COMPARISON OF OPTIMAL AIRLINE NETWORK ROUTING TO OPERATIONS IN THE UNITED STATES

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Abstract

This paper presents a comparison of an optimal flight routing network, including flight frequencies offered on that network, to the existing network operated by airlines in the United States in 2005. The routing networks, flight frequencies, and airline system profitability of the respective systems are compared. The optimal flight routing network was generated by minimising airline system costs whilst constraining true origin-ultimate destination (O-D) flight frequencies to model airline competition – a different approach to typical airline network optimisation approaches, which optimise individual airline networks. The flight routing network optimisation was run for three cases with varying constraints applied. In the first case no constraints were applied apart from those essential to model airline operations and competition. In the second case constraints were applied to reproduce the distribution of traffic between airports in multi-airport systems, the distribution of connecting itineraries between hub airports, and load factors. In addition to these constraints, the third case also constrains the types of aircraft operated. The latter two cases were run in order to capture effects that the network optimisation model does not capture directly, including airline constraints to operate at specific airports in multi-airport systems, at specific hub airports, with specific load factors, and with specific aircraft types.

The results of the comparison suggest that airline system profitability could be improved by increased use of hub and spoke operations. The results also suggest that airlines profitability is limited by constraints on the composition of their aircraft fleet, the hub airports from which they operate, the airports within multi-airport systems at which they operate, and the load factors operated. Finally, the results presented in this paper also suggest that airlines compete more by frequency than required by the competition model run, suggesting that profitability may be improved by reduced frequency from all carriers. The total decrease in system profitability resulting from sub-optimal flight network routing ranges from $1.08 Billion to $3.80 Billion (2005 US Dollars) for the 10 city/16 airport system analysed in the paper.

1. Introduction

Worldwide demand for air travel has shown significant growth over the past five decades. Between 1960 and 2005 worldwide scheduled passenger air travel grew from 109 billion passenger-km travelled to 3.7 trillion – an average growth rate of over 8% per year (IPCC, 1999 and ICAO, 2006). Despite this growth, however, the world airline industry has not shown consistent profits in recent years, but has instead cycled between net system profit and net system loss. Since 1966, world airline industry net system profits have ranged from +$9 Billion (1997) to -$13 Billion (2001) (year 2000 US Dollars) (Jiang & Hansman 2006). The causes of the challenges in making money in the airline industry, including the strong competition in the industry, are the topic of many papers and books, but are not discussed in this paper. The varied profitability of the industry does however illustrate the need for airlines to optimise their operations in order to maximise profit. Much research has been carried out by both the airlines and the research community to support this.

Lohatepanont and Barnhart (2004) describe an approach to optimise an individual airline's schedule planning process in detail, including schedule design and fleet assignment by flight. The optimisation is designed to maximise the airline's profits by simultaneously optimising the selection of flight segments and the assignment of aircraft types to those segments. Lederer and Nambimadom (1998) describe a more aggregate approach, also for an individual airline. This approach optimises total flight frequencies over specified time periods. An objective function is solved to maximise the airline's profit for a series of network alternatives. The objective function accounts for airline costs and costs to the passenger, 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).

In contrast to these approaches, which maximise an individual airline's profit, this paper seeks to examine the airline system as a whole, and to optimise the operations of all airlines together to maximise system profit while constraining the system to capture the effects of inter-airline competition. While allowing the effects of competition to be modelled exogenously, this approach maximises system profit instead of each individual airline's profit. The profitability of the resulting operations can then be compared to the operations actually flown by the airlines in the past, and the differences between them examined. This may allow potential sources of improved profitability to be identified. In order to ensure that the optimal solution modelled does not reduce the level of service offered by the airlines, only the routing network and flight frequencies are optimised, with true origin-ultimate destination[1] (O-D) passenger demand and fares specified according to the historical data to which the results are compared.

The modelling approach is described in section 2. Section 3 describes the results of the model, run for a network of 16 airports serving 10 cities in the United States in 2005, and compares these results to the actual routing network and flight frequencies operated by the airlines in 2005. This is followed by a discussion of the results in section 4, and a summary and conclusions in section 5.

2. Network Optimisation Model Description

The modelling approach applied is based on selection of a flight routing network (here referring to both the routing of flights and the frequency of flights offered in the routing network) to maximise airline system profit, whilst ensuring that sufficient frequency is offered to capture the effects of competition.

In order to simplify the problem and to avoid any change in the level of service offered by the airlines, O-D passenger demand and fares are assumed to be constant. This ignores the impact that changes in the flight routing network may have on passenger demand through changes in cost (which affect fares), and changes in passenger travel time. These effects could be captured by integrating the model with models that simulate passenger demand, airline operating costs, flight delays, and fares. Such an approach is described by Evans et al. (2008). The integration of the network optimisation model developed with such models is not examined further in this paper, but is instead reserved for future work.

