on local air quality, resulting in negative health effects and premature mortalities (Graham *et al.*, 2009). Aircraft noise in the vicinity of airports also has negative health effects (Cohen *et al.*, 1980), while also reducing property values near airports and affecting children's abilities to learn (Haines *et al.*, 2001). The climate effects of aviation are more complex and widespread. Carbon dioxide (CO_2), the emissions of which are directly proportional to fuel burn, is a greenhouse gas that impacts the atmosphere for hundreds of years, increasing radiative forcing[1] and ultimately causing the global average temperature to rise. Non-CO_2 effects are also significant. NO_x emissions at aircraft cruise altitudes lead to the production of tropospheric ozone, which has a warming effect, and accelerate the removal of methane from the atmosphere, which has a cooling effect (IPCC, 1999). Ozone and methane have different life times, so the warming effect is regional, while the cooling effect is global. Contrails from aircraft engines can increase high altitude cloud cover, which tends to produce a net warming effect in the region where the aircraft was flown, although there is significant scientific uncertainty in its overall effect.

[1] A change in average net radiation at the top of the troposphere (IPCC,1999).

Policy measures to mitigate the environmental impacts of aviation are under consideration by a number of national and regional governing authorities. These include (i) new regulations for aircraft fuel burn or emissions levels to incentivise the development of new, more fuel efficient technology and force its adoption into airline fleets (GAO, 2009); (ii) economic instruments that increase costs to passengers, such as an air passenger duty, and result in a reduction in passenger demand growth as passengers choose to travel using alternative modes of transport, or choose not to travel at all (HM Revenue and Customs, 2008); (iii) economic instruments that increase costs to airlines, such as increasing landing fees (House of Commons, 2003) or the inclusion of aviation in an emissions trading scheme (European Commission, 2006; GAO, 2009); and (iv) direct constraints on traffic growth such as limited airport capacity expansion (DfT, 2009).

In order to make informed choices with regard to which of these policy measures should be employed, the potential impacts of each policy measure must be understood in detail. This requires simulation of the relevant impacts of these policies on the air transport system. Three integrated aviation-environment system models exist for detailed assessment of the environmental impact of aviation and the mitigation potential of different policy measures: the Aviation Emissions and Evaluation of Reduction Options Modelling System (AERO-MS) (Pulles *et al.*, 2002); the Aviation Environmental Portfolio Management Tool (APMT) (Waitz *et al.*, 2006-1); and the Aviation Integrated Modelling (AIM) Project (Reynolds *et al.*, 2007). Using forecasts of passenger demand (either endogenous or exogenous) and predicted technology development, these integrated aviation-environment system models simulate air traffic growth and emissions at the airport level, regionally and globally, allowing local air quality, noise and climate impacts to be estimated. The impacts of policy measures are simulated by modifying demand inputs, airline operating costs, aircraft performance characteristics and other inputs. The models generate a partial equilibrium between supply and demand by simulating fare changes as a function of changes in airline cost, and modelling the associated demand response to these changes in fare. The response of sectors other than air transport is not modelled, although a general equilibrium model that includes the responses of other sectors is under development within APMT (PARTNER, 2009). Further details of the modelling approaches employed in each model are presented in Appendix A.

In each of the integrated aviation-environment system models described above, the supply side, in terms of air traffic growth and fleet composition, is modelled according to observed trends in historical traffic growth as a function of demand. There is no explicit modelling of airline strategic decision making to capture the effects of competition or airline operational changes. Such modelling according to observed trends is suitable for many types of analysis, such as shorter term forecasting (5 to 10 years), when the primary drivers of growth are not likely to change significantly. However, especially over longer time horizons (20 to 30 years), constraints may come into play that have not historically affected aviation growth significantly. Similarly, policies designed to mitigate the environmental impact of aviation may have unexpected effects that have not been observed historically. By not modelling these effects, the capability of the air transport system to adjust under changing conditions is neglected, resulting in the forecasting of potentially misleading impacts. In order to capture the effect of potentially increasingly binding constraints on traffic growth and the impact of unexpected policy effects, airline operational responses must be simulated, and this must be done in a way that models the underlying principles behind airline strategic decision making.

Examples of policy measures for which it may be important to simulate airline operational responses by modelling these underlying principles include (i) limitations on airport capacity expansion, (ii) the introduction of regional cost increases, and (iii) the introduction of radically new technology into the fleet. Each of these is described in more detail below.

Reynolds *et al.* (2007) show that, in the absence of other changes, average arrival delays at the 50 busiest airports in the United States could be over 1 hour per flight by 2030, even with the implementation of all existing airport capacity expansion plans. This estimate accounts for the demand-reducing effects of increased fares resulting from airlines passing on 50% of the costs associated with flight delays directly to passengers, but assumes that airlines will continue to increase air traffic to match the projected growth in demand as they have in the past. However, as suggested by both Reynolds *et al.* (2007) and Kostiuk *et al.* (2000), these delays are unlikely to occur in reality as airlines would adjust their operations to minimise the negative impacts of the increasing costs associated with delays and reductions in passenger demand.

Changes in operations in response to flight delays may include changes in the flight schedules operated; changes in the flight networks operated; and changes in the aircraft types operated. Airlines may adjust their flight schedules by moving flights to off-peak times (Kostiuk *et al.*, 2000), broadening the range of departure times into the early morning and later into the night (Kostiuk *et al.*, 2000), and “flattening” the schedule – spreading out arrival and departure banks so that flights are more evenly distributed across the day (Evans, 2002). Airlines may adjust the flight networks that they operate by avoiding congested hubs and gateways (departure routes), and by making greater use of secondary airports in preference to congested primary airports (Kostiuk *et al.*, 2000). Aircraft sizes may also be increased in order to serve the demand with fewer flights, and therefore lower delays (Kostiuk *et al.*, 2000). While each of these changes is a strategic response by the airlines to flight delays, changes in aircraft size must occur over longer time periods than the changes in the schedule and network, because of the delay between ordering new aircraft and delivery. Schedule changes have been observed historically (Kostiuk *et al.*, 2000; Evans, 2002), as have network changes to shift to secondary airports (Bolgeri *et al.*, 2008), but other changes in flight networks and changes in aircraft size have not been observed historically.

Each of the operational responses to delays described above may significantly alter how future air traffic grows. In order to generate plausible estimates of air traffic growth in a capacity-constrained system it is therefore essential to quantify how airlines are likely to respond to capacity constraints. This can be achieved by identifying trends in the way that airlines have responded to capacity constraints in the past, or by simulating how flight delays affect the underlying principles behind airline strategic decision making, i.e. increases in flight delay causing increases in cost that reduce airline profit. This latter approach is applied in this dissertation because of its potential to capture airline responses that have not been observed historically.

Modelling the underlying principles behind airline strategic decision making is also important for evaluating the impacts of environmental policies. The introduction of policy measures that increase regional costs to airlines, as would occur through regionally increased landing fees or the inclusion of aviation within a regionally applied emissions trading scheme, such as is planned for Europe in 2012 (European Union, 2009), may also have unexpected effects. There is concern that such regional increases in cost may put airlines operating from within the region at a competitive disadvantage relative to airlines operating outside the region, potentially leading to a loss in traffic within the region through airlines shifting hub operations outside the region (Ernst & Young, 2007). Quantification of this effect requires modelling of airline strategic decision making regarding the choice flight network and hub location in response to regional changes in cost.

The introduction of radically new technology into the fleet that reduces fuel burn and greenhouse gas emissions significantly may also have unexpected effects, such as enabling airlines to increase frequency in order to attract more market share, because of the reduced operating costs of the new technology. This would reduce the environmental benefits of the introduction of the technology. Quantification of this effect requires modelling of how airline competition is impacted by operating costs, requiring simulation of how airline competition impacts airline strategic decision making.

In order to capture these and related effects, this thesis describes a model of airline operational responses to environmental constraints, including environmental policy measures and airport capacity constraints. This is accomplished by modelling the underlying principles behind airline strategic decision making. Chapter 2 provides a detailed review of the literature available on existing modelling approaches to forecast traffic growth, simulate airline responses to constraints, and model airline strategic decision making. The review identifies a gap in the literature in the area of simulating airline operational responses to environmental constraints, and in the area of applying such a model to future traffic growth under alternative policy scenarios. Accordingly, Chapter 3 describes the research objectives of the dissertation to develop, validate and apply a model that simulates airline operational responses to environmental constraints in the future. This is followed by a description of the research methodology employed to fulfil the stated objectives. The model that is developed to fulfil the objectives is described in Chapter 4. This includes specification of a modelling framework that simulates the inter-relationships between changes in cost, fares, passenger demand, infrastructure capacity constraints, flight delays, aircraft performance, flight frequencies, fleet composition, and the flight network operated. The associated individual sub-models are described in Chapter 5. These include a delay calculator, travel time calculator, operating cost calculator, average fare model, passenger demand model, flight network optimisation, and emissions calculator. The iterative framework implemented to simulate competition between airlines is also described.

Chapter 6 presents model validation results reproducing observed passenger and traffic flows for a network of 22 airports serving 14 cities in the United States in 2005. The model is then applied to simulate future traffic growth and emissions within the same network for three families of scenarios in Chapter 7. These investigate airline operational responses to (i) airport capacity constraints, (ii) regional increases in costs in the form of increased landing fees, and (iii) major reductions in aircraft fuel burn, as would be achieved through the introduction of radically new technology such as a blended wing body aircraft or advanced open rotor engines.

The conclusions of the research are presented in Chapter 8. These suggest that the modelling of airline operational responses to environmental constraints is important when studying both system and local, airport level, effects, and to capture the capability of the air transport system to adjust under changing conditions. Neglecting these constraints would result in the forecasting of potentially misleading system and local responses to constraints. Chapter 9 concludes with recommendations for future research, including integration of a passenger choice model and fleet turnover model into the modelling framework, and application of the model to other regions, such as India, which is likely to see greater growth than developed regions and thus greater network change as the system shifts from a strong hub-and-spoke network to more point-to-point operations.

2 Literature Review

This chapter presents a review of the existing approaches for simulating airline operational responses to environmental constraints. As described in Chapter 1, such operational responses, which are driven by the underlying principles behind airline strategic decision making, may have a significant impact on future aircraft operations. In Section 2.1 a literature review is presented of existing approaches to forecasting future aircraft operations, which shows that airline operational responses to constraints are not explicitly simulated in any of the approaches. Section 2.2 then presents a review of existing approaches to model airline operational responses to specific constraints, including airport capacity constraints and other constraints that increase airline costs. This is followed, in Section 2.3, by a summary of approaches in the literature to model airline strategic decision making, which drives the airline responses to constraints. Conclusions are drawn in Section 2.4.

2.1 Existing Approaches to Forecasting Future Aircraft Operations

Approaches to forecasting future aircraft operations typically estimate future air traffic growth based on observed trends in historical air traffic growth, as a function of forecast passenger (and in some cases freight) demand (Pulles *et al.*, 2002; Hancox and Lowe, 2000; Bhadra, 2003; Bhadra *et al.*, 2003; Waitz *et al.*, 2006-2; Reynolds *et al.*, 2006; ICAO, 2006-1). In the majority of cases, the distribution of aircraft types operated on each flight segment is estimated first, according to observed trends in historical data (Pulles *et al.*, 2002; Hancox and Lowe, 2000; Bhadra, 2003; Bhadra *et al.*, 2003; Reynolds *et al.*, 2006). This is followed by estimation of the frequency of flights on each segment, either according to observed trends in historical data or by making key assumptions about aircraft load factors. The types of aircraft operated on each flight segment then define the number of seats available, which is a determinant of the number of aircraft required to serve the projected demand.

Bhadra (2003), Bhadra *et al.* (2003) and Reynolds *et al.* (2006) model the distribution of aircraft types operated on each flight segment using a multi-nomial logit function that captures the likelihood of specific aircraft choices. The parameters of this function are estimated through regression on historical data. The independent variables in this approach are the number of passengers on the flight segment, the flight segment length, and two dummy variables for whether the origin and destination airports are hubs or not. As the number of passengers on a flight segment increases, a greater percentage of larger aircraft types is typically operated. This is also the case as flight segment length increases, and when a flight segment connects to a hub airport. The approach is as follows: With a series of aircraft size choices, $y = j$ $(1,2,...,J)$, the probability of each aircraft size choice P_j $(P_1,P_2,...,P_J)$, given segment passenger demand, flight segment length, and traffic type defined by the vector x, is defined as follows:

$$P_{ij} = \Pr\left(y_i = j \middle| x_i\right) = \frac{\exp\left(x_i'\beta_j\right)}{1+\sum_{j=2}^{J}\exp\left(x_i'\beta_j\right)} \qquad \text{for j>1} \qquad (2\text{-}1)$$

and,

$$P_{i1} = \Pr\left(y_i = 1 \middle| x_i\right) = \frac{1}{1+\sum_{j=2}^{J}\exp\left(x_i'\beta_j\right)} \qquad \text{for j=1} \qquad (2\text{-}2)$$

where β_j is a vector of the estimated slope parameters, as specified by:

$$\begin{aligned} P_{ij} = \Pr\left(y_i = j \middle| x_i, \beta_j\right) = \alpha_{ij} &+ \beta_{j1}\left(StageLength_i\right) + \beta_{j2}\left(Demand_i\right) \\ &+ \beta_{j3}\left(OrigHubDummy_i\right) + \beta_{j4}\left(DestHubDummy_i\right) + \varepsilon_i \end{aligned} \qquad (2\text{-}3)$$

The intercept (α) and slope parameters (β) are estimated by regression on historical flight segment length (*StageLength*), passenger demand (*Demand*), and traffic type data (*OrigHubDummy* and *DestHubDummy*) using maximum likelihood estimation. With a doubling of passenger demand on a route and all else being equal, the estimated parameters predict a 25% to 50% increase in average aircraft size (in seats per flight), while a doubling of flight segment length predicts a 10% to 20% increase. On average, a flight to a hub airport has 5% to 15% more seats than a flight between spoke airports. Pulles *et al.* (2002) and Hancox and Lowe (2000) use a similar approach by identifying how the average number of seats offered per flight varies as a function of the number of passengers on the flight segment and the flight segment length. This relationship is also identified from historical data.

Different approaches are used in the literature to forecast flight segment frequencies as a function of forecast passenger segment demand. Pulles *et al.* (2002) and Hancox and

Lowe (2000) forecast flight segment frequencies by assuming a constant elasticity of flight frequency with number of passengers on the flight segment, as shown by equation 2-4 (Hancox and Lowe, 2000).

$$\frac{Fltfreq_{forecastyr}}{Fltfreq_{baseyr}} = \left(\frac{Pax_{forecastyr}}{Pax_{baseyr}} \right)^{\eta} \tag{2-4}$$

where *Fltfreq* represents flight segment frequency, and *Pax* represents passenger demand by flight segment. The subscripts *baseyr* and *forecastyr* refer to the base year and forecast year respectively. The constant elasticity is η, which is estimated from historical flight segment frequency and passenger demand data. Different elasticities are derived for a series of flight segment length categories, ranging from 0.88 to 0.96. The assumption of a constant elasticity of flight frequency with number of passengers on the flight segment was found to be reasonable when the number of passengers on a flight segment is high, but was found to under-predict flight frequencies for flight segments with low numbers of passengers.

A slightly different approach, as used by Bhadra (2003) and Bhadra *et al.* (2003), predicts flight segment frequencies by assuming that load factors remain at base year levels. Flight segment frequencies are then forecast based on forecast passenger demand and average aircraft size, calculated directly from the forecast distribution of aircraft types operated on each flight segment.

A related approach to forecasting future aircraft operations, described by ICAO (2006-1), is to assume that airlines will provide additional seats to serve projected passenger demand increases partly by increasing the frequency of flights operated, and partly by increasing aircraft seating capacity. The split between increased frequency and increased aircraft size can be calculated according to historical trends as a function of flight segment passenger demand and flight segment length. This approach is used in the Airbus Global Market Forecast (Airbus, 2007). Other details of the methodology used to make this forecast are proprietary, as are the methodologies used by Boeing to produce their Boeing Current Market Outlook (Boeing, 2007).

An alternate approach to forecasting future aircraft operations is to predict air traffic growth by airport according to historical trends in airport activity. Flight segment traffic growth can then be extracted from the estimated forecasts of airport activity growth by making assumptions about the flight network operated. This is the approach used by the U.S. Federal Aviation Administration (FAA) Terminal Area Forecast (TAF) (Waitz *et al.*, 2006). As described by the U.S. Department of Transport (DOT) and FAA (DOT and FAA, 2006), the TAF forecasts airport activity, including aircraft operations and enplanements, using historical relationships between airport passenger demand, measures of airport activity, and local and national factors that may influence aviation activity. These forecasts are then compared to historical trends in airport activity for reasonableness and consistency, and if they deviate from expected trends, other statistical techniques are used instead, such as regression analysis and the use of growth rates developed separately. Key airports receive a more in-depth review by FAA economists, including consideration of local income and employment, growth of true origin-ultimate destination (O-D)[1] and connecting traffic, the cost of operating from the airport, and seating capacity and load factors of aircraft operating at the airport. The TAF assumes unconstrained demand, which is estimated based on local and national economic conditions and conditions within the aviation industry. Thus, airport capacity constraints are not considered in the development of the forecast. However, if airports historically operate under constrained conditions, these constraints will be reflected in the forecast because they are embedded in the historical data.

Future aircraft operations can also be forecast directly from projections of economic data using statistical relationships. This is the approach used for airport air traffic forecast by the International Civil Aviation Organisation (ICAO) Committee on Aviation and Environmental Protection (CAEP) Forecasting and Emissions Support Group (FESG) (ICAO, 2006-1; Waitz *et al.*, 2006-2). In this approach, experts in the aerospace industry form a consensus on the key economic parameters required for the forecast, such as Gross Domestic Product (GDP) and aircraft retirement curves. The future growth in air traffic and its fleet requirements are then estimated accordingly from projections of world economic data. This analysis is completed at the global level and then decomposed into regional traffic projections by airline based on historical relationships between traffic and market share. The result is

[1] A true origin-ultimate destination market is the market from a traveller's initial origin city to their final destination city, irrespective of route (including both non-stop routes and routes through intermediate points).

forecast Revenue Passenger Miles (RPM) for 22 major domestic and international route groups.

Waitz *et al.* (2006-2) describe a capability that modifies the TAF and FESG airport air traffic forecasts to account for supply and capacity constraints according to changes in operating costs, assumptions about fares, and assumptions about air transport demand.

In conclusion, each of the approaches described predicts future aircraft operations based on historical trends. These approaches do not explicitly model airline operational responses to environmental constraints, or airline strategic decision making. Literature does exist, however, describing approaches to modelling airline operational responses to different constraints and changes in operating cost. Literature also exists describing approaches to model airline strategic decision making. These are reviewed in Sections 2.2 and 2.3 respectively.

2.2 Existing Approaches to Modelling Airline Responses to Constraints

As described in Chapter 1, policy measures under consideration to mitigate the environmental impacts of aviation include more stringent regulations for aircraft emissions; economic instruments that increase costs to passengers; economic instruments that increase costs to airlines; and direct constraints on traffic growth such as limited airport capacity expansion. Airlines are likely to limit the negative impacts of these policy measures on airline costs and passenger demand by making operational changes: changing the types of aircraft they operate and changing the way in which they operate those aircraft.

Shorter term airline operational responses include "parking" aircraft, where aircraft are removed from service but not sold, and modifying the allocation of aircraft in the fleet to specific flights. Other short term responses may include adjusting the shape of the schedule operated at specific airports; adjusting the frequency of flights operated on specific routes; and making small changes to the flight network operated, such as shifting some hub-and-spoke operations to point-to-point service. Each of these responses is, however, limited by the available fleet that is operated by the airline, and by the airports at which it has operations. Longer term responses include the retirement of older aircraft and the purchase or leasing of new aircraft (leasing new aircraft can be done on a shorter time scale than purchasing new aircraft); the introduction of operations at new airports; and the shifting of hub operations between airports. The purchase or leasing of new aircraft enables greater changes in airline schedules, flight frequencies, and the flight network operated because the fleet constraint is removed, while the introduction of operations at new airports and the shifting of hub operations between airports enables greater changes in the flight network operated specifically.

There are many examples of airlines making significant operational changes in response to specific policy measures or events. As a result of the introduction of progressively more stringent noise regulations in Europe and the United States from 1976, airlines retired older, noisier equipment and purchased new, quieter aircraft (de Neufville and Odoni, 2003, p182). Similarly, airlines responded to the sharp increases in oil prices in 2008 by retiring older, less fuel efficient aircraft (Clark, 2008; Schofield, 2008), as they did following the sharp decline in passenger demand following the events of 11 September, 2001 (Tomlinson, 2002). Decreases in demand and increases in operating costs have also led airlines to adjust their flight networks. US Airways closed a hub airport in Pittsburgh in 2004 because of poor economics and competition from low cost carriers, shifting traffic to their other hubs in Philadelphia and Charlotte (Grossman, 2007; Fitzpatrick, 2007). Lufthansa has threatened to respond to the inclusion of aviation within the European Union (EU) Emissions Trading Scheme (ETS), which would require CO_2 credits for all flights connecting to the EU, by shifting its hub operations to Zürich, which is outside the EU (Turner, 2007). Airlines have also responded to airport capacity constraints by adjusting daily schedules to minimise delays, examples including Continental Airlines' operations at Newark Liberty International Airport and United Airlines' operations at San Francisco International Airport (Evans, 2002). A further response to airport capacity constraints is growth at secondary airports in favour of primary airports, which has been observed at numerous locations (London, New York, Tokyo, Chicago, Boston, Paris, San Francisco, Los Angeles, Milan, Miami, Washington, etc.) (Bolgeri *et al.*, 2008). Growth at secondary airports is sometimes also driven by reduced operating costs, with airport authorities offering low landing fees to incentivize growth.

The extent and diversity of examples describing airline responses to make operational changes illustrates the complexity of airline strategic decision making. In the sections below, literature is reviewed that describes approaches to model airline operational responses to specific constraints. Airline operational responses to airport capacity constraints, which cause flight delays, have been examined extensively in the literature. This specific issue is therefore discussed in detail. It is followed by a review of the more limited available literature describing approaches to modelling airline responses to other constraints – specifically inclusion of aviation within an emissions trading scheme, and the effect of increased landing fees to induce a shift to larger aircraft.

Kostiuk *et al.* (2000) state that the large flight delays predicted in the United States and Europe as a result of forecast passenger demand will only happen if airlines attempt to meet future demand by increasing the number of flights they operate while maintaining the same scheduling practices and other operating methods in use today. As stated by Kostiuk *et al.* (2000), this is not likely to be the case, however. Instead, airlines would respond by avoiding congested hubs and gateways (departure routes), using secondary airports, moving flights to off-peak times, broadening the range of departure times, and increasing aircraft size. Kostiuk *et al.* (2000) also predict that there will be an increase in flight block times (more padding of flight schedules), creation of new hub airports, and greater use of slot-control at airports.

Evans (2002) also describes a number of airline responses to airport capacity constraints, focusing particularly on changes in the shape of the schedule operated at airports. As airports become more capacity constrained, Evans (2002) identifies a clear shift in the degree to which the airports operate a banked, or peaked, schedule. With low delays, airlines operating hub airports typically schedule a high number of arrivals in a small period – an arrival “bank”, followed by a high number of departures – a departure “bank”. This reduces passenger connecting times, reducing passenger travel times. Under airport capacity constraints, these banks of flights can experience high delays, even when average daily traffic is well below the airport capacity. In the periods between banks, flight delays can be recovered, preventing propagation of delays through the day. However, when capacity constraints become more limiting, and delays cannot be recovered in the periods between banks, a banked scheduled can lead to very high delays propagating through the day. Delays can be reduced by broadening the range of flight times, or “flattening” the schedule – spreading out banks so that flights are more evenly distributed across the day. This results in higher average connecting times, but reduces delays. Such an airline response is only effective under certain conditions, however. If an airport is not dominated by a single carrier, for example, competition effects make such a response unlikely. This is described in detail by Evans (2002), who develops a metric to describe the degree to which a schedule is banked, but does not develop a model to correlate the metric with flight delays.

Two approaches were identified in the literature to model airline operational responses to airport capacity constraints: (i) a scenario-based approach in which different known airline responses are applied exogenously, followed by simulation of the effect that they have on the system, and (ii) modelling of specific airline decision making processes, and simulating how airport capacity constraints affect them. Forms of the scenario based approach are applied by Kostiuk *et al.* (2000), Long *et al.* (1999-1) and Long *et al.* (1999-2). Kostiuk *et al.* (2000) and Long *et al.* (1999-1) describe an approach to estimate what percentage of forecast air traffic can be served by available airport capacity, making specific operational changes, while maintaining flight delays at acceptable levels. The approach employs the *LMINET* flight delay model, which, given forecast air traffic, estimates delays across a network of airports. Where delays at an airport exceed a specified airport delay tolerance value, air traffic is adjusted by moving flights to off-peak times, and broadening the range of departure times. If delays continue to exceed the delay tolerance value, demand is shaved off, and the percentage of air traffic that can be served, given the capacity of the airport, is reported. The airport delay tolerance is identified from the average padding in current schedules. Long *et al.* (1999-2) describe a similar approach assuming a greater number and variety of airline operational responses to flight delays, including increasing fares, establishing new hubs, shifting operations to include more direct services, flattening schedules, and increasing night time operations. The approach models unconstrained air traffic growth, based on the FAA TAF forecast of aircraft movements, and then adjusts variables in this model to simulate the effects of each airline response. Each airline response is specified exogenously.

In contrast to these scenario-based approaches, Elhedhli and Hu (2005) endogenously model how congestion impacts airline strategic decision making, specifically in reference to hub-and-spoke network design. A model is developed that extends typical network optimisation models, based on airline profit maximisation, by inclusion of a non-linear cost term that models the impact of congestion on airline cost as a function of flight frequencies. The cost term is a convex function that increases exponentially as more flights are assigned to an airport. The resulting non-linear large-scale mixed integer program is solved by linearisation and subsequent application of a Lagrangean heuristic. This model allows the effects of capacity constraints on network design to be simulated. The model only simulates airline decision making in terms of flight network optimisation, and does not simulate other effects impacting airline decision making, such as competition and passenger demand effects.

Other studies investigate the airline response to other constraints and policy measures. A particular policy that is currently receiving attention is the inclusion of aviation in the EU ETS, which is planned for 2012 (European Union, 2009). Literature was reviewed that simulates how airlines would respond to such a scheme (European Commission, 2006; Ernst & Young, 2007; Scheelhaase and Grimme, 2007; Albers *et al.*, 2009). The airline responses simulated in these studies differ significantly from those described above, as they focus on changes in fares that would result from changes in costs introduced by the scheme. The impact of these fares on passenger demand is then simulated. In a study by the European Commission (2006), airlines are assumed to pass on to passengers the majority, if not all, the cost increases associated with the inclusion of aviation in the scheme. This is done because passenger demand is assumed to be inelastic, and thus that increases in fares would have little effect on demand. The assumption is also made that competition between airlines would not be significantly affected by the scheme. In contrast, Ernst & Young (2007) and Scheelhaase and Grimme (2007) assume higher demand elasticities, meaning that only one third of the cost is likely to be recovered from passengers because significant increases in fare would result in significant decreases in demand. Neither the European Commission (2006), Ernst & Young (2007), nor Scheelhaase and Grimme (2007) examine airline responses beyond changes in fare. Albers *et al.* (2009) examines the specific question of whether the EU ETS will instigate airline network reconfigurations, including airlines moving hub airports outside the EU. A full network analysis is not completed though. Instead, specific routes are compared in detail in terms of costs and demand, allowing identification of potential alternative routings for connecting traffic that is impacted by the inclusion of aviation in the EU ETS.

Another policy that has been studied is the increase of airport landing fees in order to induce a shift to larger aircraft and fewer flight frequencies, which has benefits in reducing airport congestion and aviation emissions. While statistical analysis has been used to identify the relationship between costs and aircraft size (Wei and Hansen, 2003; Givoni and Rietveld, 2009), the modelling of airline strategic decision making has been applied specifically to identify the impact of landing fees on airline choice of aircraft size and flight frequency (Wei, 2006). In this analysis there is explicit consideration of competition effects, but it is limited to duopoly markets only, and does not account for full network effects, as described below in the section on modelling airline competition.

The explicit modelling of airline strategic decision making, such as by Elhedhli and Hu (2005) and Wei (2006), has a distinct advantage over other approaches because it captures the fundamental drivers behind airline responses, and is therefore able to capture effects that may not be observable in historical data. Literature exists that describes approaches to modelling different elements of airline strategic decision making specifically. Literature focusing on airline strategic decision making impacting airline operations is reviewed in Section 2.3.

2.3 Existing Approaches to Modelling Airline Strategic Decision Making

Airline strategic decision making impacting airline operational responses to environmental constraints includes primarily decisions on the flight network operated, flight scheduling, and fleet allocation. Approaches to modelling these decision making processes are described below. Competition between airlines has a significant impact on airline decision making, and for this reason approaches to model airline competition are also reviewed.

Flight Network, Scheduling and Fleet Allocation

Two approaches were identified in the literature for optimisation of airline flight networks and schedules: one on a flight-by-flight basis which has an application in airline schedule planning, and a second that is based on an aggregate optimisation which has its principle application in research. Lohatepanont and Barnhart (2004) describe an approach to optimise an airline schedule planning process, including schedule design, which involves determining when and where an airline should offer individual flights, and fleet assignment, which involves assigning aircraft types to the individual flight segments, given an existing fleet. The optimisation is designed to maximise airline profits by simultaneously optimising the selection of flight segments and the assignment of aircraft types to those segments. The approach described improves on historical airline practices whereby schedules were developed by compartmentalising key decisions and optimising sequentially. Key decisions included route development, frequency planning, timetable development, and fleet assignment.

A detailed objective function, with constraints, is specified by Lohatepanont and Barnhart (2004), followed by an algorithm for the solution of the problem. The objective function includes a number of revenue terms, which are expressed by itinerary, as opposed to by flight segment, because passengers pay fares based on their O-D market, and not the flight segments that they fly. Careful attention is given to changes in demand as a function of flight frequency, with some demand being lost to competition when flights are dropped, and some being reallocated to other flights operated by the same airline. The cost function includes individual flight operating costs, and may be extended to include passenger carrying costs (such as meals and luggage handling) and costs per revenue dollar (such as reservation commissions). The operating cost modelled does not explicitly include costs associated with flight delays or environmental policy measures, but it may be extendable to include them.

An alternative approach to the flight-by-flight optimisation of an airline schedule is a more aggregated approach which optimises total flight frequencies over specified time periods. Lederer and Nambimadom (1998) and Harsha (2005) investigate choices of flight networks and schedules defined by time period instead of by flight. Lederer and Nambimadom (1998) examine a simplified problem of 6 origin-destination airports equally spaced around a central hub airport. Four network alternatives are examined – a point-to-point network, a hub-and-spoke network, a tour network (in which each airport is visited by each aircraft consecutively), and an alternative tour network including the hub. Harsha (2005) investigates optimisation of a flight schedule under an airport arrival slot auction, with the purpose of identifying which slots an airline should bid on. In both cases an objective function is solved to maximise airline profit across the network and schedule. The objective function solved by Lederer and Nambimadom (1998) accounts for airline costs and passenger costs, including ticket price, a travel time factor, and a flight frequency factor (accounting for how close flights are to a passenger's desired departure time). Analytic, closed form expressions are derived for airline costs and passenger costs as a function of flight frequencies. The objective function described by Harsha (2005) accounts for fare revenues, costs to the airline, prices of slots, and revenues obtained through reselling unwanted slots. The costs of arrival slots are defined by a model of an arrival slot auction. Revenues are modelled assuming constant fare information, so the impact of increases in cost on revenues and demand is not simulated. Revenues are also specified by flight segment, and not itinerary, although the objective function and added constraints for an alternative model with revenues specified by itinerary are also described.

Airline Competition

Airlines compete by fare and frequency (Schipper *et al.*, 2003; Carlsson, 2002). Frequency competition, in which airlines increase flight frequencies between cities in order to increase their market share, can have a particularly significant impact on airline operations, increasing frequencies well above the levels required to serve the demand. Three approaches to modelling airline competition were identified in the literature: (i) derivation of a simple closed form equation specifying flight frequencies by making simplifying assumptions and analytically solving a game between airlines for a single market; (ii) simulation of a game between airlines, again for a single market; and (iii) simulation of a game between airlines across a complete network of markets.

Schipper *et al.* (2003) and Carlsson (2002) model the effects of competition on average fares and flight frequencies, by flight segment, by analytically solving a two stage game. In the first stage of the game, airlines simultaneously choose flight frequencies, and in the second stage, after having observed the other airlines' chosen frequencies, the airlines simultaneously choose fares. The game is solved analytically by market, as a function of passenger value of time, airline costs and passenger demand. This is done by defining the flight schedule as an address (or spatial) model with flights evenly distributed across the day, defining passenger utility as a simple function of fare, passenger value of time and schedule delay[2], and defining airline cost as a simple function including a cost per flight term and a cost per passenger term. The formulation assumes that passenger demand in the market remains constant. This assumption is relaxed and the formulation modified by Evans *et al.*

[2] Schedule delay refers to the time between when a passenger wants to fly and when the nearest available flight departs.

(2008) for variable passenger demand, which is modelled using a gravity type equation as a function of a generalized cost term including fares. Both formulations apply to individual flight segments or markets, and do not account for network effects.

Wei (2006) models the effect of competition on flight frequency in a single non-stop duopoly market by solving a one-shot simultaneous game in which profit is maximised for each of the two airlines serving the market. This approach is used to identify the impact of landing fees on airline choice of aircraft size and flight frequency, within a competitive environment. The game theoretical model applied includes a cost function relating aircraft size to airline cost, derived by econometric analysis, and a market share model, that applies a nested logit model to capture how aircraft size, flight frequency and fares affect market share. No network effects are accounted for.

Adler (2005) models the network effects of competition by solving a non-linear network optimisation within a simulation of a two-stage, Nash best-response game to identify flight frequencies and average O-D market fares for different passenger types. The impact of competition between airlines on fares and frequency within the network is modelled explicitly. To aid tractability, the airline operating cost function is defined as a simple equation with constant elasticity with respect to frequency.

In summary, although they are not typically applied to forecasting the impact of environmental constraints on future aircraft operations, approaches have been developed to model airline strategic decision making which can be applied to simulate airline responses to environmental constraints.

2.4 Conclusions

The studies reviewed in this chapter suggest that modelling the response of the aviation system to environmental constraints is still in its infancy. In each of the studies reviewed, future aircraft operations are not modelled according to the underlying principles of airline strategic decision making, but are instead modelled according to trends in historical data only (Pulles *et al.*, 2002; Hancox and Lowe, 2000; Bhadra, 2003; Bhadra *et al.*, 2003; Waitz *et al.*, 2006-2; Reynolds *et al.*, 2006; ICAO, 2006-1). These models are therefore not capable of capturing many airline operational responses to environmental policy measures and constraints. By not modelling these airline responses, the capability of the air transport system to adjust under changing conditions is neglected, resulting in the forecasting of potentially misleading system and local responses to constraints.

However, approaches do exist to model airline operational responses to specific constraints, such as airport capacity constraints (Evans, 2002; Kostiuk *et al.*, 2000; Long *et al.*, 1999-1; Long *et al.*, 1999-2; Elhedhli and Hu, 2005), and changes in operating costs introduced by policies such as emissions trading (European Commission, 2006; Ernst & Young, 2007; Scheelhaase and Grimme, 2007; Albers *et al.*, 2009) and increased landing fees (Wei and Hansen, 2003; Wei, 2006; Givoni and Rietveld, 2009). Most studies use a scenario-based approach to model airline operational responses to constraints (Long *et al.*, 1999-1; Long *et al.*, 1999-2; Kostiuk *et al.*, 2000), and do not explicitly simulate airline strategic decision making. Only two of the studies reviewed model airline strategic decision making explicitly (Elhedhli and Hu, 2005; Wei, 2006). In one case the model is only applied to hub-and-spoke networks, and does not account for other effects such as airline competition or impact on passenger demand. In the other case the model does not simulate full network effects.

Other studies exist that specifically describe approaches to model airline strategic decision making in different ways and for different functions (Lederer and Nambimadom, 1998; Lohatepanont and Barnhart, 2004; Adler, 2005; Harsha, 2005). These approaches are not applied to simulate airline responses to environmental policies and constraints, but could be used to develop such a model.

The literature review therefore suggests that there is a significant potential benefit to developing a model that simulates airline operational responses to environmental constraints specifically. Even if the resulting effect of including airline responses in such models is small, it would still be valuable to arrive at that conclusion. Such a model should ideally be based on explicitly modelling airline strategic decision making, including airline competition effects, while capturing the fundamental drivers behind cost changes and passenger responses to the service provided by the airlines. This would allow evaluation of environmental policies while capturing airline operational responses that enable the air transport system to adjust under changing conditions. Such a model would avoid the forecasting of potentially misleading system and local responses. The research objectives identified for this dissertation as a result of this literature review are described in the following chapter, Chapter 3.

3 Research Objectives

The literature review in Chapter 2 concludes that there could be significant benefits to developing a model that simulates airline operational responses to environmental constraints. In order to better reflect airline behaviour, such a model should explicitly simulate airline strategic decision making within a competitive environment, while explicitly modelling the mechanisms by which environmental constraints impact airline cost and passenger demand. This approach would allow a more realistic evaluation of environmental policies than is possible with existing approaches, as it simulates how the air transport system may adjust in response to changing conditions. Such a model would also avoid the forecasting of potentially misleading system and local responses.

The key research objectives of this dissertation are presented in Section 3.1 below, along with a description of the key benefits of the research in light of the literature review presented in Chapter 2. The research methodology employed to fulfil the stated objectives is presented in Section 3.2.

3.1 Key Research Objectives

The key objective of this dissertation is to develop a model that simulates airline operational responses to environmental constraints. This model, henceforth referred to as the Airline Response Model, is intended to simulate airline strategic decision making within a competitive environment, while capturing the mechanisms by which environmental constraints impact airline cost and passenger demand. In order to make this effort manageable and the results interpretable, but still informative, such a model should strike the appropriate balance between level of detail and computational efficiency. Operational responses modelled should specifically include changes in the flight network operated, changes in flight frequencies, and changes in the sizes of aircraft operated on each flight segment. Although other operational responses exist, such as adjusting the shape of flight schedules and introducing operations at new airports, they have only limited impact on flight delays at high traffic levels, and are not considered here in order to limit the scope of the research.

The modelling approach developed to fulfil the above objective is able to simulate airline operational responses to the application of a wide range of policy measures. The approach captures how different effects combine to define airline responses to policies by modelling the underlying principles behind airline strategic decision making. Specifically, by modelling the effects of frequency competition to increase frequencies well above system optimal levels, the effect of competition on how airlines are able to respond to constraints and policy measures is also captured. The modelling approach significantly improves on existing approaches to model future aircraft operations according to historical trends by capturing effects that do not follow historical trends or have not been observed historically.

In order to validate the Airline Response Model developed, passenger flows and flight frequencies are simulated for a network of real airports and cities using a minimum of historical input data. The simulation results are then compared to observed data for the same network.

Once validated, the Airline Response Model is used to generate plausible and internally consistent forecasts of air traffic growth from 2005 to 2030 under different policy scenarios, which may affect infrastructure capacity, regional cost increases, and the introduction of radically new technology that reduces aircraft fuel burn significantly. For each policy scenario, the environmental impact of aviation is quantified in terms of local airport landing and take-off (LTO)[1] cycle NO_x emissions, and network-wide CO_2 emissions. A comparison of the policy analyses also reveals the relative importance of modelling airline operational responses to different environmental constraints. Particularly, the policy questions that, if airline operational responses to the policies were neglected, would result in the forecasting of misleading system and local responses to the policies, are also identified.

3.2 Research Methodology

The methodology employed to fulfil the research objectives described in Section 3.1 can be decomposed into the following steps:

[1] The landing-take off cycle (LTO cycle) is the portion of aircraft operations at or near an airport, beginning with the flight arrival process (sometimes defined as when the aircraft descends below 3,000 ft) and ending after the aircraft has made its climb-out on departure (sometimes defined as when the aircraft climbs above 3,000 ft).

1. Development of a model, the Airline Response Model, that simulates airline flight frequency, aircraft size, and flight network responses to environmental constraints, by modelling the underlying principles behind airline strategic decision making. The framework developed for this model is described in Chapter 4, followed by a detailed description of each sub-model in Chapter 5. The suitability of the modelling approach to capture fundamental system effects is verified by simulating a series of scenarios applied to simplified theoretical city networks in Appendix B.

2. Validation of the Airline Response Model by simulating passenger flows and aircraft operations for a selection of real airlines operating at a set of real airports and cities, and comparing the simulation results to observed data for that network. By comparing the simulation results and observed data for the same network, the capability of the Airline Response Model to simulate real-world airline strategic decision making can be identified. Chapter 6 presents such an application of the Airline Response Model, for 5 airlines operating at 22 airports and 14 cities in the United States, using input data from 2005. The Airline Response Model is validated by comparing the simulated results to observed data for the airport and city set from 2005.

