Assessing the welfare impact of air network development

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1. Introduction

Many European airports face capacity problems, either already in the existing situation or in the near future. Amsterdam Airport is no exception. Runway capacity at Schiphol may not be the main bottleneck, but noise capacity is more problematic. Traffic growth and capacity problems may lead to changes in flight frequency, and more generally to changes in the development of the air network including the number of destinations served. In order to facilitate a rational decision making process concerning airport investment plans or possible policy measures to deal with capacity problems, it is essential to have an estimate of the welfare effects of such air network effects.

In a study commissioned by the Dutch Ministry of Transport, the authors have used a strategic air transport demand/supply equilibrium model (AEOLUS) to explore the potential future demand levels for different scenarios. The forecasts have been made for unconstrained and capacity constrained situations, in order to establish the effects of the expected air network developments and the possible policy measures on consumer value (Kouwenhoven et al, 2006).

In this short paper we describe the methodology we have used to estimate the consumer value of the different effects, and in particular air service frequency. We demonstrate how frequency increases are likely to increase the consumer value over time, at least as long as there is ample airport capacity available.

We use standard transport economic theory to explain our methodology, and examples of the practical work we have carried out for the Amsterdam Airport case to demonstrate the sorts of results we obtained. We shall demonstrate how the use of modern appraisal techniques has improved the decision making process concerning airport policy in the Netherlands.

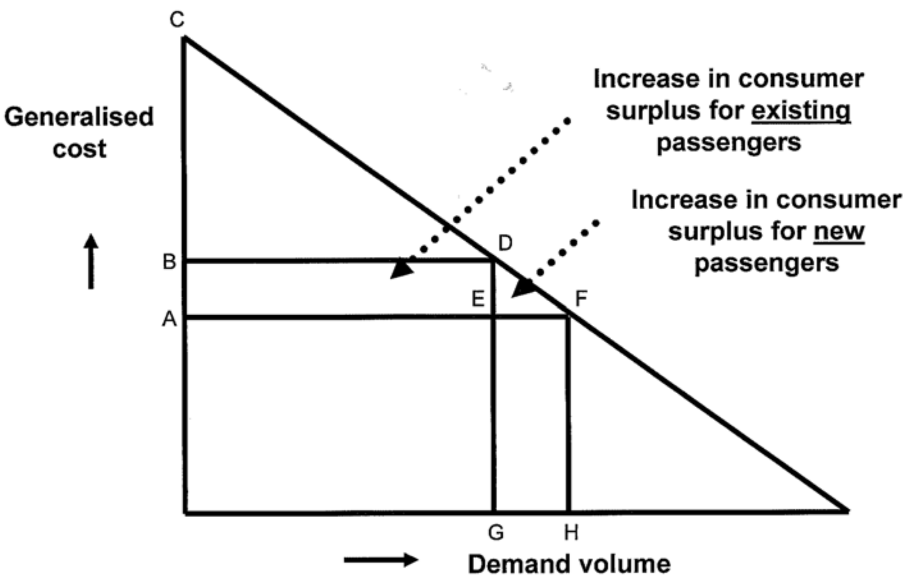
2. A bit of theory on welfare computation

In order to estimate the changes in consumer value as they arise from changes in air network level of service, we need to estimate the change in what economists call the consumer surplus. The consumer surplus is the amount that consumers benefit by being able to purchase a product for a price that is less than they would be willing to pay. To estimate the consumer surplus we need to know the demand function. In Fig. 1 this is illustrated for a simple linear demand function. In the base situation, at a generalised cost of B and volume of demand G the consumer surplus consists of the triangle BDC. When the generalised cost is reduced to A, the demand volume increases to H, and the new consumer surplus becomes AFC. The increase of the consumer surplus consists of two components:

- The area AEDB, which represents the reduced generalised cost (benefit) for the existing users, and
- The area EFD, which represents the reduced generalised cost (benefit) for the new users.

Note that the existing users obtain the full benefit, while the new users obtain in this case on average only half the benefit (this is the so-called rule of half).