Because O-D passenger demand and fares are given, system revenue remains constant. Airline system profits can then be maximised by minimising costs. This is done using large scale linear programming methods, similar to the approach used by Harsha (2005). Airline system costs are based on airline operating cost per flight, flight segment frequencies, airline cost per passenger, passengers flown by itinerary, airline spill cost, and total spill[2]. Airline operating costs are modelled as a function of fuel burn rates, stage length, and flight delay (including delays incurred in airborne holding and delays incurred on the taxiway at engine idle), each of which are taken from input data. The objective function is presented in equation 1 below.

$$\min\left(\sum_{m,n,k} C_{flt\,m,n,k}\cdot x_{m,n,k}+\sum_{i,j}\sum_{p\in P_{i,j}} C_{pax\,i,j}\cdot P_{i,j}^{p}+\sum_{i,j} Spill_{i,j}\cdot SpillCost_{i,j}\right) \tag{1}$$

where $C_{flt\ m,n,k}$ represents average cost *per flight* on the flight segment between airports m and n, for aircraft type k; $x_{m,n,k}$ represents average flight frequency per day on the flight segment between airports m and n, using aircraft type k, for all airline operating on the segment; $C_{pax\ i,j}$ represents average cost *per passenger* between O-D city pair i and j; $P_{i,j}^{\ p}$ represents passenger demand between O-D city pair i and j, on itinerary p; $Spill_{i,j}$ presents total spilled passengers between O-D city pair i and j; and $SpillCost_{i,j}$ is the cost to the airline per spilled passenger between O-D city pair i

[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 direct routes and routes through intermediate points).
[2] Spill is the total number of passengers who want to fly but cannot obtain a reservation due to insufficient capacity provided by the airlines.

and j. It is assumed that spill cost per passenger is equal to average fare between the O-D city pair.

The decision variables in the objective function are average flight frequency per day by flight segment by type ($x_{m,n,k}$), passenger demand per day *by itinerary* ($P_{i,j}{}^{p}$), and spill ($Spill_{i,j}$) per day by O-D market. The objective function is constrained by a system of linear equations describing airline routing and scheduling requirements and limitations. These are as follows:

- A demand constraint restricting the demand served (the sum of the passenger demand between O-D city pair i and j over itineraries $P_{i,j}{}^{p}$) to be equal to the total O-D demand $D_{i,j}$ between O-D city pair i and j specified from data. This implies no spill ($Spill_{i,j}=0$). This constraint is applied because the specified demand is the demand served in 2005, and does not include any spilled demand that was not served.
- A seat constraint limiting the number of passengers served on each flight segment to be less than or equal to the number of seats available. This constraint may include a specification of a maximum load factor possible in any given flight. In this paper this maximum load factor is specified at 95%.
- A balance constraint limiting the number of flights of each aircraft type departing from an airport on any day to equal the number of flights of that aircraft type arriving at that airport, and vice versa.
- A competition constraint limiting the total O-D flight frequencies ($x_{i,j}$) between O-D city pair i and j to be greater than or equal to the flight frequency required of a competitive market. This constraint ensures that the flight frequencies estimated by the model account for the effects that competition has on increasing frequencies. The identification of the minimum O-D flight frequency required of a competitive market is described below.
- It is assumed that airlines have the option to route passengers directly between their origin and destination, or on a connecting itinerary through a hub. Itineraries are, however, constrained to include no more than one connection. Multiple connections are therefore not modelled. The hubs through which the model is able to route itineraries are specified as an input.
- Segment flight frequencies per aircraft type per day ($x_{m,n,k}$) are constrained to be positive integers. Demand by itinerary per day ($P_{i,j}{}^{p}$) is also constrained to be positive.

Schipper et al., (2003) and Carlsson (2002) describe a formulation for estimating the equilibrium average fare and flight frequency on a competitive market as a function of passenger value of time, airline costs and passenger demand. This formulation is derived by defining the flight schedule as an address (or spatial) model, assuming homogenous passenger demand and homogeneous airlines, and solving a two stage game to maximise each airline's profit. 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 equations derived for equilibrium average fare and flight frequency are shown below. Equation 3 only applies to markets served by more than two airlines, and provides an estimation of the O-D flight frequency (including both direct and connecting flights) required on a market to model the effects of competition. This flight frequency is applied as a constraint in the network optimisation described above.

$$Fare^{l} = C_{pax}{}^{l} + \frac{\theta_2}{nx^{l}} \tag{2}$$

$$nx^{l} = \sqrt{\frac{\theta \cdot D}{C_{flt}{}^{l}}\left(\frac{n-2}{n}\right)} \tag{3}$$

$Fare^{l}$ represents the equilibrium average fare of airline l for the O-D city-pair market examined; $C_{pax}{}^{l}$ represents the average cost per passenger of airline l; θ represents the passenger value of schedule delay[3]; n represents the number of airlines serving the market; x^{l} represents equilibrium

[3] Schedule delay refers to the time difference between when a passenger wants to fly, and when the flight which he/she chooses to fly on departs. In this paper passenger value of schedule delay is assumed to be equal to passenger value of travel time.

O-D flight frequency of airline l on the market including direct and connecting flights, D represents O-D passenger demand on the market; and $C_{flt}^{\ l}$ represents average cost per flight of airline l.