3. Application of the Airline Response Model to simulate future aircraft operations and the resulting environmental impact for a set of real airports and cities, under a series of environmental policy scenarios. The responsiveness of airline operations to each policy can be identified by comparing these simulation results to simulation results for a baseline scenario, based on expected infrastructure capacity expansion, existing airline operating costs, and forecast population, income and oil price projections. Such a comparison also allows identification of the policy scenarios for which the modelling of airline operational responses is most important, and those for which it is least important. Chapter 7 presents such an application of the Airline Response Model, for the network of 22 airports and 14 cities described above, from 2005 to 2030. The policy scenarios formulated induce airline operational responses both at the local, airport level, and at the system-wide level. In each policy simulation, key parameters are varied in order to quantify the sensitivity of the Airline Response Model and of the air transport system to changes in the key parameters. The implications of the results, and final conclusions, are discussed in Chapter 8.

4 Modelling Framework

Airline operational responses to environmental constraints are driven by changes in costs and passenger demand, which affect airline profit and competition. The approach employed to simulate airline operational responses to environmental constraints is therefore to model the underlying principles behind airline strategic decision making, i.e. profit maximisation within a competitive environment, while capturing the fundamental drivers behind changes in airline cost and passenger demand. This approach requires the development of a modelling framework that captures the combined airline, airport and passenger system responses to future environmental policies and constraints. Before the modelling approach and framework are described, however, some factors affecting airline profit maximisation are discussed.

4.1 Factors Affecting Airline Profit Maximisation

Airline profits are defined by the difference between airline revenues and costs. Airline revenues, in turn, are the product of passenger demand and fares. These two variables are interdependent. Passenger demand is impacted by changes in the fares offered by airlines: as fares increase, passenger demand declines. Fares, in turn, depend on passenger demand and supply (airline costs). If airline costs increase, fares also typically increase. The rate of increase, however, depends on how much of the extra cost has to be absorbed by the airline, and how much can be passed on to the passengers.

Passenger demand is also impacted by changes in the level of service provided by the airlines, defined by, amongst others, nominal passenger travel times, flight delays, the number of connections a passenger must make, and the flight frequency offered on the route. Demand increases with a decrease in nominal passenger travel time and number of connections, which are determined by the airline flight network operated. Demand also increases with a decrease in flight delays and an increase in flight frequency. Flight delay is considered separately to nominal travel time because the passenger response to flight delays, which are unexpected, is significantly greater than the passenger response to changes in nominal travel time, which can be planned for. Flight delays increase with rising traffic levels at given infrastructure capacity, and are therefore a function of the number of flights and the flight network operated by airlines.

Airline costs include direct operating costs (also referred to as aircraft or flight operating costs) and indirect operating costs associated with passenger, aircraft and traffic servicing; reservation and sales; and system overheads (Belobaba, 2006). In addition to depreciation and amortization costs, direct operating costs include expenditures for fuel and oil, crew, maintenance, and aircraft rental. These costs depend on the number of flights operated, the types of aircraft flown, and the flight network operated by each airline. Indirect operating costs are generally a function of the number of passengers served. Flight delays increase operating costs by increasing crew hours and fuel burn. The level of extra fuel burn is dependent on where the delay is incurred (in the air, on an active taxiway, or at the gate).

Airline competition also has a significant impact on airline revenues and costs, and therefore airline profits. In deregulated markets, such as those in the United States and Europe, airlines compete by fare and by frequency. Airlines reduce fares in order to capture market share from other airlines. The resulting increase in passengers therefore comes at the cost of reduced revenue per passenger, as well as the added cost of serving the extra passengers. In perfect competition, airlines continue to reduce fares until the marginal revenue obtained from the decrease in fares no longer exceeds the marginal cost of serving the passengers. Similarly, frequency competition involves airlines increasing flight frequencies in order to capture market share from other airlines. The higher market share increases airline revenues but comes at the cost of the added flights. Airlines continue to add flights until the marginal revenue resulting from the increase in market share no longer exceeds the marginal cost of adding another flight. All airlines respond in a similar way, each decreasing fares and increasing frequency to capture more market share. Since airlines have different operating costs, those with the lowest costs can add more extra flights and thus gain more market share than those with higher costs.

Airlines can reduce costs by optimising the flight network they operate. In hub-and-spoke networks, certain passengers are flown to their destination by connecting through one or more central hub airports instead of flying non-stop, or point-to-point, on a single flight. As described in Chapter 1, hub-and-spoke operations induce economies of scale on flights and in ground operations, and enable flights to be offered on more markets with fewer added flights than can be achieved through a point-to-point network. However, passengers must connect and travel greater total distances, meaning that fuel burn per passenger is generally higher in hub-and-spoke networks than in point-to-point networks. The degree to which airlines operate a hub-and-spoke network versus a point-to-point network is a complex function of airline costs, passenger demand and competition.

4.2 Modelling Approach and Framework

The modelling of airline operational responses to environmental constraints requires the development of an integrated framework that captures the key effects of each relevant element of the air transport system. This can be done by maximising airline profits using an objective function that incorporates models of each relevant element of the air transport system. The effects of competition can be captured by simulating a strategic game between airlines, with each airline's profit maximised in each stage of the game, iterating until a game theoretical equilibrium is reached that specifies the key operational characteristics of each airline, i.e., the flight network, flight frequencies, and aircraft sizes operated.

In order to identify these key airline operational characteristics, the decision variables in each airline objective function are specified as the airline flight segment frequencies by aircraft size class, and passenger itinerary demand, which defines flight network operated. Other variables in the air transport system, including passenger city-pair demand, average fares, travel times, flight delays and operating costs define the cost and revenue terms that are inputs to the objective function. The modelling of these variables can therefore be extracted from the objective function, making it easier to solve, and allowing more advanced modelling of each variable, to better reflect system behaviour. Each of these variables is, however, a function of flight segment frequency and passenger itinerary demand, i.e., the decision variables. All variables can be determined using an iterative framework in which each variable is updated according to the results of the profit maximisation. The profit maximisation is then run with updated values of each variable, until convergence to an equilibrium solution. This iterative approach can be incorporated into the iterative approach required to solve the strategic game between airlines, described in the previous paragraph.

The modelling framework for the Airline Response Model is presented in Figure 4-1. A series of network optimisation models determine the key operational characteristics of each airline, which are input into the strategic game simulation between competing airlines. The strategic game is simulated using a system flight frequency calculator and an iterative framework (indicated by the decision node for convergence and the feedback loop to the right of the models, i.e., the dotted line). These components constitute the core of the Airline Response Model, which is shown in the red box in Figure 4-1. All the other models serve to generate inputs for the network optimisation models. The models include a flight delay model, operating cost calculators for each airline, a travel time calculator, an average fare model, and a passenger demand model. These models are updated after each iteration of the strategic game. The operation of the Airline Response Model and the interaction between each of its sub-models is described in greater detail below, sequentially from the top of the diagram.

As shown at the top of Figure 4-1, an initial estimate of flight segment frequencies per day is required for each aircraft size class and airport pair simulated. For the base year modelled this may come from historical flight frequency data, while for subsequent years it may come from the results of the previous year's model run, necessitating a chronological solution to a multi-year forecast, or from traffic forecasts from a different model. With the initial estimate of flight frequencies per day, average flight delays are estimated at each airport according to specified airport capacities. The Delay Calculator developed for this purpose is described in Section 5.2.

Simultaneous to the calculation of flight delays, a Travel Time Calculator estimates nominal travel times by flight segment and O-D city pair as a function of the aircraft types operated, passenger itinerary demand served (from the same source as the initial estimate of flight frequencies, giving information about passenger routing), specified aircraft performance characteristics (such as cruise speed) and flight segment length information. This model is described in Section 5.3.

The estimated flight delays and nominal travel times are inputs to a series of Operating Cost Calculators, which calculate operating costs per flight and per passenger for each airline. Other inputs include specified fuel price, aircraft fuel efficiency, and airline operating costs per hour and per passenger. Different operating costs are calculated for

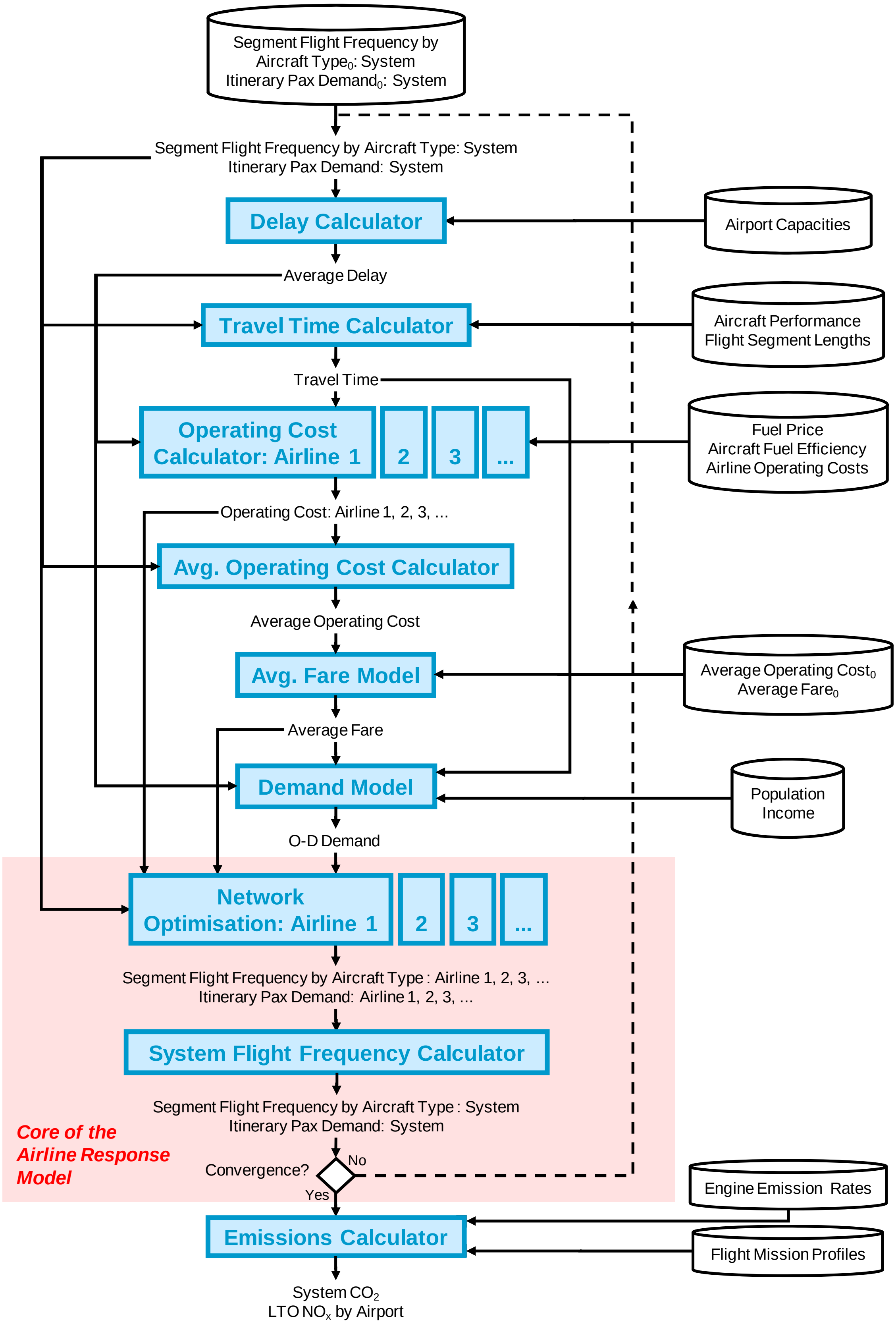


Figure 4-1. Modelling framework for the Airline Response Model, simulating airline operational responses to environmental constraints.

different airlines. The Operating Cost Calculator developed is described in Section 5.4. Average O-D operating costs by city pair, across all airlines, are calculated by an Average Operating Cost Calculator according to the operating costs per flight and per passenger of each airline, and initial estimates of flight frequencies and passenger demand. The Average Operating Cost Calculator is also described in Section 5.4.

The estimates of average operating costs are inputs to an Average Fare Model, which estimates average O-D fares by city pair, across all airlines (fares are not calculated for each airline separately). This model, which also takes base year average operating costs and fares as inputs, is described in Section 5.5. Estimated average O-D fares are output to a Passenger Demand Model. In combination with flight delays from the Delay Calculator, average travel times from the Travel Time Calculator, and specified population and income data, the Passenger Demand Module estimates available O-D passenger demand for each city pair modelled. The Passenger Demand Model is described in Section 5.6.

The estimated operating costs, average fares, and passenger demand, along with initial estimates of flight frequencies, are all inputs to the Network Optimisation Models, which calculate the segment flight frequencies and itinerary passenger demand for each airline. Each optimisation is constrained by available O-D passenger demand, available seats by aircraft size class, and a requirement that the same number of each class of aircraft arrive and depart from each airport every day. The Network Optimisation Models are described in Section 5.1. O-D passenger demand is distributed between airlines according to a market share model, which is also described in Section 5.1. Each airline’s market share for each respective O-D market is defined as the ratio of the airline’s flight frequency on that market to the flight frequency offered by all other airlines serving the market. Because the total number of flights offered by all airlines serving each market, calculated by the System Flight Frequency Calculator, depends on the results of each airline network optimisation, the individual airline network optimisations must be run iteratively, with other airline flight frequencies updated each iteration. A game theoretical equilibrium between airlines is reached when the system reaches convergence. The simulation of the strategic game between competing airlines is described in Section 5.7.

Because the Delay Model, Travel Time Calculator, Operating Cost Models, Average Fare Model, and Passenger Demand Model are not integrated within the network optimisations, they are updated in each iteration after segment flight frequencies and itinerary passenger demand are estimated by the Network Optimisation Models, as described above. These models are therefore included in the iteration loop that is required to identify the game theoretical equilibrium.

Emissions levels, particularly in terms of system CO_2 and LTO NO_x at airports, are calculated according to equilibrium flight frequencies by aircraft size class, engine emission rates in different phases of flight for the different types of aircraft modelled, and typical flight mission profiles. The Emissions Calculator developed for this purpose is described in Section 5.8.

Application of the Airline Response Model to simulate future aircraft operations requires consideration of how the constraints and inputs to each model may change over time. In many cases this may be defined by the policy scenario run. In the case of airport capacity constraints, the model may be run with exogenously specified airport capacity inputs. Other inputs may come from population, per capita income and oil price projections. All assumptions about inputs, including their development over time, are described in detail in the sections on each sub-model in Chapter 5.

5 Detailed Modelling

This chapter describes each of the sub-models presented in Figure 4-1, and the iterative framework used to solve the Airline Response Model. Section 5.1 describes the network optimisation. Inputs for this sub-model are generated by the sub-models simulating flight delay, operating cost, travel time, average fares and passenger demand, which are described in Sections 5.2 to 5.6. Section 5.7 describes the iteration procedure required to solve the airline strategic game for market share, in which each of the sub-models in the framework is updated. Once the system reaches equilibrium, system CO_2 emissions and LTO NO_x emissions are calculated, which is described in Section 5.8.

5.1 Network Optimisation

In the Airline Response Model, the Network Optimisation Model identifies airline flight segment frequencies by aircraft size class, and passenger itinerary routing, for each airline, subject to the maximisation of profits. The flight segment frequencies of all airlines are output to a System Flight Frequency Calculator, which enables simulation of airline competition effects.

The Network Optimisation Model is based on maximisation of airline profit using large scale mathematical programming methods. The objective function, which consists of a revenue term and two cost terms, is presented in equation 5-1. The revenue term is based on passengers flown by itinerary and average O-D fares. The cost terms are based on an airline cost per flight multiplied by flight segment frequency, and an airline cost per passenger multiplied by passengers flown by itinerary, capturing all categories of airline cost.

$$\max \left(\begin{array}{l} \sum\limits_{i \in Cities_a} \sum\limits_{j \in Cities_a} \sum\limits_{p \in P_{i,j,a}} \overline{Fare}_{i,j} \cdot Pax_{i,j,p,a} - \\ \qquad \sum\limits_{m \in Airports_a} \sum\limits_{n \in Airports_a} \sum\limits_{k \in SizeClasses_a} FltCost_{m,n,k,a} \cdot Fltfreq_{m,n,k,a} - \\ \qquad\qquad \sum\limits_{i \in Cities} \sum\limits_{j \in Cities_a} \sum\limits_{p \in P_{i,j,a}} PaxCost_{i,j,a} \cdot Pax_{i,j,p,a} \end{array} \right) \quad \forall a \in Airlines \qquad (5\text{-}1)$$

where $\overline{Fare_{i,j}}$ represents the fare between O-D city pair i and j, averaged over all itineraries and airlines; $Pax_{i,j,p,a}$ represents passenger demand between O-D city pair i and j, on itinerary p, for airline a; $FltCost_{m,n,k,a}$ represents average cost per flight on the flight segment between airports m and n, for aircraft size class k, for airline a; $Fltfreq_{m,n,k,a}$ represents the average number of flights per day on the flight segment between airports m and n, using aircraft size class k, for airline a; and $PaxCost_{i,j,a}$ represents average cost per passenger between O-D city pair i and j, for airline a. $P_{i,j,a}$ represents the set of all passenger itineraries p between cities i and j operated by airline a; $Cities_a$ represents all cities served by airline a; $Airports_a$ represents all airports served by airline a; $SizeClasses_a$ represents all aircraft size classes operated by airline a, and *Airlines* represents the set of all airlines modelled.

The decision variables in the optimisation are passenger itinerary demand ($Pax_{i,j,p,a}$) and segment flight frequency by aircraft size class ($Fltfreq_{m,n,k,a}$), which incorporate information to completely describe the airline flight network, daily flight segment frequencies, aircraft size choice, and passenger itinerary routing.

Note that spill costs are not included in the objective function. These are opportunity costs to the airline that result when passengers want to fly but cannot obtain a reservation due to insufficient seats. Passengers are typically spilled – either to other airlines or from the system altogether – because demand is variable, and aircraft can only be allocated to flight segments based on expected demand, not actual demand. Although spill costs are typically included in airline cost estimation, they are excluded here because of their dependence on demand variability and airline decisions on how much spill is acceptable. Demand variability is unlikely to change significantly with the changes in demand simulated by the network optimisation, so the spill term becomes a constant, which falls away in the optimisation.

The objective function is constrained by six linear equations describing airline network and scheduling requirements and limitations, including two demand constraints, one seat constraint, one passenger flow constraint, one airport balance constraint, and one integer constraint. The first demand constraint is described by equation 5-2, where the total passenger demand served by airline a between cities i and j, summed over all itineraries, must be smaller than or equal to the total available demand between cities i and j, multiplied by the market share of airline a:

$$\sum_{p \in P_{i,j,a}} Pax_{i,j,p,a} \leq MS_{i,j,a} \cdot D_{i,j} \qquad \forall i, j \in Cities_a; a \in Airlines \qquad (5\text{-}2)$$

where $P_{i,j,a}$ represents the set of all passenger itineraries p between cities i and j operated by airline a; $Pax_{i,j,p,a}$ represents passenger demand between O-D city pair i and j, on itinerary p, for airline a; $MS_{i,j,a}$ represents the market share of airline a between cities i and j; and $D_{i,j}$ represents the available demand between city i and j, as estimated by the Demand Model described in Section 5.6.

Airline market share in equation 5-2 is modelled by the ratio of the non-stop flight frequency offered between the cities by the airline under question, to that of all airlines, as shown in equation 5-3:

$$MS_{i,j,a} = \frac{Fltfreq_{i,j,a}}{\sum_{a \in Airlines} Fltfreq_{i,j,a}} \qquad (5\text{-}3)$$

where $Fltfreq_{i,j,a}$ represents the airline O-D flight frequency between city i and j, for airline a. This is a rule-of-thumb suggested by Belobaba (2008). There is empirical evidence to suggest that airline market share may be slightly more complex than this. Passengers prefer high frequency, and therefore higher frequency attracts more than simply the proportional market share, while low frequency attracts less, as described by Belobaba (2008). This “S-curve” model is not applied here, however, in order to reduce complexity. Also, connecting flights via hubs, which don’t contribute to market share in the model applied here, do contribute to market share in reality, although to a significantly lesser degree than non-stop flights (as much as 20 times less (Belobaba, 2008)). Because the effect is small, and in order to reduce complexity, only non-stop flights are considered in the formulation of market share presented in equation 5-3. Consequently, however, market share on hub-and-spoke networks is slightly underestimated.

In the network optimisation of each airline, all other airline flight frequencies are taken as constant. However, because each airline optimises its operations simultaneously, the other airline flight frequencies do change. In order to capture the effect of these changes on each airlines’ network optimisation, an iterative approach is applied in which other airline frequencies are updated, and the network optimisations repeated, until the results converge to an equilibrium, as described in Chapter 4. This iterative approach simulates a game between airlines, whereby each airline increases flight frequencies to gain more market share, until the marginal cost of adding another flight is no longer offset by the marginal revenue associated with the increased market share achieved by the flight.

Substituting the market share formulation in equation 5-3 into equation 5-2 results in the constraint becoming inherently non-linear: the total system flight frequency (the denominator in equation 5-3) is a function of the flight frequency offered by the airline under question (the numerator in equation 5-3), which is a decision variable in the objective function. Equation 5-2 is linearised with respect to the decision variable ($Fltfreq_{i,j,a}$), using flight frequencies from the previous iteration of the game to calculate the gradient and intercept of the linearised constraint. All other airline frequencies are as observed by the airline under question, and are therefore treated as known in each iteration of the game. However, because each airline optimises its operations simultaneously, these observed frequencies are also from the previous iteration of the game. The linearised constraint is shown in equation 5-4, and is updated in each iteration of the game described in Section 5.7.

$$\sum_{p \in P_{i,j,a}} Pax^{l}_{i,j,p,a} \le D^{l}_{i,j} \cdot \left(\frac{\left(\sum_{a \in Airlines} Fltfreq^{l-1}_{i,j,a}\right) - Fltfreq^{l-1}_{i,j,a}}{\left(\sum_{a \in Airlines} Fltfreq^{l-1}_{i,j,a}\right)^2} \cdot Fltfreq^{l}_{i,j,a} + \frac{\left(Fltfreq^{l-1}_{i,j,a}\right)^2}{\left(\sum_{a \in Airlines} Fltfreq^{l-1}_{i,j,a}\right)^2} \right)$$

$$\forall i, j \in Cities_a ; a \in Airlines \qquad (5\text{-}4)$$

where l is the iteration index. As can be seen, both the gradient and intercept of equation 5-4 are functions of the flight frequencies in the previous iteration (i.e. l-1) (for the airline under question, and for all other airlines serving the market).

In order to ensure that the correct behaviour of the non-linear constraint in equation 5-2 is captured by the linear constraint in equation 5-4, a second constraint is added that limits the amount by which any airline flight frequency can change in each iteration step, as shown by equation 5-5. The change in each flight frequency is limited to 1 flight per day in each iteration step.

$$\begin{aligned} Fltfreq^{l}_{i,j,a} &\le Fltfreq^{l-1}_{i,j,a} + 1 \\ Fltfreq^{l}_{i,j,a} &\ge Fltfreq^{l-1}_{i,j,a} - 1 \end{aligned} \qquad \forall i, j \in Cities_a ; a \in Airlines \qquad (5\text{-}5)$$

The seat constraint applied to the optimisation limits the number of passengers served on each flight segment to be less than or equal to the number of seats available, as described in equation 5-6:

$$Pax_{m,n,k,a} \leq LF_{\max} \cdot Seats_{m,n,k,a} \qquad \forall m,n \in Airports_a; k \in SizeClasses_a; a \in Airlines \quad (5\text{-}6)$$

where $Pax_{m,n,k,a}$ represents passengers flown by airline a between airports m and n (i.e., by flight segment), on aircraft type k. LF_{max} represents a maximum load factor permitted (set to 95% in all cases in this dissertation); and $Seats_{m,n,k,a}$ is the number of seats offered by airline a between airport m and airport n, on aircraft size class k. The number of seats offered by the airline ($Seats_{m,n,k,a}$) is a direct function of the aircraft seating capacity and the flight frequency offered.

A fourth constraint relates passengers served by flight segment ($Pax_{m,n,k,a}$) and passengers served by itinerary ($Pax_{i,j,p,a}$ – a decision variable). This constraint equates passengers by flight segment to passengers on all itineraries using that flight segment, and distributing between aircraft types, as shown in equation 5-7:

$$Pax_{m,n,k,a} = \left(\sum_{i \in Cities} \sum_{j \in Cities} \sum_{p \in P_{i,j,m,n,a}} Pax_{i,j,p,a} \right) \cdot \frac{Fltfreq_{m,n,k,a} \cdot Seats_{m,n,k,a}}{\sum_{k \in SizeClasses_a} Fltfreq_{m,n,k,a} \cdot Seats_{m,n,k,a}}$$

$$\forall m,n \in Airports_a; k \in SizeClasses_a; a \in Airlines \qquad (5\text{-}7)$$

where $P_{i,j,m,n,a}$ represents all itineraries from city i to city j operated by airline a that use the flight segment from airport m to airport n.

The airport balance constraint applied to the optimisation limits the number of flights of each aircraft size class departing from an airport on any day to equal the number of flights of that aircraft size class arriving at the airport. This is described in equation 5-8, where the left hand side of the equation represents all flights operating aircraft size class k departing from airport m, while the right hand side represents all flights operating aircraft size class k arriving at airport m:

$$\sum_{n \in Airports_a} Fltfreq_{m,n,k} = \sum_{n \in Airports_a} Fltfreq_{n,m,k} \quad \forall m,n \in Airports_a; k \in SizeClasses_a; a \in Airlines \quad (5\text{-}8)$$

In theory, a fleet constraint could also be included that limits the total hours operated by each aircraft size class to be less than or equal to that available in the existing fleet. This limits the optimisation to only select aircraft from the existing fleet. However, because the model is to be applied well into the future the fleet is instead left unconstrained, allowing the model to select its own fleet. The underlying assumption is that airlines will purchase or lease new aircraft as required.

The network optimisation only allows non-stop and single-connection itineraries. Multiple connections are not permitted. This simplification is not limiting. In the domestic United States only 2% of passengers connect more than once (DOT, 2000), and in the city set modelled in Chapters 6 and 7, which includes only larger cities, this percentage drops to 1.5% (DOT, 2000).

The airport and city sets served by each airline ($Airports_a$, $Cities_a$), as well as the hub airports operated by each airline (defined by $P_{i,j,a}$) are fixed, and are therefore not assumed to change over time. This assumption aids model tractability by limiting the number of airports and cities simulated, and the number of hubs available for routing connecting itineraries within the network optimisation routines. However, the assumption implies that the model cannot simulate airline decisions to change the markets they serve or to operate new hubs. Modelling these strategic decisions would require relaxation of this constraint and the inclusion of costs associated with setting-up operations at a new airport or converting a non-hub airport into a hub.

Finally, the flight frequencies operated by each airline, per day, are constrained to be integers. This constraint is specified in equation 5-9:

$$Fltfreq_{n,m,k} \geq 0, Integer \qquad \forall m,n \in Airports_a; k \in SizeClasses_a; a \in Airlines \qquad (5\text{-}9)$$

Passenger demand by itinerary should also be constrained to be an integer, but this is less important because passenger demand between cities, even per day, is high. Because of the integer constraint the optimisation described in this section is solved using a Mixed Integer Program (MIP). The optimisation is solved using the commercial optimisation solver CPLEX 10.2. The stopping criterion is set to a gap of 1%. The objective function and all the constraints are made linear in each of the decision variables, so the optimisation should converge to a unique solution.

5.2 Flight Delay Modelling

As air traffic demand approaches airport or airspace capacity, flights experience delays. In the case of airport capacity constraints, Idris (2001) describes the primary resources in an airport system that can constrain operations, i.e., the gates at which passengers embark and disembark aircraft, a ramp area or apron that surrounds the gates, a taxiway system that connects the gates/ramp area with the runways, and a runway system consisting of one or more runways. As stated by de Neufville and Odoni (2003, p367), the primary capacity constraint at an airport is generally the runway system. The complementary resource, the airspace system, is typically constrained by the capacity of airspace sectors – regions of airspace that are typically managed by a single air traffic controller. The capacity of these sectors may be further reduced by convective weather and flow constraints implemented by air traffic management in order to maintain safe aircraft separation, such as Miles in Trail spacing[1].

Due to the interconnectivity of the air transport system, the effects of airport and airspace constraints may propagate upstream. Arrival delays on the surface of a destination airport can propagate upstream to cause airborne arrival holding and airspace congestion, while holding and congestion in en-route airspace may propagate upstream to the surface of an origin airport to increase departure delays. This latter effect is described in detail by Evans and Clarke (2002).

Approaches to Modelling Flight Delays

Air traffic operations within an airport runway system can be viewed as a queuing system (de Neufville and Odoni, 2003, Ch23), allowing flow analysis and queuing theory to be used to study and optimise the processes within the system, and to estimate flight delays. Queuing theory can be applied by modelling the entire runway system (including all runways if a multi-runway system is operational) as a server, with the air traffic demand on the runway system (including both arrivals and departures) modelled as system demand, and the

[1] Miles in Trail spacing refers to an air traffic management procedure that specifies distances by which aircraft on a common flight path must be separated (e.g. 10 Miles in Trail, 20 Miles in Trail etc.). Miles in Trail spacing is implemented by air traffic controllers primarily through aircraft vectoring and speed control.

average time in the queue representing average flight delay, as illustrated in Figure 5-1 (Idris, 2001).

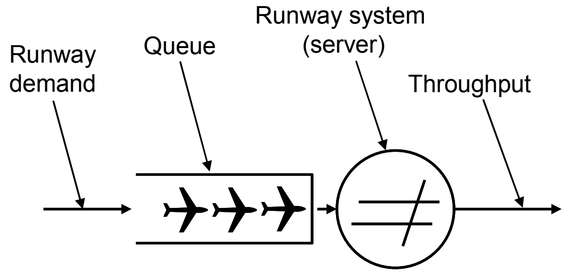


Figure 5-1. Schematic of the application of a queuing system to an airport (Idris, 2001).

The most direct approach to modelling a queuing system is through simulation. In this approach the system demand and service rates are represented by probability distributions, from which inter-arrival times and server service times are sampled. Any delays that occur when demand is not able to be served immediately are recorded. This process is repeated in a Monte Carlo simulation, and the results averaged. While this approach allows the stochastic nature of the arrival and service processes in a runway system to be simulated explicitly, it can be computationally expensive.

Alternatively the queuing system may be modelled by numerically solving a system of equations describing the evolution of the queuing system over time. Kivestu (1976) proposed to model the airport system as an M(t)/Ek(t)/k system – exponentially distributed (Memoryless) inter-arrival times, with service times defined by an Erlang-k distribution, and using k servers. He developed a numerical approximation scheme to estimate the state probabilities of the system over time, allowing estimates of average delay and average queue size to be calculated. Malone (1995) further developed the solution method, and proved the approach's appropriateness for application to time-varying queues in airport systems. This approach has good accuracy for estimating average delays in airport systems and is less computationally expensive than simulation. However, depending on the method used to numerically solve the system of equations, it may still be too slow for some applications. The approach has, however, been applied to model airport system delays by a number of authors (e.g. Hebert and Dietz, 1997; Long *et al.*, 1999-1; Stamatopoulos *et al.*, 2004). The MIT DELAYS model (Odoni and Pyrgiotis, 2009) is an example of this modelling approach.

Modelling of Flight Delays in the Airline Response Model

The modelling of flight delays within the Airline Response Model should be computationally efficient as it must be completed repeatedly within iteration loops incorporating other models, some of which are computationally expensive (e.g. the network optimisation), and must be run for a large number of airports in each iteration. However, the flight delay model does not require the high accuracy of models in some other applications because of its application to calculate average annual flight delays, and not detailed flight delay profiles by hour. Neither of the models described above were considered to have adequate computationally efficiency, and thus a new rapid airport delay model was developed (Evans, 2008). This Rapid Delay Model applies the simpler steady state and cumulative diagram approaches, described below, to those periods within a time varying flight schedule for which each approach is appropriate. Because of the outstanding importance of runway capacity in the air transportation system (Odoni, 2008; de Neufville and Odoni, 2003, Ch10), delays due to only the runway system capacity are modelled.

In classical steady state queuing theory, closed form equations can be derived for estimation of average delay and queue size when a system has reached steady state. These equations are not typically used to model airport systems, because airport demand and service rates can vary significantly during a day, preventing the system from reaching steady state (Barnhart *et al.*, 2003). Extended periods also often exist in which demand exceeds capacity, which cannot be modelled using this approach. The approach can provide accurate estimates of average delay, however, if applied over suitably long time periods, in which the airport system can be assumed to reach steady state. It also provides very high computational efficiency because the equations can be solved analytically. One queuing system for which a closed form equation for average delay and queue size exists is a single server with exponentially distributed inter-arrival and service times: the M(t)/M(t)/1 queue – Memoryless arrival rate, Memoryless service rate, and using a single server. This is a less accurate model of the airport system than the M(t)/Ek(t)/k system. For an M(t)/M(t)/1 queue, average steady state waiting time in the queue (average delay, $\overline{D}$), and average steady state queue size ($\overline{L}$) are defined as a function of average arrival rate (demand, λ) and average service rate (capacity, μ) as follows (Larson and Odoni, 1981):

$$\overline{D} = \frac{\lambda}{\mu(\mu - \lambda)} \tag{5-10}$$

$$\overline{L} = \frac{\lambda^2}{\mu(\mu - \lambda)} \tag{5-11}$$

These equations can only be applied when the arrival rate is less than the service rate (demand does not exceed capacity), that is, when the system utilisation ratio ρ (demand over capacity) is less than 1. Also, for these equations to be applicable, demand must not approach capacity (i.e., the situation where $\mu - \lambda$ is near zero, or ρ approaches 1) because average delay tends to infinity. This is because as the utilisation ratio increases, the time required for the system to reach steady state increases. Odoni and Roth (1983) identify a relationship between the time for the system to settle to within 2% of its steady-state value (the characteristic time constant τ, or "relaxation time"), the utilisation ratio ρ, and the average service rate μ, as follows:

$$\tau_R = \left(C_A^2 + C_S^2\right) \Big/ \left(2.8\mu\left(1 - \sqrt{\rho}\right)^2\right) \tag{5-12}$$

where C_A and C_S are the coefficients of variation for the inter-arrival and service times, which are 1 for exponential distributions (as in the M(t)/M(t)/1 system). By rearranging this relation, the maximum value of ρ for which an M(t)/M(t)/1 system reaches steady state within a specified time T, can be estimated:

$$\rho_{MM1\max} = \left(1 - \sqrt{\left(C_A^2 + C_S^2\right) / \left(2.8\mu T\right)}\right)^2 \tag{5-13}$$

In contrast to the steady state approach, the cumulative diagram approach ignores the stochastic nature of the system completely. This very simple approach only predicts delay if the average system arrival rate (demand, λ) exceeds the average system service rate (capacity, μ), that is, the system utilisation ratio ρ exceeds 1. In this case queue size grows linearly at a rate of the difference between the arrival and service rates, as illustrated in Figure 5-2. When the arrival rate drops below the service rate the aircraft still in the queue are served first, and the queue size drops linearly at a rate of the difference between the service and arrival rates. The total waiting time in the queue (total delay) is defined by the area under a queue size profile (number of users in the queue with time). The simplicity of this approach offers high

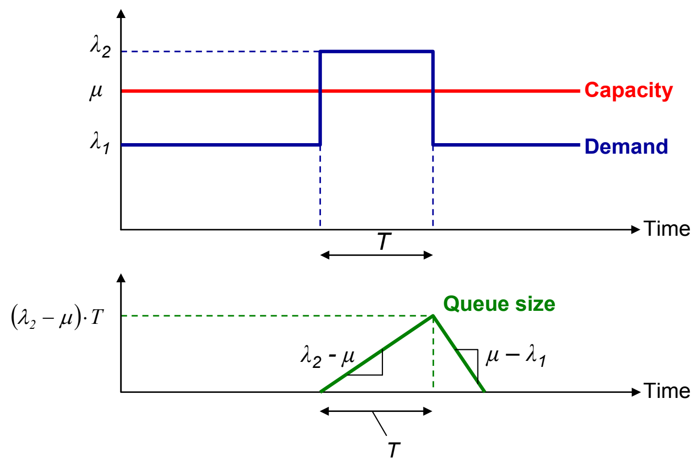


Figure 5-2. Cumulative diagram approach schematic.

computational efficiency, but it is only accurate for a stochastic system when the average arrival rate greatly exceeds the average service rate (utilisation ratio ρ is significantly greater than 1). Accuracy may be improved by modelling each flight individually, instead of specifying average demand and capacity profiles in time bins of e.g. 1 hr duration, although at the cost of computational efficiency. This approach was applied by Hansen (2002) to compute delay externalities at Los Angeles International Airport.

The utilisation ratio, above which the cumulative diagram approach provides a sufficiently accurate estimate of delay in a stochastic system, can be identified by comparing the results of the cumulative diagram approach with those of another, more accurate, model such as a queuing simulation. Such a comparison was completed by Evans (2008). The values of utilisation ratio ρ are identified at which the cumulative diagram approach estimates delay over a single time bin to within 2% (as used by Odoni and Roth (1983) in the estimation of equation 5-12) of the value estimated by an M(t)/M(t)/1 queuing simulation, over a range of average system service rates μ, and time bin durations T. The resulting utilisation ratio threshold, above which the cumulative diagram approach is accurate to within 2% of the simulation result ($\rho_{CDA\min}$), was derived statistically (with an adjusted R^2 value of 0.78, and all coefficients being significant at the 95% confidence level):

$$\rho_{CDA\min} = 1.45 - 0.508 \times 10^{-3} \cdot \mu T + 0.338 \times 10^{-6} \cdot (\mu T)^2 \tag{5-14}$$

The steady state queuing model is useful below the threshold given by equation (5-13), while the cumulative diagram approach is applicable above the threshold given by equation (5-14). However, the range of utilisation ratios encountered at airports does extend above the steady state queuing model threshold, and also extends below the cumulative diagram approach threshold. These approaches cannot therefore be applied individually to estimate airport delay. The ranges are, however, complimentary, with the steady state queuing model applying at low utilisation ratio, and the cumulative diagram approach applying at high utilisation ratio, so the approaches can be used in conjunction.

The basic modelling approach is therefore to apply the steady state and cumulative diagram approaches described above to those periods within a time varying flight schedule for which each approach is appropriate. This methodology prevents the prediction of unrealistically high delays by the steady state approach as demand approaches capacity (ρ approaches 1), and the prediction of unrealistically low delays by the cumulative diagram approach when demand only just exceeds capacity (ρ is above 1, but below ρ_{CDAmin}). In periods in which neither approach is appropriate (i.e. when ρ is between ρ_{MM1max} and ρ_{CDAmin}), a linear interpolation is applied between results for the two approaches at the respective utilisation ratio thresholds. This methodology is illustrated in Figure 5-3.

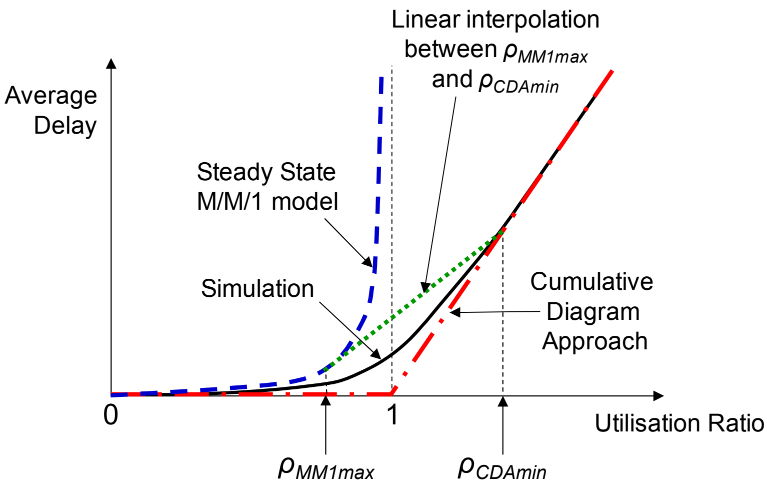
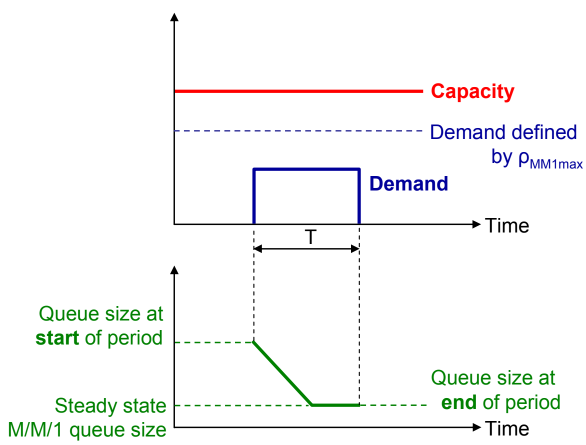


Figure 5-3. Flight delay modelling methodology

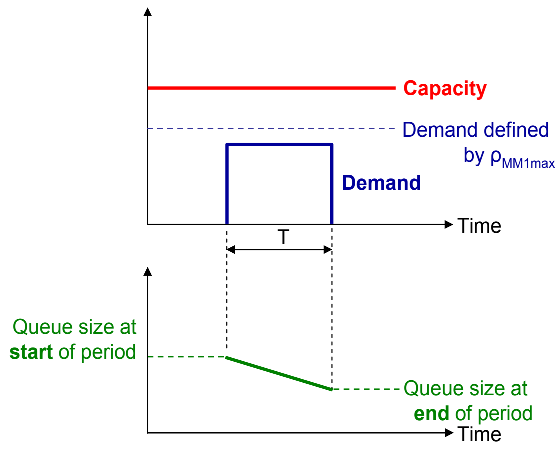
This approach provides good accuracy either side of the utilisation ratio thresholds, where the respective models are applicable, but provides limited accuracy in the transition region, where the linear interpolation is applied (as can be surmised in comparison to the actual response in Figure 5-3). A non-linear interpolation was also tested, which more closely matches the actual response between the two thresholds, but the improvement in performance was not significant enough to warrant the increase in complexity.