Figure 1: Change in consumer surplus



So in order to estimate the change in the consumer surplus we need to know the demand function. The AEOLUS model represents air demand using three distinct components:

- An observed origin-destination data base of air travel;
- A traffic growth model, using demand elasticities;
- A competition model allocating passengers to airports and airlines.

The basic demand equation, in simplified form, is given in [1]:

$$V_{id}^{t} = V_{id}^{b} \cdot (GC_{id}^{t}/GC_{id}^{b})^{elast.} \cdot P_{i}^{t} / P_{i}^{b} \quad [1]$$

where: V_{id}^{t} = number of passengers travelling from airport i to destination d in year t
V_{id}^{b} = number of passengers travelling from airport i to destination d in the base year b
GC_{id}^{t} = generalised cost from i to d in year t
GC_{id}^{b} = generalise cost from i to d in the base year

elast = demand elasticity with respect to GC
P_i^t = the market share of airport i in year t
P_i^b = the market share of airport i in the base year b.

Both the growth factor model component and the competition model component use a generalised cost formulation to express the utility of travel:

$$GC_{id} = \alpha_1.Time_{id} + \alpha_2.Freq_{id} + \alpha_3.Fare_{id} + \alpha_4 \quad [2]$$

where: GC_{id} = generalised cost for travel from i to d
α_1 to α_4 = utility coefficients
$Time_{id}$ = travel time from airport I to destination d
$Freq_{id}$ = number of flights per day between airport I and destination d
$Fare_{id}$ = standard fare for flight from airport I to destination d.

In the competition model the use of the generalised cost is as follows:

$$P_i = \exp(V_i) / \Sigma \exp(V_j) \quad [3]$$

$$V_i = \mu.\ GC_{id} + \varepsilon \quad [4]$$

where μ = scale factor
ε = random error term.

Now the demand function [1] is more complicated than the simple linear demand function as used in Fig 1: the use of the logit model formulation for P_i introduces non-linearity in the demand function. This makes the computation of the change in consumer surplus more complicated.

We proceed by computing the consumer surplus effects of the growth model and the competition model separately, and then multiplying them. We start by computing the consumer surplus effect for the competition model, by using what is called the logsum (De Jong *et al.* 2006):

$$Logsum^t = \ln \Sigma \exp(V_j^t) \quad [5]$$

This logsum is a measure of the expected utility, or generalised cost, of the choice situation for a single traveller. By taking the difference between the logsum in year t and the logsum in the base year, we obtain a measure of the change in expected generalised cost due to the change in the choice situation.

Then we use this change in generalised cost to compute the demand effect using the elasticity based growth model. Essentially this is the same as the simple method outlined in Fig. 1 above, but now assuming a constant elasticity relation between demand volume and cost. We apply this as follows:

- First we compute the change in expected generalised cost between year t and the base year, due to changes in the choice situation, using the logsum method

- Then we compute the benefits for the existing users, by multiplying the change in logsum value by the volume of travellers in the base year
- Then we compute the number of new travellers, by using the growth model
- Then we compute the benefits for the new travellers by multiplying half the change in logsum value by the volume of new travellers
- Finally we sum both benefit components to obtain the total benefits.

3. Empirical evidence on air service frequency effects

In order to apply the demand equations given in the previous section, we need to know the key coefficients. The demand growth elasticities can be obtained from meta-analyses on the main determinants of air travel, such as GDP, trade and price. These can be found for instance in Brons et al. (2002). Ratio's between the coefficients of travel time and travel cost, also called the value-of-time, can be widely found in the literature. But there is not a lot of evidence on the size of the frequency effect.

If we start from theoretical reasoning, we can develop different approaches:

- One possible approach is based upon the number of choice options: if we express the choice of a particular flight out of all available flights on that day as a discrete choice (logit) model, and if all flights are on average (for the "average" traveller) equally attractive, then the frequency cost becomes proportional to the natural logarithm of the number of choice alternatives (i.e. flight frequency):

  $$\text{Frequency cost}_{id} = 1.0\ \ln(\text{frequency}_{id})/\text{cost coefficient} \qquad [6]$$

  For instance, if we increase flight frequency from 10 flights/day to 12 flights/day, and if the cost coefficient is equal to -0.02, than this frequency increase represents a generalised cost reduction from ln(10)/-0.02=-115.1 to ln(12)/-0.02=-124.2, or decrease of 9.1 Euro.