Schipper (2001, pp.178) describes how costs are distinguished per passenger or per flight based on their escapability, or the time period needed before the cost can be avoided. Costs that are dependent on the airline schedule, and are thus escapable only by changing the schedule, may be classed as costs per flight, and may include many variable direct operating costs such as crew costs, fuel costs, and airport charges. Schipper (2001, pp.178) suggests that this includes about 50% of all total operating costs. Costs that are related to the passenger, including costs associated with in-flight meals, handling costs, and other passenger expenses are only escapable by changing fares and schedules (and thus demand). Schipper (2001, pp.178) suggests that this includes only about 8.5% of all total operating costs. These ratios of cost per flight and cost per passenger to total operating cost are applied in this paper. The results presented in this paper are not highly sensitive to these values.

The model makes a number of simplifications. Particularly, a number of constraints on the current system and on the way in which airlines currently operate are not modelled. These include the following:

- The distribution of passenger demand through the day varies significantly. This distribution is typically matched to the extent possible by the distribution of flights in the daily schedule. However, because of the requirement to make equipment and crew connections, flights must often be scheduled when there is not enough demand to fill the aircraft. Average load factors on any given route may thus vary significantly from near 100%, to well below it. The model developed in this paper does not model the distribution of passenger demand or schedules through the day, nor does it model equipment and crew connections. The model does not therefore capture the effect of these constraints on flight frequencies, unless directly constrained by actual average load factors operated per route. In this paper the model is run with and without this constraint. Without this constraint, the model is likely to under-predict some flight frequencies – particularly on routes with low load factors.
- Airlines typically operate only a few primary hub airports. Their operation of these hub airports is often for historical reasons, such as growth from regional operations in one part of the country or the take over of a regional airline. An airline’s reason for operating from a specific hub is therefore not always because the location of the hub is convenient to serve all destinations offered by the airline. The benefits of hub and spoke operations are also increased when only a few hubs are operated, because it allows more O-D markets to be served with fewer aircraft. In the model described in this paper, the airline system is optimised, including all airline operations. The model does not include any airline specific constraints to route itineraries through specific hubs. The model does not therefore capture the effect of airline hub constraints on the routing network, unless the distribution of itineraries between hubs is constrained directly to match historical data. In this paper the model is run with and without this constraint.
- As described by Bolgeri et al. (2008), airlines typically operate from specific airports in multi-airport systems. As with hub airports, airline’s operation of airports in a multi-airport system is often for historical reasons, or because of the location of the airport, and not always because the costs of operations at the airport are the lowest. The model does not include any airline specific constraints to operate from specific airports in multi-airport systems, or model demand as a function of the location of the airport. It only models the cost of operations at each airport. The model does not therefore capture the effect of airline airport constraints on the routing network, unless the distribution of flights from airports within multi-airport systems is constrained directly to match historical data. In this paper the model is run with and without this constraint.
- Airlines purchase or lease aircraft to operate their chosen schedules and routing network. While forecast network operations drive the purchasing and leasing of aircraft in the long term, at the time of aircraft delivery, the available fleet constrains airline scheduling and the selection of a routing network in the short term. The purchase and leasing of new aircraft is also constrained by the existing fleet. Airlines require flexibility to swap aircraft between different flight segments, and swap crews between different aircraft. Airlines also select aircraft of the same type to reduce maintenance costs. For this reason airlines typically operate a large number of specific types of medium to small size (100 to 200 seats, which

can serve low and medium demand routes) with transcontinental range, such as Boeing B737 series aircraft or Airbus A319/320/321 series aircraft. Fleet constraints, including both the constraints to operate aircraft already owned or leased by the airline, and the constraints on the purchase or leasing of new aircraft are not modelled. The model does not therefore capture the effects of these fleet constraints on the routing network, unless the types of aircraft on each flight segment are specifically constrained to match historical data. In this paper the model is run with and without this constraint. Without this constraint, the model may under predict the number of some classes of aircraft (such as the Boeing B737/Airbus A320 class).

- The model makes the assumption that the routing of passenger itineraries is entirely at the discretion of the airline, while the total O-D demand between city pairs is fixed. In reality O-D demand varies between direct and connecting itineraries, and is impacted by travel time and fares, which are impacted by cost. Fares particularly are specified through advanced revenue management procedures (price discrimination). These effects are also not modelled.

Because of the simplifications in the model, and the lack of any constraints specific to any one airline, it is noted that this model is not capable of recommending an optimal flight routing network for any one airline. Instead, the model is intended to generate a system optimal flight routing network that can be compared to the flight routing network actually operated by the airlines in order to identify how airline profitability could be improved generally.

3. Model Results Comparison to Airline Operations in 2005

The optimal flight routing model developed was run for a network of 16 airports[4] serving the 10 cities[5] with highest passenger demand in the United States in 2005. The resulting optimal flight routing network was compared to the flight routing network operated in 2005, according to historical data (USDOT 2007, 2005). This airport and city set includes cities served by single airports (Atlanta, Detroit, Phoenix and Seattle), cities served by multiple airports (Chicago, Dallas/Fort Worth, Houston, New York City and Washington), hub airports (ORD, ATL, DFW, LAX, IAH, EWR, IAD, DTW and PHX), and highly congested airports (average arrival delays over 15 minutes: ORD, ATL, EWR, JFK and LGA). It is noted that the airport set modelled also serves connecting O-D demand between cities not included in the city set e.g. O-D demand from Anchorage to Atlanta connecting through SEA, and therefore flown on the flight segment between SEA and ATL, but not included in the demand modelled. Because the highest demand cities are captured, the magnitude of the demand not accounted for is small. The flight frequencies estimated by the model will, however, be slightly lower than the flight frequencies operated by the airlines in 2005. In future research this extra-network demand will be accounted for.