The approach is trivial to apply to a non-time varying queue, but when applied to a time varying queue, such as an airport schedule, the propagation of the accumulated delay between time bins requires careful implementation. Any clients, i.e., aircraft, not served in a time bin remain to be served by the following time bin, where they are served before other aircraft arriving into the system in that bin. The approach is implemented by calculating the change in queue size in each time bin, chronologically through the day, as a function of the demand and capacity in each respective time bin, and the queue size at the start of the time bin. The queue size at the end of each time bin defines the queue size at the start of the next time bin. Average flight delay is estimated by integrating the queue size profile through all time bins and dividing by the total number of aircraft served.

The queue size profile for each time bin is estimated as follows. If the runway system demand in the time bin, defined by the arrival and departure schedules at the airport, is below the maximum demand threshold for the steady state approach, defined by $\rho_{MM1\max}$, the queue size at the start of the bin is reduced at the rate of the difference between the bin capacity and demand, until it reaches the steady state queue size for an M(t)/M(t)/1 queue calculated using equation 5-11. The queue size is then maintained at this value until the end of the bin, and is then the starting queue size for the following bin. This is illustrated in Figure 5-4a. If the time bin is not long enough for the queue size to reduce to this value, the queue size at the end of the bin is the value to which it has reduced by that time. This is illustrated in Figure 5-4b.



(a)



(b)

Figure 5-4. Modelled change in queue size for $\rho < \rho_{MM1\max}$, when (a) queue size drops to the steady state value, and (b) when it does not.

If, instead, the runway system demand in the time bin is above the minimum demand threshold for the cumulative diagram approach, defined by $\rho_{CDA\min}$, the queue size at the start of the bin is increased at the rate of the difference between the bin demand and capacity, until the end of the bin. The queue size at the end of the bin is the value to which it has increased by that time. This is illustrated in Figure 5-5.

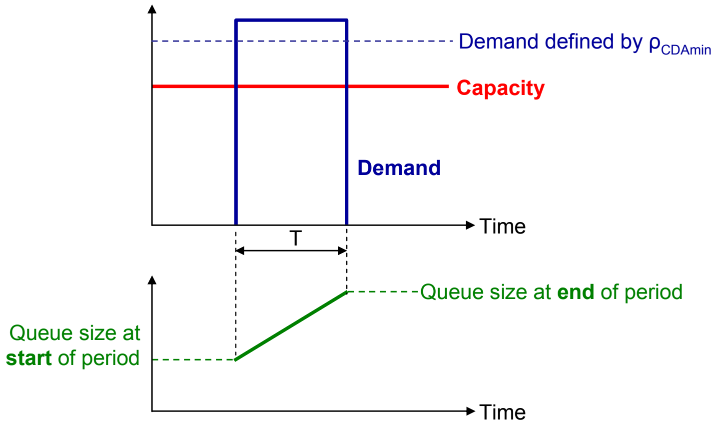


Figure 5-5. Modelled change in queue size for $\rho > \rho_{CDA\min}$.

Finally, if the runway system demand in the time bin falls between the maximum demand threshold for the steady state approach, defined by $\rho_{MM1\max}$, and the minimum demand threshold for the cumulative diagram approach, defined by $\rho_{CDA\min}$, the queue size profile for the bin is calculated by linearly interpolating between the queue size profiles calculated for demand at each threshold according to the ratio of the actual demand in the bin, and the demand thresholds. This is illustrated in Figure 5-6.

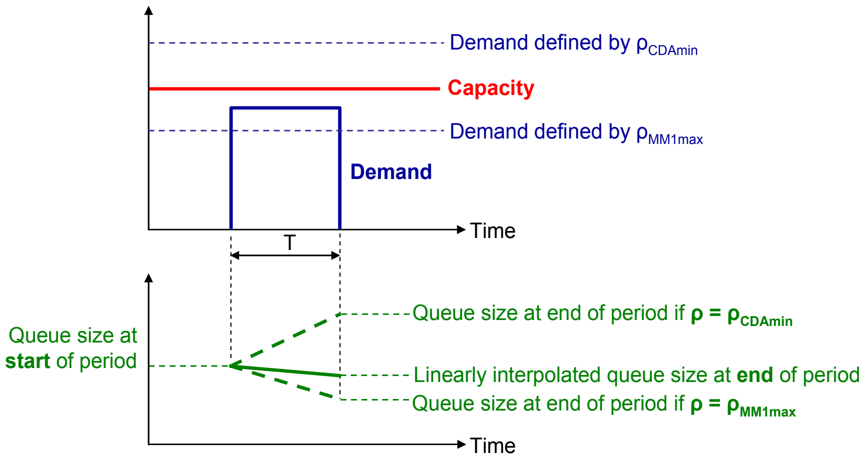


Figure 5-6. Modelled change in queue size when ρ falls between $\rho_{MM1\max}$ *and* $\rho_{CDA\min}$.

The number of clients, i.e. aircraft, to be processed by the queue through all time bins is the sum of the demand profile, through all time bins, subtracting the queue size at the end of the final bin. The total delay incurred by the served aircraft is the integral of the queue size profile, subtracting the delay incurred by the aircraft not served at the end of the last bin. These flights can be assumed to be cancelled. Average delay is estimated by dividing the total delay incurred by the served aircraft by the number of aircraft served.

Performance of the Rapid Delay Model

The performance of this Rapid Delay Model in comparison to other delay models was evaluated for a series of time varying schedules and system capacities. Aircraft demand on the runway system, as defined by a flight schedule, was scaled to define average utilisation ratios between 0.1 and 1.3, thus allowing a range of demand and utilisation ratios to be analysed. Average utilisation ratio is defined as the ratio of the total demand from 06:00 to 24:00, and the total capacity over the same period. Exclusion of the early hours of the morning allows the average utilisation ratio to better reflect the utilisation of the airport in periods when it is typically operated. The modelled schedule was followed by a second 24 hr period in which demand was zero but capacity maintained at the level of the first period. This allowed any aircraft that had not been served in the first 24 hr period to be served. This is not realistic, but allows the performance of model to be evaluated without consideration of flight cancellation policies.

The model results and performance were compared to those of a queuing simulation, averaged over 100 simulation runs. As described above, a queuing simulation provides a more accurate estimate of system delay than can be achieved using the steady state and cumulative diagram approaches. For comparison, model results are also presented for the MIT DELAYS model. An $M(t)/E_9(t)/1$ queuing system (exponentially distributed inter-arrival times, service times defined by an Erlang-k distribution with $k = 9$, and using a single server) was modelled by the queuing simulation and MIT DELAYS model, as suggested by Malone (1995) for airport systems.

The demand run by the queuing simulation and MIT DELAYS model was defined per hour. The Rapid Delay Model can be run with demand specified in different time bin sizes. As described by Evans (2008), 2 hours was found to be the best choice for the time bin size.

It balances the benefits of small bin sizes, which capture the variability of the schedule, and larger bin sizes, which have less restrictive utilisation ratio thresholds, as defined by equations 5-13 and 5-14. This results in application of the linear interpolation between the steady state approach and the cumulative diagram approach over a smaller range of demand levels.

Average delays estimated by each of the models are presented in Figure 5-7a for an average airport capacity of 100 aircraft/hr, and a banked schedule following the shape of the Dallas-Fort Worth International Airport schedule in 2000. Results are presented over the specified range of utilisation ratios. Error bars are included for the simulation results, representing one standard deviation of the average delay calculated over the 100 simulation runs. The absolute and percentage difference between the average delay predicted by the queuing simulation, and by each of the Rapid Delay Model and the MIT DELAYS model are presented in Figure 5-7b and Figure 5-7c respectively. The average runtimes for each model are presented in the caption of Figure 5-7.

All the model runs predict a transition from low delays at low utilisation ratio to approximately linearly increasing delay at high utilisation ratio (Figure 5-7a). This is expected because, with increasing utilisation ratio and constant capacity, the scheduled demand shifts from predominantly well below capacity, for which delays are due to the stochastic nature of the system only, to predominantly near or above capacity, when the cumulative effects of delay building up during the day dominate. The transition from low delay to linearly increasing delay occurs between utilisation ratios of approximately 0.8 and 0.9, at which the scheduled demand in a number of time bins reaches and exceeds capacity, even though the average demand from 6:00 to 24:00 remains below capacity.

Below a utilisation ratio of 0.7, the differences in absolute delay predicted by the simulation and Rapid Delay Model are very small (less than 2 minutes) (Figure 5-7b). At high utilisation ratios of 0.9 and above, the Rapid Delay Model matches the simulation fairly closely. The differences do not exceed 20% (at a utilisation ratio of 0.65) (Figure 5-7c) or 4 minutes (at a utilisation ratio of 1.1) (Figure 5-7b). Importantly, the model results fall within one standard deviation of the simulation results through the full range of utilisation ratios tested (the error bars in Figure 5-7a).

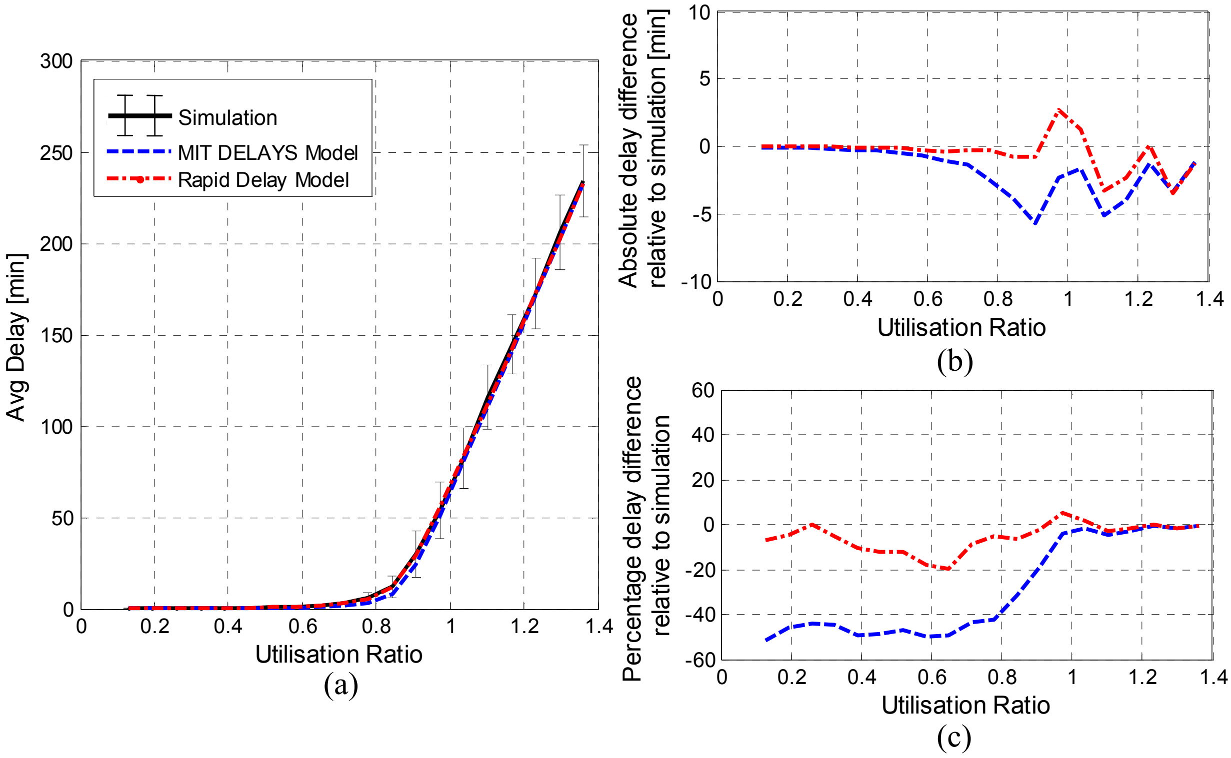


Figure 5-7. a) Average delay estimated by the simulation, MIT DELAYS model and Rapid Delay Model; b) Absolute delay difference between the simulation and other models (MIT DELAYS model and Rapid Delay Model); c) Percentage delay difference between the simulation and other models (MIT DELAYS model and Rapid Delay Model). Average simulation run time = 10 sec; average MIT DELAYS model run time = 0.61 sec; average Rapid Delay Model run time = 87×10^{-6} sec.

The results for the MIT DELAYS model are also compared to the simulation results in Figure 5-7b and Figure 5-7c, and show that it too under-predicts the simulation – by up to 50% (at low utilisation ratios), or 5 minutes (at a utilisation ratio of 0.9). The Rapid Delay Model results generally compare closely to the results for the MIT DELAYS model.

High utilisation ratios of above 1 result in unrealistically high average delays in excess of one hour (Figure 5-7a). These utilisation ratios are unlikely to occur in reality as airlines and passengers would respond to adjust the way in which they operate before these delays occurred, as discussed in Chapters 1 and 2. The utilisation ratios of most interest are between 0.9 (when average delay is 25 minutes) and 1, the range of utilisation ratios within which most capacity constrained airports will most likely converge to, given airline and passenger responses to delay. The Rapid Delay Model over-predicts the simulation between these utilisation ratios by up to 7% (Figure 5-7c), or only 3 minutes (Figure 5-7b).

The Rapid Delay Model is about 100,000 times faster than the simulation (average run times are presented in the caption of Figure 5-7), and about 10,000 times faster than the MIT DELAYS model. The Rapid Delay Model and the MIT DELAYS model run times remain approximately constant for all capacity scenarios. In contrast, the simulation run time increases as the capacity increases, given its dependence on the number of aircraft processed.

Application of the Rapid Delay Model in the Airline Response Model

In this dissertation average daily flight delays due to airport capacity constraints are calculated for each airport modelled using the Rapid Delay Model described above. A key input is airport capacity. This can generally be identified from published data. For the largest airports in the United States, airport capacities can be extracted directly from hourly arrival and departure rates from FAA Aviation System Performance Metrics (ASPM) data (FAA, 2008). Approaches also exist for estimating runway capacities according to runway and fleet mix characteristics, as described by de Neufville and Odoni (2003, Ch10). Airport capacities for each of the airports modelled in Chapters 6 and 7 are presented in Table 5-1. With the exception of specific scenarios described in Section 7.1 that model restricted airport capacity expansion, these capacities are assumed to increase over time according to airport capacity expansion plans described by airport authorities and the U.S. Department of Transport (DOT, 2004). These increases in capacity are also listed in Table 5-1.

The other key input to the Rapid Delay Model is the flight schedule. This is a function of the flight frequencies operated at the airport, input from the System Flight Frequency Calculator, and the shape of the flight schedule. The latter is extracted for each airport from 2005 FAA ASPM data (FAA, 2008), and is assumed to remain constant over time. Thus, any increase in airport traffic is assumed to cause the entire schedule to increase proportionally. Changes in the schedule in response to increasing costs, such as shifting flights to off-peak times as described by Kostiuk *et al.* (2000) and Long *et al.* (1999-1, 1999-2), and schedule de-peaking as described by Evans (2002) – both recognised airline responses to airport congestion – have only limited impact on flight delays at high traffic levels, and are therefore not modelled.

Table 5-1. Planned Airport Capacity Expansion

Airport	Year	Capacity (ac/hr)	Improvements	Reference
Chicago O'Hare	2005	187	-	FAA, 2008
	2015	260	New runway	Airport-Technology.com, 2009
Atlanta	2005	183	-	FAA, 2008
	2006	232	New runway	DOT et al., 2004; ATCMonitor.com, 2006
	2013	240	Technological & procedural	DOT et al., 2004
Dallas-Fort Worth	2005	238	-	FAA, 2008
	2013	297	Technological & procedural	DOT et al., 2004
Los Angeles	2005	151	-	FAA, 2008
	2013	190	Technological & procedural	DOT et al., 2004; Los Angeles World Airports, 2009
Houston Intercontinental	2005	158	-	FAA, 2008
	2006	189	New runway	DOT et al., 2004
	2013	224	Technological & procedural	DOT et al., 2004
Denver	2005	235		FAA, 2008
	2006	263	New runway	DOT et al., 2004
	2013	278	Technological & procedural	DOT et al., 2004
Detroit	2005	164	-	FAA, 2008
	2013	184	Technological & procedural	DOT et al., 2004
Philadelphia	2005	98	-	FAA, 2008
	2013	114	Technological & procedural	DOT et al., 2004
Newark	2005	88	--	FAA, 2008
	2013	89	Technological & procedural	DOT et al., 2004
Washington Dulles	2005	130	-	FAA, 2008
	2008	169	New runway	DOT et al., 2004
	2013	172	Technological & procedural	DOT et al., 2004
	2020	259	New runway	Adelman, 2008
New York Kennedy	2005	74	-	FAA, 2008
	2013	85	Technological & procedural	DOT et al., 2004
LaGuardia	2005	74	-	FAA, 2008
	2013	84	Technological & procedural	DOT et al., 2004
Boston	2005	99	-	FAA, 2008
	2006	126	New runway	DOT et al., 2004
	2013	127	Technological & procedural	DOT et al., 2004
Miami	2005	123	-	FAA, 2008
	2013	146	Technological & procedural	DOT et al., 2004
San Francisco	2005	86	-	FAA, 2008
	2013	111	Technological & procedural	DOT et al., 2004
Seattle	2005	87	-	FAA, 2008
	2008	99	New runway	DOT et al., 2004
Washington National	2005	72	-	FAA, 2008
	2013	86	Technological & procedural	DOT et al., 2004
Chicago Midway	2005	68	-	FAA, 2008
	2013	69	Technological & procedural	DOT et al., 2004
Oakland	2005	122	-	FAA, 2008
Houston Hobby	2005	48	-	FAA, 2008
	2008	52	Technological & procedural	Houston Airport System et al., 2004
	2019	57	Runway extension	Houston Airport System et al., 2004
	2029	61	Technological & procedural	Houston Airport System et al., 2004
	2036	63	New runway	Houston Airport System et al., 2004
Dallas Love	2005	71		FAA, 2008
	2010	72	Technological & procedural	City of Dallas Dept. of Aviation, 2001
	2020	73	Technological & procedural	City of Dallas Dept. of Aviation, 2001
Ontario	2005	55	-	FAA, 2008

Delay is distributed between arrivals and departures according to the ratio of each in each time period. Average daily departure delays at each airport are added to base year average gate departure delays due to mechanical failures and late arrivals, which are assumed to remain approximately constant. This assumes that schedule padding will increase to maintain schedule reliability, and is a simplification to avoid modelling the downstream propagation of flight delays between airports because of late arrivals (downstream propagation of delay to the destination airport due to a late departure at the origin airport is modelled). In reality, because of the stochastic nature of flight delays, airlines do not pad schedules to accommodate all flight delays. The worst delays still propagate through the system, and as delays increase, delay propagation is also likely to increase. The delays estimated by the Rapid Delay Model are thus likely to under-predict actual delays. Average gate departure delays are extracted from FAA ASPM data (FAA, 2008) for 2005. Average daily arrival delays are calculated as a function of arrival airport runway constraints only, with taxi-in delays assumed to be close to zero. This is consistent with taxi-in delay statistics from FAA ASPM data (FAA, 2008) for most airports.

It is also important to allocate arrival and departure delays to the phases of flight in which they are most likely to be incurred: at the gate, on the taxiway, or in airborne holding. Aircraft fuel burn rates are different in each phase of flight, and fuel burn is a significant portion of airline cost. Typically, if a departure delay is below a certain threshold, it is incurred on the taxiway at ground idle thrust. If the delay is greater than can be incurred on the taxiway, the aircraft is refused pushback by the air traffic service provider, and must incur the delay at the gate or in some cases in a parking area. In either case, the aircraft is not burning fuel (with the exception of fuel burn from running the auxiliary power unit, or APU). The duration of the taxi out process that is completed at taxi thrust (when the aircraft is moving) is taken to be approximately equal to the unimpeded (delay-free) taxi time.

In the case of an arrival delay, if it is below a certain threshold, it is incurred in airborne holding, at airborne holding thrust. If the delay is greater than can be incurred in airborne holding, the aircraft is refused pushback by the air traffic service provider at its origin, and must again incur the delay at the gate or a parking area. In either case the aircraft is, again, not burning fuel (with the exception of fuel burn from running the APU).

Taxi and airborne holding thresholds are not clearly defined for any airports, and vary significantly with weather and operations. In order to simplify the analysis, average thresholds were calculated for each airport as the 99^{th} percentile of historical taxi-out and airborne delay data from the FAA ASPM database (FAA, 2008). Calculated taxi-out thresholds are as high as 48 minutes with a minimum specified of 15 minutes, while calculated airborne holding thresholds vary from 11 minutes to 23 minutes. These thresholds were assumed to remain unchanged over time.

5.3 Travel Time Calculation

In the Airline Response Model, average nominal flight segment travel time is required as an input to the Operating Cost Calculator described in Section 5.4, in order to estimate airline costs per flight as a function of airline operating costs per hour. Average nominal O-D passenger travel time by city-pair is also required, as an input to the Passenger Demand Model described in Section 5.6, enabling the passenger response to changes in travel time to be simulated. Nominal travel time is the expected delay-free travel time, and does not include flight delays. The latter are input separately into the Operating Cost Calculator and Passenger Demand Model from the Delay Calculator.

Average nominal flight segment travel times are calculated as a function of aircraft type. In order to simplify the analysis, the aircraft fleet is categorised into three aircraft size classes: a small aircraft type (up to 189 seats), a medium aircraft type (between 190 and 300 seats), and a large aircraft type (over 301 seats); and two aircraft age categories: aircraft types originally certified before and after 1995. Performance characteristics are applied for representative aircraft in each of these categories. The representative aircraft types selected are as follows:

- Small, old: Boeing B737-300
- Small, new: Airbus A319
- Medium, old: Boeing 767-300
- Medium, new: Airbus A330
- Large, old: Boeing 747-400
- Large, new: Boeing 777-300

Average nominal flight segment travel times are estimated for each representative aircraft type, for each phase of flight, including: taxi-out, take-off, climb-out, cruise, descent, approach and landing, and taxi-in. Average unimpeded taxi-out and taxi-in data is available for 75 airports in the United States in the FAA ASPM Database (FAA, 2008). Typical take-off, climb-out (to 3,000 ft), descent (from 3,000 ft), and approach and landing times are available, by aircraft type, in the ICAO Aircraft Engine Emissions Databank (ICAO, 2008). Average unimpeded cruise times are calculated using the great circle distance between airports and typical cruise speeds, by aircraft type, from the EUROCONTROL Base of Aircraft Data (BADA) (EUROCONTROL, 2004).

Average nominal O-D passenger travel times are calculated according to the flight segment travel times described above, and the flight network operated by the airlines. Average nominal O-D passenger travel times are calculated for each city-pair modelled by averaging nominal O-D travel times for each passenger travelling between that city-pair, i.e., calculating the weighted average travel time. In order to simplify the model, it is assumed that passengers connect through a maximum of only one hub airport, and that the hub airports through which any passenger may connect are limited to the hubs operated by the airline that serves the passenger, as described in Section 5.1. The flight segments from which O-D travel times are calculated include the flight segments originating at each of the airports in the origin city and destined for each of the hub airports modelled (first leg of connecting flights); the flight segments originating at each of the airports in the origin city and destined for each of the airports within the destination city (non-stop flights); and the flight segments originating at each of the hub airports modelled, destined for each of the airports in the destination city (second leg of connecting flights). This is shown schematically in Figure 5-8.

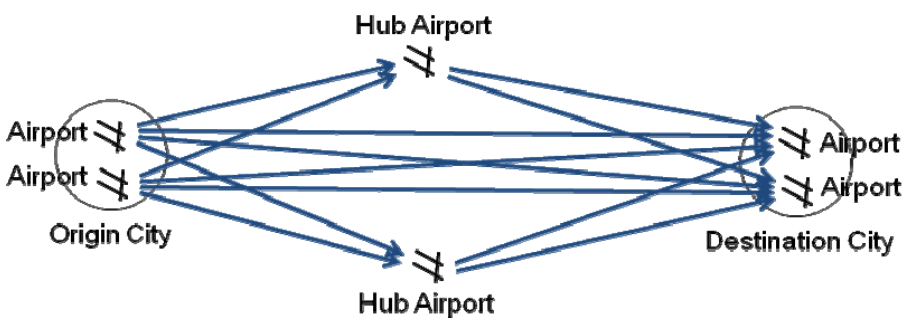


Figure 5-8. Schematic of flight segments between O-D city-pair.

5.4 Operating Cost Modelling

In the Airline Response Model, operating costs are calculated, per flight and per passenger, for each airline as a function of average nominal flight segment travel times and average flight delays, as shown in Figure 4-1. Additional inputs include fuel prices, aircraft fuel efficiencies, and operating costs per hour and per passenger. The calculated airline-specific operating costs are then output to the Network Optimisation Models, which calculate segment flight frequencies and itinerary passenger demand subject to the maximisation of airline profit. The calculated operating costs are also output to an Average Operating Cost Calculator, which calculates system average operating costs by city-pair (O-D) for input to the Average Fare Model.

As described in Section 4.1, airline operating costs modelled include direct operating costs and indirect operating costs associated with aircraft, traffic and passenger servicing; reservation and sales; and other system overheads. Direct operating costs cover fuel and oil costs, crew costs, maintenance costs, aircraft rental, depreciation and amortization costs, and en-route airspace charges. Aircraft servicing costs cover the handling of aircraft on the ground and landing fees. Traffic servicing costs cover the processing of passengers, baggage and cargo at airports. Passenger servicing costs cover meals, flight attendants and in-flight services. Reservation and sales costs cover airline reservations and ticket offices, including travel agency commissions. Other indirect and system overhead costs cover advertising and publicity expenses and general and administrative expenses.

As recommended by Belobaba (2006), some airline operating costs are modelled per flight, while others are modelled per passenger. Costs per flight include all direct operating costs and aircraft servicing costs, with the exception of the proportion of fuel burn that can be attributed directly to passengers. This extra fuel burn, along with traffic servicing costs, passenger servicing costs, reservations and sales costs, and other indirect and system overhead costs are modelled per passenger.

Direct operating costs and aircraft servicing costs are estimated for the three aircraft size classes described in Section 5.3, averaging over all aircraft types in each size class. With the exception of fuel costs and landing fees, all direct operating costs and aircraft servicing costs are derived from the U.S. DOT Form41 data Schedule P52 (DOT, 2005-1). Aircraft servicing costs, traffic servicing costs, passenger servicing costs, reservation and sales costs, and other indirect and system overhead costs are input directly from the U.S. DOT Form41 data Schedule P12 (DOT, 2005-2). It is assumed that all operating costs, with the exception of fuel costs, will not change significantly over time beyond inflation.

Landing fees are input directly for each airport from the International Air Transport Association's (IATA) Airport and Air Navigation Charges Manual (IATA, 2008). For those airports for which landing fees are not available (7 of the 22 airports simulated in Chapters 6 and 7), they are assumed to be equal to the average of those airports for which landing fees are available. Landing fees are not assumed to change over time, except in specific scenarios described in Section 7.2, in which an increase in regional costs is modelled through an increase in landing fees at a subset of airports.

Fuel costs are calculated independently as a function of fuel price and aircraft fuel burn in each of the aircraft flight phases, i.e., ground idle, taxi, take-off, climb-out, cruise, airborne holding, descent, approach and landing. The fuel price is taken from Air Transport Association (ATA) data (ATA, 2008), and is assumed to change over time according to changes in oil price forecast by the MIT Integrated Systems Model (IGSM), run for the U.S. Climate Change Science Program (CCSP) (CCSP, 2007). The IGSM is an integrated energy-economy-environment model with internally consistent population, income, and oil price scenarios. For the United States it represents a relatively high growth scenario when compared to the other energy-economy-environment models run for the CCSP.

Fuel burn rates are estimated using the EUROCONTROL Base of Aircraft Data (BADA) (EUROCONTROL, 2004) and the ICAO Aircraft Engine Emissions Databank (ICAO, 2008) for the representative aircraft in each of the aircraft size and age categories described in Section 5.3. Fuel burn rates are assumed to decrease over time because of the gradual development of more fuel efficient technology and its introduction into the fleet. Fleet fuel burn is assumed to decrease by 0.7% per year through the introduction of more advanced technology, which would replace retired aircraft and satisfy growing demand. This reduction is the average rate forecast by the Energy Information Administration to 2030 (Energy Information Administration, 2009). It does not account for reductions in fuel burn that would be achieved through the introduction of radically new technology such as an advanced open rotor engine or blended wing body aircraft, which are introduced in specific scenarios in Section 7.3.

The duration of each flight phase is input from the Travel Time Calculator, described in Section 5.3 above, with the exception of ground idle, taxi and airborne holding, which are input from the Delay Calculator, described in Section 5.3.

Most airline operating costs vary by aircraft type. However, some operating costs vary by airport, such as some aircraft, traffic and passenger servicing costs. These are lower at airports with particularly high traffic because of economies of scale. O'Kelly and Bryan (1998) estimate that economies of scale at hub airports in the United States result in aircraft, traffic and passenger servicing costs being between 40% and 95% (averaging 73%) of those at non-hub airports. These reduced costs make it attractive for airlines to operate hub-and-spoke networks. These economies of scale are modelled in this dissertation by exogenously decreasing aircraft, traffic and passenger servicing costs at hubs airports, and increasing them at non-hub airports. This is done in such a way that the aircraft, traffic and passenger servicing costs at hub airports are 73% of those at non-hub airports, and that average aircraft, traffic and passenger servicing costs across all airports equal those calculated from the DOT Form41 data Schedule P12 (DOT, 2005-2).

As described in Chapter 1, there are also other cost advantages of hub-and-spoke networks over point-to-point networks. Hub-and-spoke networks require fewer flights to connect several airports than do point-to-point networks, because they consolidate passengers along major traffic routes. The higher traffic volumes on hub-and-spoke flights allow airlines to operate larger aircraft on these routes, which typically have lower aircraft operating costs per RPM than smaller types. However, the reduction in operating costs is partly offset by the greater total distances flown by passengers and the associated increase in fuel burn. Thus, in some cases, point-to-point networks have lower cost. An example is when a hub is located far from the shortest path between two airports. The lowest cost network is therefore typically a combination of both hub-and-spoke and point-to-point networks.

After the calculation of airline operating costs per flight and per passenger, average operating costs are calculated over all airlines by the Average Operating Cost Calculator. These are output by city pair, per passenger, to the Average Fare Model, described in Section

5.5, for estimation of average fares by city-pair market. Airline costs per flight are allocated to O-D passengers according to the itinerary passenger demand for each city pair that is on board each flight, while airline costs per passenger are applied directly to O-D passengers.

5.5 Average Fare Modelling

The modelling of changes in airline airfares as a function of changes in airline cost enables simulation of how airline cost changes impact passenger demand. As described by Waitz *et al.* (2006-2), this is particularly important when modelling policy measures intended to mitigate the environmental impacts of aviation. This is because passenger demand responses to increased fares resulting from policy interventions may lead airlines to schedule fewer flights. This could result in greater reductions in emissions and noise than forecast by an analysis that does not model this effect on demand.

Airline fare strategies are, however, highly complex, particularly in the United States and Europe. This has resulted primarily from deregulation of the airline industry (in 1978 in the United States and by 1997 in Europe), the development of computerised revenue management systems (in the 1980s), and the development of web-based airline ticket distribution and on-line travel agents (in the late 1990s) (Carrier, 2006). As a result of these developments, airlines do not simply apply cost-based pricing, but apply a combination of cost-, demand-, and service-based pricing, applying price discrimination and product differentiation to increase total flight revenues, with little consideration to total operating costs (Belobaba, 2008). Airlines segment markets with different levels of willingness to pay by offering different fare products to business and leisure travellers, preventing diversion by setting restrictions on lower fare products (e.g. requiring a Saturday night stay) and limiting available seats. The result is higher revenues and load factors than could be achieved through any single fare strategy.

Approaches to Modelling Fares

Models exist that can be applied directly to airline ticket pricing, such as the probabilistic decision model described by Belobaba (1989), which identifies what booking limits should be applied to the number of seats available at different prices on the same flight in order to increase airline revenue. These models are, however, complex, and are not tailored to forecasting applications, requiring information about passengers that is difficult to predict.

Other approaches model average fare changes as a function of changes in airline cost without considering airline revenue management, and are more appropriate to forecasting applications. Fare models applied in the context of forecasting aviation growth in the future typically do not model competition effects explicitly. The Aviation System Analysis Capability (ASAC) Air Carrier Investment Model (ACIM) (Wingrove *et al.*, 1998), allows the user to specify airline yields or operating profits, and how they are expected to change over time. The model adjusts fares to produce the yields or operating profits specified. This approach has the advantage of allowing differentiation between airlines, but does not explicitly model competition beyond assuming that competition maintains profits at the levels specified.

An alternative approach optimises average fares to maximise system profit, within limits, as described by Pulles *et al.* (2002). This approach effectively identifies the cost "pass-through" to fares that results in maximum profit, modelling the impact of fare changes on passenger demand, and the impact of passenger demand changes on capacity supply (flights), which in turn impact cost. The approach also allows for user specified cost pass-through, if desired. However, it does not capture any competition effects, nor does it model any revenue price discrimination or revenue management approaches. Waitz *et al.* (2006-2) describes a similar approach in which a bounding analysis is completed. A range of scenarios are modelled with different degrees of cost pass-through to fares applied in each case. For example, scenarios are run in which airlines pass 100%, 50% and 0% of cost increases through to fares. This approach is very transparent, providing a range of outcomes with bounds, but lacks guidance as to the most likely outcome. Again, airline competition effects are not modelled explicitly, despite the fact that they may drive the degree to which cost is passed through to fare.

A further approach adjusts fares to maintain an existing airline rate of return, as described and applied by Waitz *et al.* (2006-3). This is accomplished by maintaining a proportional relationship between fares and costs. Thus, if costs are predicted to increase by a certain percentage, fares are modelled to increase by the same percentage. This approach also does not explicitly account for competition effects.

In contrast to these approaches that do not model airline competition, Adler (2005) models airline competition in a network by solving a non-linear optimisation within a two-stage, Nash best-response game, identifying flight frequencies and average O-D market fares for different passenger types, as described in Section 2.3. The impact of competition on fares and frequency is modelled explicitly, and some degree of price discrimination (different passenger types are modelled) is captured. Also as described in Section 2.3, Schipper *et al.* (2003) and Carlsson (2002) model the effects of competition on average fares and flight frequencies by solving a two stage game separately for each market, as opposed to the whole network operated by the airline. In the first stage of the game, airlines simultaneously choose flight frequencies in the market, and in the second stage, after having observed the other airlines' chosen frequencies, the airlines simultaneously choose fares for the market. The game is solved analytically as a function of passenger value of time, airline costs and passenger demand. This formulation was modified by Evans *et al.* (2008) for variable passenger demand. Both formulations, however, do not model any price discrimination or revenue management. Nor does the model distinguish between different passenger routings on the same O-D market. Fares, passenger value of time and costs may differ quite significantly for different routes in the same market, particularly between non-stop flights and connecting flights. Finally, the even distribution of flights through the day applied to define the flight schedule does not capture passenger preferences to fly at certain times of day (particularly the early morning and evening), and therefore ignores the increased demand at these times. Nero (1998) and Januszewski (2004) make similar assumptions to formulate equations for fare as a function of cost within a competitive environment in order to examine airline scheduling and the effect of flight delays on airlines' prices.

Modelling of Fares in the Airline Response Model

Ideally, average O-D fares by passenger type should be included as a decision variable in each airline's network optimisation objective function, described in Section 5.1. This would allow different fares to be identified for each airline within the competitive environment, subject to airline operating costs. However, this approach would add significant complexity, because the calculation of market share in each network optimisation would require passenger choice modelling based on both fare and flight frequency, as opposed to the relatively simple passenger choice model based on flight frequency only (equation 5-3). Such an approach would also be unlikely to add significantly to the model results, because in reality fares are set using complex revenue management techniques, and in a different cycle to the more strategic decisions of flight frequency and network choice. Instead, the modelling approach adopted for the Airline Response Model is to adjust base year fares to maintain the existing rate of return. This is identical to the approach used by Waitz *et al.* (2006-3), and is accomplished by maintaining a proportional relationship between fares and costs. Thus, any percentage change in cost is applied directly to base year fares.

Base year fares in the United States are obtained from published fare lists (DOT, 2007), while base year operating costs by O-D city pair are estimated by running the Airline Response Model with fares fixed to base year values. This ensures that modelled fares deviate from observed base year fares according to how modelled operating costs deviate from operating costs that are consistent with the observed base year fares.

5.6 Passenger Demand Modelling

The most common approach to modelling passenger demand for air transport is the gravity model, in which the equation defining trip demand between city pairs or airports resembles Newton's law of gravity. Gravity-type models have been applied to project air transport demand in a number of studies (Verleger, 1972; Jamin, 1997; Jamin *et al.*, 2004; Reynolds *et al.*, 2007; Dray *et al.*, 2008, 2009-1, 2009-2). In most cases the explanatory variables include population, per-capita income, dummy variables indicating whether a city has special attributes that may increase passenger demand (e.g. a major tourist destination or capital city), and a generalised cost term that includes supply variables. The generalised cost term can include passenger airfare and passenger travel time, multiplied by a passenger value of time. The distance between the cities is typically captured through the travel time term. In some cases (Dray *et al.*, 2009-1, 2009-2) other dummy variables are included for city pairs that are connected by other forms of transport that may compete with aviation, such as rail or road. Bhadra *et al.* (2003) use a similar approach to the gravity model in which statistical relationships are estimated to define O-D passenger demand by city pair as a function of local economic and demographic data, fares, market share of major carriers, the presence of low-cost carriers, seasonality, and the structure of airport hubs.

In the Airline Response Model, as described in Chapter 4, O-D passenger demand must be calculated by city pair as a function of various variables, including average flight delay, average nominal passenger travel time, and average fare. The demand model adopted must therefore be capable of estimating air transport passenger demand by city pair, and must account for the demand reducing effects of increased flight delays, changes in the flight network to increase travel times, and increased fares. A one-equation gravity-type model, similar to those applied by Reynolds *et al.* (2007) and Dray *et al.* (2008, 2009-1, 2009-2) was selected. Each of the demand reducing effects can be modelled within the generalised cost term, which includes travel time and fare terms. While this approach does not explicitly model passenger mode choice, it is suitable for the city set modelled in Chapters 6 and 7, where mode substitution is less significant due to the long distances travelled. The model applied is as follows:

$$D_{ij} = (P_i P_j)^{\alpha} (I_i I_j)^{\gamma} e^{\delta A_{ij}} e^{\varepsilon B_{ij}} e^{\phi S_{ij}} \left(\overline{Fare}_{i,j} + \theta_1 \cdot \overline{T}_{i,j} + \theta_2 \cdot \overline{Delay}_{i,j} \right)^{\tau} \tag{5-15}$$

where D_{ij} represents the O-D passenger demand between city i and j; P is the related greater metropolitan area or equivalent population; I is the greater metropolitan area per capita income; A is a binary variable indicating whether either city in the city pair is special, i.e., it might have increased visitor numbers (e.g. a major tourist destination or capital city); B is a complimentary binary variable indicating whether either city is not special; S is a binary variable indicating whether road transport between the city pair is competitive with air transport (specified according to a distance-based criterion of 150 nmi (173 miles)); $\overline{Fare}$ is passenger airfare between the cities averaged over all itineraries; θ_1 is the passenger value of (nominal) travel time; $\overline{T}$ is the nominal travel time between the cities averaged over all itineraries; θ_2 is the passenger value of delay time; and $\overline{Delay}$ is the average flight delay between the cities averaged over all itineraries. The exponents represent the elasticity of demand to each of the explanatory variables (i.e. % change in demand resulting from a % change in each explanatory variable) (in the case of population and income, the elasticity of demand is represented by α and γ divided by two). The expression in brackets represents the generalised cost to a passenger of air travel between the cities, and it is through this expression that it is possible to include the demand-reducing effects of increased flight delays, changes in network structure to increase travel times, and increased fares.

Note that travel time within the generalised cost term is split into nominal travel time and flight delays. Passengers dislike travel time increases due to flight delays, which are unexpected, to a greater extent than increases in nominal travel time. Forbes (2008) examines airfare responses to flight delays, and finds that fares fall in response to longer flights delays by US$(2005) 1.61 on average for non-stop passengers per additional minute of delay. The price response is smaller for connecting passengers (US$(2005) 0.87 per minute), while on competitive routes, the value can be as high as US$(2005) 2.77 per minute. Averaging over these values yields a value of US$(2005) 105 per hour. This is just over 3 times higher than the passenger value of travel time derived from data from the U.S. DOT (DOT, 1997) of US$(2005) 34.38 per hour. This difference between the passenger value of nominal travel time and the passenger value of flight delay time is consistent with other estimates (Ben-Akiva, 2009). In equation 5-15, θ_1 is specified as US$(2005) 34.38 per hour, and θ_2 as US$(2005) 105 per hour.