- Another possible approach is based upon the notion of waiting time: if we assume that all flights are spread uniformly over the day, that demand is also spread uniformly over the day, and that punctuality is perfect (all flights are on schedule), then the average waiting time for airport i can be estimated as:

  $$\text{Frequency cost}_{id} = 0.5\ .\ 16^{1}\ /\text{frequency}_{id}\ (\text{max. 4 hours})\ \text{x VoT} \qquad [7]$$

  For instance, if we increase flight frequency from 10 flights/day to 12 flights/day, and if the value of time is equal to 50 Euro/hour, than this frequency increase represents a generalised cost reduction from 0.5x16/10x50=40 to 0.5x16/10x50=33.3, or decrease of 6.7 Euro.

[1] We assume that no flights depart during the 8 hours of the night.

Both approaches are in some way related to scheduling: the decision of when to travel. The question is which approach should one apply: the first one, the second one, or both? A pragmatic way to answer this question is by looking at what empirical evidence exists on this issue.

We have reviewed some of the results reported in the literature in the context of airport choice: how does a potential air traveller choose which airport to depart from, given his destination and given the flight frequencies offered at competing airports[2].

Pels, Nijkamp and Rietveld (1998) report a study on airport choice done using data for the San Francisco Bay area, which is a multi-airport region. Using a data set for 1995, they estimated different specifications of nested logit models for business passengers and leisure passengers. They did this for different months (August and October), using a ln(freq) specification for the frequency effect in the utility function. For business passengers they found coefficients between 1.1 and 1.5, for leisure passengers between 1.0 and 1.3.

In a different publication, the same authors (Pels, Nijkamp and Rietveld, 2003) report a different analysis using the same data set. The alternative model structure but still using the ln(freq) specification lead to results which suggest slightly higher frequency effects: for both business passengers and leisure passengers they found coefficients between 1.4 and 1.8.

Hess and Polak (2005) analysed airport choices in a different region: the Greater London area. The 1996 Civil Aviation Authorities data that they analysed contains choices between 5 different airports, 37 airlines and 6 access-modes. They used different logit model specifications: multinomial logit (MNL), nested logit (NL) and cross-nested logit (CNL). The coefficients for the ln(freq) variable range from 0.6 for MNL, 0.3 to 0.6 (different NL specifications) to 0.2 (CNL).

Another publication by Hess and Polak (2004) reports a re-analysis of the same data that was used by Pels c.s.: the 1995 San Francisco Bay Area data set. Using just the observations for the business passengers, results were obtained for the ln(freq) specification using different model structures: 1.3 for MNL, 0.3 to 1.3 for NL, 0.5 to 0.9 for CNL and 1.6 for a mixed logit specification.

Finally we mention the work of Stan Abrahams (2000), who has been involved in some of the early research on airport allocation models, going back to the 1990's. He analysed market shares of different airports within the entire UK using standard MNL logit models. Although he did not estimate similar types of specifications as the authors mentioned above, his general results can be worked back into an equivalent ln(freq) specification using some assumptions. The result is a coefficient of about 1.2, which is not inconsistent with the other findings mentioned above.

Table 1: Summary of literature results

[2] Of course other variables influence this decision as well, particularly the distance to the airport. In multivariate analyses these are controlled for, and we look at the frequency effect *ceteris paribus*.