The input data to the model is derived specifically for the air transport system in the United States in 2005. Three aircraft types are modelled – a small aircraft type, a medium aircraft type, and a large aircraft type (applying aircraft performance data for a Boeing B737-300, a B767-300, and a B747-400 respectively). All performance data is derived from the EUROCONTROL Base of Aircraft Data (BADA) (EUROCONTROL 2004) and the International Civil Aviation Organisation Aircraft Engine Emissions Databank (ICAO 2007). Aircraft cost data is extracted directly from the US Department of Transport Form41 data (USDOT 2005) for 2005, with the exception of fuel costs, which are taken from Air Transport Association (ATA) data (ATA 2008), and landing fees, which are taken from the International Air Transport Association's Airport and Air Navigation Changes Manual (IATA 2008). Passenger value of time is derived from data from the US Department of Transport data (USDOT 1997), adjusted to 2005 dollars. Flight delays at each airport are extracted from the US Federal Aviation Administration's ASPM database (FAA 2008).

The optimal flight routing network generated by the model was compared to the existing network operated by the airlines in 2005 by comparing the following parameters:

[4] Chicago O'Hare (ORD), Chicago Midway (MDW), Atlanta (ATL), Dallas-Fort Worth (DFW), Dallas Love (DAL), Los Angeles (LAX), Houston International (IAH), Houston Hobby (HOU), Detroit (DTW), Phoenix (PHX), Newark (EWR), New York Kennedy (JFK), New York LaGuardia (LGA), Washington Dulles (IAD), Washington National (DCA), and Seattle Tacoma (SEA).

[5] Chicago, Atlanta, Dallas/Fort Worth, Los Angeles, Houston, Detroit, Phoenix, New York City, Washington, and Seattle.

- Seats available between O-D city pairs;
- Flight frequencies available between O-D city pairs (including direct and connecting flights); and
- Flight segment frequencies between airport pairs.

Comparison of each of these parameters allows the differences between the networks to be examined at different levels. A comparison of the seats between O-D city pairs captures how the airlines supply seats to serve the specified O-D demand, without consideration of how this is impacted by either aircraft types operated (affecting aircraft sizes), or how aircraft and passengers are routed (which hub is used, if any, and which airport is used in a multi-airport system). A comparison of the flights between O-D city pairs captures how the airlines supply seats to serve the specified O-D demand, and what aircraft are used to do this, without consideration of the exact routing operated. Comparison of the flight segment frequencies between airport pairs, however, captures all elements of how the airlines serve the demand, including how they supply seats, what aircraft they operate, and how they route the aircraft and passengers. This final parameter reveals the most information about the differences between the networks, but is also very sensitive to any differences. A relatively small change in operations, such as operation of a flight from a different airport in a multi-airport system, or routing passengers through a different hub, may completely change the segment flight frequencies, implying a misleadingly large difference in operations.

Each of the parameters described above are compared over the entire system modelled according to an average percentage difference, which indicates the extent to which the flight frequencies defining the optimal flight routing network are lower or higher than the historical data; and an R-squared value, which indicates the extent to which the optimal routing network represents the historical data.

The relative performance of the optimal flight routing network and the existing network operated by the airlines in 2005 (the historical data) is examined by comparing the total operating profit of each system. In both the optimal and historical systems operating profit is calculated from basic principles: revenues by O-D market minus costs by flight segment.

Finally, because of the limitations in the capability of the optimal model to capture certain constraints on the airline system, as described in section 2, a series of different model results were generated with different elements of the model constrained to match the historical data. This enables the differences between the optimal and historical systems to be more fully understood. The different cases that were run are as follows:

1. **Unconstrained Case:** In this case the optimal flight network routing model was run without constraints beyond those described in section 2.
2. **Constrained Case:** Because the model does not capture airline constraints to operate at specific airports in multi-airport systems, at specific hub airports, and with specific load factors, the model was run with constraints on the distribution of traffic between airports in multi-airport systems to match those of 2005 data, constraints on the distribution of connecting itineraries between hub airports to match those of 2005 data, and constraints on load factors to be no greater than those of 2005 data.
3. **Constrained Case, with Aircraft Types Specified:** Because airline selection of aircraft types is also impacted by a number of constraints that are not captured in the model, the model was also run with the proportions of aircraft types on all routes specified according to the 2005 data. All other constraints were identical to those of the constrained system case (case 2).

The results comparing the optimal flight routing network to the existing network operated by the airlines in 2005 are presented in Table 1. A map showing the routing network (with flight frequencies) flown by the airlines in 2005 is presented in Figure 1. Maps showing the differences between the flight frequencies offered by the optimal flight routing networks and by the flight routing network in 2005 in each of the three cases described above are presented in Figure 2 to Figure 4.

Table 1. Comparison of the optimal flight routing network identified by the model to the existing network operated by the airlines in 2005.