Using demand data for the United States in 2005 (United States Census Bureau, 2000; DOT, 2005-2, 2007), the coefficients (exponents) in equation 5-15 were estimated for a set of 14 cities[2], which form the city set modelled in Chapters 6 and 7. All estimated coefficients, which are presented in Table 5-2, are significant at the 95% confidence level. The adjusted R^2 for the model estimation is 0.85. The coefficients presented in Table 5-2 are similar to those estimated by Jamin *et al.* (2004) and Dray *et al.* (2009-1).

Table 5-2. Estimated Coefficients, Standard Errors (in parentheses) and Adjusted R^2 for the Passenger Demand Model

Population ($\alpha/2$)	Income ($\gamma/2$)	Special Parameter 1 (δ)	Special Parameter 2 (ε)	Special Parameter 3 (φ)	Generalised Cost (τ)	Adjusted R^2
0.79 (0.087)	0.65 (0.143)	0.46 (0.067)	-0.53 (0.079)	-3.81 (0.183)	-1.04 (0.093)	0.85

[2] New York City, Chicago, Atlanta, Washington, Los Angeles, Dallas/Fort Worth, Houston, San Francisco, Miami, Denver, Detroit, Philadelphia, Boston, and Seattle.

In Table 5-2, the coefficient for population is positive because increasing population leads to an increase in demand for air travel. The coefficient for per-capita income is also positive, because an increase in income results in increased mobility, leading to an increase in demand for air travel. The coefficient for the first binary variable, which indicates if either city in the city pair is special, is positive because special cities attract more passengers. The second binary variable indicates if either city is not special, and therefore the coefficient is negative. The coefficient for the third binary variable, indicating whether competitive road transport links exist between the city pair, is strongly negative. Significant alternative transport modes take demand away from aviation. Finally, the coefficient for the generalised cost term is also negative, because passengers respond negatively to increases in costs.

In the application of the demand model in Chapters 6 and 7, base year population and per-capita income data are derived from the United States Census (US Census Bureau, 2000) and American Community Survey (US Census Bureau, 2005). Population and per-capita income projections into the future are scenario variables, which change over time relative to the base year. Like the oil price projections, they are taken from the CCSP IGSM forecast (CCSP, 2007). This ensures that there is consistency between the modelled populations and per-capita income and the modelled oil prices.

With the exception of income elasticity, all the coefficients estimated for equation 5-15 (presented in Table 5-2), as well as passenger value of travel time and passenger value of delay time, are assumed to remain constant over time. Income elasticity, however, is assumed to increase with increasing per-capita income, because, as people become richer, they fly more. The income elasticity applied in the Airline Response Model is assumed to increase by 0.2% per year, which is consistent with increases in income elasticity estimated from longitudinal time series data presented by Schäfer *et al.* (2009).

5.7 Iteration

As described in Chapter 4, the integrated framework presented in Figure 4-1 is solved by iteration. In each iteration step operating costs, available passenger demand, and fare inputs for the network optimisations of each airline are updated, as are flight delays and passenger travel times, on which they depend.

The airline game is simulated by updating the flight frequencies offered by all airlines according to the outputs of each airline's network optimisation. These flight frequencies are inputs to the market share formulation within the demand constraint in each network optimisation (equation 5-3), which drives the gaming effect. Thereby, each airline may increase or decrease its frequency in order to capture more market share. Each airline stops increasing frequency as soon as the marginal cost of adding a flight is greater than the marginal revenue obtained from the increased market share gained by adding the flight. Since airlines experience different operating costs, those with the lowest costs can add more extra flights and thus gain more market share. The system reaches the game theoretical equilibrium when all airlines reach equilibrium on all markets.

System convergence is identified by comparing system flight frequencies over the entire network to those of the previous iteration. This is done by generating a vector of the changes in all flight segment frequencies, and calculating the Euclidian norm of this vector. The system is considered to have converged when this norm falls within the convergence criteria, as described by Haag (2009). The norm convergence criterion is set to 1×10^4. This is approximately equivalent to an R^2 value comparing all segment flight frequencies of 0.97. The efficiency of the iterative approach is improved by specifying the input flight frequencies and passenger itinerary demand to each iteration (say, x_i) as the average of the output of the previous iteration (say, $f(x_{i-1})$) and the input to that iteration (x_{i-1}), as shown in equation 5-16:

$$x_i = \frac{x_{i-1} + f(x_{i-1})}{2} \tag{5-16}$$

where x_i represents the vector of all segment flight frequencies and passenger itinerary demand (the decision variables in the network optimisation described by equation 5-1) in iteration i.

Convergence of the system to a global equilibrium that represents airline operations is not, however, guaranteed. Specifying the iterative procedure described above as a search for a fixed point (i.e., find x given $x = f(x)$), convergence is guaranteed when the magnitude of the gradient of the function f is smaller than 1 (i.e., $|f'(x)|<1$) within the range of values of x and $f(x)$ evaluated (Burden and Faires, 2005). However, the function f is difficult to define in this case, because of the complexities of the sub-models described in this chapter. Despite these difficulties in determining whether convergence is guaranteed or not, the Airline Response Model was found to converge consistently in all applications completed for this dissertation. This includes application of the Airline Response Model to a series of theoretical scenarios (described in Appendix B), a scenario representing actual operations in the United States in 2005 (described in Chapter 6), and a series of policy scenarios forecasting traffic growth from 2005 to 2030 (described in Chapter 7). In all cases, the model converged within 7 to 10 iterations. These results suggest that, within the range of values of x and $f(x)$ for which the Airline Response Model is applied, a fixed point exists and it is an attractive fixed point exhibiting convergence.

Even with convergence, it is not guaranteed that the system will converge to a global solution, but may instead converge to a local solution. In order to identify if this is the case, the sensitivity of the Airline Response Model results was tested with regard to the initial conditions applied. In the application of the model to a scenario representing actual operations in the United States in 2005 (described in Chapter 6), the model was run with a range of initial conditions. These initial conditions varied from 50% less demand and traffic to that in the observed data to 50% more demand and traffic to that in the observed data. In all cases, the Airline Response Model converged to the same equilibrium. This suggests that the system equilibrium to which the model converges is a global solution, and not a local solution that is dependent on the initial conditions.

5.8 Modelling Emissions

Once a game-theoretical equilibrium is reached, flight segment frequencies by aircraft size class and passenger itinerary demand at convergence are output by the System Flight Frequency Calculator, defining the airline networks, flight frequencies and aircraft size choice. The associated environmental impact is quantified by calculating emissions levels. This is described below. Further quantification in terms of climate, local air quality and health impacts requires additional analysis accounting for atmospheric chemistry, transport and dispersion, as well as other factors, and is not considered in this dissertation.

Two emissions types are calculated: CO_2 and NO_x. CO_2 is a key greenhouse gas affecting climate change, while NO_x has local air quality impacts as well as climate impacts by affecting the formation of ozone. NO_x emissions are calculated for the flight LTO cycle only, as an indicator of potential air quality impacts, while CO_2 emissions are calculated for the system as a whole, as an indicator of potential climate impacts. The climate impacts of NO_x emissions are not accounted for.

As with fuel burn, described in Section 5.4, CO_2 and NO_x emissions vary by engine conditions, and thus phase of flight. CO_2 and NO_x emissions are thus calculated in each flight phase: ground idle, taxi, take-off, climb-out, cruise, airborne holding, descent, approach and landing. Emissions rates are identified from the EUROCONTROL Base of Aircraft Data (BADA) (EUROCONTROL, 2004) and the ICAO Aircraft Engine Emissions Databank (ICAO, 2008) for the representative aircraft in each of the aircraft categories described in Section 5.3. The duration of each phase of flight is input from the Travel Time Calculator, described in Section 5.3, with the exception of ground idle, taxi and airborne holding, which are input from the Delay Calculator, described in Section 5.2.

In order to illustrate the capabilities of the Airline Response Model and to verify its suitability to capture fundamental system effects, Appendix B presents results applying it to a series of simplified theoretical flight networks. Fundamental system effects, including passenger demand responses to increasing cost and travel time, and airline responses to changes in demand and costs, are often difficult to clearly identify in real networks because of their inherent complexities and scale. Simplified theoretical networks allow scenarios to be simulated without these complexities, and at a smaller scale.

The capability of the Airline Response Model to reproduce real traffic flows is validated in Chapter 6 by reproducing passenger flows and flight frequencies for a network of airports in the United States in 2005. The model is then applied to simulate future traffic growth and emissions within the same network under a series of policy scenarios in Chapter 7.

6 Model Validation: Domestic United States, 2005

This chapter describes the validation of the Airline Response Model. This is achieved by simulating airline operations in a network of real cities and airports, and then comparing the flight frequency and passenger demand results to observed data for that network. The air transport system examined is the domestic air transport system of the United States. This system was selected because it is large, serving nearly 40% of global scheduled flights in 2005 (OAG, 2005), and has been deregulated since 1978, and therefore represents a stable competitive market. There is also greater data availability for the air transport system in the United States than for other regions, provided particularly by the U.S. DOT (DOT, 2000, 2004, 2005-1, 2005-2, 2005-3, 2006, 2007).

The set of cities and airports modelled is described in detail in Section 6.1. This is followed by the simulation results, which are presented and discussed in Section 6.2. In order to test the robustness of these results, their sensitivity to key input parameters is analysed in a sensitivity analysis. This is described in Section 6.3.

6.1 City and Airport Set Modelled

The air transport system modelled is made up of 14 cities[1], which are served by 22 airports[2]. The locations of these cities and airports are shown in Figure 6-1. The airlines modelled to serve this city and airport set were the five airlines with greatest market share serving the modelled city set in 2005, i.e., American Airlines, Southwest Airlines, United

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[1] New York City, Chicago, Atlanta, Washington, Los Angeles, Dallas/Fort Worth, Houston, San Francisco, Miami, Denver, Detroit, Philadelphia, Boston, and Seattle.

[2] Chicago O'Hare (ORD), Chicago Midway (MDW), Atlanta (ATL), Dallas-Fort Worth (DFW), Dallas Love (DAL), Los Angeles (LAX), Ontario (ONT), Houston Intercontinental (IAH), Houston Hobby (HOU), Denver (DEN), Detroit (DTW), Philadelphia (PHL), Newark (EWR), New York Kennedy (JFK), New York LaGuardia (LGA), Washington Dulles (IAD), Washington National (DCA), Boston (BOS), Miami (MIA), San Francisco (SFO), Oakland (OAK), and Seattle Tacoma (SEA).

Airlines, Delta Airlines, and Continental Airlines (OAG, 2005). The number of cities, airports and airlines modelled was limited in order to maintain model tractability.

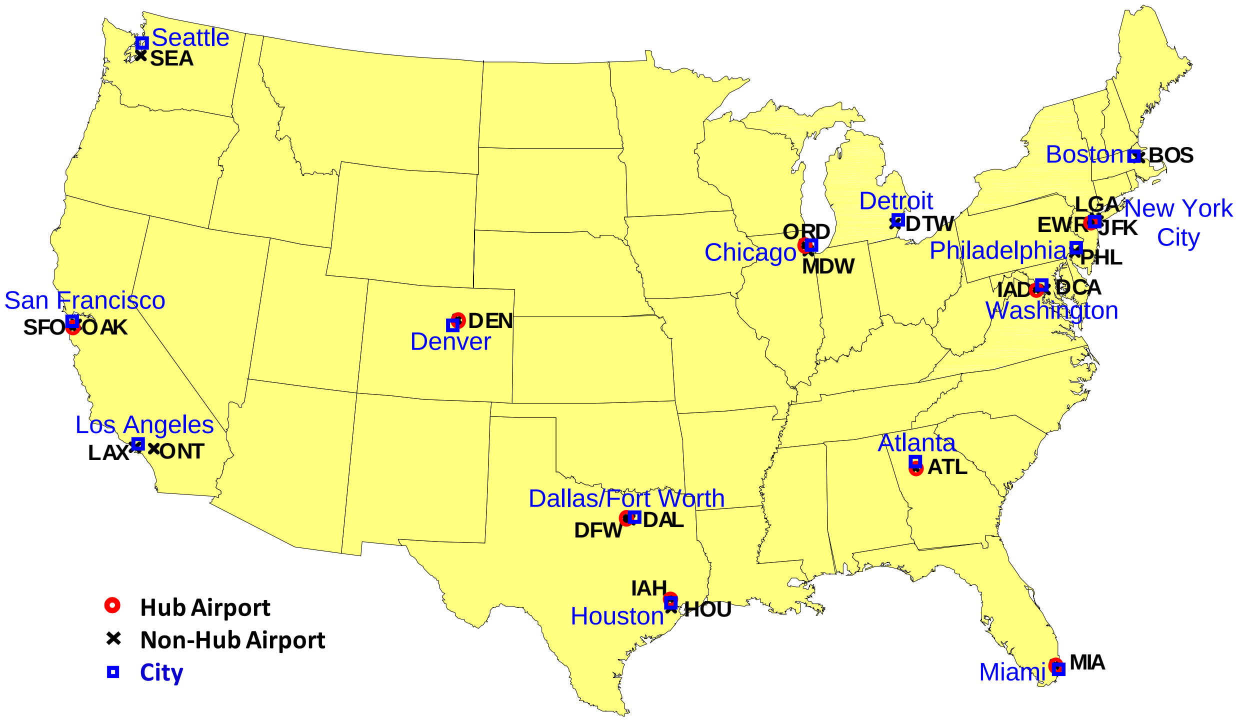

Figure 6-1. City and airport set modelled.

The cities chosen were those with the highest O-D passenger demand in 2005 (DOT, 2007), with two exceptions. To ensure that all regions were represented, Boston (New England) and Seattle (Pacific Northwest) were also included (these cities ranked 17^{th} and 19^{th} respectively). The airports selected for the analysis include the major airports in each of the modelled cities, and the primary hub airports operated by each of the modelled airlines. Although Boston and Miami are also served by secondary airports (Boston by Providence (PVD) and Manchester (MHT), and Miami by Fort Lauderdale (FLL)), these airports are considered less important secondary airports, and are thus not included in the airport set. Only two airports are modelled in any city (the primary airport and the largest secondary airport), with the exception of New York City, where three airports are modelled (LaGuardia, New York Kennedy, and Newark). This two airport limit particularly affects Los Angeles (Los Angeles International and Ontario are modelled, while Burbank (BUR) and Orange County (SNA) are not) and San Francisco (San Francisco International and Oakland are modelled, while San Jose (SJC) is not). In future work the network may be expanded to include these airports, as well as others in the system.

The modelled airport set served approximately 80% of scheduled available seat miles (ASM) flown in the United States in 2005, or nearly 35% of global ASM (OAG, 2005). Flights operating between these airports, however, account for only 25% of scheduled domestic ASM in the United States in 2005 (OAG, 2005).

Each of the five modelled airlines is constrained to route passengers through only those hubs that they operated in 2005, and to serve only those airports that they served in 2005. This means that the model does not simulate airline decisions to serve new markets, or to operate new hubs. This assumption is necessary to allow the Airline Response Model to reproduce the 2005 base year traffic flows because the costs associated with introducing operations at new airports are not modelled. The assumption also aids model tractability by limiting the number of hubs available for routing connecting itineraries within the network optimisation routines. This assumption may be relaxed in future work. The hubs operated by each airline in the analysis described in this chapter are as follows:

- American: Dallas/Fort Worth, Chicago O'Hare, and Miami (American Airlines, 2009)
- Southwest: None[3] (Southwest Airlines, 2009)
- United: Chicago O'Hare, Washington Dulles, Denver, and San Francisco (United Airlines, 2009)
- Delta: Atlanta (Delta Airlines, 2009-2)
- Continental: Newark, and Houston Intercontinental (Continental Airlines, 2009)

The hub airports modelled in this analysis are 9 of a total of 19 large hub airports in the U.S. air transport system. They include only those hub airports associated with the set of cities, airports and airlines modelled in the analysis[4]. Exceptions include Los Angeles

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[3] Southwest Airlines operates primarily point-to-point service, although they do have some hub operations at Chicago Midway and Dallas Love Field. These hubs are not as significant as other airline hubs, however.

[4] The modelled airlines also operate hubs at airports which are not included in the airport set modelled, i.e., St. Louis (STL) (American), Salt Lake City (SLC) (Delta), Cincinnati (CVG) (Delta), and Cleveland (CLE) (Continental). These airports serve cities not included in the city set modelled, and are relatively less important

International and New York Kennedy airports, which are operated as hubs by United and Delta Airlines respectively, but are not modelled as hubs here. This is because the number of hubs simulated for each airline is limited in order to maintain model tractability, and because these hubs are relatively less important to domestic operations than those modelled (DOT, 2007).

The airports served by each airline in the analysis were identified directly from the 2005 Official Airline Guide (OAG, 2005). In all cases except for Southwest Airlines, they include most of the primary airports in the airport set, and exclude some secondary airports[5]. In the case of Southwest Airlines, most secondary airports are included, while a number of the primary airports are not included.

The airport set modelled also serves connecting passengers whose origin or destination city is not included in the modelled city set, but who connect on a flight segment included in the modelled network. For example, passengers flying from Anchorage to Atlanta could connect through Seattle. The passenger demand from Anchorage to Atlanta is not modelled, because Anchorage is not in the modelled city set. The passengers would still be served, however, by the flight between Seattle and Atlanta, which is in the modelled network. In order to account for this extra-network demand, it is extracted from DOT data (DOT, 2005-3, 2007) for 2005, and scaled according to modelled changes in intra-network demand.

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hubs than those modelled (DOT, 2007). Similarly, Detroit, Philadelphia, New York Kennedy and Seattle Airports are operated as hubs by Northwest Airlines, US Airways, JetBlue and Alaska Airlines respectively. These airlines are not, however, modelled, and thus these airports are not modelled as hubs. This means, however, that the traffic at these airports is likely to be under-estimated, as the hub operations of these airlines would increase traffic, in some cases quite significantly.

[5] Those airports in the modelled airport set that are not served by the respective airlines are as follows:

- <u>American</u>: Dallas Love
- <u>Southwest</u>: Chicago O'Hare, Atlanta, Houston Intercontinental, Newark, New York Kennedy, Boston, Miami, and San Francisco
- <u>United</u>: New York Kennedy, Washington National, Chicago Midway, Houston Hobby, Dallas Love, and Ontario
- <u>Delta</u>: Chicago Midway, and Dallas Love
- <u>Continental</u>: New York Kennedy, LaGuardia, Houston Hobby, and Ontario

The Network Optimisation Models are then constrained to also serve this demand, by flight segment, distributed equally between all airlines operating on that flight segment.

Similarly, flight delays may be impacted by extra-network flights, i.e., flights between the modelled airports and other airports not within the modelled airport set. This traffic is extracted from FAA ASPM data (FAA, 2008) for 2005, and scaled according to changes in intra-network traffic at each airport.

Alliances between airlines, in which airlines agree to serve passengers for other airlines, and vice versa, are not modelled. Alliances allow airlines to increase network connectivity and frequency without adding flights. Modelling alliances is not trivial, however, as they do not simply operate as larger airlines, combining revenues and operations of all member airlines. Instead, they operate with sometimes complex contracts between member airlines governing the distribution of revenues and costs between the airlines that serve any given passenger from their true origin to ultimate destination. Because of the complexities of such contracts, and because few alliances exist between the modelled airlines[6], alliances are not modelled. Because alliances allow airlines to increase network connectivity and frequency without adding flights, the effect of not modelling alliances is to over-predict frequencies. This is only likely to occur, however, in markets served by airlines in the same alliance.

6.2 Validation Results

The Airline Response Model is validated by comparing model results, with input data as described in Chapter 5, to observed data, provided by the FAA and DOT for 2005 (FAA, 2008; DOT, 2005-3, 2007). In order to measure how well the Airline Response Model reproduces the base year observations and to identify the reasons for differences, four indicators are compared:

- O-D passenger demand between city-pairs,

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[6] Delta and Continental airlines were both members of the Skyteam Alliance in 2005 (Delta since 2000 and Continental since 2004. Continental has since left the alliance (2009) to join the Star Alliance). United is part of the Star Alliance and American is part of the One World Alliance. Southwest is not part of any major alliance.

- Flight segment frequencies offered across all airlines between airport pairs,
- Flight frequencies offered across all airlines between O-D city pairs, and
- Seats offered across all airlines between O-D city pairs.

A comparison of O-D passenger demand between city pairs, the first indicator, provides insight into how well the Passenger Demand Model reproduces the observed passenger flows. It also provides insight into the reasons for differences in flight frequencies, the second indicator, because it is this passenger demand that these flights serve. If there are significant differences in passenger demand in certain markets, similar differences in the frequencies for flights serving these markets would be expected.

A comparison of segment flight frequencies, the second indicator, reveals differences between the simulated and observed networks. However, a relatively small difference in the flight network, such as the operation of flights from a different airport in a multi-airport system, may significantly alter the segment flight frequencies at the airports within that multi-airport system, implying misleadingly large differences between the model results and the observed data. For this reason additional metrics are also compared.

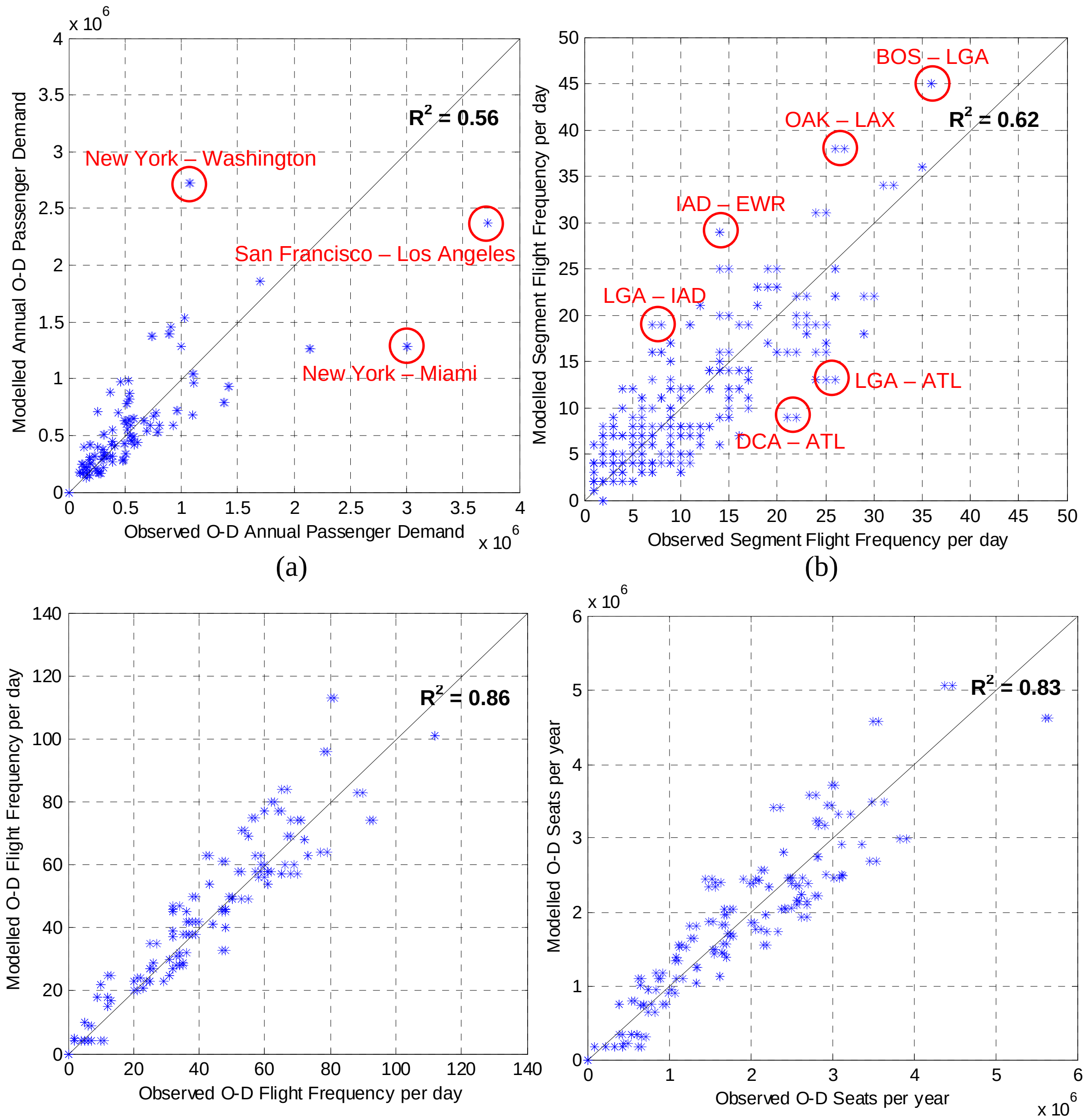
A comparison of the flight frequencies between O-D city pairs, the third indicator, captures how the airlines serve the specified O-D demand, without consideration of the distribution of traffic between airports in multi-airport systems. Comparing this indicator to differences between segment flight frequencies across multi-airport systems allows the capability of the Airline Response Model to simulate the distribution of traffic within multi-airport systems to be examined. For example, if the differences between segment flight frequencies are large, but the differences between O-D flight frequencies are small, the cause of the differences between the segment flight frequencies could be identified to be the distribution of traffic within the multi-airport system. Note that in the calculation of O-D flight frequencies, connecting flights are not included. This indicator therefore does not provide an indication of the capability of the model to simulate other network effects, such as whether passengers are connecting or flying non-stop, and if they are connecting, which hub they are connecting though.

A comparison of the number of seats offered between O-D city pairs, the fourth indicator, captures how the airlines supply seats to serve demand, without consideration of either aircraft types operated (affecting aircraft sizes), or how aircraft and passengers are routed within multi-airport systems. Comparing this indicator to the differences between O-D flight frequencies allows the capability of the Airline Response Model to simulate aircraft size choice to be examined. For example, if the differences between O-D flight frequencies are large, but the differences between O-D seats are small, the cause of the differences between the O-D flight frequencies could be identified to be aircraft size.

Each of the modelled and observed indicators described above is compared graphically in Figure 6-2 by plotting the modelled values against the corresponding observations for each city and airport pair modelled. A diagonal line is added in each case which represents an exact match between the modelled results and observed data. In order to quantify the proportion of variability in the observed data that is explained by the Airline Response Model, an R^2 value is calculated across the network for each indicator. These are presented with each plot in Figure 6-2. The actual values of modelled and observed O-D passenger demand and segment flight frequencies are presented in Appendix C.

Figure 6-2a compares modelled and observed O-D passenger demand. The data points are distributed approximately evenly along the diagonal line. Summed across all city pairs, modelled system O-D demand is only 1% higher than the observed data, which is consistent with this even distribution of data points. There are a small number of notable outliers, however, which are highlighted and labelled. These contribute to the comparatively low R^2 value of 0.56. Figure 6-2a suggests generally, however, that the Airline Response Model is capable of capturing the dominant effects driving O-D passenger demand.

Considering the outliers in Figure 6-2a in more detail, O-D demand between New York City and Washington is significantly over-predicted by the model. This is mainly because alternative modes of transport – particularly road and rail – are used by passengers travelling the relatively short distance between these cities. As described in Section 5.6, a dummy parameter is included in the demand equation to account for city pairs that have significant road and rail links. However, the highest R^2 value in the parameter estimation of the demand equation results when the distance threshold applied to identify a city-pair with road and rail links is shorter than the distance between New York City and Washington. Cities pairs with more dominant road and rail links, such as New York City and Philadelphia, and Philadelphia and Washington, are included within the threshold. The road and rail links



(c) (d)

Figure 6-2. Comparison of modelled results and observed data: (a) O-D demand, (b) segment flight frequency, (c) O-D flight frequency, and (d) O-D seats.

between New York City and Washington could be accounted for by adding another dummy parameter for "less significant" road and rail links, but this is not done in this dissertation.

In contrast to the over-prediction of O-D demand between New York City and Washington, O-D demand between New York City and Miami, and between San Francisco and Los Angeles, is under-predicted by the model. In the case of New York City and Miami, this is at least partly because of the large number of people travelling from New York City to

Florida in the winter for short “winter breaks”, or for longer periods to avoid the winter altogether (so-called “snowbirds”). Although dummy parameters are included for “special” cities, and both New York City and Miami are classed as special, this is not enough to model the particularly high demand between the cities at certain times of year. This effect could be resolved by adding another dummy parameter for “extra special” city pairs or routes, but this is not done in this dissertation. In the case of San Francisco and Los Angeles, the reason for the under-prediction of demand between the cities is that San Francisco is classified as a “special city”, but Los Angeles is not. In reality, both cities are moderately “special” – less special than the economic and political hubs of New York City and Washington, or the tourist destination of Miami, but more “special” than most other cities. The cities were classified differently because this resulted in the highest R^2 value in the parameter estimation of the demand equation. Excluding the data points for O-D demand between New York City and Washington, and between New York City and Miami, results in an increase in the R^2 value shown in Figure 6-2a to 0.70.

Figure 6-2b compares modelled and observed segment flight frequencies. The data points are also distributed approximately evenly along the diagonal line. Summed across all flight segments, modelled system segment traffic is only 3% higher than the observed data, which is consistent with this even distribution of data points. The small over-prediction of system segment traffic is partly caused by the small over-prediction of system O-D passenger demand, described above. The over-prediction of system segment traffic is also partly the result of not modelling airline alliances. As discussed above, alliances allow airlines to increase network connectivity and frequency without adding flights. The outliers in Figure 6-2b, which are highlighted and labelled, contribute to the comparatively low R^2 value of 0.62. This value is slightly higher than that for the O-D passenger demand. Figure 6-2b suggests generally that the Airline Response Model is capable of capturing the dominant effects underlying airline choice of flight frequencies.

Some of the outliers in Figure 6-2b correspond directly to outliers in Figure 6-2a. In particular, the over-prediction of flight segment frequency between Washington Dulles (IAD) and both Newark (EWR) and LaGuardia (LGA) is consistent with the over-prediction of O-D demand between New York City and Washington. Also significant, however, is that all the outliers in Figure 6-2b include at least one airport in a multi-airport system (LaGuardia

(LGA) and Newark (EWR) form a multi-airport system with New York Kennedy; Washington Dulles (IAD) and Washington National (DCA) form another multi-airport system; Oakland (OAK) forms a multi-airport system with San Francisco; and Los Angeles (LAX) forms a multi-airport system with Ontario). Half of the outliers correspond to flight segments connecting two multi-airport systems (Oakland to Los Angeles (OAK-LAX), Washington Dulles to Newark (IAD-EWR), and LaGuardia to Washington Dulles (LGA-IAD)). This suggests that the routing of passengers between airports in multi-airport systems is a significant contributor to the comparatively low R^2 value of 0.62. This can be seen by comparing modelled and observed O-D flight frequencies between city pairs, as presented in Figure 6-2c. O-D flight frequencies include flights to all airports in multi-airport systems.

The data points in Figure 6-2c are again distributed approximately evenly along the diagonal line. Summed across all city pairs, modelled system O-D traffic is only 2% higher than the observed data, which is consistent with this even distribution of data points, and with the 3% over-prediction of system segment traffic. As expected, the spread of data points in Figure 6-2c is small, with no significant outliers, translating into an R^2 value of 0.86. This suggests that the lower R^2 value comparing segment flight frequencies (0.62) is related to the distribution of passengers between airports in multi-airport systems, as suggested above. Other network effects are unlikely to contribute significantly. The degree to which airlines operate a hub-and-spoke network versus a point-to-point network does not differ significantly between the model results and the observed data. The model simulates 6.0% of passengers connecting, while 5.7% of passengers connect in the observed data. This does not, however, indicate what contribution is made by differences in the distribution of connecting traffic between hubs. The number of connecting passengers is small, however, so it is unlikely to be significant.

In the Airline Response Model, passengers are distributed between airports in multi-airport systems in such a way as to maximise airline profit. This accounts for the effects of flight delays to increase costs, and other economic effects (such as landing fees), but does not account for passenger choice of airport. In reality, passengers choose among airports in multi-airport systems for a variety of reasons, including accessibility and travel time to the airport, as described by Bolgeri *et al.* (2008). Airlines schedule flights at airports in multi-airport systems according to these passenger preferences, as well as the other effects. It is therefore expected that the distribution of passengers between airports in multi-airport systems will be a cause for differences between the model results and observed data.

As described above, the Airline Response Model also chooses aircraft size. Differences in the size of aircraft types selected by the model and those observed in the data may also contribute to differences between the modelled and observed flight frequencies. Aircraft size effects can be analysed by comparing modelled and observed O-D seats, as presented in Figure 6-2d. Figure 6-2d is fairly similar to Figure 6-2c. The data points are distributed approximately evenly along the diagonal line, and summed across all city pairs, modelled system O-D seats are approximately equal to the observed data. Similarly, the spread of data points in Figure 6-2d is small, and the R^2 value comparing O-D seats is 0.83, only slightly lower than the value of 0.86 for O-D flight frequencies. This suggests that the model choice of aircraft size is similar to that in the observed data, and that aircraft size is not a significant contributor to the comparatively low R^2 value of 0.62 comparing segment flight frequencies.

Observed and modelled flight frequency results are compared geographically, on a route-by-route basis, in Figure 6-3. The thickness of the lines indicates the modelled segment flight frequencies per day, while the line colours indicate the percentage differences between the modelled segment flight frequencies and the observed data.

Figure 6-3 shows that the percentage difference between modelled and observed flight frequencies are low (lighter colours) for many routes, but for some routes the segment flight frequencies are significantly over-predicted (red lines). The majority of routes that show percentage differences relative to observed data of 50% or more (blues and oranges/reds) are lower traffic routes (the thinner lines), so the addition or removal of one flight per day has a proportionally larger effect on the result. The higher traffic routes that do show high percentage differences between the modelled flight frequencies and observed data over-predict flight frequencies (red lines) and, in almost all cases, connect airports in multi-airport systems. This is because, as described above, the distribution of flights between airports in multi-airport systems is the primary contributor to the largest differences between the model results and the observed data.

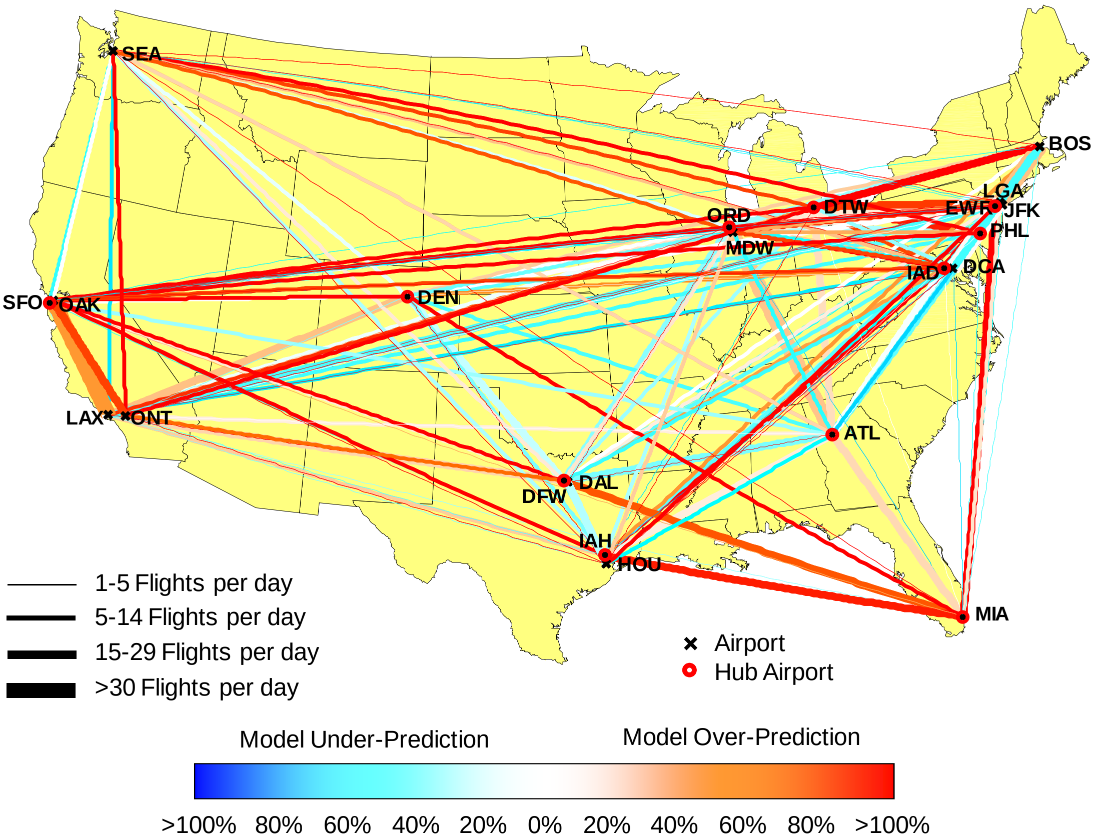


Figure 6-3. Modelled flight segment frequency results (indicated by line thickness) and percentage difference relative to observed data (indicated by line colour), United States, 2005.

In conclusion, the results presented in Figure 6-2 and Figure 6-3 suggest that the Airline Response Model is capable of capturing the dominant effects in airline choice of flight frequencies, aircraft size and flight network. The weakest element of the model appears to be the distribution of flights between airports within multi-airport systems. This is because passenger choice and other effects impacting airline operations within multi-airport systems are not modelled in detail. The Airline Response Model is applied to simulate future traffic growth and emissions under various policy scenarios in Chapter 7. Before this, however, the sensitivity of the model results to key input parameters is examined.

6.3 Sensitivity Analysis

A sensitivity analysis is performed in order to examine the sensitivity of the Airline Response Model results to changes in key input parameters, for which values are particularly uncertain. The parameters for which the model sensitivity is analysed are airport capacity and aircraft fuel burn. No other parameters are varied because all are defined in the data with little uncertainty. This includes other performance characteristics that do not typically differ significantly between aircraft type, such as cruise speed, and non-fuel related operating costs, which only vary across airlines, each of which is modelled independently.

Airport capacities, which are reported by air traffic service providers on an hourly basis, represent the air traffic service provider's best judgement for the rate at which aircraft that can be served by the airport, given weather and wind conditions. These reported airport capacities may, however, under- or over-predict the achievable capacity because of differences in the way individual air traffic controllers operate. In order to examine the sensitivity of the model results to uncertainty in airport capacities, average hourly airport capacities at all airports are increased and decreased by 15% relative to their average reported capacities calculated from FAA ASPM data (FAA, 2008). This uncertainty level was identified by comparing effective and achievable airport capacities identified by Evans and Idris (2005) to reported capacities listed by the FAA ASPM database (FAA, 2008).

The sensitivity of the model to aircraft fuel burn rates is examined because only three aircraft types are modelled, i.e., small, medium and large, represented in each case by the most widely operated aircraft of that size class. In reality, however, airlines operate many more aircraft types, each of which has different performance characteristics. The sensitivity of the model results to aircraft fuel burn rates is examined by increasing and decreasing aircraft fuel burn rates for all types modelled by 15% relative to values extracted from BADA data (EUROCONTROL, 2004) and the ICAO Aircraft Engine Emissions Databank (ICAO, 2008). This uncertainty level was identified by calculating the standard deviation of cruise fuel burn rates for all aircraft of the same size category within the BADA database.

The Airline Response Model was rerun using the modified values of airport capacities and aircraft fuel burn described above. In Table 6-1, the sensitivity of the model is examined by comparing system O-D passenger demand, system flight operations, system CO_2 emissions, and average system arrival delay for each of the sensitivity cases described above, and a baseline case with no changes to airport capacities or aircraft fuel burn. The percentage difference between the sensitivity results and the baseline result are presented in brackets below each number.

Table 6-1. Model Sensitivity Results

	Sys. O-D Pax Demand (per yr)	Sys. Flight Ops. (per yr)	Sys. CO_2 (Tonnes per yr)	Avg. Sys. Arr. Delay (min)
Baseline	104,794,000	1,310,000	24,548,000	11.9
Airport Capacities + 15%	106,252,000 (+1.4%)	1,345,000 (+2.7%)	25,207,000 (+2.7%)	10.6 (-11%)
Airport Capacities - 15%	97,111,000 (-7.5%)	1,306,000 (-0.31%)	24,785,000 (+0.97%)	17.2 (+44%)
Aircraft Fuel Burn + 15%	101,273,000 (-3.4%)	1,329,000 (+1.5%)	28,154,000 (+15%)	12.0 (+0.84%)
Aircraft Fuel Burn - 15%	105,576,000 (+0.75%)	1,381,000 (+5.4%)	22,108,000 (-9.9%)	12.6 (+5.9%)

The Airline Response Model behaves as expected in response to changes in airport capacity. An increase in airport capacity leads to a decrease in average flight delay. Lower flight delays result in an increase in passenger demand, and reduce airline operating costs. This leads to a reduction in fares, which also contributes to the increase in passenger demand. The increase in demand results in an increase in flight operations to serve the demand, which, in turn, results in an increase in system CO_2 emissions. A decrease in airport capacity generally has the opposite effect. Flight delays increase, resulting in a decrease in passenger demand and flight operations. However, system-wide CO_2 emissions increase under decreased capacity. This is because of the emissions associated with the large (44%) increase in flight delays, much of which is incurred on the taxi-way and in airborne holding, where the engines are running. These delay-related emissions offset the decrease in emissions associated with the small (0.31%) decrease in operations.