Authors	Data set	Resulting coefficients
Pels, Rietveld and Nijkamp 1998	San Francisco Bay area (1995)	1.1 to 1.5 ln(freq) business 1.0 to 1.3 ln(freq) leisure
Pels, Rietveld and Nijkamp 2003	San Francisco Bay area (1995)	1.4 to 1.8 ln(freq) business 1.4 to 1.8 ln(freq) business
Hess and Polak 2005	Greater London Area (1996)	0.6 ln(freq) for MNL 0.3 to 0.6 ln(freq) for different NL 0.2 ln(freq) for CNL
Hess and Polak 2004	San Francisco Bay area (1995)	1.3 ln(freq) for MNL 0.3 to 1.3 ln(freq) for NL 0.5 to 0.9 ln(freq) for CNL 1.6 ln(freq) for mixed logit, with a standard deviation of 0.7 ln(freq)
Abrahams 2000	United Kingdom (1990's)	Approximately 1.2 ln(freq)

The results mentioned above have been summarised in Table 1. Overall, the available empirical evidence suggests that the utility effect associated with a change in flight frequency, at least in an airport choice context, is between 0.2 and 1.8 times the natural logarithm of the frequency change. The average value is about 1.1 ln(freq), and there are more coefficients above 1.0 than below 1.0. So an estimate of 1.0 for the average ln(freq) coefficient would seem to be a reasonably prudent one. In practice a slightly higher value (e.g. 1.2) for this coefficient might be justified.

4. An example of welfare computation

In Table 2 we give an example of how the demand function including the frequency and other coefficients can be applied in practice. In this example spreadsheet we have included two possibilities to express the generalised cost of service frequency:

- the 1.0 ln(freq) specification, as in [6]
- the waiting time based specification, as in [7].

Either possibility can be applied separately, or in combination. In the example of table 2 both possibilities are combined (W.TIME and ln(freq) set to 1.0). Furthermore we assume that the air passenger Value of time equals 50 Euro/hour, and the scale coefficient equals -0.02.

The example addresses flights from Amsterdam to Madrid. In the BEFORE section five air routes are available: KLM direct flight, KLM/Air France with transfer in Paris, Lufthansa with transfer in Frankfurt, BA with transfer in London/Gatwick and BA with transfer in London/Heathrow. For each of the air routes the following information is given: the standard fare, the total travel time between Amsterdam and Madrid, and the number of flights per day. From this the waiting time is computed as 0.5 x 18/frequency (with maximum 4 hours). Under the heading GENERALISED COSTS these elements are converted into cost equivalents (using the VoT), where Freq contains the waiting time x VoT. Under the heading MARKET first the utility value is given (Total Generalised Cost x scale). The next column contains the Consumer Value: this is equal to exp(Util+1.0ln(freq)). The Choice column contains the estimated market share, which is multiplied with the total number of passengers (Pax; in this case 10,000) to obtain the estimated passenger flows per route.

In the AFTER section the same information is given for essentially the same routes. But here all flight frequencies have been doubled: KLM from 4 to 8 flights per day, KLM/AF from 6 to 12, etc. This results in a reduction of the waiting times and associated generalised cost, which leads to lower total generalised costs. This, in turn, leads lo changed utilities, consumer values, market shares and Pax.