Case	O-D Seats		O-D Flight Frequencies		Segment Flight Frequencies		Increase in Profit [2005US$ - Billions]
	Avg. % diff.	R^2	Avg. % Diff.	R^2	Avg. % Diff.	R^2	
1	7% low	0.122	20% low	0.271	30% low	-	3.80
2	3% low	0.339	11% low	0.609	30% low	0.286	2.52
3	3% high	0.830	4% high	0.808	17% low	0.464	1.08

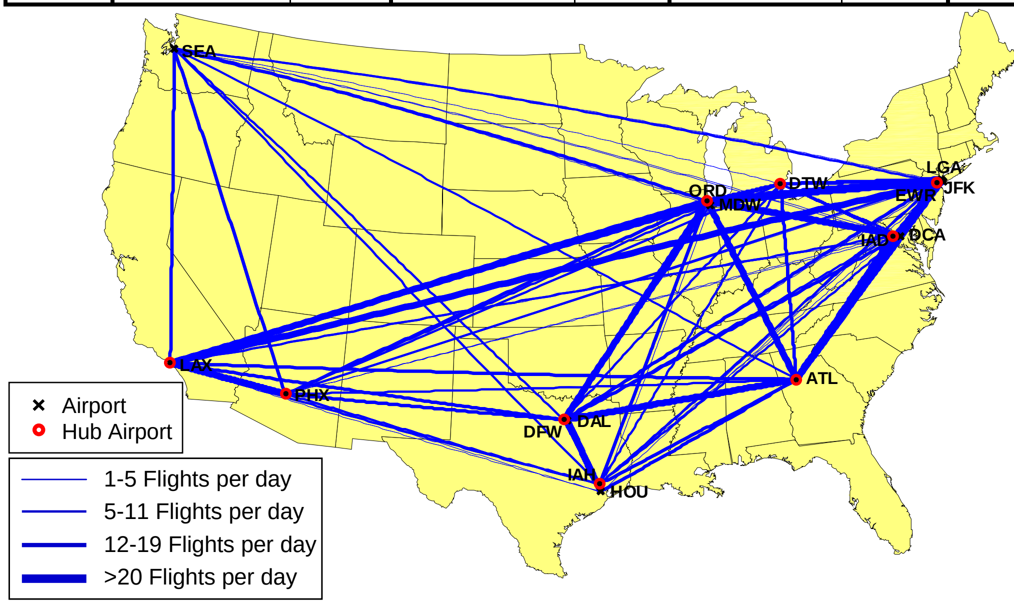

Figure 1. Flight routing network and frequencies operated in 2005 (actual data).

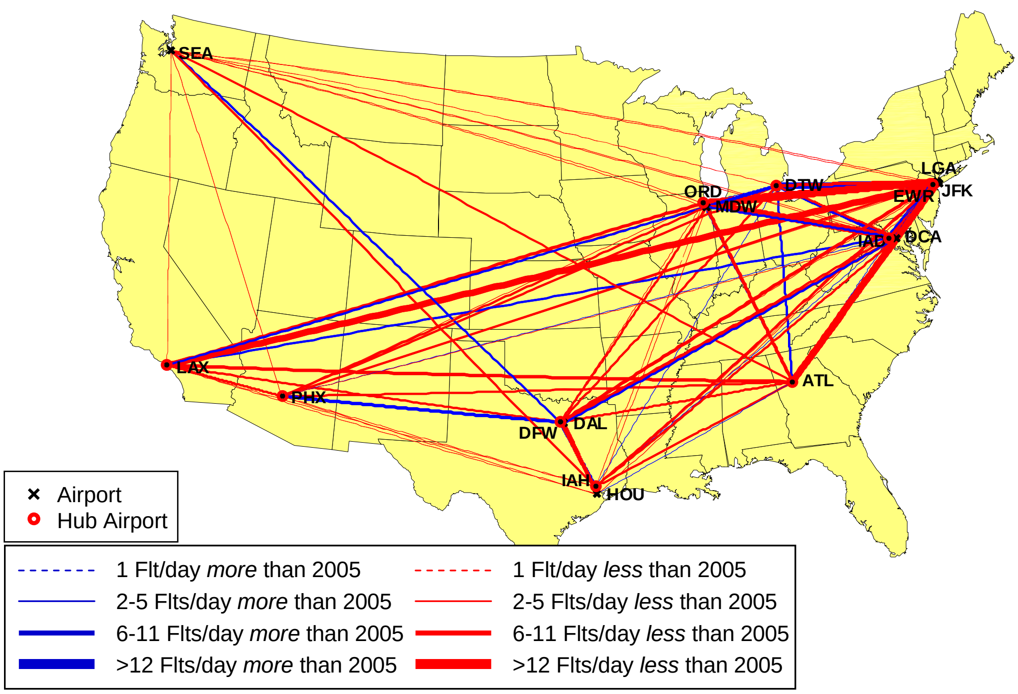

Figure 2. Difference between the optimal flight routing network modelled and the existing network operated in 2005, Case 1.