The model result with greatest sensitivity to airport capacity is average system arrival delay. With an increase in airport capacity of 15%, average arrival delays decrease by 11%, while a decrease in airport capacity of 15% results in an increase in average arrival delays of 44%. The greater sensitivity to the decrease in capacity is because of the exponential relationship between flight delays and aircraft operations. System O-D demand is also relatively sensitive to airport capacity in the case where capacity is decreased (system O-D demand decreases by 7.5%). This sensitivity is because of the passenger response to the increase in flight delays. As described in Section 5.6, the passenger value of delay time applied is high – about three times the passenger value of travel time. The other results – system aircraft operations and system CO_2 emissions – are not sensitive to changes in airport capacity. Notably, even though O-D demand decreases by 7.5% in the case where airport capacity is decreased, system operations only decrease by 0.31%. This is because competition effects keep flight frequencies high, even with reduced demand.

The Airline Response Model also behaves as expected in response to changes in aircraft fuel burn. An increase in fuel burn increases airline operating costs, leading to an increase in fares, and a decrease in passenger demand. An increase in fuel burn, and thus CO_2 emissions, also results in a small increase in flight operations, despite the decline in passenger demand. The reason for this is a shift in the flight network towards greater use of point-to-point operations in preference to hub-and-spoke operations. Although hub-and-spoke operations allow airlines to take advantage of economies of scale at hub airports, reducing traffic and passenger servicing costs, fuel costs are higher than in point-to-point operations because passengers are flown longer total distances. Thus, with an increase in fuel costs, airlines shift to greater use of point-to-point operations in order to reduce fuel costs. Point-to-point networks require more flights than hub-and-spoke networks to serve the same markets, and hence total flight operations increase. In this case the increase in flight operations from the shift in network offsets any decrease in flight operations required to serve the lower passenger demand. The increase in flight operations also results in an increase in flight delays.

A reduction in fuel burn has generally the opposite effect. Airline operating costs decrease, leading to a decrease in fares, which results in an increase in passenger demand and thus flight operations. Although there is also some shift in the flight network towards greater use of hub-and-spoke operations, any decrease in flight operations resulting from this change in flight network is limited by frequency competition effects, and does not offset the increase in flight operations required to serve the increased passenger demand. The increased flight operations result in an increase in flight delay, but do not offset the decrease in CO_2 emissions resulting directly from the decrease in fuel burn.

The model result with greatest sensitivity to aircraft fuel burn is system CO_2 emissions, which is of the same order of magnitude as the change in fuel burn. This is to be expected as CO_2 emissions are directly proportional to fuel burn. The change in system CO_2

emissions does not match the change in fuel burn exactly, however, because of small changes in the flight network, aircraft types and flight frequencies operated, all of which are induced by the change in fuel burn. The other results – system O-D demand, system aircraft operations and average system arrival delays – are not sensitive to fuel burn.

7 Model Application: Capacity Constraints, Regional Costs and New Technology

In this chapter, the Airline Response Model is applied to simulate airline operational responses to policy scenarios in the domestic United States. This model simulates the growth in passenger demand for air transport, the associated increase in aircraft operations to serve this demand, and the environmental impact resulting from these operations, from 2005 to 2030. Growth over this period is driven by exogenous forecasts of population and per-capita income growth calculated by the MIT Integrated Systems Model (IGSM). As described in Chapter 5, the IGSM, which was run for the U.S. Climate Change Science Program (CCSP) (CCSP, 2007), is an integrated energy-economy-environment model with internally consistent population, income, and oil price scenarios. For the United States it represents a relatively high growth scenario when compared to the other energy-economy-environment models run for the CCSP.

The Airline Response Model is applied to three families of policy scenarios. In order to analyse airline operational responses to policies constraining airport capacity expansion, a family of scenarios with different future levels of airport capacity is formulated. The airline response to each of these scenarios is simulated, and the results described in detail in Section 7.1. While restrictions in airport capacity expansion limit traffic growth directly, other policies may exploit market forces to reduce the environmental impact of aviation. These policies typically lead to an increase in costs, in some cases in only part of the system because of regional differences in environmental impact and political will. In order to better understand the impact of such a regional cost increase, a second family of scenarios is formulated applying different cost increases to part of the airport set modelled, while maintaining costs at the rest of the airport set at existing levels. The simulated airline response to each of these scenarios is described in detail in Section 7.2. Finally, this chapter also simulates the effect of introducing radically new technology into the airline fleet. In order to study the operational impact of introducing aircraft operating advanced open rotor engines or blended wing body aircraft, a third family of scenarios is formulated applying differing aircraft operating costs and performance characteristics. The airline response to each of these scenarios is simulated, and the results described in detail in Section 7.3. For each of these families of scenarios, the air transport system analysed is the set of 14 cities, 22 airports and 5 airlines described in Section 6.1.

7.1 The Air Transport System Response to Airport Capacity Constraints

Airport and airspace capacity already constrain flight operations at many major airports. In the United States, average arrival delay at 23 airports was greater than 15 minutes in 2006, with LaGuardia Airport experiencing 21 minutes of average delay per flight (FAA, 2008). In Europe, average arrival delays at 10 airports were greater than 15 minutes in 2006, with London Luton Airport experiencing 18 minutes of average delay per flight (EUROCONTROL, 2007). In the industrialized world, where airport capacity expansion is limited by local community resistance and environmental restrictions, system capacity is likely to become an increasingly binding constraint on air traffic growth. Limiting capacity growth at airports has also been considered for mitigating the climate impacts of aviation, most recently in the case of the third runway at London Heathrow (DfT, 2009).

This dissertation describes three scenarios that investigate the operational response and sensitivity of the air transport system to airport capacity constraints:

- Case 1: *Baseline case*, in which airport capacity is assumed to be expanded at all 22 modelled airports according to expansion plans described by the U.S. DOT (DOT, 2004) and airport authorities, as presented in Table 5-1 in Section 5.2. Across the modelled set of 22 airports this capacity expansion amounts to a 25% increase in total system capacity. It includes the construction of new infrastructure, such as runways, as well as technological and procedural improvements (described in detail by DOT (2004)).

- Case 2: *No capacity expansion case*, in which airport capacity is assumed to be maintained at 2005 levels at all 22 airports. By comparing the results of this case to those of Case 1, the operational impacts of no airport capacity expansion across the system can be examined.

- Case 3: *No Chicago O'Hare capacity expansion case*, in which airport capacity is assumed to be expanded at all airports as in Case 1, except at Chicago O'Hare

International Airport, where capacity is maintained at 2005 levels. By comparing the results of this case to those of Case 1, the operational impact of an airport capacity constraint at a single key hub airport can be examined.

For each of these three cases, simulation results from 2005 to 2030 are presented and discussed below. The impact of capacity constraints on system-wide metrics is analysed first. This is followed by an analysis of their impact on operations at congested hub airports, and in multi-airport systems. Finally, the impact of airport capacity constraints on airline choice of aircraft size is analysed.

System Wide Effects

Figure 7-1 presents simulated system-wide average arrival delay, the passenger demand in response to these delays, the aircraft operations required to serve this demand, and the resulting CO_2 emissions, for each of the airport capacity scenarios described above.

In the baseline case, simulated average system arrival delay can be seen to respond over time to the airport capacity expansions modelled. With an increase in system capacity by 22% before 2015, average system arrival delay decreases from 13 minutes in 2010 to 11 minutes in 2015 (Figure 7-1a). However, with little further capacity expansion after 2015 modelled, average system arrival delay increases to 28 minutes by 2030. This projected average system-wide level of delay is higher than the average arrival delay at the most congested airport in the U.S. in 2006, i.e., 21 minutes at LaGuardia Airport, as mentioned above. This suggests that, given projected increases in demand, existing airport capacity expansion plans may not be sufficient to maintain delays at current levels.

In the baseline case, passenger demand nearly doubles over the 25 year period shown in Figure 7-1b, with the increase in flight delays from 2020 to 2025 slowing demand growth slightly. The growth in aircraft operations to serve this demand is slightly slower than the growth in demand itself (Figure 7-1c) because of a moderate shift to operate larger aircraft, as described in the section on aircraft size choice below. Fewer flights are required to serve the available demand with larger aircraft types. The associated growth in CO_2 emissions (Figure 7-1d) is slightly slower than the growth in operations because of the assumed 0.7% annual reduction in aircraft fuel burn per year by aircraft type. The benefit of this reduced fuel burn in terms of system CO_2 emissions is limited, however, by the increase in average aircraft size.

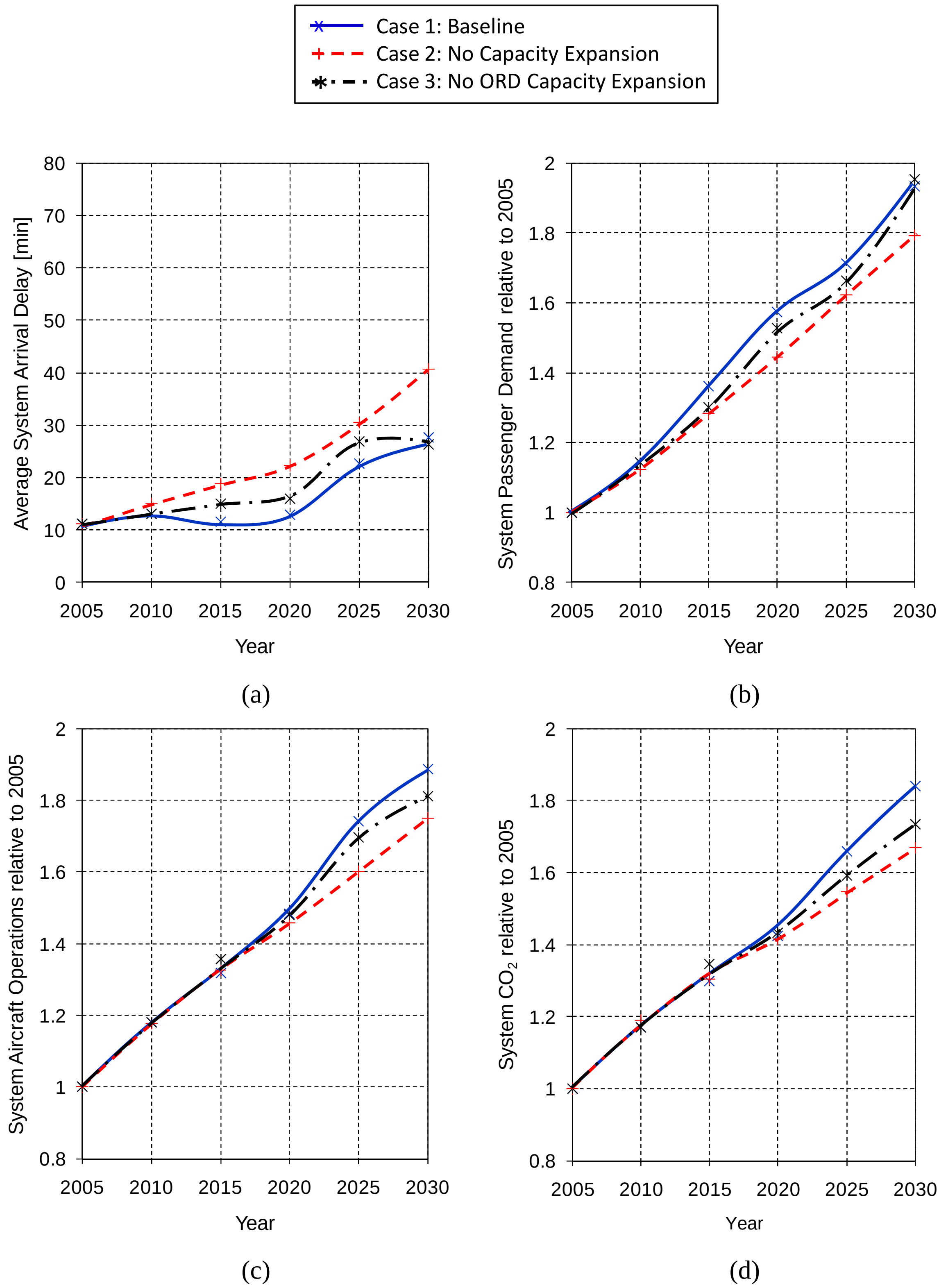


Figure 7-1. Simulated air transport system response to airport capacity constraints through 2030: (a) average arrival delay, (b) passenger demand, (c) aircraft operations, and (d) CO_2 emissions.

Although fewer flights are operated, and the aircraft types operated have lower fuel burn than previously operated aircraft of that type, a greater number of larger aircraft types are operated, which burn more fuel than smaller types.

In Case 2, in which capacity is not expanded at any airport, average system arrival delay could increase to over 40 minutes in 2030 (Figure 7-1a), about 40% higher than in the baseline case. This drastic growth is a result of the exponential increase in flight delay as operations approach airport capacity limits. A slightly different effect is evident in Case 3, in which capacity is expanded at all airports except Chicago O'Hare. After 2010, average system arrival delay grows faster than in the baseline case, as operations at Chicago O'Hare approach the (lower) capacity limit at that airport. This indicates the importance of this airport, and others like it, within the system. After 2025, however, delay levels off to the baseline value in 2030, which can be attributed to a significant drop in aircraft operations at Chicago O'Hare, and a shift in operations from Chicago O'Hare to other, less congested, airports. This is described in detail below and in the section on hub operations.

Flight delays impact passenger demand (Figure 7-1b), aircraft operations (Figure 7-1c) and CO_2 emissions (Figure 7-1d). Figure 7-1b shows that the increased flight delay in Case 2 results in a reduction in network-wide passenger demand growth relative to the baseline case by roughly 7% in 2030. In Case 3, the fixed capacity at Chicago O'Hare results in initially slower growth in network-wide passenger demand relative to the baseline. However, as average system delay levels off, passenger demand grows to the value in the baseline case. The decline in passenger demand in response to flight delays is party determined by a passenger value of delay time of US$ 105 per hour. The extra flight delays impose an extra time cost to each passenger of up to US$ 21 per flight (Case 2 versus Case 1 in 2030), which compares to an average ticket price of US$ 188. An average delay of 40 minutes also represents a significant portion of passenger travel time, with average O-D passenger travel times across the modelled network just over 3 hrs in 2005. A further contribution to the reduction in passenger demand in Cases 2 and 3 is that flight delays increase airline costs, which result in an increase in fares.

Figure 7-1c shows that the constrained capacity in Case 2 ultimately limits system-wide air traffic growth (by roughly 7% relative to the baseline case in 2030). Air traffic growth is limited to a lesser degree in Case 3 (by roughly 4% relative to the baseline case in

2030), because capacity is only constrained at Chicago O'Hare. The slower growth in operations after 2025 can be attributed to the saturation of operations at Chicago O'Hare (see below). Because aircraft operations grow slower in Cases 2 and 3 than in the baseline, system-wide CO_2 emission growth is also reduced – by between 6% and 9% by 2030 (Figure 7-1d). These results show that while airport capacity constraints may increase flight delays, they can reduce system-wide CO_2 emissions from aviation. Note that some of the passengers that choose not to fly in Cases 2 and 3 may still travel, but using alternate modes such as rail or road. The growth in system-wide CO_2 emissions by all transport modes in Cases 2 and 3 may therefore not be reduced relative to the baseline case to the extent shown in Figure 7-1d.

Airport capacity constraints may also lead to changes in the distribution of connecting and O-D traffic, and in aircraft size. These are described in the following three sections, respectively.

Hub Operations

A key airline response to airport capacity constraints is to shift connecting traffic away from congested hub airports. This strategy allows airlines to continue to increase the number of passengers they serve, while limiting increases in flight delay. The impact of airport capacity constraints on flight delays, passenger demand, aircraft operations and NO_x emissions at Chicago O'Hare are shown in Figure 7-2. The results are presented from 2005 to 2030, for each of the airport capacity scenarios described above.

In the case where capacity is expanded at all airports according to expansion plans (baseline case), a new runway is assumed to become operational at Chicago O'Hare in 2015, increasing the airport capacity from 190 to 260 aircraft per hour. In this case, average Chicago O'Hare arrival delay, passenger demand, and aircraft operations follow similar trends to those for the modelled system presented in Figure 7-1. Note that even with this planned capacity increase, average arrival delays would be nearly 25 minutes by 2030, up from 8 minutes in 2005. These capacity expansion plans may therefore not be sufficient to maintain delays at current levels given the projected increase in demand. Airport LTO NO_x emissions (Figure 7-2d) grow at a faster rate than aircraft operations. This is because they are a function of both the increasing number of flights operated and the growing flight delay incurred on the airport surface.

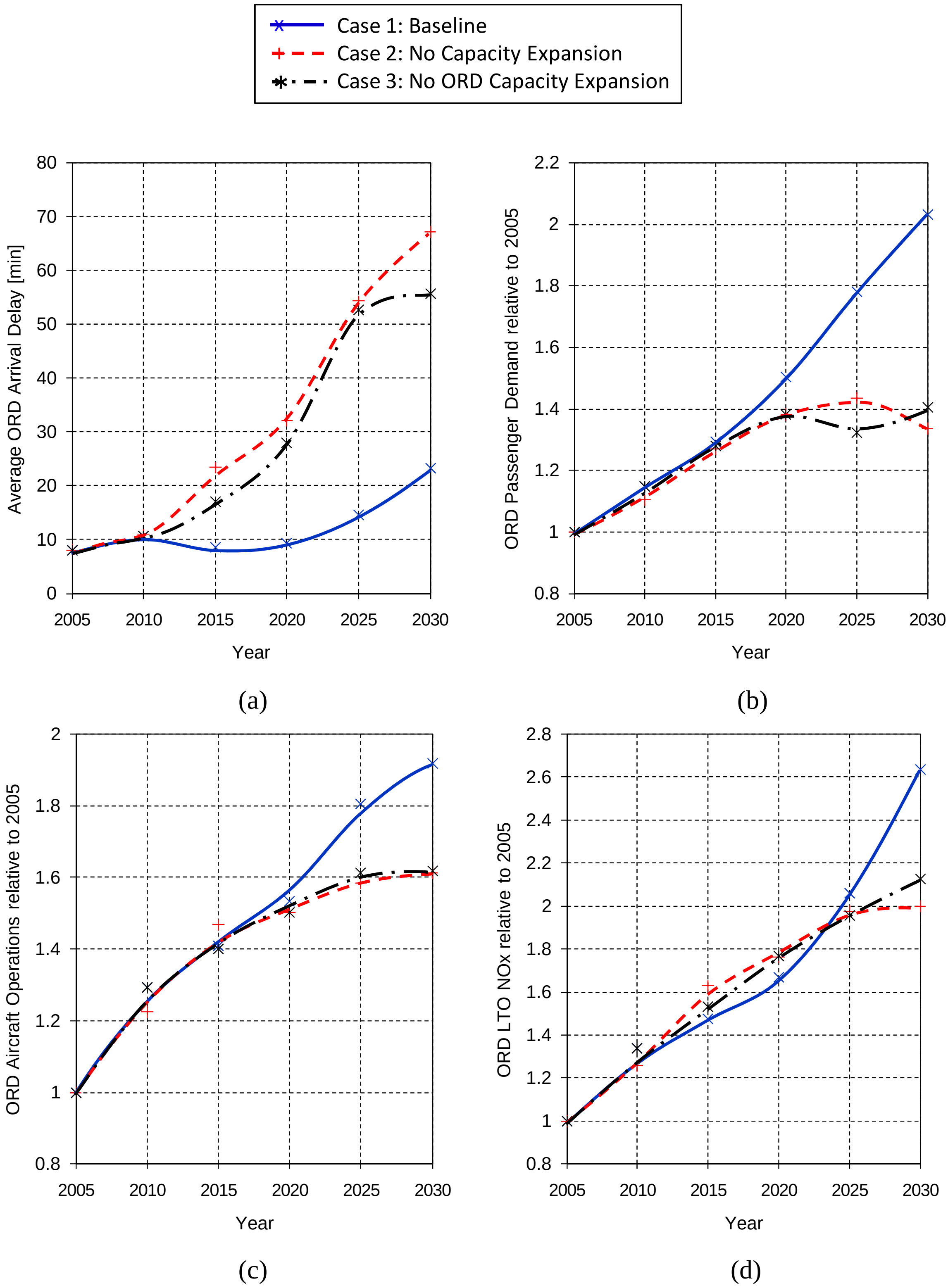


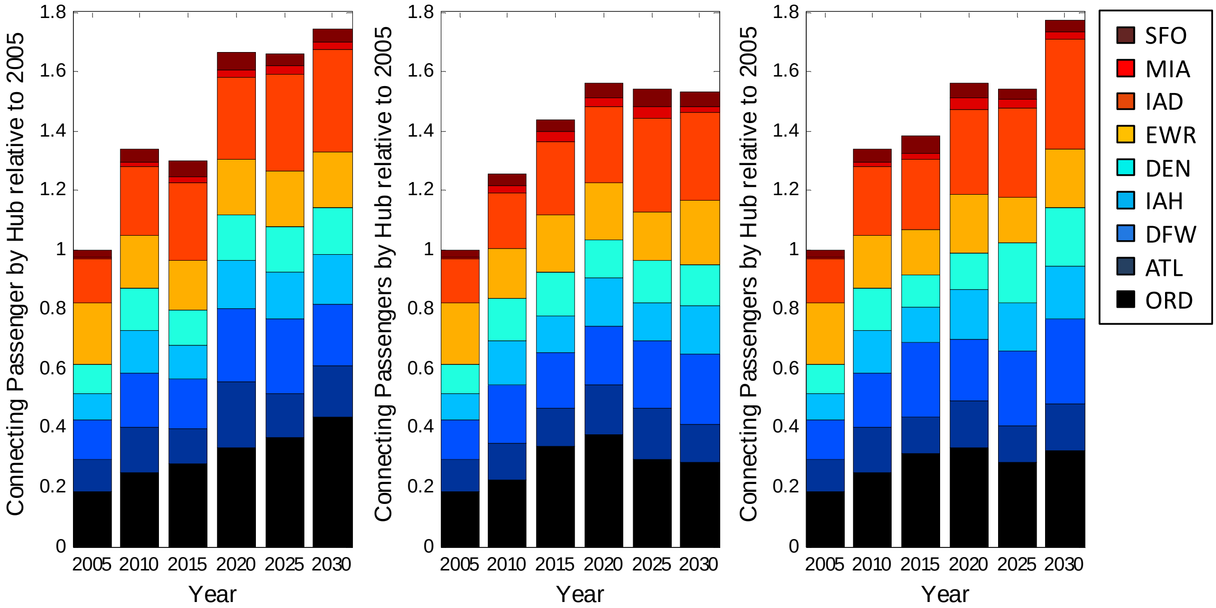
Figure 7-2. Simulated Chicago O'Hare (ORD) response to airport capacity constraints through 2030: (a) average arrival delay, (b) passenger demand, (c) aircraft operations, and (d) LTO NO_x emissions.

The impact of airport capacity constraints on Chicago O'Hare flight delays, passenger demand and traffic growth in Cases 2 and 3 in Figure 7-2 are significantly greater than the system impacts shown in Figure 7-1. If capacity is not expanded at any airports (Case 2), average arrival delays at Chicago O'Hare may increase to nearly 70 minutes by 2030 (Figure 7-2a). This projected delay is primarily caused by congestion at Chicago O'Hare itself, but also includes delay propagated from other congested airports. This latter component is strongly reduced in Case 3, where Chicago O'Hare is the only airport where capacity is not expanded. Note that no changes in schedule shape, such as shifting flights to off-peak times or schedule de-peaking, are simulated by the Airline Response Model. With delays as high as those modelled here, airlines are likely to make changes to the shape of the schedules operated in order to reduce delays. The consequence is that the delays simulated here may be over-predicted. Implementing a flatter schedule at Chicago O'Hare, such as that operated at Newark Airport in 2005, reduces the delay simulated in Case 2 in 2030 by 10 minutes. Therefore, the delay at Chicago O'Hare in Cases 2 and 3, even with changes to the schedule shape, is likely to be high.

The high delay at Chicago O'Hare in Cases 2 and 3 significantly reduces the growth in O-D passenger demand to the airport relative to the baseline (Figure 7-2b). By 2030 O-D passenger demand to Chicago in Case 2 is roughly 34% less than in the baseline case, while in Case 3 it is 31% less. The ultimate reason for this large decrease in O-D demand relative to the baseline is the passenger response to flight delays, which is partly determined by the passenger value of delay time of US$ 105 per hour, as described above. The extra flight delays impose an extra time cost to each passenger of up to US$ 80 per flight (Case 2 versus Case 1 in 2030), which is half the average ticket price to Chicago of US$ 159. In 2025, passenger demand in Case 3 drops below that in Case 2, despite similar delays. This is because of a moderate shift in O-D traffic from Chicago O'Hare to Chicago Midway, where capacity is expanded. This is discussed in greater detail in the section on multi-airport systems below. By 2030, the higher delays in Case 2 dominate, reducing demand below that of Case 3.

The decline in passenger demand to Chicago O'Hare contributes to lower growth in aircraft operations relative to the baseline case – by roughly 16% in 2030 in Cases 2 and 3 (Figure 7-2c). This significant decline in operations relative to the baseline, however, is also caused by a decrease in the amount of connecting traffic at Chicago O'Hare. This is described in detail below. In Case 3, the decline in operations relative to the baseline results in a levelling off of average flight delay at Chicago O'Hare (Figure 7-2a). This is less the case in Case 2, however, because of the propagation of delay to the airport from other congested airports. Because LTO NO_x emissions are a function of both traffic levels and taxi delays, Cases 2 and 3 show faster growth in NO_x emissions than the baseline case before 2020 (Figure 7-2d), when delays are significantly higher than in the baseline, but the number of aircraft operations is similar. After 2020, however, the slower growth in operations in Cases 2 and 3 relative to the baseline dominates, reducing LTO NO_x emissions at Chicago O'Hare to between 19% and 23% lower than in the baseline in 2030.

While the percentage of connecting passengers in the system does not change significantly between the three cases (remaining at roughly 5.5% in 2030), in Case 3 there is a shift in connecting traffic away from Chicago O'Hare to other hub airports in the system. This is shown in Figure 7-3, which shows the distribution of connecting passengers across all the hub airports operated within the modelled system. The number of connecting passengers at Chicago O'Hare (ORD) increases steadily in the baseline case (Figure 7-3a). In Cases 2 (Figure 7-3b) and 3 (Figure 7-3c), however, the number of connecting passengers increases initially, but decreases again after 2020. By 2030 the number of connecting passengers at Chicago O'Hare is 30% (Case 3) to 40% (Case 2) lower than in the baseline. In Case 2, there is no corresponding increase in connecting passengers at other hubs, which are also capacity constrained (Figure 7-3b). However, in Case 3 (Figure 7-3c), particularly in 2030, there is an increase in the number of passengers connecting through Dallas-Fort Worth (DFW) (by roughly 35%), Denver (DEN) (by roughly 55%) and Washington Dulles (IAD) (by roughly 10%), relative to the baseline. Denver and Washington Dulles are operated as hubs by United Airlines, which also operates a hub at Chicago O'Hare. In Case 3, the capacity of both Denver and Washington Dulles is assumed to be expanded through the construction of new runways, as well as through technological and procedural changes. Dallas-Fort Worth is operated as a hub by American Airlines, which is the other airline operating a hub at Chicago O'Hare. In Case 3, the capacity of Dallas Fort-Worth is assumed to be expanded through technological and procedural changes. These results suggests that as the flight delays at



(a) (b) (c)

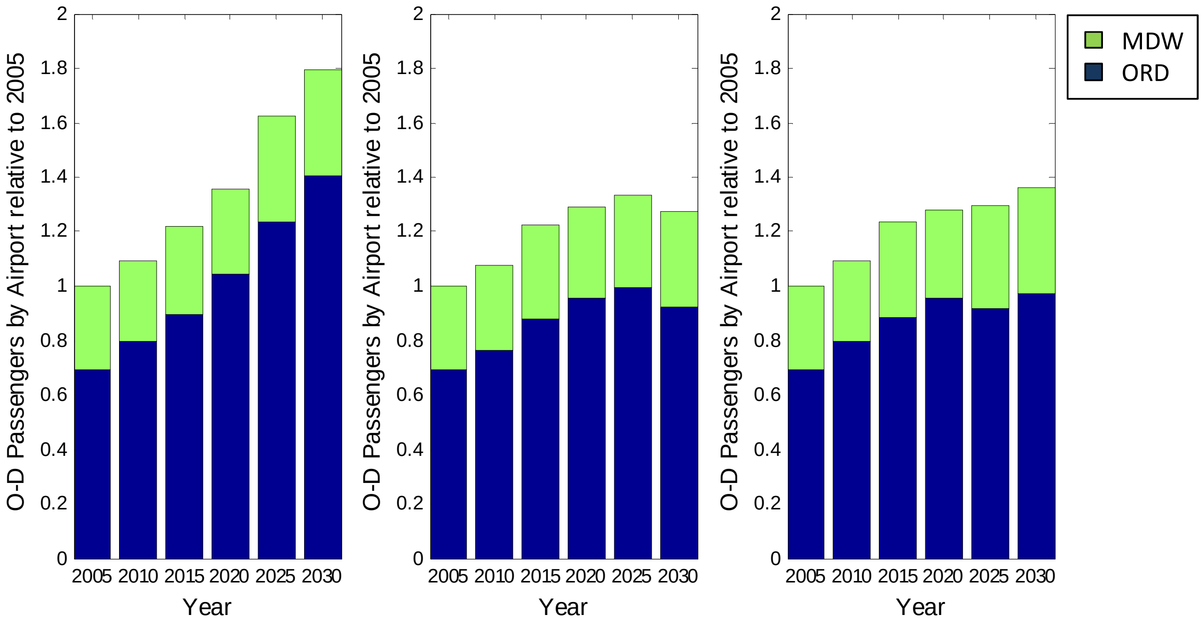
Figure 7-3. Simulated connecting passenger distribution across system hubs through 2030: (a) Case 1: Baseline airport capacity expansion, (b) Case 2: No airport capacity expansion, and (c) Case 3: No airport capacity expansion at Chicago O'Hare (ORD), but capacity expansion at all other airports.

Chicago O'Hare increase, airlines may route some connecting passengers through other hubs, if there is available capacity, instead of through Chicago O'Hare.

Apart from the redistribution of connecting traffic, airport capacity constraints may also lead to changes in the distribution of O-D traffic. This is described in the section below.

Multi-Airport System Operations

A key airline response to airport capacity constraints is to shift O-D traffic, that has its true origin or ultimate destination in a multi-airport system, from congested primary airports to less congested secondary airports. This strategy would allow airlines to serve increasing passenger demand, while limiting increases in flight delay. The impact of airport capacity constraints on operations in multi-airport systems is examined by considering the distribution of O-D passenger demand from 2005 to 2030 across airports within multi-airport systems in two cities: Chicago, served by Chicago O'Hare (ORD) and Chicago Midway (MDW) airports, shown in Figure 7-4; and New York City, served by Newark (EWR), LaGuardia (LGA) and New York Kennedy (JFK) airports, shown in Figure 7-5.



(a) (b) (c)

Figure 7-4. Distribution of Chicago O-D demand across multi-airport system (MDW, ORD) through 2030: (a) Case1: Baseline airport capacity expansion, (b) Case 2: No airport capacity expansion, and (c) Case 3: No airport capacity expansion at ORD, but baseline airport capacity expansion at all other airports.

In the baseline case, where capacity is expanded at all airports, O-D passenger demand at Chicago O'Hare (ORD) doubles from 2005 to 2030 (Figure 7-4a). This is in contrast to Chicago Midway (MDW), where O-D demand increases by roughly 25%. The primary reason for this difference in growth is the significant increase in capacity at Chicago O'Hare (from 190 aircraft per hour in 2005 to 260 aircraft per hour in 2030), compared to the small increase in capacity at Chicago Midway (from 68 aircraft per hour in 2005 to 69 aircraft per hour in 2030). The greater market share of Chicago O'Hare is also enabled, however, by economies of scope – Chicago O'Hare is used for both connecting and O-D traffic, while Chicago Midway is used for O-D traffic only.

The airport capacity constraints at Chicago O'Hare in Cases 2 (Figure 7-4b) and 3 (Figure 7-4c) significantly reduce growth in demand at the airport after 2015. By 2030 O-D demand at Chicago O'Hare is between 30% and 35% lower than in the baseline. Because Chicago Midway is also capacity constrained in all cases, however, it can absorb very little of this traffic (flight delays at Chicago Midway closely match those at Chicago O'Hare). Only in Case 3, where there is a small increase in capacity at the airport, is there a small increase in O-D demand at Chicago Midway when there is a decrease in demand at Chicago O'Hare (after 2020).

The situation is different in New York City, where Newark and New York Kennedy are projected to be less capacity constrained than LaGuardia. In the baseline case, O-D demand grows by nearly 150% at Newark (EWR) from 2005 to 2030, and by 200% at New York Kennedy (JFK) (Figure 7-5a). O-D demand at LaGuardia (LGA), however, grows by only 20%, indicating a significant shift in market share from LaGuardia to Newark and New York Kennedy. Airport capacity is not assumed to increase significantly at either Newark (from 88 aircraft per hour to 89 aircraft per hour), New York Kennedy (from 74 aircraft per hour to 85 aircraft per hour) or LaGuardia (from 74 aircraft per hour to 84 aircraft per hour). However, average arrival delays at the airports indicate significant differences in the degree to which each airport is capacity constrained. By 2030, average delays of over 40 minutes are simulated at LaGuardia – significantly more than those at either Newark (15 minutes) or New York Kennedy (19 minutes).

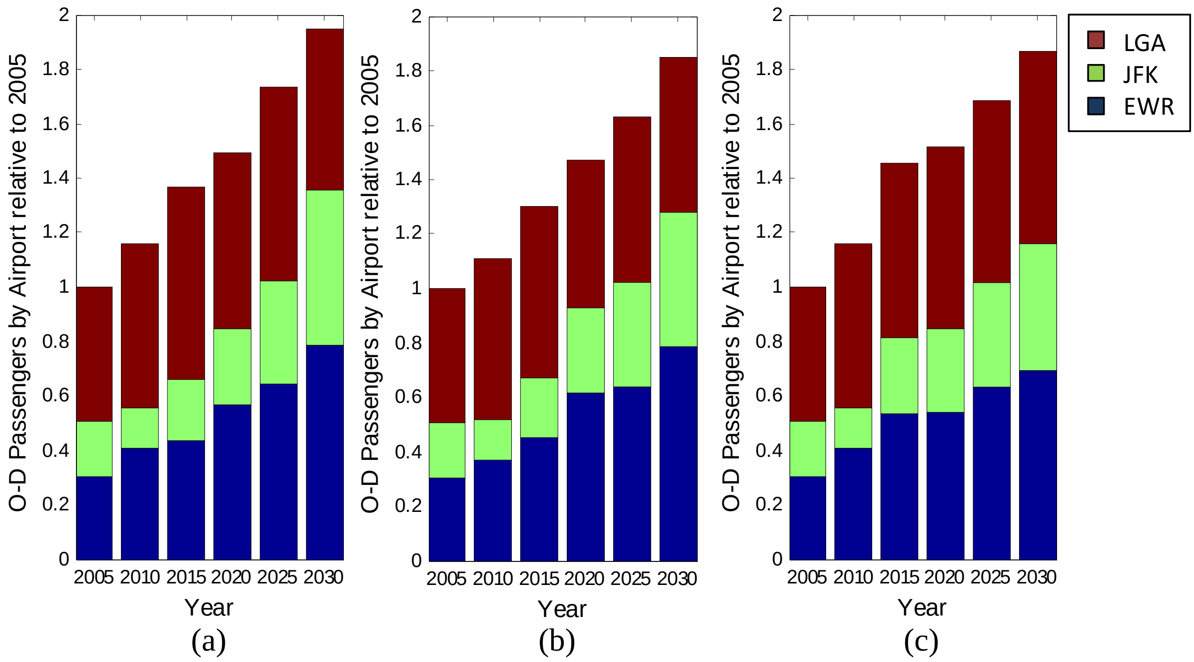


Figure 7-5. Distribution of New York City O-D demand across multi-airport system (LGA, JFK, EWR) through 2030: (a) Case1: Baseline airport capacity expansion, (b) Case 2: No airport capacity expansion, and (c) Case 3: No airport capacity expansion at ORD, but baseline airport capacity expansion at all other airports.

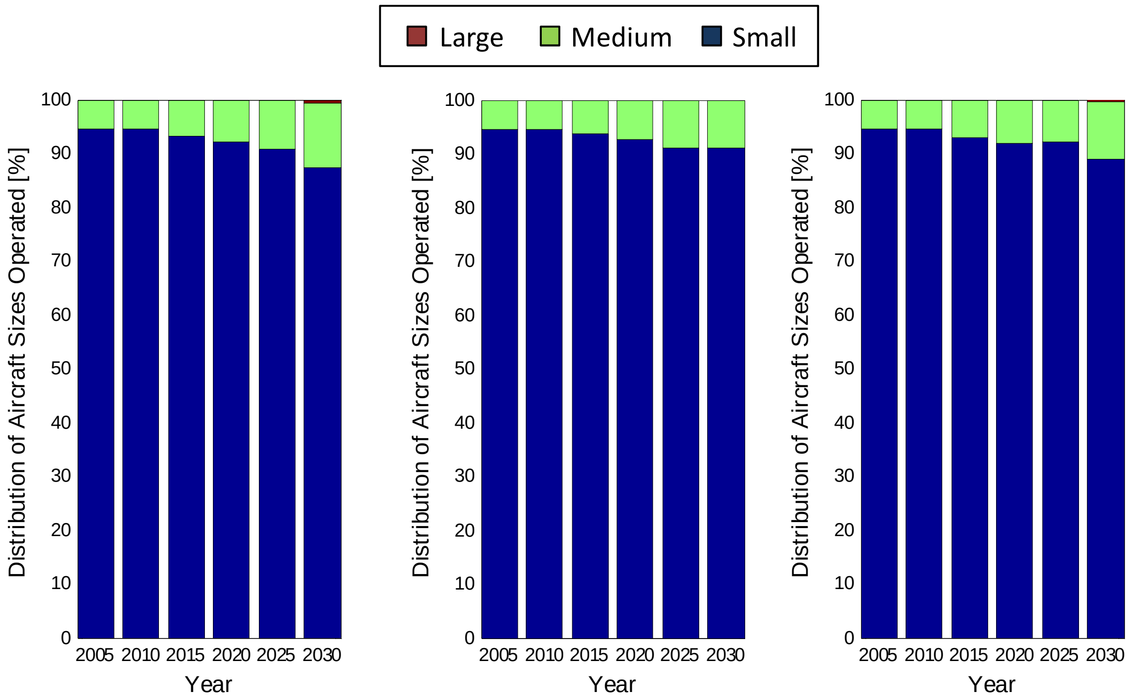
Note that New York Kennedy is currently slot controlled. Continued control of the number of operations at the airport in this way would lead to significantly less growth in demand than projected above.

Because the capacities of the three New York City airports do not differ significantly across the three capacity scenarios, the distribution of New York City O-D passengers between airports does not change significantly in Cases 2 (Figure 7-5b) and 3 (Figure 7-5c) relative to the baseline (Figure 7-5a). In both cases, the slight reduction in total O-D demand to New York City by 2030, relative to the baseline is, instead, because of the propagation of delay to the airports from Chicago O'Hare.

Fleet Response: Aircraft Size

Another key airline response to airport capacity constraints is to increase aircraft size. This strategy would allow airlines to continue to increase the number of passengers that they serve, while limiting any increase in the number of flight operations in order to limit an increase in flight delays. This response is examined in Figure 7-6, which presents the simulated distribution of aircraft sizes operated across the modelled system by all airlines, from 2005 to 2030, for each of the airport capacity scenarios described above.

In 2005, the small aircraft size category modelled (representing the single-aisle, short/medium-haul Boeing B737, B757, and Airbus A320 families of aircraft) accounts for 95% of all operations (Figure 7-6a). This high proportion of small aircraft is because of the definition of the category to include all aircraft with seating capacity below 190 seats. The remaining 5% of flights operate the medium size category of aircraft (representing the twin-aisle, medium/long-haul Boeing B767 and Airbus A330 families of aircraft). As passenger demand grows over time, the proportion of medium aircraft types in the baseline case increases to roughly 12% by 2030. A small proportion of large aircraft types (representing the twin-aisle, long-haul Boeing B747, B777 and Airbus A380 families of aircraft) are also operated. This trend is consistent with the modelling results of Bhadra (2003), Bhadra *et al.* (2003) and Pulles *et al.* (2002), who use statistical relationships to estimate the proportion of different aircraft sizes used on a flight segment as a function of forecast passenger demand, flight segment length (stage length), and traffic type (hub-hub, hub-spoke, or point-to-point). According to these relationships, the proportion of larger aircraft types increase with



(a) (b) (c)

Figure 7-6. Simulated distribution of aircraft size operated across the system through 2030: (a) Case1: Baseline airport capacity expansion, (b) Case 2: No airport capacity expansion, and (c) Case 3: No airport capacity expansion at ORD, but baseline airport capacity expansion at all other airports.

increasing passenger demand. The underlying reasons for this are that larger aircraft typically offer lower costs per RPM than smaller aircraft, and that required airline flight frequencies, driven by frequency competition, grow at a slower rate than passenger demand. As described in Section 4.1, frequency competition forces airlines to increase flight frequencies until the marginal cost of adding another flight is no longer offset by the marginal revenue associated with the increased market share achieved by the flight. However, the increase in market share achieved by adding another flight diminishes as total flight frequency increases, displaying a law of diminishing returns. Therefore, with increasing demand and operations over time, the equilibrium frequency at which marginal cost equals marginal revenue does not grow at the same rate as the growth in passenger demand.