Table 2: Example of computation of welfare effect of frequency doubling

								V. of time:	50	Euro/hour		Scale:	-0.02	W.TIME	1.00
														ln(freq)	1.00
BEFORE						FREQUENCY		GENERALISED COSTS				MARKET			
AIRLINE	APX	HUB1	APY	FARE	T.TIME	FRQ	W.TIME	Time	Freq	Fare	Total	Util	ConsVal	Choice	Pax
				Euro	Hours	Flight/day	Hours								
TOTAL	AMS		MAD			20					455.85	-9.12	1.10E-04	100%	10,000
KLM	AMS	---	MAD	330	2.50	4	2.00	125.00	100.00	330.00	555.00	-11.10	6.04E-05	55%	5506
KLM/AF	AMS	CDG	MAD	300	4.67	6	1.33	233.50	66.67	300.00	600.17	-12.00	3.67E-05	33%	3347
Lufthansa	AMS	FRA	MAD	340	4.50	4	2.00	225.00	100.00	340.00	665.00	-13.30	6.70E-06	6%	610
BA	AMS	LGW	MAD	270	5.50	2	4.00	275.00	200.00	270.00	745.00	-14.90	6.76E-07	1%	62
BA	AMS	LHR	MAD	290	5.75	4	2.00	287.50	100.00	290.00	677.50	-13.55	5.22E-06	5%	475
AFTER						FREQUENCY		GENERALISED COSTS				MARKET			
AIRLINE	APX	HUB1	APY	FARE	T.TIME	FRQ	W.TIME	Time	Freq	Fare	Total	Util	ConsVal	Choice	Pax
TOTAL	AMS		MAD			40					375.60	-7.51	5.47E-04	100%	11,022
KLM	AMS	---	MAD	330	2.50	8	1.00	125.00	50.00	330.00	505.00	-10.10	3.29E-04	60%	6013
KLM/AF	AMS	CDG	MAD	300	4.67	12	0.67	233.50	33.33	300.00	566.83	-11.34	1.43E-04	26%	2619
Lufthansa	AMS	FRA	MAD	340	4.50	8	1.00	225.00	50.00	340.00	615.00	-12.30	3.64E-05	7%	666
BA	AMS	LGW	MAD	270	5.50	4	2.00	275.00	100.00	270.00	645.00	-12.90	9.99E-06	2%	183
BA	AMS	LHR	MAD	290	5.75	8	1.00	287.50	50.00	290.00	627.50	-12.55	2.84E-05	5%	519
												Total Welfare Effect of captive passengers:	80.25		
												In % of Generalised Cost:	17.6%		
												Change in Demand:	10.2%		
												Old Demand:	10,000		
												New Demand:	11,022		
															*000 Euro
												Captive demand:	10,000	80.25	1,605.09
												Changed Demand:	1,022	40.13	82.01
												Total Welfare Effect of Consumers (*000 Euro):			**1,687.10**

The section at the bottom summarises the computation of the welfare effect for passengers. The total welfare effect of the frequency doubling is equal to 80.25 Euro per passenger. In terms of generalised cost this means a 17.6% reduction. Using an average GC demand elasticity of 0.6 this results in an increase of demand by 10.2%. The implied frequency demand elasticity is 0.1 for this frequency doubling. Note that the frequency elasticity will be substantially higher for a single airline that increases its frequency.

Now the welfare effects are computed separately for existing demand and changed demand:

- for existing demand the welfare effect is 10,000 x 80.25 x 2 directions = 1.605 mln Euro/year
- for changed demand the effect is 1,022 x 0.5 (rule of half) x 80.25 x 2 = 0.082 mln Euro/year.

The total welfare effect of the frequency doubling is the sum of both: about 1.7 million Euro/year.

The above example has been computed under the assumption that both the waiting time effect plus the ln(frequency) effect may be added. As we have seen before it is not clear whether or not this is the correct specification; maybe including just 1.0 x ln(frequency) is a more realistic estimate. In Table 3 we give the computed welfare effect of the frequency doubling for various combinations of waiting time effect and frequency effect. The estimated effect for the 1.0 x ln(freq) specification is about 0.7 million Euro/year.

Table 3: Results for various combinations of coefficient values

Waiting time coefficient	0	1	1
ln(frequency) coefficient	1	0	1
Passenger volume	10,563	10,529	11,022
Welfare effect x 1,000 Euro/year	713	977	1,687

5. Conclusions

In this short paper we have presented a simple method to estimate the benefits of changes in generalised costs, and more specifically the benefits of changes in air service frequency, for use in Cost Benefit Analyses.

We have shown that in order to estimate the consumer value for frequency effects we need to have (1) a demand function and (2) an appropriate utility specification and corresponding coefficient(s) for the frequency effect. We have recommended a simple demand model structure for that, consisting of three components: (i) a data base of existing demand, (ii) a growth model, and (iii) a market share model. The data base can usually be derived by combining airport surveys with detailed airport statistics. The growth model can use simple demand elasticity values for key drivers such as GDP, trade, price, population which can be obtained from meta-analyses carried out internationally. The market share model can be a (nested) logit formulation, with utility functions (values of time, scale parameter) obtained from previous studies.

The utility specification of the frequency effect is not obvious. We have discussed two possibilities:

- a ln(frequency) specification,
- a waiting time based specification.

Based upon a limited review of the international airport choice literature, we recommend using the 1.0 ln(freq) specification for frequency cost, although there is evidence that the utility effect of frequency increases may be somewhat higher. More empirical research in this area would be useful to through more light on this issue.

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