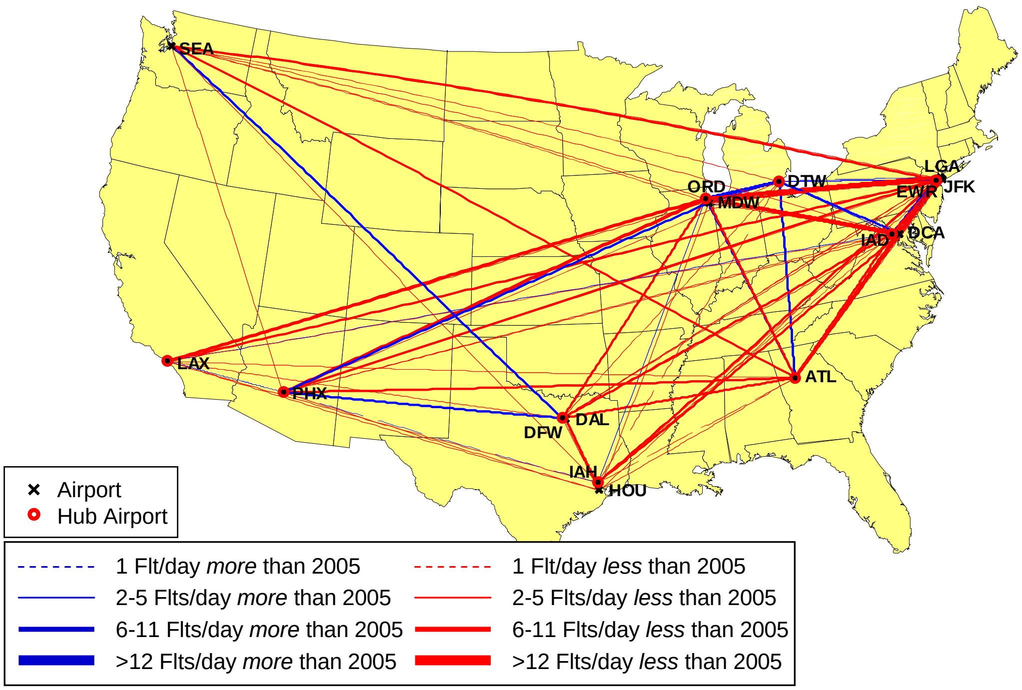

Figure 3. Difference between the optimal flight routing network modelled and the existing network operated in 2005, Case 2.

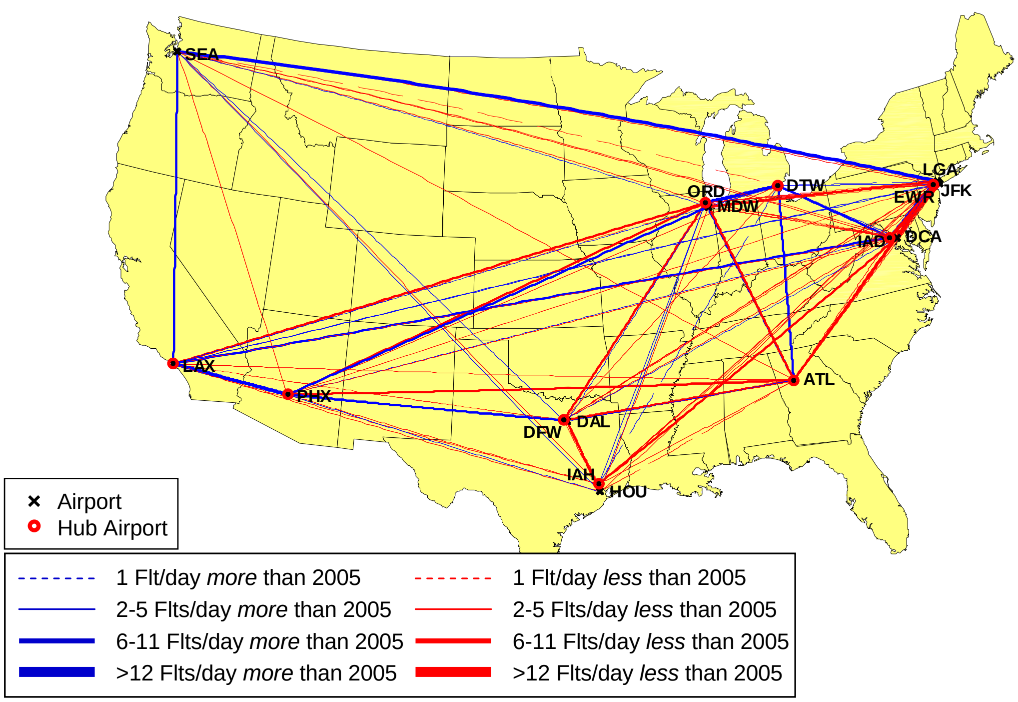

Figure 4. Difference between the optimal flight routing network modelled and the existing network operated in 2005, Case 3.

4. Discussion

Case 1: Unconstrained

The results presented in Table 1 for case 1, in which the unconstrained model results are compared to 2005 operations, show that the modelled flight routing network differs significantly from the existing network operated by the airlines in 2005. The model serves the O-D demand by offering slightly fewer seats on average between the O-D city pairs than were offered by the airlines in 2005 (7% less), although the variability in this difference over all O-D city pairs modelled is large, evidenced by the low R-squared of 0.122.