The impacts of airport capacity constraints on aircraft size choice can be analysed by comparing the baseline case (Figure 7-6a) to Cases 2 (Figure 7-6b) and 3 (Figure 7-6c). As can be seen, the simulation results suggest that airport capacity constraints do not lead airlines to increase aircraft size, but rather to use slightly higher percentages of smaller aircraft. This is contrary to the expectations of Kostiuk *et al.* (2000), who assume that increasing airport capacity constraints would result in a shift to larger aircraft types. Kostiuk *et al.* (2000) do not model frequency competition, however, which is the primary cause of the effects shown here. While flight delays increase airline operating costs, reducing the flight frequency at which marginal cost equals marginal revenue, the resulting reduction in aircraft operations is not sufficient to offset the decrease in demand associated with the flight delays, shown in Figure 7-2c. This is because much of the delay, particularly when delays are high, is incurred at the gate, where aircraft are burning very little fuel, and therefore incurring less cost penalty. The result is that, instead of capacity constraints leading to an increase in aircraft size, there is a slight shift to use smaller aircraft. This is particularly clear under high delays, such as in Case 2 in 2030 (Figure 7-6b). This result is, however, contingent on high levels of competition between airlines, and flight frequency being of particular importance to define market share. This result would not be the case at airports with dominant carriers, where capacity constraints may instead lead to an increase in aircraft size, as suggested by Kostiuk *et al.* (2000). Similarly, if other policies were in place to limit growth in aircraft operations, such as airport slot control, there may also be a shift to larger aircraft, instead of the slight shift to smaller aircraft shown here.

In summary, the analysis presented in this section suggests that while airport capacity constraints may have a significant impact on system-level flight delays, demand, aircraft operations, and emissions, the impact at congested airports is significantly greater. If capacity is available at alternative airports, airlines are likely to respond to airport capacity constraints by making changes in the flight network operated to avoid congested hubs and to shift some traffic to secondary airports. Airlines are less likely, however, to increase the sizes of aircraft operated, particularly under high frequency competition. This may not be the case, however, with an increase in landing fees, which has a greater impact on increasing airline marginal cost, as described in the next section.

7.2 The Air Transport System Response to Regional Cost Increases

While restrictions in airport capacity expansion limit traffic growth directly, other policies may exploit market forces to reduce the environmental impact of aviation. These policies typically lead to an increase in costs, in some cases in only part of the system because of regional differences in environmental impact and political will. While increases in cost may generally be effective at reducing the environmental impact of aviation, if implemented in only part of the system, these benefits may be eroded because of changes in the flight network.

One policy that has been proposed to mitigate the environmental impact of aviation is to adjust airport landing fees in such a way as to penalise the most polluting aircraft, driving airlines to operate less polluting aircraft types (House of Commons, 2003). The proposed implementation of such a policy is through increased landing fees, which has been shown to drive airlines to increase the size of aircraft they operate, while reducing flight frequency (Wei, 2006; Givoni and Rietveld, 2009). This is because landing fees are applied per flight and not per passenger, so larger aircraft can reduce airline costs per passenger by serving the same number of passengers with fewer flights. Increasing aircraft size while reducing flight frequency has significant advantages in reducing airport congestion, and therefore surface emissions, and some advantages in reducing other environmental impacts, because some larger aircraft have slightly lower emissions per RPM than some smaller aircraft. It is unclear, however, how high landing fees must be to induce an increase in aircraft size, and to what extent total emissions can be reduced. If applied to only one region within a system, increases in landing fees may also induce airlines to reroute connecting passengers through hub airports outside the region, increasing flight distances and therefore total emissions. It is also unclear, however, how high landing fees must be to induce such network change. It is therefore useful to analyse the effects of regional increases in landing fees on aircraft size, the flight network, and emissions.

Changes in the flight network may also result from the inclusion of aviation within a regional emissions trading scheme (also called a cap-and-trade scheme). Such a policy mechanism has gained increased attention since the EU legislated that all flights taking off or landing in Europe will be included in the EU ETS from 2012 (European Union, 2009). Concern has been expressed about the potential for traffic to avoid the region in order to reduce costs (Association of European Airlines, 2007; Ernst & Young, 2007; Scheelhaase and Grimme, 2007). This would have a negative impact on the economy of the region, and would also reduce the effectiveness of the scheme to reduce emissions. Individual airlines have even threatened to move hubs to non-EU locations (Turner, 2007).

The Airline Response Model captures full network and aircraft size effects, optimising the flight network and aircraft size choice by airline. It may thus be useful for analysis of the network, aircraft size and emissions implications of regional cost increases, such as would occur under a regional increase in landing fees or a regional emissions trading scheme. A limitation of the Airline Response Model, however, is that it does not simulate fares by itinerary or by airline, but only by O-D city-pair, averaged over all airlines. An airline that operates a hub outside a region with increased costs would have lower costs than an airline operating a hub within the region. It may thus be able to offer lower fares for connecting flights between cities outside the region, potentially leading to a shift in demand between airlines. Because the Airline Response Model does not simulate fares by itinerary or by airline it is not able to capture this effect. In future work the model will be developed to simulate fares by itinerary and by airline in order to support such analysis.

The effects of regional cost increases are simulated in the set of cities, airport and airlines in the United States described in Section 6.1. Cost increases are implemented in the form of increased landing fees, enabling analysis of their impact on the flight network, aircraft size choice and emissions. A regional increase in landing fees is more likely within the United States than an emissions trading scheme restricted to only one region. Landing fees are implemented by airport, while an emissions trading scheme would be a national initiative, if implemented. In future work, other air transport systems will be simulated, such as the European air transport system, in which it is more appropriate to simulate emissions trading.

The region selected for increased landing fees in this analysis is Texas. The reason for this is that there are two important intercontinental hub airports in Texas: Dallas-Fort Worth and Houston Intercontinental, both of which are included in the modelled airport set. These hub airports serve the cities of Dallas/Fort Worth and Houston, along with secondary airports Dallas Love Field and Houston Hobby. American and Continental Airlines operate hubs at Dallas-Fort Worth and Houston Intercontinental respectively, and also serve a number of other airports outside Texas.

Existing airport landing fees in the United States range from as low as US$ 40 per flight (small aircraft size class, Atlanta) to as high as US$ 5,700 per flight (large aircraft size class, Newark) (IATA, 2008). In Texas, landing fees range from US$ 390 per flight (small size class, Houston Intercontinental), to US$ 2,560 per flight (large size class of aircraft, Dallas Fort-Worth). In order to simulate the response of the air transport system to regional cost increases, and to identify the level of cost increase required to drive changes in the flight network and aircraft choice, three scenarios are formulated:

- Case 1: A baseline case, in which landing fees are maintained at existing levels at all airports.
- Case 2: A case in which all existing landing fees are increased by US$ 1,000 per flight in 2015 at each airport in Texas, and by a further 4% per year following that. This case models a small to medium cost increase relative to existing landing fees.
- Case 3: A case in which all existing landing fees are increased by US$ 5,000 per flight in 2015 at each airport in Texas, and by a further 4% per year following that. This case models a large cost increase relative to existing landing fees.

Policy measures that implement cost increases in order to mitigate the environmental impacts of aviation typically increase the value of the cost increase applied, over time, in order to counter the effects of increasing passenger demand. The CCSP IGSM, for example, models an increase in carbon price by 4% per year (CCSP, 2007). This is the value applied to Cases 2 and 3 here, after the initial increase in landing fees in 2015.

Airport capacities at all airports are assumed to be increased in all cases according to expansion plans described by the U.S. DOT (DOT, 2004) and airport authorities, as shown in Table 5-1 in Section 5.2.

Regional Effects

The regional impacts of increased landing fees on Texas O-D demand, aircraft operations, and CO_2 emissions, in each of the three cases described above, are presented in Figure 7-7. The implications of these results are discussed below, followed by presentation and discussion of the system-wide effects.

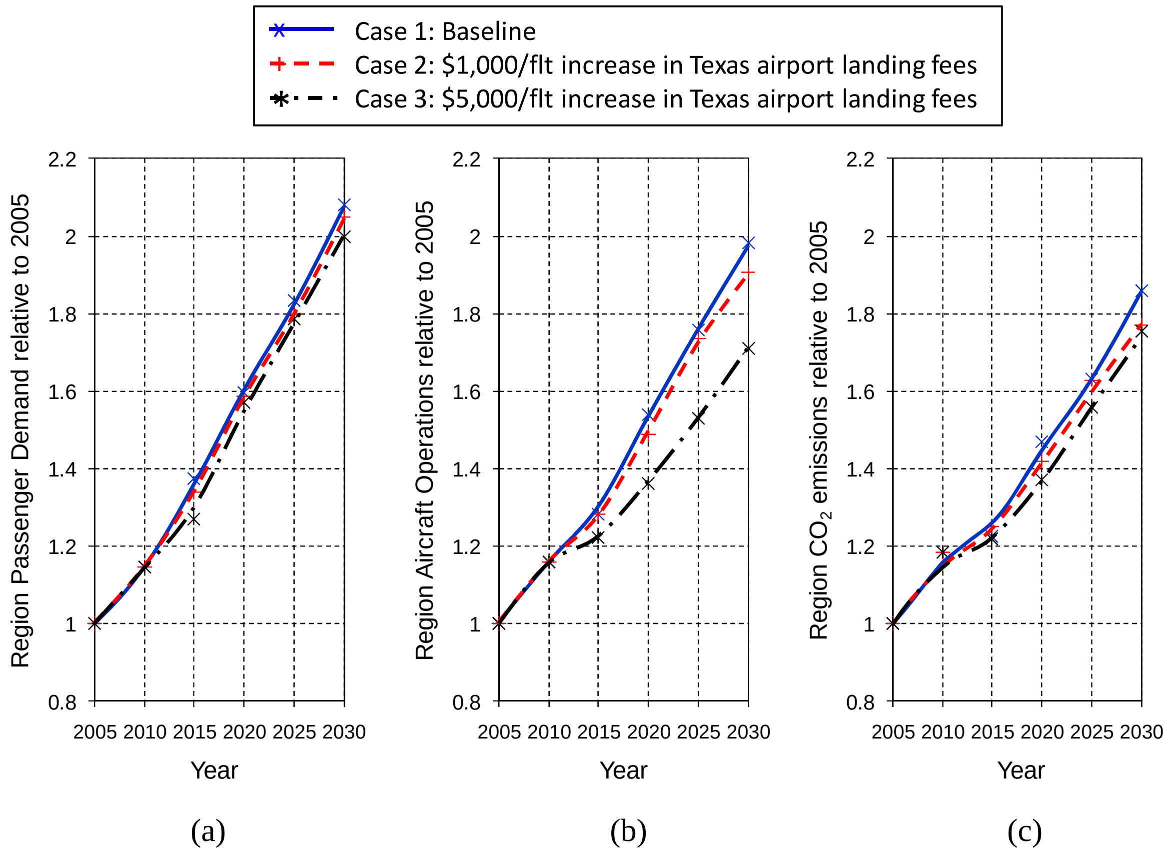


Figure 7-7. Simulated Texas response to airport capacity constraints through 2030: (a) passenger demand, (b) aircraft operations, and (c) CO_2 emissions.

The baseline case, in which no increases in landing fees are applied to any airports, is identical to the baseline case in the analysis of airport capacity constraints described in Section 7.1. The growth in Texas passenger demand, aircraft operations and CO_2 emissions in this baseline case, shown in Figure 7-7, follow similar trends to the system as a whole, shown in Figure 7-1. The growth in CO_2 emissions in 2015 is slightly lower than in other periods. This is related to airport capacity expansion at a number of airports system-wide in 2013, which leads to a small reduction in flight delays, and a correspondingly small increase in passenger demand growth. This increased demand growth leads to slightly greater use of point-to-point operations (shown by a reduction in the number of connecting passengers in Figure 7-8a below). In point-to-point networks passengers are flown directly, reducing total fuel burn and CO_2 emissions relative to hub-and-spoke networks. Because Texas air traffic is dominated by the hub operations at Dallas-Fort Worth and Houston Intercontinental, this small change in system-wide airport capacity has an exaggerated impact on Texas CO_2 emissions.

In Case 2, in which landing fees at all airports in Texas are increased by US$ 1,000 per flight, the growth in O-D passenger demand to Dallas/Fort Worth and Houston (Figure 7-7a) is only slightly lower than in the baseline case (by roughly 2% in 2030). In Case 3, in which landing fees at all airports in Texas are increased by US$ 5,000 per flight, the effect is greater, with the growth in passenger demand roughly 5% lower than in the baseline case by 2030. These reductions in demand are the result of the higher landing fees, which increase airline costs. These increased costs are passed on to passengers in the form of increased fares. The increase in fares is not large enough, however, to have a significant impact on passenger demand. By 2030, the increases in airline costs are US$ 8.40 and US$ 42.20 per passenger in Cases 2 and 3 respectively, which compare to an average ticket price within the modelled network of US$ 188.

By 2030, aircraft operations at airports in Texas (Figure 7-7b) are also slightly lower than in the baseline case in Case 2 (by roughly 4%), but in Case 3, they are significantly lower (by roughly 15%). This large decrease in aircraft operations relative to the baseline case, despite little change in passenger O-D demand to the region, is the result of an increase in the sizes of aircraft operated in the region, and a shift in connecting traffic from the hub airports in the region – Dallas-Fort Worth and Houston Intercontinental – to other hubs airports outside the region. These effects are described in detail below. In contrast to the effect on aircraft operations, CO_2 emissions from all flights arriving at or departing from airports in Texas (Figure 7-7c) are only slightly lower than the baseline case in both Case 2 (roughly 4% lower) and Case 3 (roughly 5% lower). The large decrease in operations in Case 3 relative to the baseline is not matched by the CO_2 emissions because of the shift to larger aircraft, which burn more fuel per flight than smaller aircraft, with correspondingly greater CO_2 emissions.

While the percentage of connecting passengers in the system does not change significantly between the three cases (remaining at roughly 5.5% in 2030), in Case 3 there is a small shift in connecting traffic away from Dallas-Fort Worth and Houston Intercontinental to other hub airports in the system. This is shown in Figure 7-8, which shows the distribution of connecting passengers across all the hub airports operated within the modelled system.

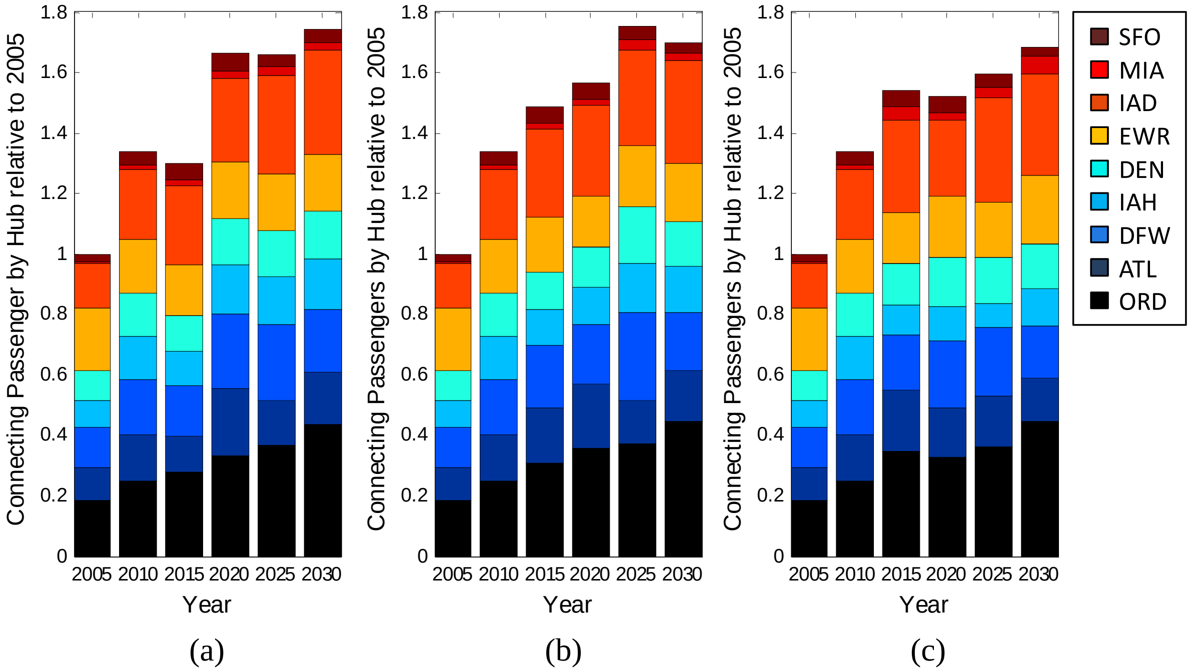
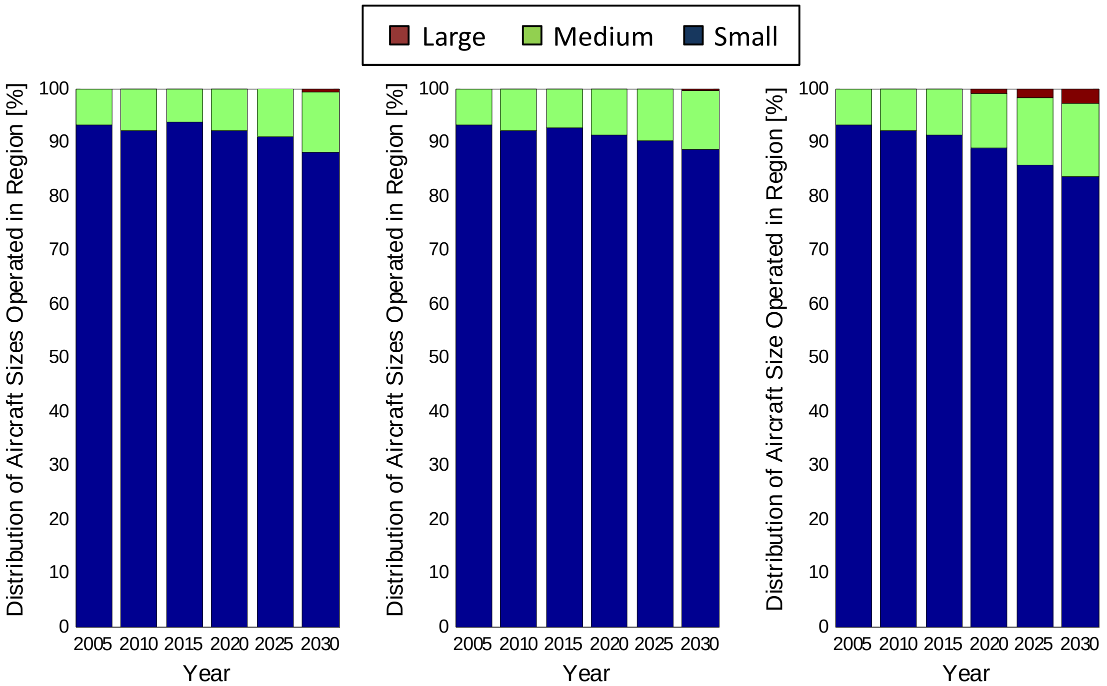


Figure 7-8. Simulated connecting passenger distribution across system hubs through 2030: (a) Case1: Baseline, (b) Case 2: Increased landing fees at all Texas airports of US$ 1,000 per flight, and (c) Case 3: Increased landing fees at all Texas airports of US$ 5,000 per flight.

While the total number of connecting passengers in the system is not significantly impacted by the increased landing fees in Texas in Case 2 (Figure 7-8b), a small reduction can be seen in Case 3 (Figure 7-8c), relative to the baseline case (Figure 7-8a). Relative to the baseline case, there is also little change in the number of passengers connecting at Dallas-Fort Worth (DFW) or Houston Intercontinental in Case 2 (Figure 7-8b), but in Case 3, there is a noticeable decrease by 2030 (Figure 7-8c) – by roughly 20% at Dallas-Fort Worth, and by 35% at Houston Intercontinental (IAH). In this case, there are corresponding increases in the number of connecting passengers at Miami (MIA) (by roughly 150% in 2030) and Newark (EWR) (by roughly 10% in 2030) relative to the baseline. Miami and Newark, at which there are no increases in landing fees, are operated as hubs by American and Continental Airlines respectively, which also operate hubs at Dallas-Fort Worth and Houston Intercontinental respectively. These results suggest that sufficiently high landing fees may induce airlines to route some connecting traffic away from impacted hubs. The result is a reduction in the number of aircraft operations in the region, as shown for Case 3 in Figure 7-7b.

Changes in aircraft size as a result of increased landing fees are investigated by plotting the distribution of aircraft sizes among flights arriving at or departing from airports in Texas, shown in Figure 7-9. The increase in landing fees in Case 2 (Figure 7-9b) in not sufficient to produce any significant shift to greater use of larger aircraft relative to the baseline case (Figure 7-9a). However, the larger increase in landing fees in Case 3 does produce such a shift (Figure 7-9c), with growth in both the percentage of medium aircraft types operated as well as large aircraft types. While landing fees are higher for larger aircraft, these differences are not sufficient to offset the reductions in airline costs per passenger that can be achieved by using larger aircraft to serve the same number of passengers with fewer flights. Unlike in the case of airport capacity constraints, frequency competition does not limit this effect here. Landing fees directly impact airline operating costs, reducing the frequency at which marginal cost equals marginal revenue to a greater extent than airport capacity constraints, while the impact of increased landing fees on passenger demand is only through increased fares, and not through any direct demand response to flight delays.



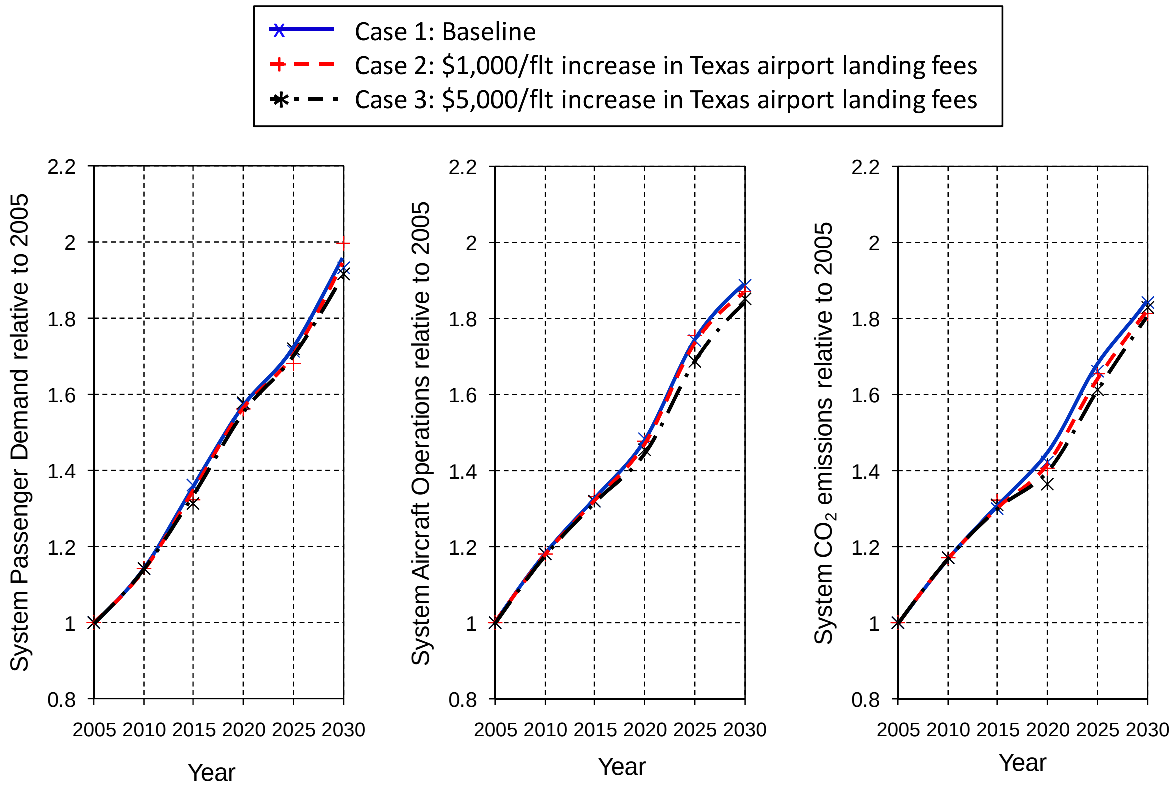
(a) (b) (c)

Figure 7-9. Simulated distribution of aircraft size operated at Texas airports through 2030: (a) Case1: Baseline, (b) Case 2: Increased landing fees at all Texas airports of US$ 1,000 per flight, and (c) Case 3: Increased landing fees at all Texas airports of US$ 5,000 per flight.

The result is that aircraft operations are reduced to a greater extent than passenger demand, as shown in Figure 7-7, and average aircraft size increases.

System Effects

The system effects of increased landing fees in Texas are presented in Figure 7-10. The baseline results are identical to those in the analysis of airport capacity constraints, shown in Figure 7-1. Comparing Cases 2 and 3 to the baseline case suggests that the impact of the regional increases in landing fees on system demand (Figure 7-10a), aircraft operations (Figure 7-10b) and CO_2 emissions (Figure 7-10c) is very small. The greatest impact is on aircraft operations in Case 3 (which is roughly 2% lower than the baseline case by 2030). This very small impact is because of the large size of the system in comparison to the region with increased landing fees, and the generally small impact of the increased landing fees on the region itself (Figure 7-7), except in the case of aircraft operations.



(a) (b) (c)

Figure 7-10. Simulated system response to airport capacity constraints through 2030: (a) passenger demand, (b) aircraft operations, and (c) CO_2 emissions.

In summary, the results presented in this section indicate that regional cost increases, in the form of increased landing fees, are likely to have relatively little impact on passenger demand to the region, but may have a significant impact on aircraft operations, if the increase in landing fees is large enough. Such landing fees can induce some shift in the flight network, with some connecting passengers being rerouted through hubs outside the region. Increased landing fees can also induce a shift to greater use of larger aircraft. The impact on CO_2 emissions is not as large as on aircraft operations, and the impacts of system demand, aircraft operations and CO_2 emissions is very small. System-wide CO_2 emissions may be reduced to a greater extent by the introduction of new technology into the fleet, which reduces aircraft fuel burn significantly. This is described in the next section.

7.3 The Air Transport System Response to the Introduction of New Technology

Another key policy mechanism that is proposed to mitigate the negative environmental impacts of aviation growth is the specification of new regulations for aircraft fuel burn or emissions levels (GAO, 2009). This would incentivise the development of new technology and encourage its adoption into airline fleets. Leads time are, however, long, because of the time required to develop the new technology, and fleet turnover is slow in the aviation industry. Enabling such technology development is still attractive to policymakers, however, because it does not have the negative effects on economic growth associated with other mitigation policies, such as taxes and emissions trading. However, it is not clear how the air transport system will respond to new technology, and whether it will be sufficient to mitigate the negative environmental impacts of aviation growth without other policies.

Two scenarios are formulated introducing radically new technology into the fleet in order to investigate the response and sensitivity of the air transport system to reductions in aircraft fuel burn. The technologies introduced are an aircraft operating advanced open rotor engines (also called ultra-high bypass ratio engines) and a blended wing body aircraft. The response of the air transport system to each of these technologies is compared to a baseline case in which no radically new technology is introduced.

Advanced open rotor technology reduces engine fuel burn by gaining some of the efficiencies of turbo-prop engines, such as the weight and drag reductions associated with no nacelle, while limiting some of the drawbacks associated with turbo-prop engines, such as low aircraft speed. Open rotor engines have been under study for many years but are currently receiving renewed attention because of their potential to reduce CO_2 emissions. The fuel burn reduction from an aircraft designed to operate advanced open rotor engines may be up to 30% over conventional aircraft (Lawrence *et al.*, 2009), although cruise speed is also likely to be slower, by approximately 8% (Hoff, 1990). For this and other reasons aircraft operating advanced open-rotor engines are only likely to be appropriate for the smallest aircraft size class modelled in this analysis – short/medium haul, single aisle aircraft that would replace the Boeing B737 and Airbus A320 families of aircraft.

The blended wing body aircraft concept blends the aircraft fuselage into the wings, and eliminates the empennage, to form a kind of "flying wing". The design has a significantly improved lift-to-drag ratio over conventional aircraft, reducing fuel burn by as much as 30% (Greener by Design, 2005). The concept has also been under study for many years, and like the advanced open-rotor technology has recently received renewed attention because of its potential to reduce CO_2 emissions. Because of configuration issues related to blending the fuselage into the wing, the blended wing body design is only likely to be practical for the largest aircraft size class modelled in this analysis – long haul, twin aisle aircraft that would replace the Boeing B747, B777, and Airbus A380 families of aircraft. Although this large class of aircraft is barely used domestically at all, this is likely to change with the introduction of a new large aircraft with significantly reduced operating costs.

The cost of developing both advanced open rotor and a blended wing body aircraft is highly uncertain. This is also the case for their likely dates of availability. Two scenarios are therefore simulated – one in which development costs are assumed to be absorbed by governments and other agencies in such a way that the aircraft amortization costs incurred by the airline are no different to those of existing aircraft, and one in which development costs lead to amortization costs that are twice those of existing types. Dray *et al.* (2009-2) suggests that open rotor technology may be available by 2020, while the date of introduction of blended wing body technology is likely to be beyond 2020. For the purposes of this analysis, however, both technologies are assumed to be available in 2020.

In contrast to the other two families of scenarios considered, the introduction of radically new technology requires making assumptions about the rate at which these technologies enter airline fleets. Fleet turnover is a complex process involving the retirement of older, less cost effective aircraft, and the purchase of new aircraft to replace them and to serve increased demand. A fleet model capturing these effects is not included in the Airline Response Model. Instead, the turnover of the fleet to include the radically new technology aircraft described above is modelled using simple assumptions about fleet retirement rates and the simulated growth in aircraft operations. Morrell and Dray (2009) present retirement curves for different types of aircraft, modelled by (logistic) S-curve functions. For most aircraft types, the roughly linear portion of the S-curve has a gradient of approximately 4% of the fleet per year. The growth rate in aircraft operations simulated in the baseline scenarios in Figure 7-1c and Figure 7-10b is 2.4% per year. Assuming aircraft utilisation rates remain approximately constant, this growth rate can also be assumed for the fleet. Making the simplifying assumption that all aircraft added to the fleet are new types, the rate at which radically new technology would enter the fleet is therefore 6.4% per year.

In reality, the rate at which radically new technology will enter the fleet is a function of the operating costs of the technology, the purchase price of the aircraft, the fuel price, and the growth in demand. On the one hand, if the fuel burn reductions introduced by the technology are large and the fuel price is high, fleet turnover may be faster than the rate modelled. On the other hand, if the costs associated with the development of the technology that are passed on to airlines are high, and fuel prices are low, fleet turnover may be slower than the rate modelled. For the purposes of this analysis, however, both radically new technologies are assumed to enter the fleet at the rate of 6.4% per year, from 2020. In order to fully examine the impact of the new technologies in the fleet, the simulation is run to 2040.

Note that the fuel burn of the rest of the fleet is assumed to improve at the same rate applied in Sections 7.1 and 7.2, i.e., 0.7% per year.

Advanced Open Rotors

Figure 7-11 presents simulated system-wide passenger demand, aircraft operations and CO_2 emissions for the set of airlines, airports and cities in the United States described in Section 6.1. Results are presented for a baseline scenario in which no radically new technology is introduced, and for two scenarios in which an advanced open-rotor aircraft is introduced in the small size class of aircraft. In the first case (Case 2), amortization costs are

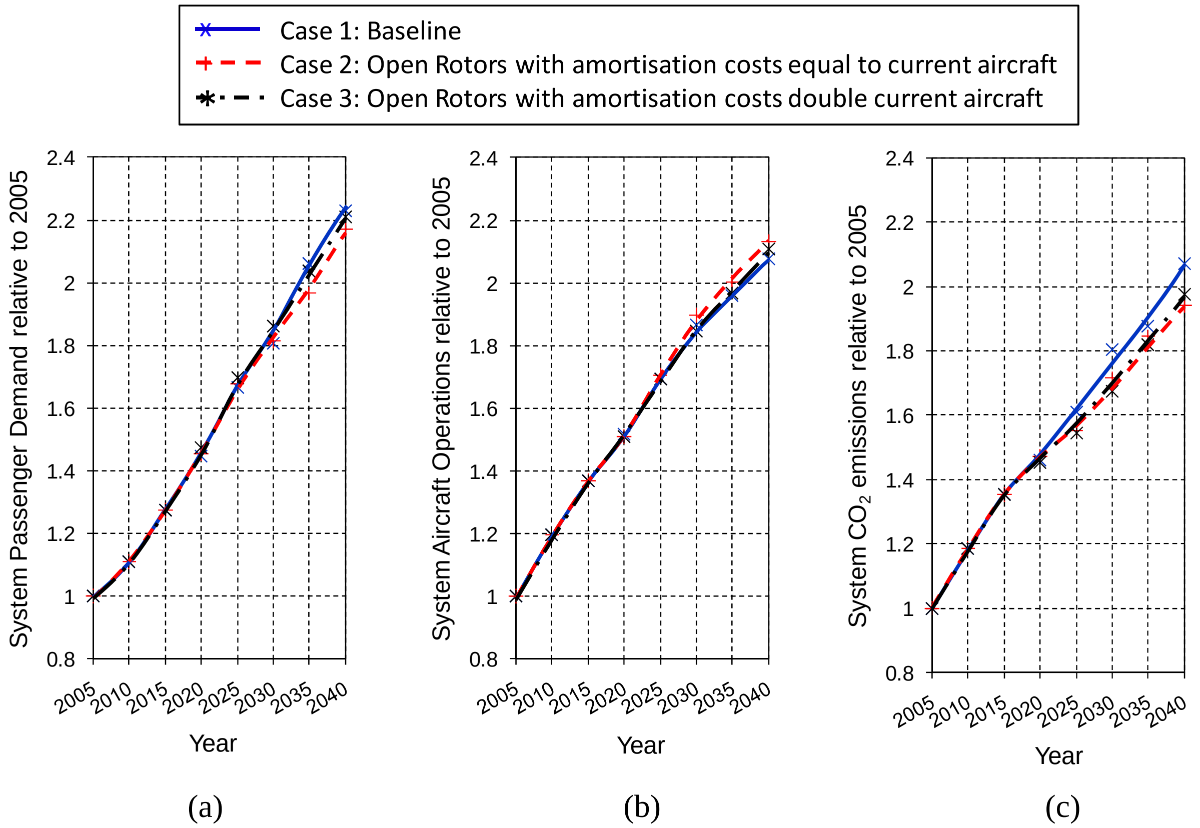


Figure 7-11. Simulated air transport system response to the introduction of advanced open rotors through 2040: (a) passenger demand, (b) aircraft operations, and (c) CO_2 emissions.

assumed to be identical to existing small aircraft, while in the second case (Case 3) they are assumed to be double those of existing small aircraft.

The baseline results in Figure 7-11 are identical to those in the analysis of airport capacity constraints through 2030, shown in Figure 7-1. Comparing Cases 2 and 3 to the baseline case suggests that the introduction of radically new technology which reduces fuel burn of the small aircraft size class has relatively little impact on system demand (Figure 7-10a), aircraft operations (Figure 7-10b) and CO_2 emissions (Figure 7-10c). This can be attributed, at least in part, to the slow fleet turnover rate simulated, which is representative of the aviation industry.

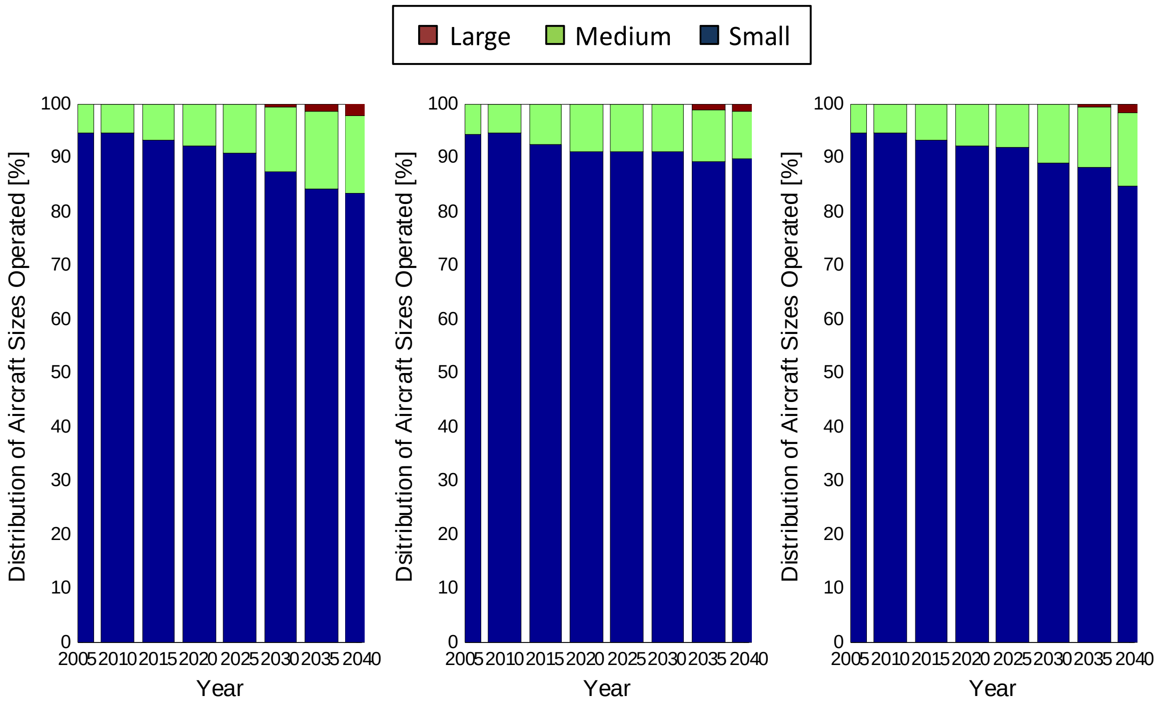
In the case where amortisation costs associated with an open rotor aircraft are identical to those of existing aircraft (Case 2), the impact of the new technology on passenger demand is to decrease it slightly relative to the baseline case (by roughly 3% in 2040) (Figure

7-11a). A reduction in fuel burn reduces operating costs, leading to an increase in frequency competition. As described above, airlines increase flight frequency until the marginal cost of adding a flight is no longer offset by the marginal revenue associated with the increased market share achieved by the flight. With a decrease in marginal cost, this equilibrium frequency increases. Thus, reduced fuel burn can result in a small increase in aircraft operations, shown in Figure 7-11b. The increased aircraft operations result in an increase in flight delays – by more than 10 minutes on average per flight relative to the baseline case by 2040. Flight times also increase over the baseline case because of the slower cruise speed of open rotor aircraft. Both these effects lead to a slight reduction in passenger demand, as shown in Figure 7-11a. The effect is partially offset by the demand impact of lower fares, which result from the lower operating costs of the new technology. This latter effect is not dominant, however.

Beyond the competition effects described above, another reason for the slight increase in aircraft operations in Figure 7-11b is a shift to greater use of the small size class of aircraft. Because of the reduced cost associated with operating the open rotor aircraft, which falls within this aircraft size class, airlines make greater use of this aircraft type than in the baseline case. This effect can be seen in Figure 7-12, which shows the distribution of aircraft size classes operated in each case. In the baseline case the percentage of small aircraft steadily decreases from 2005 to 2040, with the percentage of medium aircraft increasing, and, after 2025, large aircraft also (Figure 7-12a). This is because of economies of scale of larger aircraft, as described in Section 7.1. Case 2 follows a similar trend to the baseline, until after 2020 when the percentage of small aircraft remains approximately constant (Figure 7-12b). This indicates that the cost savings benefit of advanced open rotor engines offsets the benefits of the economies of scale associated with the larger aircraft.

The introduction of advanced open rotor aircraft in Case 2 also results in a reduction in system CO_2 emissions from aviation relative to the baseline case, as shown in Figure 7-11c (by roughly 5% in 2030). This is a direct result of the reduction in fuel burn of the new technology, which is sufficiently great that it is not offset by the increase in aircraft operations shown in Figure 7-11b.