The model also serves the demand using on average a 20% lower O-D flight frequency (including direct and connecting flights) than was offered by the airlines in 2005. This is despite the application of the competition model described in section 2, suggesting that the airlines compete more by frequency than is captured by this model. Note that all the demand is still served, but that it is done so with fewer flights. On closer examination of the results this is found to be because the load factors operated by the model are significantly higher than those operated by the airlines in 2005 (in fact all are close to the maximum load factor of 95%), the model makes greater use of the hub and spoke system, and larger aircraft are operated. The R-squared for the O-D flight frequencies is also low (0.271), corresponding to the high average percentage difference.

The effect of the lower O-D flight frequencies offered by the model is carried through to the segment flight frequencies with the model operating 30% fewer flights on average per flight segment than operated by the airlines in 2005. Part of this is because of the extra-network demand that is not accounted for by the model. This large difference is also impacted by the model's inability to capture airline constraints to operate at specific airports in multi-airport systems, and at specific hub airports. These effects have a particularly large impact on the R-squared comparing modelled segment flight frequencies to those operated in 2005, because of the sensitivity of this parameter. The R-squared is outside the acceptable range, and is therefore not reported.

The differences between the optimal flight routing network and the existing network operated by the airlines in 2005 can be examined directly in Figure 2. It is clear that the optimal flight routing network operates fewer flights on most routes (red lines) than operated by the airlines in 2005. The greater use of the hub and spoke system is also visible, with the only increases in flights being to hubs. The largest differences in results are between cities with multi-airport systems, particularly New York City (EWR, LGA and JFK), where the model does not capture airline specific constraints to operate at specific airports.

The difference in system profit presented in Table 1 for case 1 suggests that, were the airlines able to operate a routing network and flight frequencies as generated by the model, they would be able to increase their profits (for all airlines) by $3.80 Billion (2005 US Dollars). This is a significant amount given that the routing network and flight frequencies operated by the airlines in this system (from the data) made a total loss of $2.53 Billion (2005 US Dollars) (calculated from first principles).

Case 2: Constrained

The results presented in Table 1 for case 2, in which the constrained model results are compared to 2005 operations, show that the modelled flight routing network differs significantly less from the existing network operated by the airlines in 2005 than in the unconstrained case (case 1), but still differs quite significantly. As in case 1, the model serves the O-D demand by offering slightly fewer seats on average between the O-D city pairs than were offered by the airlines in 2005 (3% less), although the variability in this difference over all O-D city pairs modelled is still large, although not as large as in case 1, evidenced by the R-squared of 0.339.

In case 2 the model serves the demand using on average a 11% lower O-D flight frequency (including direct and connecting flights) than was offered by the airlines in 2005. This still suggests that the airlines compete more by frequency than is captured by the competition model described in section 2, but to less of an extent than was suggested in case 1. The decrease in difference is because this case constrains the load factors operated by the model to be equal to those operated by the airlines in 2005. However, the model continues to operate larger aircraft and make greater use of the hubs than was done by the airlines in 2005. The R-squared for the O-D flight frequencies is significantly higher than in case 1 (0.609 versus 0.271), corresponding to the lower average percentage difference, and suggesting that the lower load factors have a significant impact on OD flight frequency.

The effect of the lower O-D flight frequencies offered by the model is again carried through to segment flight frequencies, but the added constraints do not appear to make much difference relative to case 1, as the model continues to operate 30% fewer flights on average per flight segment than operated by the airlines in 2005 – the same as in case 1. This is because the model does not account for extra-network demand, continues to operate larger aircraft, and makes greater use of the hubs than was done so by the airlines in 2005. The routing of connecting itineraries through hub airports is constrained to match those of the airlines in 2005, but the routing of passengers on direct or on connecting itineraries is not constrained. The operation of flights from specific airports within multi-airport systems is also constrained to match those of the airlines in 2005 in this case. Although these effects do not have a large impact on the percentage difference in flight frequencies, they do have a significant impact on the R-squared comparing modelled segment flight frequencies to those operated in 2005, increasing it to 0.286 (from -1.05).

The differences between the optimal flight routing network and the existing network operated by the airlines in 2005 can be examined directly in Figure 3. Figure 3 shows significantly less under-estimation of flight frequencies by the optimal flight routing model relative to 2005 operations than in case 1. The greater use of the hub and spoke system is still visible, although to a lesser extent, with the only increases in flights still being to hubs. The differences in flight frequencies to some of the multi-airport systems, particularly New York City (EWR, LGA and JFK), are smaller than in case 1, suggesting that the airline constraint to operate flights from specific airports in multi-airport systems has a significant effect on the flight routing network operated.

The difference in system profit presented in Table 1 for case 2 suggests that, were the airlines able to operate a routing network and flight frequencies as generated by the model, they would be able to increase their profits (for all airlines) by $2.52 Billion (2005 US Dollars). Although not as large as for case 1 it is still significant, and almost equal to the total loss made by the airlines in this system in 2005 of $2.53 Billion (2005 US Dollars) (calculated from first principles). It is also more realistic given the constraints applied to more accurately model the constraints on the real system.

Case 3: Constrained, with aircraft types specified

The results presented in Table 1 for case 3, in which the constrained model results, with ratios of aircraft types specified, are compared to 2005 operations, show that the modelled flight routing network differs significantly less from the existing network operated by the airlines in 2005 than in the unconstrained case (case 1) or the constrained case (case 2). The model serves the O-D demand by offering slightly more seats on average between the O-D city pairs than were offered by the airlines in 2005 (3% more). The variability in this difference over all O-D city pairs modelled is also very small in this case, evidenced by the high R-squared of 0.830.

In case 3 the model serves the demand using on average a 4% higher O-D flight frequency (including direct and connecting flights) than was offered by the airlines in 2005. This is because the aircraft sizes are constrained to match those operated by the airlines in 2005. In comparison to the model results in cases 1 and 2, smaller aircraft types are operated in this case, forcing the model to increase frequency to serve the demand. Like the R-squared for O-D seats, the R-squared for the O-D flight frequencies is also high (0.808), corresponding to the small average percentage difference.

The effect of the slightly higher O-D flight frequencies offered by the model is not carried through to the average segment flight frequencies in this case, with the model operating 17% fewer flights on average per flight segment than operated by the airlines in 2005. This difference is lower than that in cases 1 and 2, but is still significant. The model does not account for extra-network demand, and continues to make greater use of the hubs than was done by the airlines in 2005. The smaller difference between the average segment flight frequencies modelled and operated by the airlines in 2005 versus cases 1 and 2 carry through to increase the R-squared value to 0.464. This is larger than in cases 1 and 2, but is still not high, even for cross-sectional data. The optimal routing network, even with constraints applied to capture airline constraints and specifying aircraft types to match operations in 2005, is still therefore quite different from that operated in 2005.

The differences between the optimal flight routing network and the existing network operated by the airlines in 2005 can be examined directly in Figure 4. The majority of differences in flight frequencies in Figure 4 are less than 6 flights per day. The exceptions continue to be generally to hubs, illustrating the greater use of the hub and spoke system. Because of the increase in aircraft sizes, there are also more over-estimations of flight frequency relative to 2005 operations than in the other cases. Differences if flight frequencies can still be seen for New York City (EWR, LGA and JFK), but are not generally as large as in previous cases.

The difference in system profit presented in Table 1 for case 3 suggests that, were the airlines able to operate a routing network and flight frequencies as generated by the model, they would be able to increase their profits (for all airlines) by $1.08 Billion (2005 US Dollars). Although not as large as for case 1 or 2, it is still significant relative to the total loss made by the airlines in this system in

2005 of $2.53 Billion (2005 US Dollars) (calculated from first principles). It is also more realistic given the added constraints applied. It suggests that changes to how much the hub and spoke system is applied may indeed save the airlines money.

5. Summary and Conclusions

This paper presents a comparison of an optimal flight routing network, including flight frequencies offered on that network, to the routing network and frequencies operated by airlines in the United States in 2005. The optimal routing network and flight frequencies were generated by minimising airline system costs whilst constraining O-D flight frequencies to model the effects of airline competition. The flight routing network optimisation was run for three cases with varying constraints applied. In the first case no constraints were applied apart from those essential to model airline operations and competition. In the second case constraints were applied to reproduce the distribution of traffic between airports in multi-airport systems, the distribution of connecting itineraries between hub airports, and load factors. In addition to these constraints, in the third case also constrains the types of aircraft operated. The latter two cases were run to capture effects that the network optimisation model does not capture directly, including airline constraints to operate at specific airports in multi-airport systems, at specific hub airports, with specific load factors, and with specific aircraft types. These constraints had a significant impact on the results, suggesting future research to develop the model to include these effects endogenously.

The results of the comparisons suggest that airline system profitability could be improved by increased use of hub and spoke operation. It is noted, however, that the model does not treat direct and connecting flights serving the same O-D city pair as different markets, but as the same market. This allows connecting flights to be used in increase O-D flight frequency, when in fact, if direct routes could be considered a separate market, only increasing direct flights would provide the frequency required to be competitive.

The results also suggest that airlines profitability is limited by constraints on the composition of their aircraft fleet, the hub airports from which they operate, the airports within multi-airport systems at which they operate, and the load factors operated. The benefits of constraints on aircraft types, such as the increased flexibility and reduce maintenance costs from operating fewer aircraft types, must be compared to the decreases in profitability resulting from sub-optimal aircraft types on routes. Similarly, the costs of growing operations at more optimal hubs and less costly airports within multi-airport systems instead of at airports at which airlines already operate must be compared to the estimated decreases in profitability from sub-optimal flight network routing. Airlines must also optimise schedules to increase load factors, as is already underway in recent years.

The results presented also suggest that airlines compete more by frequency than required by the competition model used, suggesting that profitability may be improved by reduced frequency. Any reduction in frequency, however, would have to come from all airlines, in order to prevent loss in market share. This may be difficult to achieve in reality without incentives or regulation.

The total decrease in system profitability resulting from sub-optimal flight network routing was found to range from $1.08 Billion to $3.80 Billion (2005 US Dollars) for the 10 city/16 airport system analysed in this paper. This is significant in comparison to the total loss made in the system in 2005 of $2.53 Billion (2005 US Dollars).

The analysis presented can be extended by integrating the network optimisation model developed with other models that simulate passenger demand, airline operating costs, flight delays, and fares. Particularly, modelling of direct and connecting demand separately may improve the analysis.

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