In Case 3 the amortisation costs associated with advanced open rotor aircraft are assumed to be double those of existing aircraft. The effect of this is to significantly reduce the



(a) (b) (c)

Figure 7-12. Simulated distribution of aircraft size operated across the system through 2040: (a) Baseline with no advanced open-rotor technology, (b) Advanced open rotor technology introduced with amortisation costs equal to existing aircraft types, and (c) Advanced open rotor technology introduced with amortisation costs double those of existing aircraft types.

operating cost benefit achieved by the reduction in fuel burn. The result is to limit almost all the effects observed in Case 2. The increase in frequency competition is reduced, limiting any increase in aircraft operations shown in Figure 7-11b (to roughly 1% relative to the baseline by 2040). While the increase in travel time resulting from increased cruise speeds remains the same, the increase in flight delays associated with the increase in operations is reduced (to roughly 5 minutes on average per flight greater than the baseline case by 2040). Also, the reduction in fares resulting from the decrease in operating costs is less. In response to these effects, passenger demand is reduced only slightly relative to the baseline case (by roughly 1% by 2040) – less than in Case 2. There is, however, still a moderate shift to greater use of the small aircraft types relative to the baseline case, as seen by comparing Figure 7-12c to Figure 7-12a, which contributes to the small increase in aircraft operations observed in Figure 7-11b.

In contrast to the other results, system CO_2 emissions in Case 3, shown in Figure 7-11c, are similar to those in Case 2. The reason for this is that, while the cost benefit of the new technology to the airline is reduced by the doubled amortization costs in Case 3, the reduction in CO_2 emissions is not affected. This indicates that even if the development costs of a radically new technology result in increased amortization costs for airlines, reduction in system CO_2 emissions may still be possible. This does, however, require the implementation of policy measures to ensure adequate fleet entry, which is taken as given in this family of scenarios.

Blended Wing Body Aircraft

Figure 7-13 presents simulated system-wide passenger demand, aircraft operations and CO_2 emissions for the same set of airlines, airports and cities in the United States described in Section 7.1. Results are presented for a baseline scenario and two scenarios in which a blended wing body aircraft is introduced. In the first case (Case 2), amortization costs are assumed to be identical to existing large aircraft, while in the second case (Case 3) they are assumed to be double those of existing large aircraft.

The baseline results in Figure 7-13 are again identical to those in the analysis of airport capacity constraints through 2030, shown in Figure 7-1. Comparing Cases 2 and 3 to the baseline case suggests that the introduction of a blended wing body aircraft that reduces the fuel burn of the large size class of aircraft has very little impact on system demand (Figure 7-10a), aircraft operations (Figure 7-10b) and CO_2 emissions (Figure 7-10c). This can primarily be attributed to the slow fleet turnover rate simulated, and the small percentage of large aircraft types operated in the system.

In the case where amortisation costs associated with a blended wing body aircraft are identical to those of existing aircraft (Case 2), the impact of the new technology on passenger demand is to increase it slightly (by roughly 3% in 2040) (Figure 7-13a). This is because the reduced fuel burn of blended wing body aircraft reduces operating costs, and therefore fares, leading in an increase in passenger demand. Unlike with the introduction of an advanced open rotor aircraft, aircraft operations do not increase with the introduction of a blended wing body aircraft (Figure 7-13b), so flight delays do not increase. Blended wing body aircraft also cruise at the same speeds as existing aircraft, so flight times remain the same as existing

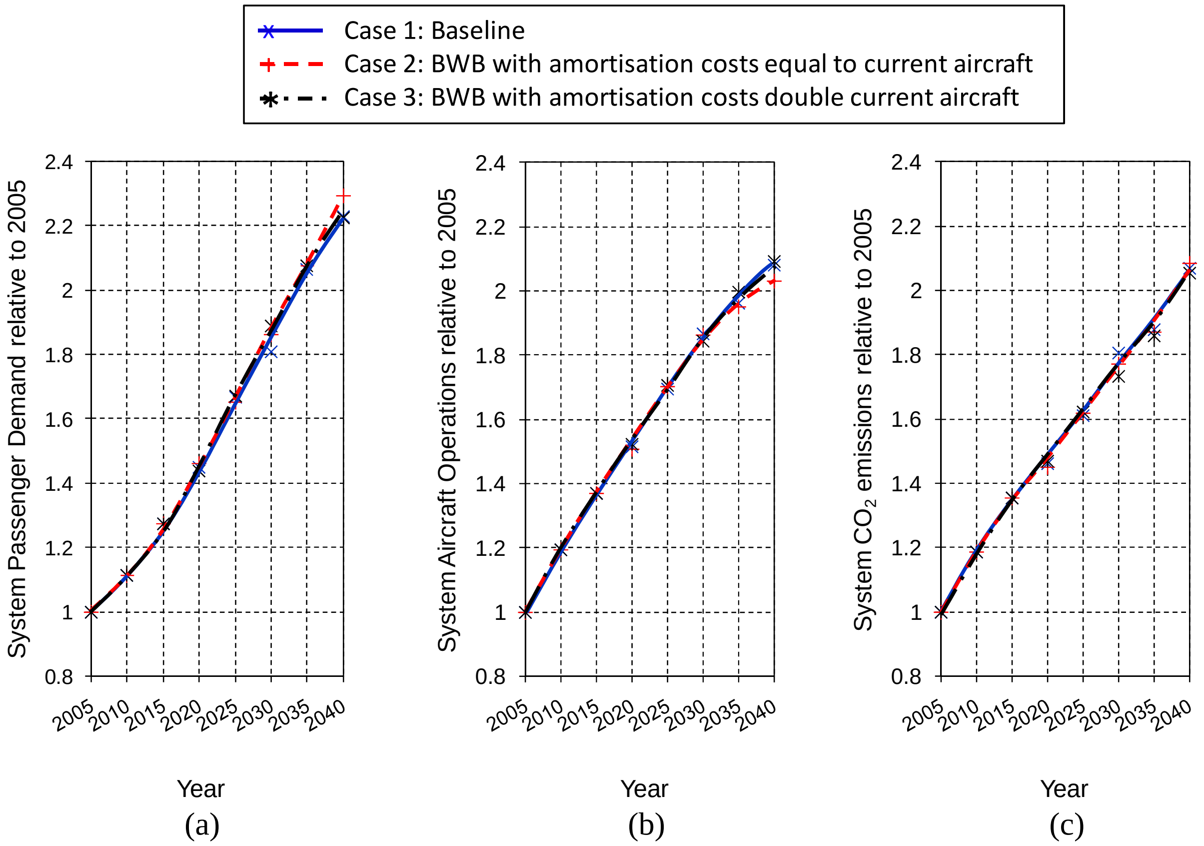
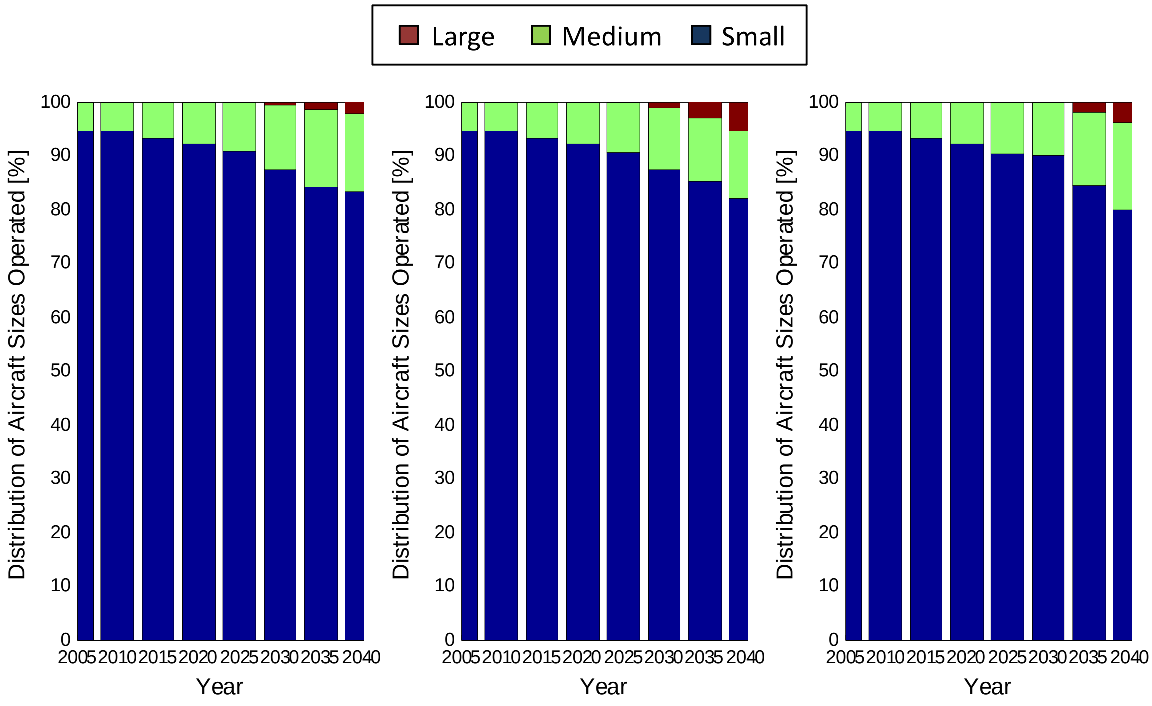


Figure 7-13. Simulated air transport system response to the introduction of a blended wing body aircraft through 2040: (a) passenger demand, (b) aircraft operations, and (c) CO_2 emissions.

aircraft. The result is that fare effects dominate the passenger demand response to the introduction of blended wing body aircraft.

Aircraft operations decrease slightly with the introduction of blended wing body aircraft (by roughly 2% in 2040) (Figure 7-13a). This is because of a shift by airlines to operate more large aircraft, which can be seen in Figure 7-14 by comparing the percentage of large aircraft operated in Case 2 (Figure 7-14b) to the percentage operated in the baseline case (Figure 7-14a). Despite the small increase in demand to be served (Figure 7-13b), the shift to larger aircraft is sufficient to result in a total decrease in number of flights operated. This effect on aircraft size is also sufficient to offset any frequency competition effects in response to the reduced operating costs, described above for the introduction of open rotor aircraft.



(a) (b) (c)

Figure 7-14. Simulated distribution of aircraft size operated across the system through 2040: (a) Baseline with no blended wing body technology, (b) Blended wing body technology introduced with amortisation costs equal to existing aircraft types, and (c) Blended wing body technology introduced with amortisation costs double those of existing aircraft types.

The introduction of a blended wing body aircraft into the fleet in Case 2 has essentially no impact on system CO_2 emissions (Figure 7-13c). The reason for this is that the decrease in aircraft operations shown in Figure 7-13b is achieved through increased operation of larger aircraft. These aircraft, although they have lower fuel burn than older technology large aircraft, still have higher fuel burn than small and medium sized aircraft. The decrease in CO_2 emissions achieved through fewer operations and the lower fuel burn of the large aircraft type is offset by the increase in use of the large aircraft type over the small and medium aircraft types. Also, although fuel burn per RPM of the new aircraft is lower than that of the older aircraft, passenger demand has increased slightly relative to the baseline case. The small percentage of new aircraft in the fleet and the increase in passenger demand mean that total CO_2 emissions are no lower than in the baseline case.

In Case 3 the amortisation costs associated with blended wing body aircraft are assumed to be double those of existing aircraft. As in the advanced open rotor case, the effect of this is to significantly reduce the operating cost benefit achieved by the reduction in fuel burn. Again, the result is to limit almost all the effects observed in Case 2. There is a small shift to larger aircraft types, as seen by comparing Figure 7-14c (Case 3) to Figure 7-14a (baseline), but it is not as large as that in Case 2. The result is that there is essentially no change in aircraft operations (Figure 7-13b), passenger demand (Figure 7-13a) or CO_2 emissions (Figure 7-13c) relative to the baseline.

In conclusion, the introduction of radically new technology into the fleet that reduces aircraft fuel burn significantly is likely to have very little impact on passenger demand and aircraft operations. The impact on system CO_2 emissions from aviation may vary from small, in the case of technology that could be taken up by the majority of the fleet (such as a replacement for the small aircraft size class of aircraft), to insignificant, in the case of technology that could be taken up by only a small portion of the fleet (such as a replacement for the large aircraft size class of aircraft). It is noted that these small to insignificant impacts are, at least in part, because of the slow fleet turnover rates typical of the aviation industry, and because no international flights are modelled, which would make greater use of the large aircraft size class. If fleet turnover rates can be accelerated, these impacts would be larger. It is also noted that the environmental impact of introducing radically new technology is not significantly impacted by whether or not the development costs of the technology are covered by the airlines operating the aircraft, assuming that policy measures are in place to ensure adequate fleet entry. Without policy measures to ensure adequate fleet entry, increased amortization costs may significantly slow the rate at which the new technology enters the fleet, reducing the environmental benefit of the new technology further.

8 Conclusions

Given insights from the application of the Airline Response Model, several conclusions can be drawn from this dissertation concerning the modelling approach itself and the behaviour of the air transport system.

Perhaps most importantly, it can be concluded that it is possible to simulate airline operational responses to environmental constraints and policies by simulating airline strategic decision making within a competitive environment. This was done by explicitly modelling airline profit maximisation, frequency competition, and changes in airline cost and passenger demand. The model was validated by comparing simulation results to observed data for a network of 22 airports and 14 cities in the United States in 2005. Passenger demand and flight frequencies were predicted to be within 1-3% of observed values, while R^2 values comparing modelled and observed passenger demand and flight frequencies range from 0.56 to 0.86. The model was found to capture all dominant effects in airline strategic decision making regarding airline choice of flight frequencies, aircraft size and flight network. The Airline Response Model can therefore be applied to simulate airline operational responses to policy measures impacting airline costs and passenger demand within a competitive environment. The greatest differences between modelled and observed data are between airports in multi-airport systems, indicating that the modelling of the distribution of traffic between airports in multi-airport systems has most potential for further development.

By applying the Airline Response Model to a series of environmental policy scenarios, a number of conclusions can be drawn regarding the response of the air transport system to airport capacity constraints, regional increases in cost in the form of increased landing fees, and the introduction of radically new low-fuel burn technology into the fleet.

Airport capacity constraints may have some significant system-wide effects, including high delays and reductions in passenger demand, aircraft operations and CO_2 emissions. The simulation results indicate that, with no airport capacity expansion in the United States, average system-wide arrival delays in 2030 may be quadruple the 2005 level of 11 minutes per flight. Passenger demand and aircraft operations may be almost 10% lower than in a case in which airport capacity is expanded by 25%, as planned. At the same time, however, airport capacity constraints may also limit growth in system-wide CO_2 emissions from aviation. In the case of no capacity expansion in the United States, CO_2 emissions from aviation may be nearly 10% lower than in the case in which airport capacity is expanded. This suggests that restrictions in airport capacity expansion may lead to reductions in aviation CO_2 emission growth, although this may come at the cost of high delays and some reductions in demand and operations.

While airport capacity constraints may have some significant system-wide effects, they are the result of local airport effects which are much greater. Simulation results indicate that, with no capacity expansion, average arrival delays at a congested hub airport such as Chicago O'Hare may be over 70 minutes per flight by 2030, up from less than 10 minutes per flight in 2005. This would cause passenger O-D demand and aircraft operations to drop by up to 20% relative to a case in which the airport capacity is expanded by 40%, as planned. Such a dramatic decrease in the growth of aircraft operations would have a significant effect on local airport emissions: the growth of LTO NO_x emissions would decrease by up to 25% relative to the case in which capacity is expanded at the airport. This suggests that, despite the increases in delay, restrictions in airport capacity expansion can have a significant impact on reducing growth in local emissions. The high simulated delays also indicate, however, that, in the case where capacity expansion is not possible at a congested hub airport, other policy measures, such as slot control or increased landing fees, may have to be applied to reduce delays to manageable levels, because the air transport system may not adjust sufficiently on its own.

The simulation results do show, however, that if there is available capacity at other airports, airlines may respond to capacity constraints by adjusting their flight networks to avoid the congested airports. This may include making changes to the distribution of connecting traffic across their hubs and the distribution of O-D traffic between airports in multi-airport systems. Therefore, while the air transport system may not adjust sufficiently to prevent some significant increases in delay, airlines may shift some traffic to avoid airports with high delays. These changes in flight network would be more limited in an air transport system with less slack capacity, such as Europe, leading to even higher delays and greater demand reduction than modelled here. Also, the redistribution of connecting passengers between hubs is limited in developed air transport systems generally, such as the United States and Europe, because many passengers in these systems fly non-stop. In less developed systems, such as in India or China, which make greater use of hub-and-spoke networks, the rerouting of connecting passengers through alterative (and in some cases, new) hubs is more likely. While less developed air transport systems do not currently operate many multi-airport systems, a number of new second airports are under construction and in planning. The redistribution of traffic within these new multi-airport systems may become the most important approach to accommodating increased operations in these systems.

It can also be concluded from this dissertation that, under high frequency competition, airport capacity constraints are unlikely to induce a significant shift to larger aircraft. This is because of frequency competition effects that maintain high flight frequencies despite reductions in passenger demand in response to flight delays. This indicates that, in order to increase aircraft size at congested airports with high levels of competition, other policy measures may have to be applied, such as slot control or increasing landing fees.

This dissertation shows that regional increases in landing fees, if sufficiently high, can lead to significant reductions is aircraft operations by increasing average aircraft size and inducing airlines to shift connecting traffic to unaffected hubs. Passenger demand and CO_2 emissions, however, are less likely to be significantly impacted. For example, if landing fees in a region such as Texas (which range from US$ 400 per flight to US$ 2,600 per flight) are increased by US$ 5,000 per flight, aircraft operations in the region may be reduced by as much as 15%. O-D demand and CO_2 emissions in the region would be reduced by up to 5%. While the shift to larger aircraft types is likely to occur in most air transport systems, the shift in flight network would again be limited to air transport systems in which there is excess capacity, and in which there is sufficient connecting traffic.

Aircraft operations may also be impacted by the introduction of radically new technology that reduces aircraft fuel burn. While the simulation results presented in this dissertation indicate that the impacts on passenger demand and aircraft operations is small, the reduction in operating cost associated with the new technology can result in an increase in frequency competition, increasing flight frequencies relative to a case with no new technology by nearly 5% in 2040. The impact of new low-fuel burn technology on system

CO_2 emissions may be slightly greater than its impact on demand and operations, but only in the case where the technology could be taken up by the majority of the fleet. An aircraft equipped with open rotor engines, for example, which may reduce aircraft fuel burn by up to 30%, could replace short/medium hall single aisle aircraft such as the Boeing B737 and Airbus A320 families of aircraft. These aircraft account for much of the existing domestic fleet. The simulation results indicate that the introduction of such an aircraft at typical fleet turnover rates would result in a reduction in CO_2 emissions in 2040 by up to 5% relative to a case with no new technology. This dissertation therefore suggests that new technology alone cannot be relied upon to significantly reduce CO_2 emissions, unless fleet turnover is significantly accelerated. It also suggests that technology that can replace the majority of the existing fleet must take priority over other technology.

Finally, it can be concluded from this dissertation, that, while the primary impacts of environmental constraints are captured through changes in passenger demand, there are a number of secondary effects that can only be captured by simulating airline operational responses to environmental constraints. These effects include flight network effects, airline frequency competition effects, and aircraft size effects. The modelling of these airline operational responses to environmental constraints is important when studying both system and local, airport level, effects. It is also important to capture the capability of the air transport system to adjust under changing conditions, which may alter the effectiveness of some environmental policies. Because of the importance of capturing these effects, this thesis makes a valuable contribution.

9 Recommendations for Future Research

Recommendations for future research in modelling airline operational responses to environmental constraints are presented below. Recommendations for further development of the modelling approaches used are presented in Section 9.1, followed by recommendations for future applications of the model in Section 9.2.

9.1 Recommendations to Develop the Modelling Approach

Recommendations to further develop the modelling framework described in Chapter 4 and the modelling approaches for each of the sub-models described in Chapter 5 are presented below. They include integration of a more advanced passenger choice model and a fleet turnover model into the modelling framework, and simulation of changes in schedule shape in response to airport capacity constraints.

- It is recommended that a more advanced passenger choice model be integrated into the modelling framework described in Chapter 4. In the existing framework, passenger choice is only modelled between airlines, and only as a function of flight frequency. A key assumption made in the development of the modelling framework described in Chapter 4, and in the network optimisation for each airline described in Section 5.1, is that passenger routing (non-stop or connecting through one of the hubs operated by the airline) is an airline decision. Thus, in the network optimisation, passengers are routed in such a way as to maximise airline profit. In reality passengers choose which itineraries to fly based on a number of criteria, including ticket price, total travel time, how many connections make up the itinerary, and which airline operates the itinerary (frequent flyer programs have increased airline loyalty, meaning that passengers may choose to fly with a specific airline despite the ticket price or travel time being less attractive than for a competitor). Airlines do, however, sell tickets for itineraries that maximise their profit, so in many cases the simplification modelled in this dissertation is adequate. This was demonstrated in Chapter 6, where the model described in Chapter 4 and 5 was validated against observed data. Certain effects are not captured, however, limiting the capability of the model to simulate some air transport system responses to environmental constraints. One such effect is passenger choice of itineraries. Inclusion of more advanced passenger choice modelling would enable the distribution of passengers on each itinerary to be calculated as a function of fares and travel time. This would require integration of a more advanced passenger choice model between the Passenger Demand Model and Network Optimisation Models presented in Figure 4-1, and would require development of the Fare Model to simulate fares by itinerary, as opposed to estimation of average fares across all itineraries. Inclusion of passenger demand modelling by itinerary would enable more realistic simulation of the distribution of traffic across airports in a multi-airport system. In the current framework, such distribution is based entirely on airline costs, including landing fees and delay costs. In reality, however, airline choice of airports within a multi-airport system is also a function of the location of the airport relative to urban centres and its accessibility (Bolgeri *et al.*, 2008). These criteria, along with flight delays and other factors affect passenger choice.

Inclusion of a more advanced passenger choice model within the modelling framework to model passenger demand by itinerary would also allow improved modelling of the effects of regional increases in costs. The current modelling framework is capable of simulating airline decisions to shift connecting passengers from a hub airport within the region of increased cost to a hub airport outside the region. This requires, however, that the airline operate hubs both inside and outside the region. For many regions this is not the case, but there may still be a shift in connecting traffic to other regions. This is because an airline that does not operate a hub outside the region of increased cost may be forced to increase fares because it is not able to avoid the cost increase within the region. A connecting passenger response to this increase in fares may be to choose to fly with other airlines that do not operate in the region, and therefore offer lower fares. Inclusion of a more advanced passenger choice model within the modelling framework would allow this effect to be simulated, providing a more complete picture of the effects of regional cost increases than is currently possible.

- It is recommended that a fleet turnover model be integrated into the modelling framework described in Chapter 4. Because modelling of airline fleet turnover is already a developed component of most models in the literature that simulate the environmental impacts of aviation (described in Appendix A), development of another model to simulate fleet turnover was not considered to be a significant contribution to the field of study in this dissertation. Such a fleet turnover model was therefore not included in the framework described in Chapter 4. However, as described in Section 2.2, one airline response to environmental constraints is to upgrade equipment. The entry of this equipment into the fleet and the turnover of the existing fleet are complex functions of the operating costs and performance of the old and new equipment. The development of the technology and its market readiness, however, are also functions of costs (particularly oil price) and environmental constraints. These affect airline demands for improved economic and environmental performances, which increase the pressure on manufacturers to develop suitable technology. Airline responses to environmental constraints by upgrading equipment may also have an impact on other airline responses. It has been demonstrated in Section 7.4, where the effect of introducing radically new technology is investigated, that the relationship between aircraft operating costs and the flight network is complex, and that the introduction of new technology with significantly reduced fuel burn does not necessarily result in a significant reduction in emissions. In order to model the impact of new technology more accurately, it is recommended that a fleet turnover model be included in the modelling framework described in Chapter 4. Such a fleet turnover model may be integrated in different ways. In the simplest case, it would be integrated within the iteration framework, but outside the network optimisation, modelling airline fleet decisions separately to airline network optimisation decisions. A more complex integration would be to include fleet choice between different technologies, with different costs and performance, within the network optimisation, simulating airline optimisation of the flight network and fleet purchase simultaneously. In both cases it is noted that a fleet constraint would be added to the network optimisation described in Chapter 5.1. This has others benefits as fleet constraints limit the change in operations from one year to the next. In the current framework each year is modelled independently, including specification of aircraft types by flight segment to maximise profit. In reality, only aircraft in the available fleet can be utilised, constraining the optimisation. The current implementation therefore neglects constraints limiting the change in operations from year to year. Introduction of a fleet constraint would allow this effect to be modelled.

- It is recommended that a component be included in the modelling framework that simulates changes in schedule shape in response to airport capacity constraints. As described in Section 2.2, one airline response to increased airport capacity constraints is to flatten the schedule, reducing the degree to which a banked schedule is operated. This response is not modelled in the framework developed in this dissertation. It is however, a response to airport capacity constraints that has been observed (Evans, 2002). It is therefore recommended that the modelling framework be expanded to simulate this effect also. This may be done, for example, by correlating the banking metric described by Evans (2002) to flight delays, and adjusting a schedule to match the required banking metric as delays increase.

9.2 Recommendations for Future Applications of the Model

Recommendations for future applications of the Airline Response Model are presented below. They include application of the model to developing world regions, and to regions that are most likely to see implementation of policies to attempt to mitigate the environmental impacts of aviation, particularly Europe.

- It is recommended that the Airline Response Model be applied to developing world regions with high aviation growth rates. The growth rates in population and per-capita income in regions such as India, China and parts of South America mean that aviation growth rates in these regions are significantly higher than in more developed regions such as the United States and Europe. Many of these regions have relatively under-developed air transport systems, which may see significant change, irrespective of environmental constraints. Part of the reason for this change is the potential for a significant shift in the types of flight networks operated: from the strong hub-and-spoke systems currently operated to the systems comprising both hub-and-spoke and point-to-point operations that are typical of more developed systems with higher passenger demand. This transition is a direct result of increasing passenger demand between smaller cities, making the introduction of non-stop service profitable. By neglecting these network changes, any forecasts of airport noise and local emissions – particularly at hub airports – may be significantly exaggerated. Similarly, because passengers travel greater distances in hub-and-spoke networks than point-to-point networks, system CO_2 emissions may also be exaggerated by neglecting these network changes. It is therefore recommended that these regions – particularly India, China and Brazil – be simulated using the Airline Response Model. It is noted that data collection for these areas may be difficult and that simplifying assumptions may have to be made in many cases.

- It is recommended that the Airline Response Model be applied to those regions that are most likely to see implementation of policies to attempt to mitigate the environmental impacts of aviation, particularly Europe. Although Europe is not likely to experience the growth rates forecast for India and China, it is currently the region with the most political will to implement policies to attempt to mitigate the environmental impacts of aviation, evidenced by the planned inclusion of aviation in the EU ETS in 2012 (European Union, 2009). Europe also has significant airport capacity constraints, some of which are politically sensitive, such as the building of a third runway at London Heathrow. Application of the Airline Response Model to Europe would contribute to the debates on each of these issues. One key question under debate is the extent to which connecting traffic would move from European hub airports to hub airports outside Europe as a result of the increases in costs associated with the EU ETS. Modelling of passenger responses to these effects would require the inclusion of more advanced passenger choice modelling, as described in Section 9.1 above. The modelling of airline operational responses, however, including the threatened shift of hubs to non-EU locations (Turner, 2007), may be examined in detail by the model described in this dissertation.

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Appendix A: Existing Integrated Aviation-Environment System Models

This appendix presents a detailed description of the three existing integrated aviation-environment system models described in Chapter 1: (i) the Aviation Emissions and Evaluation of Reduction Options Modelling System (AERO-MS) (Pulles *et al.*, 2002); (ii) the Aviation Environmental Portfolio Management Tool (APMT) (Waitz *et al.*, 2006-1); and (iii) the Aviation Integrated Modelling (AIM) Project (Reynolds *et al.*, 2007). The modelling approaches employed by these models are presented in the sections below, followed by a summary and comparison of the key characteristics of each model in Table A-1.

A.1 Aviation Emissions and Evaluation of Reduction Options Modelling System

AERO-MS was developed by the Dutch Civil Aviation Authority from 1994 to 2002 with the objective to "assess the problems related to air pollution from aircraft engine emissions and to analyse possible measures to reduce the impacts of air transport on the atmosphere, taking into account the environmental benefits and the economic impacts of such measures." (Pulles *et al.*, 2002, p15) The model is specifically designed to simulate the climate and economic impacts of economic policies such as emissions trading and the entry of new technology into the fleet. It differs most significantly from other integrated aviation-environment system models in that it only models global climate impacts, using a simplified global chemistry transport model. It does not model local air quality or noise impacts. Due to this focus on climate impacts, the modelling of detailed airport operations and the associated emissions is not required. Flight frequencies (defining the schedule explicitly and the flight network implicitly) are forecast by aircraft type and technology, enabling aircraft flight paths, fuel use and emissions, and air transport revenues and costs to be estimated. Modelling of flight delays is incorporated through a factor that increases flight paths over great circle distances. This detour factor accounts for all airborne delays. No ground delays are simulated. Both passenger and freight demand are modelled using an endogenous demand model, while 6 aircraft size categories, 3 range categories, and 2 technology age categories are simulated by a fleet model. The development of future technology is modelled through the application of a fixed percentage improvement in fuel burn each year. In terms of economic impacts, only the economic benefits of aviation are estimated in detail. Climate change impacts, output in terms of changes to radiative forcing, are not converted to monetary costs. The model operates with a 1992 base year, with some data updated to 1997. The characteristics of AERO-MS are summarised and compared to those of the other integrated aviation-environment system models in Table A-1.

A.2 Aviation Environmental Portfolio Management Tool

APMT is under development by PARTNER, the Partnership for AiR Transportation Noise and Emissions Reduction, a Center of Excellence headquartered at the Massachusetts Institute of Technology (MIT) and sponsored by the U.S. FAA, the U.S. National Aeronautics and Space Administration (NASA), and Transport Canada. APMT utilises a suite of software tools with the objective to "assess the interdependencies between aviation-related noise and emissions effects, and to provide comprehensive cost analysis of aviation environmental impacts." (Waitz *et al.*, 2006-1, p3) Unlike AERO-MS, APMT addresses local air quality, community noise and climate change impacts. The climate change impacts are modelled using impulse response functions only, which are derived from other sources. Unlike AERO-MS, no form of global chemistry transport model is used. The modelling of local air quality and noise impacts requires detailed modelling at the airport level. Of the three integrated aviation-environment system models described, the level of fidelity to which airport and air traffic operations is modelled in APMT is the highest, with flight delays due to airport and airspace capacity constraints modelled in extensive detail using queuing theory. Nine aircraft size categories are simulated. In contrast, the forecasting of demand and air traffic growth is simulated at a lower level of detail than the other integrated aviation-environment system models. Both passenger and freight demand are based on exogenous demand forecasts from the FAA TAF, and the ICAO FESG airport air traffic forecast. These forecasts are based on regression analysis on historical data and consensus views from experts. Partial equilibrium is simulated by modifying the demand forecasts according to predicted changes in fare, which are calculated according to simulated changes in cost. Air traffic growth is also simulated based on forecasts from the FAA TAF and ICAO FESG airport air traffic forecast. Another significant difference between APMT and the other integrated aviation-environment system models is that future aircraft technologies are modelled within APMT using a special Engineering Design Space (EDS) module that optimises future aircraft design according to requirements simulated within APMT. This allows the characteristics of new technology to be simulated to a high level of detail. APMT also includes components that calculate and monetize the benefits and costs of aviation (including costs of negative environmental effects: air quality impacts, noise impacts and climate impacts). This provides the tool with a benefit-cost assessment capability that is necessary if alternative policies with different impacts are to be assessed and compared. The characteristics of APMT are summarised and compared to those of the other integrated aviation-environment system models in Table A-1.

A.3 Aviation Integrated Modelling Project

The AIM project is under development by the Institute for Aviation and the Environment (IAE) at the University of Cambridge. The project has the goal of “developing a policy assessment tool for aviation, environment and economic interactions at local and global levels.” (Reynolds *et al.*, 2007) It is into this tool that the Airline Response Model described in this dissertation is ultimately to be integrated. AIM simulates local air quality and climate change impacts, while noise is to be an added functionality after further development. Climate impacts are modelled using a parametric model developed based on runs from a global chemistry transport model. Because of the requirement to model local air quality impacts, the model includes detailed modelling at the airport level, like APMT, although this is accomplished by modelling flight delays at a lower level of fidelity than by APMT, and only as a function of airport capacity constraints, and not airspace capacity constraints. AIM models only 3 aircraft size categories, and, like AERO-MS, 2 age categories. The number of aircraft size categories is to be increased in future developments of the model. Passenger demand and air traffic growth are forecast using endogenous models, similar to AERO-MS, allowing partial equilibrium between supply and demand to be simulated by modelling changes in demand according to forecast fares, which, in turn, are modelled as a function of changing airline costs. Changes in demand are also modelled as a function of changes in passenger travel time, which is impacted by flight delays. The modelling of future technology development is not as advanced as that of APMT, but is more advanced than that of AERO-MS. The entry of specific new technologies into the fleet is modelled in detail using a fleet model as a function of the performance and costs of the new technology. AIM models environmental impacts, but does not take them to monetary values.

It also does not model the economic benefits of aviation. The estimation of both environmental costs and economic benefits is planned for future development. AIM operates with a base year of 2005. The characteristics of AIM are summarised and compared to those of the other integrated aviation-environment system models in Table A-1.

Table A-1. Comparison of Integrated Aviation Environment System Models

	AERO-MS	APMT	AIM
Developer	Dutch Civil Aviation Authority	MIT	University of Cambridge
Base year	1992 (some data updated to 1997)	Rolling, based on TAF and FESG)	2005
Fare modelling	• According to changes in airline cost	• According to changes in airline cost	• According to changes in airline cost
Demand modelling	• Passenger and freight • Partial equilibrium • Endogenous, as a function of changes in fares	• Passenger and freight • Partial equilibrium (to be upgraded to general equilibrium in future) • Input from TAF and FESG, modified according to changes in fares	• Passenger only • Partial equilibrium • Endogenous, as a function of changes in fares
Supply (air traffic) modelling	• Historical trends as a function of demand	• Input from TAF and FESG, modified according to modified demand	• Historical trends as a function of demand
No. of aircraft classes modelled	• 6 size categories • 3 range categories • 2 age categories	• 9 size categories • No range categorisation • No age categorization	• 3 size categories • No range categorisation • 2 age categories
Modelling flight network	Assumed identical to base year	Assumed identical to base year	Assumed identical to base year
Modelling of competition effects	None	None	None
Flight delay modelling	• Detour factor only	• Airport and airspace queuing models	• Airport queuing model
Modelling fleet turnover	Yes	Yes	Yes
Future technology modelling	• Fixed % fuel burn improvement	• Aircraft design optimisation	• Simulated fleet entry of specific technologies
Environmental impacts modelled	• Climate change	• Noise • Local air quality • Climate change	• Local air quality • Climate change
Climate modelling	• Simplified chemistry transport model	• Impulse response functions	• Parametric model based on chemistry transport model runs
Economic impact modelling	• Economic benefits	• Economic benefits • Environmental Costs (in Monetary values)	• None

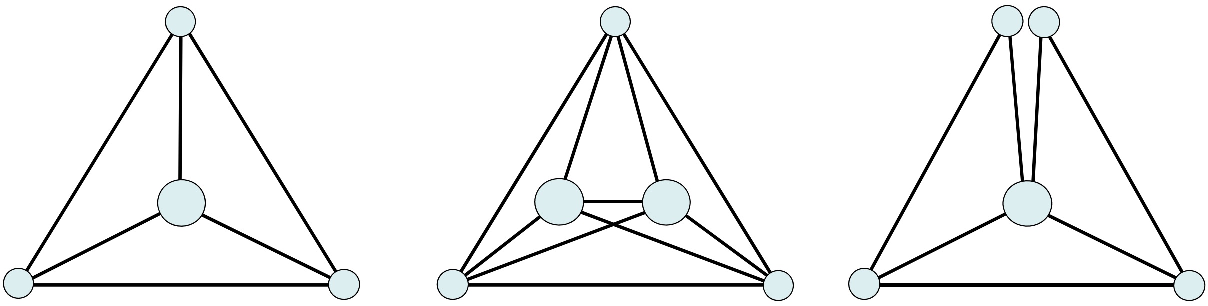
Appendix B: Model Application to Theoretical Networks

In order to test and illustrate the basic capabilities of the Airline Response Model, and to verify its suitability to capture fundamental system effects, the Airline Response Model was applied to several simplified networks. These networks were selected to be sufficiently simple to allow the airline operational responses to constraints to be clearly identifiable, and to make interpretation of the model results clear. The key airline operational responses simulated include changes in flight frequencies; changes in the degree to which a hub-and-spoke network is operated in favour of a point-to-point network; changes in the distribution of connecting traffic in a hub-and-spoke system between alternative hub airports; and changes in the distribution of O-D traffic within a multi-airport system. Each of these airline operational changes was examined in response to an airport capacity constraint, a key operational constraint in the air transport system. The networks selected for the analysis are as follows:

- Three spoke airports equidistant from a central hub airport, as illustrated in Figure B-1a. This network allows analysis of the effect of airport capacity constraints at a hub airport on a hub-and-spoke network, in which the hub capacity constraint can cause a reduction in traffic throughout the network, and a shift from hub-and-spoke operations to greater use of point-to-point operations.

- Three spoke airports surrounding two hub airports, as illustrated in Figure B-1b. This network allows analysis of the effect of airport capacity constraints at a hub airport on the distribution of traffic between that hub and an alternative hub, in which the hub capacity constraint can cause a shift in connecting traffic from the constrained hub to the alternative hub.

- Four spoke airports, two of which serve the same market (forming a multi-airport system), equidistant from a central hub airport, as illustrated in Figure B-1c. This network allows analysis of the effect of airport capacity constraints at one airport within a multi-airport system on the distribution of traffic within the system, in which the capacity constraint can cause a shift in O-D traffic from the constrained airport to the alternative.



(a) (b) (c)

Figure B-1. Simplified theoretical networks modelled – a) a hub-and-spoke network; b) a hub-and-spoke network with two hub airports; and c) a hub-and-spoke network with one spoke served by a multi-airport system of two airports.

The application of the model to each of these theoretical networks is described in detail below, followed by descriptions of the results in each case.

B.1 Simplified Hub-and-Spoke Network

Key input data used in the simulation of a simplified hub-and-spoke network is shown in Table B-1. While these inputs are hypothetical, they are based on typical values for the air transport system in the United States in 2005. Similarly, hypothetical populations and per-capita incomes are selected to generate the unconstrained demand between the cities accommodating the airports in Figure B-1a. The unconstrained passenger demand to the hub city is significantly greater than between the spoke cities. The reason for this is that hub-and-spoke networks take advantage of economies of scale at the hub, and therefore typically form with hubs in cities with high O-D demand (e.g., Chicago, Atlanta, Dallas, Houston, etc.).

Table B-1. Input Parameters for the Analysis of a Hub-and-Spoke Network.

Input Parameters		
Unconstrained demand [pax/yr]	Hub City – Spoke City	530,000
	Spoke City – Spoke City	230,000
Hub-spoke stage length [nmi]		430
Number of airlines serving each O-D market		2
Extra-network traffic[1] [flts/day]	Hub Airport	2,000
	Spoke Airport	500

[1] Flights between the modelled airports and other airports not within the modelled airport set.

The geographical distribution of the airports is defined by a spoke length of 430 nmi (500 miles), representing a relatively short-haul network. Given the network design presented in Figure B-1a, the distance between each of the spoke airports is therefore 750 nmi (866 miles). Competition is modeled by simulating two airlines serving the network, both of which operate the modeled hub airport as a hub. For simplicity, these two competing airlines are assumed to operate identical fleets and experience identical operating costs. Extra-network traffic, required to simulate airport flight delays, accounts for all flights from airports outside the network modelled. Revenues and costs from this extra-network traffic are not included in the profit maximization run by the Airline Response Model. Other key parameters, particularly airport capacities and aircraft performance and costs, are described in detail below. These are followed by a description of the modelling of airline fares and passenger demand.

Three scenarios are investigated, applying different airport capacities. While airport capacities are unconstrained at all spoke airports in each scenario, the capacity of the hub airport is increasingly restricted, from unconstrained, to 100 aircraft per hour (a medium capacity constraint, resulting in delays roughly equivalent to those at the worst delayed airports in the United States today), to 70 aircraft per hour (a severe capacity constraint, resulting in delays roughly equivalent to those projected for the worst delayed airports in the United States 20 to 25 years in the future, if airport capacities are not expanded). In the modelling of flight delays in each of these three scenarios, gate departure delays due to mechanical failures and late arrivals are ignored.

For simplicity, only one class of aircraft is modelled, representing the single-aisle, short/medium-haul Boeing B737 and Airbus A320 families of aircraft, which are the most widely operated commercial aircraft in the world (Kingsley-Jones, 2005). Aircraft performance data and cost data is specified by assuming that 25% of the fleet is an older aircraft type in this class, represented by the Boeing B737-300, and 75% is a newer aircraft type, represented by the Airbus A319. These percentages represent the distribution of aircraft in this class designed before and after 1995 in the United States in 2005 (OAG, 2005). Aircraft performance and cost data are applied as described in Sections 5.3 and 5.4. No landing fees are applied. Economies of scale, as described in Section 5.4, are applied to reduce the ground servicing costs at the hub airport relative to those at the spoke airports.

As described in Chapter 5.5, fares are modelled in the Airline Response Model by scaling base year observed fares according to modelled changes in operating costs per passenger. However, in the theoretical networks modelled, no base year fares exist. Therefore, it is assumed that fares are consistently 20% higher than city-pair O-D costs per passenger. Passenger demand is modelled to change in response to these fares, and changes in travel time and flight delay, as described in Section 5.6. Passenger value of travel time, passenger value of delay time and all parameter elasticities in the demand equation are specified as described in Section 5.6. Flight connecting times at the hub airport are assumed to be 40 minutes.

The Airline Response Model was run using the inputs from Table B-1 and those summarized above for each of the three airport capacity scenarios described. The results are presented in Figure B-2. The solid lines indicate flight frequencies, while the dashed lines indicate O-D passenger demand. In both cases, the thickness of the line provides an indication of its magnitude. Average O-D fares and the percentages of connecting passengers flying between the spoke airports are also shown.

In order to serve the 530,000 passengers per year between each spoke city and the hub, and the 230,000 passengers per year between each spoke city (non-stop and connecting), the network that maximises airline profit in the unconstrained scenario (Figure B-2a) is dominated by hub-and-spoke operations, with 16 flights per day (8 flights for each airline) between the spoke airports and the hub, and only 2 non-stop flights per day (1 for each airline) between the spoke airports. Slightly more than half of the passenger demand between the spoke cities, 57%, connects through the hub airport. The average fare between the spoke cities is nearly double that between the spoke cities and the hub ($159 versus $86). This is because of the greater distance travelled between the spoke cities, either non-stop (750 nmi) or connecting through the hub (860 nmi), than directly between the spoke cities and the hub (430 nmi). The airline cost per passenger between the spoke cities is therefore higher than that to the hub. If larger aircraft were operated between the spoke airports and the hub, the costs per passenger on this segment would be lower (larger aircraft typically have lower aircraft operating costs per passenger), reducing both fares, but particularly the fare from the spoke city to the hub. Because all airport capacities are unconstrained, flight delays are zero at both the hub and spoke airports.

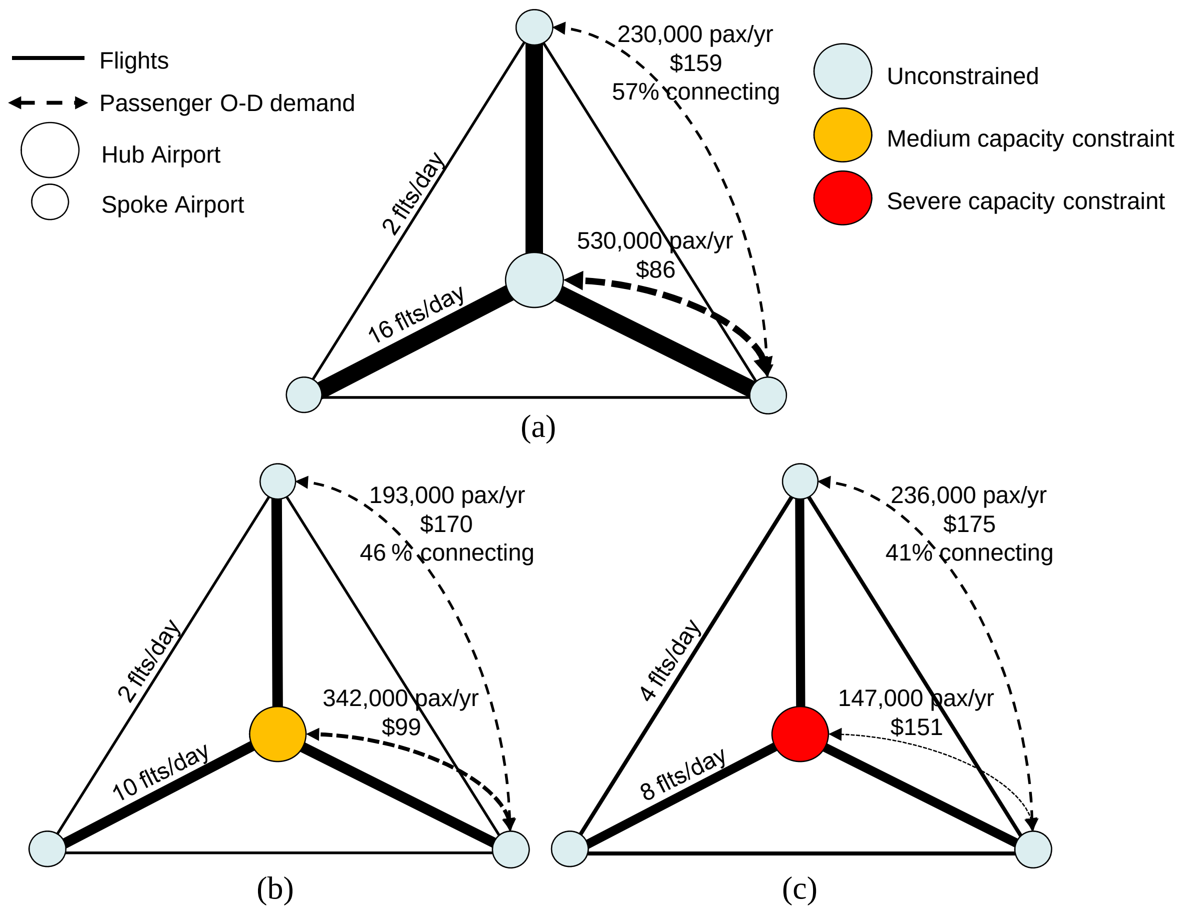


Figure B-2. Results for a simplified hub-and-spoke network with – (a) unconstrained airport capacities; (b) a medium capacity constraint at the hub; and (c) a severe capacity constraint at the hub.

The effect of a medium capacity constraint at the hub airport on the network can be seen in Figure 6-2b. The flight network that maximises airline profit is less dominated by hub-and-spoke flights, with the flight frequency between the spoke airports and hub dropping from 16 flights per day to 10 flights per day (5 for each airline). Although the number of flights between the spoke cities remains at 2 flights per day (1 for each airline), the percentage of passengers flying between the spoke cities that connect through the hub drops from 57% to 46%. O-D passenger demand between the hub and spoke cities reduces from 530,000 passengers per year predicted in the unconstrained scenario, to 342,000 passengers per year under the medium hub capacity constraint. This reduction in O-D passenger demand primarily results from an increase in flight delay, caused by an average arrival delay of 35 minutes at the hub airport. The demand response is particularly sensitive to the increase in flight delays at the hub because of the passenger value of delay time applied, which is about three times the passenger value of travel time applied. Average fare also increases, because of an increase in airline costs from the hub to the spoke airport, associated with the increase in flight delays. This increased fare is also a contributor to the decrease in O-D passenger demand between the hub and the spoke cities. Because of the reduced O-D passenger demand on the route, and the reduction in connecting passengers, the number of flights that are operated between the spoke and hub is reduced by 6 flights per day (3 flights by each airline).

Under the medium hub capacity scenario, O-D passenger demand between the spoke cities decreases from 230,000 passengers per year, predicted in the unconstrained scenario, to 193,000 passengers per year. This decrease in demand is due to both the 35 minute flight delay incurred by the 46% of passengers that connect through the hub airport, and the increase in average fares between the spoke cities from $159 to $170. The overall drop in demand is not as severe as the drop in demand between the spoke and hub cities because 56% of passengers fly non-stop, avoiding the flight delays at the hub. Average fares increase between the spoke cities because of the passengers connecting through the hub airport, to whom a portion of the cost increases associated with the flight delays are allocated.

The effects observed in Figure B-2b are stronger in Figure B-2c, where the hub airport capacity is further constrained. The network that maximises airline profit under this severe hub capacity constraint is characterized to an even lesser degree by hub-and-spoke flights, with the flight frequency between the spoke airports and hub dropping to 8 flights per day (4 for each airline), and the flight frequency between the spoke airports increasing to 4 flights per day (2 for each airline). The percentage of passengers flying between the spoke cities that connect through the hub drops further to 41%. O-D passenger demand between the hub and spoke cities reduces further, to 147,000 passengers per year, primarily as a result of an increase in the average arrival delay at the hub airport to 57 minutes. Average fares between the spoke cities and the hub also increase significantly to $151 because of the increase in costs associated with the increase in delays.

In contrast to the declining demand between the spoke cities and the hub, O-D passenger demand between the spoke cities in Figure B-2c increases to 236,000 passengers per year. This is greater even than the 230,000 passengers per year predicted in the unconstrained scenario. This increase in demand is because the weighted average O-D passenger travel time between the spoke airports, including both the non-stop and connecting passengers, is reduced relative to the unconstrained scenario, despite the increase in delay at the hub. Only 41% of the O-D passengers between the spoke airports connect through the hub, and thus experience the 57 minute delay at the hub. The rest fly non-stop. The combined effect is a slight increase in O-D demand between the spoke cities. Average fares increase from $159 to $175 because of the 41% of passengers connecting through the hub airport, to whom a portion of the large cost increases associated with the flight delays are allocated. However, this increase in fare is not enough to offset the benefit of the lower delays incurred by the non-stop passengers and the shorter travel time.

The simplified theoretical network modelled in this example shows how the network selected by an airline to maximise its profits can change as hub airports become capacity constrained. It is noted, however, that the dominant impact of flight delays is to reduce passenger demand, and that network change is a secondary effect. This network change may, however, still have a significant effect on the environmental impact of aviation, causing a shift in the distribution of emissions between airports. It is also noted that the degree to which an airline operates a hub-and-spoke network is highly dependent on demand and competition in each city-pair market, so the effect of airport capacity constraints to cause a shift from hub-and-spoke operations to point-to-point operations may be hidden by demand and competition effects in more complex networks. Particularly, as demand between spoke cities increases, there is a general shift to more point-to-point operations, as there is enough passenger demand between smaller city-pairs to make a larger number of point-to-point flights profitable.

Airport capacity constraints may also cause changes in the distribution of connecting traffic between hub airports; and changes in the distribution of O-D traffic within a multi-airport system. These effects are examined in the following two sections, although in less detail than the example above.

B.2 Distribution of Traffic between Hubs

The second theoretical network simulated – a system of three spoke airports surrounding two hub airports, shown in Figure B-1b – illustrates the capability of the Airline Response Model to distribute traffic between hub airports with different capacity constraints.

Key input data is shown in Table B-2. As for the hub-and-spoke network in Section B.1, these inputs are hypothetical, but are based on typical values for the U.S. air transport system in 2005. Two airlines are again modelled, and both are assumed to operate hubs at both hub airports, so they compete directly. All other input data, with the exception of airport capacities, are identical to that described in Section B.1. Airport capacities are described in detail below.

Table B-2. Input Parameters for Analysis of the Distribution of Traffic between Hubs.

Input Parameters		
Unconstrained demand [pax/yr]	Hub City – Hub City	750,000
	Hub City – Spoke City	330,000
	Spoke City – Spoke City	120,000
Spoke-centre distance [nmi]		430
Hub-hub distance [nmi]		260
Number of airlines serving each O-D market		2
Extra-network traffic [flts/day]	Hub Airport	2,000
	Spoke Airport	500

Airport capacities are specified for each of the airports for two scenarios. In the first scenario, airport capacities are unconstrained at all airports. In the second scenario, the capacity of one of the two hub airports is limited to 95 aircraft per hour, while the other hub airport and the spoke airports are left unconstrained. Under the simulated traffic levels, the capacity constraint of 95 aircraft per hour is severe, resulting in delays roughly equivalent to those projected at the worst delayed airports in the United States 20 to 25 years in the future, if airport capacities are not expanded. The Airline Response Model is run using the inputs from Table B-2 and those summarized above for each of the two airport capacity scenarios described. Figure B-3 presents flight frequency results for each of the scenarios. Passenger demand, fares and the percentage of connecting passengers are not included in order to aid readability. Changes in passenger demand and the flight network are, however, described below.

In order to serve the 330,000 passengers per year between each spoke city and each hub city, and the 120,000 passengers per year between each spoke city (non-stop and connecting), the network that maximises airline profit in the unconstrained scenario (Figure B-3a) distributes the traffic between the spoke airports symmetrically between the two hub

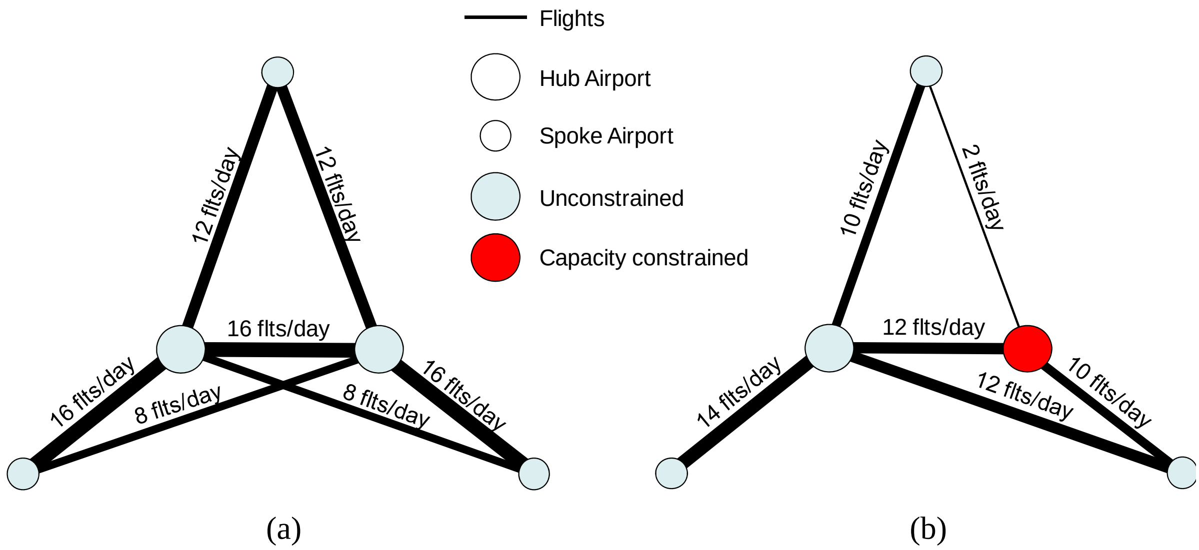


Figure B-3. Results for distribution of traffic between two hubs – (a) both of which are unconstrained; and (b) one of which is capacity constrained.

airports in a pure hub-and-spoke network. An equal number of flights (12 flights per day) are scheduled to each hub when the spoke airport is equidistant from both hub airports (the top spoke airport in Figure B-3a), while more flights (16 flights per day versus 8 flights per day) are scheduled to the respective closer hub, because of the lower costs associated with flying the shorter distance to the closer hub. Flights are also scheduled between the two hub airports (16 flights per day) to serve the 750,000 passengers per year between the hub cities and any connecting passengers from the spoke airports.

The effect of a capacity constraint at one of the two hub airports (the right hub) on the network can be seen in Figure B-3b. Because of delays at the constrained hub airport, O-D passenger demand to the constrained hub drops and connecting traffic shifts away from the constrained hub to the unconstrained hub. These effects result in a sharp decrease in all flight frequencies to the constrained hub, and a sharp increase in the flight frequency between the spoke airport located closest to the constrained hub (the lower right spoke airport) and the unconstrained hub (from 8 flights per day to 12 flights per day). Other flight frequencies to the unconstrained hub reduce slightly, because of a reduction in O-D passenger demand connecting through the unconstrained hub to the constrained hub. This decrease in demand is larger than the increase in passengers connecting through the unconstrained hub between the spoke airports. All O-D demand between the constrained hub airport and the spoke airport closest to it (the lower right spoke airport) flies non-stop, hence the still relatively high flight frequency between these airports (10 flights per day), even if it is significantly lower than in the unconstrained scenario (16 flights per day). All passengers flying between the constrained hub airport and the spoke airport furthest from it (the lower left spoke airport) connect through the unconstrained hub. Hence there are no non-stop flights between these airports.

This example illustrates the capability of the model to simulate airline decisions to distribute traffic between hubs, based on the delays experienced at each hub. It is noted, however, that a number of factors that affect an airline's decision in selecting hubs for connecting flights are not captured in the model, including existing airline presence at the hub airport and incentives provided by airport authorities. The model may however indicate to what extent airlines may switch operations to alternative hubs that they already operate.

B.3 Distribution of Traffic in a Multi-Airport System

The third and final theoretical network simulated – a simplified hub-and-spoke network with one spoke served by a multi-airport system of two airports, shown in Figure B-1c – illustrates the capability of the Airline Response Model to distribute traffic between airports in a multi-airport system with different capacity constraints. Key input data is shown in Table B-3. As in Sections B.1 and B.2, these inputs are hypothetical, but are based on typical values for the U.S. air transport system in 2005. Two airlines are again modelled, and both are assumed to operate at both airports in the multi-airport system, so they compete directly. All other input data, with the exception of airport capacities, are identical to that described in Section B.1. Airport capacities are described in detail below.

Table B-3. Input Parameters for Analysis of the Distribution of Traffic in a Multi-Airport System.

Input Parameters		
Unconstrained demand [pax/yr]	Hub City – Spoke City	650,000
	Spoke City – Spoke City	140,000
Hub-spoke stage length [nmi]		430
Number of airlines serving each O-D market		2
Extra-network traffic [flts/day]	Hub Airport	2,000
	Spoke Airport	500

Airport capacities are specified for each of the airports for three scenarios. In the first scenario, airport capacities are unconstrained at all airports. In the second scenario, the capacity of one of the spoke airports in the multi-airport system is limited to 35 aircraft per hour, while the other airports, including the hub, are left unconstrained. Under the simulated traffic levels, the capacity constraint applied to the spoke airport in the multi-airport system is severe, and results in delays roughly equivalent to those projected for the worst delayed airports in the United States 20 to 25 years in the future, if airport capacities are not expanded. In the final scenario, the capacity of both airports in the multi-airport system is limited, but to different degrees – one with a medium capacity constraint of 40 aircraft per hour, and the other with a severe capacity constraint of 35 aircraft per hour. The other airports in the network are left unconstrained. Under the simulated traffic levels at the airport, the medium capacity constraint results in delays that are roughly equivalent to those at the worst delayed airports in the United States today, while the severe capacity constraint is the same as for the second scenario.

The Airline Response Model was run using the inputs from Table B-3 and those summarized above for each of the three airport capacity scenarios described. Figure B-4 presents the flight frequency results for each of the scenarios.

In order to serve the 650,000 passengers per year between each spoke city and the hub, and the 140,000 passengers per year between each spoke city (non-stop and connecting), the network that maximises airline profit in the unconstrained scenario (Figure B-4a) distributes the traffic between the airports in the multi-airport system equally between the two airports (9 flights per day each), with the rest of the system forming a pure hub-and-spoke network. 18 flights per day are operated from the hub to each of the other spoke airports.

The effect of a capacity constraint at one of the airports in the multi-airport system (the left airport) on the otherwise unconstrained network can be seen in Figure B-4b. In this scenario, all the flights from the hub airport are routed to the unconstrained airport because of the flight delays at the constrained airport. The constrained airport does not serve any traffic in the network. Instead the system forms a pure hub-and-spoke network with the unconstrained airport in the multi-airport system forming a spoke in the system, with 18 flights per day operated between each of the spokes and the hub. All O-D passenger demand from the multi-airport city is routed through the unconstrained airport. It is noted that because

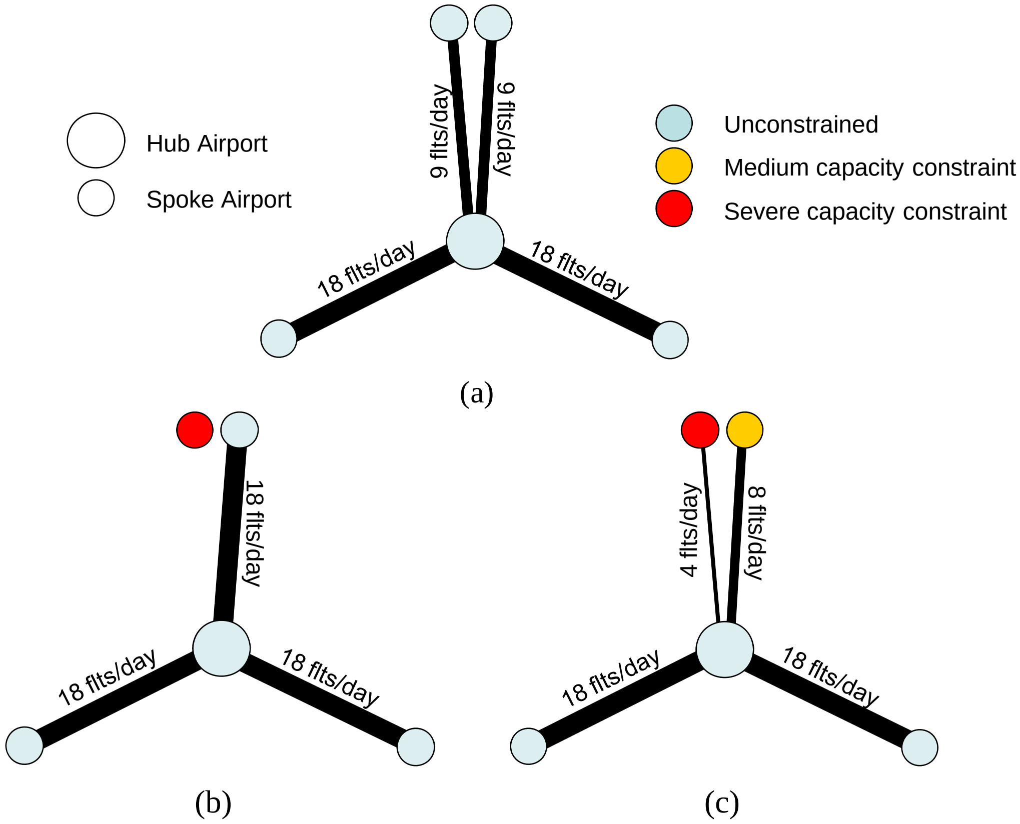


Figure B-4. Results for distribution of traffic in a multi-airport system of two airports – a) both of which are unconstrained; b) one of which is capacity constrained; and c) both of which are capacity constrained, but to different degrees.

each airport has exogenously specified extra-network traffic, there are still high delays at the constrained airport, even though no traffic operates there in the network modelled.

The effect that different capacity constraints at the airports in the multi-airport system have on the network can be seen in Figure B-4c. One airport (the left airport) has a severe capacity constraint, while the other has a medium capacity constraint. In this scenario, the flights from the hub airport to the multi-airport city are distributed between the two airports. Because of the higher flight delays, the more constrained airport (the left airport) receives less traffic than the less constrained airport (4 flights per day versus 8 flights per day). It is noted that the total number of flights between the two airports in the multi-airport system (12 flights per day) is less than the number of flights to the other spokes (18 flights per day). The reason for this is the reduction in demand caused by the flight delays in the multi-airport system.

This example illustrates the capability of the model to simulate airline decisions to distribute traffic between airports in a multi-airport system, based on the delays experienced at each airport. It is noted that a number of factors not captured in this model also affect an airline's choice of airports in a multi-airport system, such as proximity to urban areas, accessibility, facilities, and existing airline presence at an airport.

Appendix C: Detailed Model Validation Results

This appendix presents the data and model results validating the Airline Response Model, referenced in Section 6.1. The data and results presented include the following:

- Table C-1. Observed Annual O-D Demand.
- Table C-2. Modelled Annual O-D Demand.
- Table C-3. Observed Segment Flight Frequencies (Flights per Day)
- Table C-4. Simulated Segment Flight Frequencies (Flights per Day)
- Table C-5. Difference between Simulated and Observed Segment Flight Frequencies (Flights per Day).
- Table C-6. Percentage Difference between Simulated and Observed Segment Flight Frequencies.

Table C-1. Observed Annual O-D Demand.

	Non-Network Airports	New York	Chicago	Atlanta	Washington	Los Angeles	Dallas / Fort Worth	Houston	San Francisco	Miami	Denver	Detroit	Philadelphia	Boston	Seattle
Non-Network Airports		363,000	183,000	177,000	269,000	292,000	186,000	114,000	167,000	184,000	144,000	98,000	93,000	112,000	225,000
New York	367,000		1,697,000	1,376,000	1,076,000	2,133,000	724,000	522,000	1,418,000	2,999,000	553,000	538,000	16,000	898,000	416,000
Chicago	186,000	1,705,000		579,000	1,034,000	1,105,000	556,000	392,000	774,000	739,000	497,000	458,000	543,000	539,000	320,000
Atlanta	179,000	1,384,000	569,000		962,000	558,000	479,000	290,000	339,000	576,000	280,000	233,000	388,000	391,000	162,000
Washington	272,000	1,082,000	1,031,000	966,000		997,000	549,000	387,000	752,000	908,000	489,000	371,000	15,000	1,112,000	324,000
Los Angeles	293,000	2,151,000	1,114,000	567,000	1,002,000		807,000	513,000	3,719,000	529,000	692,000	379,000	439,000	586,000	1,102,000
Dallas / Fort Worth	186,000	726,000	558,000	483,000	548,000	806,000		791,000	371,000	258,000	313,000	154,000	200,000	244,000	184,000
Houston	114,000	525,000	392,000	297,000	388,000	516,000	796,000		304,000	192,000	262,000	128,000	189,000	158,000	127,000
San Francisco	166,000	1,422,000	773,000	344,000	752,000	3,723,000	371,000	305,000		259,000	507,000	191,000	314,000	615,000	926,000
Miami	185,000	3,006,000	744,000	583,000	914,000	531,000	260,000	196,000	257,000		201,000	317,000	520,000	674,000	113,000
Denver	143,000	552,000	499,000	286,000	486,000	692,000	312,000	261,000	509,000	201,000		136,000	190,000	265,000	272,000
Detroit	98,000	541,000	457,000	234,000	369,000	377,000	152,000	128,000	192,000	312,000	136,000		133,000	157,000	94,000
Philadelphia	94,000	15,000	538,000	389,000	13,000	438,000	200,000	188,000	314,000	516,000	191,000	133,000		501,000	111,000
Boston	111,000	885,000	535,000	392,000	1,107,000	580,000	242,000	157,000	613,000	667,000	264,000	155,000	491,000		165,000
Seattle	226,000	416,000	317,000	162,000	323,000	1,102,000	184,000	126,000	934,000	112,000	268,000	94,000	111,000	164,000	

Table C-2. Modelled Annual O-D Demand.

	Non-Network Airports	New York	Chicago	Atlanta	Washington	Los Angeles	Dallas / Fort Worth	Houston	San Francisco	Miami	Denver	Detroit	Philadelphia	Boston	Seattle
Non-Network Airports		363,000	183,000	177,000	269,000	292,000	186,000	114,000	167,000	184,000	144,000	98,000	93,000	112,000	225,000
New York	367,000		1858,000	789,000	2,724,000	1,266,000	591,000	551,000	928,000	1,287,000	457,000	874,000	33,000	1391,000	409,000
Chicago	186,000	1858,000		647,000	1,538,000	1,043,000	589,000	547,000	705,000	1,375,000	432,000	972,000	817,000	635,000	349,000
Atlanta	179,000	789,000	647,000		723,000	451,000	275,000	288,000	294,000	488,000	169,000	312,000	318,000	267,000	126,000
Washington	272,000	2,724,000	1,538,000	723,000		1,280,000	502,000	450,000	666,000	1,459,000	291,000	880,000	20,000	958,000	323,000
Los Angeles	293,000	1,266,000	1,043,000	451,000	128,0000		591,000	597,000	2,373,000	979,000	544,000	414,000	697,000	422,000	678,000
Dallas / Fort Worth	186,000	591,000	589,000	275,000	502,000	591,000		533,000	317,000	399,000	214,000	228,000	261,000	208,000	148,000
Houston	11,4,000	551,000	547,000	288,000	45,0000	597,000	533,000		380,000	422,000	188,000	250,000	287,000	200,000	168,000
San Francisco	166,000	928,000	705,000	294,000	666,000	2,373,000	317,000	380,000		712,000	342,000	304,000	317,000	441,000	588,000
Miami	185,000	1287,000	1,375,000	488,000	1,459,000	979,000	399,000	422,000	712,000		249,000	507,000	785,000	633,000	244,000
Denver	143,000	457,000	432,000	169,000	291,000	544,000	214,000	188,000	342,000	249,000		174,000	182,000	164,000	176,000
Detroit	98,000	874,000	972,000	312,000	880,000	414,000	228,000	250,000	304,000	507,000	174,000		395,000	216,000	176,000
Philadelphia	94,000	33,000	817,000	318,000	2,0000	697,000	261,000	287,000	317,000	785,000	182,000	395,000		629,000	167,000
Boston	111,000	1,391,000	635,000	267,000	958,000	422,000	208,000	200,000	441,000	633,000	164,000	216,000	629,000		154,000
Seattle	226,000	409,000	349,000	126,000	323,000	678,000	148,000	168,000	588,000	244,000	176,000	176,000	167,000	154,000	

Table C-3. Observed Segment Flight Frequencies (Flights per Day).

	Non-Network Airports	ORD	ATL	DFW	LAX	IAH	DEN	DTW	PHL	EWR	IAD	JFK	LGA	BOS	MIA	SFO	SEA	DCA	MDW	OAK	HOU	DAL	ONT
Non-Network Airports		754	777	507	222	162	342	252	290	116	304	167	198	152	61	124	302	350	253	205	157	108	101
ORD	533		24	24	22	17	16	19	22	22	18	1	32	20	11	16	13	24	0	2	0	0	0
ATL	530	25		29	13	14	17	15	25	25	26	7	25	17	20	10	5	21	12	2	12	0	3
DFW	363	25	30		18	16	22	9	12	11	8	4	13	9	9	11	10	13	9	4	10	0	5
LAX	205	23	13	18		9	19	7	9	11	11	24	0	8	5	23	16	1	6	26	4	0	0
IAH	140	17	14	16	10		15	9	10	9	3	1	9	5	9	7	6	10	0	2	0	3	3
DEN	261	17	17	23	20	15		7	9	6	7	2	6	7	3	14	14	4	10	5	0	0	4
DTW	169	18	14	10	6	9	7		9	6	11	4	15	7	4	3	3	10	8	0	0	0	0
PHL	244	23	25	12	8	10	9	9		1	6	1	3	19	7	6	2	5	6	1	1	0	0
EWR	113	21	25	11	11	10	7	5	1		14	0	0	14	8	7	7	4	6	0	0	0	0
IAD	249	19	26	8	11	3	9	11	6	14		15	7	15	4	9	5	0	2	4	0	0	0
JFK	150	1	7	4	25	1	2	4	1	0	15		0	14	6	14	5	5	0	5	0	0	2
LGA	179	31	26	13	0	9	7	14	4	0	8	0		36	9	0	0	35	9	0	2	0	0
BOS	132	20	17	9	7	5	5	7	19	15	17	14	36		6	7	2	29	3	2	0	0	0
MIA	58	10	20	9	5	9	3	4	7	8	4	6	9	6		3	1	7	0	0	0	0	0
SFO	102	16	10	11	23	7	14	3	6	7	9	14	0	8	3		15	0	2	0	0	0	1
SEA	288	13	6	10	16	6	15	4	2	7	4	5	0	2	1	15		2	3	14	0	0	4
DCA	332	24	22	13	1	10	4	9	6	4	0	5	35	29	7	0	2		4	0	0	0	0
MDW	245	0	12	9	6	0	10	8	6	6	2	0	9	3	0	2	3	4		6	5	0	0
OAK	199	3	2	4	27	2	5	0	1	0	4	5	0	2	0	0	14	0	6		1	0	12
HOU	138	0	12	10	4	0	0	0	1	0	0	0	2	0	0	0	0	0	5	1		26	0
DAL	88	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	26		0
ONT	101	0	3	5	0	3	4	0	0	0	0	2	0	0	0	1	4	0	0	12	0	0	

Table C-4. Simulated Segment Flight Frequencies (Flights per Day).

	Non-Network Airports	ORD	ATL	DFW	LAX	IAH	DEN	DTW	PHL	EWR	IAD	JFK	LGA	BOS	MIA	SFO	SEA	DCA	MDW	OAK	HOU	DAL	ONT
Non-Network Airports		754	777	507	222	162	342	252	290	116	304	167	198	152	61	124	302	350	253	205	157	108	101
ORD	533		31	19	22	14	19	23	19	16	23	2	34	16	4	14	12	13	0	8	0	1	3
ATL	530	31		22	14	15	11	16	17	17	25	3	13	13	23	8	7	9	7	0	6	1	3
DFW	363	19	22		21	12	20	8	8	7	11	2	14	9	15	12	11	8	10	12	3	0	8
LAX	205	22	14	21		12	25	10	5	8	5	16	4	8	4	18	7	4	11	38	3	2	0
IAH	140	14	15	12	12		11	4	5	8	9	2	6	7	17	4	5	3	0	7	0	5	2
DEN	261	19	11	20	25	11		7	6	7	13	2	7	6	8	14	14	4	7	12	1	0	3
DTW	169	23	16	8	10	4	7		17	9	19	3	25	16	4	4	7	7	11	5	3	0	3
PHL	244	19	17	8	5	5	6	17		4	6	2	4	17	4	4	5	4	8	6	1	0	0
EWR	113	16	17	7	8	8	7	9	4		29	0	0	20	16	6	4	7	11	7	0	0	0
IAD	249	23	25	11	5	9	13	19	6	29		12	19	10	4	4	5	0	6	7	2	0	0
JFK	150	2	3	2	16	2	2	3	2	0	12		0	9	3	6	2	2	1	2	0	0	2
LGA	179	34	13	14	4	6	7	25	4	0	19	0		45	10	3	3	36	12	3	7	0	2
BOS	132	16	13	9	8	7	6	16	17	20	10	9	45		4	4	4	18	7	0	0	0	2
MIA	58	4	23	15	4	17	8	4	4	16	4	3	10	4		4	4	3	0	0	0	0	0
SFO	102	14	8	12	18	4	14	4	4	6	4	6	3	4	4		9	3	2	0	0	0	2
SEA	288	12	7	11	7	5	14	7	5	4	5	2	3	4	4	9		4	5	14	3	0	10
DCA	332	13	9	8	4	3	4	7	4	7	0	2	36	18	3	3	4		7	2	3	0	0
MDW	245	0	7	10	11	0	7	11	8	11	6	1	12	7	0	2	5	7		3	6	0	7
OAK	199	8	0	12	38	7	12	5	6	7	7	2	3	0	0	0	14	2	3		3	0	21
HOU	138	0	6	3	3	0	1	3	1	0	2	0	7	0	0	0	3	3	6	3		22	4
DAL	88	1	1	0	2	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22		0
ONT	101	3	3	8	0	2	3	3	0	0	0	2	2	2	0	2	10	0	7	21	4	0	

Table C-5. Difference between Simulated and Observed Segment Flight Frequencies (Flights per Day). (Positive numbers indicate model over-prediction, while negative numbers indicate model under-prediction.)

	Non-Network Airports	ORD	ATL	DFW	LAX	IAH	DEN	DTW	PHL	EWR	IAD	JFK	LGA	BOS	MIA	SFO	SEA	DCA	MDW	OAK	HOU	DAL	ONT
Non-Network Airports		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ORD	0		7	-5	0	-3	3	4	-3	-6	5	1	2	-4	-7	-2	-1	-11	0	6	0	1	3
ATL	0	6		-7	1	1	-6	1	-8	-8	-1	-4	-12	-4	3	-2	2	-12	-5	-2	-6	1	0
DFW	0	-6	-8		3	-4	-2	-1	-4	-4	3	-2	1	0	6	1	1	-5	1	8	-7	0	3
LAX	0	-1	1	3		3	6	3	-4	-3	-6	-8	4	0	-1	-5	-9	3	5	12	-1	2	0
IAH	0	-3	1	-4	2		-4	-5	-5	-1	6	1	-3	2	8	-3	-1	-7	0	5	0	2	-1
DEN	0	2	-6	-3	5	-4		0	-3	1	6	0	1	-1	5	0	0	0	-3	7	1	0	-1
DTW	0	5	2	-2	4	-5	0		8	3	8	-1	10	9	0	1	4	-3	3	5	3	0	3
PHL	0	-4	-8	-4	-3	-5	-3	8		3	0	1	1	-2	-3	-2	3	-1	2	5	0	0	0
EWR	0	-5	-8	-4	-3	-2	0	4	3		15	0	0	6	8	-1	-3	3	5	7	0	0	0
IAD	0	4	-1	3	-6	6	4	8	0	15		-3	12	-5	0	-5	0	0	4	3	2	0	0
JFK	0	1	-4	-2	-9	1	0	-1	1	0	-3		0	-5	-3	-8	-3	-3	1	-3	0	0	0
LGA	0	3	-13	1	4	-3	0	11	0	0	11	0		9	1	3	3	1	3	3	5	0	2
BOS	0	-4	-4	0	1	2	1	9	-2	5	-7	-5	9		-2	-3	2	-11	4	-2	0	0	2
MIA	0	-6	3	6	-1	8	5	0	-3	8	0	-3	1	-2		1	3	-4	0	0	0	0	0
SFO	0	-2	-2	1	-5	-3	0	1	-2	-1	-5	-8	3	-4	1		-6	3	0	0	0	0	1
SEA	0	-1	1	1	-9	-1	-1	3	3	-3	1	-3	3	2	3	-6		2	2	0	3	0	6
DCA	0	-11	-13	-5	3	-7	0	-2	-2	3	0	-3	1	-11	-4	3	2		3	2	3	0	0
MDW	0	0	-5	1	5	0	-3	3	2	5	4	1	3	4	0	0	2	3		-3	1	0	7
OAK	0	5	-2	8	11	5	7	5	5	7	3	-3	3	-2	0	0	0	2	-3		2	0	9
HOU	0	0	-6	-7	-1	0	1	3	0	0	2	0	5	0	0	0	3	3	1	2		-4	4
DAL	0	1	1	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-4		0
ONT	0	3	0	3	0	-1	-1	3	0	0	0	0	2	2	0	1	6	0	7	9	4	0	

Table C-6. Percentage Difference between Simulated and Observed Segment Flight Frequencies. (Positive numbers indicate model over-prediction, while negative numbers indicate model under-prediction.)

	Non-Network Airports	ORD	ATL	DFW	LAX	IAH	DEN	DTW	PHL	EWR	IAD	JFK	LGA	BOS	MIA	SFO	SEA	DCA	MDW	OAK	HOU	DAL	ONT
Non-Network Airports		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ORD	0		29	-21	0	-18	19	21	-14	-27	28	100	6	-20	-64	-13	-8	-46	0	300	0	Inf	Inf
ATL	0	24		-24	8	7	-35	7	-32	-32	-4	-57	-48	-24	15	-20	40	-57	-42	-100	-50	Inf	0
DFW	0	-24	-27		17	-25	-9	-11	-33	-36	38	-50	8	0	67	9	10	-38	11	200	-70	0	60
LAX	0	-4	8	17		33	32	43	-44	-27	-55	-33	Inf	0	-20	-22	-56	300	83	46	-25	Inf	0
IAH	0	-18	7	-25	20		-27	-56	-50	-11	200	100	-33	40	89	-43	-17	-70	0	250	0	67	-33
DEN	0	12	-35	-13	25	-27		0	-33	17	86	0	17	-14	167	0	0	0	-30	140	Inf	0	-25
DTW	0	28	14	-20	67	-56	0		89	50	73	-25	67	129	0	33	133	-30	38	Inf	Inf	0	Inf
PHL	0	-17	-32	-33	-38	-50	-33	89		300	0	100	33	-11	-43	-33	150	-20	33	500	0	0	0
EWR	0	-24	-32	-36	-27	-20	0	80	300		107	0	0	43	100	-14	-43	75	83	Inf	0	0	0
IAD	0	21	-4	38	-55	200	44	73	0	107		-20	171	-33	0	-56	0	0	200	75	Inf	0	0
JFK	0	100	-57	-50	-36	100	0	-25	100	0	-20		0	-36	-50	-57	-60	-60	Inf	-60	0	0	0
LGA	0	10	-50	8	Inf	-33	0	79	0	0	138	0		25	11	Inf	Inf	3	33	Inf	250	0	Inf
BOS	0	-20	-24	0	14	40	20	129	-11	33	-41	-36	25		-33	-43	100	-38	133	-100	0	0	Inf
MIA	0	-60	15	67	-20	89	167	0	-43	100	0	-50	11	-33		33	300	-57	0	0	0	0	0
SFO	0	-13	-20	9	-22	-43	0	33	-33	-14	-56	-57	Inf	-50	33		-40	Inf	0	0	0	0	100
SEA	0	-8	17	10	-56	-17	-7	75	150	-43	25	-60	Inf	100	300	-40		100	67	0	Inf	0	150
DCA	0	-46	-59	-38	300	-70	0	-22	-33	75	0	-60	3	-38	-57	Inf	100		75	Inf	Inf	0	0
MDW	0	0	-42	11	83	0	-30	38	33	83	200	Inf	33	133	0	0	67	75		-50	20	0	Inf
OAK	0	167	-100	200	41	250	140	Inf	500	Inf	75	-60	Inf	-100	0	0	0	Inf	-50		200	0	75
HOU	0	0	-50	-70	-25	0	Inf	Inf	0	0	Inf	0	250	0	0	0	Inf	Inf	20	200		-15	Inf
DAL	0	Inf	Inf	0	Inf	67	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-15		0
ONT	0	Inf	0	60	0	-33	-25	Inf	0	0	0	0	Inf	Inf	0	100	150	0	Inf	75	Inf	0	